Infectious disease modelling to inform policy

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Summary

With modelling becoming increasingly important in helping inform decisions about animal diseases it is important that the process is optimised to get the maximum benefit to the decision maker. We set out here ten steps that can improve this process for all concerned. Four steps describe the initialisation to ensure the question, answer and timescale are defined; two steps describe the modelling process and quality assurance; and four steps describe the reporting. We believe that this greater emphasis at the start and end of a modelling project will increase the relevance of the work and understanding of the results, and thus contribute toward better decision making.

Keywords

Decision making – Modelling process – Quality assurance.

Introduction

Over the last decades, models are being increasingly used to influence decision making, particularly in the policy arena. The Department for Environment, Food and Rural Affairs (Defra) in the United Kingdom

(UK) has published requirements for evidence-based decision making in animal health [1] and bovine tuberculosis [2] that clearly state that mathematical/simulation models should be used to inform the development of policy. Evidence plans for public health (zoonoses) [3] and biodiversity [4] also suggest that modelling may help pull evidence together to inform future decision making. In addition, the UK HM Treasury has reviewed quality assurance of analytical models that inform policy decisions across government [5] and provides guidance for quality assurance in analysis that can be used for modelling [6]. There is also international guidance for conducting modelling studies in animals health [7].

Historically, the UK's 2001 foot-and-mouth (FMD) epidemic quickly spawned a variety of models [8] all testing different control strategies and potentially supplying information that could be used for decision making. Modelling has also been used extensively over the past two decades to evaluate different approaches to the control of bovine tuberculosis (bTB) both in the UK [9, 10, 11, 12, 13] and elsewhere [14, 15, 16]. More recently, the emergence and spread of African swine fever in Eastern Europe has prompted a burgeoning of policy-orientated mathematical modelling studies [17, 18, 19, 20] and decision-making on strategies to achieve eradication of peste des petits ruminants (PPR) is also being supported by modelling [21]. Reviews of modelling have also been produced for viral zoonoses [22], wildlife disease generally [23] and rabies [24] specifically.

A recent review has shown that there is an increasing incorporation of theory in the management of wildlife and livestock diseases, with more than two thirds of these involving a government agency [7, 25]. We can infer from this that a large proportion of these publications were used at some level to inform decision making, although the use of modelling is not necessarily involved. What is not clear from many scientific publications, including ones using models, is whether the results have been presented to the decision makers responsible for the issue, or whether they have influenced any change in management. Commonly, the actual decision maker or policy official is not versed in modelling so may be unable to evaluate the weight that should be applied to the

model output, since they cannot evaluate the importance of the assumptions and data limitations that are necessarily applied to the model.

Suggestions for documenting the model process to improve transparency already exist in a variety of contexts [26, 27] although there is little evidence that these have had a substantial impact. A standard protocol has been suggested for documenting individual-based and agent-based models [28] which is making headway and may become a standard in model documentation. Guidance on good software practices for maintaining information generated from modelling also exist [29, 30]. Here we concentrate on the modelling process with the objective of using the results to inform a decision. This requires the modeller to document the process in a way that a non-modeller can best understand and utilise the information. There are some recent guidelines for this, with five principles identified for neglected tropical diseases [27] and four principles articulated in the general context of evidence synthesis [31]. These should apply to any disease modelling and emphasise the importance of screening questions on a model's purpose, assumptions and evidence [32] before relying on the output. Here we assume that a model will be used for predicting different outcomes of disease management decisions, so the purpose is predictive rather than academic or exploratory. We do not discuss the choice of model, which is done elsewhere [33], but rather we provide a toolkit to enhance the whole modelling process.

