learned, for example, from the long-stand- ing success of the arXiv e-print repository in the fields of physics, mathematics, and computer science, fueled by a combination of grants, in-kind support, and institu- tional memberships.

The struggle for control over information and knowledge looms large. When Berners- Lee created the World Wide Web, his inten- tion was to enable researchers to share their work. Not only have our research commu- nication tools and practices thus far fallen short of the decentralization that the Web made possible, but the evolution of the Web itself also reminds us that making vast amounts of linked data readily accessible to third parties can trigger a number of unin- tended consequences. The dominance of a limited number of social networks, shop- ping services, and search engines shows us how internet platforms based on data and analytics can tend toward monopoly. In the research information space, contracts are being negotiated establishing de facto terms and conditions for how data analytics services are being provided. Learned societ- ies are being wooed. Research assessment metrics are being proposed. Building blocks for establishing discipline portals are being assembled. The time for the academic com- munity to act in coordination is now. ■

REFERENCES AND NOTES

1. Press release, 8 April 2020; https://group.springernature.com/gp/group/media/ press-releases/ springer-nature-plan-s/17877246.
2. K. Smith, Three Questions with Don Waters. *Council on Library and Information Resources (CLIR) Newsletter* 131 (2019); https://www.clir.org/2019/10/clir-issues-131/.
3. T. C. Bergstrom, P. N. Courant, R. P. McAfee, M. A. Williams, *Proc. Natl. Acad. Sci. U.S.A.* 111, 9425 (2014).
4. L. Hinchliffe, Transformative Agreements: A Primer. *The Scholarly Kitchen* (23 April 2019); https:// scholarlykitchen.sspnet.org/2019/04/23/ transformative-agreements/.
5. Leaked document on Elsevier negotiations sparks controversy, *Science Guide* (2019); www.scienceguide.nl/2019/11/leaked-document-on-elsevier-negotiations-sparks-controversy/.
6. B. Upton, Dutch universities agree 'new way of working' with Elsevier. Research Professional News. 12 December 2019; www.researchprofessionalnews.com/rr-news-europe-infrastructure-2019-12-dutch-universities-agree-new-way-of-working-with-elsevier/.
7. Elsevier Launches PracticeUpdate, a Free Information Portal for Physicians; www.elsevier.com/about/ press-releases/clinical-solutions/elsevier-launches-practiceupdate,-a-free-information-portal-for-physicians.
8. Elsevier and Society of Petroleum Engineers Collaboration will Empower Geoscientists to Make More Informed and Confident Decisions; www.prnewswire.com/news-releases/elsevier-and-society-of-petroleum-engineers-collaboration-will-empower-geoscientists-to-make-more-informed-and-confident-decisions (2019).
9. SPARC Roadmap for Action (2019); https://sparcopen.org/our-work/roadmap-for-action/.
10. J. W. Maxwell *et al.*, Mind the Gap: A Landscape Analysis of Open Source Publishing Tools and Platforms, posted July 2019; https://mindthegap.pubpub.org/.

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SCIENCE AND DECISION-MAKING: COVID-19

Harnessing multiple models for outbreak management

Expert elicitation methods and a structured decision-making framework will help account for risk and uncertainty

By **Katriona Shea[1], Michael C. Runge[2], David Pannell[3], William J. M. Probert[4], Shou-Li Li[5], Michael Tildesley[6], Matthew Ferrari[1]**

The coronavirus disease 2019 (COVID-19) pandemic has triggered efforts by multiple modeling groups to forecast disease trajectory, assess interventions, and improve understanding of the pathogen. Such models can often differ substantially in their pro- jections and recommendations, reflecting different policy assumptions and objectives, as well as scientific, logistical, and other un- certainty about biological and management processes (*1*). Disparate predictions during any outbreak can hinder intervention planning and response by policy-makers (*2, 3*), who may instead choose to rely on single trusted sources of advice, or on consensus where it appears. Thus, valuable insights and information from other models may be overlooked, limiting the opportunity for decision-makers to account for risk and uncertainty and resulting in more lives lost or resources used than necessary. We advocate a more systematic approach, by merging two well-established research fields. The first element involves formal expert elicita- tion methods applied to multiple models to deliberately generate, retain, and synthesize valuable individual model ideas and share important insights during group discus- sions, while minimizing various cognitive biases. The second element uses a decision-theoretic framework to capture and account for within- and between-model uncertainty as we evaluate actions in a timely manner to achieve management objectives.

