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Commentary

A risky business or a safe BET? A Fuzzy Set Event Tree for estimating hazard in biotelemetry studies

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The use of biotelemetry methods can provide information on animal behaviour, movement ecology and energetics. However, deployment of biotelemetry equipment on free-living animals incurs risk of damage or loss, which can result in high cost and low sample sizes. To facilitate the uptake of these methods, we have recognized the need for a prescribed procedure for assessing failure risk in biotelemetry studies. Here, we have adapted a commonly used technique in industry and engineering, Event Tree analysis, to facilitate risk estimation and deployment procedure critique. This method can incorporate the use of fuzzy logic to accommodate the uncertainty and scarcity of technical data that are often associated with animal biotelemetry equipment and techniques. Alternatively, probabilistic data may be used for procedures where appropriate models have been established. To encourage the adoption of this method by the scientific community, we have developed a freeware program, Biotelemetry Event Tree (BET). We advocate the use of this method, in the interests of scientific robustness and animal welfare.

Biotelemetry uses sophisticated technology for the remote measurement of animal position, physiology, energetic status and behaviour, and is now an established practice for biologists (see Cooke et al., 2004; Priede & Swift, 1993). These methods allow the acquisition of data in situ, which enables insight into animal behaviour, physiology and energetics to inform basic biology, as well as conservation and management practices (Bidder et al., 2014; FitzGibbon, 1993; Ropert-Coudert & Wilson, 2005; Rosen & Trites, 2002). Developments in biotelemetry over the past two decades have made possible paradigm-shifting work that has altered our understanding of animal ecology (Block et al., 2001, 2005; Sims et al., 2008; Weimerskirch et al., 2002).

However, one of the factors hindering the widespread adoption of biotelemetric methods is cost, because the equipment (e.g. tags) required to conduct these studies can be expensive (many over £1k) and represent a significant investment for any research group (Cooke et al., 2004). Deployment of this equipment on free-living animals, often operating in environmentally harsh environments, comes with inherent risk of loss or failure, so any means that may mitigate the risk of undesired deployment outcomes is beneficial.

The deployment of biotelemetric devices also has implications for animal welfare (Hawkins, 2004), as capture, handling and device attachment, either externally (Wikenros, Sand, Wabakken, Liberg, & Pedersen, 2009; Wilson & McMahon, 2006) or internally by surgical procedure (e.g. Green, Butler, Woakes, Boyd, & Holder, 2001; Minetti, Cazzola, Seminati, Giacometti, & Roi, 2011; Woakes, Butler, & Bevan, 1995), are likely to result in some degree of discomfort to the subject animal. For every failed deployment on an animal, stress has been induced fruitlessly. Thus, biotelemetric projects should be as robust in design as possible, not just to avoid tag loss, but in order to obtain an adequate data set from as few animals as possible (cf. Hawkins, 2004).

A commonly employed method for estimating failure risk in industrial systems is Event Tree analysis, sometimes referred to as cause–consequence diagrams (Andrews & Ridley, 2002). The method was first used to audit the safeguards in the nuclear power industries (Andrews & Moss, 1993), but has since been used for chemical processing, offshore oil and gas production, and transport (Andrews & Dunnett, 2000). Event Trees have also been elegantly applied to nonindustrial disciplines, namely fisheries management (Linder, Patil, & Vaughan, 1987) and public health (Dowie, Campbell, Donohoe, & Clarke, 2003).

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Event Trees are a diagrammatic method that makes use of inductive logic to explore possible system outcomes given an initiating event (Huang, Chen, & Wang, 2001). Systems are divided into the stages required for their proper function. This method should also be applicable for use in auditing risk in biotelemetric studies because the sequential stages of device deployment are analogous with those of the safeguards designed into many industrial systems (Huang et al., 2001). Similarly, the stages of biotelemetric deployments are also dependent on the correct functioning of previous stages, and all stages must function in order for the deployment to be fully successful.

The probabilities of the system outcomes (i.e. the extent to which system outcomes are likely to occur or not) can be calculated in conventional Event Trees by inclusion of component reliability data (Smith, 2001). When relevant data are available for the sequential stages of biotelemetry deployments, they can be incorporated directly into the Biotelemetry Event Tree. These data may be available for specific activities for which models have already been constructed, such as that for detection probability of acoustic tags described in McMichael et al. (2010). However, in many cases, precise calculations of failure probabilities using precise values are difficult because of the inherent uncertainty, imprecision or unavailability of relevant data. This too is often the case in biotelemetric studies (for more information, see Discussion), where relevant models for estimating the probabilities of success of specific actions/stages are not widely available (cf. Patterson & Hartmann, 2001). In cases such as this, the use of fuzzy logic to estimate the probability of success may be possible (Dumitrescu, Ulmeanu, & Munteanu, 2002; Huang et al., 2001; Kenarangui, 1991).

