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Title: Rapid prototyping for quantifying belief weights of competing hypotheses about emergent diseases.

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Research Highlights

- We developed methods for rapidly assessing hypotheses about disease etiology
- Methods included formal expert elicitation and Bayesian hierarchical modeling
- We illustrate this approach for a recently emerged disease in coral reefs
- These methods are useful for fast decision-making for conservation issues
- These methods can help adapt management decisions over time as knowledge accumulates

Abstract

Emerging diseases can have devastating consequences for wildlife and require a rapid response. A critical first step towards developing appropriate management is identifying the etiology of the disease, which can be difficult to determine, particularly early in emergence. Gathering and synthesizing existing information about potential disease causes, by leveraging expert knowledge or relevant existing studies, provides a principled approach to quickly inform decision-making and management efforts. Additionally, updating the current state of knowledge as more information becomes available over time can reduce scientific uncertainty and lead to substantial improvement in the decision-making process and the application of management actions that incorporate and adapt to newly acquired scientific understanding. Here we present a rapid prototyping method for quantifying belief weights for competing hypotheses about the etiology of disease using a combination of formal expert elicitation and Bayesian hierarchical modeling. We illustrate the application of this approach for investigating the etiology of stony coral tissue loss disease (SCTLD) and discuss the opportunities and challenges of this approach

for addressing emergent diseases. Lastly, we detail how our work may apply to other pressing management or conservation problems that require quick responses. We found the rapid prototyping methods to be an efficient and rapid means to narrow down the number of potential hypotheses, synthesize current understanding, and help prioritize future studies and experiments. This approach is rapid by providing a snapshot assessment of the current state of knowledge. It can also be updated periodically (e.g., annually) to assess changes in belief weights over time as scientific understanding increases. *Synthesis and applications*: The rapid prototyping approaches demonstrated here can be used to combine knowledge from multiple experts and/or studies to help with fast decision-making needed for urgent conservation issues including emerging diseases and other management problems that require rapid responses. These approaches can also be used to adjust belief weights over time as studies and expert knowledge accumulate and can be a helpful tool for adapting management decisions.

1. Introduction

The combination of anthropogenic activities and globalization may facilitate the spread of new diseases (Biota, 2002; Bradley and Altizer, 2007; Semenza et al., 2016; Vanwambeke et al., 2019; Vega Thurber et al., 2020), the emergence of which can have devastating impacts on wildlife and the ecosystem services that they provide (Aguirre and Tabor, 2008; MacPhee and Greenwood, 2013). In many cases, the etiology of these diseases may be hard to determine, and this uncertainty can have important management implications as the appropriate management responses may be highly dependent on the type of causative agent(s). One way to address this scientific uncertainty is to use a multi-hypotheses approach to science (e.g., Burnham and Anderson, 1998; Chamberlin, 1890; Nichols, 2021; Nichols et al., 2019, 2015). Under this paradigm, information from multiple studies can be combined and belief weights or model

weights can be assigned to competing hypotheses. Ideally, these beliefs would be determined based on experiments and targeted observation studies. Some authors have further proposed applying Bayes' theorem to update these beliefs as more information becomes available (e.g., Nichols et al., 2021, 2019; Williams et al., 2002) to allow for the incorporation of the latest scientific knowledge. In addition to providing an appealing framework for learning, this paradigm can greatly benefit management decisions, as combining information from multiple studies and updating the current state of knowledge over time may reduce scientific uncertainty and lead to substantial improvement of the decision-making process and application of management actions (e.g., Johnson, 2011; Johnson et al., 2015; Martin et al., 2011, 2009).

One consideration when responding to emergent diseases is the need to act quickly, as preventing further spread of the disease is more likely to succeed early in the emergence process (Grant et al., 2017; Langwig et al., 2015). Otherwise, the disease may become so well established that it proves infeasible to eradicate (Canessa et al., 2020). There may therefore be a high cost to delaying actions until rigorous research and monitoring protocols have been put in place and reliable epidemiological models have been developed (Canessa et al., 2018; Grant et al., 2017). In this context, formal expert elicitation offers an opportunity to rapidly address important scientific questions and inform management activities (Choy et al., 2009; Martin et al., 2017, 2012; Moore et al., 2022; O'Hagan et al., 2006). It also provides a means to structure existing knowledge into a framework that can guide future research and monitoring efforts (Kuhnert et al., 2010; Martin et al., 2011).

The process of identifying disease etiology, however, is often haphazard and without a framework for organizing the current state of knowledge or future knowledge that will be accumulating over time across experts and studies. With diseases, time is rarely taken to develop

hypotheses and combine knowledge among experts before management actions are pursued to try to stop disease spread. Frameworks have been developed to compile expert knowledge for structured risk assessments of emerging bat disease (Cook et al., 2021; Runge et al., 2020) but rarely for assessing hypotheses for disease etiology. In coral reef research, formal expert elicitation has been used to classify the condition of coral reefs (Bradley et al., 2020; Santavy et al., 2022b, 2022a) but there is a need for a framework to compile expert knowledge to rapidly assess disease etiology to inform management efforts. Here we present a rapid prototyping method (Garrard et al. 2017) for developing competing hypotheses, quantifying belief weights for these hypotheses using a combination of formal expert elicitation and statistical modeling techniques and illustrate the application of this approach for investigating the etiology of a recently emerged disease of coral reefs: stony coral tissue loss disease (SCTLD). We discuss the opportunities and challenges of this approach for addressing emergent diseases and discuss applications to other management and conservation problems that require rapid responses.