EXPERT ELICITATION AND JUDGMENT

Formal methods for elicitation of informa- tion from individuals were developed to har- ness the collective knowledge of many minds while avoiding the frailties of individual experts (e.g., overconfidence) and the problems that arise in group interactions, such as agreeing with field "leaders" (dominance effects), focusing on suggestions raised early in the process to the detriment of other ideas (starting-point bias, groupthink, anchoring), the dominating effects of "loud voices," and overly rapid adoption of early ideas that might, on more careful consideration, be in- correct (*4, 5*). In these formal methods, idea generation and idea evaluation are deliber- ately separated, allowing a fuller range of possibilities to be explored and a wide range of uncertainties to be assessed. As one example, in the IDEA protocol for expert elici- tation (*6*), once experts are clear about the questions, they individually provide initial best estimates and ranges, receive feedback on how their estimates compare with others, discuss the results, and then provide a final individual estimate. Some protocols, includ- ing IDEA, are designed to work remotely— an essential requirement in the present COVID-19 context.

To harness both the creativity of individu- als and the insights of groups, variations on the Delphi method (developed by the RAND Corporation in the 1950s and included within the IDEA protocol) and the Nominal Group Technique (*7*) involve both independent and interactive stages in an iterative elicitation process (*8, 9*). The expert judgment litera- ture shows that a failure to manage the elici- tation process well can lead to generation of biased information and overconfidence (*4, 5*). Expert judgment approaches have been used for elicitation from individual experts in a wide range of relevant settings, such as development of clinical guidelines (*8*), and in conservation and ecology (*9*).

MULTIPLE MODELS

There are a number of existing approaches for dealing with multiple models in weather and climate research (*10*), fisheries (*11*), and disease forecasting (*2, 12*). Such fore- casting efforts generally focus on statisti-

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cal averaging of model outputs (ensemble averaging, super-ensemble modeling) and are growing in popularity and impact. A few multiple-model protocols also address optimal management (*1, 3, 13, 14*), specifi- cally asking "what should we do to most increase the benefits or reduce the costs?", instead of "what will happen?" In the cur- rent COVID-19 outbreak, there has been unprecedented sharing of data and models in curated discussion groups, on preprint servers, and in working groups coordinated by policy agencies such as the World Health Organization (WHO) and the U.S. Centers for Disease Control and Prevention (CDC). These efforts save duplication of research and allow for rapid dissemination of new information, and are essential in a crisis.

Unfortunately, there is a downside to rapid sharing. Poor, as well as good, in- formation may spread rapidly; a failure to prevent this leads to bias. If premature consensus is reached, models predicated on poor assumptions will inevitably propagate bias. Such propagation of initial bias is well documented in the elicitation literature (*4, 5*) and is clearly a potential concern in an epidemiological context.

