National SCIENCE Challenges

SUSTAINABLE SEAS

Ko ngā moana whakauka

A review of risk assessment frameworks for use in marine ecosystem-based management (EBM) in Aotearoa New Zealand

Clark DE, Gladstone-Gallagher R, Stephenson F & Ellis J

May 2021

Report

Report for Sustainable Seas National Science Challenge project *Communicating Risk and Uncertainty (Project code 3.2)*

Report authors

Clark DE, Gladstone-Gallagher R, Stephenson F & Ellis J

Date of publication

May 2021

Reviewed by

Judi Hewitt

For more information on this project, visit: www.sustainableseaschallenge.co.nz

SUSTAINABLE SEAS Ko ngā moana whakauka

National Science Challenges

CAWTHRON

THE UNIVERSITY OF WAIKATO Te Whare Wānanga o Waikato

NIWA Taihoro Nukurangi

THE UNIVERSITY OF AUCKLAND Te Whare Wānanga o Tāmaki Makaurau NEW ZEALAND

About Sustainable Seas Challenge

Our vision is for Aotearoa New Zealand to have healthy marine ecosystems that provide value for all New Zealanders. We have 60+ research projects that bring together around 250 scientists, social scientists, economists, and experts in mātauranga Māori and policy from across Aotearoa New Zealand. We are one of 11 National Science Challenges, funded by Ministry of Business, Innovation & Employment.

www.sustainableseaschallenge.co.nz

Cover image: Waves crashing at Piha, New Zealand. Credit to Tim Marshall.

Acknowledgements

We wish to thank the following people for their contributions during the development of the research proposal and on-going co-development of the *Risk and Uncertainty* project: Amanda Leathers (WWF), Ben Sharp (MPI), Ben Moginie (EPA), David Taylor (Aquaculture NZ), Erica Gregory (EPA), Hannah Jones (Waikato Regional council), Joe Harawira (DOC), Katherine Short (Terra Moana), Kris Ramm (DOC), Kura Paul-Burke (University of Waikato), Martin Cryer (MPI), Michelle Cherrington (Terra Moana), Megan Carbines (ARC), Paula Blackett (NIWA), Ray Wood (CRP), Richard Bulmer (NIWA), Simon Lamping (MFE), Shane Geange (DOC), Shaun Awatere (Landcare Research), Shelton Harley (MPI).

Mihi

Kia hora te marino
Kia whakapapa pounamu te moana
Kia tere te kārohirohi i mua i te huarahi i a tātou katoa

CONTENTS

Executive summary 1

1. Introduction 4

2. Literature Review 6

2.1 Literature review methods 6

2.2 Suitability of risk assessment methods and frameworks for ecosystem-based management in Aotearoa New Zealand 8

2.2.1 Likelihood-Consequence (LC) 8

2.2.2 Ecological Risk Assessment for the Effects of Fishing (ERAEF) 9

2.2.3 Management Strategy Evaluation (MSE) 12

2.2.4 Spatially Explicit Fisheries Risk Assessment (SEFRA) 14

2.2.5 Bayesian Networks (BNs) 15

2.2.6 Biosecurity 17

2.2.8 Review summary 18

2.2.9 Consideration of non-linear dynamics in ecosystem response and recovery 21

3. Research co-developer elicitation approach 22

3.1 Research co-developer elicitation approach 22

3.2 Outcomes of the workshop 23

4. International risk assessments for EBM 25

4.1 Hierarchical Frameworks for EBM 26

4.2 Coupled Natural Human (CNH) systems and feedbacks 27

4.2.1. Level 1: Qualitative Assessments 28

4.2.2 Level 2: Semi Quantitative Assessments 28

4.2.3 Level 3: Quantitative Analysis 29

4.3 Cumulative effects assessments and risk 30

5. Conclusion 31

References 34

Appendix: Minutes from Sustainable Seas Project 3.1 & 3.2 joint co-developer workshop 44

Morning session 44

Survey 46

Afternoon Session 46

Executive summary

A review of risk assessments currently used in Aotearoa New Zealand revealed that, except for Bayesian Network models, most presently used risk assessments are not fit-for-purpose to support Ecosystem-Based Management and the needs and aspirations of Māori. Internationally, the area of risk assessment is under development, with no standard methods yet completely useful for Ecosystem-Based Management. We recommend a mixed approach for future use and testing in Project 3.2 that focuses on developing a three-level hierarchical framework, based around Bayesian Networks for the two simpler levels. For the highest level, we suggest testing two different approaches: highly mechanistic biophysical models with separate social models; and a Coupled Natural Human model.

Managing the multiple and cumulative effects of human activities in marine ecosystems is one of the most complex problems facing environmental decision-makers today. Globally, ecosystem-based management (EBM) has been advocated as a holistic and inclusive way to manage the competing demands on our marine environment. Central to decision-making within an EBM context is the need for methods and frameworks that can assess risks (and their associated uncertainties) arising from multiple and cumulative pressures. The uncertainty associated with complex ecosystem responses to pressures is often very high, primarily due to difficulties in collecting baseline knowledge and in understanding how ecosystems respond to pressures against a background of environmental variability and climate change.

This report aimed to identify, through a literature review and discussion with project co-development partners, the utility of risk assessment methods presently used in Aotearoa New Zealand (Aotearoa NZ), and the frameworks and methods used internationally, for supporting EBM, including the needs and aspirations of Māori. The results of this report are intended to be used to determine methods or frameworks to use for future work in Sustainable Seas Project 3.2 *Communicating risk and uncertainty*.

Workshops with iwi and stakeholders interested in Sustainable Seas had previously identified for Aotearoa NZ: i) two general methods for assessing risk: Likelihood-Consequence and Bayesian Networks; ii) three fisheries methods/frameworks: Management Strategy Evaluation, Spatially Explicit Fisheries Risk Assessment, and Ecological Risk Assessment for the Effects of Fishing; and iii) a set of approaches for assessing marine biosecurity risks. A literature review did not find any other risk assessment methods that were widely used in Aotearoa NZ.

The six risk assessment methods were assessed against 10 criteria that were considered important for supporting EBM in Aotearoa NZ, including the needs and aspirations of Māori. These criteria were the ability to; 1) assess risk to multiple ecosystem components; 2) include indirect effects; 3) estimate uncertainty; 4) accommodate different knowledge types; 5) assess risk to social, cultural, and economic values; 6) model interactions; 7) incorporate feedbacks; 8) produce spatial outputs; and 9) produce temporal outputs. Our final criterion was an assessment of the complexity of each method/framework, as an indication of how easy it would be to communicate model outputs and how much data, money, and time each approach would take to set up and run.

Of the risk assessments currently applied in an Aotearoa NZ context, only Bayesian Networks (BNs)met all 10 criteria required for EBM. This approach was highly ranked by research co-developers, many of whom had experience in seeing BNs being applied, for informing EBM and supporting Māori values and aspirations. Other methods were generally capable of meeting some of the criteria, but often their application in Aotearoa NZ did not do so or would require adaptations to do so. Criteria generally met included the ability to incorporate multiple types of knowledge, estimate uncertainty and produce spatial outputs. However, most of the methods/frameworks were not able to cope with interactions, feedbacks and indirect effects very well and few were able to assess risk through time or produce diverse outputs reflecting ecological, cultural, social or economic values of interest. Additionally, many of the studies we reviewed failed to account for non-linear dynamics in ecosystem response and recovery and could not identify threshold responses.

Internationally, we found no methods yet available that fulfilled all 10 criteria required for EBM, but some frameworks and methods under development. These can be categorised as: cumulative effect assessments; hierarchical frameworks; and Coupled Natural Human models.

- Cumulative effects assessments are currently being extended to assess biophysical risk from multiple pressures, allowing for multiple knowledge types and ecosystem components, non-linear, indirect and interactive effects and feedbacks to be incorporated. Notable developments include the application of cumulative impact maps where the probability and the related uncertainty of cumulative impacts under different scenarios can be analysed, for example using spatially explicit BNs.
- Hierarchical frameworks usually have three levels and move from simple risk assessments of a single pressure on a subject (Class 1) to more complex assessments of the reciprocal and cumulative interactions among multiple pressures and multiple subjects (Class 3) which can be data-driven or mechanistically modelled. Different types of data are often used in the different levels.
- The frameworks above generally focus solely on the biophysical ecosystem or consider the biophysical and social systems separately. For the latter, separate ecological risk and socio-economic analysis are conducted sequentially and then weighed against each other where the individual and joint risk to both the human and natural components of the system are considered. Coupled Natural Human conceptual models evaluate the risk to human and natural components of the system simultaneously and have the potential to amplify or attenuate risks from a given pressure. However, there are very few examples of studies that include dynamic feedbacks between social and ecological components of the system.

The outcomes of this review and workshop discussion may inform the selection of tools/methods that will be used in subsequent research in the Sustainable Seas Project 3.2 (*Communicating risk and uncertainty*).

1. Introduction

Human activities both rely on and affect our environment. Understanding how multiple human activities impact our coastal and marine ecosystems is one of the most urgent and complex problems facing environmental decision-makers today (Davies et al. 2020). Globally, ecosystem-based management (EBM) has been advocated as a holistic and inclusive way to manage the competing demands on our marine environment (Arkema et al. 2006, Ruckelshaus et al. 2008, Long et al. 2015). EBM is an integrated approach to management that aims to address the full suite of interactions and relationships within ecosystems, including the impact humans often have on these systems through multiple and cumulative activities (Sustainable Seas 2018). EBM in an Aotearoa New Zealand (Aotearoa NZ) context must consider the role of Māori as partners to the Crown under the Treaty of Waitangi, and their right to be included in planning and decision-making. This requires decision-making tools that can incorporate Māori world views and facilitate communication with a range of end-users.

Effective implementation of EBM in the marine environment relies on an estimation of how marine ecosystems respond to cumulative anthropogenic effects. However, uncertainty in direct ecological responses to pressures is often very high, primarily due to difficulties in collecting baseline knowledge and in understanding how ecological functioning responds to pressures against a background of environmental variability and climate change (Hill et al. 2007, Hewitt et al. 2016). This uncertainty is further extended by a lack of understanding of how direct effects propagate through ecological and social systems to create indirect effects on ecological health, economic health and social and cultural values (Holsman et al. 2017). Making decisions in the face of uncertainty is challenging because outcomes may differ from predicted outcomes, which may result in management failures or decision paralysis (Link et al. 2012, Foley et al. 2019). Indeed, uncertainty is viewed as one of the major obstacles to progressing cumulative effects management in Aotearoa NZ (Foley et al. 2019). Consequently, decision-making tools that can communicate the degree of uncertainty associated with a particular decision are urgently required.

Uncertainty may arise from multiple sources, including epistemic causes associated with knowledge of the state of a system (e.g., resulting from measurement error, insufficient data, extrapolations, interpolations, natural variability over space and time) and linguistic causes associated with ambiguous, context-dependent or vague vocabulary (Regan et al. 2002). Natural variability is a significant source of uncertainty in the management of natural resources. This refers to any observable change in a state variable that occurs in nature, including differences among populations within a community, changes in spatial distributions through time, density-dependent or independent variation, seasonal or interannual variability in realized environmental conditions and so forth (Link et al. 2012). Natural variability can arise from random differences associated with environmental stochasticity or individual differences (process noise) or endogenous or exogenous factors (Turchin 2003). Endogenous factors are the biologically or ecologically driven feedbacks that affect variables. Exogenous factors are externally driven trends, oscillations, or step changes in the environment (e.g., changes observed with seaonality or between year variability due to changes in oceanographic conditions; Link et al. 2012). Sources of uncertainty can be classed along a spectrum of complete certainty to total ignorance, with five intermediate levels (Walker et al. 2013). At an intermediate level, there may be a range of possible consequences, but we can assign a probability to each of the alternatives or rank the likelihood of their occurrence.

Decision-making about uncertain events and their consequences is often carried out via a risk assessment process. Risk can be defined in numerous ways (Haimes 2009, Aven 2010) but generally refers to the likelihood that an undesirable event will take place and the potential consequences that may arise as a result (Holsman et al. 2017). As part of the Phase I Sustainable Seas Project 5.1.3 (*Risk and Uncertainty*), Inglis et al. (2020) undertook a comprehensive review of analytical tools and processes that can be used to support risk assessment. These range from simple, qualitative assessments in which risk is expressed as categories (e.g., high and low), to quantitative assessments that use empirical data to model risk and approaches that explore a broad range of possible future scenarios (Inglis et al. 2020). A specific focus of Inglis et al. (2020) was to review methods that addressed deep uncertainty (for further information on these specific tools see Section 6.2 in Inglis et al. 2020). In presenting risk assessment estimates it is important that underlying sources of variability, and therefore uncertainty, are acknowledged. The underlying ecological complexity and feedbacks within ecosystems should be recognised and communicated where possible. Uncertainty at other stages of the modelling and decision-making process (e.g., arising from inadequate communication, unclear management objectives or outcome uncertainty; Link et al. 2012) should also be addressed where possible.

Our report aimed to identify and review existing risk assessment tools that would be suitable for supporting EBM in Aotearoa NZ (either as is or with future development), including the needs and aspirations of Māori. The scope of this report was guided by findings from Phase I of the Sustainable Seas challenge (i.e., the review by Inglis et al. 2020) and a group of research co-development partners. Co-development partners included a wide range of stakeholders, end-users, iwi and decision-makers operating at a variety of management scales. At a workshop (held in Wellington, February 2019) and during the development of the project proposal, iwi and stakeholders identified a list of methods and frameworks used in Aotearoa NZ for assessing risk in the marine environment. These included Likelihood-Consequence (LC), Ecological Risk Assessment for the Effects of Fishing (ERAEF), Management Strategy Evaluation (MSE), Spatially Explicit Fisheries Risk Assessment (SEFRA), Bayesian Networks (BNs), and general approaches for assessing marine biosecurity risks. Although we recognise that deep uncertainty is an important consideration for EBM, methods for decision-making under deep uncertainty (DMDU) are complex and have not yet been widely applied, therefore, our review does not consider approaches to support DMDU (but see Inglis et al. 2020 for review).

The objectives of this report were to:

1. Search for other frequently used Aotearoa NZ marine risk assessment methods, beyond the six described above, and review all the methods against a set of criteria to determine their suitability for supporting EBM in an Aotearoa NZ context, including the needs and aspirations of Māori;
2. Present a summary of the findings from a research co-developer elicitation workshop that discussed the usefulness of these methods/frameworks for risk assessment within a kaupapa Māori (with regards to Māori values and aspirations) and EBM context;
3. Present a relevant subset of international frameworks to evaluate whether there are approaches that could be integrated into existing risk methodologies to support EBM frameworks for Aotearoa NZ.

