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Original Article

Network approaches for formalizing conceptual models in ecosystem-based management

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Qualitative Network Models (QNMs), Fuzzy Cognitive Maps (FCMs), and Bayesian Belief Networks (BBNs) have been proposed as methods to formalize conceptual models of social–ecological systems and project system responses to management interventions or environmental change. To explore how these different methods might influence conclusions about system dynamics, we assembled conceptual models representing three different coastal systems, adapted them to the network approaches, and evaluated outcomes under scenarios representing increased fishing effort and environmental warming. The sign of projected change was the same across the three network models for 31–60% of system variables on average. Pairwise agreement between network models was higher, ranging from 33 to 92%; average levels of similarity were comparable between network pairs. Agreement measures based on both the sign and strength of change were substantially worse for all model comparisons. These general patterns were similar across systems and scenarios. Different outcomes between models led to different inferences regarding trade-offs under the scenarios. We recommend deployment of all three methods, when feasible, to better characterize structural uncertainty and leverage insights gained under one framework to inform the others. Improvements in precision will require model refinement through data integration and model validation.

Keywords: Bayesian Belief Network, ecosystem-based management, food webs, Fuzzy Cognitive Map, Georges Bank, Mid-Barataria Basin, Pribilof Islands, Qualitative Network Model.

Introduction

Ecosystem-based management (EBM) of resources, services, and human activities is complex due to the array of interacting system components and processes, the many sources of uncertainty, and the necessity of trade-offs in decision-making. Conceptual models can be highly valuable tools in addressing these challenges. They can be developed to depict components, processes, and linkages that make up a social–ecological system, and can encompass environmental processes that influence basic physical, chemical, and biological properties through to the governance systems and social patterns that regulate and influence human activities (e.g. Heemskerk *et al*., 2003; Harvey *et al*., 2016). By focusing on the essential elements of the system, the visual depiction of conceptual models can help provide clarity and context to decision-makers, managers, stakeholders, and scientists to better navigate the complexity of EBM (Kelble *et al*., 2013; Dale *et al*., 2019; Carriger and Parker, 2021). In addition, conceptual models are often naturally constructed as networks that can be expressed mathematically as graphs, where vertices correspond to variables and edges indicate causality, interactions, or associations between variables. The formalization of conceptual models as network models provides a powerful tool for exploring how management-relevant perturbations propagate through interaction pathways to impact the model system as a whole, which can aid identification of potential trade-offs or unexpected outcomes relevant to EBM (Reum *et al*., 2020a; Baker and Bode, 2021; Carriger and Parker, 2021).

Three network modelling approaches have received particular attention for their ability to formalize conceptual models of social-ecological systems and simulate potential responses to change: Qualitative Network Models (QNMs), Fuzzy Cognitive Maps (FCMs), and Bayesian Belief Networks (BBNs). The approaches are considered "soft" network methods in that they can be formulated with little or no quantitative information and as a minimum require only a qualitative (QNM), semi-qualitative (FCM), or subjective understanding (BBN) of system structure, though quantitative data integration is feasible (McCann *et al*., 2006; Ramsey and Norbury, 2009; Melbourne-Thomas *et al*., 2012; Baker *et al*., 2018). While quantitative or "hard" network modelling approaches (e.g. Yodzis, 1998; Fulton, 2010) produce more precise numerical projections, they also demand significant amounts of data, which are limited in many systems, raising the danger that model structure will reflect data availability rather than essential features of the underlying system (Dambacher *et al*., 2003). Further, they require substantial investment of resources (Dambacher *et al*., 2009) and their ability to represent coupled social and ecological systems can be constrained by their capacity to represent only a limited range of "currencies" such as units of energy or material (Harvey *et al*., 2016). In contrast, soft network approaches emphasize understanding of the system as whole, are well-suited to synthesizing diverse information sources and representing coupled systems, and can be rapidly prototyped and deployed, albeit at the cost of precision (Puccia and Levins, 1985; Özesmi and Özesmi, 2004; McCann *et al*., 2006). The benefits make soft network approaches practical options for formalizing conceptual models in support of EBM.

The use of soft network models to explore system responses to management-relevant scenarios has grown considerably in the environmental and ecological literature (Aguilera *et al*., 2011; Landuyt *et al*., 2013; Papageorgiou and Salmeron, 2013; Carriger *et al*., 2018) and all three methods have been applied widely to issues ranging from coastal planning and fisheries management to global climate change and species conservation (e.g. Ramsey and Norbury, 2009; Landuyt *et al*., 2013; Melbourne-Thomas *et al*., 2013; Gray *et al*., 2015; Pittman *et al*., 2020; Reum *et al*., 2020a). However, practitioners typically adopt only one modelling framework to evaluate scenarios and it remains unclear the general extent to which projections may differ between QNMs, FCMs, and BBNs. The models are similar in that the underlying conceptual model is represented as a graph, but differ in terms of their mathematics, assumptions, inputs, and the nature of their predictions (i.e. qualitative, semi-qualitative, or probabilistic, respectively; Puccia and Levins, 1985; Kosko, 1986; Pearl, 1986). The models are thus structurally distinct and if projections differ between models, failure to account for model (structural) uncertainty may result in misleading inferences. This gap in understanding contrasts with efforts to characterize sources of uncertainty within each framework (Melbourne-Thomas *et al*., 2012; Ramsey *et al*., 2012; Baker *et al*., 2018).

Here, we sought to evaluate the level of agreement in projections from QNMs, FCMs, and BBNs. To develop a more general understanding of model agreement in EBM contexts, we recast conceptual models developed for three different coastal and marine systems as QNMs, FCMs, and BBNs. The conceptual models were developed by independent research partnerships and reflect different motivating issues, but are suitable for exploring similar management interventions (fishing) and environmental change (warming) scenarios. The first model (Figure 1) represents the Pribilof Islands (PI) in the eastern Bering Sea, and focuses on the ecology and management of blue king crab (BKC; *Paralithodes platypus*), which once supported a significant fishery but is now at historically low population levels (Reum *et al*., 2020a). The second model (Figure 2) depicts the Georges Bank (GB) ecosystem of the northwestern Atlantic, including environmental, ecological, and human subsystems, and focuses on relationships between commercial and recreational fishing, ecosystem services, and human well-being (DePiper *et al*., 2017). The third model (Figure 3) focuses on efforts to mitigate coastal erosion in the Mid-Barataria Basin (MB), a region near the mouth of the Mississippi River, by diverting river flow and sediment through the proposed Mid-Barataria Sediment Diversion (https://coastal.la.gov/project/mid-barataria-sediment-diversion/). The model aims to represent the relationships among physical, biological, social, and economic components to examine the potential effect and trade-offs from proposed sediment diversions and ecosystem restoration.

For each conceptual model, we developed corresponding QNMs, FCMs, and BBNs; evaluated model agreement in outcomes under fishing and warming scenarios; and examined whether models produced outcomes that implied different management-relevant trade-offs. In addition, we compare the effort required to adapt conceptual models to conform to the assumptions of each modelling framework, and clarify the strengths and weaknesses of the approaches from a practical perspective.

