# Effective use of models in intelligence-to-decision workflows within and across One Health sectors

**Kim Pepin**

kim.m.pepin@usda.gov

U.S. DEPARTMENT OF AGRICULTURE

**Keith Carlisle**

USDA

**Richard Chipman**

USDA

**Dana Cole**

USDA

**Dean Anderson**

Manaaki Whenua - Landcare Research

**Michael Baker**

University of Otago, Wellington https://orcid.org/0000-0002-1865-1536

**Jackie Benschop**

Massey University

**Michael Bunce**

Department of Conservation

**Rachelle Binny**

Landcare Research

**Nigel French**

Massey University

**Suzie Greenhalgh**

Manaaki Whenua - Landcare Research

**Dion O'Neale**

University of Auckland https://orcid.org/0000-0002-3827-3480

**Scott McDougall**

Cognosco https://orcid.org/0000-0002-9865-0532

**Fraser Morgan**

Landcare Research https://orcid.org/0000-0002-7964-3361

**Petra Muellner**

Epi-interactive

**Emil Murphy**

Deer Industry New Zealand https://orcid.org/0000-0002-5338-8382
**Michael Plank**
University of Canterbury
**Daniel Tompkins**
Predator Free 2050 Limited
**David Hayman**
Massey University https://orcid.org/0000-0003-0087-3015

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# Abstract

Decision-makers in public service face uncertainty. Operational management or policy decisions need to be made about system-level ecological and sociological processes that are complex, poorly understood, and change over time. Relying on intuition, evidence, and experience for robust decision-making is challenging without a formal assimilation of these elements (a model), especially when the decision needs to consider potential impacts if an action is or is not taken. Models can provide assistance to this challenge, but effective use of modeling tools in decision-making can be difficult due to lack of trust, expertise, and transparency and consistency in modeling methods and results. We conducted 41 semi-structured interviews of researchers, operational managers, and policy decision-makers with direct experience in intelligence-to-decision workflows involving models within and across human health, animal health, or environmental sectors (One Health sectors). Qualitative analysis of the interview data reveals important ingredients for effective development and use of quantitative models in informing management or policy decisions in One Health sectors. Two of the priorities we identified for implementing improved workflows include establishing different standards for development of modeling intelligence before or after decisions are made and investment in knowledge brokers with modeling expertise working in teams with decision-makers. These and other priorities we identified are important considerations for developers and users of modeling intelligence in a broad range of institutional contexts.


# Introduction

Every decision people make is based on a model. A model is an idea about how a process works based on previous experience, observation, or other data. Models may not be explicit or stated[1], but they serve to simplify a complex world. Models vary dramatically from conceptual (idea) to statistical (mathematical expression relating observed data to an assumed process and/or other data) or analytical/computational (quantitative algorithm describing a process). Predictive models of complex systems describe an understanding of how systems work, often in mathematical or statistical terms, using data, knowledge, and/or expert opinion. They provide means for predicting outcomes of interest, studying different management decision impacts, and quantifying decision risk and uncertainty[2,3].They can help decision-makers assimilate how multiple pieces of information determine an outcome of interest about a complex system[2,4].

People rely daily on system-level models to reach objectives. Choosing the fastest route to a destination is one example. Such a decision may be based on either a mental model of the road system developed from previous experience or a traffic prediction mapping application based on mathematical algorithms and current data. Either way, a system-level model has been applied and there is some uncertainty. In contrast, predicting outcomes for new and complex phenomena, such as emerging disease spread, a biological invasion risk[5-7], or climate change impacts on ecosystems is more uncertain. Here public service decision-makers may turn to mathematical models when expert opinion and experience do not resolve enough uncertainty about decision outcomes. But using models to guide decisions also has uncertainty[6] and might not appear straightforward[8]. This situation can lead to apprehension or lack of trust about using models to inform decisions.

Models may be particularly advantageous to decision-making in One Health sectors, including health of humans, agriculture, wildlife, and the environment (hereafter called One Health sectors) and their interconnectedness[9]. Because interdisciplinary health fields require collaboration among professionals with different professional backgrounds, methodologies, and traditions, a model is a useful tool to bring diverse data, concepts, and knowledge into a single framework. In a policy-making context, cross-agency and cross-sector collaboration is crucial. It requires integration of diverse perspectives for making decisions about system-level ecological and sociological processes that are complex, often poorly understood, and change over time (e.g., pandemic response, agricultural biosecurity preparedness, invasive species control, ecosystem conservation). Here, traditional risk assessment approaches involving experiments in pre-defined contexts can be infeasible or insufficient for science-informed decision-making. Instead, predictive models of complex systems may provide a better understanding of how systems work, preferably using mathematical or statistical terms, and including data, knowledge, and/or expert opinion from different sectors. Decision theory has demonstrated that models can improve decisions in One Health sectors by making risks more transparent and improving outcomes[2], but challenges remain[8].

Our objective was to identify guidance for effective use of predictive models in practical decision-making within and across One Health sectors by understanding challenges and solutions in situations where this has been successful, and summarizing recommendations from experts who have experience with intelligence-to-decision workflows that involve science from models. We focused our inquiry on Aotearoa New Zealand (NZ) – a country with a reputation for effective consideration of model outcomes in policy decisions[10-14]to understand conditions that lead to successful use of models for informing decisions. We conducted 41 semi-structured interviews across One Health sectors (Fig. S1), professional backgrounds (Fig. S2), organizational contexts, and professional roles (Fig. S1). All participants had experience working on a practical application of models with decision-makers.

# Results and Discussion

We synthesize responses from participants (direct quotes from participants in single quotes, sometimes modified slightly to hide identity) and concurrently interpret the responses and indicate consistency with previous work where applicable.

### Diverse definitions and familiarity with models

When asked what a model is, participants most commonly said: a tool for understanding a system, a decision-support tool, and/or a simplification of real-world complexity (Fig. S3). The top three types of models participants were familiar with included: computation or simulation models including scenario trees, statistical models, or mathematical models that solve equations (Fig S3), highlighting an emphasis on knowledge of quantitative models among the professionals interviewed.

### Useful applications of models

When participants were asked how models could be useful for guiding decisions in One Health sectors, 80% (33/41) said models were useful for comparing disease control policy scenarios. The second most frequently described use was in creating a joint understanding among stakeholders. Here, the process of developing the model was seen as the most useful deliverable - it helped decision-makers understand the system well enough to make informed decisions. Models provide a robust method for assimilating relevant information and bridging information gaps that cannot be resolved through other means.