The outcomes of this review and workshop discussion may inform the selection of tools/methods that will be used in subsequent research in the Phase II Sustainable Seas Project 3.2 (*Communicating risk and uncertainty*).

2. Literature Review

This section first outlines the methods and suitability criteria that we used for the literature review. We then discuss the suitability of each of the risk assessment methods/frameworks for use in an Aotearoa NZ EBM context. We conclude with a summary of our review findings and a discussion of other criteria that are important for EBM. These additional criteria capture non-linear dynamics in ecosystem response and recovery (refer Table 2.3 for definitions of these criteria).

2.1 Literature review methods

We identified 120 reports and peer-reviewed journal articles that had applied these methods/frameworks in Aotearoa NZ. Of these, we reviewed at least five recent publications for each risk assessment method/framework, intentionally selecting reports and papers from a wide range of applications where possible. Some methods/frameworks were restricted in their application in an Aotearoa NZ context, for example, MSE has only been applied to assess risk from fishing activities. Where the Aotearoa NZ application was limited, or we needed more information to assess the true capability of a method/framework, we reviewed additional recent (> 2015) international papers and reports.

The criteria used to evaluate the suitability of each of the identified risk assessment methods/frameworks for EBM in Aotearoa NZ (Table 2.1) were developed from aspects raised by iwi and stakeholders in the Sustainable Seas Phase II strategy development workshops, Sustainable Seas Challenge Leadership Team members and research participants from Projects 1.1, 1.2, 3.1, T1 and T3.

Table 2.1 Criteria used to score risk assessment methods and frameworks for their suitability in supporting ecosystem-based management (EBM) in Aotearoa NZ, including the needs and aspirations of Māori.

Risk to multiple ecosystem components

Can the risk assessment consider more than two of the following?

- Physical disturbance
- Multiple species removal and effects on benthic habitats
- Changes to trophic levels, productivity and size of important species
- Alteration of food quantity and quality
- Species addition (e.g., invasive species)
- Biodiversity loss
- Contamination, including behavioural changes and toxicity
- Changes to ecosystem function (e.g., movement/connectivity, biological traits, chemical balances and elemental cycles)

Where multiple ecosystem components can be considered, are the components assessed separately or can they be assessed in a fully integrative way (e.g., in a network)?
Indirect effects Can the risk assessment include indirect effects on the variable of interest? For example, terrestrial sedimentation reduces seafloor primary productivity, indirectly decreasing denitrification rates.
Estimates of uncertainty Can the risk assessment estimate uncertainty? If so, is uncertainty quantified and is it only related to data limitations?
Ability to accommodate different knowledge types Can the risk assessments incorporate different types of knowledge (non-numeric, narrative information e.g., expert opinion, mātauranga Māori, local knowledge, as well as quantitative data) and be routinely used in a variety of knowledge situations and data limitations? Or is quantitative data required?
Includes risks to social, cultural and economic values Can the risk assessments provide outputs of values other than biophysical ones (e.g., ecosystem services, social and cultural values, economic cost)?
Interactions Can the risk assessment model interactions between different pressures or different ecosystem components?
Feedbacks Can the risk assessment incorporate temporal feedbacks between ecosystem components (i.e., where changes in one component feedback to affect another component)?
Production of spatial outputs Can the models produce spatially explicit outputs (e.g., maps of risk)?
Production of temporal outputs Can the models produce temporally explicit outputs (e.g., changes in risk through time)? For this criterion to be met, outputs from one time period must feed into the assessment for the next time period.
Model complexity Is the risk assessment method/framework generally quick to set up and run with multiple scenarios?

2.2 Suitability of risk assessment methods and frameworks for ecosystem-based management in Aotearoa New Zealand

In this section, we will use a set format to describe the method/framework, its present use in Aotearoa NZ, its advantages and disadvantages, and adaptations that would be required to ensures that it is fit for use EBM.

2.2.1 Likelihood-Consequence (LC)

Description and use

LC (Box 1) is used in a wide variety of applications, including ecological and business settings. This simple method uses non-numeric and/or quantitative data to produce a matrix of the likelihood and consequence associated with each activity. The output is a risk score for each ecological component, which is a product of the expected likelihood and consequence of an event. LC assessments can be referred to by various names including 'vulnerability index' (e.g., Clark & Tittensor 2010) and 'Estuarine Vulnerability Assessment' (e.g., Robertson & Stevens 2012, Stevens & Robertson 2017) or more generically as 'risk assessment', 'ecological impact assessment', 'qualitative risk assessment', and 'risk matrix' (e.g., Burgman 2005, Fletcher 2005, Cliff & Campbell 2012, Boyd 2013, Heath 2014, Johnston 2017, 2019, Cunningham et al. 2020).

BOX 1: Likelihood-Consequence (LC)

Method description	Key applications in Aotearoa New Zealand	Key advantages
Produces a matrix of likelihood and consequence for each activity	Used to assess risks associated with: • Species invasions • Fishing • Cruise ships • Oil spills • Wastewater overflows • Land-based coastal stressors	• Easy to setup and run • Multiple knowledge types • Highly flexible • Can categorise data quality • Easy to communicate • Can produce multiple output types

Key references: Bermingham 2015, Campbell and Gallagher 2007, Campbell and Hewitt 2013, Heath 2014, Johnston 2017, Johnston 2019, MacDiarmid et al. 2012, Robertson and Stevens 2012, Stevens and Robertson 2017.

Risk assessments based on likelihood and consequence appear to be the most widely applied form of risk assessment in Aotearoa NZ, largely due to their flexibility and the simple model structure. We found examples of LC risk assessments applied in many different contexts in Aotearoa NZ, including assessment of the ecological risk of species invasions (e.g., Campbell & Hewitt 2013, Heath 2014), fishing (e.g., Campbell & Gallagher 2007), cruise ship routes (e.g., Johnston 2019), oil spills (e.g., Bermingham 2015), wastewater overflows (e.g., Johnston 2017), and land-based coastal pressures (e.g., Robertson & Stevens 2012, Stevens & Robertson 2017). This method is commonly used for assessing coastal risks associated with environmental consent applications, following the EIANZ guidelines (Roper-Lindsay et al. 2018). MacDiarmid et al.'s (2012) assessment of the risk of 65 activities on 62 marine habitats in Aotearoa NZ showcases the flexibility and wide application of LC assessments in the marine environment.

Advantages

The main advantage of LC risk assessment is the simplicity of the approach and the flexibility to assess risk to multiple ecosystem components (e.g., species, habitats, ecosystem function) using different types of knowledge. The LC approach can assess risks to social, cultural and economic values as well as biophysical components (e.g., Cliff & Campbell 2012, Campbell & Hewitt 2013, Bermingham 2015) and can deal with both non-numeric (most common) and quantitative data (e.g., MacDiarmid et al. 2012). In some cases, interactions between pressures were considered, though only in a simple additive manner. For example, in MacDiarmid et al.'s (2012) assessment of anthropogenic threats to marine habitats in Aotearoa NZ, cumulative effects were accounted for by averaging vulnerability scores for each habitat. Indirect effects are sometimes informally evaluated through the expert judgement of consequence (e.g., Cliff & Campbell 2012, Boyd 2013, Johnston 2019).

Disadvantages

A shortfall of LC risk assessments is that they cannot incorporate feedbacks or interactions between ecosystem components and when uncertainty is assessed, it is usually only evaluated by categorising data quality (e.g., Campbell 2011, MacDiarmid et al. 2012), although quantitative approaches are possible (e.g., Clark & Tittensor 2010). No examples of temporally explicit risk outputs were found, and most assessments did not produce spatially explicit risk outputs.

Adaptations required

Future application of this method could use hierarchies in the risk matrix to deal with cumulative effects (refer Section 4.1 on hierarchical risk assessments suggested in the international literature). Adapting the LC method to include spatial outputs, as demonstrated by Bermingham (2015) and Clark and Tittensor (2010) also represents a potential advancement for using this method within an EBM risk assessment framework in Aotearoa NZ.

2.2.2 Ecological Risk Assessment for the Effects of Fishing (ERAEF)

Description and use

ERAEF (Box 2) is a hierarchical risk assessment framework developed to manage Australian fisheries in the context of Ecosystem-Based Fisheries Management (Hobday et al. 2011). It moves from a comprehensive but largely qualitative analysis of risk at Level 1, through to a more focused and semi-quantitative approach at Level 2, to a highly focused and fully quantitative model at Level 3. The different levels of assessment provide a series of filters to screen out low risks, with the assessment moving to the next level only if the risk is judged to be above a determined threshold. Five ecological components are evaluated: 1) target species, 2) by-product and by-catch species, 3) threatened, endangered and protected species, 4) habitats, and 5) ecological communities. These components can be evaluated independently and often only a single component is included in a risk assessment if a particular focus is required. ERAEF is based on an exposure–effects approach, rather than a likelihood–

consequence approach, because most fishing activities are considered to be common and deliberate. In Aotearoa NZ, hierarchical risk assessments like ERAEF have primarily been developed and applied to assess risks of fishing activities on bycatch of threatened and endangered species (e.g., Waugh et al. 2012, Ford et al. 2018, Georgeson et al. 2020), and on benthic habitats (e.g., Clark et al. 2011, Clark et al. 2014). The hierarchical nature of ERAEF means that it comprises three levels that each use a different risk assessment method, and so in our review, we assessed each of these separately (Table 2.2), but we discuss the benefits and weaknesses of the framework as a whole.

BOX 2: Ecological Risk Assessment for the Effects of Fishing (ERAEF): Hierarchical risk assessment framework with three levels

Method description	Key applications in Aotearoa New Zealand	Key advantages
Level 1: SICA: Scale-Intensity Consequence Analysis (qualitative)	Used to assess risks of fishing on: • Threatened, endangered and protected species Overseas it is also used to assess risks of fishing on: • Target species • By-product and by-catch species • Habitats • Ecological communities	• Multiple knowledge types • Highly flexible • Easy to communicate
Method description	**Key applications in Aotearoa New Zealand**	**Key advantages**
Level 2: PSA: Productivity-Susceptibility Analysis (semi - quantitative)	Used to assess risks of fishing on: • Threatened, endangered and protected species • Vulnerable habitats	• Spatial estimates possible • Easy to communicate
Method description	**Key applications in Aotearoa New Zealand**	**Key advantages**
Level 3: SAFE: Sustainability Assessment for Fishing Effects (quantitative)	Used to assess risks of fishing on: • Threatened, endangered and protected species	• Quantifies uncertainty • Can assess cumulative risk

Key references: Clark et al. 2011, Ford et al. 2018, Hobday et al. 2006, Hobday et al. 2011, Holmes et al. 2020, Smith et al. 2007, Waugh et al. 2012, Zhou et al. 2011, Zhou et al. 2019, Zhou & Griffiths 2008.

Scale Intensity Consequence Analysis (SICA) is often used in the Level 1 analysis of the ERAEF framework. The plausible worst-case impact of each fishing activity on each ecological component is assessed using expert judgement and a six-point scale from negligible to catastrophic. The scale and intensity of the activity are each scored (≈exposure), and then the consequence score (≈effect) is selected from a component-specific set of scoring guidelines. The output is a risk score that is the sum or product of the intensity and consequence scores. Only elements that score > 2 are assessed in the next level of the framework. SICA used at Level 1 of the ERAEF can be used to generate risk scores for multiple ecosystem components (e.g., Hobday et al. 2011), but in Aotearoa NZ it has predominantly been applied to assess the risk of various fishing activities on threatened and endangered bycatch species (e.g., Ford et al. 2018).

Productivity-Susceptibility Analysis (PSA) is often used in the Level 2 analysis of the ERAEF framework. Using semi-quantitative data, productivity (i.e., the ability of the unit to recover from impact) and susceptibility (i.e., exposure of the unit to impact) attributes are scored from 1-3 (low to high). Productivity is usually determined by averaging scores for attributes that estimate the intrinsic rate of population increase (e.g., fecundity, growth rate), but it can include attributes that influence the ability of habitats to recover from fishing impacts (e.g., levels of naturalness, and connectivity to other habitats). Susceptibility is estimated as the product of four attributes: availability, encounterability, selectivity and post-capture mortality. The overall risk score for each unit is the Euclidean distance from the origin on a two-dimensional plot of productivity and susceptibility. PSA used at Level 2 of ERAEF has been primarily applied in Aotearoa NZ to assess the risks that fishing poses to both threatened and endangered species (e.g., Waugh et al. 2012), as well as vulnerable habitats (e.g., seamounts; Clark et al. 2011, Clark et al. 2014).

Sustainability Assessment for Fishing Effects (SAFE) is often used to assess fishing effects on by-catch species in the Level 3 analysis of the ERAEF framework. Although fully quantitative, this simple and rapid assessment can be simultaneously applied to many species in a batch process, making it useful for assessing effects on by-catch species. Fishing impact (mortality rate) is calculated by estimating spatial overlap between species distribution and fishing effort distribution, catchability resulting from the probability of encountering the gear and size-dependent selectivity, and post-capture mortality. The fishing impact is then compared to sustainability reference points based on basic life-history parameters. We found only one Aotearoa NZ application of SAFE (Holmes et al. 2020), but it has been used by Australia and in the High Seas of the Southwestern Pacific (by Australian and New Zealand Scientists) to quantitatively assess the risks of fishing on populations of threatened and endangered bycatch species (e.g., Zhou et al. 2019, Georgeson et al. 2020).

Advantages

Overall, the ERAEF framework is an efficient risk assessment method because it filters out 'low' risk impacts at lower, qualitative levels meaning that resources are not wasted quantitatively assessing impacts with predicted low risks. This aspect also allows a level of flexibility where impacts are either assessed qualitatively or quantitatively depending on the data availability and as new data becomes available (for example on the efficacy of different management mitigations). Additional levels can be added to assess the residual risk (e.g., AFMA 2012). The hierarchical nature of this framework also allows model complexity to increase at different levels of assessment so that complex and computationally demanding models are only used when deemed appropriate. The framework explicitly accounts for uncertainty at the higher quantitative levels of assessment (e.g., in SAFE).