Methods

Our primary goal was to compare agreement in projections between QNMs, FCMs, and BBNs as commonly implemented in the ecological literature. We first provide brief overviews of QNMs, FCMs, and BBNs to highlight key distinctions between the approaches and their outputs, and note differences in terminology that reflect their different origins and mathematics. Where pertinent, we

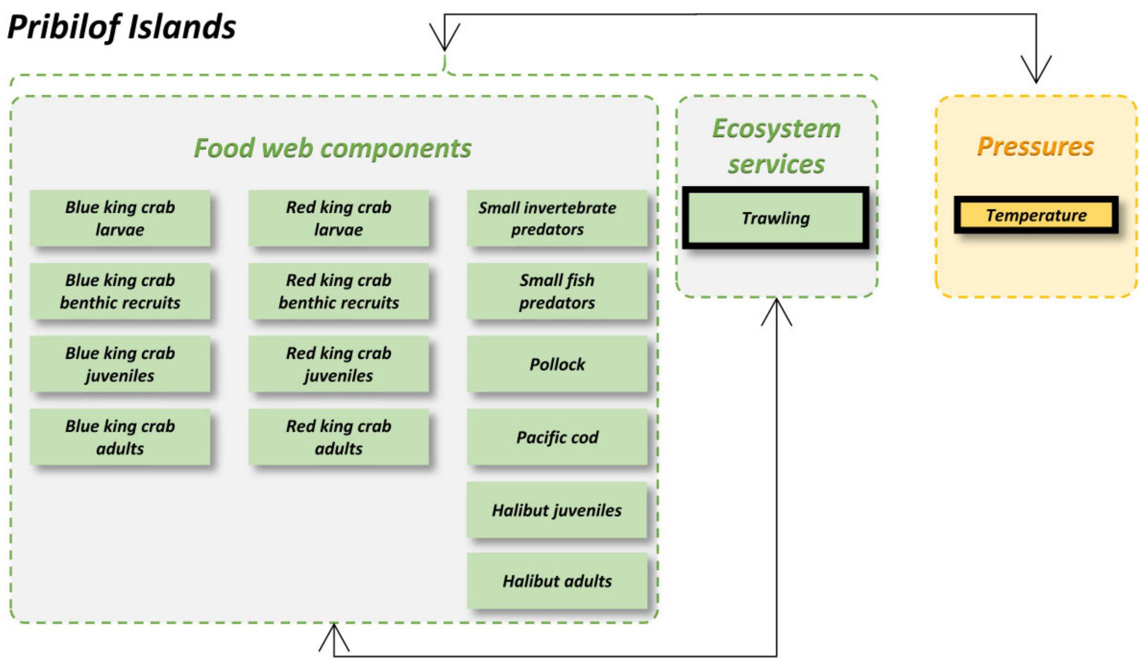

Figure 1. Overview of variables included in the PI BKC conceptual model. For clarity, variables are organized into descriptive groups. Variables that were perturbed in the warming and fishing scenarios are indicated by thick outlines. Arrows symbolize general interaction within and across groups of variables; a detailed diagram with all pairwise links is provided in the Supplementary Materials.

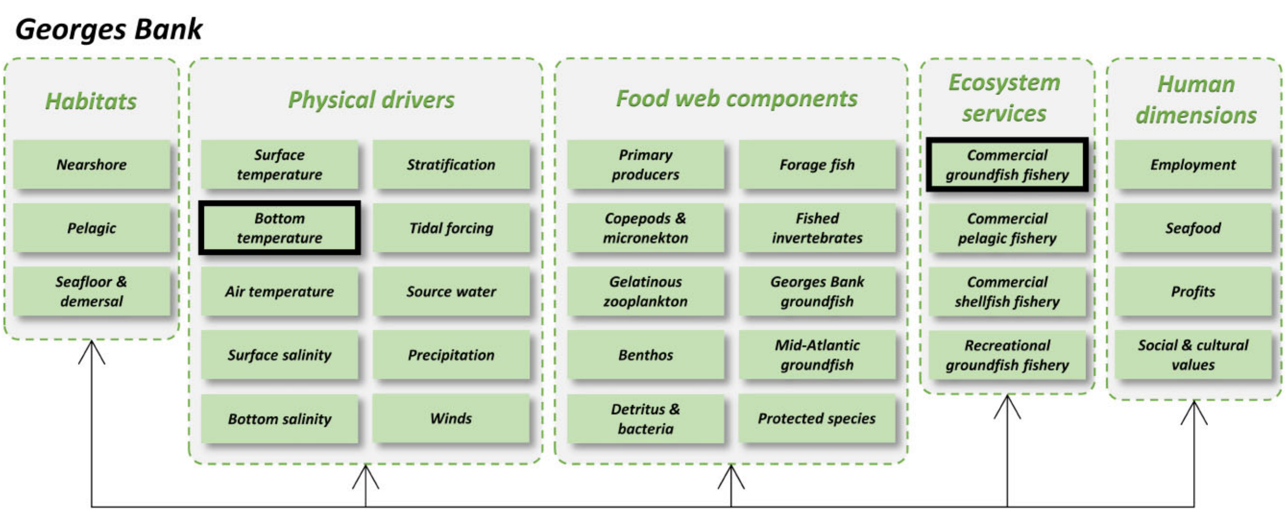

Figure 2. Overview of variables included in the GB conceptual model. For clarity, variables are organized into descriptive groups. Variables that were perturbed in the fishing and warming scenarios are indicated by thick outlines. Arrows symbolize general interaction within and across groups of variables; a detailed diagram with all pairwise links is provided in the Supplementary Materials.

direct interested readers to more in-depth treatments of the underlying theory. For each case study system we provide a summary of the conceptual model and the issues motivating its construction. Detailed procedures for recasting the conceptual models as either a QNM, FCM, or BBN are provided in the Supplementary Materials. To facilitate comparisons of the models, adjacency matrices corresponding to the final QNMs and FCMs and matrices indicating the structure of the DAGs used in the BBNs are also provided in Supplementary Materials. Input files used to run the models are available online (Reum *et al.*, 2021b).

Network models

QNMs

QNMs were developed from Loop Analysis that was first introduced in the ecological literature (Levins, 1974). Under Loop Analysis, conceptual models are represented as signed, directed graphs (or digraphs), where edges (links) represent interactions between nodes (variables) and encode the sign (+, −, or 0) of the effect of one variable on another. The matrix representation of the signed digraph corresponds to the community matrix **A**, which encapsulates the pairwise interactions of variables composing the system.

