Towards Improved Event Evaluation and Decision Support: A Systems-Based Tool

G. Michael McGrath
Centre for Tourism and Services Research
Victoria University
michael.mcgrath@vu.edu.au

Abstract

There would appear to be little point in promoting specific events if social and environmental costs outweigh the economic benefits. In recognition of this, a number of tourism researchers have proposed and experimented with more all-encompassing (or holistic) approaches to event evaluation. A weakness of these approaches, however, is that most do not readily allow impacts over time and delays to be factored into the evaluation process. In this paper, ‘system dynamics’ is proposed as the basis for a solution to this problem. An additional benefit of the recommended approach is that the events evaluation model can readily be implemented as a decision support system.

1. Introduction

Events often bring considerable economic benefits to their host regions. At the same time, many events have substantial environmental and social impacts and, quite frequently, these are negative. One consequence of this is an increasing, recent body of research directed at a more holistic approach to event evaluation (see e.g. [1, 2, 3]).

Events though, are also highly-complex phenomena. The many variables within each of the economic, environmental and social (sub)systems interact with each other (within and between systems) in a myriad variety of unpredictable and complex ways. The result is a classic example of a problem domain described by Vennix [4] as ‘messy’: i.e. a domain characterized by complexity, uncertainty, recursive dependencies and interrelated sub-problems[4: 13-25].

System dynamics (SD) is a problem-solving, modelling and simulation approach that has proven itself to be well-suited to understanding and analysing messy problems [5] and, in this paper, we explore its application to the events domain. We contend that two significant benefits result from this: first, time-dependent factors are inherent in the evaluation framework, thereby addressing a significant weakness with other approaches to holistic event evaluation [2: 4]; and, second, our events model may readily be implemented as a powerful, simulation-based decision support tool.

Note, however, that this research is very-much conceptual and preliminary. While the SD, events and more-general tourism literature bases have been drawn on liberally, the various models presented here are not supported by any detailed, empirical research. Our intention in this paper is simply to draw attention to the power and potential of the SD approach and to specify a broad framework that might serve as a useful foundation for more serious development of a detailed and evidence-based model (and associated decision support system).

2. Background

2.1. Holistic event evaluation

There is an increasing recognition that, consistent with more general trends in tourism research and industry practice, event evaluation must move beyond its traditional focus on economic issues to encompass the social and environmental dimensions [3]. Essentially, this is in recognition of the fact that, while some events may result in significant economic benefits for the host region, they may also have other, negative consequences: e.g. increased traffic noise, crime, waste, spikes in energy and water usage, and more general environment despoilment. Thus, any serious attempt to specify a holistic events evaluation framework must include both: i) factors within each of the economic, social and environmental systems; and ii) interactions within and between each of these three systems.

One of the more significant, recent attempts at specifying such a framework is that of Fredline et al. [2]. Their approach is grounded squarely in the ‘triple
bottom line’ (TBL) concept [6, 7] and one of their key objectives is to represent the outcomes of an event evaluation in a form that is comprehensive but sufficiently non-complicated that it affords an overall view without the need for complicated interpretation and analysis. To accomplish this, they employ a ‘synthesis diagram’ an example of which is presented in Figure 1. Here, the TBL impact of an event can “be expressed by the ratio between the area of the plotted triangle and the theoretical maximum defined by the outer limits of the diagram” [2: 12]. Thus, Figure 1 might represent a moderately successful event overall, an extremely successful event from an economic viewpoint but something of a worry when viewed from an environmental perspective (e.g. some sort of motorsport event might fit this profile).

Figure 1. Synthesis diagram for TBL event evaluation.

Each of the three TBL dimensions represented in the radar chart presented in Figure 1 is composed of a number of underlying variables and many of these variables impact on each other (within and between dimensions). Moreover, many of these cause-effect relationships will vary significantly with time and this suggests that the ‘snapshot’ view of an event evaluation could usefully be extended to encompass dynamic (or time-dependent) aspects. We now turn our attention to a modelling and simulation approach that seems to have much to offer in this respect.