Disadvantages

From the perspective of EBM, a management framework that recognises that ecosystem components are part of complex interaction networks, the filtering aspect of ERAEF is likely to overlook cumulative effects, where impacts on one component assessed in isolation of other components may present as a low risk, but accumulation and feedbacks between components result in larger effects and environmental surprises (Thrush et al. 2016). Because ecosystem components (e.g., species populations, habitats) are assessed separately from each other, the framework also does not consider the effects of indirect effects (e.g., the effects of suspended sediment created by a trawl net) or feedbacks between ecosystem components. Generally, ERAEF does not generate spatially or temporally explicit risk outputs. Methods within the ERAEF framework are sometimes applied across multiple time periods (e.g., Waugh et al. 2012, Zhou et al. 2019), however, we do not consider these applications to be temporally explicit because the results from the first time period do not feed into the second time period.

Adaptations required

Although ERAEF does not generally produce spatial outputs, PSA (Level 2) has been used to map spatial variability in fishing risk to seabirds (Waugh et al. 2012), representing a potential adaptation of this method for use in an EBM context. The SAFE method has been recently extended to assess cumulative fishing risk, but only using a simple additive model, and could be further adapted to assess risk from other activities (e.g., habitat loss and marine transportation) provided their impact in terms of mortality can be estimated (Zhou et al. 2019).

2.2.3 Management Strategy Evaluation (MSE)

Description and use

MSE (Box 3) is not strictly a risk assessment methodology, rather it uses simulations to compare the relative effectiveness of different management strategies (Fulton et al. 2014). MSE is the development of a rule (or set of rules) that are simulation-tested in a range of possible real-world scenarios that include all foreseen combinations of variability, uncertainty, incorrect model specification, and bias, and which must meet pre-specified goals chosen by managers, with a probability that they also decide. Once the simulation testing is complete, managers evaluate the performance of each strategy against the specified objectives. The chosen rules are then locked in and enacted in the real world, until the end of the pre-specified period, when the MSE is repeated in the light of any new information or change of policy. This method requires quantitative data, and the outputs are usually values of a variable of interest (e.g., fish stock biomass) through time, with levels of uncertainty around the estimate. MSE can be applied using a range of process-based model types from single-species populations (e.g., fish stocks) to 'whole-ecosystem' contexts (e.g., using Atlantis models) to determine how different management strategies influence different ecosystem components. In an Aotearoa NZ context, MSE is primarily used to assess how fishing activities impact fish stock biomass of a single species (i.e., a single-sector, single-ecosystem component context; e.g., Holland et al. 2005, Cordue 2014, Haist & Middleton 2014). Atlantis models have been developed in Aotearoa NZ but have only been applied in a single-sector context (e.g., to assess the effects of fishing on the Chatham Rise; McGregor et al. 2019, McGregor et al. 2020). An Atlantis model was also developed for Tasman and Golden Bay as part of Phase I of Sustainable Seas to test a range of environmental and management scenarios (e.g., effects on scallop population dynamics). Outputs from this model have not yet been published.

BOX 3: Management Strategy Evaluation (MSE)

Method description	Key applications in Aotearoa New Zealand	Key advantages
Uses simulation to compare effectiveness of management strategies	Used to assess risk of fishing on: • Single-species stock biomass Overseas it has been used in 'whole-ecosystem contexts'	• Incorporates feedbacks • Temporal estimates • Identifies robust management scenarios • Can produce multiple output types • Quantifies uncertainty

Key references: Butterworth 2007, Dichmont et al. 2008, Fulton et al. 2007, Fulton et al. 2014, Punt et al. 2016, Smith et al. 2007.

Advantages

MSE has many advantages that make it a useful approach for EBM. The managed system is simulated as a whole, allowing trade-offs to be considered while identifying and accounting for uncertainty. The explicit quantification of uncertainty focuses attention on robust management strategies that produce satisfactory outcomes under a range of future scenarios, reducing the likelihood of unwelcome ecological surprises (Sainsbury et al. 2000). The operating model can exhibit time trends and incorporate feedback effects, allowing simulation testing of adaptive management strategies and outputs to be evaluated through time (Butterworth et al. 2010). However, it should be noted that these feedbacks only exist between stock biomass and fishing effort rather than between different ecological components of the system, which is essential in an EBM context. In addition to biological performance measures, MSE can also consider economic and social objectives (e.g., Dichmont et al. 2008, Fulton et al. 2014), allowing different values to be incorporated into decision-making. For example, an MSE-type approach was used by Maunder et al. (2000) to consider trade-offs between reducing fisheries catch and achieving conservation objectives for Hooker's sea lions.

Disadvantages

MSE relies on quantitative input data, is complex to set up and run and indirect effects and interactions are not usually considered. Although MSE can be applied in a 'whole-ecosystem' context to evaluate how different management strategies influence multi-species or ecosystem objectives (e.g., marine mammal bycatch, trophic interactions and benthic effects; Sainsbury et al. 2000), these applications are uncommon and have not been carried out in Aotearoa NZ. Ecosystem applications using MSE have been relatively simple, incorporating only a limited number of uncertainties and ecosystem objectives (Sainsbury et al. 2000).

Adaptations required

The use of MSE in an EBM-context would require the use of highly complex operating models (e.g., Atlantis) and they would need to cope with greater levels of uncertainty and complexity than has been attempted so far. Model uncertainty could be addressed by executing MSE simulations across several alternative operating models (Perryman et al. 2021). However, despite substantial improvements in complex problem analysis over recent decades (Gelman et al. 1995), computational constraints still limit the range of uncertainties, ecosystem components and feedbacks that can be considered in a given model. In addition, many critical decisions, such as the selection and weighting of hypotheses to include in the analysis, are not guided by objective criteria or methods (Sainsbury et al. 2000). Thus, even if a highly complex model could be created, it would be unlikely to produce scientifically defensible or practically useful outputs (Sainsbury et al. 2000, Plaganyi 2007).

2.2.4 Spatially Explicit Fisheries Risk Assessment (SEFRA)

Description and use

SEFRA (Box 4) was developed in Aotearoa NZ to assess the population-level risk to non-target species (e.g., seabirds, marine mammals; Ochi et al. 2018, Sharp 2018, Large et al. 2019, Richard et al. 2020) arising from direct incidental mortality in commercial fisheries. The core of SEFRA is a detailed Bayesian model. It combines a spatially explicit impact assessment to estimate the level of incidental fisheries mortality with a biological assessment of the associated effect on the population, as a function of population size and demographic parameters influencing population productivity. The primary output of the SEFRA is a Risk Ratio, a measure that can be presented as a single number, or disaggregated by species, species group, fishery, fishing fleet, spatial area or even fishing event.

BOX 4: Spatially Explicit Fisheries Risk Assessment (SEFRA)

Method description	Key applications in Aotearoa New Zealand	Key advantages
Detailed Bayesian model in which risk is expressed as a ratio between estimate of deaths and Population Sustainability Threshold	Used to assess risk associated with: • Effects of fishing on non-target species (e.g., seabirds, marine mammals) • Toxoplasmosis in marine mammals	• Spatially explicit • Uncertainty quantified in a spatial manner

Key references: Sharp et al. 2018.

Advantages

Unlike many of the approaches we evaluated, SEFRA can spatially characterise risk and uncertainty. The risk assessment is generally static, however, it is possible to model risk through time using an assumption of linear density dependence (e.g., Large et al. 2019). Although the model requires quantitative data on the spatial distributions of non-target species and fishing effort, the assessment does not rely on species-specific population models or comprehensive fisheries observer data.

Disadvantages

The SEFRA approach is limited by its inability to incorporate indirect effects, feedbacks or interactions between ecosystem components. Although non-numeric data and expert opinion can be incorporated into the models, the method primarily relies on quantitative data and is complex to set up and run. We found no examples where this method has provided outputs associated with other values (e.g., cultural, economic and social).

Adaptations required

Although SEFRA was developed to assess the effects of fishing activities on non-target species, this approach could be adapted to assess the effects of additional anthropogenic activities on other ecosystem components. For example, SEFRA was recently used to assess the effects of toxoplasmosis on Māui and Hector's dolphins (Roberts et al. 2019) and the method is fully compatible with a spatially explicit bottom fishing impact assessment approach (Sharp et al. 2009, Mormede & Dunn 2013). Application of this approach to other pressures and ecosystem components would require sufficient information to model the distribution of the ecosystem components and estimate the effect of the pressures of concern. For example, full implementation of a SEFRA model for benthic invertebrates would be limited by the difficulties of modelling their spatial distribution, given the sparse and scale-dependent nature of species distribution information and environmental data (Sharp 2018) and limited information on both responses to other pressures and how they accumulate.

2.2.5 Bayesian Networks (BNs)

Description and use

BNs (Box 5) are probabilistic models that provide a graphical representation of a network of variables (called nodes) and their interactions (Kaikkonen et al. 2020). The relationships between variables are displayed as links (arrows), with the direction, strength and shape of these dependencies quantified using conditional probabilities (Marcot & Penman 2019). In Aotearoa NZ, BNs have been applied to assess a range of environmental problems including the benthic impacts of fish farms (Giles 2008), the effects of multiple pressures on estuarine ecosystem functioning (Bulmer et al. 2019, Bulmer & Hewitt 2020), and the effects of multiple pressures on fish populations (Parsons et al. 2021).

BOX 5: Bayesian Networks (BNs)

Method description	Key applications in Aotearoa New Zealand	Key advantages
Probabilistic model that graphically presents a set of variables and their interdependencies	Used to assess risks associated with: • Benthic impacts of fish farms • Effects of multiple stressors on estuary functioning • Effects of multiple stressors on fish populations	• Highly flexible • Multiple knowledge types • Quantifies uncertainty • Easy to communicate • Can produce multiple outputs • Spatial predictions possible

Key references: Bulmer et al. 2019, Kaikkonen et al. 2020, Marcot et al. 2019.

Advantages

BNs can synthesize different types of knowledge (e.g., expert, mātauranga Māori, local, empirical) and explicitly account for the probabilities of different scenarios, making them a useful tool for assessing risk and uncertainty in an EBM context. For example, scientific and traditional indigenous knowledge were combined in a BN to assess the cumulative impacts of multiple stressors on ecosystem health in a Canadian study (Mantyka-Pringle et al. 2017). They integrated field data, interview transcripts, existing models and expert judgement to assess socio-ecological risk. In BNs, model parameters take on a probability distribution, rather than a single value, allowing risk and uncertainty to be estimated more accurately than approaches that rely on mean values (Piffady et al. 2020). The approach is very flexible, enabling multiple ecological components and pressures to be integrated into a single model. In addition to biophysical data, other forms of information (e.g., socio-economic) can be incorporated into BNs enabling a wide range of values to be considered by decision-makers. For example, Batstone et al. (2011) used a BN to generate indicators of economic and social wellbeing associated with the effects of urban stormwater run-off on freshwater and estuarine receiving waters in Aotearoa NZ (e.g., suitability for recreation, food extraction, non-use values, cost and benefits of development options). The BN structure allows for the incorporation of indirect effects and interactions between different nodes which are determined by conditional probability tables. BNs can be spatially explicit (Marcot & Penman 2019) and even those that are not can be parameterized with spatial data (e.g., Bashari et al. 2016, Helle et al. 2016, Piffady et al. 2020), supporting spatial risk assessments and making outputs more user friendly (Jolma et al. 2014).

One of the key strengths of BNs is that they lend themselves to participatory modelling, allowing stakeholders to be involved in the process of model building and scenario testing. BNs are relatively easy to communicate to stakeholders because scientific and technical complexity is translated into an easily understandable graphical representation. In addition, once they are set up they are easy to run, allowing stakeholder questions and scenarios to be tested and compared in near-real time.

Participatory modelling increases stakeholder understanding of the model structure and assumptions, promotes open discussion and acceptance of model results and helps to ensure the model meets the diverse needs of end-users, who often have differing values and knowledge sets (Henriksen et al. 2012, Laurila-Pant et al. 2019). For example, the inclusion of decision makers in model development can ensure that BN decision and utility nodes are meaningful for their objectives (Kaikkonen et al. 2020).

Disadvantages

Whilst BNs met all the EBM suitability criteria, they do have limitations. A major limitation initially was the inability to incorporate feedback loops and cross-scale interactions. Because the relationship between two nodes is required to be unidirectional, direct feedbacks cannot be incorporated. Recently, however, time-steps and hierarchies have been proposed as a potential solution creating dynamic BNs (Marcot & Penman 2019, Bulmer & Hewitt 2020, Kaikkonen et al. 2020). For example, Uusitalo et al. (2018) used dynamic BNs to model major structural changes in the Baltic Sea food web. A remaining limitation is that expert elicitation can be challenging particularly with respect to avoiding bias (Kaikkonen et al. 2020). It should be noted that this challenge is one that applies across all risk assessment methodologies utilising expert elicitation.

Adaptation required

Despite the identified weaknesses, BNs met all 10 criteria for supporting EBM and the needs and aspirations of Māori, therefore, no adaptions are required.

2.2.6 Biosecurity

Description and use

Most marine biosecurity risk assessments rely on qualitative approaches, likely due to a lack of available data and the time and costs associated with developing detailed models (Leung et al. 2012). These qualitative marine biosecurity risk assessments are often undertaken in the form of a simple LC matrix and generally rely on expert opinion (Box 1). Although quantitative biosecurity risk assessment methods are in use overseas (refer Lodge et al. 2016 for a summary), these generally focus on risks associated with a single species and are seldom used in policy (Leung et al. 2012). Within Aotearoa NZ, quantitative approaches have been used to determine the likelihood of exposure of ports to non-indigenous species from internationally arriving commercial vessels (Hatami et al. 2021). Quantitative techniques using BN models are also currently in development (pers. comm. Daniel Kluza Ministry for Primary Industries 18/09/20), but we did not include them in our review as they have not yet been implemented in Aotearoa NZ.

Advantages

Marine biosecurity risk assessments in Aotearoa NZ generally evaluate the consequence of a species invasion on a range of ecosystem components (e.g., biodiversity, benthic habitats, trophic interactions). In addition to the biophysical consequences, the economic, social and cultural consequences of an invasion are often included in biosecurity risk assessments (e.g., Cliff & Campbell 2012, Campbell & Hewitt 2013, Muellner et al. 2013). Marine biosecurity risk assessments share many attributes with LC assessments, including the ability to account for additive interactions (e.g., MacDiarmid et al. 2012) and incorporate indirect effects through the assessment of consequence. For example, Cliff and Campbell (2012) assessed the potential for an invasive diatom to indirectly affect trout size by smothering the trout's food. Spatially explicit risk assessments often estimate the likelihood of invasion by modelling the potential distribution of marine non-indigenous species using niche models (Lee et al. 2008).