MODELING-GROUP ELICITATION

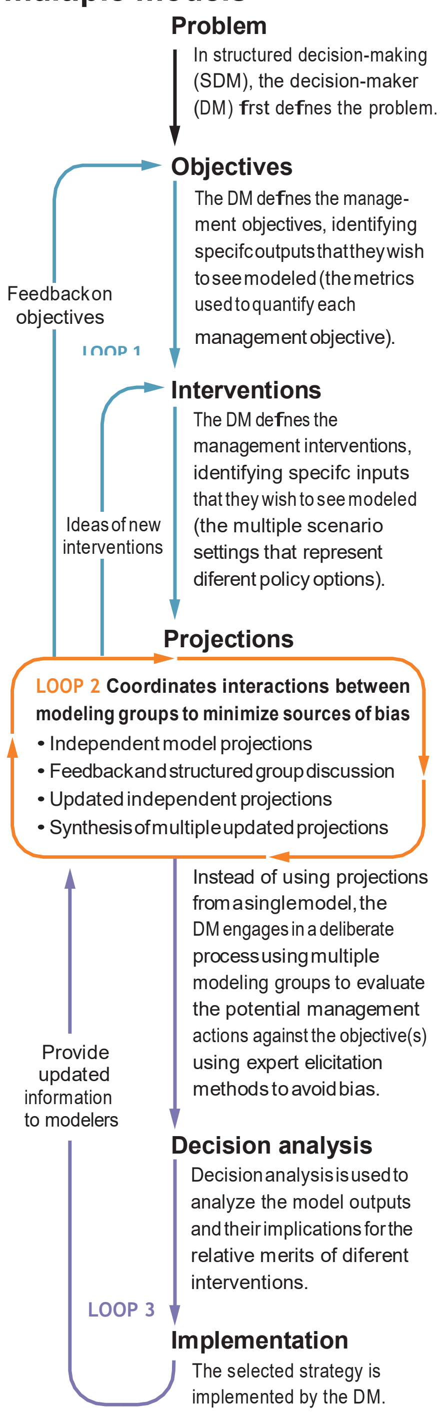
We present an elicitation process for mul- tiple modeling groups based on a modified- Delphi approach to expert elicitation (*6*) embedded in a structured decision-making (SDM) process (*15*). The overall process is coordinated by the decision-maker (DM)— for instance, the public health policy agency with authority to act. The adoption of a for- mal protocol for SDM (see the figure for an overview of the SDM process) allows us to assess the same set of actions in different models to address key objectives in a timely manner, and with an appropriate expres- sion of uncertainty to enable risk-based decision-making. We expand the SDM ap- proach in loop 2 of the figure to explicitly involve multiple modeling groups in a modified Delphi expert elicitation process. In general overview, the modeling groups initially work alone, then together (coordi- nated by the DM), and finally alone again.

The DM first outlines the process, and the required information, for the model- ing groups. This includes description of the management objective and associated metrics (e.g., minimization of total morbid- ity or mortality) and of the potential man- agement interventions. Note that projecting spatial spread or caseload trajectory under some baseline scenario of no action is still a management intervention ("do nothing"). Thus, efforts to forecast and to assess in- terventions should be fully integrated and presented consistently. The DM also pro- vides instructions about how within-model uncertainty should be documented (e.g., provide a full probability distribution of outcomes—not just a mean value—for in- tervention-objective projections, and docu- ment sources of variation). Uncertainty may be structural (e.g., should asymptomatic carriers be modeled explicitly?), or para- metric with respect to the biology (e.g., what is the expected time between sequen- tial cases in a chain of transmission?), or it may relate to the interventions (e.g., what is the expected impact of social distancing?). The DM must also provide background in- formation and access to current relevant data, information on intervention efficacy (if known), and guidance on data curation. The DM next must assemble modeling groups for the elicitation process. In the current COVID-19 outbreak, hundreds of research groups around the world are as- sisting national and international agencies with forecasts and management recom- mendations. Any type of new or existing model that encapsulates a scientific research groups best understanding of the situation effectively represents a hypothesis about the system, and should be eligible; however, re- strictive criteria may be applied with justi- fication in some situations (*3*). To construc- tively participate, all groups must agree to examine how the interventions of interest meet the DMs stated objectives. However, if some models cannot assess all interventions (e.g., if nonspatial models cannot address spatially explicit interventions), incomplete results may nevertheless be informative (*14*). During a first round of analysis, indi- vidual modeling groups, working indepen- dently, project the outcomes for each of the interventions, capturing their own within- model uncertainty. The DM invites a first report of results in a short period of time; this may be facilitated by providing a tem- plate format for model outputs. The DM then compiles and compares the results, provides feedback to the individual groups about their projections, and provides re- sults (anonymized, to reduce peer pressure) from all participants to the whole group.