When asked to describe an experience where participants were involved in an intelligence-to-decision workflow involving models, few participants said the model did not provide a critical role. Critical roles described included:

- Motivating policy development through risk assessment
- Facilitating communication, collaboration, and understanding at the science-management-policy interface
- Identifying important knowledge gaps for focusing future data collection
- Providing inference for processes that cannot be directly measured
- Identifying refined resource prioritization strategies
- Building knowledge in the early stages of a new event (e.g., COVID-19 emergence) when knowledge of the system is poor
- Motivating decision-makers by rapidly building evidence about whether action is needed when experiments are infeasible and when they are unmotivated to act on sparse information
- Building agreement among stakeholders on priorities
- Quantifying and framing decision risk – providing numbers alongside intuition about the likelihood of outcomes.
- Managing stakeholder expectations and social licensing for a policy by providing intelligence about how long it might take before changes are observed

### Reported risks and challenges

Participants reported effective use of models in decision-making is challenged by decision-makers not being trained sufficiently in the development, evaluation of robustness, and interpretation of answers from models. Participants thought lack of understanding can lead to misinterpretation of evidence, inability to understand what can and cannot be asked from a model, or misunderstanding uncertainty, including having a false sense of precision. 'Some models can be very bad at distinguishing unlikely from very unlikely' categories in practice, yet a decision-maker may want to feel confident about this distinction. Also, with increasing misinformation [15] and scientific specialization, it is challenging to bridge information gaps between the *two cultures* (scientists and policy-makers)[16]. The average level of scientific literacy for decision-makers and increased scientific misinformation are obscuring the ability of decision-makers to efficiently and effectively consider scientific evidence.

Another risk described by participants is that models ‘do what the user tells them to do’. A user can refine a model to deliver a desired output through inserting narrow ranges of parameter values that meet a desired outcome (e.g., prior distributions in a Bayesian analysis or parameter ranges in a sensitivity analysis of a computational or mathematical model), excluding processes one does not want effects from, or interpreting uncertainty in a way that supports one’s agenda (e.g., [17,18]). Users who do not understand how using models this way violates the scientific process are susceptible to unintentional misuse, while users who understand this well can be susceptible to intentional misuse. Risk of unintentional and intentional misuse affects trust in models. These concerns suggest that it’s important to develop standards for intelligence-to-decision workflows that use models, including transparent and professional expert peer review to reduce misinterpretation and misuse.

Relatedly, several participants thought models should not be developed and used for real-time forecasting during emergencies – the appropriate use of models is for preparedness when time is available for appropriate rigor and consideration (i.e., during non-emergency situations). One reason is that scientists are eager to provide real-time intelligence provision and advocate for their approaches even though each has uncertainty and potentially conflicting results. For example, ‘On the day we say we've got an outbreak, every university in NZ and some offshore will start modeling our outbreak. I'd like us to be a little bit ahead and to have had some of these conversations because I'm not gonna be in a conversation with 10 academics who all think their model is God’s gift’ while managing an emergency. This suggests that staff dedicated to preparedness modeling may increase use of models in management and policy decisions. Some participants thought real-time forecasting might also open the door for selecting models that provide confirmation bias or support political agendas that might not align with robust science, which erodes trust in science quality from models. Also, participants said models may have too much uncertainty to provide the level of precision that the public would hold decision-makers accountable for when different numbers play out in reality. It can be counterproductive to put ‘scary numbers with high uncertainty in the public domain’ and equally counterproductive to provide numbers with the the wrong level of detail because often decision-makers need intelligence on a relative (or qualitative) scale (e.g., outcome likely to be worse than X or better than Y).

Participants warned that modeling should be one source of evidence considered alongside other sources. However, some people may value numerical comparisons more than qualitative information, and numerical comparisons can give the semblance of clear-cut answers, when reality is more complex. Participants warned that modelers should not be ‘let out of their pens unaccompanied’, and that subject-matter-expert practitioners (e.g.public health specialists, physicians, veterinarians, wildlife managers) should be working hand-in-glove with them to shape their questions and interpret the results in terms of policy, social, or health impacts. Several participants referenced  the outbreak of foot-and-mouth in the

United Kingdom in 2001 as an example for why it's important to emphasize communication and not to have modelers translating the health policy intelligence from modeling results (e.g., [19,20]). Even though NZ has set up effective workflows for modeling intelligence-to-decisions in some sectors, there is a legacy effect due to both past experiences and ongoing current hurdles that have made it difficult to build trust.

Participants highlighted that models can reveal contextual details that impact other policy-making challenges because models can identify phenomena that were unanticipated. Participants said this could hinder the policy-making process due to a need to consider new factors that could delay important actions. Policy impacts can vary dramatically for different groups of people or animals and when this variation is accounted for, policy decision-making can require longer to achieve consensus among stakeholders. Whether this leads to better decisions or not would require further analyses and is likely dependent on the consequences of 'getting the call wrong'.

### Effective use of models

When asked to describe experience in intelligence-to-decision workflows involving models, participants mentioned a variety of applications. These ranged from - What transportation policies should we implement to improve human and environmental health? to What is the local probability of disease freedom of bovine tuberculosis? We summarize two examples participants described to show common themes that led to use of the models in practical decision-making (Box 1).In both cases, individuals in decision-making roles successfully championed the use of models and acted as 'navigators' (knowledge brokers) of the models into the decision-making ecosystem. The drive to champion models often came from long-term trusted relationships between the decision-maker and scientists that develop models. The decision-maker that championed the models invested substantial effort in regular communication between modelers and decision-makers to ensure the models addressed context-specific needs and constraints and provided a trusted source of evidence. Thus, trusted relationships and dedicated knowledge brokers are essential for successful uptake of modeling intelligence in policy decisions.

**Box 1.** Two examples where participants described their experience with using predicting models for informing decisions in One Health sectors: 1) COVID-19 pandemic response in humans and 2) bovine tuberculosis biosecurity in cattle and possums. Participants described conditions that led to models informing decision-making in high-stake applications.

***SARS-CoV-2 – humans***. Roughly 27% of participants reported playing a role in the modeling intelligence-to-decision workflow for control of COVID-19 in humans in NZ (see [21]). Key objectives for the models included comparing control policy scenarios (mathematical and computational models) and inferring the source of new cases for contact tracing and identifying and managing local introductions or outbreaks (phylodynamic models of genomic data) 14-17. Modelers in NZ reached out to government agencies to ask how they could help. Science advisors from the Office of the Prime Minister's Chief Science Advisors ([22]) saw the value in leveraging the research community and developed a system to integrate modeling expertise. Modelers rapidly leveraged available epidemiological models of SARS- CoV-2 in other countries and adapted them to the NZ context to address decision-maker needs. This application was followed by adaptation of the models for informing control policies (e.g., when to do local lockdowns, quarantine duration) throughout the pandemic.

We interviewed participants involved in the modeling intelligence-to-decision workflow including modelers, policy advisors, and policy decision-makers to understand what led to the acceptance and use of modeling intelligence by decision-makers. Models were viewed as important tools for informing the evidence landscape that support policy decisions during the pandemic for several reasons.

First, NZ decision-makers had recently leveraged models in a similar capacity to inform control policies for an introduction of *Mycoplasma bovis* in the country[23].