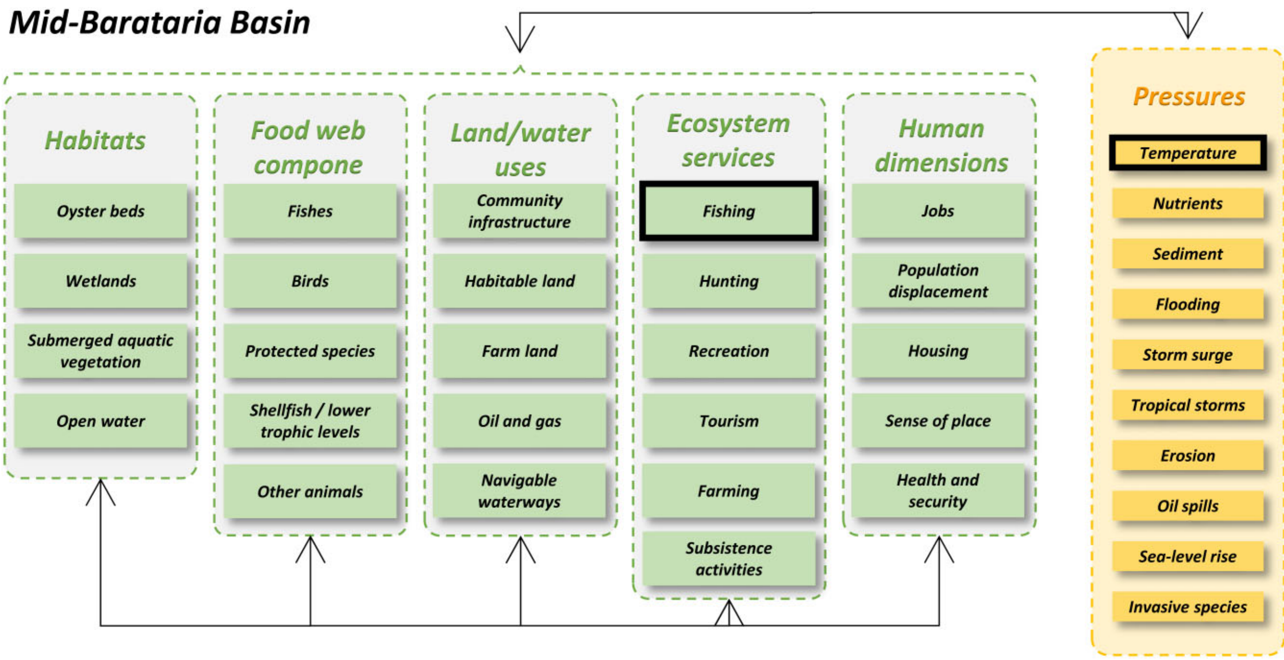

Figure 3. Overview of variables included in the MB conceptual model. For clarity, variables are organized into descriptive groups. The model was based in part upon the EBM–DPSER conceptual modelling framework (Kelble *et al.*, 2013) and distinguishes between pressure variables and response variables. Variables that were perturbed in the fishing and warming scenarios are indicated by thick outlines. Arrows symbolize general interaction within and across groups of variables; a detailed diagram with all pairwise links is provided in the Supplementary Materials.

By assuming the system is in equilibrium and that pairwise interactions between variables are approximately linear near equilibrium, the qualitative response of the system to a press perturbation can be calculated from the inverse of the negative community matrix ($-\mathbf{A}^{-1}$; Puccia and Levins 1985). A press perturbation corresponds to a sustained increase (or decrease) in the level of the perturbed variable (the exact value is not specified but assumed to be small) and the response of the perturbation is the sign of the direction of changes in the equilibrium level of variables composing the system (Bender *et al.*, 1984). A key feature of the approach is that feedbacks in conceptual models are preserved and incorporated into the projected responses (Puccia and Levins, 1985).

For small systems (e.g. less than five to seven variables), **A** can be analyzed symbolically to identify criteria for system stability or conditions needed to obtain a sign outcome for a particular node (Puccia and Levins, 1985; Dambacher *et al.*, 2003). However, in larger systems, simulation methods are more practical and can be used to rapidly assess the sign response of nodes and characterize uncertainty (Dambacher *et al.*, 2002, 2003). QNMs are synonymous with simulation-based approaches to Loop Analysis (Raymond *et al.*, 2011; Melbourne-Thomas *et al.*, 2012). The simulation approach proceeds by first sampling non-zero elements of **A** from uniform probability distributions. The sign of the link is retained, but the magnitude is sampled over two orders of magnitude (0.01–1), reflecting vague priors (Raymond *et al.*, 2011; Melbourne-Thomas *et al.*, 2012). The simulated **A** is tested against stability criteria (Melbourne-Thomas *et al.*, 2012), and if stable, the sign response of system variables to a given press perturbation scenario is recorded. In practice, as the number of variables and links in QNMs increase, the likelihood of drawing a stable community matrix decreases, and the issue is exacerbated if few negative feedbacks are present. To counteract this, negative self-loops are applied to all nodes in the system (e.g. Raymond *et al.*, 2011; Melbourne-Thomas *et al.*, 2013). In ecological communities, negative self-loops can represent negative density-dependence but more broadly can represent stabilizing control by variables outside the formal model (Puccia and Levins, 1985).

Outcomes are summarized from a large number of stable community matrices (10^4) to obtain estimates of uncertainty. Sign agreement (*SA*) is calculated as $(P - N)/T$, where P, N, and T correspond to the number of positive, negative, and total simulated outcomes. Values of *SA* range from -1 to 1; larger absolute values reflect higher confidence in the projected sign outcome and values near zero indicate higher ambiguity. If P and N are identical (e.g. 50% positive and 50% negative), then every positive outcome is matched by a negative outcome and the level of agreement is 0. All else being equal, the absolute value of *SA* decreases as the number of countervailing feedbacks increases (Dambacher *et al.*, 2003). The QNMs developed for each system were analyzed using the R package "QPress" (Melbourne-Thomas *et al.*, 2012).

FCMs

FCMs were first introduced and popularized in the social sciences (Kosko, 1986) but have been used to represent systems across disciplines including coupled social–ecological systems (Özesmi and Özesmi, 2004; Papageorgiou and Salmeron, 2013). Cognitive maps are static, graphical depictions of perceived causal relationships between variables (or concepts) composing a system (Axelord, 1976). In FCMs, the magnitude of the effect or degree of causality is designated according to linguistic categories (e.g. weak, moderate, strong; rarely, sometimes, usually and so on) and fuzzy causal algebra is used to propagate causal relationships and infer the system-wide effects of perturbation scenarios (Kosko, 1986). The use of linguistic categories captures uncertainty or fuzziness in the nature of the relationships and is easily understood using human reasoning (Kosko, 1986). To propagate causal relationships, linguistic categories are first converted to real numbers on the interval $[-1, 1]$ based on fuzzy set theory or, alternatively, designation of linguistic categories can be bypassed and causal weights specified directly.

