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Point of truth calibration for disease prioritisation—A case study of prioritisation of exotic diseases for the pig industry in Australia

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ABSTRACT

The objective of this study was to trial point of truth calibration (POTCal) as a novel method for disease prioritisation. To illustrate the application of this method, we used a previously described case-study of prioritisation of exotic diseases for the pig industry in Australia. Disease scenarios were constructed from criteria which described potential impact and pig-producers were asked to score the importance of each scenario. POTCal was used to model participants' estimates of disease importance as a function of the criteria, to derive a predictive model to prioritise a range of exotic diseases.

The best validation of producers' estimates was achieved using a model derived from all responses. The highest weighted criteria were attack rate, case fatality rate and market loss, and the highest priority diseases were the vesicular diseases followed by swine fevers and zoonotic encephalitides. Comparison of results with a previous study in which probabilistic inversion was used to prioritise diseases for the same group of producers highlighted differences between disease prioritisation methods. Overall, this study demonstrated that POTCal can be used for disease prioritisation. An advantage of POTCal is that valid models can be developed that reflect decision-makers' heuristics. Specifically, this evaluation of the use of POTCal in animal health illustrates how the judgements of participants can be incorporated into a decision-making process. Further research is needed to investigate the influence of scenarios presented to participants during POTCal evaluations, and the robustness of this approach applied to different disease issues (e.g. exotic versus endemic) and production types (e.g. intensive versus extensive). To our knowledge, this is the first report of the use of POTCal for disease prioritisation.

1. Introduction

Disease prioritisation is used to identify diseases for which resource allocation would achieve the greatest benefit to human and animal health. In general, disease impacts are described by a group of criteria, and diseases are compared based on the importance of the criteria to decision-makers and the scale of impact of the criteria for each disease. Methods for disease prioritisation have included rapid risk analysis (McKenzie et al., 2007), qualitative decision trees (Palmer et al., 2005), consensus (Weinberg et al., 1999) and semi-quantitative scoring techniques based on levels of severity of disease criteria (Carter and National Advisory Committee on Epidemiology Subcommittee, 1991; Rushdy and O'Mahony, 1998; Doherty, 2000; Valenciano and Working Group, 2001; Krause and Prioritization Working Group, 2008; Balabanova et al., 2011). More recently, prioritisation in health contexts has been undertaken using multi-criteria decision analysis (MCDA) (Havelaar et al., 2010; Mintiens and Vose, 2012; Del Rio Vilas et al., 2013a,b; Brookes et al., 2014a; Kadohira et al., 2015). MCDA consists of a group of approaches from the field of decision science, and its use has increased exponentially over the last 60 years to aid decision-making across a variety of disciplines including natural resource sciences, engineering and health sciences (Bragge et al., 2010). MCDA is considered to deliver consistent results when making complex decisions by using methods that are transparent and repeatable (von Winterfeldt, 1980; Keeney, 1982), making MCDA ideal for decision-making in health policy planning.

Although assessment of the validity of models and their results is standard practice in other fields, the validity of MCDA models and results has rarely been assessed (Neslo and Cooke, 2011). This is understandable given that in many cases, MCDA models have been focussed on transparency for single, albeit complex, decisions. Nev-

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ertheless, rational decision making requires models that produce results reasonably consistent with real world outcomes. Therefore, it is useful to consider the validation of these techniques, and has practical application if the MCDA model is for decision prediction for updated groups of alternatives as is required for disease prioritisation.

The term "validation" in the context of disease prioritisation has a similar definition to validation in the context of epidemiological modelling, in that it refers to an assessment of both the accuracy of the model in reflecting a "real-world" state and the relevance of the model for predicting future states (Garner and Hamilton, 2011). In the few studies in which validation of MCDA has been undertaken, results have been variable (Havelaar et al., 2010; Teck et al., 2010; Flari et al., 2011; Neslo and Cooke, 2011; Brookes et al., 2014b). For example, Brookes et al. (2014b) found that preferences were represented well for decision-makers who prioritised diseases that only affected livestock, but validation was poor for the model derived to predict priorities for decision-makers who prioritised zoonotic diseases. Understanding the sources of both systematic error (bias) and random error that can affect model validation is important to both improve methods underlying disease prioritisation, as well as provide confidence that the results reflect decision-makers priorities and are a useful tool for resource allocation (the ultimate goal of any disease prioritisation exercise).