Second, they integrated a modeling team into the incident command system (ICS). The ICS communication structure involved a dedicated communicator between the modeling team and policy decision-makers. Communication occurred at least weekly early on, sometimes daily, where modelers provided guidance about resource needs and timelines for each decision-maker request, explained uncertainties in results and provided guidance on appropriate selection of models for each question. Decision-makers were able to specify high-priority questions.

Third, public health experts were integrated in the communication structure through an advisory group to interpret modeling results through a public health lens. Participants felt this helped to avoid the nonsensical public health policy decisions that can occur when evidence from models is interpreted directly without expertise from a practitioner in the appropriate health field.

Fourth, decision-makers first asked a very clear-cut, simple question: “should we continue with an elimination strategy?” NZ effectively implemented an elimination strategy on 23 March 2020 with an announced move towards a national stay at home order (‘lockdown’) and other measures aimed at eliminating Covid-19 [24]. Elimination is a well-established approach for ending transmission of endemic infectious diseases but was not previously used for pandemics where mitigation was the response strategy built into preparedness plans [25]. Modelers first started tackling this question by estimating the consequences of a poorly controlled pandemic wave [26]. They subsequently developed a framework that could query what the course of the pandemic could look like if an elimination strategy was continued versus a mitigation strategy [27]. Starting with a feasible, simple question helped to develop a functioning workflow that was viewed as useful by users, which led to greater demand. The validity of this work was reinforced by successful elimination of Covid-19 from New Zealand, 103 days after the first identified case [25]. Subsequent modeling also showed that making this decision early in the pandemic produced better outcomes than if it had been delayed [28].

Fifth, trusted government employees with strong quantitative skills were seconded from The Treasury into the COVID-19 modeling teams to act as knowledge brokers. These individuals provided two important elements: 1) a trusted source of expert oversight and 2) national government context knowledge to facilitate communication. Sixth, the Ministry of Health conducted regular surveys of public perspectives to understand perceived impacts of different policies and used the information to specify constraints in formulating questions for modelers. This example mainly concerns the beginning of the pandemic (~first 6 months of 2020). More nuanced policy questions were addressed later during the pandemic (e.g., [13,28]). Participants said that the successful incorporation of models early on to address simple, pressing questions helped to show the value for uptake later on (good return on investment), and infrastructure that could be readily leveraged (accessibility).

***Mycobacterium bovis – cattle/possum interface***. Another 22% of participants described the use of models for informing control policies for bovine tuberculosis (bTB) in NZ. In contrast to COVID-19, bTB rarely infects humans in NZ, and poses an ongoing threat to cattle due to its persistence in invasive, non-native brushtail possums (Trichosurus vulpecula)[29-31]. NZ has been managing bTB in domestic cattle since the mid-to-late 1900's[31,32]. Currently the mission of OSPRI (an organization including TBfree NZ Ltd, a shareholder and government-funded organization) includes bTb elimination. Models are used as standard practice for estimating local bTB freedom during control operations (for evaluating local bTB status in possum populations and planning surveillance design; [33,34]) and planning how much and how often possum control (i.e., killing) is necessary for reaching bTB freedom in local areas [35], including efficient strategies for resource allocation [30]. This involves a suite of models that have been developed, iteratively refined, and used routinely over the years [36]. We interviewed both modelers and bTB operational managers to understand how modeling intelligence is integrated in bTB operational decisions.

First, in the early years of the bTB elimination program there was a decision-maker who believed evidence from models was necessary for effective strategic planning and program evaluation. This decision-maker spent time building relationships with modelers and championed the approach.

Second, the trusted relationship with frequent communication included facilitating the decision-maker to shape model development with their expertise and knowledge (similar to the 'co-design' concept mentioned in Box 2), which enhanced confidence in the approach.

Third, long-term continuity in the use of modeling tools have allowed them to be tested and adapted against their predictions over time and have shown that the predictions met the needs of decision-makers.

Fourth, the initial champion of modeling tools incorporated these tools as a 'rule of business' and trained subsequent operational managers on the function and utility of the tools.

## How models are trusted

There are many ways to build models[37], each with advantages and disadvantages, so what gives professionals confidence in using results from models? Participants described a variety of metrics that gave them confidence. The most frequent answer was having a trusted interpersonal (often collaborative) relationship between scientists (and/or science advisors) and decision-makers[38]. Also, that model predictions proved accurate (validation of the model predictions against eventual real-life outcomes) and that the decision-maker was 'brought on the journey of model development' and 'understood what was under the hood.' It was also important that the  model and results were peer-reviewed, rigorous statistical evaluation was conducted and well-established scientific theories were applied (trust in scientific method). It was equally important that the model led to a high-impact policy change (added value to the decision-maker's bottom line). One participant said having models was considered essential by other colleagues or stakeholders, thus the model was trusted to meet a variety of participants' demands.

### Models for shaping versus supporting decisions

Models can be applied before a decision is made to shape decisions, or *post hoc* to evaluate decisions. Most participants felt use of models *a priori* is ideal but *post hoc* use can be valuable and appropriate when decisions need to be made more quickly than the science can be produced. Retrospective evaluation of decisions with models was seen as advantageous for providing support for further investment, providing scientific evidence for high-stakes decisions, or evaluating whether the decision should be revised to improve outcomes. Participants said it's useful to have a model for evaluation as conditions change and to identify alternatives. However, many thought there are special considerations and increased risk for model development as *post hoc* decision intelligence.

Participants said when modeling for *post hoc* decision intelligence it's important to understand whether the decision could be changed with additional intelligence. They said more safeguards are needed for conducting the science objectively because of the risk of confirmation bias[39], meaning it can be difficult to design the scientific questions objectively and comprehensively when a desired outcome is known. Using multiple independent scientific groups[3] may be important to safeguard against this risk.

Participants said 'policy-based evidence' (research engineered to support already made policy decisions) is simply bad practice and violates the scientific method. Based on risks previously described regarding decision-makers lacking expertise in modeling, there may be additional risk of misuse of science relative to other intelligence production techniques because one can construct and parametrize a model to produce a desired result. Using models for *post hoc* evaluation of decisions requires good-faith decision-making. One participant described this as: 'you need to have clean governance over decisions - you need to separate the decision-making from the people who are going to benefit from the decisions'.

Other participants said that *post hoc* use of models requires encouraging decision-makers to ask the right (objective) questions with an understanding of what is and what isn't scientific evidence that aligns with robust practice. Otherwise, evidence claimed to be derived from science is actually misinformation. Examples of bad practice with models relayed by participants included 'asking questions that pre-suppose an answer', asking a modeler to 'provide support for a decision', and choosing one result or model from a set that have similar scientific rigor, probabilities of being true, and/or similar levels of uncertainty about the truth. Science has developed a variety of methods for objectively combining information gained from divergent sources of data to produce intelligence (e.g., [3]). *Post hoc* modeling needs to be about testing the value and effectiveness of a decision and evaluating potential impacts of alternative decisions. Because political pressure can be high to not 'rock the boat', and humans have a natural tendency to trust evidence that best matches their understanding (confirmation bias), it is especially important to develop standards for appropriate use of models in *post hoc* decision-making.