The cognitive map is transformed into an adjacency matrix E, a square matrix with nodes C_i listed on the vertical axis and nodes C_j on the horizontal axis. The elements of the matrix (e_{ij}) contain the values of the causal relationships. If $e_{ij} < 0$, then C_i causally decreases C_j; if $e_{ij} = 0$, no causality is implied; and if $e_{ij} > 0$, then C_i causally increases C_j (Kosko, 1986). Baseline equilibrium values of concepts are obtained through forward propagation of the causal weights (Kosko, 1986). Specifically, the initial states of concepts are set to a value of 1, stored in the state vector $\boldsymbol{c}$, and updated following:

$$\boldsymbol{c}^{[t+1]} = f\left(\boldsymbol{E}\boldsymbol{c}^{t}\right), \tag{1}$$

where the superscript t denotes the simulation time step and function f is the "activation function," typically the logistic function, which rescales all values between 0 and 1. The state vector is updated until an equilibrium is reached (typically less than 50 iterations in most applications), though limit cycles or chaotic behaviour may also emerge (Özesmi and Özesmi, 2004).

To implement a scenario, the forward propagation procedure is repeated but the states of concepts are fixed at values that reflect the scenario under consideration. The change in the resulting equilibrium state vector relative to the baseline equilibrium state vector conveys the magnitude and direction of change of concepts under the scenario. The numerical difference can be "fuzzified" back into linguistic categories or treated as the final output. Similar to QNMs, the method permits representation of feedbacks, causal weights (pairwise interactions) are assumed to be linear, and scenario outcomes convey change relative to assumed equilibrium conditions (Papageorgiou and Salmeron, 2013). Self-loops are also permitted to represent specific processes, though they are not required to address computational challenges as in QNMs. In conventional FCMs, the magnitudes of outcomes are interpreted in qualitative, relative terms, and lack quantitative uncertainty estimates; however, methods to represent uncertainty are evolving (Ramsey *et al.*, 2012; Baker *et al.*, 2018). In all case studies, we used the R package "FCMapper" to run scenarios (Turney and Bachhofer, 2016) because of transparency in the underlying code and post-processing capabilities in the R environment, but note that other software platforms implement FCMs with potentially more user-friendly graphical user interfaces (e.g. Mental Modeler; Gray *et al.*, 2013).

BBNs

BBNs have grown in popularity in environmental modelling (Aguilera *et al.*, 2011) and are probabilistic graphical models that consist of two structural components: (1) a directed acyclic graph (DAG) and (2) a conditional probability table (CPT). Graph nodes represent a random variable with a finite set of mutually exclusive states and graph edges are directed from a "parent" node to a "child" node to indicate conditional dependency relationships. These directed dependence relationships flow from at least one node with no parents to at least one node with no children without creating cycles. Thus, BBNs by definition cannot include feedbacks, unlike QNMs and FCMs. The CPTs represent the strength of the dependence relationships corresponding to edges in the DAG and denote the likelihood of the state of a child node, given the states of its parent nodes (Renken and Mumby, 2009; Landuyt *et al.*, 2013). Values composing the tables can be constructed from empirical data where available, or assigned based on expert judgment.

The joint probability distribution for variable X consisting of $i = 1, 2, \ldots, n$ states, where x denotes state, is given by the chain rule:

$$P\left(x_1, x_2, \ldots, x_n\right) = \prod_{x_i \in X} P(x_i | parents(x_i)). \tag{2}$$

Using the model, information on the states of nodes is propagated through the DAG, and the posterior distribution is updated based on proposed changes in node states or the introduction of new data or evidence. That is, to specifically evaluate a scenario, the state of a node is changed, and the conditional probabilities are propagated through the model structure. The resulting change in the posterior distribution of variable state probabilities reflects the outcome. Similar to QNM and FCMs, outcomes under the framework correspond to equilibrium conditions and do not represent temporal dynamics. The software *Genie* (BayesFusion, LLC., v. 2.3) was used to parameterize the BBN networks for all case studies and obtain posterior probabilities under the perturbation scenarios.

Case studies

PI BKC

The PI BKC conceptual model represents important ecological interactions between BKC and the benthic community, and was originally developed to identify potential management interventions for promoting BKC stock recovery under climate change (Reum *et al.*, 2020a). The model is built around the life history of BKC that is separated into four stages (larvae, benthic recruit, juvenile, and adult), and includes six additional species or functional groups that are competitors and predators of BKC (Figure 1). To develop the model, multiple workshops were convened that included academic, indigenous government, state, and federal agency scientists, PI community members, and representatives from local fishing organizations. At each workshop, participants were guided through activities intended to encourage discussion and elicit input on the key ecological processes influencing BKC and other key benthic species or functional groups that interact with BKC. The conceptual model reflects a synthesis of information from the literature and opinions and views encountered at the workshops, and was developed with the original intention of informing a QNM (Reum *et al.*, 2020a).

Georges Bank

The GB conceptual model was developed by the Northeast Fisheries Science Center in support of NMFS's Northeast Integrated Ecosystem Assessment and as part of the ICES Working Group on the Northwest Atlantic Regional Sea (ICES, 2016; DePiper *et al.*, 2017). Over the course of several workgroup meetings, scientists with expertise on regional management issues and ecosystem dynamics built the conceptual model with the intent of informing QNMs, FCMs, and BBNs in follow-on studies. The conceptual model focuses on four managed groups (shellfish, forage fish, groundfish, and protected species) and was motivated in part by a need to better understand how these groups may respond to management actions or environmental change. Consequently, the model emphasizes resolution of human activities (commercial and recreational fishing), environmental drivers, trophic interactions, and lower trophic levels with strong relationships to the focal groups. Additional details regarding development of the conceptual model are available in DePiper *et al*. (2017) and working group reports (ICES, 2015, 2016).

MB

The MB is a shallow, brackish embayment located in southeast Louisiana that is bounded to the North by the Mississippi River and to the south by barrier islands that separate it from the Gulf of Mexico. In response to rapid land loss and erosion in the region, construction of a large sediment diversion project is currently underway that will divert sediment and fresh water from the Mississippi River (Peyronnin *et al*., 2017). The project intends to sustain and build land to reduce sea level rise impacts, stabilize wetland loss, and enhance wildlife populations. However, impacts on the larger social–ecological systems are not fully understood (Peyronnin *et al*., 2017). To examine potential social–ecological trade-offs, a team of scientific experts from NOAA's Gulf of Mexico Integrated Ecosystem Assessment (IEA) team initiated development of a conceptual model for the MB based on the EBM-Driver, Pressure, State, Ecosystem service, and Response framework (Kelble *et al*., 2013), which organizes variables in the system according to pressures (e.g. flooding), ecosystem states (e.g. wetlands), and ecosystem services (e.g. farming). This framework was modified to include human dimension variables (e.g. jobs). The conceptual model was vetted with stakeholders and refined based on feedback until consensus was achieved. Similar to GB, the conceptual model was built with the intent of informing subsequent development of QNMs, FCMs, and BBNs.

Model comparison

Network metrics

In addition to the total number of nodes and links (connectivity), we compared differences in network size and structure across models and systems based on link density (average number of links per node), connectance (the number of realized links relative to the total number possible), the total number of self-loops, and the hierarchy index (Özesmi and Özesmi, 2004; Lau *et al*., 2017). The latter ranges from 0 to 1, where 1 corresponds to a fully hierarchical network (a linear network where a node influences only one other node) and 0 indicates a fully democratic network where all nodes influence all others (Özesmi and Özesmi, 2004).