Outline

The modelling process should follow a series of pre-defined steps. Wrong decisions can be very costly in disease control, so maintaining quality and an audit trail are important. These steps can be broken down into three areas:

Initialisation

1. clearly define the question to be answered and the output metric

2. agree the timescale and the output (e.g. results, recommendations and the model)
3. agree the extent of the system under study and options for management
4. define and agree the structure(s) of the system

Production

5. produce the model and parameterise [33]
6. quality assurance:
   (i) verification
   (ii) validation

Reporting

7. produce preliminary output and report back
8. sensitivity analysis
9. produce the full evaluation of output
10. produce the report

Details

1. The question

Modelling is a formal abstract representation of reality and producing a model is often instructive since you are forced to be precise about the relationships of all components. The decision maker and other stakeholders should be involved [27] as this builds confidence that the model includes all necessary parameters. It is also vital that the decision maker and the modeller both understand what output is required. We highly recommend this is achieved by drawing hypothetical output (e.g. a graph of resources versus reduction in disease, or a map showing areas of increased risk) and agreeing how uncertainty should be represented.

We suggest not only to present the 'best' option, but also an estimate of the probability of a particular decision being the best option. The latter requires at least the incorporation of stochastic processes but also integration of parametric uncertainty which may, in turn, be associated with other variables (e.g. geographic/spatial variability in parameters). For example, culling may be preferred to vaccination for disease control in a specific model and population, but if this is true in only 60% of simulations, then the choice of management strategy may depend more heavily on other factors and may vary among populations.

2. The timescale and output

Decision makers often have a strict timetable, extending this may not be possible, and decision makers generally understand that these decisions are made with imperfect information. It is therefore important to decide the timescale in advance, and initial results need to be available early, as secondary questions often occur. Thus, model construction and presentation are often only the first stage. Requests for 'what if …' scenarios inevitably arise. It is important for all to be aware of the available resources within any project since iterative reporting commonly leads to 'project creep': boundless additional scenarios and questions being asked within the current project. The scope of additional questions/scenarios needs to be made clear at the outset, akin to terms of reference. Establishing this is also crucial to avoid 'model creep': the model is being used for situations where it was not originally designed. The modeller needs to be very clear when this may occur and to state that the current model does not allow for the suggested scenarios. Using a model outside its validated working 'envelope' will lead to loss of credibility in the output. It is also important to determine cases where models should not be used for decision making. In early outbreak situations with very limited reliable data models can be constructed and examined, but if the uncertainty in model input is very high no weight should be given to the output at this stage, and any such model adjusted in real time [34]. In such situations it may be better to delay producing model output for decision making, and concentrate on collecting suitable data [35]. Here however, data-light models may be very useful in exploring output sensitivity and help determine which

field parameters are most important to collect. Indeed, collecting data, including management effort, during the outbreak response should be prioritised in such situations even if it slows down the progress slightly, as it will vastly improve the ability to manage later outbreaks.

3. Extent and options

It is important to define the scope of the system under study and which options are being considered by the decision maker. This should include a 'business as usual' scenario as a baseline (or, equivalently a counterfactual to any management/control/intervention scenarios considered). Requested management options may be restricted for logistical, practical or political reasons, so the range of options to model must be defined at an early stage, but the full range of realistic management options should be examined for completeness and should not be otherwise restricted. The output that the modeller wants is evidence-based policy and not policy-based evidence (i.e. limited options investigated that would likely favour a specific outcome), although at times there may be pressure for the latter approach. Since models are generally more reliable when making comparative predictions (rather than exact predictions), this full inclusion will make results more reliable.

4. System structure

The system should then be defined and agreed with the decision maker. For complex models, different parts of the system should be checked or developed in collaboration with different experts from relevant disciplines. For example, testing cattle for bTB can involve different tests that may be performed in different ways during an outbreak. Where the process is relatively complex it is important that the decision maker, or other suitable experts, can agree with the structure to be modelled, for example with a flow chart.

It is quite common that the exact process is not fully known. In this case several different model structures can be produced and examined, and/or using different parameterisations. Where two or more models appear to be equally 'good' and it is not possible to choose between

them, it is preferable to run them all and consider the combined output to be used for decision making (i.e. ensemble modelling). Where there is a quantitative assessment of model weight, the number of simulations in the combined output may be chosen by this weighting. This multi-model approach is used for simulating climate change scenarios [36], as well as infectious diseases [37, 38, 39, 40]. In such situations it is important that decisions are made based on the accumulated results, and not a subjective choice of any preferred model based on its output. Indeed, ensemble disease modelling is starting to gain ground in recent years with the potential to improve decision making and reduce output uncertainty [41, 42].

