Measuring Tourism: Methods, Indicators, and Needs

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Abstract

This contribution examines the wicked problem of adequately measuring tourism in its many facets. This concise survey examines the main techniques used today for assessing tourism flows and their direct, indirect, and induced effects on environmental, socio-cultural, and economic macro-scenarios.

Demand and supply evaluations are explored through the description of traditional time series and econometric models and the main national tourism statistical measurements together with cutting-edge techniques such as the artificial intelligence methods that use the most recent advances in computer science. The important task of estimating the impacts of tourism related activities on the socio-economic environment is discussed by looking at the most popular methods such as the Input-Output model, the Social Accounting Matrix, the Computable General Equilibrium model and the Tourism Satellite Account. Moreover, computerised numerical simulation techniques are called into play for their capability to provide useful insights and outcomes in complex and uncertain situations, typical of the tourism domain.

The analysis discusses the main shortcomings of all these approaches. In an increasingly complicated and fast changing World, many of the foundations up to now considered relatively set have seen, in recent times, a number of disruptive modifications. As a consequence our traditional approaches have lost most of their validity and seem no more fully able to provide useful and reliable insights. Methodological and instrumental changes are sketched as a possible answer to the question.

Keywords

tourism measurement, demand supply, impact of tourism, quantitative methods, numerical simulations, artificial intelligence

Introduction

Tourism is, we all know, a complex phenomenon. Actually tourism is a blanket term under which we strive to include an incredible number of entities, behaviours, activities, sectors or subjects, all more or less related to the movement of people across places or countries. The so many diverse elements that are commonly grouped in the concept even raise the question "as to whether or not tourism is, in fact, too varied and chaotic to deserve separate consideration as a subject or economic sector" (Cooper et al., 2008: 5). Despite this complexity, a wealth of actions, strategies, policies , at local or global level, depend on some kind of measurement of the phenomenon or of its effects.

Now, whenever an action is needed or wanted that concern a phenomenon or a system, our cultural tradition call for the need of a definition of the object and some measurement of its characteristics and evolution in time. This is what we mean by “scientific” approach (Andersen & Hepburn, 2016). When tourism comes into play, however, we have to consider several difficulties that come, essentially, from the fact that we deal with complex adaptive systems. The complexity derives not much from the number or diversity of the items we consider, but rather from the characteristics of the phenomenon and its associated systems., that are relatively easy to recognise. They consist, essentially, of the presence of a certain (large) number of components of different nature that have often non-trivial relationships between them and with the external environment, and whose evolution (individually and as a group) is highly sensitive to the initial conditions. This gives rise to what are called “emergent” phenomena, that is events or configurations that cannot be easily inferred from the individual characteristics of the components that, in a way, come out almost as a surprise and can be only foreseen by using simulation techniques. Moreover the system has a “memory” or includes feedback loops that allow it to adapt itself in accordance with its history or feedback (Johnson, 2009). As many scholars have shown, these are common features of all tourism systems and manifestations (Baggio, 2008; Baggio & Sainaghi, 2011; Farrell & Twining-Ward, 2004; Faulkner & Russell, 1997).

One of the main consequences of having to deal with complex systems is the claimed inherent unpredictability of the system’s dynamics (Boffetta et al., 2002). However, never declared but implicitly assumed in almost all forecast works, a common hypothesis is that all systems exhibit some kind of inertia which drives them along a temporarily stable evolutionary path. This means that while correct long-term predictions are impracticable, with the limitation of not extending a forecast too far in time, we may still use the methods devised so far to attempt a forecast (Andersen & Sornette, 2005; DelSole & Tippett, 2009).

In this chapter we examine the most common methods used in the tourism domain for measuring its aspects and impacts (mainly economic) and discuss their limitations as a requisite for future improvements and refinements.

Measuring tourism: The problem of defining what you want to measure

There is a widespread conviction that managing, governing, controlling or simply understanding phenomena, firms, countries or individuals cannot be achieved without some kind of quantitative measurement, especially since our socio-economic environment has become heavily performance-oriented. In tourism this translates into the need of unified data-driven bases for making decisions, designing plans and strategies, be accountable of the investments made.

Whether real objects or abstract models, an obvious prerequisite for the measurability is the possibility to define the object of study or at least to frame it by delimiting what we want to measure. In many cases (especially psychology or social sciences) this is not possible, therefore we resort to an operationalisation process that allows expressing fuzzy or ill-defined concepts so that they become measurable and understandable in terms of empirical observations. Then, the act of measuring essentially consist of the assignment of a number to a certain feature, object or event so that it can be compared with others (Nagel, 1931; Stevens, 1946).

Modern measurement theory calls for two important characteristics: accuracy, the absence of systematic errors, and precision, the smallness of random measurement errors. In other words measurements are accurate if they are close to the *true* value of what we measure, and precise if all measurements of a quantity are close to each other (Tal, 2016).