2. Methods

2.1 Case study: SCTLD

Coral reefs are currently experiencing a multi-year disease-related mortality event, SCTLD, which began in 2014 and has now spread to infect reefs throughout Florida's Coral Reef and the Caribbean, resulting in massive die-offs of multiple coral species (Brandt et al., 2021; Dahlgren et al., 2021; Heres et al., 2021; Muller et al., 2020; Precht et al., 2016; Walton et al., 2018; Williams et al., 2021). The disease, which impacts at least 24 species of coral including Endangered Species Act-listed and primary reef-building species, presents as tissue loss lesions which often result in whole colony mortality (Precht et al., 2016; Walton et al., 2018; Williams et al., 2021). While numerous individual studies have been conducted to understand the etiology of

SCTLD (e.g., Aeby et al., 2019; Landsberg et al., 2020; Meiling et al., 2021; Meyer et al., 2019; Neely et al., 2020; Rosales et al., 2020; Traylor-Knowles et al., 2021; Ushijima et al., 2020; Walker et al., 2021; Work et al., 2021), the causative agent of the disease remains unknown, complicating disease response efforts and highlighting the need to quickly integrate existing data and new findings to rapidly inform decision-making for this recently emerged disease.

SCTLD provides an appealing example for illustrating our approach because the causative agent of SCTLD remains unclear, yet research has been accumulating over the last 8 years from both experts and published studies on the etiology of SCTLD that can be used for demonstrating these methods. We captured our process in a flow diagram (Figure 1) and detail the specific steps below. Our data (Robertson et al., 2023) and code (Walsh et al., 2023) can be accessed by links within the data availability section.

2.2 Expert panel

The first step was to identify a panel of experts with knowledge of SCTLD and its impacts on coral reefs. We contacted scientists with diverse expertise who had previously worked on SCTLD. From those contacted, a group of 15 participants were willing to participate in the study including microbiologists, pathologists, disease ecologists, population ecologists, and coral experts at universities and various government agencies. Participants represented marine disease experts in Florida, Hawaii, South Carolina, and the US Virgin Islands.

2.3 Rapid Prototyping

We then used a rapid prototyping approach to elicit, structure, and evaluate existing knowledge regarding the etiology of SCTLD. Rapid prototyping, which has been used in engineering, business, and decision science, is a structured approach to produce a “prototype” product quickly, often through a multi-day workshop (Garrard et al. 2017). In our context the

prototypes were two methodologies to quantify belief weights of competing hypotheses about the cause of SCTLD (see Figure 1 for a graphical representation of the rapid prototyping approach that we used). Our approach began with eliciting hypotheses about the cause of SCTLD from the expert panel. This was done over the course of four meetings, conducted via videoconference between 8/13/2021 and 11/09/2021, which collectively took ~11.5 hours of meeting time. However, because we separated the participants into two groups for the third meeting, the total meeting time required of each expert was only 9.5 hours.

2.3.1 *Introduction of Goals/Process*–During the first meeting we introduced the goals of the project to our expert panel and described the expert elicitation process and formal expert elicitation techniques employed. We also emphasized the importance of considering cognitive biases (such as anchoring, authority bias, small sample bias, overconfidence; Sutherland and Burgman, 2015) and had the experts go through examples to better understand the potential for over- or under- confidence when providing elicited values (Kuhnert et al., 2010; Martin et al., 2012). After this initial meeting, to assess the potential for expert over- or under-confidence when providing elicited values, we had each expert provide their "best guess" as well as the associated uncertainty with this guess to three training questions for which the correct answer was known to the workshop coaches but not the experts. During the second meeting we presented the results of the training questions so the experts could see their responses compared to the "truth" and assess their own level of over- or under-confidence. Each expert was assigned a unique identification number (*ID*) that was displayed with their responses in place of experts' names to keep results anonymous and reduce the risk of "authority bias", "peer pressure", and other potential cognitive biases. Experts discussed the results and issues of over- or under-confidence as a group.

179 *2.3.2 Hypothesis Generation*–A key aspect of our approach was structuring the problem
180 into a series of competing scientific hypotheses that served as the foundation for assessing the
181 current state of knowledge. After the first meeting, we asked each expert to identify 2 – 6
182 hypotheses and associated predictions for the causative agent(s) of SCTLD. We consolidated the
183 experts' hypotheses and removed redundant ones. During the second meeting, we presented the
184 panel's proposed hypotheses and discussed these as a group by framing the disease etiology
185 around the epidemiological triangle ("Agent-Host-Environment"; Scholthof, 2007; vander Wal et
186 al., 2014) to help stimulate ideas about the multiple hypotheses and identify alternative
187 mechanisms. We then revised the hypotheses based on the input of the panel. We encouraged the
188 experts to limit the number of hypotheses to approximately ten to keep the number of hypotheses
189 manageable and mutually exclusive. This resulted in ten hypotheses (*Hyp)* (Table 1). All
190 meetings were recorded and if some participants could not attend a meeting, they were given
191 access to the recording and any presented material.

192 *2.3.3 Expert elicitation method M1*–We considered two elicitation approaches that
193 hereafter we refer to as method 1 (M1) and method 2 (M2) (Figure 1). M1 was intended to get an
194 overall assessment of the state of knowledge across experts regarding the cause of SCTLD.
195 During the third meeting we explained the process for M1 and asked the experts to allocate 100
196 points across the 10 hypotheses based on the weight of evidence that they believe existed in
197 support of each hypothesis. Experts were allowed to use their own knowledge and any sources of
198 information available to them, but not to confer with each other regarding their scores. We
199 presented and discussed the elicitation results for M1 to the panel during the fourth meeting. The
200 purpose of the discussions was not to reach consensus but to reduce linguistic uncertainty and
201 misunderstandings. Following the discussions and based on the input of the experts, we revised

the definition of the hypotheses. We then asked the experts to revise their estimates, if needed, and used these revised estimates for the M1 analyses.