Model evaluation

We measured similarity of outcomes predicted by the different network models under three scenarios that could conceivably occur across all three systems. The first scenario ("fishing") simulated an increase in fishing mortality (both directed and bycatch) relative to current fishing levels on groups vulnerable to trawling. The second scenario ("warming") simulated an increase in ocean temperature and its potential impacts on species or functional groups. The final scenario evaluated the combined effect of both fishing and warming ("fishing + warming"). The nodes representing temperature and trawl fishing effort in models for each system along with their direct effects on variables are provided in Supplementary Table S1.

In the QNMs, the warming, fishing, and fishing + warming scenarios were implemented by positively pressing the corresponding temperature and fishing nodes individually or jointly. Outcomes for QNMs were expressed as SA. For FCMs, scenario runs were performed by fixing the value of temperature or trawl fishing concepts to 1 individually or jointly, and outcomes were calculated in terms of the change in the magnitude of each node relative to baseline levels (that is, scenario/baseline – 1). A similar procedure was also applied to the BBNs, where the probability of a warmer state or higher state of trawl fishing effort was set to 1, reflecting a 100% probability. BBN outcomes consisted of the difference in the probability of observing the high (or highest) state of each node between scenario and baseline conditions.

We measured agreement between network model outcomes in three ways based on responses from nodes that were susceptible to direct or indirect influence from the pressed nodes under the fishing + warming scenario (a total of 14, 12, and 31 response nodes for the Pribilof Island, George's Bank, and MB systems, respectively). Doing so removed nodes from the calculations that were unable to change under the scenarios or that were perturbed directly in the scenarios. In the case of the MB and GB models, nodes in the former category tended to be associated with processes that were resolved for evaluating other ecosystem stressors in the original model application.

For each pair of network methods, we first calculated "sign match", which we defined as the ratio of the number of nodes that had the same sign outcome under each modelling framework (that is, they matched in sign) to the total number of nodes susceptible to direct or indirect influence from the pressed nodes in the same system. Second, we calculated "category match", which we defined as the ratio of the number of nodes with outcomes that had both the same sign and magnitude to the total number of nodes susceptible to the perturbations. For all three network frameworks, we considered the absolute values of outcomes in the intervals $[0, 0.1)$, $[0.1, 0.5)$, and $[0.5, +\infty]$ as weak, moderate, and strong, respectively, similar to intervals used elsewhere (e.g. Marcot *et al*., 2001; Raymond *et al*., 2011). Placement of outcomes on the same scale facilitated comparison, but we note that outcome values have different interpretations based on the network model. In using the same scale, we made the reasonable assumption that relatively strong responses (FCMs) would be associated with a higher probability of occurrence (BBNs) and high *SA* (QNMs) and that the converse would also hold. Given the low frequency of strong responses, we considered either a strong or moderate response with *SA* a match.

For the third similarity measure, we focused on agreement between moderate and strong responses, as stronger responses are of particular interest in many decision-making contexts. Specifically, we calculated "strong category match" as the ratio of the number of nodes with outcomes of the same sign and that were either moderate or strong under both modelling frameworks to the total number of nodes with outcomes that were moderate or strong under at least one of the modelling frameworks. For each similarity measure, we also calculated agreement in node outcomes across all three network modelling frameworks.

In addition, we compared whether potential trade-offs as inferred from node outcomes under the scenarios differed between models. Specifically, we examined a subset of focal nodes, which represented variables that were important to the management issues motivating the conceptual models of each system and evaluated their responses in the scenarios for consistency across the three

Table 1. Network summary statistics for QNM, FCM, and BBN models developed for the PI, GB, and MB systems.

	PI			GB			MB		
	QNM	FCM	BBN	QNM	FCM	BBN	QNM	FCM	BBN
Node number	16	16	11	31	31	31	35	35	35
Connectivity (link number)	77	66	34	118	87	78	220	185	167
Link density	4.81	4.12	3.09	3.8	2.81	2.52	6.29	5.29	4.77
Connectance (connection density)	0.30	0.25	0.28	0.12	0.09	0.08	0.18	0.15	0.14
Self-loop number	16	5	0	31	0	0	35	0	0
Hierarchy	0.0115	0.0022	0.0310	0.002	0.0002	0.0019	0.0042	0.0012	0.0040

Table 2. Percentage of nodes with responses categorized as weak, moderate, and strong under fishing, warming, and fishing + warming scenarios for the PI, GB, and MB systems. Percentages are based on the total number of response nodes that were susceptible to direct or indirect influence from nodes pressed under the fishing + warming scenario and corresponded to 14, 12, and 31 nodes, respectively. Values greater than 50% are in bold.

		% Weak			% Moderate			% Strong		
Scenario	**System**	**QNM**	**FCM**	**BBN**	**QNM**	**FCM**	**BBN**	**QNM**	**FCM**	**BBN**
Fishing	PI	43	**97**	**56**	43	3	44	14	0	0
	GB	8	**85**	**92**	0	8	8	**92**	8	8
	MB	16	**86**	**100**	34	14	0	**50**	0	0
Warming	PI	14	**100**	**50**	**79**	0	**50**	7	0	0
	GB	15	**100**	**100**	**54**	0	0	31	0	0
	MB	22	**71**	**100**	**50**	29	0	28	0	0
Fishing + warming	PI	36	**97**	44	43	3	**56**	21	0	0
	GB	8	**85**	**92**	23	8	8	**69**	8	8
	MB	19	**71**	**86**	**50**	29	14	31	0	0

network modelling methods. Focal nodes for the PI system included adult BKC, its competitor red king crab (*Paralithodes camtschaticus*), and two of its predators, Pacific cod (*Gadus macrocephalus*) and adult halibut (*Hippoglossus stenolepis*). The GB focal nodes included two important functional groups (groundfish and forage fish), an indicator of habitat quality (seafloor and demersal habitat), and an indicator of a key ecosystem service (fishery catches and the provisioning of seafood). Last, the MB focal nodes included total fish biomass (fish), the aerial extent of wetland habitat, the availability of habitable land, and an index of recreational opportunities.

Results

Network summaries

All network metrics differed primarily by system, and to a lesser degree by model type (Table 1). Overall, the MB network models had the most nodes and links, approximately twice and three times, respectively, the number for PI models, which were the lowest (Table 1). Further, link densities were also highest for the MB models, and were approximately double the values of the GB models, which were the lowest (Table 1). Connectivity, however, was highest for the PI model, followed by MB and then GB (Table 1). Hierarchy indices were all low (less than 0.05; Table 1). Between network models, QNMs consistently had the highest numbers of links, link densities, and connectance values, while BBNs had the lowest (Table 1). This was related to the large number of self-loops in the QNMs and the reconfiguration of networks to remove cycles in BBNs (Table 1; see Supplementary Material for details).