Defining tourism is a complicated matter. Actually, as well known, the discussion on "what is tourism?" and on what elements should be considered as belonging to this domain is quite old and many works have been devoted to the analysis of the problem. Practically any book on the subject start with a chapter in which it is possible to find some discussion on these difficulties followed by what a scientist would call an *operational definition*. The fact is that a formal conceptual definition does not exist, and probably will never exist, so we need to resort to something that can allow some kind of practical treatment, mainly for what concerns the decision on what to consider and therefore measure.

This is the case of one of the most used approach, that of the UNWTO which defines tourism as comprising: "the activities of persons travelling to and staying in places outside their usual environment for not more than one consecutive year for leisure, business and other purposes not related to the exercise of an activity remunerated from within the place visited." (UNStats, 2008b: 1) Even in this case, however, the fuzziness of the terms used poses a number of issues for an *accurate* and *precise* measurement of the phenomenon, for what attains to both the 'tourists' and the entities that provide products and services (that which many call 'the industry'). In the latter case, for example, not having a common, shared and agreed, delimitation generates an incredible and often non compatible variety of classifications, so that, practically, no country has been able to clearly and fully define what elements (companies, groups, services, products) belong to the *tourism sector* and no easy way of measuring the activities exist.

However, even in this situation many methods have been devised for assessing the extent and the impacts of tourism in a geographically (or administratively) defined area.

Current methods and main issues

Given tourism's economic importance, it looks natural to adopt an economic terminology and reason in terms of supply and demand.

Demand is made of all those travelling to some place (tourists and destination). It can be measured by taking into account four elements: people (tourists), money (expenditure, receipts), time (stays and travels durations) and space (distances, lengths of trips) (Song et al., 2010). The first two classes of measurements are by far the most common. Despite the efforts of many national and international organisations (see e.g. the recommendations by the UN statistical division, the UNWTO or the European statistical office: (EUROSTAT, 2014; UNStats, 2008a), though, sources and collection methods for demand data differ, often substantially, across countries. Data come often from border counts (police, immigration), supplemented by surveys at entry points (airports, ports); in other cases measurements are taken at tourism accommodation establishments. In some cases peculiar areas are sampled and the results extended by estimation, in other cases counts reflect an actual coverage of all the establishments. Moreover, same people may be counted several times if they travel across a country and stay at different accommodations.

Finally, most of the collection procedures are performed at some local level and must then be aggregated, following the administrative hierarchy, with all the issues related to possible transcription errors, missing items or wrong assessments (Volo, 2004). It must be noted that the issues are the same for both international and domestic travels.

Rather obviously, and possibly with more problems, the same can be said when expenditures are at play, both for a natural reluctance by the travellers in declaring their expenses, and for an intrinsic difficulty in distinguishing whether certain expenses are tourism related or not (Frechtling, 2006). In summary, the overall reliability, consistency, and comparability of the demand measurements, at least at a basic level, is relatively poor, and this raises a number of challenges when parallels and comparisons are made between different areas or countries, or, more importantly, when forecasts are required for making decisions or preparing plans.

Besides the usual figures on tourist arrivals and length of stays, a number of other characteristics are measured, even if not in all countries. These range from socio-demographic distributions (age, gender, education etc.) to economic conditions, to motivations for the trip, to means used for booking and planning, to in-depth analyses of the different geographical origins. A thorough list of the data available in many countries is reported by Lam and McKercher (Lam & McKercher, 2013).

Most of the demand metrics are collected (more or less) regularly at different times. They are then assembled into time series and used for making predictions. Planning, managing, setting policies, defining strategies, deciding investments, at an individual or aggregate level are activities that require a certain “knowledge” of possible future developments, thus forecasting is considered of great importance in the field by both researchers and practitioners, and is one of the most relevant trends in tourism research (Moro & Rita, 2016). Several methods have been devised for forecasting tourism demand. Today we can identify three major groups (Peng et al., 2014): time series models, that use historical data for predicting future trends; econometric models, that look for relationships between demand and some explanatory variables of economic or social nature, so that future demand can be predicted by building scenario of these variables evolution; and artificial intelligence models that use the most recent advances in computer science and apply methods such as neural networks, rough sets theory, fuzzy time-series theory or genetic algorithms for deriving informative outcomes.

Time series analysis is the most popular way for examining the general dynamic behaviour of a tourism system (be it a destination or a single operator) and to forecast possible future situations. A wealth of proposals exist in this field: simple naïve models and exponential smoothing techniques, more elaborate autoregressive integrated moving average (ARIMA) methods with their many variations, sophisticated econometric and statistical approaches. However, according to many studies (Smeral, 2007; Witt et al., 2003) no single forecasting method outperforms the others, and there is a need to combine different methods, better if then the outcomes are revised by using some qualitative judgements (Baggio & Antonioli Corigliano, 2008).

Recent advances in technology and software development have made available a number of techniques rooted in the principles of machine learning. The idea is to let the application iteratively *learn* from data, in order to find insights without explicitly programming where and what to look. Essentially there are three ways to *teach* a machine:

- supervised learning: given a set of inputs and their outputs, a machine is instructed to recognise the pattern in outputs for their respective inputs and attempts to make decisions;
- unsupervised learning: the machine is given only a set of inputs and uses different algorithms to find by itself patterns and structures in the input;
- reinforcement learning: the machine learns dynamically from the data and the environment trying to optimise and maximise some function.