2.3.4 Modeling of elicited values for M1– We derived a Bayesian hierarchical model to estimate expert belief weights (± 95% credible intervals) for each of the hypotheses regarding causes of SCTLD. Specifically, we modeled the expert-elicited points as follows:

$$y_{i,j} \sim ddirch(\vec{\boldsymbol{\alpha}}),$$

$$\alpha_j \sim dgamma(1, 1),$$

where $y_{i,j}$ is the normalized weight (i.e., between 0 and 1) for the i^{th} expert for the j^{th} hypothesis, and α_j is a concentration parameter for the Dirichlet distribution (Gelman et al., 1995) associated with the j^{th} hypothesis. The belief weights (W_j) were then derived as follows:

$$W_j = \frac{\alpha_j}{\sum_{j=1}^{m} \alpha_j},$$

where *m* is the number of hypotheses investigated. We plotted the resulting belief weights. A detailed description of the model and code are provided in the Supp. File. Note that using the Dirichlet distribution to model belief weights has been considered by others (Rozowski 2022).

2.3.5 Expert elicitation method M2– The second approach, M2, was developed to provide a framework for deriving belief weights for the hypotheses based on assessments of individual studies. We initially asked panel members to select four studies relevant to the etiology of SCTLD and to consider the following criteria when selecting the studies: (*a*) relevance to the hypotheses, (*b*) scientific rigor, (*c*) accessibility, (i.e., that the studies were available as a publication or a report), and (*d*) that the studies would be easily understandable/interpretable by a diverse group of experts. From these, we selected the five studies that received the most votes

from the experts including: Aeby et al., 2019; Kellogg and Evans, 2021; Landsberg et al., 2020; Ushijima et al., 2020; Work et al., 2021. For all studies, we provided background information and/or the associated publication, and authors associated with these studies either discussed the results directly or provided written comments about the studies to the expert panelists. Under the M2 approach, experts were asked to evaluate whether hypothesis *h* was supported or not by a given study *s*. The experts were asked to allocate 100 points between two options for each hypothesis and for each study: "yes" there is supportive evidence for hypothesis *h*, or "no" there is no support for hypothesis *h* according to study *s*. For example, "yes: 80; no: 20" (hereafter noted as "80/20") for hypothesis *h* indicates that expert *e* considered that study *s* provided strong supportive evidence for hypothesis *h* (i.e., there was an 80% chance that the study supports hypothesis *h* and a 20% chance that it did not). If the study was irrelevant with regards to hypothesis *h* (i.e., the study could not by its design provide evidence for or against the hypothesis), the experts entered "Not Applicable" ("*NA*"). Note that there is a difference between "*NA*" and "50/50". "*NA*" means that the study was irrelevant to the hypothesis, whereas "50/50" means that the study could have potentially provided support for or against the hypothesis, but the results were such that the study provided similarly weighted evidence for and against the hypothesis. Initially the experts were assigned to two separate studies and results were discussed with the entire group to familiarize the panel with the process. Experts were given the opportunity to revise their estimates for the initial two studies and then to assess the remaining three studies.

2.3.6 Modeling of elicited values for M2– We derived a Bayesian hierarchical hurdle model to estimate temporal changes in the belief weights for each of the hypotheses as knowledge accumulated when additional disease studies became available. We fit a hurdle model

to properly account for cases where the experts indicated a given study *s* provided unequivocal evidence against hypothesis *h*:

$$zeros_{i,h,s} \sim dbern\left(pzero_{h,s}\right),$$

$$p_{i,h,s} = \Phi\left(L_{i,h,s}\right) \forall\, p_{i,h,s} > 0,$$

$$L_{i,h,s} \sim dnorm\left(\mu_{h,s}, \sigma_{h,s}\right)$$

where $zeros_{i,h,s}$ is an indicator of whether the i^{th} expert assigned a value of zero (i.e., $p_{i,h,s} = 0$) for the *h* hypothesis and *s* study, $pzero_{h,s}$ is the probability of a zero assigned value, $L_{i,h,s}$ is the latent evidence in support of the hypothesis, $p_{i,h,s}$ is the normalized number of points assigned for each study and hypothesis by the i^{th} expert, $\mu_{h,s}$ is the mean latent evidence and $\sigma_{h,s}$ is the associated standard deviation. To complete the Bayesian specification, we specified the following hyperpriors:

$$pzero_{h,s} \sim dbeta\ (1, 1),$$

$$\mu_{h,s} \sim dnorm(0, 1),$$

$$\sigma_{h,s} \sim dunif(0, 1).$$

To quantify the accumulation of knowledge with respect to evidence for/against our hypotheses, we ordered the five studies in chronological order based on the date of publication and then calculated the estimated posterior distribution for the accumulated learning/evidence, $W_{h,s}$ for a hypothesis, given the s^{th} study was considered:

$$E\left(T_{h,s}\right) = \left(\frac{1}{s+1}\right) \sum_{s=0}^{s} \mu_{h,s},$$

$$W_{h,s} = \Phi\left(E\left(T_{h,s}\right)\right) \times \left(1 - \Phi\left(\left(\frac{1}{s}\right)\sum_{s=1}^{s} \Phi^{-1}\left(pzero_{h,s}\right)\right)\right).$$