Disadvantages

Like LC, consideration of risk to different ecosystem components is usually carried out in parallel with no consideration of feedbacks between ecosystem components. Uncertainty is usually assessed by ranking confidence in the data or indicating where data is highly variable, rather than a quantitative evaluation.

Adaptations required

Temporal outputs are uncommon but information on how risk might change through time with climate change effects is being considered in terrestrial biosecurity assessments (pers. comm. Daniel Kluza Ministry for Primary Industries 18/09/20). Although not a formal risk assessment, Floerl et al. (2013) similarly examined whether changes in the global ocean climate will alter the risk of non-indigenous species' survival and establishment in the future. Combining these types of environmental projections with trade forecasts could enable managers to identify geographic areas of emerging risk.

2.2.8 Review summary

Our review found that of the risk assessments currently in use in Aotearoa NZ, only BNs met all 10 criteria required to support EBM and the needs and aspirations of Māori (Table 2.2). The remaining risk assessment methods/frameworks were generally capable of meeting some of the criteria, but often their applications in Aotearoa NZ did not do so or would require adaptations to do so. For example, MSE met 8 of our 10 criteria, but the use of this approach in an EBM-context would require the use of highly complex operating models that would be unlikely to produce scientifically defensible or practically useful outputs. LC also met most of our criteria, however this approach cannot incorporate feedbacks or produce temporal outputs and is limited in its ability to assess risk to multiple components and estimate uncertainty. Overall, most approaches can incorporate multiple knowledge types and characterise uncertainty (although many of these only characterised data limitations) and many could be adapted to produce spatial outputs. However, most approaches assessed risk to different ecosystem components separately, rather than in an integrative manner. In general, most methods/frameworks did not cope with interactions, feedbacks and indirect effects very well and few were able to assess risk through time. Importantly, apart from LC, BNs and MSE, if risks to social, cultural or economic values were to be assessed, this would need to be done separately. For example, a cost-benefit analysis was used in conjunction with a PSA to evaluate the economic trade-offs associated with spatial fishery closures to protect vulnerable marine systems (Penney & Guinotte 2013).

Table 2.2. Summary of the ability of the risk assessment methods/frameworks to meet the criteria to determine their suitability to support ecosystem-based management in in an Aotearoa New Zealand (NZ), including the needs and aspirations of Māori (described in Table 2.1). Risk assessment methods/frameworks reviewed included Likelihood-Consequence (LC), methods within the Ecological Risk Assessment for the Effects of Fishing framework (including Scale Intensity Consequence Analysis (SICA), Productivity-Susceptibility Analysis (PSA) and Sustainability Assessment for Fishing Effects (SAFE)), Management Strategy Evaluation (MSE), Spatially Explicit Fisheries Risk Assessment (SEFRA), Bayesian Networks (BNs) and general approaches for assessing marine biosecurity risks. A ranking of 'Yes' was assigned if the criterion was met in Aotearoa NZ applications, 'Possible' was used when method papers or overseas applications demonstrated this criterion could be met, but this was not demonstrated in Aotearoa NZ applications, and 'No' was used when no examples were found that met the criterion. Further details on rankings are provided as footnotes.

	LC	ERAEF			MSE	SEFRA	BN	Biosecurity
		SICA	PSA	SAFE*				
Risk to multiple ecosystem components	Yes (in parallel)	Yes (in parallel)	Possible (in parallel)	No	Possible (integrative)	Possible (in parallel)	Yes (integrative)	Yes (in parallel)
Indirect effects	Yes	No	No	No	Possible	No	Yes	Yes
Estimates of uncertainty	Data quality only	Data quality only	Data quality only	Yes	Yes	Yes	Yes	Data quality only
Ability to accommodate different knowledge types	Good	Good	Good	Moderate	Poor	Moderate	Good	Good
Includes risks to social, cultural and economic values	Yes	No	No	No	Yes	No	Yes	Yes
Interactions	Yes	No	No	Yes	Possible	No	Yes	Possible
Feedbacks	No	No	No	No	Yes	No	Yes	No
Can produce spatial outputs	Yes	No	Yes	No	No	Yes	Yes	Possible
Can produce temporal outputs	No	No	No	No	Yes	Yes	Yes	No
Model complexity	Simple	Simple	Moderate	Moderate	Complex	Complex	Simple to complex	Simple
Source data	a	b	c	d	e	f	g	h

* SAFE was also assessed in an Australian context because we only found one example of this method applied in Aotearoa New Zealand.

Definitions of ranking:

'Risk to multiple components' = 'No' if the method can only be applied to one component (e.g., single species); 'Yes – in parallel' if the method can assess risk to multiple components in parallel but not within the same model; and 'Yes - integrative' if the method can assess risk to multiple components in a fully integrative way.

'Estimates of uncertainty' = 'Data quality only' if only data quality was categorised for each variable, 'Yes' if uncertainty was quantified.

'Ability to accommodate different knowledge types' = 'Good' if a large amount of non-numeric data can be used, 'Moderate' if both non-numeric and quantitative data can be used but at least some quantitative data is required, and 'Poor' if only quantitative data can be used.

'Model complexity' = ranges from Simple' to 'Moderate' to 'Complex'.

Source data = a (Campbell & Gallagher 2007, Clark & Tittensor 2010, Cliff & Campbell 2012, MacDiarmid et al. 2012, Robertson & Stevens 2012, Boyd 2013, Campbell & Hewitt 2013, Heath 2014, Bermingham 2015, Johnston 2017, Stevens & Robertson 2017, Johnston 2019, Cunningham et al. 2020), b (Hobday et al. 2011, Ford et al. 2018), c (Clark et al. 2011, Hobday et al. 2011, Waugh et al. 2012, Penney & Guinotte 2013, Clark et al. 2014, Georgeson et al. 2020), d (Zhou & Griffiths 2008, Hobday et al. 2011, Zhou et al. 2011, Zhou et al. 2019, Georgeson et al. 2020, Holmes et al. 2020), e (Maunder et al. 2000, Holland et al. 2005, Breen & Kim 2006, Dichmont et al. 2008, Cordue 2014, Fulton et al. 2014, Haist & Middleton 2014, McKenzie et al. 2018), f (Ochi et al. 2018, Sharp 2018, Abraham et al. 2019, Large et al. 2019, Richard et al. 2020), g (Giles 2008, Batstone et al. 2011, Bulmer et al. 2019, Marcot & Penman 2019, Bulmer & Hewitt 2020, Kaikkonen et al. 2020, Parsons et al. in review), h (pers. comm. Daniel Kluza Ministry for Primary Industries 18/09/20, Bell et al. 2011, Campbell 2011, Forrest et al. 2011, Cliff & Campbell 2012, Newcombe & Forrest 2012, Campbell & Hewitt 2013, Muellner et al. 2013, Heath 2014, Rowden et al. 2015, Cunningham et al. 2020, Hatami et al. 2021).

2.2.9 Consideration of non-linear dynamics in ecosystem response and recovery

In addition to the EBM suitability criteria (Table 2.1), risk assessments applied within an EBM context must also consider the non-linear dynamics of ecosystem responses and recovery (Table 2.3). The reviewed studies varied in their ability to cope with these complex system dynamics, and this was not consistent across methods/frameworks. Therefore, rather than ranking each method against these criteria, we discuss non-linear dynamics here as an additional consideration when undertaking risk assessments in an EBM context.

Table 2.3. Additional criteria that are important for risk assessment methods and frameworks in an Aotearoa New Zealand ecosystem-based management context.

Location modifiers Can the risk assessment incorporate location modifiers? These are location-specific variables that influence how a particular location will *respond* to an impact (i.e., it does not relate to the likelihood of an impact happening but to the response). For example, legacy effects, high dilution rates, waves, currents, temperature, species densities.
Confounded by the assumption of recovery Are the risk assessment outcomes confounded by assumptions of recovery? For example, models that incorporate assumptions of recovery based on population logistic growth equations into its risk categorisation are confounded.
Threshold responses Can the risk assessment incorporate threshold responses in the outputs?

Very few of the reviewed risk assessments incorporated place-based attributes that influence how a particular location will respond or recover from an impact (e.g., legacy effects, high dilution rates, waves, currents, temperature, species densities). Flexible risk assessment methods such as LC provide a simple way of accounting for these location modifiers when risk is assessed for a particular location, such as the risk assessment carried out by Johnston (2019) for the effects of cruise ships in Akaroa Harbour. A similar approach could be used in marine biosecurity assessments, for example, one might assess the likelihood of invasion to be higher at ports because communities in these areas are impacted by multiple pressures and therefore less resilient. The influence of location modifiers can be quantitatively assessed using BNs by including place-based attributes as nodes (e.g., site-specific sediment and water column properties as in Bulmer et al. 2019; flushing rates etc.). Complex MSE models, such as Atlantis, would also allow the incorporation of location modifiers.

Many of the risk assessments in the reviewed studies (e.g., in some applications of SICA, PSA, SAFE, SEFRA, MSE) merged the impact with the predicted recovery from it, with recovery assumed from population growth estimates. However, disturbance-recovery dynamics and ecosystem responses to stress are multifactorial, depending heavily on location-specific biophysical interactions (e.g., between species or among species and their physical environment; Thrush et al. 2021). It is therefore important that risk assessments in an EBM context can separate the effects of an activity from assumptions of recovery. Flexible risk assessment methods that can either account for interactions through expert opinion (e.g., LC and PSA) or integrate effects on multiple ecosystem components into the models (e.g., MSE and BN) are the most likely to be able to consider the complexities of ecosystem recovery and responses in a holistic EBM context. For example, although most PSAs are confounded by assumptions of recovery (e.g., Waugh et al. 2012, Georgeson et al. 2020), this limitation can be partially addressed by including habitat attributes when assessing the effects of an impact. This adaptation is demonstrated by Clark et al. (2011, 2014), who incorporated 'naturalness' and 'levels of natural disturbance' in their assessment of the effects of fishing on seamounts.

Most risk assessments can include non-linear responses into their risk categories (i.e., threshold responses in levels of risk). For example, MSE and SAFE set sustainability thresholds for populations after which the population is expected to be at high risk of collapse. However, some risk assessment methods are better than others as explorative tools for decision-making when there is a risk of crossing environmental thresholds. Of the reviewed methods/ frameworks, MSE and BNs would be the most useful for exploring how different scenarios influence the shape of stress response curves. Simpler methods such as LC also often include threshold responses. For example, Clark and Tittensor (2010) compared the relationship between fishing intensity and coral cover to determine a threshold value of catch that denoted a fisheries impact beyond which seamounts were no longer considered to be 'at risk' due to their already likely having suffered serious impact. This could be adapted in a biosecurity context, for example, by comparing the number of vessels entering a port with invasion success to determine a threshold for invasion likelihood. Research into ways of incorporating information on how climate change could make an area more vulnerable to invasion, or create thresholds that increase invasion likelihood, is being carried out for terrestrial risk assessments (pers. comm. Daniel Kluza Ministry for Primary Industries 18/09/20).

3. Research co-developer elicitation approach

The research co-developer elicitation aimed to review and discuss the usefulness of the identified risk assessment methods/frameworks for use within a kaupapa Māori (with regards to Māori values and aspirations) and EBM context. This section outlines methods and key findings of a workshop that was held via Zoom in November 2020 with co-development partners (refer to the Appendix for a list of participants).

3.1 Research co-developer elicitation approach

During the workshop, the six identified risk assessment methods and the 10 suitability criteria were presented. Research co-developers provided feedback with regards to their experience of working with different risk assessment methods/frameworks. An online survey was developed to elicit research co-developer opinions on their views: of the most important criteria and methods to support Māori needs and aspirations and be fit-for-purpose for EBM.

Specifically, co-developers were asked to score the importance of each criteria listed in Table 2.1 (with a total of 20 votes that could be assigned in any amount to each of the 10 criteria) for two questions:

1. Based on your knowledge, which criteria do you think are most important for methods to support Māori needs and aspirations?
2. Based on your knowledge, which criteria do you think are most important for methods to be fit for purpose for EBM?

Similarly, co-developers were asked to score the importance of each method (with a total of 10 votes that could be assigned in any amount to each of the five method groups) for two questions:

1. Based on your knowledge, which methods are best able to able to support Māori needs and aspirations?
2. Based on your knowledge, which methods may be the best fit for informing EBM?

The full questionnaire can be found in the Appendix. Co-developer responses to the survey questions were collated anonymously and importance scores were averaged (mean ± standard deviation of the mean). Co-developers discussed the anonymised survey results in a follow-up session of the workshop.

3.2 Outcomes of the workshop

The results of the prioritisation exercise of the model criteria (Figure 3.1) suggest that all the identified model criteria have at least some perceived importance for supporting Māori needs and aspirations and being fit for purpose for EBM (all importance scores > 0.5, Figure 3.1). The criteria *Ability to accommodate different knowledge types*, *Includes risks to social, cultural and economic values* and *Risk to multiple ecosystem components* were perceived to be the most important criteria to support Māori needs and aspirations (in descending order, black bars in Figure 3.1) while other criteria had similar importance scores. In contrast, there was a much more even spread in the perceived importance of criteria to be fit for purpose for EBM (grey bars in Figure 3.1). Some of the co-developers mentioned that they did not feel qualified to answer questions about which criteria would support Māori needs and aspirations, as they were not Māori researchers. Accordingly, results from these surveys will be further trialled through case studies within Sustainable Seas Project 3.2 to ensure that any outputs are fit for purpose in a kaupapa Māori context.

Criterion *Model complexity* was not highly ranked in the survey but after general discussion was deemed to be important for EBM to convey various elements of the system in a way that produced useful information. Co-developers discussed model complexity at some length before reaching a consensus that simple models are easier to communicate than more complex ones but may be less representative of reality. Model selection must therefore consider whether these are fit for purpose (regardless of complexity) but with the aim to select the simplest possible model. Co-developers also agreed that a single model is unlikely to meet all the requirements to support EBM.