Algorithms such as artificial neural networks (a technique derived from the artificial intelligence attempt to mirror human brain and neural processing) or support vector machines, genetic algorithms, fuzzy systems and hybrid models, have shown to be able to provide comparable or better results than those obtained with more traditional techniques (Asensio et al., 2014; Moro et al., 2014; Pai et al., 2010). Although needing good technical expertise in computer science (and not exactly user-friendly tools), these methods allow the researcher to consider a number of different elements (data) in the process so that more realistic models of the tourists' behaviours can be attained, giving better possibilities to overcome some of the limitations existing when only the *movement* parts (arrivals, stays) of the problem are taken into account (Moro & Rita, 2016).

When it comes to measuring the supply side of tourism, the situation is even more complicated. One of the reasons is that tourism is mainly a consumption phenomenon; the supply side is defined and measured in terms of the demand side. In other terms demand guides the identification of its suppliers, and the characteristics of tourism supply may vary greatly from destination to destination. Moreover, in a single place the distinction between tourism and non-tourism activities can be extremely difficult since there is no possibility to separate fully these types of activities. We can only resort to the SICTA (Standard International Classification of Tourism Activities) proposal, put forward by the UN Statistical Division, that attempts to classify activities distinguishing those that would not exist without travels and those that continue to exist even if there were no travel, albeit at a reduced level (UNStats, 2008a). However, in most cases supply is measured by resorting to counts of accommodation or catering (food and drink) companies thus excluding many components of the tourism system from the national statistics when tourism is considered (Cooper & Hall, 2008). It is no surprise then to find that the supply side of tourism has not received much attention and that, apart from routine counts (hotels, travel agents and similar establishments), not much is done for measuring this component in its entirety.

It must be noted here that a number of recent developments in the way tourism is consumed by travellers have, if possible, worsened the situation. In fact, even if badly defined, we have considered the supply of certain products such as accommodation as a fixed, limited and perishable goods (Vanhove, 2005). On this idea several methods have been developed for the optimisation of the distribution and for maximising the possible revenues. Today, however, the incredible diffusion of alternative forms of accommodation have altered this scenario and modified the traditional view in that, with their capacity of responding dynamically to demand variations, accommodation supply is no more a fixed resource but varies (often in opaque ways) trying to follow the variations of demand (Guttentag, 2015; Tussyadiah & Pesonen, 2016).

Assessing the impacts of tourism

In the second part of last century, tourism has become probably one of the largest sectors of the World economy, and one of the few able to recover quickly from the many crises we have experienced, continuing in a growth at rates that do not seem to fade (UNWTO, 2016; WTTC, 2016). It is no surprise, then, to see a flourishing activity devoted to assess the impact tourism has at global and local levels on the social and economic conditions (Dwyer et al., 2004; Song et al., 2012).

Research, mainly of economic origin, has provided a number of methods and tools for the purpose. The most popular are the Input-Output model, the Social Accounting Matrix, the Computable General Equilibrium model and the Tourism Satellite Account, which is the only specialised tool born in the field .

The input-output (IO) model was first introduced by Leontief (1986) and is a quantitative method to represent, in general, the relationships between different industries of a national economy or different regional economies. Essentially, the model consists in building a table (a matrix) containing the relationship between producers and consumers as well as the interdependencies among industries for a given period (a year) thus reflecting the technical relationship between the level of output and the required inputs, and the balancing of supply and demand for each type of good or service. Relatively simple matrix calculations provide then the so-called multipliers, that show the intensity of interactions by assessing how changes in demand generate changes in output, labour earnings, and employment (Fletcher, 1989; Frechtling & Horvath, 1999). In this way, an input-output model allows estimating direct, indirect and induced impacts of the tourism activities in a defined region. It must be noted here that the model is based on a (strong) assumption linearity in the relations between inputs and outputs from different sectors as well as between outputs and final demand. Additionally, all businesses in a given industry are supposed to employ the same production technology.

A Social Accounting Matrix (SAM) represents the flows of the economic transactions existing in an economy (regional or national). Here too, a matrix is used to represent the national accounts (even if it can be extended to include other accounting flows) and is created for whole regions or areas. SAMs refer to a single year and provide a static picture of the economy. SAMs have been used, when appropriate data were available or could be reasonably estimated, to estimate the weight of tourism and the redistribution effects of tourists' expenditures (Akkemik, 2012; Wagner, 1997).

Computable general equilibrium (CGE) are simulation models that use actual economic data to estimate how changes in policy, technology, production or even external factors might impact the general behaviour of an economy. They build upon a general theory that combines the assumptions on rational economic agents with the investigation of equilibrium conditions. These conditions are usually specified as a system of equations where the functional forms are calibrated to benchmark data. Different methods exist for writing these equations so that their coefficient can be given even when the calibration of the parameters is complicated by their inherent dynamicity (Dixon & Parmenter, 1996).