2.2 The systemic view of a sustainable tourism system

The systemic or holistic view of a ‘sustainable tourism system’ is considered by some (e.g. [8: 1]) to have its roots in the work of Brundtland [9] and its many manifestations include the Mill and Morrison model [10] (focusing on a ‘chicken-and-egg’ like relationship between consumer travel decisions and destination marketing), the TBL concept (see above), and the ‘competitive destination’ model of Ritchie and Crouch [11]. The WTO [12] defines a sustainable tourism destination as a region where:

“----- tourism development meets the needs of present tourists and host regions while protecting and enhancing opportunities for the future. It is envisaged as leading to management of all resources in such a way that economic, social and aesthetic needs can be fulfilled while maintaining cultural integrity, essential ecological processes, biological diversity and life support systems.”

The holistic view of a tourism destination seems to be now almost universally accepted among researchers and policy makers (if not industry practitioners) and, given this, it is perhaps a little surprising that greater advantage has not been taken of methods, tools and techniques commonly employed in ‘system dynamics’ (SD) (or ‘systems thinking’) research and practice. SD has its origins in the work of Forrester [13] and, more recently, has enjoyed something of a resurgence – largely due to Peter Senge’s [14] very influential work on ‘the learning organization’ and the development and release of easy-to-use, powerful, SD-based software modelling and simulation tools (such as iThink, Vensim and Powersim). Recent examples of where SD has been used to good effect in tourism include the ‘Tourism Futures Simulator’ of Walker et al. [15], the hotel value chain modeling work of Georgantzas [16], the tourism multipliers model of Loutif et al. [17] and the tourism information architecture modelling work of McGrath and More [18].

In their simplest form, SD models are represented as ‘causal-loop diagrams’ (CLDs). The reader looking for a more thorough introduction to CLDs is referred to [5] but, essentially, only one modelling construct is employed; an arrow connecting two domain variables, indicating a causal connection between them. Arrows are generally annotated with either a ‘+’ or ‘-‘; a ‘+’ symbol meaning that both variables move in the same direction (i.e. increase or decrease together) and a ‘-‘ symbol meaning that the variables move in opposite directions. We employ a third annotation symbol, the question mark, ‘?’ – meaning that we are unsure of the exact nature of the causal connection or that the connection is too complex to represent with the two basic annotations.

The usual approach in developing a SD model though, is to: i) specify the problem domain as a CLD and, then, ii) implement it in the slightly more complex stock-flow syntax employed by the software packages referred to above. In this section we restrict ourselves to CLDs. Examples of stock-flow models (implemented in Powersim [19]) will be introduced in later sections.
An example of a CLD is presented in Figure 2. This is a high-level representation of the ‘Tourism Enterprise Planning Simulator’ (TEPS) detailed in [20]. The aim here was to provide prospective and existing tourism enterprise operators with a planning tool, based on a total systems view and designed to complement traditional business planning tools.

Figure 2. SD representation of factors associated with tourism enterprise profitability.

Region attractiveness is at the heart of the model presented in Figure 2. An attractive region makes local enterprises more attractive themselves and, together, region and enterprise attractiveness lead to more tourists. More tourists result in healthier room occupancy rates and (with qualifications) this, in turn, improves enterprise profitability. As enterprises become more profitable, more development takes place and, up to a point, developed regions and enterprises will draw even more tourists, resulting in a classic reinforcing loop. This, of course, holds true only to a point as, consistent with the ‘tourism life-cycle model’ [21], over-development eventually leads to a tourism decline. (This accounts for the ? annotation on the development → tourists link in Figure 2: i.e. early in the life-cycle, more development generally results in more tourists but, once a certain point is reached, (over)development may well cause a visitor downturn.) Reinforcement is also moderated by the tendency of development to impact negatively on both enterprise profitability and occupancy rates.

In addition, development leads to environment despoilment and, in turn, this detracts from both region and enterprise attractiveness. Thus, with the addition of this balancing loop, we now have the essence of the classic sustainable tourism model [11]. Damage to the environment, however, may be limited by appropriate mitigation measures. There is a cost associated with effective and committed environment despoilment mitigation though and, ultimately, part of this must be borne by local tourism enterprises (as indicated by the despoilment mitigation → profitability link in our diagram).