Fuzzy logic allows the quantification of uncertain parameters, expressing them by a degree of membership to groups, or 'fuzzy sets'. Rather than using precise values, some processes, such as the likelihood of failure as a result of human error, are better represented by fuzzy sets. Huang et al. (2001) argued that human error is difficult to model accurately with traditional 'crisp values' because there are so many possible contributing factors, which are difficult to quantify accurately. This is also true of many activities in biotelemetric studies. For example, factors such as the weather may have a substantial influence on the availability of animals for capture (e.g. Ford & Reeves, 2008; Garcia et al., 2007; Humphries et al., 2010), but it is particularly difficult to quantify and incorporate the state of the weather into Event Tree analysis, especially if the Event Tree is prepared an appreciable time before the tag deployment is to take place. These often intangible quantities make traditional Event Tree computation with precise values difficult. Thus, in instances where there is an absence of reliable data, Fuzzy Set Event Trees have the capacity to derive stage success probabilities from an aggregated poll of expert opinions, and thus are far easier to quantify.

Although methods for Event Tree analysis in industrial systems exist, their calculation by hand is difficult. Software for these purposes has been developed, but their application to biotelemetry studies is problematic, often because the input fields require data that are not always available or the fields themselves are not applicable. Recognizing the value in assessing risk in biotelemetry studies, our purpose in this paper is to outline a method for constructing Biotelemetry Event Trees based on the Fuzzy Set Event Tree outlined in Huang et al. (2001). This method allows researchers to incorporate probabilistic data where they are available, and continue analysis for instances when they are not. The merit of such an activity lies in helping researchers identify weaknesses in deployment protocol in a robust and formal way, without necessarily requiring them to perform complex modelling or obtain substantial additional data. The Event Tree analysis deals with the probability of successful data acquisition rather than explicit welfare considerations; however, some benefit to animal welfare is implicit because more robust deployment procedures require that fewer animals are equipped to obtain a sufficient sample size (see above). To encourage the adoption of this method, we have developed a purpose-built freeware program 'BET' (Biotelemetry Event Tree) for use by the scientific community.

METHODS

Event Tree Analysis

The Event Tree is a diagrammatical representation of the 'system', whereby the system includes the combination of equipment and actions required to obtain data for the purposes of the study. Event Trees are usually constructed horizontally, starting on the left with the initiating event. This initiating event describes a scenario or situation whereby the system is required or in demand (for industrial systems this is usually a fault or error; Andrews & Moss, 1993). In the case of biotelemetry studies, the initiating event is usually taken to be the commencement of the study. The tree then continues in stages, which are ordered from left to right in the chronological sequence in which they occur. The combination of these sequential stages should be sufficient for the successful acquisition of data from the subject, and can differ according to the parameters of the study and the equipment used. For example, the information saved in some biotelemetry units for access upon recovery, usually by retrapping the animal (e.g. Wilson, Shepard, & Liebsch, 2008), can be obtained remotely by others, such as via antenna or satellite relay (e.g. Dyo et al., 2012; G. C. Hays et al., 2003). Despite these minor differences in procedure, we propose that there are five broad stages required for acquisition of data in biotelemetry studies. These stages are; 'Capture', 'Attachment', 'Recording', 'Detachment' and 'Recovery'. Each of the stages will result in a branch point on the tree, with upward and downward branches representing success or failure of the system at these stages, respectively. The stages are qualified as follows.

'Capture' describes the exercise of obtaining an animal (e.g. by trapping) and equipping it with telemetry equipment (Cooke et al., 2004) for the acquisition of data, followed by the release of the equipped subject.

'Attachment' represents the period for which the device is animal-borne, for which consistent attachment is required. If the device fails to maintain attachment (either by detaching entirely, or in the case of accelerometer studies, changing position, see below) the system will fail, and an incomplete data set will be obtained.

'Recording' may be taken to include the successful initiation of the device, all its proper function and cooperation by the subject animal (be it performance of a target behaviour or residence in a required area) required for successful data acquisition. Failure at this stage may occur as a result of incorrect set-up of the device, in which case the device may fail to initiate recording, or insufficient battery/memory capacity or transducer failure (in the case of archival tags), in which case only part of the required data set is obtained. In the case of telemetry systems that require some form of signal transmission (e.g. VHF or transmitter data loggers), failure can occur if the device cannot transmit the data, because, for example, the transmission antenna breaks (however, reception of the data falls under the recovery stage, see below).

'Detachment' is the stage that involves the removal of the device from the animal. This may involve either some form of pop-off mechanism (e.g. Cover & Hart, 1967), or by manual removal of the device once the animal is recaptured (this includes any surgical procedure to remove devices planted subcutaneously). For studies in which device detachment is not necessary for achieving data acquisition (e.g. the device transmits the data) this stage may be disregarded although it may be applicable if data transmission requires that the device-carrying animal has to be within a particular distance of a receiver (e.g. Gao, Campbell, Bidder, & Hunter, 2013).