All the modeling groups then participate in a formal, structured discussion to com- pare results, assess common features, dis- cuss what caused differences, identify valu- able information that might not have been available to all groups, generate important insights about the nature of the disease and its dynamics, and identify important in- sights to share. This structured discussion is an important step, allowing modelers and the DM to assess why models disagree.

After these discussions, individual mod- eling groups, again working independently, update their models and projections based on the insights from the whole-group dis- cussion. All groups have the opportunity to revise and rerun their models, using their judgments and data, taking account of the all-group discussion to the extent they think it is warranted, but not asking for consensus. The DM then compiles the second round of results, reporting both the central tenden- cies and the uncertainties within and across models. The Round 2 results are also then

Making the most of multiple models



combined into an ensemble projection for each management strategy (*1*, *14*). For example, an ensemble projection for different "reopening" scenarios could show the best estimate of COVID-19 case load across mod- els, for different policies for reinstating so- cial interaction, including full expression of the uncertainty captured by the model set.

The full set of results can then be used to guide policy deliberation. Two particu- lar techniques from the field of decision analysis are relevant here: first, risk analy- sis (which assesses the probability of poor outcomes for different interventions, and judges the tolerability of such risk) (*15*); and second, value of information analysis (which estimates the value to the DM of resolving one or more uncertainties prior to the implementation of a decision) (*13*). Central to these approaches is the recognition that projections may be wrong; by documenting uncertainty, a DM can evaluate which inter- ventions may be most robust to uncertainty and can allocate research effort to reduce the most consequential uncertainty.

Two rounds of modeling (instead of one) are key to the modeling-group elicita- tion process. Current sharing of early ideas through preprint servers and curated discus- sion groups permits communication of inde- pendent ideas that might otherwise not be shared; however, broad sharing also runs the risk of losing independent idea generation (*3*). The Round 1 projections, undertaken before the groups start collaborating with each other, are essential to avoid starting-point bias and groupthink, by encouraging independent idea generation and creative thinking. Asking modeling teams to formally review collective results and determine the reasons for differences in model projections highlights key uncertainties and helps mod- eling groups to detect flaws in their assump- tions or modeling approach. Nevertheless, the inclusion of a second, postdiscussion round of modeling need not delay the DM from taking action: The first round of results can be used for initial policy recommenda- tions if time is of the essence.

There are major advantages to embedding the model group elicitation process in a structured decision-making framework (*15*), relative to the ad hoc decision pro- cesses that are often employed. First, one iteration of the whole elicitation process can be used by the DM to decide on an ini- tial course of action to meet a clearly stated objective. Second, an important advance with expert elicitation is to elicit a relatively unbiased and full expression of uncertainty. The process provides policy-makers with two crucial pieces of information: a sense of the central tendency of the projections across models, and an understanding of the underlying uncertainty, as captured by the range of projections for different in- terventions. The results can be analyzed to identify which uncertainties most strongly affect the choice of action. It may be that one intervention is ranked best by all mod- els despite uncertainty, or it may be that the top-ranked intervention is highly sensitive to a particular uncertainty, indicating the need for research on that particular fac- tor. Third, if the outbreak is ongoing, and if models disagree (so that uncertainty is an impediment to choosing a course of action), and if new information on dynamics or management outcomes can be incorporated into the process, an adaptive management (AM) approach, involving management with a plan for learning, is warranted (*13*).