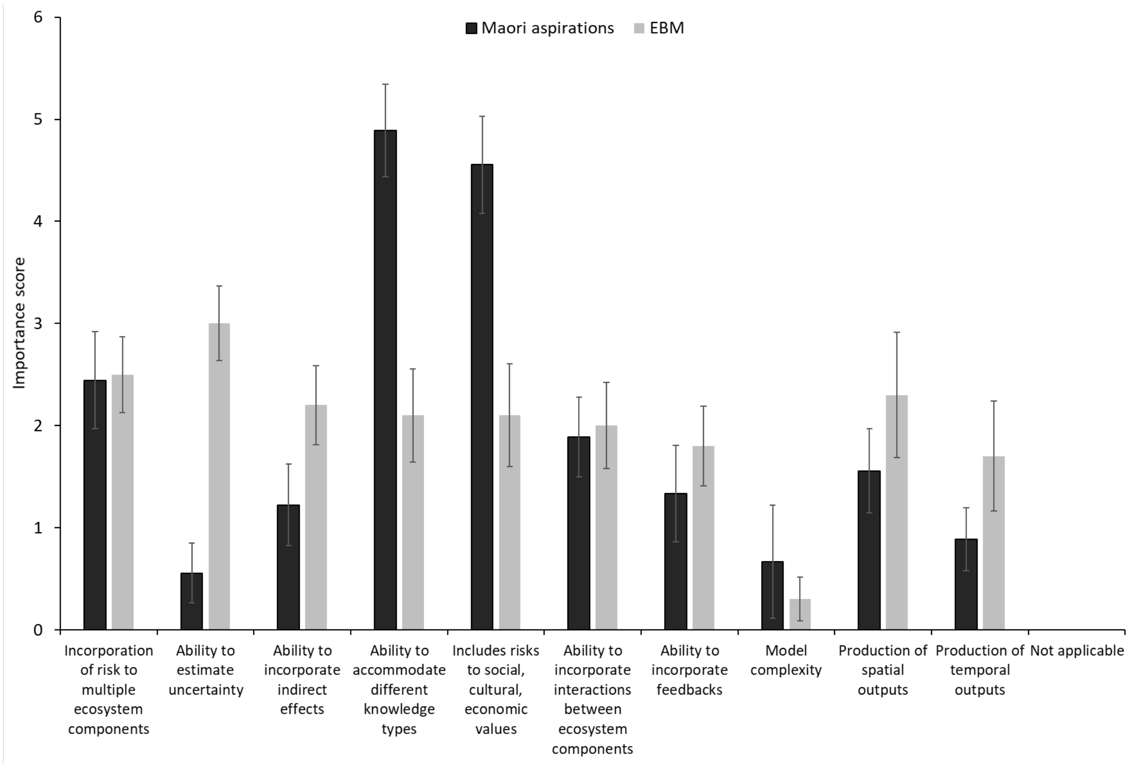

Figure 3.1 Mean (n = 10) importance score (± SD) for criteria in response to survey Question 1 (black bars) and Question 2 (grey bars).

The largest difference between model criteria to support Māori needs/aspirations and being fit for purpose for EBM was for model *Ability to estimate uncertainty* (Figure 3.1). Co-developers discussed this criterion and there was consensus that uncertainty is often misunderstood, but that models need to be able to stand up to scrutiny because it is important that results can be trusted. However, the importance of uncertainty in any given situation will be linked to the specific problem being addressed. For example, where the potential impacts of an action are high (e.g., human health) uncertainty plays a more important role than when the potential impacts are low. Where uncertainty and impacts are both high, the precautionary principle could be applied.

There was congruence in the perceived importance of different risk assessment methods/frameworks best able to support Māori needs and aspirations and which are fit for informing EBM (Figure 3.2). BN models were scored the highest in response to both Questions 3 and 4 (Figure 3.2). Co-developers discussed the reasons for these high scores and concluded that this was likely due to the flexibility of this modelling approach which means it meets all EBM suitability criteria (see Section 2.2.5 for further detail). Despite the high perceived value of BN modelling for risk assessment, there was some discussion around whether the outputs were likely to be oversimplified using this approach (i.e., because in most cases continuous data must be categorised into discrete categories – often between 2-5). Following a discussion, it was concluded that the simplification of the outputs was necessary when lacking the evidence or data to make these more complex and therefore is a problem linked to the availability of the information rather than the modelling approach itself. There was a much more even spread in the perceived importance of other models, although co-developers seemed to somewhat favour

MSE and SEFRA (Figure 3.2), possibly because these methods can produce detailed spatial and/or temporal outputs.

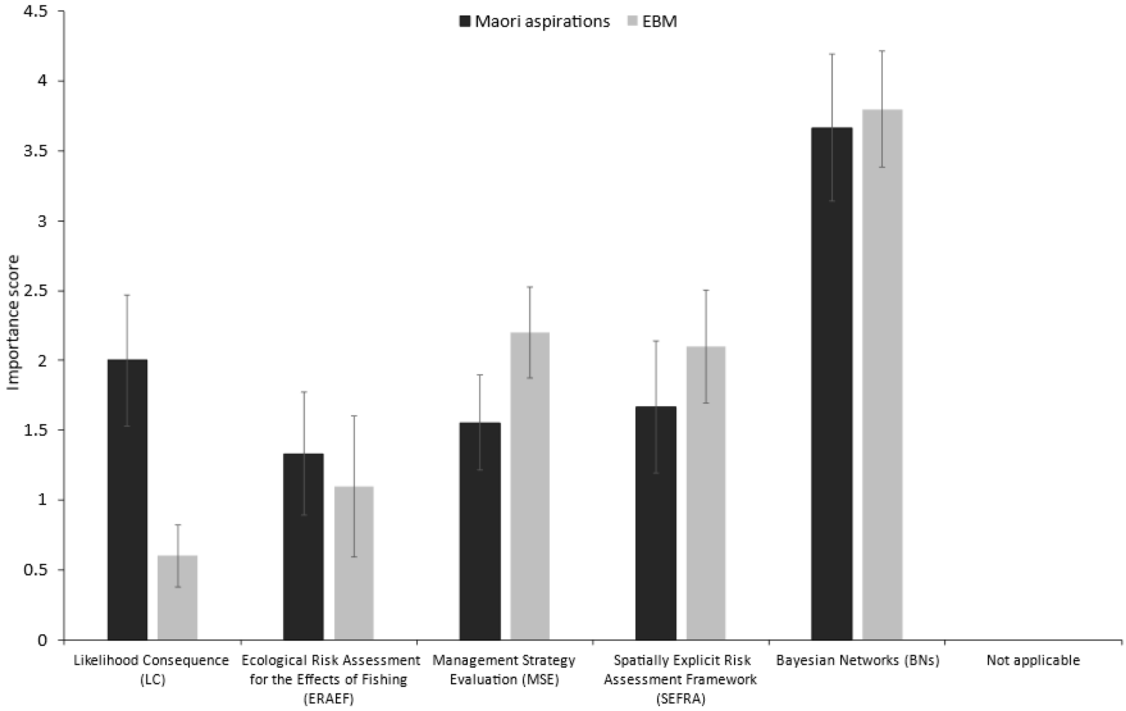

Figure 3.2 Mean (n = 10) importance score (± SD) of risk assessment methods/frameworks in response to survey questions 1 (black bars) and question 2 (grey bars).

Co-developers discussed the need for all risk assessment methods/frameworks used in an Aotearoa NZ EBM context to be able to incorporate different world views in ways that support the inclusion of mātauranga Māori in the decision-making process. This could include (but would not be limited to) approaches that accommodate and aim to restore mauri. This shift in thinking (which would be unique to Aotearoa NZ) will require re-orienting models to incorporate different world views. However, further support for additional Māori models and evolution of the decision-making process to include Māori worldviews will be needed. This is least likely to be problematic for BN as they are generally developed within a workshop/hui to meet the needs and views of the participants.

One important discussion in the workshop centred around the lack of risk assessments using process-based models outside the fisheries realm. These do exist but are rarely used and are generally very location-specific in terms of the models and the components used (Senior et al. 2003, Jones et al. 2018). A summary of the discussion points is provided in the Appendix.

4. International risk assessments for EBM

Several international applications of ecosystem-based risk assessments in the marine environment have been applied, including the potential impact of human or natural perturbations on coastal habitats and communities (Halpern et al. 2008, Samhouri & Levin 2012) as well as the vulnerability of human communities to climate change (Cinner et al. 2012, Morzaria-Luna et al. 2014, Himes-Cornell & Kasperski 2015, McClanahan et al. 2015, Cinner et al. 2016). These approaches generally have a limited ability to deal with multiple interacting pressures. However, common attributes include hierarchical or tiered frameworks. More recent developments have also included consideration of Coupled Natural Human (CNH) systems that include feedbacks between ecological and social components as well as the development of cumulative risk frameworks due to multiple activities.

4.1 Hierarchical Frameworks for EBM

A common aspect of risk assessment frameworks is that they adopt a hierarchical or tiered approach with a progression from conceptual to quantitative analytical approaches. Level 1 qualitative Environmental Risk Assessments (ERAs) provide a rapid and comprehensive assessment to identify a broad range of components at risk from a given pressure (Hobday et al. 2011, Holsman et al. 2017). Components identified as "at risk" during the Level 1 assessment are further considered in the Level 2 semi-quantitative assessments (Holsman et al. 2017). Level 2 ERAs may involve rank-based exposure sensitivity analyses. Components identified as medium to high risk in Level 2 can then be further evaluated using quantitative model-based approaches. Level 3 ERAs may provide an explicit description of the probability of error and uncertainty measures around scenarios (Holsman et al. 2017). Examples of such hierarchical approaches include the application of ERAEF reviewed in Section 2.2.2.

Sequential approaches with increasing levels of quantitative analyses can further be extended to also consider social-ecological models. Here complexity can range from the direct impact of a single pressure on a given social or ecological subject (Class 1) to the direct and indirect effects of a pressure on multiple interacting subjects or multiple pressures on a single subject (Class 2). Finally, complexity can range up to the direct and indirect effects of multiple interacting pressures on multiple interacting subjects that consider *both* social and ecological components (Class 3; Figure 4.1).

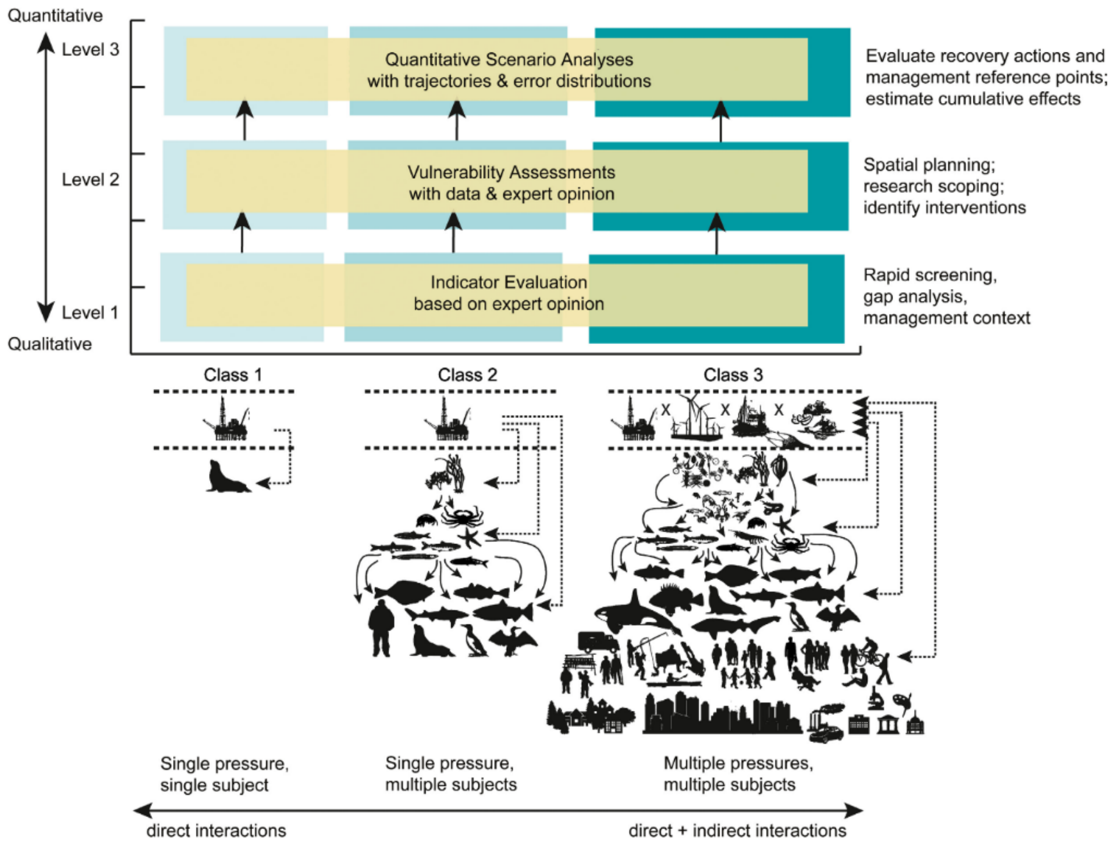

Figure 4.1 Hierarchical frameworks for supporting ecosystem risk assessment. Class 1 represents single risk assessments of single pressures on a single subject, Class 2 assessments consider impacts of a single pressure on multiple ecosystem subjects or pressures while Class 3 analyses consider the reciprocal and cumulative interactions among multiple pressures and multiple subjects. Source: Holsman et al. 2017.

4.2 Coupled Natural Human (CNH) systems and feedbacks

Risk assessments have historically inhibited merging different knowledge types under a single cohesive analytical framework (Benson & Craig 2014, Gao et al. 2014, Bennett et al. 2015, Gibbs & Browman 2015). But there is an emerging consensus that holistic frameworks for understanding multiple direct and indirect interactions between human and natural system components is adopted (Schlüter et al. 2012, Cinner et al. 2016). Connected socio-ecological analysis can be conducted in several ways.

Firstly, separate ecological risk and socio-economic analysis can be conducted sequentially and then weighed against each other where the individual and joint risk to both the human and natural components of the system are considered. An example includes ecological risk screening using Scale Intensity Consequence Analysis (SICA) which has been applied to a number of fisheries and ecosystem components in the southwest coast of England (Cotter et al. 2014; refer also Section 2.2.2). A recommendation from this work was that a separate socio-economic analysis is conducted by a specialist working group. The two sets of analysis could then be weighed against each other for decision making (see also Fletcher 2005).