A detailed description of the model and code are provided in the Supp. File. Because we had some NAs in our data, where experts did not feel that a study addressed a particular hypothesis, we also developed a mixture formulation that weighs past knowledge against current knowledge based on the proportion of experts who felt a study addressed a specific hypothesis (i.e., the proportion of non-NAs):

$$E\left(T_{h,s}\right) = \begin{cases} s = 0 \rightarrow 0 \\ s > 0 \rightarrow \left(\frac{1}{s+1}\right)\left(\left(\sum_{l=0}^{s-1} \mu_{h,l}\right) \times \left(1 + \frac{a_{h,s}}{N_{h,s}}\right) + \mu_{h,s} \times \left(\frac{N_{h,s} - a_{h,s}}{N_{h,s}}\right)\right), \end{cases}$$

where $a_{h.s}$ is the number of experts out of $N_{h.s}$ experts who felt the study s did not address hypothesis h. This assumes that prior to any studies being conducted $T_{h.s}$ is 0 because no knowledge exists about the etiology *a priori*. We used this mixture formulation in our analyses and plotted the resulting belief weight values to show the evolution of the learning process over time based on the accumulation of knowledge as the experts considered additional studies in the chronological order they were published. We started the plots at $s = 0$ to represent the initial lack of knowledge where no studies had yet been considered and where the belief weights for all hypotheses were defined to be 50% for "yes, there was supportive evidence for the hypothesis". Deviations of the estimated belief weights away from 50% show that learning had occurred as expert knowledge had shifted the belief weights in favor of (i.e., > 50%) or against (i.e., <50%) a hypothesis.

2.4 Study weights

After entering the values under method M2, the participants were asked to assign 100 points to the five studies, based on overall study design and strength of inference regarding the etiology of SCTLD. As an example of this process, assume that for two studies *X* and *Y* (among a larger set of studies) an expert assigned the following weights to each study: $w(X) = 30$; $w(Y) = 15$, where $w(X)$ and $w(Y)$ are the weights of study *X* and *Y*, respectively. This weight allocation implies the study design and strength of inference provided by Study *X* was twice that of Study *Y*.

We averaged the study weights across all experts and used these study weights to better understand the relative study design strengths and inference provided by each of the studies. Although we did not do so here, these study weights could also be used as weighing factors in downstream analyses to account for these inherent differences among studies.

3. Results

3.1 Expert elicitation M1

The aggregated belief weights across the experts for the ten hypotheses indicated large uncertainty surrounding the belief weights, although some hypotheses appeared to be ruled out by the experts based on the current state of knowledge, given their low weights relative to the other hypotheses (e.g., Hypotheses 4 and 10 and also potentially 7, 8, and 9) (Figure 2, Supp. Figure 1). Hypothesis 3 had the most support with 15.0% of the weight, followed closely by Hypothesis 6 that had 14.9% of the weight. Hypothesis 10 had the least support with 1.9% of the weight, followed by Hypothesis 4 that had 5% of the weight. Hypotheses that considered a single agent (Hypotheses 1, 2, 7, 10) represented 35% of the weight, whereas hypotheses that

considered multiple agents (Hypotheses 3, 4, 5, 6, 8, 9) had 65% of the weight, suggesting that the panelists currently believe multiple agents are likely involved in the etiology of SCTLD.

3.2 Expert elicitation M2

Fourteen out of the 15 experts provided all M2 values and one participant provided M2 values only for Work et al. (2021) and Kellogg and Evans (2021). Belief weights for the different hypotheses changed over time as the experts considered additional studies (Figure 3, Supp. Figure 2). For example, there was a 19% increase in belief weight for Hypothesis 1 after the addition of Work et al. (2021) compared with the belief weights based only on the first four studies. Over time, support for Hypotheses 3, 4, 7, 8, 9, and 10 decreased. The other hypotheses had less obvious trends over time, however belief weights for Hypotheses 2 and 5 remained above 50% weight while the other hypotheses mostly remained below this line.

3.3 Study weights

Fourteen out of the fifteen experts provided study weights for the five studies. The average study weights across all experts for each study were 0.19, 0.22, 0.19, 0.19, and 0.21, for studies 1-5 respectively, indicating that study weights were similar across studies (equal weights would have been 0.2 for each of the five studies), and experts considered all five studies to be nearly equal in study design and strength of inference regarding the etiology of SCTLD.

4. Discussion

When a novel disease emerges, there is a need to act quickly so that rapid decisions can be made for limiting its spread (Grant et al., 2017; Langwig et al., 2015). It is particularly important to identify the etiology of the disease so that management can target key underlying drivers. Here, we developed a rapid prototyping approach to formalize the process for combining expert

knowledge regarding disease etiology that (*a*) identifies competing hypotheses about the agent(s) causing disease; (*b*) quantifies the belief weights for each hypothesis using two expert elicitation techniques; and (*c*) presents techniques to update the belief weights.