### Tension in the scientist-decisionmaker relationship

There is tension between professionals working where the mission is more research-focused versus public policy or government-based operational programs. Considering the frustrations expressed on "both sides" collaboration could be improved[40]. Key frustrations from research-focused professionals include difficulty keeping up with which scientific questions are most helpful to pursue. Reasons cited included not understanding the government context, little transparency on who to contact for different issues (leading to relationship-building with someone at the wrong level of government for use of the science in decision-making), and not having the capacity to develop and maintain relationships among all the other responsibilities of a research scientist. Participants said there is high turnover in government positions, which leads researchers to not invest time in building relationships because when collaborators move positions, the knowledge and relationship is lost. Additionally, participants said government professionals are unhelpful in connecting researchers in a meaningful way, seeming that 'government professionals don't care about important scientific findings'. One participant said the solution to improving relationships involves actively discussing and planning for 'how to go about building an ecosystem where there's a richer, more resilient network of relationships between researchers and policy makers so that policy makers can quickly take soundings from the research community in a very informal way and build those relationships that enable deeper pieces, whether the scientists are really coming together with a more proactive, long-term evidence base for more strategic work.'.

Decision-makers expressed that policy-making processes take a very long time with numerous reviews that involve input from a variety of stakeholders. An original policy proposal that was well justified by scientific evidence can be refined repeatedly by different people so the rationale is changed or lost altogether. It can be difficult to bring outside modelers in later in the process, making it important to have involvement from the beginning and a clear mechanism for incorporating new evidence. Decision-makers admitted that researchers often understand so little about policy processes that they cannot bridge the gap to work with researchers. Potential solutions include increasing opportunities for scientist secondments into government contexts[38], such as AAAS Science & Technology Policy Fellowships in the USA for early career researchers or science advisors for those more senior.

Modeler behavior can prohibit collaboration. For example, saying 'I told you so' when an adverse event occurs 'instead of just jumping in and rolling up the sleeves' can be counterproductive to engagement, and shows a lack of sensitivity or awareness to the position of other professionals. Counterproductive behaviors can be minimized with more transparent communication between modelers and decision-makers about the constraints experienced by each group and opportunities for engagement. Relatedly, it's important for researchers to come to the table with the attitude that the 'modeling is only one piece in the puzzle' and 'park the self-importance attitude'. The contribution from any one modeler will be considered in a team environment that may or may not have capacity for direct communication between the modeler and the decision-maker. For this reason, some decision-makers are replacing the term 'science-based decisions' with 'science-informed decisions'[38].

Finally, similar to research-focused professionals, decision-makers are usually overburdened with little flexible time and have very tight timelines for decision-making. These constraints generally do not align well with, for example, participation of graduate students. Limitations for decision-makers include that most graduate students cannot solve problems fast enough nor can they communicate the results effectively. Involving graduate students in solutions for decision-makers can lead to needs not being met and a lack of willingness for a decision-maker to want to involve outside scientists in the future. Yet, involvement of graduate students is part of the business structure for research organizations and prepares scientists to join the workforce.

### What professionals recommend for effective workflows

Consistent with previous work, several participants said one important feature for successful workflows of modeling intelligence in decision-making is to have a knowledge broker [38,41]. The knowledge broker is often a science advisor but may be a subject-matter expert that serves as a trusted advisor or navigator to the decision-maker (e.g., health practitioner or health/environment policy expert in our system, Table 1). A good knowledge broker for modeling intelligence will be experienced in science communication to decision-makers, be able to quickly convert complex science into intelligence, have a strong grasp on quantitative analysis techniques, understand the decision-maker's context, be objective about consideration of relevant intelligence, and have a trusted relationship with the decision-maker.

Being explicit about roles and responsibilities of team members is important for minimizing miscommunication or unwanted communication. In decision-making for public policy, the role of science producers is to explain to the decision-maker, not the public. The role of science advisor is to recommend decisions to the decision-maker based on a broad set of intelligence (Table 1). This can be confusing because, for example, NZ's Education Act encourages academic freedom and a role for academics as critics and conscience of society, making it important to discuss roles when academic scientists engage with decision-makers as science producers.

Decision-making is a values-based process[42]. Because decision-makers use different criteria for gaining trust in intelligence, it's important to understand the value system used to gain confidence about information quality. This can be done when modelers work with decision-makers to define the problem. When identifying the decision-makers objectives, it is important to understand what the decision-maker's constraints are (e.g., timelines for answers, budget, infrastructure, time they or their knowledge broker have to participate) and ensure decision-makers understand what the scientist's constraints are (data quality needs, resources, feasible timelines, the type of answers that can be generated). During NZ's early COVID-19 experience, this exchange was facilitated through a key knowledge broker who set up regular communication among modelers and policy developers in an incident command type of structure. All participants we interviewed that were part of this workflow commented about how effective this approach was in developing models and appropriate timelines for policy decisions. These conversations are important for determining the level of investment needed for modeling and appropriate modeling techniques. An ability to clearly understand the problem the decision-maker is trying to solve is a critical skill for building trust and adding value. When done effectively, the modeler and knowledge broker can assist and empower the decision-maker to refine questions in the most effective way for their problem. This approach is synergistic with how participants described their vision for collaboration with Māori - NZ's Indigenous population - to address inequities (Box 2).

Making a communication plan to establish the preferred frequency and method of communication can help manage inefficient delivery of products, which causes frustration.  Establishing early on who the science producer should work with to access data and get input for model development is important for efficiency.

It is good practice to make sure the decision-maker understands what value modeling can and cannot bring to the problem. This helps to manage expectations and regret in the investment, which can have legacy effects for future investment. For emerging fields, it is important to articulate to decision-makers the long-term benefits of investment in terms of capacity building and readiness. Relatedly, it is useful to understand concerns the decision-maker might have about the modeling and identify a workflow that minimizes those risks. After the model has been developed and used, demonstrating the return on investment is important for continued building of trust in the use of models for future decision-making.