A second approach is to evaluate the risk to human and natural components of the system simultaneously using Coupled Natural Human (CNH) conceptual models (Liu et al. 2007). Currently, there is much less literature and research in this space; "Tractable approaches to move CNH systems theory into practice for assessing risk in marine ecosystems are nascent, but developing" (Holsman et al. 2017). In this second approach, reinforcing feedbacks have the potential to amplify or attenuate risks from a given pressure. There are very few examples of studies that include dynamic feedback between social and ecological components of the system. A bioeconomic model to investigate human responses to, and influence on, species interactions to understand thresholds in a CNH lake ecosystem has been applied (see Horan et al. 2011). Another example included assessing adaptive capacity, resource dependence, local climate change exposure and biological sensitivity to assess the socioeconomic vulnerability to climate change of three Australian coastal communities (Metcalf et al. 2015). Proposed analytical tools that enable "adaptive" systems to be investigated include the development and application of agent-based models (McDonald et al. 2008). These approaches represent advances in terms of including linked feedback in an integrated risk analysis framework, however, the application of such methods is still in its infancy. These can especially be used in conjunction with hierarchical frameworks by including the consideration of reciprocal interactions between ecological and social components of a system notably at Level 2 and 3 assessment levels.

4.2.1. Level 1: Qualitative Assessments

Level 1 approaches generally reply upon a rapid evaluation of qualitative data and often are used as a screening or scoping step in a risk assessment framework. Advantages include that they are rapid and inexpensive and can be used to identify high-risk interactions for Level 2 and 3 assessments. Level 1 assessments are particularly useful for considering responses to emergent issues and for quickly identifying a range of pressures that may be affecting a wide range of habitats, species or social components of a system.

4.2.2 Level 2: Semi Quantitative Assessments

Level 2 risk assessments employ a combination of quantitative and qualitative data using semi-quantitative analyses to assess the risk posed to a system component (see Table 1 in Holsman et al. 2017 and also see Stelzenmüller et al. 2015). These methods often use an exposure–sensitivity–adaptive capacity framework. Exposure is usually determined using quantitative methods that predict the likely future exposure to the pressure(s) of interest. The sensitivity and impact can then be determined using a mixture of qualitative and quantitative methods to assess risk to focal ecosystem or human system components, providing a basis for prioritizing management actions and further analysis.

Recent examples include a rapid climate change vulnerability assessment for the northwest Atlantic which combined quantitative climate projections with expert opinion to rank species most at risk to climate change (Hare et al. 2016). The relative vulnerability of 12 coastal fishing communities to cumulative anthropogenic pressures including climate change was similarly assessed using semi-quantitative methods (Morzaria-Luna et al. 2014). The novel aspect is that vulnerability included consideration of socio-economic information as well as the fishing impact data. Further indirect effects have been modelled using dynamic conceptual models such as qualitative network models (QNM; Puccia & Levins 1985, Melbourne-Thomas et al. 2012, Reum et al. 2015). For example, loop analysis has been applied to understand potential interactions between crustacean predators and cultured bivalves (Reum et al. 2015). Notably, Level 2 risk assessments consider the risk to the focal ecosystem and human system components using a combination of qualitative and quantitative data.

4.2.3 Level 3: Quantitative Analysis

Internationally the most common examples of Class 3 assessments have been applied to fisheries, toxicology and endangered species and tend to be structured around quantitative estimates of risk. Level 3 assessments have employed methods such as food-web models (e.g., Watters et al. 2013, Anh et al. 2014), multispecies size-spectrum models (Blanchard et al. 2012, Woodworth-Jefcoats et al. 2015), multispecies assessment models (e.g., MICE; Plagányi et al. 2014, Holsman et al. 2017) and fully coupled end-to-end models (e.g., Atlantis; Fulton 2010). Further quantitative modelling approaches are increasingly used to evaluate regional management actions under differing large-scale climate change scenarios (Fulton 2010, Plagányi et al. 2014, Woodworth-Jefcoats et al. 2015). These studies generally reveal indirect, non-intuitive outcomes resulting from interacting pressures (e.g., climate and fishing on multiple target species; an example of Level 3-Class 3) and reinforcing feedbacks that attenuate or amplify impacts, especially over longer projection periods.

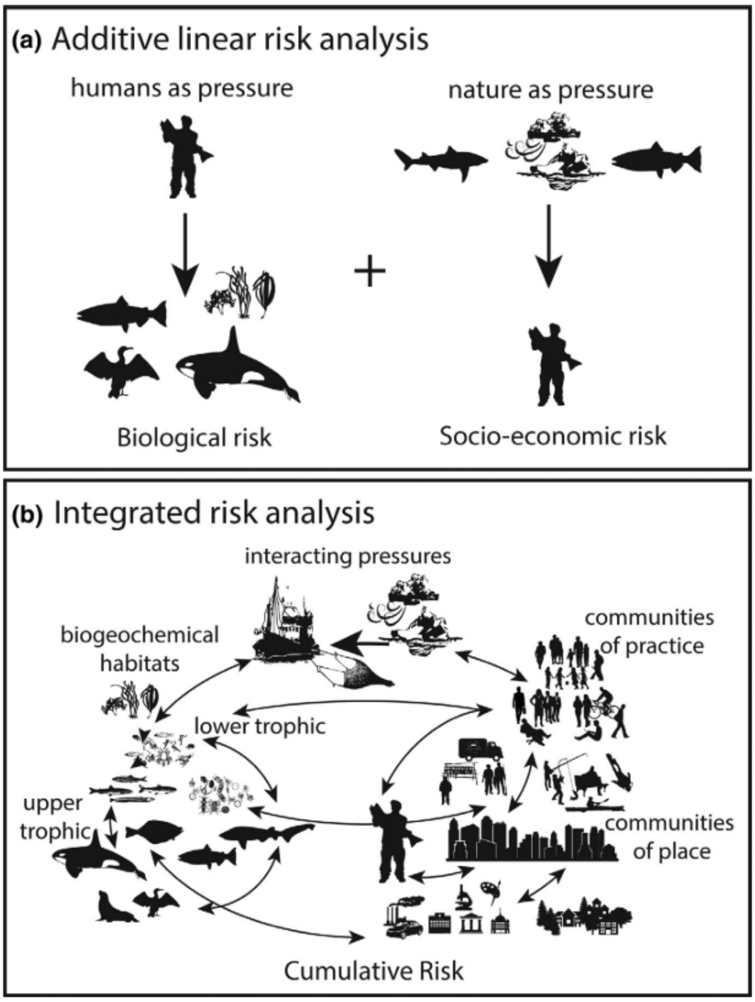

Figure 4.2 Conceptualization of environmental risk via a simple linear impact risk analysis (a) and integrated coupled natural-human risk analysis (b). Source: Holsman et al. 2017.

In summary, integrated frameworks include the need to consider feedback between natural and human components of the system as well as cumulative risk (Figure 4.2). Natural systems will not simply absorb pressures posed on them, rather they will respond to change and exert pressures back on the human system. Similarly, the risk is often not distributed equally between different stakeholders in the community (Cook & Heinen 2005). As such, careful consideration of the role of cumulative impacts and feedbacks is an area of importance for risk assessment in an EBM context. Advancements include the application of integrated risk analysis frameworks whereby socio-economic and ecological analyses are conducted sequentially or in an integrated framework as well as the application of novel tools such as agent-based models to evaluate feedbacks.

4.3 Cumulative effects assessments and risk

Cumulative effects assessments (CEA) have gained traction for marine conservation priorities and management actions (Halpern et al. 2008, Halpern et al. 2015). Mapping of local and global pressures in a standardised way enables the spatial pattern and temporal change of individual human pressures, as well as their total impact on natural systems, to be evaluated. As such quantitative methods to map cumulative human impacts have been developed and applied in marine environments (Halpern et al. 2008). Despite the considerable advancements, there are still a number of assumptions that limit the application of these methods, including: spatial accuracy of input data (Ban et al. 2010), assumptions about the additivity of impact where synergistic and antagonistic effects are often neglected and simple additive models are used (Crain et al. 2008) and that most models apply linear responses only even though many marine processes are known to be non-linear (Halpern & Fujita 2013). The improvement of CEA frameworks that address cumulative impacts more appropriately within the principles of EBM and ERA has, however, been suggested as a promising approach (Judd et al. 2015, Stelzenmüller et al. 2018). For example, recent research has developed a comprehensive CEA which includes methodological advancements including the ability to model non-linear ecosystem response to anthropogenic pressures as well as antagonistic and synergistic pressure effects (Menegon et al. 2018).

A similar approach has also been applied by Furlan et al. (2019) where methods beyond simple additive approaches were developed for cumulative impact assessment. In this case, a Cumulative Impact Index (CI-Index) applied advanced Multi-Criteria Decision Analysis techniques to spatially model relationships between interactive climate and anthropogenic pressures, the environmental exposure and vulnerability patterns and the potential cumulative impacts for the marine ecosystems at risk. However, interactions between different hazards were additive only and no interactions or feedbacks between different components were allowed. Outputs of the CI-index were then used to evaluate multi-risk scenarios and to drive sustainable maritime spatial planning. Cumulative assessment approaches can therefore be used to explore risk and may be particularly informative for risk analysis under future scenarios in an EBM context. For example, the cumulative impact maps developed by Furlan et al. (2019) were then taken another step where the probability and the related uncertainty of cumulative impacts under different climate and management scenarios was analysed using a spatially explicit BN. The main aim was to test the potential of an integrated GIS-based BN framework to support adaptive marine management. Specifically, BNs were used to 1) simulate and evaluate potential climate change scenarios, and 2) assess different management options responding to regulatory and marine strategy requirements. In this example management options were also explored to achieve predefined objectives of good environmental status. Hence the developed BN was used to support the design of more robust and adaptive management measures that were able to explicitly assess risk and uncertainty.

5. Conclusion

Our review found that of the risk assessment methods/frameworks currently in use in Aotearoa NZ, only BNs met all 10 criteria required to support EBM and the needs and aspirations of Māori. The remaining methods/frameworks were generally capable of meeting some of the criteria, but often their application in Aotearoa NZ did not do so or would require adaptations to do so. Most approaches can incorporate multiple knowledge types (e.g., expert opinion, mātauranga

Māori, local knowledge, quantitative data) and characterise uncertainty, and many can be adapted to produce spatial outputs. Although most methods/frameworks can assess risk to multiple ecosystem components, this is usually done in a parallel manner, with risk to each component assessed separately. Effective EBM, however, requires approaches that can integrate anthropogenic effects across multiple ecosystem components. In general, most methods/frameworks did not cope with interactions, feedbacks and indirect effects very well, and few were able to assess risk through time or time or assess risk to cultural, social or economic values. Additionally, many of the studies we reviewed failed to account for non-linear dynamics in ecosystem response and recovery and could not identify threshold responses. Our examination of the international literature found that the inability of risk assessment methods/frameworks to deal with these ecosystem complexities is not unique to Aotearoa NZ, with few international examples of risk assessment frameworks that deal with cumulative effects or dynamic feedback between social and ecological components of the system.

The ability to assess risk to multiple ecosystem components, accommodate multiple knowledge types and assess risk to other values were identified by our research co-developers as being important criteria for supporting Māori needs and aspirations. All criteria, except model complexity, were identified by co-developers as being important for EBM. BNs were ranked as the best risk assessment method for both informing EBM and supporting Māori needs and aspirations. This highly flexible approach is one of the few reviewed methods that was able to integrate interactions across multiple ecosystem components and cope with indirect effects and feedbacks between components of the model. BNs can accommodate a range of knowledge types and assess risk to multiple values, both spatially and over time. They allow for the inclusion of information on habitat attributes that might influence ecosystem recovery and can be used to identify threshold responses. BN modelling is a rapidly advancing field and the full capability of these models has not yet been demonstrated in Aotearoa NZ (refer Marcot & Penman 2019 for a review).

MSE and SEFRA were also favoured by co-development partners, possibly because these methods can produce detailed spatial and/or temporal outputs. Although MSE met many of the same criteria as BNs, the use of MSE in an EBM-context would require the use of highly complex process-based operating models (e.g., Atlantis) and need to cope with greater levels of uncertainty and complexity than has been attempted by these models so far. Although complex models are often perceived to reflect natural systems more accurately than simple models, how true that is depends on what components are modelled, whether the relationships between components represent important scales and how well the models are calibrated (Pethybridge et al. 2019). Adding additional parameters to a model can lead to uncertainty and problems with the interpretation and validation of the model's predictions (Duarte et al. 2003, Fulton et al. 2003, Merow et al. 2014). Complex models are also often limited by their considerable data requirements and the high effort and cost associated with their development (Perryman et al. 2021). Simple models, conversely, are cost effective to construct and easy to communicate and quick to implement. But they may not accurately reflect the intricacies of the system. Thus, there is an optimal level of model complexity (Fulton et al. 2003).

Models to inform decision-making associated with EBM must be able to cope with incomplete or non-numeric data, particularly in a small country such as Aotearoa NZ where resources for environmental monitoring are limited. Consequently, models that can use expert judgement to bridge the gap between limited local-scale empirical data and the need to make management decisions at an ecosystem-scale are advantageous in an EBM-context (e.g., BNs; Gladstone-Gallagher et al. 2019). Although less complex models may be perceived to be imprecise, BNs can easily mix expert opinion, mātauranga Māori, and non-numeric local knowledge with experimentally derived mechanistic relationships. The ability of these models to make generalisable predictions while accounting for non-linear dynamics, ecosystem interactions and feedbacks will be more useful for EBM than numeric estimates from complex models, particularly as BNs can transparently quantify the uncertainty associated with their predictions. The complex nature of ecosystems means that knowledge gaps will always exist for many ecological components, connections and places. However, models like BNs that can use expert judgment to fill those gaps and make those connections can help ensure that robust decisions are still made even when there are unknowns (Gladstone-Gallagher et al. 2019).

The complex nature of environmental risk means that it cannot be considered in isolation of the social context within which it is embedded. Engagement of stakeholders is a critical component of effective risk assessment as it helps to define the purpose of the assessment, decide how risks are assessed and by whom, and build trust in the approach. Risk assessment methods that lend themselves to participatory modelling, such as BNs, are often most effective because they facilitate stakeholder understanding of the underlying model structure, its assumptions, and any sources of uncertainty (Henriksen et al. 2012, Laurila-Pant et al. 2019). Participatory approaches also promote social learning through the sharing of diverse values and perspectives (Johnson et al. 2012), which can promote consensus-building. Internationally, advancements in this field include the application of integrated risk analysis frameworks whereby socio-economic and ecological analyses are conducted sequentially or in an integrated or coupled framework. Integrated frameworks consider feedbacks between natural and human components of the system as well as cumulative risk.