'Recovery' is the final stage, and involves all actions by which the data are transferred from the recording device onto another for analysis. This may involve the physical location (e.g. via VHF; Keller, Gray, & Givens, 1985) and retrieval of the device or simply the acquisition of the data from the device via a transmission mechanism. For studies in which the device has been removed from the animal after recapture, this stage may be disregarded, as recovery is implicit in the device removal procedure.

For elements of deployment procedures that may apply to more than one of the broad stages qualified here, we advocate assigning the element to only one of the stages so that the same risk of failure is not applied to both. While the outcomes of the majority of stages will be binary (stages are either successful or fail), it is possible in some cases that a spectrum of outcomes are possible. For example, when deploying a device equipped with a triaxial accelerometer it is necessary that the device orientation relative to the animal remain consistent in order to identify behaviour (Shepard et al., 2008). Thus if during the 'Attachment' stage, the harness that holds the device in place on the subject alters position at all, accurate identification of behaviours is not possible. However, this failure is by no means terminal, as the device may still drop off at the correct time and be recovered successfully, and the data may be useful for other purposes such as the calculation of metrics such as Vectorial Dynamic Body Acceleration (VeDBA; see Qasem et al., 2012), which may be used as activity indices, or to estimate energy expenditure and speed (Bidder, Qasem, & Wilson, 2012; Duda & Hart, 1973; Gleiss, Wilson, & Shepard, 2011). In this example, it is possible for the system to experience a partial failure at the 'Attachment' stage, resulting in an incomplete, but not entirely useless, data set.

Quantification by Fuzzy Logic

In this section we give an explanation of the fuzzy mechanism required to perform Fuzzy Set Event Trees; however, for a detailed introduction to fuzzy logic theory, see Klir & Yuan (1995). All formulae in this section are presented according to the standards set out in Larson et al. (1994), with a summary of the calculations given in the text. A Fuzzy Event Tree is based on the event structure described in the previous section and the associated uncertainties corresponding to its events. In many instances, such as those considered here, it is not practically possible to obtain sufficient data for event uncertainties to be quantified objectively. Instead, we adopt a semiautomatic paradigm, whereby subjective, human ('expert') judgement is used to assess the likelihood of successful completion of each event in the tree. Specifically, in our system each expert quantifies his/her personal assessment of the likelihood of an event succeeding using one of seven linguistic descriptors. The reason for the use of seven linguistic categories is motivated by evidence in psychology which suggests that on average the limits of the human working memory are achieved at the granularity level of 7 ± 2 choices of this type (Wickens, 1992). In the increasing order of the likelihood they express, these categories are 'very low', 'low', 'fairly low', 'medium', 'fairly high', 'high' and 'very high'. Each linguistic descriptor is then translated into computer-understandable form ('fuzzified') by mapping onto a trapezoidal fuzzy set. A trapezoidal fuzzy set is specified by a quadruplet (a_1, a_2, a_3, a_4) such that:

$$a_1,\ a_2,\ a_3,\ a_4 \in R \quad \text{and} \quad 0 \le a_1 \le a_2 \le a_3 \le a_4 \le 1 \tag{1}$$

where R is used to represent the set of real numbers.

With the corresponding fuzzy set membership of $x \in R$ given by:

$$\mu(x) = \begin{cases} 0 & \text{if } x \le a_1 \text{ or } x \ge a_4 \\ \dfrac{x - a_1}{a_2 - a_1} & \text{if } a_1 \le x \le a_2 \\ 1 & \text{if } a_2 \le x \le a_3 \\ \dfrac{a_4 - x}{a_4 - a_3} & \text{if } a_3 \le x \le a_4 \end{cases} \tag{2}$$

This equation defines the membership using a trapezoidal form over the interval (a_1, a_4). At the 'ends' of the trapezoid, that is at a_1 and a_4, the membership value is 0 wherefrom it increases to its maximum value of 1 which is attained over the interval (a_2, a_3). To explain the idea in more intuitive language, instead of representing a specific linguistic descriptor using a single number, to account for the uncertainty associated with the subjective nature of linguistic quantifiers as well as their different understanding by different individuals, a descriptor is represented using a range of values. Values in the middle interval (a_2, a_3) are considered most probable and equally likely, and are thus assigned the same membership value of 1. To clarify, a membership value describes the extent to which that interval 'belongs' to the fuzzy set (Klir & Yuan, 1995). Moving away from these middle intervals in either direction (i.e. towards a_1 or a_4) the corresponding values are decreasing in agreement with the linguistic descriptor and consequently their membership value slowly decreases too, vanishing at a_1 and a_4. For example, it is highly unlikely that an expert quantifying linguistically the probability of an event occurring as 'Very high' corresponds to the numerically quantified probability of 0.1. Therefore the fuzzy membership value of 0.1 should be very low.