4.1 Insights from expert elicitation M1

The experts identified ten primary competing hypotheses. The results from M1 indicated that substantial uncertainty existed within and among experts about SCTLD etiology. Some hypotheses carried minimal weight based on the experts' current knowledge (e.g, Hypotheses 10 and 4; Figure 2). Thus, M1 is an efficient and rapid means to narrow down the number of potential hypotheses and help prioritize future studies and experiments to reduce uncertainty around remaining hypotheses. Advantages of this approach include that it provides a rapid snapshot assessment of the current state of knowledge and it can also be repeated periodically (e.g., annually) to assess changes in belief weights over time. Hypotheses can be added or removed using this process, and uncertainty can be quantified to capture an increase in precision as the number of experts grows. A useful aspect of this approach is it aggregates knowledge experts have gained from multiple sources such as through reading scientific papers, attending meetings and presentations, informal information exchange with other researchers, and recent research findings that have been discovered but not yet published. A disadvantage is the results may be sensitive to the expertise of the participants, their initial background level of knowledge, their unconscious decision biases (e.g., pet hypotheses), and results also may be influenced by the number of experts and the time they invest into the elicitation. There may also be some linguistic uncertainty among experts (e.g., understanding the hypotheses). This uncertainty should decline over time with additional meetings and discussions, and the number of elicitation

rounds could be extended depending on the needs of a study. In our situation, we limited the number of elicitation rounds because we wanted to demonstrate a rapid response.

4.2 Insights from expert elicitation M2

For M2, the experts were asked to assess studies individually and look for supportive evidence for each hypothesis. Beliefs weights for the different hypotheses changed over time as the experts consider additional studies (e.g., support for Hypothesis 10 decreased over time; Figure 3). One advantage of M2 over M1 is that it may be easier to assess the contribution of a single study to the learning process. Indeed, it is possible to compute the change in belief weights associated with a given study. For example, the 19% increase in belief weights toward *Hypothesis 1* based on the study of Work et al. (2021) indicated that this study was highly influential regarding *Hypothesis 1*. A disadvantage of M2 is that assessing individual studies takes additional time on the part of the experts and M2 is therefore a slower overall approach than M1 due to the need of experts to ideally review many studies. As with M1, this approach can be useful through aggregating knowledge (experts' reading of the literature), although M2 is more limited than M1 by not incorporating unpublished sources of information (e.g., from presentations, meetings, informal exchange) that experts may have. Similar to M1, M2 can also be biased by the expertise of the participants, their initial background levels of knowledge, their unconscious decision biases, and the time they invest into reading each publication. Future studies could mitigate some of these biases in various ways such as by selecting experts with a broad range of expertise, by discussing ways to avoid decision biases as a group, or by requiring that each expert spends a certain amount of time reading each publication.

Ideally, method M2 would lead to results that are consistent among experts, but we noted variations in the assessment of the experts in the weights assigned to the studies. Studies or

experiments that would lead to a clear "signal detection" should theoretically lead to more consistency among experts. For example, strong evidence of the effectiveness of specific groups of antibiotics tested using a rigorous randomized experiment should yield similar expert-elicited weights. However, as with our case study and ecological systems in general, clear signal detection is often difficult or even impossible to achieve because of the complexity of the system. Another way to increase consistency among experts is to use the Delphi process instead of the modified Delphi process that we implemented (Gustafson et al., 1986; MacMillan and Marshall, 2006). The Delphi approach is more of a consensus-driven process, whereas our approach did not aim at reaching consensus. The benefit of the Delphi process is that it may reduce the risks of misunderstanding the findings of a study because the experts discuss both the study and scoring in more detail as a group (Kuhnert et al., 2010). There are important downsides to consider, however, such as the Delphi method may not capture uncertainty as effectively and may also induce more biases such as "authority bias" in which the most outspoken participants may exert an undue influence on the decisions of the group. The Delphi process may also be more time-consuming to implement because of additional discussion time to achieve a consensus, which is undesirable in situations requiring rapid decision-making (Kuhnert et al., 2010).

During implementation of M2, we considered the case where a hypothesis *h* was supported or not by a study (with "*NA*" if the study was irrelevant to the hypothesis). This binary approach makes it easier to integrate studies that are very different from each other. For example, here experts were able to simultaneously evaluate Kellogg and Evans (2021), an experiment-based study, with Work et al. (2021), a histological analysis. If they had been selected by the experts, we could also have included observational/modeling studies within our framework such

as Muller et al. (2020), which suggested a pattern of spread in space and time consistent with an infectious disease.

There are limitations and perspectives for further improvement regarding method M2. In our case, the aggregated *study weights* were similar across studies, despite there being substantial variation among experts. If the aggregated study weights had been substantially different, we could recompute the belief weights to account for these differences. Although here we asked the experts to provide study weights that incorporated considerations such as sample sizes and the rigor of study designs, we could also envision approaches that would more explicitly quantify these considerations. With M2, the selection of studies may influence the ultimate relative belief weights. For example, if studies that address certain hypotheses are overrepresented, this could influence the results; however, this is not an issue with the estimated mean belief weights because we explicitly account for studies that do not address a certain hypothesis. Thus, the belief weights will not change if a study is not applicable to a particular hypothesis.

The concern regarding the representativeness of studies is a larger concern for any meta-analytical approach. Care must be taken in selecting studies, particularly when only considering published studies, because of the potential for "publication bias" (e.g., certain journals and reviewers may favor the publication of statistically significant results; Thornton and Lee, 2000). For our analysis, we did not restrict ourselves to including only published studies, which may have helped reduce the risk of "publication bias". Another benefit of not waiting for publication is that it can help accelerate the process by allowing for the consideration of recently acquired data or results, which may be particularly important for emerging diseases that require a rapid response. Note, however, that there can be a tradeoff between timeliness and reliability of the results (e.g., the peer review process can help identify study flaws).

Here, we asked the experts to consider the following criteria when selecting the studies: (*a*) relevance to the hypotheses, (*b*) scientific rigor, (*c*) accessibility, (i.e., that the studies were available as a publication or a report), and (*d*) that the studies would be easily understandable/interpretable by a diverse group of experts. Although the last criterion (*d*) was well-suited for the purpose of method development, we acknowledge that it may have restricted the subset of studies selected for consideration. Because of this issue, combined with the fact that we only considered five studies, we intend for the M2 results to only be used as a simple demonstration of these methods rather than for interpretation of SCTLD etiology. Ideally, many more studies will need to be incorporated before these results can be used for conservation decision making. These studies could also be gathered over longer time periods (e.g., years to decades) and belief weights updated as new papers are published on the topic.