Comparison of model projections

Overall, a majority of nodes responded weakly under the FCM and BBN models to the individual and joint fishing and warming scenarios across systems (Table 2). For BBN and FCMs, weak responses composed between 44–100% and 71–100%, respectively, of node outcomes across systems and scenarios. In contrast, the majority of outcomes were moderate or strong under the QNMs (Table 2). Strong QNM responses occurred most frequently under the fishing scenario for two of the three systems, moderate responses occurred most frequently under the warming scenario for all three systems, and the proportion of responses that were moderate and strong were more similar under the joint scenario (Table 2).

In general, outcomes matched in sign across all network models for 32–65% of nodes; lower sign match rates occurred for systems under the fishing scenario and the highest values occurred under the warming + fishing scenario (Table 3). In comparison, pairwise sign matching rates were higher overall, ranging from 33 to 92% (Table 3). Among network model pairs, FCM–QNM sign match rates were equal to or higher than other model pairs for Pribilof Island system outcomes, ranging from 64% (fishing scenario) to 86% (both the warming and fishing + warming scenarios; Table 3). FCM–QNM sign match rates were also higher than other model pair for GB outcomes across scenarios, with values ranging from 67 to 92%. In contrast, MB sign match rates were lower but identical across model pairs under the fishing scenario (52%), highest for BBN–FCM under the warming and fishing + warming scenarios (90% and 77%, respectively).

Match rates based on outcome sign and strength category were substantially lower than those for sign alone; match rates all three network models ranged from 0 to 21% and pairwise match rates

Table 3. Summary of prediction similarities across network types and under different perturbation scenarios for PI, GB, and MB systems. Sign match is the percentage of nodes with the same sign response. Sign and strength category match is the percentage of node responses with matching response signs and magnitudes. Strong and moderate match indicates the percentage of nodes in which moderate or strong responses were projected for nodes by both network model relative to the total number of nodes (indicated in parentheses) in which either network predicted a strong or moderate response. Matches equal to or greater than 50% are in bold. Percentages are based on the total number of response nodes that were susceptible to direct or indirect influence from pressed nodes under the fishing + warming scenario and corresponded to 14, 12, and 31 nodes for PI, GB, and MB, respectively.

		% Sign match				% Sign and category match				% Strong category match			
Scenario	**System**	**FCM-QNM**	**BBN-QNM**	**BBN-FCM**	**All**	**FCM-QNM**	**BBN-QNM**	**BBN-FCM**	**All**	**FCM-QNM**	**BBN-QNM**	**BBN-FCM**	**All**
Fishing	PI	64	43	**64**	36	21	7	**50**	0	14 (7)	0 (6)	0 (2)	0 (1)
	GB	**92**	33	42	33	17	0	33	0	10 (10)	0 (5)	0 (1)	0 (1)
	MB	**52**	**52**	**52**	32	3	42	29	3	0 (15)	**85 (13)**	0 (7)	0 (6)
	Average	**63**	46	**53**	33	11	25	35	2	6 (32)	46 (24)	0 (10)	0 (8)
Warming	PI	**86**	**57**	**79**	**57**	29	29	**57**	21	20 (10)	17 (6)	**50 (4)**	**50 (2)**
	GB	**67**	**50**	42	33	8	8	42	0	13 (8)	0 (6)	0 (1)	0 (1)
	MB	**58**	**65**	**90**	**52**	10	32	39	3	0 (15)	41 (22)	0 (12)	0 (5)
	Average	**67**	60	**77**	49	14	26	44	7	9 (33)	29 (34)	12 (17)	13 (8)
Fishing + Warming	PI	**86**	**64**	**71**	**64**	29	7	50	7	27 (11)	0 (9)	0 (4)	0 (3)
	GB	**75**	**67**	**50**	42	8	8	42	8	0 (8)	0 (4)	0 (0)	0 (0)
	MB	**65**	**65**	**77**	**65**	3	32	39	3	0 (19)	35 (26)	0 (16)	0 (9)
	Average	**72**	**65**	**70**	**60**	11	21	42	5	8 (38)	23 (39)	0 (20)	0 (12)

were lower for all models and scenarios (Table 3). Overall, sign and strength category match rates decreased the most for FCM–QNM and BBN–QNM outcomes relative to sign match rates (Table 3). This was related in part to the higher proportion of moderate and strong QNM outcomes relative to BBN and FCM outcomes across systems and scenarios (Table 2). Consequently, sign and strength cateogry match rates were typically highest for BBN–FCM outcomes, which were dominated by weak responses (Table 3).

Match rates for only strong outcomes were also low: values for all but two pairwise comparisons were less than 50% and the mode of the match rate was 0% (Table 3). Overall, pairwise strong match rates were lowest for BBN–FCM outcomes and all but two match rates were greater than 0%. Strong match rates were slightly better for FCM–QNM and BBN–QNM outcomes (Table 3), with the highest match rate (85%) occurring between BBN and QNM for MB under the fishing scenario (Table 3).

Focal nodes

Outcomes for focal nodes were predominately moderate to strong under the QNM in all three systems, and tended to be weaker for BBNs in the PI and GB systems and for FCMs in all three systems (Figure 4). For a subset of nodes, the signs of outcomes were consistent within scenarios across modelling methods, indicating a degree of robustness (e.g. Pacific cod, PI; Demersal Habitat, GB; and Wetlands, MB; Figure 4). However, for other nodes differences in outcomes between models resulted in different inferences regarding potential trade-offs under the three scenarios (Figure 4).

In the PI system, under increased fishing effort the QNM projected higher BKC and RKC levels (moderate and weak strength, respectively) and reductions in Pacific cod and adult halibut (moderate strength). In the model the groundfish fishery increases mortality on all four species, but Pacific cod and halibut are also predators on early life history stages of BKC and RKC. The net effect of their removal increased BKC and RKC levels. The strong trade-off, however, was not evident under the FCM and BBN, where outcomes were uniformly negative, albeit weakly in terms of strength (Figure 4). Under warming, three of the four PI focal species had consistent sign responses across modelling approaches; the exception was halibut, which increased, decreased and remained unchained under the QNM, FCM, and BBN, respectively. Under the joint fishing + warming scenario, the sign of most focal nodes were also uniform across models, though strengths were again highest under the QNM.

For GB, under the fishing scenario in the QNM, a trade-off was apparent between groundfish and demersal habitat on the one hand and seafood and foragefish on the other. Groundfish, demersal habitat, and seafood are all directly linked to fishing effort, and their outcomes reflect the sign of the direct linkage, while the increase in foragefish likely reflects release from predation from groundfish. Under the FCM and BBN models, the strength of the trade-offs decreased overall and the sign of the outcome for seafood reversed under the BBN (Figure 4). Under warming, sign disagreement across modelling methods also occurred for foragefish and seafood, and additionally, under the joint fishing + warming scenario groundfish outcomes were inconsistent, indicating heightened ambiguity in their response (Figure 4).