It is also possible for policy-makers to tailor the degree to which the elicitation ex- ercise itself feeds into targeted research or management decisions. Scientists can con- tribute to the process by providing input on new or better-specified objectives to policy- makers and by providing suggestions for additional or modified interventions for the whole group to assess. For example, in loop 1, if a policy-maker requests advice on the optimal intervention to "control" a disease, modeling groups may demonstrate that a more precise objective statement is needed (e.g., while zero cases equates to zero deaths, a small outbreak of COVID-19 in a nursing home may lead to more deaths than a large outbreak in a university setting; reducing caseload and mortality are not equivalent objectives). Similarly, in the 2014 Ebola outbreak, model forecasts ranged wildly, yet a focus on minimizing the number of cases brought surprising consensus on the best approach to intervention (*1*). In loop 1, modeling work by one group may also sug- gest potentially fruitful interventions that all groups could evaluate (e.g., earlier inter- vention triggers than proposed by the DM, or previously unconsidered interventions).

The proposed process encourages a healthy conversation between scientists and decision- makers and engenders a stronger integration of science and policy, enabling policy agen- cies to more effectively achieve their manage- ment goals. Furthermore, it helps the DM to embrace uncertainty, rather than hastening to a premature consensus that could derail or deflect management efforts (*9*).

Adoption of elicitation methods for mul- tiple modeling groups should be relatively straightforward; all structures to support and facilitate such a process are already in place [e.g., the "forecasting challenges" exemplified by (*4, 12*), and channels for communication between DMs and model- ing groups]. Thus, additional costs of this approach relative to traditional approaches should be minimal. A strength of this ap- proach is that individual modeling groups may preserve their autonomy and unilater- ally conduct additional analyses and pub- lish their work independently, as before, yet gain additional benefits from being in- volved formally in the group exercise, both in terms of access to information and feed- back, and in terms of contributing to the greater good. As a result, high participation of modeling groups should be achievable. We suggest that this strategy will prompt better outbreak management outcomes for similar effort by deliberately leverag- ing more value from the modeling process. As such, the risks and stresses inherent in implementing the approach are also mini- mized and should not be deterrents.

Leveraging the contributions of multiple modeling groups is likely to pay dividends in preventing morbidity and death. In short, managing any disease, including a disease outbreak, requires that policy ob- jectives be well defined, the decision-mak- ing process be carefully structured, and multiple contributing modeling groups be handled in a manner that shares knowledge while avoiding bias. Intertwining expert judgment methods with multiple model comparisons, in a planned and de- liberate manner, will thus increase the benefits derived from multiple groups' ef- forts to model outbreaks. ∎

REFERENCES AND NOTES

1. S. L. Li *et al.*, *Proc. Natl. Acad. Sci. U.S.A.* 114, 5659 (2017).
2. C. J. Carlson, E. Dougherty, M. Boots, W. Getz, S. J. Ryan, *Sci. Rep.* 8, 4921 (2018).
3. S. den Boon *et al.*, *BMC Med.* 17, 163 (2019).
4. P. E. Tetlock, D. Gardner, Superforecasting: The Art and Science of Prediction (Random House, 2016).
5. M. A. Burgman, Trusting Judgements: How to Get the Best out of Experts (Cambridge Univ. Press, 2015).
6. V. Hemming, M. A. Burgman, A. M. Hanea, M. F. McBride, B. C. Wintle, *Methods Ecol. Evol.* 9, 169 (2018).
7. A. Delbecq, A. Van de Ven, *J. Appl. Behav. Sci.* 7, 466 (1971).
8. M. K. Murphy *et al.*, *Health Technol. Assess.* 2, 1 (1998).
9. M. C. Runge, S. J. Converse, J. E. Lyons, *Biol. Conserv.* 144, 1214 (2011).
10. T. N. Krishnamurti *et al.*, *Science* 285, 1548 (1999).
11. S. C. Anderson *et al.*, *Fish Fish.* 18, 732 (2017).
12. C. Viboud *et al.*, *Epidemics* 22, 13 (2018).
13. K. Shea, M. J. Tildesley, M. C. Runge, C. J. Fonnesbeck, M. J. Ferrari, *PLOS Biol.* 12, e1001970 (2014).
14. W. J. M. Probert *et al.*, *Epidemics* 15, 10 (2016).
15. R. Gregory *et al.*, Structured Decision Making: A Practical Guide for Environmental Management Choices (Wiley-Blackwell, 2012).

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