**Table 1:** Synthesis of the actions recommended by participants for an effective intelligence-to-decision workflow in determining management strategies or control policies in One Health sectors.

| Actors | Actions → | | | | | | |
|---|---|---|---|---|---|---|---|
| | Identify management/policy question | Develop model | Obtain outputs | Evalute output | Provide intelligence | Make decision | Return on investment |
| Decision-maker (DM; Operational manager or policy maker) | Explain information gap and constraints (e.g., timelines, budget, infrastructure, availability for consultation), Explain concerns and potential risks | Answer questions that arise about developing the best model for the question given constraints | Understand uncertainty of the evidence | Determine confidence in output relative to other intelligence by applying DM-specific values | Weigh the relative importance of modeling intelligence alongside other pieces of intelligence | Consider intelligence from models alongside other intelligence, make and communicate decision using DM-specific values | |
| Knowledge broker (KB) | Facilitate communication between M and DM, establish a communication plan | Advise parameter values and processes or context-specific details to include, facilitate acquiring appropriate data, Evaluate whether model assumptions are appropriate | Facilitate communication between M and DM | Advise DM about the level of confidence in output and importance to the question | Collate other intelligence in collaboration with DM, interpret intelligence from M weighed up next to other intelligence and communicate recommendations to DM | | Facilitate communication of value added to decision |
| Modeler (M) | Understand DM question, risks to DM, and how DM comes to trust and value evidence, explain constraints (e.g., timelines, data needs, resources needs), Understand role DM would like M to play | Identify appropriate modeling techniques, explain what can and can't be answered, collate and process data into appropriate formats, Explain model assumptions and limitations | Produce visualization of desired outputs in a way that is accessible to the DM, Explain uncertainty | Apply rigorous statistical techniques to evaluate robustness of output | Interpret modeling results in terms of the question | | Demonstrate value added to decision (including capacity building & new methods development) |

* Note some modelers may also be knowledge brokers; examples of knowledge brokers include science advisors, health practitioners, health or environment policy experts.

**Box 2.** Synergies in successful relationship characteristics for researcher-Māori relationships and modeler-decision-maker relationships.

The relationship between the NZ government (representing The Crown) and Māori, the Indigenous people, tangata whenua, of NZ, is governed by te Tiriti o Waitangi, where one of the principles recognizes Māori and The Crown as equal partners, including in public policy[43,44]. There is a requirement for research that is funded by government agencies to consider Māori rights to determine processes and priorities, and for funding panels to consider this in their decisions. Thus, we asked participants how they partnered with Māori in their work, and to describe any challenges and guidance for doing so. Several participants mentioned that Māori objectives often have synergies with One Health, as Māori have concepts such as wai ora, a concept relating to the importance of the environments in which we live on health and wellbeing, kaitiakitanga, a concept of custodianship, and whakawhanaungatanga, or relationship building[45].

Prioritizing consideration of Māori perspectives is an example of other factors besides modeling intelligence that need to be considered in decision-making in One Health sectors in NZ. The most commonly cited challenges by participants include: Māori representatives being overwhelmed by requests to participate without having appropriate resources and infrastructure, underrepresentation of

Māori in research due to inequity and historic discrimination, and a general feeling that efforts to incorporate Māori perspectives are motivated by the requirement rather than a genuine desire to collaborate. All of these challenges are consistent with previous work[46-48]. For professionals that have little experience with Māori culture, participants described many practical challenges to collaboration. These include how best to integrate Mātauranga (Māori knowledge), which is generated using methods consistent with the scientific method but presented differently than standard reporting in the scientific literature[49], working over timescales that are slower than funding cycles for research, working within a different system of governance, and using a different system for communicating ideas - features that have a steep learning curve. Investing in sincere long-term relationship building was viewed by participants as the only effective way forward. This view aligns well with one of the most important elements participants described for effective uptake of science (including from models) by decision-makers[50]. However, participants mentioned it can sit at odds with the high turn-over seen in some decision-making roles and rapid funding cycles. Similar to the scientist-decision-maker relationship, participants said that successful collaborations of non-Māori with Māori include co-leadership and co-design of objectives, where the role of non-Māori collaborator (or modeler in this analogy) is to help resource and provide skills or technology for empowering Māori decision-makers to identify their own objectives, i.e., tino rangatiratanga – self-determination. Useful pursuits for addressing the challenges include developing centers where Māori have resources and infrastructure to engage with non-Māori scientists and decision-makers to communicate important objectives, and increased opportunity to work in research. Participants thought that similar infrastructure development may be useful for better engagement of modelers with decision-makers in One Health sectors.

### Application beyond New Zealand

Many of NZ's professionals (66% of participants) trained or originated from other countries, providing insight beyond NZ. However, NZ has some unique features with its remote location and small government, suggesting not all results from our study may transfer to other contexts. Although several participants cited increasing scientific misinformation as a challenge for science-informed decision-making, these challenges may be lower than in other contexts [15]. Thus decision-makers in NZ might be more likely to use accurate science and scientific methodologies or have more trust in science as a starting point when faced with the potential for predictive models to help their decision. One participant did say that they believed scientific misinformation tendencies in media in the USA is influencing the NZ public, suggesting this difference from other contexts might be changing. For example, when discussing science supporting control of bTB: 'I feel a bit discouraged at the moment. I feel like the things that I and my colleagues have worked on for years carry less weight than they used to, and that that's worrying for the future problems that are going to arise.', and referring to misinformation about science in the public relative to COVID-19 control policy: 'a lot of it honestly is coming in from American social media. And so you see the exact same arguments that you are seeing in Tennessee replaying here'.

Also, most participants mentioned that NZ's small size provides a unique advantage for rapid cross-agency and science-community/agency coordination at a national scale. Several participants mentioned that finding the right scientist or agency professional for a given problem is only ‘one or two phone calls away’. This potential advantage was described as: ‘In NZ, because it's small and everybody knows each other, it is slightly easier than in other places and especially in emergencies. So, one thing NZ does well is scramble’. Speaking about NZ’s response to COVID-19: ‘It wasn't perfect but talking to my counterparts from around the world, they really struggled to scramble like we scrambled because there were much more formal mechanisms and fewer relationships to draw on. So I think if we could somehow use the mechanism we used for Covid and apply it when there's no emergency on, we'd find some sweet spot.‘. In countries with larger or decentralized governments, building relationships for effective modeling-intelligence-to-decision workflows requires more strategic planning and dedicated resources.

**Priorities for improving the intelligence-to-decision workflow involving models**

After reflection on the synthesized data from participants, our own experience, and scientific literature, we suggest the following priorities for improving effectiveness of the modeling intelligence-to-decision workflow:

- Address diverse value systems. Decision-makers differ in how they value or trust different sources of information, including Indigenous knowledge/people, which can vary with each specific issue and across One Health sectors. Thus, it’s important to establish how scientific information from models is valued relative to other sources of information, and what criteria need to be met beyond scientific rigor for information to be trusted. This will help deliver results in a format that is useful to decision-makers.
- Effective communication to decision-makers. Consistent with learnings from the field of science communication[51], communication about models needs to meet people where they are at. This means modelers need to understand what decision-makers know and do not know and have flexibility to adapt their communication style (and visual assets) accordingly. Iterative improvements and designs underpin effective communication. Decision-makers are ‘time poor’, needing information and communication that is triaged, prioritized, and presented in a way that enables rapid uptake. Thus, effective communication about models for decision-makers requires clear and concise communication so that time-limited decision-makers can rapidly interpret output and limitations but delivered to not demean the knowledge-level of the decision-maker.
- Effective communication to the public. Modelers need to be cautious in providing information and advice directly to the public without expert training in environmental, human or animal health or as acting as spokespersons for relevant agencies. There is potential to add to misinformation and damage trust in science-informed advice through inconsistent messaging. It is important to work with other disciplines, particularly colleagues with medical, public health, veterinary, environmental and cultural expertise, as appropriate, to shape consistent messages about current and future risk levels, and risk management approaches for prevention and control measures.
- Expand relationship- and network-building opportunities between modelers and knowledge brokers or decision-makers. Effective intelligence-to-decision workflows require trusted relationships that

can be accessed readily. Dedicated capacity building of broad scientific networks of modeling expertise that have trusted relationships with decision-makers is needed for cutting-edge modeling tools to be used more readily in high-impact policy decisions. Key gaps include opportunities for communication for relationship building and cross-education, and developing mechanisms that both expand the breadth of trusted modeling-science networks and allow next-generation modelers to be trained and incorporated.