In this work we used the fuzzification mapping summarized in Table 1.

A further graphical illustration of the corresponding membership functions is shown in Fig. 1. Note that the trapezoidal fuzzy sets associated with 'very low', 'low', 'medium', 'high' and 'very high' are degenerate and have the triangular fuzzy set form because of the collapse of the middle interval (a_2, a_3) into a point (i.e. $a_2 = a_3$).

To harness as much human expertise as possible and increase the estimation robustness, the uncertainty of success of each event is ideally assessed by more than one expert. When multiple opinions are available, we compute the trapezoidal fuzzy set associated with the uncertainty of the event by averaging the trapezoidal fuzzy set memberships corresponding to different expert assessments. Specifically, if the i-th expert assessment of success is represented by the quadruplet $(a_1^{(i)}, a_2^{(i)}, a_3^{(i)}, a_4^{(i)})$, the average trapezoidal fuzzy set (a_1, a_2, a_3, a_4) of N expert opinions can be computed by averaging the corresponding parameters of the sets:

$$a_k = \frac{1}{N}\sum_{i=1}^{N} a_k^{(i)} \quad \text{for} \quad 1 \le k \le 4. \tag{3}$$

Table 1
Trapezoidal fuzzy sets assigned to each of the linguistic descriptors

Linguistic description	Trapezoidal fuzzy set (a_1, a_2, a_3, a_4)
Very low	(0.0, 0.1, 0.1, 0.2)
Low	(0.1, 0.2, 0.2, 0.3)
Fairly low	(0.2, 0.3, 0.4, 0.5)
Medium	(0.4, 0.5, 0.5, 0.6)
Fairly high	(0.5, 0.6, 0.7, 0.8)
High	(0.7, 0.8, 0.8, 0.9)
Very high	(0.8, 0.9, 0.9, 1.0)

These are used by human experts to express the likelihood of success of a particular event in a fuzzy Event Tree, see Fig. 1.

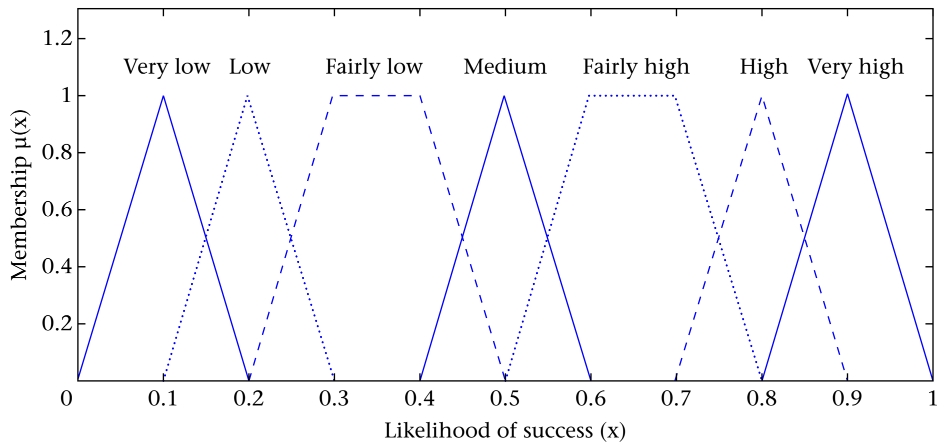

Figure 1. Graphical representation of trapezoidal fuzzy sets used by human experts to express the likelihood of success of a particular event in a fuzzy Event Tree; see equation (2).

The fuzzy Event Tree adopted in the present paper is binary: each event is followed by a bifurcation depending on its successful completion or failure. If (a_1, a_2, a_3, a_4) is the trapezoidal fuzzy set quantifying the likelihood of the event being successfully completed, the trapezoidal fuzzy set describing the likelihood of its failure is ($1-a_4$, $1-a_3$, $1-a_2$, $1-a_1$). Note the reversal of the ordering of the terms corresponding to the parameters a_1, a_2, a_3, a_4, necessary to maintain the condition expressed in equation (1).

The ultimate goal of fuzzy Event Tree analysis is to quantify the likelihood of each final outcome where a final outcome is defined by a path from the root of the tree to one of its leaves. In other words, a final outcome corresponds to a particular sequence of successful or unsuccessful events captured by the tree structure, as shown in Fig. 2. This is achieved by multiplying the trapezoidal fuzzy set membership functions associated with each outcome along the path. For example, the trapezoidal fuzzy set (a_9, a_{10}, a_{11}, a_{12}) associated with 'Outcome 2' in Fig. 2 is obtained by multiplying (a_1, a_2, a_3, a_4) and ($1-a_5$, $1-a_6$, $1-a_7$, $1-a_8$). To maintain the trapezoidal form of fuzzy sets throughout the analysis, we adopt a simple product rule whereby two trapezoidal set membership functions are multiplied by multiplying their corresponding parameters:

$$(a_1,\ a_2,\ a_3,\ a_4)\times(a_5,\ a_6,\ a_7,\ a_8)\doteq(a_1a_5,\ a_2a_6,\ a_3a_7,\ a_4a_8) \tag{4}$$