The model comprises the equations with their variables and parameters, and a database (usually large and detailed) of transaction values and elasticities consistent with the model equations. These are often expressed by IO tables or SAMs. Market clearance, zero profit and income balance are used as conditions to solve the system for the set of prices and the allocation of goods and factors that support a general equilibrium. In some cases, however, the equilibrium conditions may be relaxed and the model may accept non-market clearing (e.g. for labour or commodities), imperfect competition (e.g. monopoly pricing) or demands not influenced by price (e.g. by government). CGE models are widely used for evaluating the impact of economic and policy changes (reforms) because they are reputed to reproduce in the most realistic way the structure of a whole economy and hence the nature of the existing economic transactions among diverse economic agents. Despite their computational complexity and the requirements for great amounts of reliable data, CGE models have seen a good interest in the tourism community and their importance has been stated several times (Dwyer, 2015).

The Tourism Satellite Account (TSA) is a statistical framework jointly developed by a number of international organisations (UNWTO, OECD, Eurostat, UN Statistical Division) as a standardised tool to assess the measurement of the economic impacts of tourism (Frechtling, 2010).

Essentially, a TSA consist of a set of tables that account for the use of resources, the assets, the liabilities of the tourism activities in a certain region for a certain period of time. The different tables contain data on international and domestic tourism expenditures (in- and out-bound), employment, investments (private and public), accounts of tourism industries, and the gross value added (GVA) and gross domestic product (GDP) attributable to tourism plus some non-monetary indicators (same-day trips, overnight stays). The *Tourism Satellite Account: Recommended Methodological Framework* (TSA:RMF, 2008) provides the conceptual framework and the guidelines (definitions, classifications, tables, aggregates etc.) for creating a TSA. All the guidelines are in line with the international standards for reporting national economic activities (SNA, 1993).

The purpose of a TSA is that of harmonising tourism statistics from an economic perspective in the framework of the national accounts, taking into account the balance between demand-side (acquisition of goods and services by tourists on a trip) and supply-side (value of the production by industries). In this way tourism economic data become comparable with other economic statistics.

A TSA is a powerful and useful tool and many countries and regions have put their efforts in building such reports (see e.g. (EUROSTAT, 2017). However, also in this case the solution is far from optimal. Many issues have been raised with the methodology (heavily data-hungry) and with the conceptual approach that seems to adopt a too simplified view of the economic relationships between tourism and the rest of the activities (Smeral, 2006).

In closing this section it must be noted that the methods described here are not to be seen as alternative tools, but they are often used in combination for better assessing tourism impacts (see e.g. (Chou & Huang, 2011).

What's missing towards intelligent futures. How can modern technology help?

The discussion so far, although limited to only a succinct description of the most popular methods for measuring tourism activities and their impacts on the socio-economic environment in which they evolve, makes possible to highlight a number of issues connected with this enterprise.

The first and foremost problem is in the definition of the terms and of the subjects we want to measure. This is a well-known problem that, however, has not received yet a solution. We have temporarily answered the question by using an operational definition that identifies tourists as people who move to some place (where they do not usually live) and tourism suppliers as those entities (companies, associations etc.) that derive their main subsistence from providing some form of assistance to the tourists (place to live, food, entertainment, guidance etc.). This ill-definition of the terms poses a number of severe issues mainly in the measurement of the demand, which is the most important part of the industry (Lam & McKercher, 2013).

However, and more strongly in recent times, a number of different options have been made available to tourists and travellers, mostly originated from the incredible advances in the Information and Communication Technology (ICT) world. Online applications make today the life of travellers much easier than before giving them the possibility to perform all the activities related to the choice and the organisation of their trips without the need for "touching base" with any *physical* entity, or leaving physical traces of their passage. In addition, these tools provide easy access to functions, traditionally well-defined and identifiable such as accommodation for example, that can be now satisfied by a brand new series of operators (if they can be called so) that are out of the usual classifications. These customers, called sometimes *silent travellers* (SKIFT, 2014), do not appear in any of the traditional measurements. The phenomenon is difficult to quantify, but some estimate around 40% the size of the travellers' component using *para-hotellerie* establishments, most of which go practically unreported (IPK, 2014).