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The model presented in Figure 2 is specified at a very-high level. Already though, a degree of complexity is apparent and this illustrates one of the benefits of SD modelling as claimed by its proponents: specifically, the approach can counter our tendency to over-simplify complex problems and issues into simple cause-effect relationships we can readily understand within the limits of our cognitive powers [4]. Of course, this is true of many conceptual modelling approaches and each of these have their own strengths and weaknesses. SD, however, is particularly well-suited to domains where feedback loops and time are significant [22] and both of these feature prominently in tourism models (see e.g. [11: 60-78].

A further strength of SD models is that, in basic CLD form, they are comprised of combinations of only one, simple construct (a causal connection between two variables), meaning that key stakeholders and end-users may readily contribute to modelling sessions. As noted earlier, CLD models are generally implemented in the stock-flow form favoured by the more popular SD software packages. This increases complexity but it also enables the specification of critical concepts such as delays, queues, events and major environmental perturbations (e.g. the impacts of SARS or the periodic, dramatic increase in global oil prices).

At the same time, the more variables a problem has, the more difficult it is to solve. In fact, problem difficulty tends to increase exponentially with the number of variables. Thus, (seemingly) simple systems can rapidly become very complex – and even our gentle introductory example above should leave little doubt that, in tourism, we are dealing with a very complex system.

The essence of our TEPS model is that we have specified the operations of a tourism enterprise within a destination-level model of the type described by Walker et al. [15]. Essentially, there seems to be no reason why tourism events should not be treated in the
same way and this is our focus in the remainder of the paper.

3. Top-level model (CLD representation)

Any non-trivial events model that attempts to take a multi-dimensional (or holistic) view of the domain will necessarily be fairly complex [2]. To manage this complexity, we employ the time-honoured modelling approach of decomposition and, in particular, we (loosely) adopt conventions and techniques used in ‘data flow diagrams’ [23]. Thus, our top-level model is a simple CLD representation of the TBL view of an event, indicating that each event has economic, social and environmental dimensions and that these are all interrelated. At Level 1, the economic impacts component has been (arbitrarily) designated as Model 1, the social impacts component as Model 2 and the environmental impacts component as Model 3. In this paper we focus to a large extent on event transport impacts (and the consequences of these for the social and environmental subsystems).

We turn our attention to transport in the following section. Before that, however, we illustrate some of the more important causal connections between transport and social system variables in Figure 3 following. A number of these connections are considered in greater detail later in the paper but, to follow just one chain of causal connections, starting from top-left: the larger the event size, the greater the crowding and this, in turn, may lead to an increase in both crime and restrictions. Restrictions may cause frustration and this (together with crime) may result in increased levels of anger and stress among the local community. Some of this anger will be directed at the event and, consequently, local attitudes (towards the event) may suffer, leading to a decline in local participation etc.

As Maani and Cavana [5] note, the beauty of CLDs (such as that in Figure 3) is that they improve our ability to cope with and analyse complex problems and phenomena. To unleash the full potential of SD, however, and provide ourselves with a useful policy-making aid and decision-support tool, CLDs must be converted into stock-flow form. We now turn our attention to this issue.

Figure 3. Level 1 – Model 2: CLD representation of some transport-related social impact variables.
4. Transport impacts (stock-flow) view

The SD simulator has been initialized to run for 40 quarters from the commencement of the current year ($t = 1$). All variables are specified as indices. For example, $TransportImpact_t$ is an index of the predicted impact of an event on transport, plotting percentage changes over time, on a quarterly basis against a base quarter. The December quarter year 0 is used as the base quarter and is assigned a value of 100. Where later values exceed 100, it indicates growth in comparison to the base quarter while values less than 100 indicate decline. The method is the same as that employed in [24] and, where possible, the assumption is made that trends will be similar to actual figures that are generally available. Most model variables (real and artificial) are standardized in this way.

The broad approach employed here is based loosely on that detailed by Burns et al. [25]. Here, the total value of time lost in traffic, at a particular destination at time $t$ ($TravelCost_{raw,t}$), and where $t$ is measured in quarters, is specified as:

$$TravelCost_{raw,t} = GNPCont \sum_{i=1}^{n} TravTime_i TravPop_i TIVarn$$

where:

$TravelCost_{raw,t}$ is the is the total quarterly dollar value of the destination travelling population’s time lost in traffic, while commuting via location route $i$ at time $t$;

Each $i$ signifies one of a representative sample of $n$ commuter routes within the destination; $\text{GNPCont}_t$ is the average (national) quarterly contribution to GNP per individual at time $t$;

$TravTime_i$ is the is the average, daily travelling time (in hours) for the travelling population using route $i$; and

$TravPop_i$ is the size of the travelling population using route $i$.