Lastly, to allow for the results of the analysis to be readily understood by nonexpert users, our system performs 'defuzzification' of the fuzzy sets associated with each final outcome i.e. each fuzzy set is mapped back into the linguistic domain. A trapezoidal fuzzy set (a_1, a_2, a_3, a_4) is defuzzified as follows. First, we compute two salient values, $(a_1+a_2)/2$ and $(a_3+a_4)/2$, as designated by red circles in Fig. 3. These are then independently defuzzified, each into a simple linguistic descriptor as per Table 2 (also see Fig. 3). The two simple linguistic descriptors are then used to construct a compound descriptor of the entire set in the form 'from <simple_descriptor> to <simple_descriptor>'. For example, a trapezoidal fuzzy set (0.12, 0.50, 0.75, 0.90) has 0.31 and 0.825 for the two salient values. Since 0.31 lies in the interval 0.25–0.45 it is defuzzified as 'fairly low'. Similarly, 0.825 being in the interval 0.75–0.85 is defuzzified as 'high'. Thus, (0.12, 0.50, 0.75, 0.90) leads to the linguistic description of the associated likelihood 'from fairly low to high'. In cases in which both constituent simple descriptors are the same (e.g. 'from very low to very low'), the result is shortened to the form of the simple descriptor only (e.g. 'very low').

CASE STUDIES

For the purpose of illustrating how this analysis is undertaken, two contrasting case studies are presented (see Supplementary material). The case studies detail two separate deployments made by researchers (the authors) previously, one on Andean condors, *Vultur gryphus* (case study 1, see Supplementary material) and the other on Magellanic penguins, *Spheniscus magellanicus* (case study 2, see Supplementary material). Both of these studies were undertaken in Argentine Patagonia.

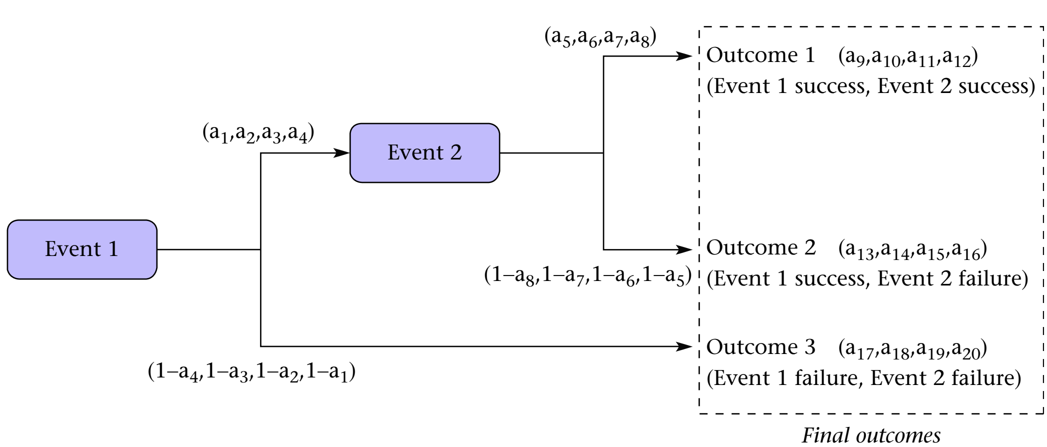

Figure 2. Key elements of a simple fuzzy Event Tree which comprises two events (stages) and three final outcomes.

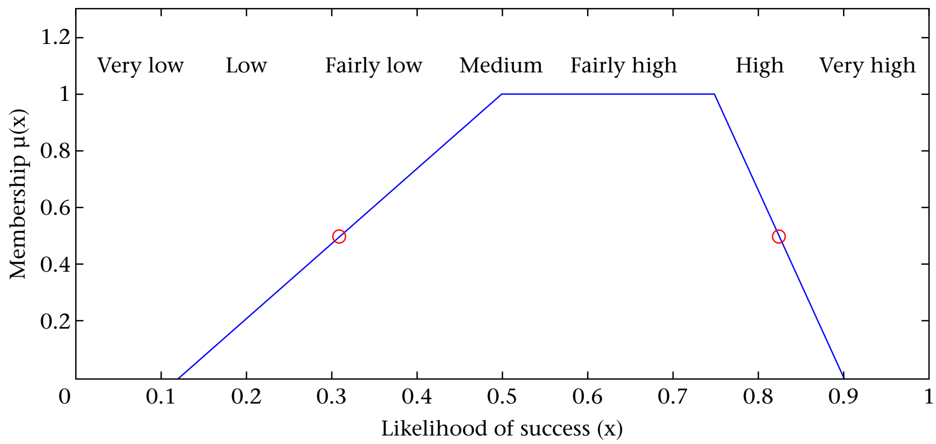

Figure 3. The sources of the two salient values used in the defuzzification procedure are indicated by the red circles. These can be converted into linguistic descriptions as per Table 2.

