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## Six challenges in modelling for public health policy



C.J.E. Metcalf<sup>a,\*</sup>, W.J. Edmunds<sup>b,1</sup>, J. Lessler<sup>c,1</sup>

<sup>a</sup> Department of Ecology and Evolutionary Biology and the Woodrow Wilson School, Princeton University, Princeton, NJ, USA

<sup>b</sup> London School of Hygiene and Tropical Medicine, London, UK

<sup>c</sup> Johns Hopkins Bloomberg School of Public Health, Baltimore, MD, USA

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### ABSTRACT

The World Health Organisation's definition of public health refers to all organized measures to prevent disease, promote health, and prolong life among the population as a whole (World Health Organization, 2014). Mathematical modelling plays an increasingly important role in helping to guide the most high impact and cost-effective means of achieving these goals. Public health programmes are usually implemented over a long period of time with broad benefits to many in the community. Clinical trials are seldom large enough to capture these effects. Observational data may be used to evaluate a programme after it is underway, but have limited value in helping to predict the future impact of a proposed policy. Furthermore, public health practitioners are often required to respond to new threats, for which there is little or no previous data on which to assess the threat. Computational and mathematical models can help to assess potential threats and impacts early in the process, and later aid in interpreting data from complex and multifactorial systems. As such, these models can be critical tools in guiding public health action. However, there are a number of challenges in achieving a successful interface between modelling and public health. Here, we discuss some of these challenges.

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### Introduction

The interface between modelling and public health plays out in diverse forums. Modellers may be invited to join working groups for a specific and general issue, e.g., in the development of World Health Organization position papers (e.g., World Health Organization, 2011) or to aid with planning for the public health response to an emerging or potential public health threat. For instance, modelling played an important role in pandemic planning and the response to the 2009 pandemic in the U.S., the U.K. and elsewhere (Germann et al., 2006; Ferguson et al., 2006). Models may also play an important role in estimating disease burden and the evaluation of public health questions (e.g., progress towards measles mortality goals (Simons et al., 2012)). In all cases, a varied perception of modelling and attitude towards its utility for public health is likely to be represented – ranging from the very negative to the indifferent to positive. Negative positions may be largely a function of high expectations relative to what can actually be delivered. In the below, we detail some of the challenges that emerge

for modelling in this context, ranging from fundamental issues, to more concrete, specific ones.

### 1. Communicating the limits of modelling

The public health practitioner might prefer clear quantitative statements of the outcomes of control strategies or the future impact of health threats. Models are rarely in a position to provide this. Communicating exactly why this is the case is key to making modelling useful for public health.

Communicating how model projections depend on underlying assumptions is essential, as problematic assumptions can lead to flawed public health projections (Cooper, 2006). The details of models of the time-course of infection, in particular, are central to predicting infection trajectories for individuals, and thus scaling up to populations (Wallinga and Lipsitch, 2007). If these underlying models are poorly defined, subsequent modelling is necessarily very speculative. This issue is a particular challenge in emerging infections, where there is a paucity of evidence on the time course of disease (Lloyd-Smith et al., 2014). In addition to communicating the challenges they face, the modelling community may also be able to improve public health response by increasing awareness of the critical pieces of data needed to model emerging threats.

\* Corresponding author. Tel.: +1 609 258 6228.

E-mail address: [cmetcalf@princeton.edu](mailto:cmetcalf@princeton.edu) (C.J.E. Metcalf).

<sup>1</sup> These authors contributed equally to this work.

Appropriate assumptions will depend on the purposes of the modelling. However, even with the most appropriate assumptions in place, the quantitative predictions desired by the public health practitioner are unlikely to be feasible for most problems. Modelling generally performs well in contrasting very general hypothetical scenarios (strategy A is more successful than strategy B); but poorly in quantitatively predicting outcomes of specific contexts (strategy A will reduce cases by 27.2%). Modellers need to meet the challenge of communicating the distinction between “scenarios” and “predictions”, where “scenarios” can be thought of as what could happen if  $x$ ,  $y$  and  $z$  hold, and “predictions” are our best guess of what will actually happen given what we know about the state of the system (i.e., epidemic) at the moment.