The problem of measuring the unobserved component of tourism is not an easy one, and many attempts have been made for improving the measurements using different sources such as electricity consumption, newspaper sales, or other quantities that see variations due to the presence of non-residents such as solid waste; all data that can be available through several official sources with good spatial and temporal resolution (De Cantis et al., 2015; Ezeah et al., 2015; Petrosillo et al., 2006)

Although *silent* the XXI century travellers leave behind them a wealth of digital traces in their movements. Online applications (social networks, search engines, comments and review platforms), given their widespread diffusion, are an exceptional source of information on a wide range of topics (preferences, needs, activities etc.) and can provide good means to assess the real dimensions of tourist flows. On this use of the so-called big data many researchers and practitioners are working and a number of proposals exist for their use for the purpose. (Heerschap et al., 2014; Wood et al., 2013). The same can be said of the data collected by telephone companies (or through the use of other devices capable of GPS positioning) that can provide (when and where available) an even better and more reliable input for estimating the presence of individuals in certain areas (Baggio & Scaglione, 2017; Lin & Hsu, 2014; Shoval & Isaacson, 2010). It is then natural to think then that forecasting can be greatly improved when different sources and methods are used (Bangwayo-Skeete & Skeete, 2015; Choi & Varian, 2009; Gunter & Önder, 2016; Jungherr & Jürgens, 2013; Pan & Yang, 2016). Here the advances in artificial intelligence methods, machine learning and predictive analytics can be of incredible help.

Many of these methods are currently under development and, despite the various examples that have started to appear in the tourism field, no verified and trustworthy way has been found yet for addressing these issues. Specifically, in tourism too little has been achieved, probably for the increased complexity of the environments and the tools needed, not in the tradition of a mainly qualitative or standardised approaches to the measurement of the phenomenon (Baggio, 2016).

It could be trivial to state that, from a methodological perspective, the integration between traditional data collection techniques and the new methods based on varied sources, when correctly applied and rigorously considered (Boyd & Crawford, 2012; Chen & Zhang, 2014), allows for a greater reliability and precision of all the dimensions related to the tourism domain. In fact, all the traditional techniques, even with the many limitations that here too have been highlighted, preserve their validity when, as often happens, are employed with the necessary rigour (Kitchin & Lauriault, 2015). The harmonisation of these two worlds is a known issue and a number of statistical agencies are committed to find common positions on conceptual, methodological and operational approaches, on resolving the issues related to validity, reliability, accessibility, standardisation, on the treatment of privacy, ethics, security, and, obviously, on putting together the right set of competences, resources and funding necessary to face the problem (Kitchin, 2015).

When it comes to the analysis of the impacts, besides any consideration on the economic models at the base of the different assessment methods, the major issue is that their principal characteristic is that practically all of them are static exercises. They provide (if well fed with the right data) a good picture of the situation for a certain region and a certain period of time, but are quite difficult to use for building dynamic evolutionary scenarios and do not provide useful means for assessing the effects of changes (whether smooth or not) in some of the main elements that may determine the outcomes.

Patterns and impacts emerge from the trips of billions of tourists (international and domestic) to countless places. A highly complex phenomenon that, in the last years, has seen a further increase in the dynamicity of both demand and supply sides. While it is relatively simple to enclose in administrative boundaries a place and label it a destination, the real situation is quite different. Movements of people and resources in and out and the environmental, social and economic changes characterise a destination as far from being a closed system, tending to an equilibrium state (Baggio, 2008; Baggio & Sainaghi, 2011). It is clear then that different approaches must be taken if we want to assemble realistic views and, mainly, if we want to achieve a better capability to envisage the possible effects of the changes in one or more of the millions of parameters that enter the game. A promising solution (or at least a reasonable attempt to) is to resort to numerical simulation modelling, that looks well-suited for improving the understanding of socio-economic systems for their capacity to examine and take into account the many dynamic correlations among different human and environmental factors (Gilbert, 1999; Henrickson & McKelvey, 2002).

In this respect agent-based models (ABMs) seem particularly appropriate (Srbljinovic & Skunca, 2003; Toroczkai & Eubank, 2005). An ABM is a way of representing a complex systems and of simulating its multiple potential configurations and outcomes. In an ABM "relations and descriptions of global variables are replaced by an explicit representation of the microscopic features of the system, typically in the form of microscopic entities ('agents') that interact with each other and their environment according to (often very simple) rules in a discrete space-time" (Gross & Strand, 2000: 27). Such simulations are usually relatively easy to set and, with a good attention to their calibration with empirical data and to testing their validity in known situations, are able "to overcome all the simplifying assumptions of homogeneity, linearity, equilibrium, and rationality typical of traditional modelling techniques" (Nicholls et al., 2017: 3). The practice of ABMs in tourism, both for theoretical and practical uses, is still in its infancy, but there is a growing interest in this techniques (Amelung et al., 2016; Johnson et al., 2016).

Concluding remarks: the future of measuring

Measuring tourism is a wicked enterprise to which many, for theoretical or practical reasons, have directed their efforts and knowledge. Despite the innumerable methods and resources put into this enterprise, we have realised that, today, there is a big gap between what we do and can do and we would achieve. This contribution has provided a view (although limited and partial) to what the state of the art is and to what the major problems are.

For the future many possibilities exist, but they require a different mindset, principally from the academic side, seen as the environment able to guarantee the rigour and the validity of the methods and the tools to be used. It is not an easy task, as it requires a profound revision of the attitude towards research and research methodology. Essentially the need is in expanding (or implementing) an active cooperation with other disciplinary environment in order to overcome traditional (and today dysfunctional) distinctions, and to acquire and improve new skills and competences, chiefly for what concerns the treatment of data and the interpretation of the outcomes of procedures that are still being developed and validated. In few words the future tourism researchers must get used not to limit themselves to push buttons of some predetermined standardised software package, but rather strive to better understand and analyse the issues at stake and learn to choose, from the vast catalogue of possibilities offered today, the best, or most suitable, set of algorithms, libraries and techniques for the task.