The researchers were asked to detail the field method for each stage, using the questions given in the Supplementary material as an aid. In this example, it was impossible to conduct the analysis a priori, so analysis was undertaken retrospectively. In practice, we advocate that researchers perform the analysis prior to device deployment in order to achieve maximum benefit, although a review of the procedure post hoc is also advised in order to review and refine the procedure used.

Once the field procedure had been detailed, three of the researchers were asked to estimate the probability of failure according to the linguistic descriptions detailed in Table 2. These opinions were then used (for details see Methods) to produce an Event Tree using the BET program, with final probability of success computed according to the calculations detailed in the Methods. For case study 1, the BET analysis probability of success was 'very low' (0.01, 0.02, 0.04, 0.09). For case study 2, the BET analysis probability of success was 'medium to high' (0.36, 0.62, 0.62, 0.95).

DISCUSSION

Considerations in Light of Case Studies

It is evident that deployment of biotelemetry equipment onto free-living animals is risky. Even when success seems virtually certain, as was the case of finding Magellanic penguins at a colony site during the second case study (see above), there is always a chance of failure (albeit minimal). Despite the extensive colony at the field site (Simeone & Wilson, 2003), the capture stage could have failed because of a catastrophic event, such as those that have caused declines or nest desertion at seabird colonies elsewhere (C. Hays, 1986). The probability of this type of event occurring is small, but still worthy of consideration. It is for this reason that no linguistic category of 'Certain' (i.e. a fuzzy set of 1, 1, 1, 1) was included in the Biotelemetry Event Tree method proposed; in essence, none of the sequential stages is ever certain to succeed.

Table 2
The mapping used to defuzzify the two salient values of a trapezoidal fuzzy set

Interval	Linguistic description
0.00–0.15	Very low
0.15–0.25	Low
0.25–0.45	Fairly low
0.45–0.55	Medium
0.55–0.75	Fairly high
0.75–0.85	High
0.85–1.00	Very high

The number of stages undertaken during the deployment procedure has an effect on the overall probability of success, as success of any deployment is dependent on the successful operation of all prerequisite stages (Fig. 2). Following the chain rule of probability, in the absence of certain success, the overall probability of success diminishes with each additional stage. The practical implication for the design of biotelemetry field procedures is that, all things being equal, simpler procedures with fewer sequential stages are more likely to be successful. This is illustrated well in the case studies, with a contrast in recovery procedures between the two. Case study 1 required that the detachment mechanism operated correctly and the researchers were subsequently able to locate the detached device via its VHF beacon (Supplementary material). To obtain the device, both these stages would have to operate without fault, which is less likely than a single event operating without fault, for example the location of the equipped individual in case study 2.

The risk of failing to capture sufficient animals for the purposes of research can be avoided by choosing more common animals. However, often researchers must deploy biotelemetry equipment on less common or endangered species, because this is where the need for information is greatest. Also, biotelemetric methods may need to be used because others are inadequate to answer the questions posed (Cooke, 2008; Wilson et al., 2008). In such cases more time and resources must be invested in order to obtain sufficient individuals to meet the requirements of the study. If sufficient individuals cannot be caught, it is better to reconsider the study procedure than inflict the implicit discomfort on the few that are caught needlessly (cf. Hawkins, 2004). This is particularly germane for endangered species (Cooke, 2008; Hebblewhite & Haydon, 2010).

Biotelemetry Event Trees

In Biotelemetry studies there are mechanical, electronic and human components, the interactions between which are difficult to quantify and model. In the present paper, we have aimed to illustrate how Event Tree analysis, which is already utilized in other disciplines (Andrews & Moss, 1993; Dowie et al., 2003; Linder et al., 1987), may be used to estimate the loss or failure of biotelemetry equipment.

In industry, Event Tree analysis is conventionally undertaken using detailed component reliability data (Smith, 2001). However, for biotelemetric studies, these data are often unavailable because devices are either designed and constructed 'in house', i.e. by the research group, or device manufacturers do not have access to specific component reliability data. If research groups report their experiences (e.g. in research articles) with the equipment they use, reliability data could be compiled and this may alleviate this difficulty in the future.