There are many potential sources of error in disease prioritisation. Most are not specific to decision-analysis – for example, uncertainty and variability in disease impacts and selection bias of the group of decision-makers – and can controlled either quantitatively or qualitatively. For example, Havelaar et al. (2010) incorporated disease impact uncertainty by using ranges for disease criteria measurements; Brookes et al. (2014b) prioritised multiple combinations of criteria for diseases with variable impacts dependent on strain or control options; and qualitative assessments can be made about how well decision-makers' opinions can be generalised to a target group of people. However, accurately modelling decision-makers' heuristics so that results represent decision-makers' preferences, and therefore, their priorities – an integral part of decision-analysis – presents an additional source of bias specific to decision analysis.

The weighted sum model is commonly used as the underlying model structure for disease prioritisation using MCDA because it is straightforward to implement due to its simplicity and transparency (Dodgson et al., 2009). However, the weighted sum model might not always reflect decision-makers' heuristics, potentially contributing to the limited validation of prioritisation results in previous studies; a different structure for the model might be more appropriate. In a traditional MCDA framework using multi-attribute value or utility theory, this requires assessments of decision-makers' preferences in terms of their values or utility, adding complexity to the MCDA procedure.

Point of truth calibration (POTCal) has been advocated as a method for complex decision-making, and offers an alternative approach to traditional MCDA by using regression methods with which epidemiologists are familiar (Barry and Xunguo, 2010). POTCal has not been used for disease prioritisation, but has been used to assist decision-making in operational biosecurity problems (Knight et al., 2007). Elicitation of preferences for POTCal is similar to that used for probabilistic inversion and conjoint analysis—decision-makers provide judgements about constructed risk scenarios; both are techniques that have previously been used for disease prioritisation (Havelaar et al., 2010; Ng and Sargeant, 2012, 2013; Brookes et al., 2014b). The POTCal method models the experts' judgements conditional on the scenario cues. In particular, the POTCal analysis does not assume the underlying form of the model; instead, regression methods are used to determine the most appropriate structure by defining the relationship between the criteria (calibration) and the decision-makers' score of importance for a particular scenario (the point of truth). Thus, experts do not need to consider explicit weightings of criteria but rather do this implicitly through the scenario scores.

The objective of the current study was to trial POTCal for disease prioritisation using a case-study – prioritisation of exotic diseases for the pig industry in Australia. We compare prioritisation results using POTCal to those of a concurrent study in which probabilistic inversion was used to assess preferences and a weighted sum model described heuristics of the same group of decision-makers (Brookes et al., 2014a,b). We discuss whether POTCal resulted in valid representation of decision-maker heuristics and its potential use in disease prioritisation.

2. Methods

2.1. Overview of POTCal

A comprehensive description of the mathematical background of POTCal is presented in Barry and Xunguo (2010). For disease prioritisation, POTCal can be structured using the multi-criteria decision-analysis framework recommended by Keeney (1982) and used to define the preferences of decision-makers. To be consistent with Keeney (1982), we refer to the experts engaged in the process as decision-makers but note that in many situations the pool of experts is a source of information for a single decision maker.

If an individual decision-maker is given information about disease criteria that describe disease impacts – such as attack rate and case fatality rate – that decision-maker can measure the importance of the disease via a score based on their perception of the value of those criteria influencing the outcome. A function of the criteria is used to model the score for the disease, in which Ii is the score of importance for the ith disease, and $g()$ is a function of Xi, the vector of criteria for disease i, and β, the associated parameters that calibrate the importance of the criteria to the overall score, and e_i is an error term for components of the score not explainable by the criteria:

$$I_i = g\left(X_i, \beta\right) + e_i \quad (1)$$

This approach can be extended to group decision making: a group of individuals' scores for disease scenario i ($\hat{I}_{ij}$), provide estimates across the population of decision-makers of the true (but unknown) importance score for scenario i (I_i). If a group of individuals score a set of disease scenarios that are designed to elicit preferences for importance of criteria, the functional relationship, $g()$, between X and I can be estimated using regression techniques, and the variation between decision-makers incorporated into this analysis using statistical techniques. Selection of the form of the function, $g()$, is based on standard statistical or machine learning procedures. Quantification of variation in score between individuals allows generalisation to the population of individuals. The final definition of the model can be used to infer the estimated score of importance ($\hat{I}$) for a range of diseases that the individuals have not assessed. For example, the model might be specified to describe the importance of zoonotic disease to public health workers (the decision-makers) and the vector of criteria included in the model could be case fatality rate, incidence and cost of treatment associated with disease. A range of zoonotic diseases (Z_{i-n}) – including diseases that emerge subsequent to the initial prioritisation – can be prioritised by adjusting the values of the vector of criteria (X_{Zi-n}) to reflect the case fatality rate, incidence and cost of treatment associated with each zoonotic disease. Since the importance of each of these criteria has already been calibrated (β), the relative importance of each disease (I_{Zi-n}) can be estimated. Thus, the model emulates the choices of the population of decision-makers.