The tension around ‘prediction’ comes from both sides. As scientists, modellers are often uncomfortable producing multiple scenarios, all of which are based on assumptions that are poorly supported, and feel more comfortable with a single scenario based on their best evidence. At the same time, policy makers often want a clear, single number to use for concrete actions, and may face significant criticism if this number is perceived to be wrong (e.g., a vaccination threshold). Hence both sides have pressure to come up with numbers that can be perceived as predictions, even if all involved are well aware that the intention is only to make planning scenarios. By becoming more integrated in the public health process the modelling community can reduce occurrences of misinterpretation and perhaps find ways that predictive modelling could usefully be incorporated into the process of public health (see points 4 and 5 below).

If the assumptions are reasonable, and the model performs well in contrasting scenarios, the next challenge may be communicating the limits of performance of the model – in particular, some models perform well under the conditions for which they were developed but break down when the context changes. For example, when populations reach small numbers, deterministic models may fail spectacularly (as in the example of the ‘Atto’ fox allowing re-invasion of rabies without reintroduction from an outside source (Mollison, 1991)); shifts in incidence may also make population heterogeneities more important (e.g., the Ross McDonald model of malaria has been extended to capture aspects of immune dynamics and transmission heterogeneities (Smith et al., 2012)).

Finally, a slightly counter-intuitive issue in communicating the limits of modelling is the challenge of communicating when something is a model at all – i.e., burden of disease estimates at global or national scales are usually based on models (generally phenomenological rather than mechanistic), but are not necessarily identified as such, even by their creators, and taken as ‘truth’, and thus presented without any consideration of uncertainty.

## 2. Maintaining the value of models in the face of long time horizons

Models often make qualitative predictions that play out over decades. Classic examples include the shift in the age profile of incidence following vaccination for rubella (Knox, 1980); or the existence of honeymoon periods as a consequence of successful control that may be followed by large outbreaks for measles (McClean and Anderson, 1988) and other childhood infections (e.g., Brisson and Edmunds, 2003). The natural history and pathogenesis of diseases such as tuberculosis or HPV mean it may take generations for the effects of interventions or other changes to the system to be seen at any significant level. Such long time frames of projection make it very hard to validate predictions, and seriously affect what modellers can and cannot say; particularly since many

model assumptions are unlikely to hold over the years or decades required for these predictions to play out. Modellers must identify approaches to clarify the value of such predictions despite their likely inaccuracies and highlight predictions that must be revisited in the face of situational changes. The development of methods, both technical and operational, of updating and checking model assumptions as more data becomes available or assumptions lose validity will require collaboration with those working on the policy side. Such methods have the potential to create models that can be used in ongoing planning (e.g., for continual reassessment of outbreak risk during the honeymoon period). However, maintaining systems over the long term is a challenge (an issue that is, of course, not unique to modelling) as enthusiasm wanes or as people lose sight of original goals.

## 3. Usefully deploying modelling in the context of ‘black swans’

Unexpected events are a repeated feature of our experience of infectious disease. Models cannot anticipate rare events, such as the emergence of HIV. However, models can potentially be used to prepare for low probability, high impact events (often referred to as black swans). Challenges include the fact that low probability events are inherently likely to be under-represented in data streams (i.e., the tails of parameter distributions). For example, individuals with high numbers of sexual partners are key to the spread of HIV, but quantifying their role and partner change rates was a major challenge, resulting in large scale surveys of sexual behaviour in many countries around the globe (Liljeros et al., 2001). There are also technical and analytical directions in which expansion of our capacity for the modelling of rare events is still somewhat underserved.