Some probabilistic models have been devised that are applicable to the stages of deployment detailed in the present paper. For instance the probability of obtaining animals may be described as the typical catch per unit effort (e.g. Andersson, 1976), or derived from a population density estimated cheaply by camera traps prior to initiation of the live trapping (Karanth & Nichols, 2011; Soisalo & Cavalcanti, 2006). The likelihood of area fidelity, necessary for recovery of archival loggers, may also be modelled (Casale, Freggi, Basso, Vallini, & Argano, 2007). The probabilistic Barker–Burnham–White models (Barker, Burnham, & White, 2004; Barker & White, 2001, 2004) were initially devised to describe the encounter history of mark–recapture methods, with estimations of tag resighting and recovery. Such models could also be applied to biotelemetry deployment and device recovery. However, a solution is required that allows researchers to undertake risk assessment in biotelemetry deployments when data are deficient for probabilistic models, or those models have not yet been devised. We believe that the method of Biotelemetry Event Trees detailed in the current paper presents a workable means to audit risk for biotelemetry studies, even when probabilistic data are missing, as it does not require precise reliability data or detailed modelling skills. Nevertheless, if quantitative ('hard') data are available, they can be readily incorporated in the described framework. For example, if the probability of an event occurring can be estimated to be p, this can be represented by a trapezoidal fuzzy set $(p - \varepsilon, p, p, p + \varepsilon)$, where ε is used to quantify the corresponding confidence interval of the estimate. Thus the method described is able to make use of probabilistic data and account for its absence with fuzzy estimations substituted.

A promising direction in which the methodology described in this paper may be extended includes the abandonment of fuzzy sets in favour of probability density functions employed within a Bayesian framework. This would facilitate a principled treatment of all the challenges we have discussed herein and also allow us to include in the model further subjective quantifiers such as the confidence of an expert in his/her estimate. The two main reasons why in this work we decided to use fuzzy sets stem from their simplicity of implementation, use and presentation to the user, and their demonstrated success in other research disciplines such as engineering. The Biotelemetry Event Tree procedure is based on the Fuzzy Set Event Tree outlined in Huang et al. (2001). The incorporation of fuzzy data relies on expert opinion and so is subjective, being reliant on perceived assessment of failure risk. However, as an exercise, the Biotelemetry Event Tree requires researchers to analyse their deployment procedure in a prescribed manner, providing a diagnostic tool for evaluating proposed procedures, and is preferable to the absence of any such risk assessment. Subjectivity could be mitigated by the inclusion of neutral expert opinions, obtained perhaps from outside the research group. Increasing the number of expert opinions gathered may make evaluations more accurate. However, large groups that adopt the 'wisdom of the crowd' approach (Yi, Steyvers, Lee, & Dry, 2012) may result in high variability between estimations and may prove impractical. For smaller groups, if there is discord among the opinions used in the Biotelemetry Event Tree, this will result in very broad result classes, for example low to high. This feature is important because it indicates clearly that there is disagreement about the reliability of a certain procedure, and may be used to suggest that researchers address bottlenecks or problematic stages in the experimental design. Once these issues are addressed, and there is agreement, result classes will be less broad.

Expert opinion is often used in the field of reliability engineering, and there are numerous methods to aggregate multiple opinions (Bonano & Apostolakis, 1991; Wheeler, Hora, Cramond, & Unwin, 1989). One such method, of weighting opinions, is described in Moon and Kang (1999); however, this was discounted here because it was felt that weighting some opinions over others would result in greater subjectivity. Although the use of expert opinion suffers from subjectivity, it is the simplest way of incorporating uncertainty and complexity into a risk analysis. Onisawa (1996) argued that probabilistic methods are narrow because they are based on the principle that system operation is either successful or not, and that it cannot be both. This is an oversimplification for biotelemetry studies because it is possible for a component to fail but for some usable results to be obtained (a partial failure, see above). Expert opinion is trusted in the safety analysis of complex technical systems (Svenson, 1989), and even forms some component of the decision-making process in IUCN Red List classification (Akcakaya et al., 2000), so its use in many disciplines is not uncommon. During a biotelemetry study, there are numerous factors that can affect the success of each deployment stage; some of them are often unforeseen and difficult to predict, so any probabilistic method may suffer from the same subjectivity because ultimately it is the researcher's decision as to which components and probabilistic models merit inclusion in the risk analysis. In the absence of 'harder' forms of data, the flexibility of a Fuzzy Set Event Tree and its ability to deal with uncertainty make this method robust for this type of risk assessment analysis (Huang et al., 2001; Onisawa, 1996).

If the Biotelemetry Event Tree is to be adopted as best practice when deploying biotelemetry equipment on wild animals, further work must be undertaken to establish benchmarks for what defines 'acceptable' and 'unacceptable' risk. Presently, this judgement can only be made on a case by case basis. If funding bodies and peer-review journals are to make use of the method detailed here, work must be undertaken to improve its objectivity. This could be achieved by surveying a large number of researchers in order to correlate a priori assessment with project outcomes for a range of device configurations and target taxa. Such an endeavour represents an interesting avenue for further research, and may ultimately improve communication between research groups in the interest of refining their common practices.