The standardised cost of travel at time $t$ may then be specified as:

$$TravelCost_t = (TravelCost_{raw,t}/TravelCost_{raw,0}).100$$

The stock-flow implementation of the transport impact component of our model is presented in Figure 4.

4. The basic building blocks of system dynamics models are stocks (represented as rectangles), flows (represented as arrows with circular flow regulators attached), converters (represented as circles) and constants (represented as diamonds). In our model, examples of stocks are $Travel Cost$ and $Transport Impact$. There is a level associated with each stock, which can be an actual value or a value bounded by some artificial scale. $Transport Impact$ for example, is measured on an artificial scale (as defined previously) and we have set the system up so that, when its value is 100, the system is in equilibrium. That is, any other system parameters, dependent on errors, will also remain constant (at 100). Stock levels vary with flows, which may be inflows, outflows or bidirectional. For example, $TIVarn$ (transport impact variation) is a bidirectional flow such that:

$$TransportImpact_t = f(TransportImpact_{t-1}, TIVarn_t).$$

That is, in our model, the transport impact level at time $t$ is a function of the transport impact level at time, $t-1$, and its variation at time, $t$. These equations are the foundation of Powersim’s formidable simulation capabilities. The third of our basic constructs, converters, serve a utilitarian role: they hold values for constants, calculate mathematical relationships and serve as repositories for graphical functions. In general, they convert inputs into outputs (hence, the name, “converter”). A converter with double circles indicates an array and a diamond

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1 The $n$ locations must be representative demographically: e.g. in terms of both geographical position (in relation to major residential areas, and commercial and industrial centres) and socio-economic groupings.
indicates a constant (essentially a converter that does not change its value during the course of a simulation). A model construct represented in the style of *period* indicates a *snapshot* (a copy of a variable specified primarily in some other area of the model).

For a major metropolitan city, where a large percentage of commuters use their cars to get to and from work and where the bulk of transport infrastructure investment is directed towards roads (rather than rail and other forms of public transport), travel costs over a 10-year period might look something like the pattern illustrated in Figure 5. This, of course, is the classic ‘freeway effect’, where major road projects are completed every few years. This results in a short-term improvement in travel times, followed by a fairly rapid return to the longer-term worsening trend (as the number of vehicles increases—and then exceeds—available freeway capacity).

![Figure 5. Base travel costs (standardized) over 10 years.](image)

Events may have an impact on travel and transport in two basic ways: first, if significant enough, events may generate new transport infrastructure (both public and private); and, second, additional transport costs are generally associated with the running of the events themselves. Thus:

\[
\text{TransportImpact}_t = \text{EventTransport}_t \times \text{TransportInfrast}_t(\text{TravelCost}_t)
\]

where:

- \(\text{TransportImpact}_t\) is a standardised index indicating the impact of transport at time \(t\) on the population of the location where an event is held;
- \(\text{TravelCost}_t\) is the standardised cost of travel at time \(t\) (as defined above);
- \(\text{TransportInfrast}_t\) is the standardised impact of the development of transport infrastructure at time \(t\) (and is a 1\(^{st}\)-order function applied to \(\text{TravelCost}_t\)); and
- \(\text{EventTransport}_t\) is the standardised impact of the conduct of an event on the cost of transport (and is a 2\(^{nd}\)-order function applied to \(\text{TravelCost}_t\)).

Rarely will an event have an immediate, direct and clearly identifiable impact on a destination’s transport infrastructure. Consequently, \(\text{TransportInfrast}_t\) (for all \(t\)) is set to neutral (i.e. it does not transform its argument).

A large event (relative to location size) may result in transport infrastructure changes that can be readily identified and, perhaps, quantified. For example, the development of enhanced road and rail links was clearly (at least in part) a direct result of the Sydney 2000 Olympics. Similarly, an annual series of semi-large events at a medium-sized provincial location (or even one annual, relatively-large event at a remote location) may also have an impact on transport infrastructure. Where this does occur (and a quantifiable impact can be estimated with a reasonable degree of confidence), the model can be adjusted by directly instantiating the \(\text{IofTIIonTI} (\text{impact of transport infrastructure impact on transport impact})\) variable at the level of the base model (see Figure 4).