- Ensure multiple modeling groups for quality assurance. Trust in modeling work will be enhanced by supporting establishment of more than one modeling group to look at similar questions [52], allowing for multi-model comparisons [53]. Achieving this goal depends on resourcing workforce development and effective networks.
- Increase transparency about institutional and decision-making contexts. Decision-makers may have constraints that modelers are unaware of and that decision-makers do not think to communicate. Both parties need to identify these constraints for consideration in models, or even for starting the collaboration early enough that a model could be more useful. The difference in context often comes with very different jargon that complicates understanding each other's needs and roles. The knowledge broker role is key for bridging this communication gap. It would be helpful to increase opportunities for temporary co-appointments of university-based scientists into government roles or for knowledge brokers and decision-makers to run lectures or workshops at research institutes to better expose researchers to the operational environment where science and models are used.
- Create more model-educated knowledge broker positions. Decision-makers frequently do not understand the state of the science in an area they are making decisions about, and science from models can be complicated. There is a lack of knowledge brokers in One Health sectors in government positions that understand the scope of possibilities from different data sources, and what is and is not rigorous modeling science. This gap and the increase in science misinformation make it challenging for decision-makers to identify rigorous modeling intelligence. Increasing the number of professionals in government with strong quantitative backgrounds that could serve as knowledge brokers is essential for unlocking the full potential for modeling intelligence in decision-making. It is naive to think these positions (and expertise) will occur organically, rather such roles need to be identified, supported, and valued.
- Establish standards for development and use of models as *a priori* or *post hoc* decision-informing tools. It can be challenging to use modeling results for decision-making partly because modelers use a variety of different modeling workflows[37] and decision-makers use a variety of different decision-making processes and value systems. In general, establishing standards for how to use modeling results in decisions (see [54-56] for progress) will improve the uptake and efficiency of decision-support models. *Post hoc* modeling for decision evaluation must have different methodological standards relative to *a priori* decision-informing modeling to maintain integrity of the scientific process.

# Methods

We chose a qualitative case study approach [57] to gain an in-depth understanding of individuals' perceptions of models and insights into the conditions under which they find models useful in decision-making. Data were collected using semi-structured interviews, a less formal interview approach that is well suited to exploratory research, as it allows the interviewer to follow up on and explore relevant and meaningful ideas that emerge in the course of the interview [58]. The semi-structured interview approach had two benefits for this research. First, it allowed us to identify and learn more about additional themes that participants raised that we did not directly describe in our interview guide *a priori*. This was important as the interviewers did not have a deep knowledge of the NZ landscape and the interview guide was aimed at targeting areas the US research team had identified from the literature and from the US context they were most familiar with. Second, the semi-structured interview format enabled the interview to go into greater depth in those areas where an interviewee had the most expertise, and to explore in greater detail contrasting opinions and approaches to other interviewees. This qualitative data collection approach enabled us to provide greater nuance to the themes than using a quantitative survey or similar approach [59].

Interview topics were developed based on the US-based team's experience with working at the interface of modeling science, disease management, and policy, primarily in the animal health and wildlife sectors of One Health, and scientific literature on science communication, models in decision-making, and strategies for co-developing objectives among numerous stakeholders (such as structured decision-making). The interview guide evolved throughout the study as reflections were made about both the US and NZ context (see SI for interview guide). The initial interview guide was reviewed by two US-based One Health professionals in operational decision-making roles and pre-tested by two other US-based One Health professionals in other operational decision-making roles.

We used snowball sampling combined with purposive sampling[60,61], a non-random sampling that involves participants suggesting other participants (snowball; [60]) and deliberate selection based on experience or knowledge (purposive; [61]). Our process included identifying an initial subset of individuals who met our inclusion criteria using our own professional network. Inclusion criteria were (a) experience informing management or policy decisions that consider science, (b) some exposure to building, interpreting, or making decisions using science from models, and (c) a professional background within or across diverse One Health sectors (Public health, Agriculture, Wildlife, Environment). We aimed to include at least 2-3 participants working in each One Health sector and for each level of the following dimensions that were not mutually exclusive from the One Health sector experience: <u>organizational context</u> (levels: National Government, Local government, University, other non-governmental organization), and <u>professional role</u> (levels: Science production, Science advisor to decision-maker, Operational management, Policy decision-maker). The initial subgroup consisted of 7 professionals who were thought to be well connected in their professional networks and represented a variety of contexts (1 national government agency, 2 non-profit research with a national mission, 1 non-profit operation with a national mission, 3 university), domains (3 domestic animal, 1 environment, 1 public health, and 2 wildlife health), and roles (3 science producer, 2 senior or chief scientists, or 2 decision-maker). Of the 7 initial individuals, 6 agreed to participate and all suggested additional colleagues. The process repeated itself until we had at least 2-3 individuals across all dimensions of interest. We continued to add new participants after the interviews started until we reached theme saturation (no new themes) in the recommendations for effective intelligence-to-decision workflows. This process resulted in a grand total of 41 interviews being conducted.

Our study protocol was submitted to an Institutional Review board and determined to be exempt due to it's very low risk for negative impacts to participants. Prior to conducting the interviews each interviewee received a participant information sheet to review, which described the purpose, objectives, participant roles, and methods of the study, and an informed consent form that participants signed to acknowledge their understanding of the expectations and role of the interview process and reporting of results. Interviews lasted 45 to 90 minutes, were audio recorded, and then transcribed using artificial intelligence software (Descript) and manual verification. All interviews were conducted by the first author. For manual verification, each audio file was listened to while reading the text file and edited for accuracy. Text transcripts were then sent to participants for review (if desired) to check for additional errors. No additional errors that changed the meaning of the text were found. Content analysis of text transcripts [62] was conducted by the first author to identify and synthesize themes. For this, the first author first developed a spreadsheet that listed each interview question topic as column headers. For each interview question topic, the first author analyzed each participant's transcript and identified themes. As more transcripts were analyzed for each question topic consistent labeling for each theme was developed. Previous transcripts were re-visited as needed to verify consistency and accuracy of each theme label. This produced a synthesized spreadsheet of all themes that could be visually scrolled by question topic to identify and quantify (when appropriate) themes for each question topic.

# Declarations

### Competing interests

The authors declare no competing interests. None of the authors are on the editorial board of Humanities and Social Science Communications.