A full integration between qualitative and quantitative approaches is becoming increasingly important. It is no more a matter of highlighting the well-known benefits of the combination (Baran, 2016), but rather a must if we want to avoid the risks and the pitfalls of unexpected, counter-intuitive or even wrong outcomes (one famous example is the story of Google flu predictions: (Lazer et al., 2014) that might arise from the use of the new analysis methods, or to avoid perpetuating many myths that have been around in the field and that "can be damaging, promulgating falsehoods and inhibiting the development of a field" (McKercher & Prideaux, 2014: 16).

Finally, and rather obviously, without strong decisive collaboration, understanding and support from the industry and public agencies, these goals will stay in the realm of unfulfilled dreams. In this collaborative effort much should be devoted to basic research, as without solid theoretical foundations, the building up of practical (applied) methods and tools seems a highly unlikely endeavour.

References

Akkemik, K. A. (2012). Assessing the importance of international tourism for the Turkish economy: A social accounting matrix analysis. *Tourism Management, 33*(4), 790-801.

Amelung, B., Student, J., Nicholls, S., Lamers, M., Baggio, R., Boavida-Portugal, I., Johnson, P., de Jong, E., Hofstede, G.-J., Pons, M., Steiger, R., & Balbi, S. (2016). The value of agent-based modelling for assessing tourism-environment interactions in the Anthropocene. *Current Opinion in Environmental Sustainability, 23*, 46-53.

Andersen, H., & Hepburn, B. (2016). Scientific Method. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy (Summer 2016 Edition)*. Retrieved July, 2015, from http://plato.stanford.edu/archives/sum2016/entries/scientific-method/.

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

Asensio, J. M. L., Peralta, J., Arrabales, R., Bedia, M. G., Cortez, P., & Peña, A. L. (2014). Artificial intelligence approaches for the generation and assessment of believable human-like behaviour in virtual characters. *Expert Systems with Applications, 41*(16), 7281-7290.

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

Baggio, R. (2016). Big Data, Business Intelligence and Tourism: a brief analysis of the literature. In M. Fuchs, M. Lexhagen & W. Höpken (Eds.), *IFITT workshop on Big Data & Business Intelligence in the Travel & Tourism Domain* (pp. 9-17). Östersund (SE): European Tourism Research Institute (ETOUR), Mid-Sweden University.

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

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

Baggio, R., & Scaglione, M. (2017). Strategic Visitor Flows (SVF) analysis using mobile data. In R. Schegg & B. Stangl (Eds.), *Information and Communication Technologies in Tourism 2017 (Proceedings of the International Conference in Rome, Italy, January 24-26)* (pp. 145-157). Berlin - Heidelberg: Springer.

Bangwayo-Skeete, P. F., & Skeete, R. W. (2015). Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach. *Tourism Management, 46*, 454-464.

Baran, M. L. (Ed.). (2016). *Mixed Methods Research for Improved Scientific Study*. Hershey, PA: IGI Global.

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

Boyd, D., & Crawford, K. (2012). Critical questions for big data: Provocations for a cultural, technological, and scholarly phenomenon. *Information, Communication & Society, 15*(5), 662-679.

Chen, C. P., & Zhang, C. Y. (2014). Data-intensive applications, challenges, techniques and technologies: A survey on Big Data. *Information Sciences, 275*, 314-347.

Choi, H., & Varian, H. R. (2009). *Predicting the present with Google Trends*: Google Inc. Retrieved January 2011, from http://google.com/googleblogs/pdfs/google_predicting_the_present.pdf.

Chou, C. E., & Huang, Y. C. (2011). *Accurately Estimate Tourism Impacts: Tourism Satellite Account and Input-Output Analysis.* Paper presented at the TTRA International, London, Ontario, Canada (June 19-21). Retrieved February 2017 from http://scholarworks.umass.edu/ttra/2011/Visual/36/.

Cooper, C., Fletcher, J., Fayall, A., Gilbert, D., & Wanhill, S. (2008). *Tourism Principles and Practice* (4th ed.). Harlow, UK: Pearson Education.

Cooper, C., & Hall, C. M. (2008). *Contemporary Tourism: An International Approach*. Oxford: Butterworth-Heinemann.

De Cantis, S., Parroco, A. M., Ferrante, M., & Vaccina, F. (2015). Unobserved tourism. *Annals of Tourism Research, 50*, 1-18.

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

Dixon, P. B., & Parmenter, B. R. (1996). Computable general equilibrium modelling for policy analysis and forecasting. In H. M. Amman, D. A. Kendrick & J. Rust (Eds.), *Handbook of computational economics* (Vol. 1, pp. 3-85). Amsterdam: North-Holland.