Biotelemetry Event Tree Program

To encourage the use of Event Tree analysis in the discipline of animal biotelemetry, we have developed a freeware program, Biotelemetry Event Tree (BET, Fig. 4) which is available for download at http://www.deakin.edu.au/~ognjen/download/swansea_BET.jar (for detailed user instructions, see Supplementary material). The program is written in Java (Oracle Corporation, Santa Clara, CA, U.S.A.), a widespread programming language compatible with most operating systems. BET allows researchers to produce and annotate a bespoke Event Tree for use in biotelemetry studies and calculate probabilities automatically according to the method described above. For ease of use, Event Trees can then be saved for later use or to be sent to other parties (files are ca. 20 kb). We aim to encourage researchers in this field to conduct Event Tree analysis in the interests of scientific robustness and animal welfare, and advocate its use as best practice. Eventually, once a procedure for its use can be formalized by the scientific community, we envisage that this method can be used by individuals and funding bodies, as part of the decision-making process prior to undertaking these studies.

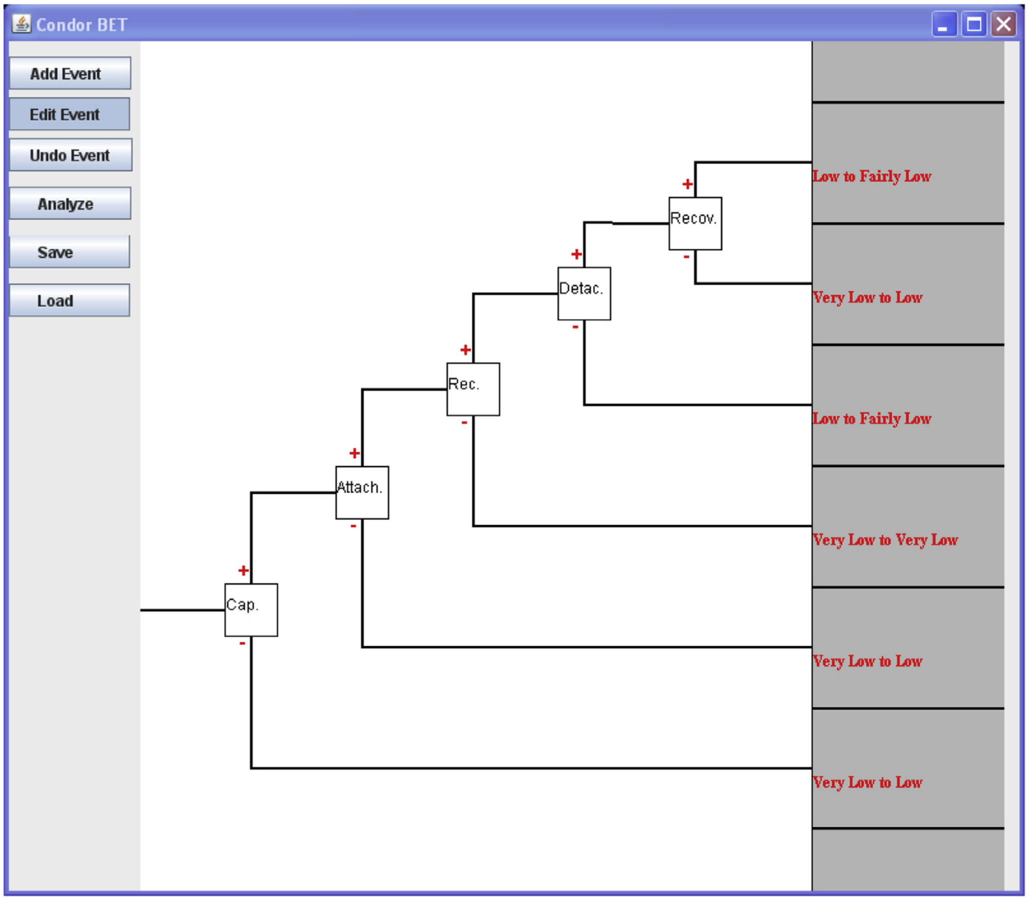

Figure 4. Screenshot of an Event Tree produced in BET. Each of the possible system outcomes is assigned a linguistic probability value for interpretation by the researchers.

Conclusion

We have recognized the need for some method by which risk assessment for the successful deployment of biotelemetry equipment on free-living animals may be undertaken. By adapting a method that is already in use within industrial and engineering circles, it has been possible to develop a method by which undesirable deployment outcomes may be considered and avoided prior to undertaking biotelemetry equipment deployment. Moreover, we have shown how this method can be used to review the procedures of previous surveys in order to refine deployment procedures. Through the development of freeware software, BET, we hope to encourage the adoption of this procedure as best practice, in the interests of scientific robustness and animal welfare.

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Supplementary Material

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