### Author contributions

KP designed the study, conducted the interviews, analyzed the data and wrote the first draft of the manuscript, KC provided guidance on study design and analysis using qualitative methods, RC and DC helped develop the question guide and edited the manuscript, all other authors contributed to data collection and editing the manuscript draft.

### Data Availability

Summarized data is available upon request. We cannot share raw transcript material due to our agreement with participants.

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[currently removed for anonymization]

# References

1. Johnson-Laird, P. N. Mental models and human reasoning. *P Natl Acad Sci USA* **107**, 18243-18250, doi:10.1073/pnas.1012933107 (2010).
2. Berger, L. *et al.* Rational policymaking during a pandemic. *P Natl Acad Sci USA* **118**, doi:ARTN e2012704118/pnas.2012704118 (2021).
3. Li, S. L. *et al.* Essential information: Uncertainty and optimal control of Ebola outbreaks. *P Natl Acad Sci USA* **114**, 5659-5664, doi:10.1073/pnas.1617482114 (2017).
4. Hemming, V. *et al.* An introduction to decision science for conservation. *Conserv Biol* **36**, doi:10.1111/cobi.13868 (2022).
5. Chen, Z., Lemey, P. & Yu, H. Approaches and challenges to inferring the geographical source of infectious disease outbreaks using genomic data. *Lancet Microbe*, doi:10.1016/S2666-5247(23)00296-3 (2023).
6. Elderd, B. D., Dukic, V. M. & Dwyer, G. Uncertainty in predictions of disease spread and public health responses to bioterrorism and emerging diseases. *P Natl Acad Sci USA* **103**, 15693-15697, doi:10.1073/pnas.0600816103 (2006).
7. Pepin, K. M. *et al.* Optimizing management of invasions in an uncertain world using dynamic spatial models. *Ecol Appl* **32**, doi:ARTN e2628/eap.2628 (2022).
8. Bedson, J. *et al.* A review and agenda for integrated disease models including social and behavioural factors. *Nat Hum Behav* **5**, 834-846, doi:10.1038/s41562-021-01136-2 (2021).
9. Adisasmito, W. B. *et al.* One Health: A new definition for a sustainable and healthy future. *Plos Pathog* **18**, doi:ARTN e1010537/journal.ppat.1010537 (2022).
10. Bremer, S. & Glavovic, B. Exploring the science-policy interface for Integrated Coastal Management in New Zealand. *Ocean Coast Manage* **84**, 107-118, doi:10.1016/j.ocecoaman.2013.08.008 (2013).
11. Cowled, B. D. *et al.* Use of scenario tree modelling to plan freedom from infection surveillance: Mycoplasma bovis in New Zealand. *Prev Vet Med* **198**, 105523, doi:10.1016/j.prevetmed.2021.105523 (2022).
12. Mazey, S. & Richardson, J. Lesson-Drawing from New Zealand and Covid-19: The Need for Anticipatory Policy Making. *Polit Quart* **91**, 561-570, doi:10.1111/1467-923x.12893 (2020).
13. Mccaw, J. M. & Plank, M. J. The Role of the Mathematical Sciences in Supporting the Covid-19 Response in Australia and New Zealand. *Anziam J* **64**, 315-337, doi:10.1017/S1446181123000123 (2022).
14. Rouse, H. L. & Norton, N. Challenges for freshwater science in policy development: reflections from the science-policy interface in New Zealand. *New Zeal J Mar Fresh* **51**, 7-20,

doi:10.1080/00288330.2016.1264431 (2017).

15. Scheufele, D. A. & Krause, N. M. Science audiences, misinformation, and fake news. *P Natl Acad Sci USA* **116**, 7662-7669, doi:10.1073/pnas.1805871115 (2019).
16. Snow, C. P. *The Two Cultures*. 179 pgs (Cambridge UNiversity Press, 2012).
17. Pepin, K. M., Kay, S. L. & Davis, A. J. Comment on: ‘Blood does not buy goodwill: allowing culling increases poaching of a large carnivore’. *Proceedings of the Royal Society B* **284** (2017).
18. Stien, A. Blood may buy goodwill: no evidence for a positive relationship between legal culling and poaching in Wisconsin. *Proceedings of the Royal Society B* **284** (2017).
19. Kitching, R. P., Thrusfield, M. & Taylor, N. M. Use and abuse of mathematical models: an illustration from the 2001 foot and mouth disease epidemic in the United Kingdom. *Rev Sci Tech Oie* **25**, 293-311, doi:DOI 10.20506/rst.25.1.1665 (2006).
20. Mansley, L. M., Donaldson, A. I., Thrusfield, M. V. & Honhold, N. Destructive tension: mathematics versus experience - the progress and control of the 2001 foot and mouth disease epidemic in Great Britain. *Rev Sci Tech Oie* **30**, 483-498 (2011).
21. NZ, S. https://data.govt.nz/assets/Uploads/Covid-19-lessons-learnt-full-report-Mar-2021.pdf (Stats NZ Tatauranga Aotearoa, Wellington, New Zealand, 2021).
22. Advisors, O. o. t. P. M. s. C. S. *Chief Science Advisor Forum*, 2024).
23. Ministry for Primary Industries, M. A. M. *Mycoplasma bovis disease eradication programme*.
24. Baker, M. G., Kvalsvig, A., Verall, A. J., Telfar-Barnard, L. & Wilson, N. New Zealand’s elimination strategy for the COVID-19 pandemic and what is required to make it work. *he New Zealand Medical Journal* **133**, 10-14 (2020).
25. Baker, M. G., Wilson, N. & Blakely, T. Elimination could be the optimal response strategy for covid-19 and other emerging pandemic diseases. *Bmj-Brit Med J* **371**, doi:ARTN m4907/bmj.m4907 (2020).
26. Hendy, S. *et al.* Mathematical modelling to inform New Zealand's COVID-19 response. *J Roy Soc New Zeal* **51**, S86-S106, doi:10.1080/03036758.2021.1876111 (2021).
27. James, A., Hendy, S. C., Plank, M. J. & Steyn, N. Suppression and mitigation strategies for control of COVID-19 in New Zealand. (https://www.medrxiv.org/content/10.1101/2020.03.26.20044677, 2020).
28. Binny, R. N. *et al.* Early intervention is the key to success in COVID-19 control. *Roy Soc Open Sci* **8**, doi:ARTN 210488/rsos.210488 (2021).
29. Barron, M. C., Tompkins, D. M., Ramsey, D. S. & Bosson, M. A. The role of multiple wildlife hosts in the persistence and spread of bovine tuberculosis in New Zealand. *N Z Vet J* **63 Suppl 1**, 68-76, doi:10.1080/00480169.2014.968229 (2015).
30. Gormley, A. M., Holland, E. P., Barron, M. C., Anderson, D. P. & Nugent, G. A modelling framework for predicting the optimal balance between control and surveillance effort in the local eradication of tuberculosis in New Zealand wildlife. *Prev Vet Med* **125**, 10-18, doi:10.1016/j.prevetmed.2016.01.007 (2016).