Dwyer, L. (2015). Computable general equilibrium modelling: an important tool for tourism policy analysis. *Tourism and Hospitality Management, 21*(2), 111-126.

Dwyer, L., Forsyth, P., & Spurr, R. (2004). Evaluating tourism's economic effects: new and old approaches. *Tourism Management 25*, 307-317.

EUROSTAT. (2014). *Methodological manual for tourism statistics*. Luxembourg: Office for the Official Publications of the European Communities.

EUROSTAT. (2017). *Tourism Satellite Accounts in Europe - 2016 edition* Luxembourg: Office for the Official Publications of the European Communities. Retrieved February 2017, from http://ec.europa.eu/eurostat/documents/7870049/7880233/KS-FT-17-002-EN-N.pdf.

Ezeah, C., Fazakerley, J., & Byrne, T. (2015). Tourism Waste Management in the European Union: Lessons Learned from Four Popular EU Tourist Destinations. *American Journal of Climate Change, 4*(5), 431-445.

Farrell, B. H., & Twining-Ward, L. (2004). Reconceptualizing Tourism. *Annals of Tourism Research, 31*(2), 274-295.

Faulkner, B., & Russell, R. (1997). Chaos and complexity in tourism: in search of a new perspective. *Pacific Tourism Review, 1*, 93-102.

Fletcher, J. E. (1989). Input-output analysis and tourism impact studies. *Annals of Tourism Research, 16*(4), 514-529.

Frechtling, D. C. (2006). An assessment of visitor expenditure methods and models. *Journal of Travel Research, 45*(1), 26-35.

Frechtling, D. C. (2010). The tourism satellite account: A primer. *Annals of Tourism Research, 37*(1), 136-153.

Frechtling, D. C., & Horvath, E. (1999). Estimating the multiplier effects of tourism expenditures on a local economy through a regional input-output model. *Journal of Travel Research, 37*(4), 324-332.

Gilbert, N. (1999). Simulation: A New Way of Doing Social Science. *American Behavioral Scientist, 42*(10), 1485-1487.

Gross, D., & Strand, R. (2000). Can agent-based models assist decisions on large-scale practical problems? A philosophical analysis. *Complexity, 5*, 26-33.

Gunter, U., & Önder, I. (2016). Forecasting city arrivals with Google Analytics. *Annals of Tourism Research, 61*, 199-212.

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current Issues in Tourism, 18*(12), 1192-1217.

Heerschap, N., Ortega, S., Priem, A., & Offermans, M. (2014). *Innovation of tourism statistics through the use of new big data sources.* Paper presented at the 12th Global Forum on Tourism Statistics, Prague, CZ, 15-16 May. Retrieved July 2014 from http://www.tsf2014prague.cz/assets/downloads/Paper%201.2_Nicolaes%20Heerschap_NL.pdf.

Henrickson, L., & McKelvey, B. (2002). Foundations of ‘‘new’’ social science: Institutional legitimacy from philosophy, complexity science, postmodernism, and agent-based modeling. *Proceedings of the National Academy of the Sciences of the USA, 99* (suppl. 3), 7288-7295.

IPK. (2014). *ITB World Travel Trends Report*. Berlin: Messe Berlin GmbH. Retrieved February 2017, from http://www.itb-berlin.de/media/itbk/itbk_dl_en/WTTR_Report_A4_4_Web.pdf.

Johnson, N. F. (2009). *Simply complexity: A clear guide to complexity theory*. Oxford, UK: Oneworld Publications.

Johnson, P., Nicholls, S., Student, J., Amelung, B., Baggio, R., Balbi, S., Boavida-Portugal, I., de Jong, E., Hofstede, G.-J., Lamers, M., Pons, M., & Steiger, R. (2016). Easing the adoption of agent-based modelling (ABM) in tourism research. *Current Issues in Tourism,* (doi: 10.1080/13683500.2016.1209165).

Jungherr, A., & Jürgens, P. (2013). Forecasting the pulse. How deviations from regular patterns in online data can identify offline phenomena. *Internet Research, 23*(5), 589-607.

Kitchin, R. (2015). The opportunities, challenges and risks of big data for official statistics. *Statistical Journal of the IAOS, 31*(3), 471-481.

Kitchin, R., & Lauriault, T. P. (2015). Small data in the era of big data. *GeoJournal, 80*(4), 463-475.

Lam, C., & McKercher, B. (2013). The tourism data gap: The utility of official tourism information for the hospitality and tourism industry. *Tourism Management Perspectives, 6*, 82-94.

Lazer, D. M., Kennedy, R., King, G., & Vespignani, A. (2014). The parable of Google Flu: Traps in big data analysis. *Science, 343*(14), 1203-1205.

Leontief, W. (1986). *Input-Output Economics*. Oxford: Oxford University Press.

Lin, M., & Hsu, W. J. (2014). Mining GPS data for mobility patterns: A survey. *Pervasive and Mobile Computing, 12*, 1-16.