The actual running of an event though, will have an impact on transport in many cases. Thus, \(\text{EventTransport}_t\) is not assumed to be neutral and the user is required to establish a base value for this variable by selecting the appropriate option from a ‘Transport Impact’ control box (part of the users ‘control panel’). This has the effect of setting the base \(\text{ITI} (\text{base immediate transport impact})\) variable in Figure 4 to a value that will remain constant for the duration of the simulation.

The user is also required to select an ‘Event Quarter’. This is the quarter in which the event takes place. It is recognized that some events may take place in more than one quarter, that others may straddle quarters and that still others may not take place in the same quarter every year. At present, the model does not cater for these. That is, at this stage the model has been customized for annual events run at the same time each year.

\[3\] For example, the annual 8-11 (major national league) football games held at the Victorian provincial city of Geelong has clearly been a factor in the various upgrades to Melbourne-Geelong road links over the last 100 years. However, clearly distinguishing this from the effects of daily commuter Geelong-Melbourne traffic (or the steady stream of summer holiday and tourist traffic heading for Victoria’s Western region surf beaches and Great Ocean Road via Geelong) would not be easy.
Results of a sample simulation run are presented in Figure 6. This is, essentially, the base travel cost graph presented earlier (see Figure 5), inverted and modified to take into account the transport impacts of a major annual event. This profile could fit (for example) a Formula 1 Grand Prix, where the transport impacts are almost entirely negative and are indicated by the regular, annual, blips (negative pulses) clearly evident on the graph.

![Figure 6. Transport impacts – sample simulation output.](image)

To this point, development of our SD model has been reasonably straightforward, in that we should be able to instantiate our base transport impacts model variable (see Figure 4) with values that are reasonably accurate. In addition, much of the base data required is publicly available or can be derived from same and, thus, standard statistical variance tests can be performed against simulation outputs to ensure that the model behaves ‘sensibly’. Event transport, however, may impact significantly on a number of variables that belong primarily to the social domain and many of these are more ‘fuzzy’ in nature. We now turn our attention to how we might extend our base transport impacts model to include some key variables from the social subsystem.

### 5. Extensions to the transport impacts model: the social dimension

In this section, we extend the transport impacts model presented in Figure 4 to include the impacts of event transport on community anger and stress, health, event attitudes and consequent participation levels. A CLD representation of this extended model is presented in Figure 7.

![Figure 7. The extended transport impacts model.](image)

Starting from centre-left of Figure 7, one event transport impact may be traffic congestion and this, in turn, is likely to cause anger and stress. Anger and stress may have impacts on community health in two ways: first, there may be an increase in traffic accidents; and, second, it may have more direct impacts as a result of heart problems, nervous conditions etc. Next, it is highly probable that at least some of this anger might be directed towards the event, with a consequent decrease in local support (local attitudes). In addition, if health-related problems (and costs) increase beyond a certain point, this may also reflect itself in decreased levels of local support. Finally, if support suffers, so too will local participation and, if this happens, event-related transport problems may well diminish to some extent.

Space does not permit the presentation of the extended stock-flow model but results of a typical simulation run are presented in Figure 8. It can readily be seen that when the event is first run, participation is average (=100) and anger and stress levels are low. As time goes by though, the event becomes more popular and anger and stress increase. Eventually, a point is reached where the event becomes so unpopular that participation levels begin to drop off (at about year 6) and continue to do so for some time. Note that there is a reasonably significant time lag before locals’ anger has a noticeable effect on participation. This is typical of many real-world problems and a failure to factor such delays into decision-making processes is a frequent cause of policy failures [4].
In reflecting on this simulation though, we might (for example) be concerned about the accuracy of the values we have assigned to some variables. Powersim has a powerful risk analysis package\(^4\) and, using this, we may investigate our model’s sensitivity to changes in independent variables (or, more precisely, variables we decide to declare ‘independent’ for some particular purpose). Basically, all that is required is to specify a mean and standard deviation for each of our independent variables, stipulate that some other variable is the dependent (or ‘effect’) variable and, then, initiate a series of simulation runs (the default is 40 runs) through the risk analysis software.