31. Nugent, G., Buddle, B. M. & Knowles, G. Epidemiology and control of Mycobacterium bovis infection in brushtail possums (Trichosurus vulpecula), the primary wildlife host of bovine tuberculosis in New Zealand. *N Z Vet J* **63 Suppl 1**, 28-41, doi:10.1080/00480169.2014.963791 (2015).
32. Livingstone, P. G., Hancox, N., Nugent, G. & de Lisle, G. W. Toward eradication: the effect of infection in wildlife on the evolution and future direction of bovine tuberculosis management in New Zealand. *New Zeal Vet J* **63**, 4-18, doi:10.1080/00480169.2014.971082 (2015).
33. Anderson, D. P., Gormley, A. M., Bosson, M., Livingstone, P. G. & Nugent, G. Livestock as sentinels for an infectious disease in a sympatric or adjacent-living wildlife reservoir host. *Prev Vet Med* **148**, 106-114, doi:10.1016/j.prevetmed.2017.10.015 (2017).
34. Anderson, D. P. *et al.* A novel approach to assess the probability of disease eradication from a wild-animal reservoir host. *Epidemiol Infect* **141**, 1509-1521, doi:10.1017/S095026881200310x (2013).
35. Ramsey, D. S. L. & Efford, M. G. Management of bovine tuberculosis in brushtail possums in New Zealand: predictions from a spatially explicit, individual-based model. *J Appl Ecol* **47**, 911-919, doi:10.1111/j.1365-2664.2010.01839.x (2010).
36. Nugent, G., Gormley, A. M., Anderson, D. P. & Crews, K. Roll-Back Eradication of Bovine Tuberculosis (TB) From Wildlife in New Zealand: Concepts, Evolving Approaches, and Progress. *Front Vet Sci* **5**, doi:ARTN 277/fvets.2018.00277 (2018).
37. Silberzahn, R. *et al.* Many Analysts, One Data Set: Making Transparent How Variations in Analytic Choices Affect Results. *Adv Meth Pract Psych* **1**, 337-356, doi:10.1177/2515245917747646 (2018).
38. Gluckman, P. D., Bardsley, A. & Kaiser, M. Brokerage at the science-policy interface: from conceptual framework to practical guidance. *Hum Soc Sci Commun* **8**, doi:ARTN 84/s41599-021-00756-3 (2021).
39. Nickerson, R. S. Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology* **2**, 175-220 (1988).
40. Power, N. Extreme Teams: Towards a Greater Understanding of Multi-Agency Teamwork During Major Emergencies and Disasters. *Am Psychol* **73**, 478-490 (2018).
41. Kiem, A. S., Verdon-Kidd, D. C. & Austin, E. K. Bridging the gap between end user needs and science capability: decision making under uncertainty. *Clim Res* **61**, 57-74, doi:10.3354/cr01243 (2014).
42. von Winterfeldt, D. Bridging the gap between science and decision making. *P Natl Acad Sci USA* **110**, 14055-14061, doi:10.1073/pnas.1213532110 (2013).
43. Came, H., O'Sullivan, D., Kidd, J. & McCreanor, T. Critical Tiriti Analysis: A prospective policy making tool from Aotearoa New Zealand. *Ethnicities*, doi:10.1177/14687968231171651 (2023).
44. Came, H. A., McCreanor, T., Doole, C. & Simpson, T. Realising the rhetoric: refreshing public health providers' efforts to honour Te Tiriti o Waitangi in New Zealand. *Ethnic Health* **22**, 105-118, doi:10.1080/13557858.2016.1196651 (2017).
45. Harrison, S. *et al.* One Health Aotearoa: a transdisciplinary initiative to improve human, animal and environmental health in New Zealand. *One Health Outlook* **2**, 4, doi:10.1186/s42522-020-0011-0 (2020).

46. Haar, J. & Martin, W. J. He aronga takirua: Cultural double-shift of Māori scientists. *Hum Relat* **75**, 1001-1027, doi:Artn 00187267211003955/00187267211003955 (2022).
47. McAllister, T. G. 50 reasons why there are no Māori in your science department. *Journal of Global Indigeneity* **6**, 1-10 (2022).
48. McAllister, T. G., Naepi, S., Wilson, E., Hikuroa, D. & Walker, L. A. Under-represented and overlooked: Māori and Pasifika scientists in Aotearoa New Zealand's universities and crown-research institutes. *J Roy Soc New Zeal* **52**, 38-53, doi:10.1080/03036758.2020.1796103 (2022).
49. Hikuroa, D. Matauranga Maori-the ukaipo of knowledge in New Zealand. *J Roy Soc New Zeal* **47**, 5-10, doi:10.1080/03036758.2016.1252407 (2017).
50. Greenhalgh, S., Müller, K., Thomas, S., Campbell, M. L. & Harter, T. Raising the voice of science in complex socio-political contexts: an assessment of contested water decisions. *J Environ Pol Plan* **24**, 242-260, doi:10.1080/1523908x.2021.2007762 (2022).
51. Fischoff, B. The sciences of science communication. *Proceedings of the National Academy of Sciences* **110**, 14033-14039 (2013).
52. Shea, K. *et al.* Multiple models for outbreak decision support in the face of uncertainty. *P Natl Acad Sci USA* **120**, doi:ARTN e2207537120/pnas.2207537120 (2023).
53. den Boon, S. *et al.* Guidelines for multi-model comparisons of the impact of infectious disease interventions. *Bmc Med* **17**, doi:ARTN 163/s12916-019-1403-9 (2019).
54. Committee on Models in the Regulatory Decision Process. *Models in Environmental Regulatory Decision Making*. (The National Academies Press, 2007).
55. Modeling, C. f. R. E. *Guidance on the Development, Evaluation, and Application of Environmental Models*. (U.S. Environmental Protection Agency, 2009).
56. Treasury, H. *The Aqua Book:: guidance on producing quality analysis for government*. (The National Archives,, 2015).
57. Yin, R. K. *Case Study Research and Applications: Design and Methods*. (Sage Publications, Inc., 2018).
58. Adeoye-Olatunde, O. A. & Olenik, N. L. Research and scholarly methods: Semi-structured interviews. *Journal of the American College of Clinical Pharmacy* **4**, 1358-1367 (2021).
59. Grigoropoulou, N. & Small, M. L. The data revolution in social science needs qualitative research. *Nature Human Behaviour* **6**, 904-906, doi:10.1038/s41562-022-01333-7 (2022).
60. Parker, C., Scott, S. & Geddes, A. *Snowball Sampling*. (SAGE Publications Ltd, 2019).
61. Tongco, D. C. Purposive sampling as a tool for informant selection. *Ethnobotany Research and Applications* **5**, 147-158 (2007).
62. Hsieh, H. F. & Shannon, S. E. Three approaches to qualitative content analysis. *Qual Health Res* **15**, 1277-1288, doi:10.1177/1049732305276687 (2005).

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