4.3 Management applications

An advantage of the rapid prototyping approach that we have described is that it can be implemented very quickly to address management questions. It took less than 12 hours (and less than 10 hours if we consider the fact that we separated the participants into two groups for the third meeting) of meeting time to implement both methods (M1 and M2). Updating the estimates under M1 or adding new studies under M2 would take even less time if the same group of experts was to be used, since they are now familiar with the methodologies. We scheduled the meetings over multiple months, but the rapid prototyping could have been conducted over a few days (e.g., in a workshop setting). The belief weights obtained can be used to rapidly inform management actions that may be needed such as medicinal treatment (e.g., antibiotics, probiotics) or restoration of corals through outplanting of corals grown in captivity. Belief weights could also be incorporated more formally in the decision-making process under a

441 structured decision making and/or adaptive management process (Martin et al., 2009; Williams
442 et al., 2002; Williams and Johnson, 1995). There are several limitations of the rapid prototyping
443 approach that we used. For instance, the results can be influenced by the expertise of the
444 participants, their training and cognitive biases, and the time they invest in the elicitation
445 (Sutherland and Burgman 2015). Although, we employed a structured approach to the elicitation
446 and multiple rounds of elicitation to address some of these issues, some errors likely remain
447 (Sutherland and Burgman 2015; Hanea et al., 2017). We also note that ideally weights would be
448 derived through a data driven process such as the one described by Nichols et al. (2021), but
449 problems arise when there are few studies, a subset of non-randomly selected studies are used, or
450 critical experiments that directly address the cause of the disease are lacking. In such situations,
451 the expert elicitation approaches that we present can help provide a useful assessment of the
452 cause of the disease.

453 *4.4 Quantifying advances in scientific knowledge*

454 The approaches to updating belief weights that we have mentioned herein (e.g., through
455 Bayesian updating) could be used to track the gain in knowledge from individual studies and to
456 prioritize future sequences of experiments. The approaches to track learning over time can be
457 simple, such as repeated implementation of M1 or M2 over time as new studies are added. A
458 further level of complexity would be the use of adaptive optimization algorithms in which the
459 belief weights are folded within an optimization algorithm (e.g., Martin et al., 2011; Nichols,
460 2021).

461 *4.5 Conclusion*

462 The approaches described in this paper could be useful for the management of not only
463 SCTLD, but also other coral diseases, including both existing and new diseases as they emerge
464 in the future. These approaches are also relevant to diseases affecting other systems (e.g., chronic
465 wasting disease in deer; Williams, 2005). More broadly, they are relevant to other kinds of
466 management problems that likewise require rapid responses, such as invasive species
467 management or the conservation of endangered species, both issues which may lead to
468 irreversible states (e.g., extinction in the case of endangered species; and uncontrolled growth in
469 the case of invasives; Ducatez and Shine, 2017). In each of these cases, the rapid prototyping
470 approaches demonstrated here can be used to combine knowledge from multiple experts and/or
471 studies to help with fast decision-making needed for urgent conservation issues. These
472 approaches can also be used to adjust belief weights over time as studies and expert knowledge
473 accumulate and can be a helpful tool for adapting management decisions.

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482 **Competing Interests**

483 The authors declare no competing interests.

Data Availability

Data are available at ScienceBase (https://doi.org/10.5066/P9DLNEBY) (Robertson et al. 2023).

Code is available at the USGS Official Source Code Archive

(https://doi.org/10.5066/P9S9JDVB) (Walsh et al. 2023).

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Julien Martin: Conceptualization, Methodology, Formal analysis, Investigation, Writing-Original Draft, Supervision, Project administration, Funding acquisition.

Thierry M. Work: Investigation, Writing-Review & Editing.

Christina A. Kellogg: Investigation, Writing-Review & Editing.

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Andrew Bruckner: Investigation, Writing-Review & Editing.

510 **Table 1.** Ten hypotheses explaining the etiology of stony coral tissue loss disease (SCTLD)

511 based on expert elicitation of fifteen experts.

Hyp. 1	SCTLD is caused by viral agent(s)
Hyp. 2	SCTLD is caused by a pathogenic bacterial agent that directly affects the [coral and/or zooxanthellae (defined as 'algal symbiont')]
Hyp. 3	SCTLD is initially caused by a viral agent in the coral with secondary bacterial infection(s) of the [coral and/or zooxanthellae];
Hyp. 4	SCTLD is initially caused by a bacterial agent with secondary viral infection of the [coral and/or zooxanthellae]
Hyp. 5	SCTLD is caused by multiple, coinfections of bacterial agents that directly affect the [coral and/or zooxanthellae]
Hyp. 6	SCTLD is initially caused by a viral agent in the zooxanthellae AND a secondary bacterial infection of the [coral and/or zooxanthellae]
Hyp. 7	SCTLD is caused by a metabolite from zooxanthellae directly affecting the [coral and/or zooxanthellae]
Hyp. 8	SCTLD is caused by a viral agent in combination with endogenous toxins that directly affects the [coral and/or zooxanthellae]
Hyp. 9	SCTLD is caused by a combination of interactions between infectious and non-infectious agents
Hyp. 10	SCTLD is caused by fungal agent(s)