In the MB system, sign outcomes were consistent across methods under the fishing scenario for Fish and Wetlands, but inconsistent for Recreation and Habitable Land (Figure 4). For Habitable Land, no change was projected under the BBN, which reflected the removal of pathways that in the other models indirectly connected it to fishing effort. The difference in network structure reflected the obligatory removal of links to prevent feedbacks in the BBN (see Methods). Under warming, sign reversals were limited to Fish, which increased under warming in the QNM, but decreased in the FCM and BBN; all other nodes responded negatively across models (Figure 4). Under the joint fishing + warming scenario, sign disagreement across modelling methods were limited to Fish and Recreation, which increased under the QNM and FCM, respectively (Figure 4). Outcomes for all other nodes and models were negative (Figure 4).

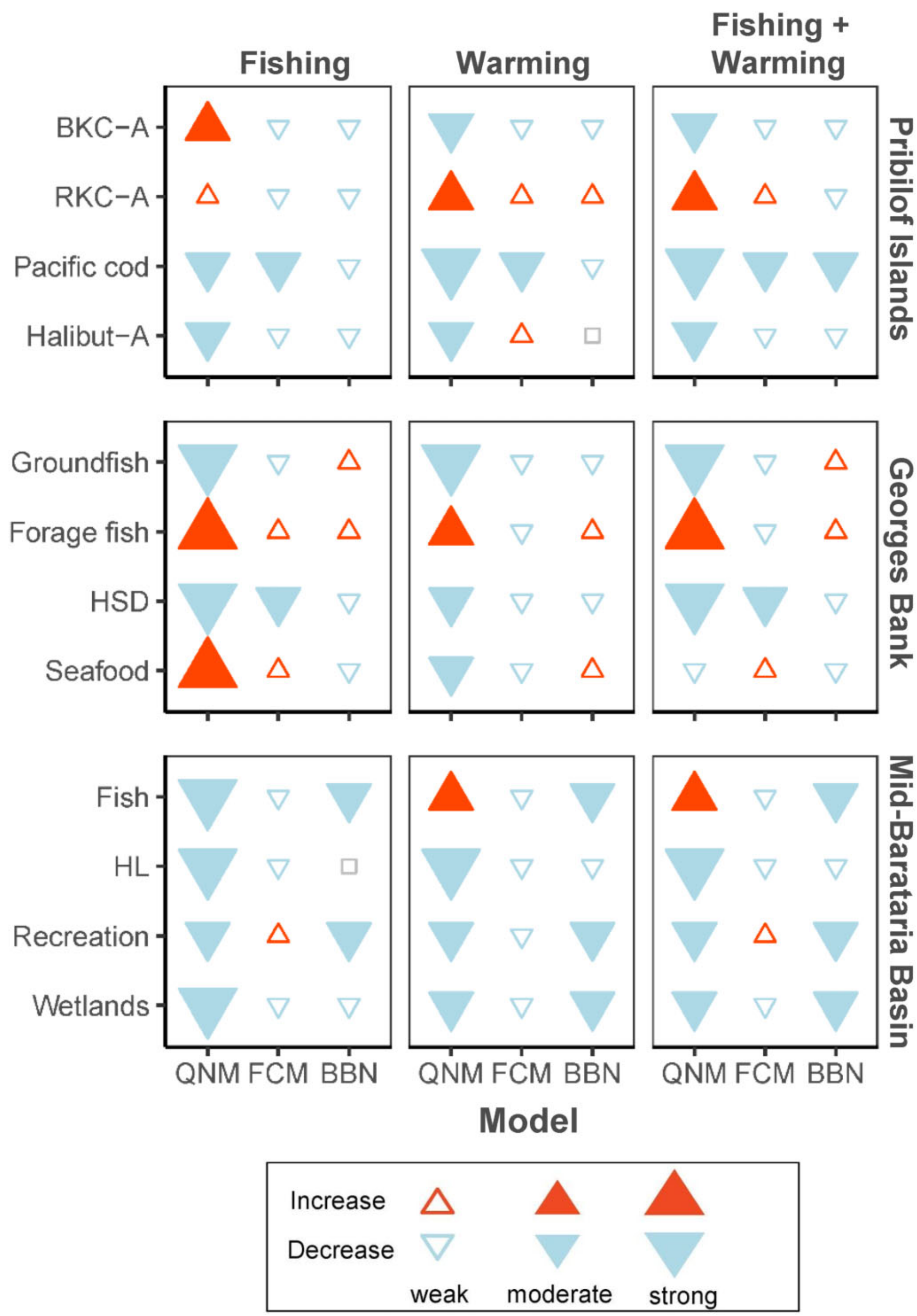

Figure 4. Response of focal nodes in network models of the Pribilof Island, GB, and MB system under fishing, warming, and fishing + warming perturbation scenarios. Nodes with no direct or indirect pathways linking them to the perturbed node in a given scenario are indicated by an open grey square. For the Pribilof Island nodes, BKC and RKC correspond to blue king and red king crab; A indicates adult life history stages. For the GB nodes, HSD corresponds to seafloor and demersal habitat; for the MB nodes, HL corresponds to habitable land.

DISCUSSION

Soft network approaches are increasingly applied in EBM settings, but few studies have attempted to compare outcomes across methods. Our main results indicate that differences in projections can be considerable depending on whether QNMs, FCMs, or BBNs are utilized and that outcomes based on a single method should be interpreted with caution. Currently, practitioners tend to use only one framework when exploring management-relevant scenarios, and while different types of uncertainty (e.g. parametric, structural) can be represented within frameworks to varying degrees (Marcot *et al.*, 2006; e.g. Melbourne-Thomas *et al.*, 2012; Baker *et al.*, 2018), structural uncertainty between frameworks is considerable.

Characterizing this uncertainty should be a high priority, particularly when network approaches are applied in contexts where data to validate models or criteria to select outcomes from one framework over another are lacking. In the three case studies, QNM outcomes for the focal nodes tended to have higher strengths relative to the other network methods across scenarios. If considered in isolation, QNM outcomes in these instances could potentially lead to overconfidence in projection certainty. For example, in the PI system, the management action to increase fishing effort results in the desirable effect of promoting population recovery of BKC under the QNM, but when the outcome is considered in concert with the negative, weak outcomes from the FCM and BBN, the projection likelihood is tempered and a need for heightened caution is indicated. The same issue arises for groundfish and foragefish in the GB system, where strong, contrasting outcomes under the QNM for the fishing, warming and joint scenarios, were tempered by weaker outcomes, some in opposing directions, under the FCM and BBN. Conversely, agreement across methods improves confidence in projections and suggests that the outcome may be robust in the face of structural uncertainty (Cheung *et al.*, 2016). For instance, projections for Wetlands in the MB system were variable in strength, but consistently negative across methods under the fishing, warming, and joint scenarios. From a management perspective, agreement across the different methods adds weight to the plausibility of this undesirable outcome and highlights a possible indirect effect under the scenarios. Like their quantitative counterparts, soft network models are best suited to informing strategic decision-making, and a fuller assessment of prediction uncertainty through multimodel comparisons could potentially advance their uptake in EBM (e.g. Addison *et al.*, 2013).