Based on the outcomes of our review and workshop, we recommend a mixed approach for future use and testing in Sustainable Seas Project 3.2 that focuses on developing a three-level hierarchical framework, based around BNs for the two simpler levels. For the highest level, we suggest testing two different approaches: highly mechanistic biophysical models with separate social models; and a Coupled Natural Human model. In order to achieve the most effective outcomes, testing of these approaches should be done in in close association with stakeholders.

References

Abraham E, Richard Y, Walker N, Gibson W, Daisuke O, Tsuji S, Kerwath S, Winker H, Parsa M, Small C, Waugh S (2019) Assessment of the risk of surface longline fisheries in the Southern Hemisphere to albatrosses and petrels, for 2016. 13th meeting of the Ecologically Related Species Working Group of the Commission for the Conservation of Southern Bluefin Tuna. Fisheries New Zealand

AFMA (2012) Residual Risk Assessment of the Level 2 Productivity Susceptibility Analysis: non-Teleost and non-Chondrichthyan species Australian Fisheries Management Authority. Report for the otter board trawl method of the Commonwealth trawl sector

Anh PV, De Laender F, Everaert G, Vinh CT, Goethals P (2014) An integrated food web model to test the impact of fisheries management scenarios on the coastal ecosystem of Vietnam. Ocean & Coastal Management 92:74-86

Arkema KK, Abramson SC, Dewsbury BM (2006) Marine ecosystem-based management: from characterization to implementation. Frontiers in Ecology and the Environment 4:525-532

Aven T (2010) On how to define, understand and describe risk. Reliability Engineering & System Safety 95:623-631

Ban NC, Alidina HM, Ardron JA (2010) Cumulative impact mapping: Advances, relevance and limitations to marine management and conservation, using Canada's Pacific waters as a case study. Marine Policy 34:876-886

Bashari H, Naghipour AA, Khajeddin SJ, Sangoony H, Tahmasebi P (2016) Risk of fire occurrence in arid and semi-arid ecosystems of Iran: an investigation using Bayesian belief networks. Environmental Monitoring and Assessment 188:531

Batstone C, Moores J, Semadeni-Davies A, Green M, Gadd J, Harper S (2011) Derivation of Economic and Social Indicators for a Spatial Decision Support System to Evaluate the Impacts of Urban Development on Water Bodies in New Zealand. New Zealand Agricultural & Resource Economics Society Conference, Nelson, New Zealand

Bell A, Phillips S, Georgiades E, Kluza D (2011) Risk Analysis: Vessel Biofouling. Ministry of Agriculutre and Forestry

Bennett NJ, Blythe J, Tyler S, Ban NC (2015) Communities and change in the anthropocene: understanding social-ecological vulnerability and planning adaptations to multiple interacting exposures. Regional Environmental Change 16:907-926

Benson MH, Craig RK (2014) The end of sustainability. Society & Natural Resources 27:777-782

Bermingham G (2015) Marine Oil Spill Risk Assessment 2015. Prepared by Navigatus Consulting for Maritime New Zealand

Blanchard JL, Jennings S, Holmes R, Harle J, Merino G, Allen JI, Holt J, Dulvy NK, Barange M (2012) Potential consequences of climate change for primary production and fish production in large marine ecosystems. Philosophical Transactions of the Royal Society B: Biological Sciences 367:2979-2989

Boyd RO (2013) Assessment of ecological effects of four New Zealand orange roughy fisheries. Boyd Fisheries Consultants Ltd. Report for Deepwater Group Limited

Breen PA, Kim SW (2006) Development of an operational management procedure (decision rule) for CRA 4. New Zealand Fisheries Assessment Report 2006/53

Bulmer R, Hewitt J (2020) Bayesian modelling of multiple stressors on six Hawke's Bay estuarine ecosystems. Hawke's Bay Regional Council Publication No. 5478

Bulmer RH, Stephenson F, Lohrer A, Hewitt JE (2019) Exploring the impact of multiple stressors on estuarine ecosystems using a Bayesian Network model. Prepared for Parliamentary Commissioner for the Environment

Burgman M (2005) Risks and Decisions for Conservation and Environmental Management. Cambridge University Press

Butterworth DS, Bentley N, De Oliveira JAA, Donovan GP, Kell LT, Parma AM, Punt AE, Sainsbury KJ, Smith ADM, Stokes TK (2010) Purported flaws in management strategy evaluation: basic problems or misinterpretations? ICES J Mar Sci 67:567-574

Campbell M, Hewitt C (2013) Protecting high-value areas from introduced marine species. Management of Biological Invasions 4:171-189

Campbell ML (2011) Assessing biosecurity risk associated with the importation of non-indigenous microalgae. Environmental Research 111:989-998

Campbell ML, Gallagher C (2007) Assessing the relative effects of fishing on the New Zealand marine environment through risk analysis. ICES J Mar Sci 64:256-270

Cinner JE, McClanahan TR, Graham NA, Daw TM, Maina J, Stead SM, Wamukota A, Brown K, Bodin Ö (2012) Vulnerability of coastal communities to key impacts of climate change on coral reef fisheries. Global Environmental Change 22:12-20

Cinner JE, Pratchett MS, Graham NAJ, Messmer V, Fuentes MMPB, Ainsworth T, Ban N, Bay LK, Blythe J, Dissard D (2016) A framework for understanding climate change impacts on coral reef social–ecological systems. Regional environmental change 16:1133-1146

Clark M, Tracey D, Anderson O, Parker S (2014) Pilot ecological risk assessment for protected corals. Prepared for Marine Species and Threats, Department of Conservation

Clark MR, Tittensor DP (2010) An index to assess the risk to stony corals from bottom trawling on seamounts. Marine Ecology 31:200-211

Clark MR, Williams A, Rowden AA, Hobday AJ, Consalvey M (2011) Development of seamount risk assessment: application of the ERAEF approach to Chatham Rise seamount features. Ministry of Fisheries New Zealand Aquatic Environment and Biodiversity Report No. 74, Wellington

Cliff N, Campbell M (2012) Perception as a tool to inform aquatic biosecurity risk assessments. 7:387-404

Cook GS, Heinen JT (2005) On the uncertain costs and tenuous benefits of Marine reserves: a case study of the Tortugas Ecological Reserve, South Florida, USA. Natural Areas Journal 25:390-396

Cordue PL (2014) A Management Strategy Evaluation for orange roughy. ISL Client Report for Deepwater Group Ltd

Cotter J, Lart W, de Rozarieux N, Kingston A, Caslake R, Le Quesne W, Jennings S, Caveen A, Brown M (2014) A development of ecological risk screening with an application to fisheries off SW England. ICES Journal of Marine Science 72:1092-1104

Crain CM, Kroeker K, Halpern BS (2008) Interactive and cumulative effects of multiple human stressors in marine systems. Ecology Letters 11:1304-1315

Cunningham S, South P, Cahill P (2020) Biosecurity Considerations for Farming Non-Native Seaweeds: A Case Study of *Undaria pinnatifida* in New Zealand

Davies KK, Fisher KT, Couzens G, Allison A, van Putten EI, Dambacher JM, Foley M, Lundquist CJ (2020) Trans-Tasman Cumulative Effects Management: A Comparative Study. Frontiers in Marine Science 7

Dichmont CM, Deng A, Punt AE, Ellis N, Venables WN, Kompas T, Ye Y, Zhou S, Bishop J (2008) Beyond biological performance measures in management strategy evaluation: Bringing in economics and the effects of trawling on the benthos. Fish Res 94:238-250

Duarte CM, Amthor JS, DeAngelis DL, Joyce LA, Maranger RJ, Pace ML, Pastor JJ, Running SW (2003) The limits to models in ecology. In: Canham CD, Cole JJ, Lauenroth WK (eds) Models in Ecosystem Science. Princeton University PressEditors

Fletcher WJ (2005) The application of qualitative risk assessment methodology to prioritize issues for fisheries management. ICES J Mar Sci 62:1576-1587

Floerl O, Rickard G, Inglis G, Roulston H (2013) Predicted effects of climate change on potential sources of non-indigenous marine species. Divers Distrib 19:257-267

Foley M, Lundquist CJ, Couzens G, Davies KK (2019) The implications of uncertainty on cumulative effects management. Resource Management Journal:22-27

Ford RB, Francis MP, Holland L, Clark MR, Duffy CAJ, Dunn MR, Jones E, Wells R (2018) Qualitative (Level 1) risk assessment of the impact of commercial fishing on New Zealand chondrichthyans: an update for 2017. New Zealand Aquatic Environment and Biodiversity Report No. 201

Forrest B, Hopkins G, Webb S, Tremblay L (2011) Overview of marine biosecurity risks from finfish aquaculture development in the Waikato region. Prepared for Waikato Regional Council. Cawthron Report No. 1871

Fulton EA (2010) Approaches to end-to-end ecosystem models. Journal of Marine Systems 81:171-183

Fulton EA, Smith ADM, Johnson CR (2003) Effect of complexity on marine ecosystem models. Marine Ecology Progress Series 253:1-16

Fulton EA, Smith ADM, Smith DC, Johnson P (2014) An Integrated Approach Is Needed for Ecosystem Based Fisheries Management: Insights from Ecosystem-Level Management Strategy Evaluation. PLoS ONE 9:e84242

Furlan E, Torresan S, Critto A, Lovato T, Solidoro C, Lazzari P, Marcomini A (2019) Cumulative Impact Index for the Adriatic Sea: Accounting for interactions among climate and anthropogenic pressures. Science of The Total Environment 670:379-397

Gao J, Li D, Havlin S (2014) From a single network to a network of networks. National Science Review 1:346-356

Gelman A, Carlin JB, Stern HS, Rubin DB (1995) Bayesian Data Analysis. Chapman and Hall, London

Georgeson L, Rigby CL, Emery TJ, Fuller M, Hartog J, Williams AJ, Hobday AJ, Duffy CAJ, Simpfendorfer CA, Okuda T, Stobutzki IC, Nicol SJ (2020) Ecological risks of demersal fishing on deepwater chondrichthyan populations in the Southern Indian and South Pacific Oceans. ICES J Mar Sci 77:1711-1727

Gibbs MT, Browman HI (2015) Risk assessment and risk management: a primer for marine scientists. ICES Journal of Marine Science 72:992-996

Giles H (2008) Using Bayesian networks to examine consistent trends in fish farm benthic impact studies. Aquaculture 274:181-195

Gladstone-Gallagher RV, Hope JA, Bulmer RH, Clark DE, Stephenson F, Mangan S, Rullens V, Siwicka E, Thomas SF, Pilditch CA, Savage C, Thrush SF (2019) Old Tools, New Ways of Using Them: Harnessing Expert Opinions to Plan for Surprise in Marine Socio-Ecological Systems. Frontiers in Marine Science 6

Haimes YY (2009) On the Complex Definition of Risk: A Systems-Based Approach. Risk Analysis 29:1647-1654

Haist V, Middleton DAJ (2014) Management Strategy Evaluation for the Coromandel Scallop Fishery. New Zealand Fisheries Assessment Report 2014/48

Halpern BS, Frazier M, Potapenko J, Casey KS, Koenig K, Longo C, Lowndes JS, Rockwood RC, Selig ER, Selkoe KA (2015) Spatial and temporal changes in cumulative human impacts on the world's ocean. Nature communications 6:7615

Halpern BS, Fujita R (2013) Assumptions, challenges, and future directions in cumulative impact analysis. Ecosphere 4:131

Halpern BS, Walbridge S, Selkoe KA, Kappel CV, Micheli FDA, C., Bruno JF, Casey KS, Ebert C, Fox HE, Fujita R, Heinemann D, Lenihan HS, Madin EMP, Perry MT, Selig ER, Spalding M, Steneck R, Watson R (2008) A Global Map of Human Impact on Marine Ecosystems. Science 319:948-952

Hare JA, Morrison WE, Nelson MW, Stachura MM, Teeters EJ, Griffis RB, Alexander MA, Scott JD, Alade L, Bell RJ (2016) A vulnerability assessment of fish and invertebrates to climate change on the Northeast US Continental Shelf. PloS one 11:e0146756

Hatami R, Lane S, Robinson A, Inglis G, Todd-Jones C, Steward K (2021) Improving New Zealand's marine biosecurity surveillance programme: A statistical review of biosecurity vectors. Biosecurity New Zealand Technical Paper No: 2021/01

Heath P (2014) Aquaculture in the Bay of Plenty Biosecurity Risk Assessment. Prepared for Bay of Connections. Tisbe Client Report 14-0501

Helle I, Jolma A, Venesjärvi R (2016) Species and habitats in danger: estimating the relative risk posed by oil spills in the northern Baltic Sea. 7:e01344

Henriksen HJ, Zorrilla-Miras P, De La Hera A, Brugnach M (2012) Use of Bayesian belief networks for dealing with ambiguity in integrated groundwater management. Integrated Environmental Assessment and Management 8:430-444

Hewitt JE, Ellis JI, Thrush SF (2016) Multiple stressors, nonlinear effects and the implications of climate change impacts on marine coastal ecosystems. Global Change Biology 22:2665-2675

Hill SL, Watters GM, Punt AE, McAllister MK, Quéré CL, Turner J (2007) Model uncertainty in the ecosystem approach to fisheries. Fish and Fisheries 8:315-336

Himes-Cornell A, Kasperski S (2015) Assessing climate change vulnerability in Alaska's fishing communities. Fisheries Research 162:1-11

Hobday AJ, Smith ADM, Stobutzki IC, Bulman C, Daley R, Dambacher JM, Deng RA, Dowdney J, Fuller M, Furlani D, Griffiths SP, Johnson D, Kenyon R, Knuckey IA, Ling SD, Pitcher R, Sainsbury KJ, Sporcic M, Smith T, Turnbull C, Walker TI, Wayte SE, Webb H, Williams A, Wise BS, Zhou S (2011) Ecological risk assessment for the effects of fishing. Fish Res 108:372-384

Holland DS, Bentley N, Lallemand P (2005) A bioeconomic analysis of management strategies for rebuilding and maintenance of the NSS rock lobster (*Jasus edwardsii*) stock in southern New Zealand. Canadian Journal of Fisheries and Aquatic Sciences 62:1553-1569

Holmes SJ, Arnold R, Clendon G, Doonan I, Edwards CTT, Goeden Z, Langley AD, Liu I, MacGibbon DJ, McMillan L, Middleton D, Stephenson F, Webber D, Zhou S, Dunn MR (2020) Low Information Stock Status Assessment. New Zealand Fisheries Assessment Report 2020/05

Holsman K, Samhouri J, Cook G, Hazen E, Olsen E, Dillard M, Kasperski S, Gaichas S, Kelble CR, Fogarty M, Andrews K (2017) An ecosystem-based approach to marine risk assessment. Ecosystem Health and Sustainability 3:e01256

Horan RD, Fenichel EP, Drury KL, Lodge DM (2011) Managing ecological thresholds in coupled environmental–human systems. Proceedings of the National Academy of Sciences 108:7333-7338

Inglis G, Soliman T, Djanibekov U (2020) Tools for risk assessment under uncertainty Prepared by NIWA and Landcare Research for Sustainable Seas

Johnson KA, Dana G, Jordan NR, Draeger KJ, Kapuscinski A, Schmitt Olabisi LK, Reich PB (2012) Using Participatory Scenarios to Stimulate Social Learning for Collaborative Sustainable Development. Ecology and Society 17

Johnston O (2017) Nelson regional sewerage business unit (NRSBU) aberrational wastewater overflows. Prepared for Nelson Regional Sewerage Business Unit. Cawthron Report No. 3091.