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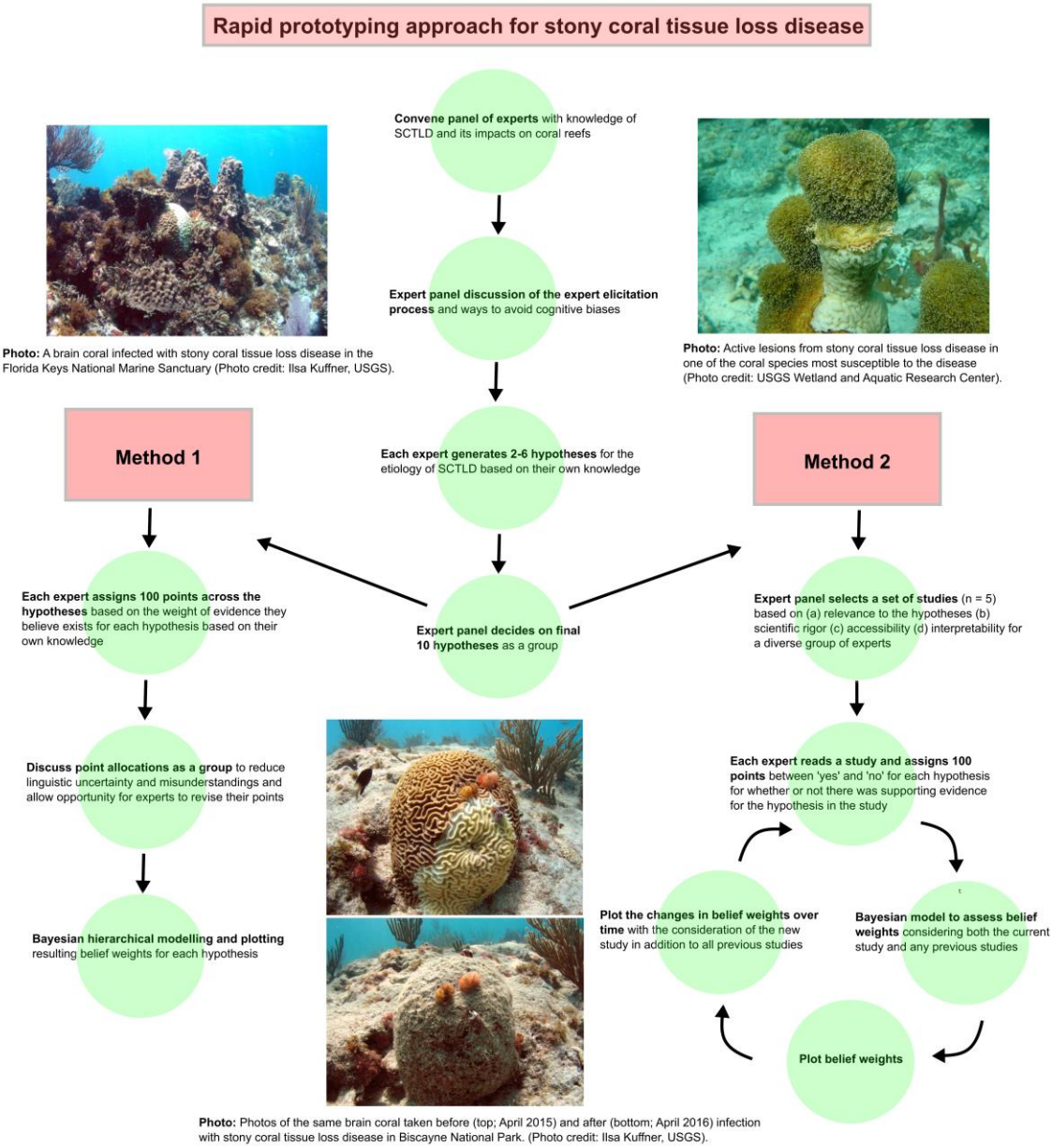

Figure 1. Flow diagram of the rapid prototyping approach used for understanding etiology of stony coral tissue loss disease (SCTLD).