A classic example of a low probability high impact event is a rare, lethal pandemic. In the early half of the last decade there was a flurry of interest in preparing and planning for an influenza pandemic, spurred on by sporadic human infections and deaths with H5N1 avian influenza. Many of these models showed a potential utility for antivirals in the control or response to a pandemic (Germann et al., 2006; Ferguson et al., 2005), with containment perhaps even being possible if the emergent strain was detected early enough. These models were centred around a black swan event, the emergence of an extremely virulent pandemic influenza strain, and admitted the possibility of another arguably unlikely event, the very early detection of human-to-human transmission. When the awaited pandemic eventually occurred in 2009, it proved to be mild, and had already spread widely in Mexico by the time it was detected. Subsequently, governments, international organizations and modellers were subject to criticism for unnecessarily stockpiling antivirals and causing panic (Doshi, 2011; Hine, 2010). This is despite the fact that models and policy makers were aiming for, and may have achieved, the best possible plan for a rare, catastrophic event – that has happily not yet occurred. While not necessarily the fault of the modellers (though they may have contributed), this planning process also left many with the impression that all influenza pandemics will be catastrophic, high case fatality, events. Appropriately helping in planning while not fuelling misperceptions of risk is a difficult challenge – particularly as, by definition, there will be very little actual information on what a black swan event will be like. Values and perception of values are a crucial consideration in this dialogue (Tversky and Kahneman, 1981). For example, since gains and losses are often perceived in strikingly different terms, both modellers and policy makers should work hard to frame rare, probabilistic outcomes in terms that are desirable. This is particularly challenging in black swan situations where very little is known about any of the outcomes.

#### 4. Integrating modellers and model-building into the policy process

Following challenges 1 and 2, a major and general challenge in modelling and policy is reducing the divide between policy makers and modellers. The creation of an environment where modellers successfully communicate clearly how models can and should be used (e.g., for scenario comparison rather than projection; burden estimation, and not prediction, etc.) and policy makers successfully communicate questions they want answers to is essential. One solution may be the development of incentives to academics that go beyond the current reward structure that is grounded on publishing novel results. Ongoing modelling support for the 'same' decision over long term is likely to be of much greater value to policy makers; and, overall, changes in the community that act to narrow the gap between the "need to know" vs. "what is being done" should be seriously considered. The needs are often relatively simple (e.g., estimation of burden, or Case Fatality Ratios (Baguelin et al., 2011)) but what is actually being modelled may be unnecessarily complicated (pulsed vaccination, etc.) and not of great policy interest.

Creating an ongoing interaction between modellers and policy makers rather than a one-off process will contribute greatly to this goal. Currently, organizations such as CDC tend to enter into short-term project-specific arrangements with academic groups, and this can lead to modelling teams that are poorly integrated, not updated on all valid sources of evidence, and who may not have enough time to do the work, or fully engage with the problem. The English and Dutch systems in which modelling teams are integrated within the national surveillance systems are notable exceptions to this. Facilitating the process of screening quality in modelling teams is also an essential component of improving the interaction between modellers and policy makers – mathematicians capable of deploying elaborate models but who know very little about epidemiology and public health might misdirect policy making. Responsibility for developing this capacity must lie within the modelling community.

Ongoing interactions create the possibility for more effective use of both scenario based and predictive models. Scenario based models can serve as the basis for war-gaming the response to high priority public health threats, adding more realism and unpredictability to training exercises. Long term prediction is a task that models are poorly suited to do (see challenge 2), but it may be possible to develop a class of statistical and mechanistic models that can provide continually updated forecasts that capture uncertainty and gain accuracy as new information becomes available. While longer term predictions are unlikely to ever be accurate, forecasts on the scale of days or weeks may still be useful in an ongoing public health response, particularly as data on even the current situation may be slow to come in.

Integration of modellers within the policy making process will also help in defining the degree of 'realism' that it is appropriate to include within models. For all policy-related modelling, models should be simple as possible, but not so simple that a realistic relaxation of assumptions will alter policy recommendations. For some scenario models, increased 'realism', resulting in more complex models with a finer description of the outcomes may be desirable. By contrast, for models that are statistically driven, added detail and realism may lead to increased uncertainty (the complexity-uncertainty trade-off); rather than the more accurate predictions that one might intuitively expect.