McKercher, B., & Prideaux, B. (2014). Academic myths of tourism. *Annals of Tourism Research, 46*, 16-28.

Moro, S., Cortez, P., & Rita, P. (2014). A data-driven approach to predict the success of bank telemarketing. *Decision Support Systems, 62*(1), 22-31.

Moro, S., & Rita, P. (2016). Forecasting tomorrow’s tourist. *Worldwide Hospitality and Tourism Themes, 8*(6), 643-653.

Nagel, E. (1931). Measurement. *Erkenntnis, 2*(1), 313-335.

Nicholls, S., Amelung, B., & Student, J. (2017). Agent-based modeling: A powerful tool for tourism researchers. *Journal of Travel Research, 56*(1), 3-15.

Pai, P. F., Lin, K. P., Lin, C. S., & Chang, P. T. (2010). Time series forecasting by a seasonal support vector regression model. *Expert Systems with Applications, 37*(6), 4261-4265.

Pan, B., & Yang, Y. (2016). Forecasting destination weekly hotel occupancy with big data. *Journal of Travel Research, doi: 10.1177/0047287516669050*.

Peng, B., Song, H., & Crouch, G. I. (2014). A meta-analysis of international tourism demand forecasting and implications for practice. *Tourism Management, 45*, 181-193.

Petrosillo, I., Zurlini, G., Grato, E., & Zaccarelli, N. (2006). Indicating fragility of socio-ecological tourism-based systems. *Ecological Indicators, 6*, 104-113.

Shoval, N., & Isaacson, M. (2010). *Tourist mobility and advanced tracking technologies*. New York, NY: Routledge.

SKIFT. (2014). *The 14 Trends That Will Define Travel In 2014*. Retrieved June 2016, from http://skift.com/2014/01/06/skift-report-14-global-trends-that-will-define-travel-in-2014/.

Smeral, E. (2006). Tourism satellite accounts: a critical assessment. *Journal of Travel Research, 45*(1), 92-98.

Smeral, E. (2007). World tourism forecasting - keep it quick, simple and dirty. *Tourism Economics, 13*(2), 309-317.

SNA. (1993). *System of National Accounts*. New York: United Nations Statistical Division.

Song, H., Dwyer, L., Li, G., & Cao, Z. (2012). Tourism economics research: A review and assessment. *Annals of Tourism Research, 39*(3), 1653-1682.

Song, H., Li, G., Witt, S. F., & Fei, B. (2010). Tourism demand modelling and forecasting: how should demand be measured? *Tourism Economics, 16*(1), 63-81.

Srbljinovic, A., & Skunca, O. (2003). An Introduction to Agent Based Modelling and Simulation of Social Processes. *Interdisciplinary Description of Complex Systems, 1*(1-2), 1-8.

Stevens, S. S. (1946). On the theory of scales and measurement. *Science, 103*, 677-680.

Tal, E. (2016). Measurement in Science. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy (Winter 2016 Edition)*. Retrieved July, 2015, from http://plato.stanford.edu/archives/win2016/entries/measurement-science/.

Toroczkai, Z., & Eubank, S. (2005). Agent-Based Modeling as Decision-Making Tool. *The Bridge, 35*(4), 22-27.

TSA:RMF. (2008). *Tourism Satellite Account: Recommended Methodological Framework*. Madrid: UN World Tourism Organization.

Tussyadiah, I. P., & Pesonen, J. (2016). Impacts of peer-to-peer accommodation use on travel patterns. *Journal of Travel Research, 55*(8), 1022-1040.

UNStats. (2008a). *International Recommendations for Tourism Statistics 2008*. New York: United Nations, Department of Economic and Social Affairs - Statistics Division.

UNStats. (2008b). *Tourism Satellite Account: Recommended Methodological Framework 2008*. New York: United Nations, Department of Economic and Social Affairs - Statistics Division.

UNWTO. (2016). *Tourism Highlights, 2016 Edition*. Madrid: World Tourism Organization.

Vanhove, N. (2005). *The Economics of Tourism Destinations*. London: Elsevier Butterworth-Heinemann.

Volo, S. (2004). *A journey through tourism statistics: accuracy and comparability issues across local, regional and national levels.* Paper presented at the 24th SCORUS Conference on Regional and Urban Statistics and Research, Minneapolis, USA (19-21 May). Retrieved January 2017 from http://scorus.org/wp-content/uploads/2012/10/2004MinnP6.2.pdf.

Wagner, J. E. (1997). Estimating the economic impacts of tourism. *Annals of Tourism Research, 24*(3), 592-608.

Witt, S. F., Song, H., & Louvieris, P. (2003). Statistical testing in forecasting model selection. *Journal of Travel Research, 42*(2), 151-158.

Wood, S. A., Guerry, A. D., Silver, J. M., & Lacayo, M. (2013). Using social media to quantify nature-based tourism and recreation. *Scientific reports, 3*, art.2976.

WTTC. (2016). *Travel & Tourism Economic Impact 2016 World Report*. London: World Travel & Tourism Council.