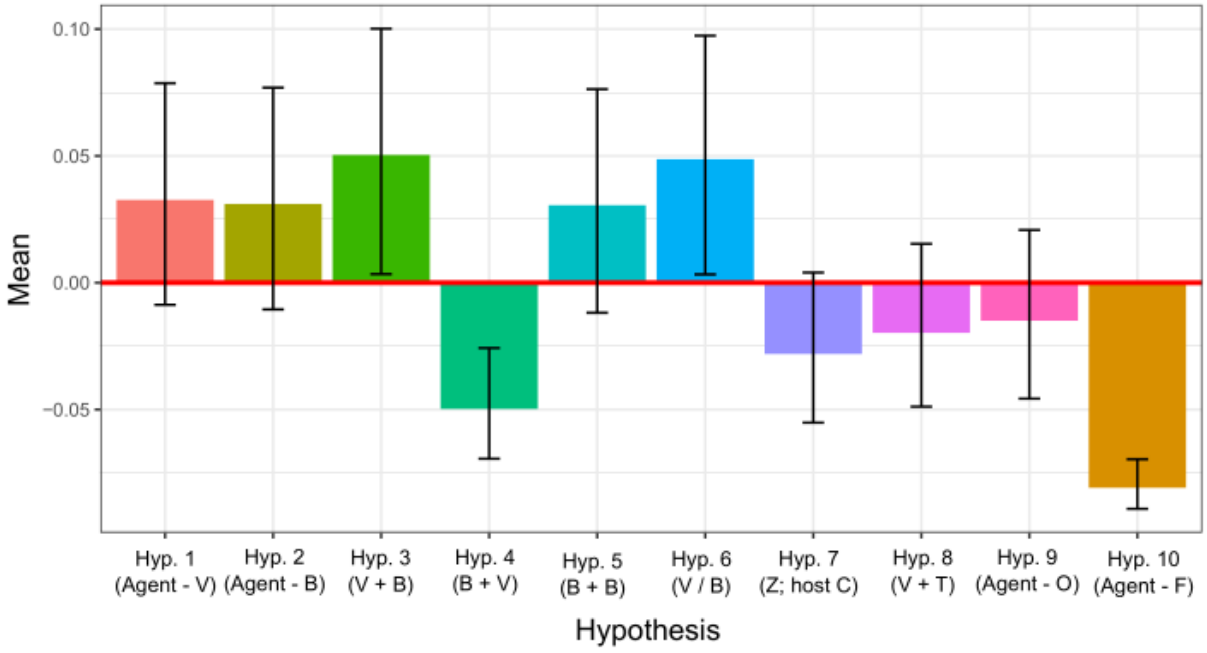

Figure 2. Relative support (mean ± 95% credible intervals) for each of ten hypotheses explaining the etiology of stony coral tissue loss disease (SCTLD) based on expert elicitation of 15 experts using Method 1. Relative support here is the belief weight for each hypothesis minus 0.10 (which indicates the belief weight for each of the 10 hypotheses if they are equally weighted). The relative support takes on positive values (above the red line) where there is evidence for a hypothesis and negative values (below the red line) where there is evidence against a hypothesis based on the experts' assessments. The B indicates a bacterial agent, F indicates a fungal pathogen, O indicates a combination of infectious and non-infectious agents, T indicates toxins, V indicates a viral agent, and Z corresponds with metabolites from zooxanthellae (defined as 'algal symbiont') that directly affect the coral (C) and/or zooxanthellae.

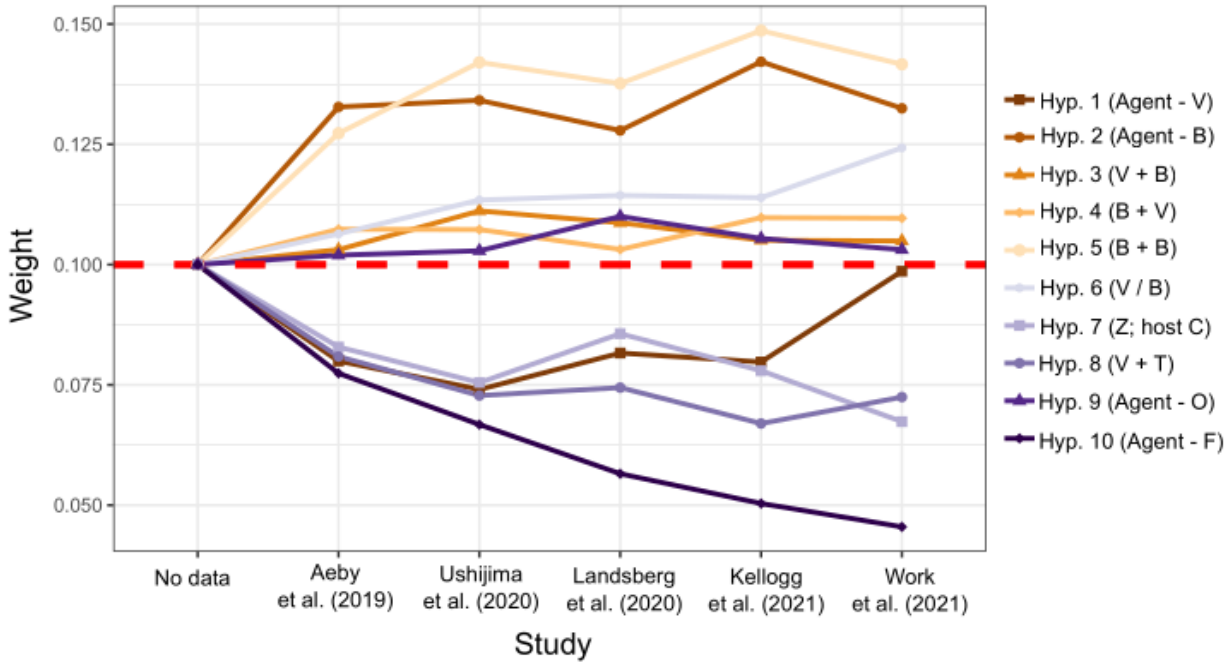

Figure 3. Relative support for each of ten hypotheses explaining the etiology of stony coral tissue loss disease (SCTLD) based on expert elicitation of fifteen experts using Method 2 where belief weights change over time as more studies are considered. Relative support here is the belief weight for each hypothesis (for the probability that 'Yes' the hypothesis is supported by the study) divided by the sum of the belief weights for all hypotheses for that study. The five studies considered are shown on the x-axis in chronological order where belief weights are calculated using the current study and all prior studies. The B indicates a bacterial agent, F indicates a fungal pathogen, O indicates a combination of infectious and non-infectious agents, T indicates toxins, V indicates a viral agent, and Z corresponds with metabolites from zooxanthellae (defined as 'algal symbiont') that directly affect the coral (C) and/or zooxanthellae. The dashed line represents complete uncertainty surrounding the etiology of SCTLD (i.e., each hypothesis is equally plausible). Deviations of the estimated belief weights from this line show that expert knowledge shifted the belief weights towards some hypotheses (above the red line) and away from others (below the red line).

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