#### 5. Economic analysis and decision support

In public health policy, the question that one would like models to answer is "what should I do?" What is generally required is not simply a mean estimate of what is likely to happen, or a scenario

based analysis, but rather an analysis of the cost and benefits of a set of possible public health policies to guide the decision in favour of one over the others. Weighing of costs and benefits is in the domain of economic analysis, and a dimension generally lacking in most infectious disease models; while at the same time economists' models are rarely designed to account for the non-linear effects that emerge from infectious disease dynamics. This area is ripe for development and will play an essential role in making models more useful in the formation of public health policy. As part of this effort, it is essential that costs and benefits and how they may change be an integral part of the modelling (rather than simply an add-on), with appropriate assumptions that can be relaxed appropriately, etc. (Brisson and Edmunds, 2003; Baguelin et al., 2010). Costs and benefits may even feed back into model systems. For instance, the individual benefits of vaccination go down with disease risk, so more intensive government efforts may be needed to maintain high rates of immunization in the face of disease elimination.

Making decisions about public health priority and the relative cost or benefit of various outcomes should not be the purview of modellers, or even economists; but rather is the responsibility of governmental and international public health groups (World Health Organization, 2014). It is important that policy makers understand that if they want models that give an "answer" to a policy decision, they must identify priorities and identify the costs and benefits important to their decision, so that modellers and economists can work together to incorporate this into their analysis. When they are able to do so, the marriage of mechanistic models and economic analysis may be able to provide powerful decision support that would not be possible if the two were combined post hoc based on summaries of their individual results. The Joint Committee on Vaccines and Immunization (which advises the UK government on vaccine policy) is a good example of this in practice: with a modeller represented on the committee, an explicit role of economic analysis in the decision-making process, the regular use of transmission dynamic models integrated within economic analyses, and feedback from the committee on the assumptions underlying the models being routinely incorporated.

#### 6. Creating a cycle where results inform decisions and vice versa

Each of the challenges here has both a technical component and a communication component. Challenges in communication may be mitigated by establishing an initial dialogue about what modelling has to offer and what data may be of value, particularly in light of changing technologies and novel methodologies. This may facilitate interactions, but does not solve the problem that as long as modelling activities are considered as separate from public health practice, the full potential cannot be realized. Ultimately, communication issues are best resolved by creating long term relationships that foster understanding and trust. Ongoing relationships can avoid a "one-off" approach to modelling, and create a cycle where models inform policy, which leads to new data and policy questions, thereby demanding model refinement. This idealized relationship is not merely a cultural challenge, but also requires technical innovation. Models that are more flexible in how they are updated using new information may encourage better ongoing interaction; or methods that speed up simulation and check for input highly inconsistent with previous data might facilitate the use of models directly by the planners that will use the output. The benefits from overcoming the technical and cultural barriers to creating an ongoing cycle of decision and reanalysis are significant, as only in such a cycle will consumers of model output gain an intuition for how to interpret results, while the results remain current and relevant to policy decisions.

## Conclusions

Having national or international health policy change as a direct consequence of your own work can be enormously fulfilling for the analyst. However, for this to occur, and to ensure that the policy adequately represents the modelling work, proper engagement with policy makers is necessary. Productive engagement is a long-term process, and involves a deeper understanding of the needs and constraints of policy makers combined with a willingness to alter models in order to try and better reflect these needs and constraints. At the same time, both modellers and their policy partners must work hard to appropriately interpret results, in particular appropriately communicating uncertainty. This engagement should help ensure that policy makers understand the limitations and constraints of the models better, while giving them more opportunities to use models as tools for decisions. Deeper engagement with policy makers will help modellers find the best ways of communicating clear and scientifically accurate information to best guide the development of policy.

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