As an example, assume we are concerned about the model’s sensitivity to changes in traffic congestion. We declare this variable (traffic congestion) to be the independent variable and local participation to be the dependent variable. The result is the ‘high-low’ graph presented in Figure 9 and, here, it can be seen that around 80% of the variance (the area between the (90% and 10% lines) is within a 14-15% range (approximately)\(^5\). We conclude, therefore, that the model is somewhat sensitive to change in traffic congestion but not unduly so. We could then conduct further risk analysis experiments to determine precisely which variables (or combination of variables) do influence model behaviour most. The importance of conducting this type of ‘sensitivity analysis’ has long been known in SD circles – early guidelines having been formulated by Coyle [26: 193] over 30 years ago.

### 6. Model validation

SD models are notoriously difficult to validate [22]. As noted by Forrester and Senge [27: 209-210], there is no single test which might be employed to validate an SD model but, rather, confidence in the model accumulates gradually as it passes more tests and as new points of correspondence between the model and empirical reality are identified. Maani and Cavana [5: 69-70], drawing on the work of Coyle [28: 362], describe this process as consisting of:

- **Verification tests** – which focus on the equivalence between the structure and parameters of the real system and the model;
- **Validation tests** – which are concerned with demonstrating the correspondence between the behaviour of the real system and the model; and
- **Legitimation tests** – which determine whether the model is in accord with any generally-accepted system rules.

Essentially, the aim of validation is to “show that there is nothing in the model that is not in the real system and nothing significant in the real system that is not in the model” [5: 69]. An excellent example of how much of this can be accomplished through desk checking has been provided by Georgantzas [16] where statistical measures, such as coefficient of determination and Theil’s inequality statistics (TIS) [29], were employed to compare the predictive results of an SD model focused on various key measures of the performance of Cyprus hotels against actual data (over a 40 year period). Similarly, we could subject our own model to similar tests, concentrating on measures for which data is readily available (such as accidents, community health and local participation). An example of the type of output that results from this type of analysis is presented in Figure 10.

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\(^4\) These packages, together with Powersim’s underlying SD simulation capability, are the basis of the DSS referred to earlier. In effect, the SD model *is* the DSS – although some care generally needs to be taken in designing a user-friendly front-end.

\(^5\) e.g. the range is roughly 125-145 at year 2011 and 60-70 at the end of the simulation (year 2015).
The basis of Theil’s approach is that the mean square error (MSE) is divided into three components: i) bias ($U^b$); ii) unequal variation ($U^v$); and iii) unequal co-variation ($U^c$). The sum of all three components equals one and, briefly, a large $U^b$ indicates a potentially serious systemic error and, to a somewhat lesser extent, this applies to $U^v$ as well. If $U^c$ is large though, most of the error is unsystematic and, as noted by Sterman [30: 877]: “a model should not be faulted for failing to match the random component of the data”. The sample TIS results presented in Figure 10 indicate that, in this case, model behaviour provides a reasonable approximation to reality. Nevertheless, there is significant room for improvement: specifically, the variance in our model is considerably greater than that of the actual data. The TIS results, however, are also useful in that they quantify the extent of the various error types.

7. Conclusion

Few would argue that the tourism landscape is evolving at an express (indeed, some might say terrifying) pace and issues that need to be considered when developing tourism events are certainly messy (according to the criteria listed earlier). For example, Buhals [31] nominates the number of different stakeholders, stakeholder relationships and goals, contradictions between these goals, and difficulties in maintaining an acceptable and sustainable balance between the interests of stakeholders, natural resources and development activity as major problems that must be confronted in destination marketing and management – and exactly the same factors must be taken into account when analysing the impact of any significant event.

We have argued that the SD approach is well-suited to events evaluation, policy development and operational-level decision-making. Moreover, building on previous applications of SD in the tourism domain, we have specified the outline of a model (and associated decision support tool) designed for these tasks. Examples, designed to demonstrate the potential power and utility of our proposed approach, were presented.

This, however, is probably the easy part: i.e. filling out the detailed, lower-levels of the conceptual model presented here will be a challenging undertaking, as will the task of turning the model into a convenient, easy-to-use, fully-functioning decision support system. Substantial input from experienced events researchers and managers will be absolutely essential if this is to be accomplished successfully.

8. References