Despite originating from a common conceptual model, outcomes between network models were moderately similar only in terms of sign match. Moreover, the relative level of similarity in outcomes between network models varied across scenarios and systems. That is, outcome similarity was not consistently higher or lower for any specific pair of methods. Among comparisons involving BBNs, the lack of consistency may partly be related to differences in how the conceptual models were simplified to remove feedbacks across systems. For the MB model, a DAG was constructed by preferentially removing links that were scored low by experts in terms of being relevant to representing systems responses to sediment diversions (a major scenario motivating the model). In contrast, feedback loops in the GB and Pribilof Island models were broken based on expert judgment with the goal of emphasizing drivers on focal species and to reflect explicit ecological assumptions (e.g. bottom-up control), respectively. The different approaches were driven by the different issues motivating the conceptual models, and reflect the absence of any single best practice for simplifying systems with feedbacks into DAGs. Variation in the similarity of FCMs and QNMs outcomes also ranged widely across systems and scenarios, despite retention of feedbacks and more consistent topological differences (namely, the addition of negative self-effects in the QNMs relative to FCMs to address practical computational constraints; Raymond *et al.*, 2011). For these models, topological differences may play a smaller role relative to link weight in driving differences in outcomes. However, quantifying the extent to which network topology, interaction strength, and fundamental differences in the underlying mathematics drive dissimilarity in projections is challenging because the topological differences are necessitated by the approaches themselves. Evaluation of the effects of network topology could potentially be evaluated within the FCM framework as it can accommodate both DAGs and negative self-loops, but similar comparisons are less feasible due to constraints under the BBN and QNM frameworks (Marcot *et al.*, 2006; Raymond *et al.*, 2011).

While we have focused on comparisons of the model outcomes, researchers could potentially consider treating the model set as an ensemble and blend projections across methods. In the simplest case, model outcomes could be reduced to a common currency such as the sign of the response or to the strength categories used in the current study, and unweighted quantities (e.g. mean, standard deviation) could be calculated assuming a "democracy of models." Alternatively, if predictive performance metrics are available, model outcomes could be weighted accordingly or provide a basis for selecting a "best" model (Burnham and Anderson 2002; King *et al.*, 2009). That said, soft network approaches are often used because information is sparse, in which case other more subjective criteria such as the relative plausibility of model assumptions may provide more relevant weighting criteria. For instance, the assumption that network structure must conform to a DAG in a BBN could be a basis for down-weighting BBN outcomes relative to the other methods if feedbacks are considered essential to representing the system under study. Ultimately, the approach taken to synthesize outcomes will depend on the management question and characteristics of the system, and we note that the technical challenge of combining outcomes from the three approaches in a statistically coherent manner requires further study.

In each case study, researchers formulated individual QNMs, BBNs, and FCMs without particular regard to the outcomes of the other two models. This approach helped to indicate the possible level of variation in outcomes that can go undetected when researchers adopt only one method. However, in practice, EBM modelling should follow an iterative process (Levin *et al.*, 2009; Addison *et al.*, 2013) and future efforts to simultaneously apply all three methods could draw from lessons learned in other multimodel research endeavors (Townsend *et al.*, 2014; Reum *et al.*, 2021a). For instance, information learned under one modelling approach could be used to inform subsequent iterations of network structure under all frameworks or aid revision of the common underlying conceptual model. The sharing of information across models, or the "mingling of models," entails updating models with knowledge gained through the process of building the model set itself (Townsend *et al.*, 2014). Similarly, sharing model outcomes with stakeholder groups is an important step in the model building cycle, and the level of similarity or divergence in projections can stimulate useful dialogue and spur further model refinement (Reum *et al.*, 2021a). A key advantage of soft network models is that they are easy to revise and should be considered working hypotheses of system structure.

The present study provides an evaluation of outcome uncertainty across network methods, but we note that operationalizing these models to support EBM decision-making will require consideration of additional uncertainty sources and further refinement. Specifically, we have not addressed model uncertainty at the conceptual model level. The set of conceptual models considered represent composite models and average over different beliefs, opinions, or levels of evidence for processes operating within the system to varying degrees. Important components of each system may have been omitted from the conceptual models as well, due to factors such as who participated in model development and the degree to which conceptual model simplification was emphasized.

Such uncertainty could be considered explicitly by developing alternative conceptual models in consultation with stakeholders and managers (Stier *et al.*, 2017). The corresponding network models could be added to the model set and variance partitioning methods applied to quantify the relative importance of conceptual model uncertainty to outcome variance (Cheung *et al.*, 2016; Reum *et al.*, 2020b). Similarly, each BBN was represented with one DAG, but alternative DAGs may also be plausible and could be added to the model set. We recommend follow-on studies that aim to (1) evaluate which processes and linkages disproportionately drive outcome uncertainty to focus model revision and data collection efforts, (2) attempt model validation using empirical data where available, and (3) undertake vetting of all models with stakeholders to improve transparency, familiarity, and potential uptake of results.

We have focused on comparisons of projected outcomes across network model methods, but disagreement in outcomes does not diminish the larger benefits of developing conceptual models in tandem with network models. First, the process of developing conceptual models can provide a framework for querying stakeholders of their system knowledge, facilitate synthesis and organization of system understanding, and place different knowledge sources (e.g. formal scientific research, experiential knowledge, or a combination thereof) on equal footing (Harvey *et al.*, 2016; DePiper *et al.*, 2021). Second, conceptual modelling exercises can generate optimism that is often lacking when stakeholders face long-term environmental challenges (Freitag *et al.*, 2019) and facilitate dialogue between stakeholders, managers, and scientists, which can broaden the perspectives of each group and increase buy-in to model building enterprises (Reum *et al.*, 2021a). Third, representing conceptual models using multiple network models explicitly acknowledges model uncertainty, which can help build credibility with stakeholders along with confidence in projections (Addison *et al.*, 2013; Cheung *et al.*, 2016). Last, disagreement in outcomes across model methods indicates sensitivity to system specification and the need for closer scrutiny of the models, their assumptions, and the underlying conceptual model from different vantages (Reum *et al.*, 2021a). The networks can be analyzed within each framework to identify important links or relationships that drive the outcome of important nodes. Insights obtained from closer evaluation can help inform research priorities, future data collection needs, and areas to focus quantitative modeling efforts. These and other benefits common to broader classes of ecological models (Addison *et al.*, 2013; Geary *et al.*, 2020) make conceptual and network models useful tools in the EBM modelling toolbox. The intercomparison of network modeling approaches is a critical step towards operationalizing conceptual models and we strongly encourage continued research into the synthesis of outcomes across frameworks.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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Data availability

Signed digraphs, adjacency matrices, and CPTs utilized in the QNM, FCM, and BBN analyses are available in Figshare at https://dx.doi.org/10.6084/m9.figshare.14825133.

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