5. Produce model

It is not our here intention to define any specific modelling approach. Model choice and level of detail should depend on the exact question, time available and the data [33]. We do recommend that any model used for decision making takes account of uncertainty, although this could be stochastic, parametric, structural or a suitable combination that can articulate clearly and transparently appropriate bounds of uncertainty.

Any model coding should be annotated with explanatory comments, the model should be well documented [28] so that others can follow the logic and it should be subjected to version control with a master list of all versions and their changes recorded on a single document. The source of all data used should be documented whether peer-reviewed, grey literature or just educated guesses. All assumptions should be explicitly stated in the documentation, and the model version used in the final decision should be stated explicitly. Where possible the source code could also be made available.

6. Quality assurance

It is often regarded that there are two levels of quality assurance, verification and validation, although there is a grey area between them. Verification is checking that the model is doing what it was created to do. This can be done by checking programming code, by exploratory sensitivity analysis, by running the model for known input and output

values, or for complex models, by creating a second independent model and comparing output.

Model validation and improved parameter estimation may be performed by using the model to predict output not used in its creation, or by predicting secondary, emergent output at different scales [43]. This can be an iterative process; the model being updated as new data become available. However, in certain circumstances, such as when modelling disease outbreaks or long-term prospects for disease elimination, it may not be possible to validate a model as similar scenarios may not exist. In these cases, it may still be possible to validate certain sections of the model.

7. Preliminary output

Preliminary output of the chosen management/control/intervention options should be performed promptly. This is a useful point to present this output to the decision maker as this maintains communication, avoids surprises and clarifies the required output. It is an opportunity to check the time frame for delivery and whether the policy requirement has changed in the interim.

8. Sensitivity analysis

In terms of decision making, sensitivity analysis (or parametric uncertainty) can be used to explore the range of possible outcomes. There is no point in changing all parameters by 10% if some vary by substantially more than others. One can use the bounds of variability (e.g. 80th percentiles) or the bounds of uncertainty in a parameter value. Performing a sensitivity analysis and then reporting the most important driving factors can also help to:

a) identify those with the most important uncertainty where further data collection would be most beneficial (this may be a valid end point for the model) and

b) identify those factors that can be managed by the decision maker to influence the system.

9. Provide output

This is the last point at which you can step backward to adjust the model. At this stage the work should just be 'cranking the handle' and repeating the model for each set of scenarios. However, production of the results should never be the last step. The output needs to be interpreted by the modeller, preferably in combination with the decision maker or another suitable expert. A statistical difference is not necessarily an important biological difference between scenarios. Results should be interpreted with relation to the caveats and assumptions used in the model, but not in relation to the use of the results (i.e. there should be no political agenda or subjectivity in interpretation). Ideally this should be done as an 'honest broker' rather than from an academic ivory tower, or an advocate [44]. Models can be used to examine scenarios that are not publicly, nor politically acceptable. They may be used to examine unethical choices. The modeller's role is to provide the output and its interpretation and impose no weight on one set of outcomes over another. Thus, the model does not define the decision, but merely informs the decision maker on the likely consequences of each choice.

However, during a disease outbreak it may be useful, and even necessary, to re-run the model with updated parameter estimates which include the management responses to date [34].

10. Report

While there is a clear difference in the production of an academic paper and the requirements of a report for decision makers, it is often possible to produce a single report that is easily transferred into an academic paper, and thus suitable for peer review, which may enhance credibility. Decision makers may find it useful to see a flow diagram of the model but may not find the mathematics and/or model code accessible. While these details must be documented, (e.g. in an appendix) they are not essential for a wider audience. Similarly, only key results of principal interest, and major assumptions, need to be included in the main body of a report or paper, with remaining results and assumptions appended, albeit it is important to avoid obfuscating uncertainty or the range of

potential outcomes and be aware that 'headline' results can be misinterpreted.

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