Johnston O (2019) Akaroa harbour cruise ship visits: Preliminary ecological risk assessment Prepared for Environment Canterbury. Cawthron Report No. 3387

Jolma A, Lehikoinen A, Helle I, Venesjärvi R (2014) A software system for assessing the spatially distributed ecological risk posed by oil shipping. Environmental Modelling & Software 61:1-11

Jones HFE, Özkundakci D, McBride CG, Pilditch CA, Allan MG, Hamilton DP (2018) Modelling interactive effects of multiple disturbances on a coastal lake ecosystem: Implications for management. Journal of Environmental Management 207:444-455

Judd A, Backhaus T, Goodsir F (2015) An effective set of principles for practical implementation of marine cumulative effects assessment. Environmental Science & Policy 54:254-262

Kaikkonen L, Parviainen T, Rahikainen M, Uusitalo L, Lehikoinen A (2020) Bayesian Networks in Environmental Risk Assessment: A review. Integrated Environmental Assessment and Management 17:62-78

Large K, Roberts JM, Francis M, Webber D (2019) Spatial assessment of fisheries risk for New Zealand sea lions at the Auckland Islands. New Zealand Aquatic Environment and Biodiversity Report No. 224

Laurila-Pant M, Mäntyniemi S, Venesjärvi R, Lehikoinen A (2019) Incorporating stakeholders' values into environmental decision support: A Bayesian Belief Network approach. Science of The Total Environment 697:134026

Lee CH, Lee DK, Ali MA, Kim PJ (2008) Effects of oyster shell on soil chemical and biological properties and cabbage productivity as a liming materials. Waste Management 28:2702-2708

Leung B, Roura-Pascual N, Bacher S, Heikkilä J, Brotons L, Burgman MA, Dehnen-Schmutz K, Essl F, Hulme PE, Richardson DM, Sol D, Vilà M (2012) TEASIng apart alien species risk assessments: a framework for best practices. Ecology Letters 15:1475-1493

Link J, Ihde T, Harvey C, Gaichas S, Field JC, Brodziak J, Townsend H, Peterman RM (2012) Dealing with uncertainty in ecosystem models: The paradox of use for living marine resource management. Progress in Oceanography 102:102-114

Liu J, Dietz T, Carpenter SR, Alberti M, Folke C, Moran E, Pell AN, Deadman P, Kratz T, Lubchenco J, Ostrom E, Ouyang Z, Provencher W, Redman CL, Schneider SH, Taylor WW (2007) Complexity of Coupled Human and Natural Systems. Science 317:1513-1516

Lodge DM, Simonin PW, Burgiel SW, Keller RP, Bossenbroek JM, Jerde CL, Kramer AM, Rutherford ES, Barnes MA, Wittmann ME, Chadderton WL, Apriesnig JL, Beletsky D, Cooke RM, Drake JM, Egan SP, Finnoff DC, Gantz CA, Grey EK, Hoff MH, Howeth JG, Jensen RA, Larson ER, Mandrak NE, Mason DM, Martinez FA, Newcomb TJ, Rothlisberger JD, Tucker AJ, Warziniack TW, Zhang H (2016) Risk Analysis and Bioeconomics of Invasive Species to Inform Policy and Management. Annual Review of Environment and Resources 41:453-488

Long RD, Charles A, Stephenson RL (2015) Key principles of marine ecosystem-based management. Marine Policy 57:53-60

MacDiarmid A, McKenzie A, Sturman J, Beaumont J, Mikaloff-Fletcher S, Dunne J (2012) Assessment of anthropogenic threats to New Zealand marine habitats. New Zealand Aquatic Environment and Biodiversity Report No. 93

Mantyka-Pringle CS, Jardine TD, Bradford L, Bharadwaj L, Kythreotis AP, Fresque-Baxter J, Kelly E, Somers G, Doig LE, Jones PD, Lindenschmidt K-E (2017) Bridging science and traditional knowledge to assess cumulative impacts of stressors on ecosystem health. Environment International 102:125-137

Marcot BG, Penman TD (2019) Advances in Bayesian network modelling: Integration of modelling technologies. Environmental Modelling & Software 111:386-393

Maunder MN, Starr PJ, Hilborn R (2000) A bayesian analysis to estimate loss in squid catch due to the implementation of a sea lion population management plan. Marine Mammal Science 16:413-426

McClanahan TR, Maina J, Ateweberhan M (2015) Regional coral responses to climate disturbances and warming is predicted by multivariate stress model and not temperature threshold metrics. Climatic Change 131:607-620

McDonald A, Little L, Gray R, Fulton E, Sainsbury K, Lyne V (2008) An agent-based modelling approach to evaluation of multiple-use management strategies for coastal marine ecosystems. Mathematics and Computers in Simulation 78:401-411

McGregor VL, Fulton EA, Dunn MR (2020) Addressing initialisation uncertainty for end-to-end ecosystem models: application to the Chatham Rise Atlantis model. PeerJ 8:e9254

McGregor VL, Horn PL, Fulton EA, Dunn MR (2019) From data compilation to model validation: a comprehensive analysis of a full deep-sea ecosystem model of the Chatham Rise. PeerJ 7:e6517

McKenzie JR, Bentley N, Bian R (2018) A new Spatially-Disaggregated Agent-Based Simulation Modelling Tool for use in Fisheries Management Strategy Evaluation. New Zealand Fisheries Assessment Report 2018/34

Melbourne-Thomas J, Wotherspoon S, Raymond B, Constable A (2012) Comprehensive evaluation of model uncertainty in qualitative network analyses. Ecological Monographs 82:505-519

Menegon S, Depellegrin D, Farella G, Gissi E, Ghezzo M, Sarretta A, Venier C, Barbanti A (2018) A modelling framework for MSP-oriented cumulative effects assessment. Ecological Indicators 91:171-181

Merow C, Smith MJ, Edwards TC, Guisan A, McMahon SM, Normand S, Thuiller W, Wüest RO, Zimmermann NE, Elith J (2014) What do we gain from simplicity versus complexity in species distribution models? Ecography 37:1267-1281

Metcalf SJ, van Putten EI, Frusher S, Marshall NA, Tull M, Caputi N, Haward M, Hobday AJ, Holbrook NJ, Jennings SM (2015) Measuring the vulnerability of marine social-ecological systems: a prerequisite for the identification of climate change adaptations. Ecology and Society 20:35

Mormede S, Dunn A (2013) An initial development of spatially explicit population models of benthic impacts to inform Ecological Risk Assessments in New Zealand deepwater fisheries New Zealand Aquatic Environment and Biodiversity Report No 106

Morzaria-Luna HN, Turk-Boyer P, Moreno-Baez M (2014) Social indicators of vulnerability for fishing communities in the Northern Gulf of California, Mexico: implications for climate change. Marine Policy 45:182-193

Muellner P, Newfield M, Kluza D, Oakley L (2013) Organism Ranking System Scientific Rationale. Prepared for the Ministry for Primary Industries

Newcombe E, Forrest B (2012) Risk of harvest–associated spread of the invasive kelp, *Undaria pinnatifida* in Southland. Prepared for Environment Southland. Cawthron Report No. 2266

Ochi D, Abraham E, Inoue Y, Oshima K, Walker N, Tichard Y, Tsuji S (2018) Preliminary assessment of the risk of albatrosses by longline fisheries. Scientific Committee Fourteenth Regular Session, Busan, Republic of Korea

Parsons DM, Hartill BW, Broekhuizen N, McKenzie JR, Stephenson F, Petersen GL, Lundquist CJ (2021) Integrating multi-disciplinary data sources relating to inshore fisheries management via a Bayesian network. Ocean & Coastal Management 208:105636

Parsons DM, Hartill BW, Broekhuizen N, McKenzie JR, Stephenson F, Petersen GL, Lundquist CJ (in review) Meshing multi-disciplinary data sources relating to inshore fisheries management via a Bayesian network.

Penney AJ, Guinotte JM (2013) Evaluation of New Zealand's High-Seas Bottom Trawl Closures Using Predictive Habitat Models and Quantitative Risk Assessment. PLOS ONE 8:e82273

Perryman HA, Hansen C, Howell D, Olsen E (2021) A Review of Applications Evaluating Fisheries Management Scenarios through Marine Ecosystem Models. Reviews in Fisheries Science & Aquaculture:1-36

pers. comm. Daniel Kluza Ministry for Primary Industries (18/09/20)

Pethybridge HR, Weijerman M, Perrymann H, Audzijonyte A, Porobic J, McGregor V, Girardin R, Bulman C, Ortega-Cisneros K, Sinerchia M, Hutton T, Lozano-Montes H, Mori M, Novaglio C, Fay G, Gorton R, Fulton E (2019) Calibrating process-based marine ecosystem models: An example case using Atlantis. Ecol Model 412:108822

Piffady J, Carluer N, Gouy V, Le Henaff G, Tormos T, Bougon N, Adoir E, Mellac K (2020) ARPEGES: a Bayesian belief network to assess the risk of pesticide contamination for the river network of France. Integrated Environmental Assessment and Management 17:188-201

Plaganyi EE (2007) Models for an ecosystem approach to fisheries. FAO Fisheries Technical Paper 477

Plagányi ÉE, Punt AE, Hillary R, Morello EB, Thébaud O, Hutton T, Pillans RD, Thorson JT, Fulton EA, Smith AD (2014) Multispecies fisheries management and conservation: tactical applications using models of intermediate complexity. Fish and Fisheries 15:1-22

Puccia CJ, Levins R (1985) Qualitative modeling of complex systems: an introduction to loop analysis and time averaging. Harvard University Press, Cambridge, Massachusetts, USA

Regan HM, Colyvan M, Burgman MA (2002) A taxonomy and treatment of uncertainty for ecology and conservation biology. Ecological Applications 12:618-628

Reum JC, McDonald PS, Ferriss BE, Farrell DM, Harvey CJ, Levin PS (2015) Qualitative network models in support of ecosystem approaches to bivalve aquaculture. ICES Journal of Marine Science 72:2278-2288

Richard Y, Abraham ER, Berkenbusch K (2020) Assessment of the risk of commercial fisheries to New Zealand seabirds, 2006–07 to 2016–17. New Zealand Aquatic Environment and Biodiversity Report 237

Roberts JO, Webber DN, Roe WD, Edwards CTT, Doonan IJ (2019) Spatial risk assessment of threats to Hector's and Māui dolphins (*Cephalorhynchus hectori*). New Zealand Aquatic Environment and Biodiversity Report No. 214

Robertson B, Stevens L (2012) Tasman Coast Waimea Inlet to Kahurangi Point Habitat Mapping, Ecological Risk Assessment, and Monitoring Recommendations. Prepared for Tasman District Council by Wriggle Ltd.

Roper-Lindsay J, Fuller S.A., Hooson S, Sanders MD, Ussher GT (2018) Ecological Impact Assessment. EIANZ guidelines for use in New Zealand: terrestrial and freshwater ecosystems. 2nd edition.

Rowden AA, Clark MR, Lundquist CJ, Guinotte JM, Anderson OF, Julian KA, Mackay KA, Tracey DM, Gerring PK (2015) Developing spatial management options for the protection of vulnerable marine ecosystems in the South Pacific Ocean region. New Zealand Aquatic Environment and Biodiversity Report No. 155

Ruckelshaus M, Klinger T, Knowlton N, DeMaster DP (2008) Marine Ecosystem-based Management in Practice: Scientific and Governance Challenges. Bioscience 58:53-63

Sainsbury KJ, Punt AE, Smith ADM (2000) Design of operational management strategies for achieving fishery ecosystem objectives. ICES J Mar Sci 57:731-741

Samhouri JF, Levin PS (2012) Linking land- and sea-based activities to risk in coastal ecosystems. Biological Conservation 145:118-129

Schlüter M, Mcallister RR, Arlinghaus R, Bunnefeld N, Eisenack K, Hoelker F, MILNER-GULLAND EJ, Müller B, Nicholson E, Quaas M (2012) New horizons for managing the environment: A review of coupled social-ecological systems modeling. Natural Resource Modeling 25:219-272

Senior A, Oldman J, Green MO, Norkko A, Hewitt J, Collins RP, Stroud MJ, Cooper AB, Thrush S (2003) Risks to Estuarine Biota Under Proposed Development in the Whitford Catchment Prepared by NIWA for Manukau City Council and Auckland Regional Council

Sharp BR (2018) Spatially-explicit fisheries risk assessment (SEFRA): a framework for quantifiying and managing incidental commercial fisheries impacts on non-target species. Aquatic Environment and Biodiversity Annual Review 2017. Ministry for Primary Industries

Sharp BR, Parker SJ, Smith N (2009) An impact assessment framework for bottom fishing methods in the CAMLR convention area. CCAMLR Science 16:195-210

Stelzenmüller V, Coll M, Mazaris AD, Giakoumi S, Katsanevakis S, Portman ME, Degen R, Mackelworth P, Gimpel A, Albano PG, Almpanidou V, Claudet J, Essl F, Evagelopoulos T, Heymans JJ, Genov T, Kark S, Micheli F, Pennino MG, Rilov G, Rumes B, Steenbeek J, Ojaveer H (2018) A risk-based approach to cumulative effect assessments for marine management. Science of the Total Environment 612:1132-1140

Stevens LM, Robertson BP (2017) Nelson Region Estuaries: Vulnerability Assessment and Monitoring Recommnedations. Report prepared by Wriggle Coatsal Management for Nelson City Council

Sustainable Seas (2018) Discussion paper: Advancing Ecosystem Based Management in Aotearoa New Zealand through current governance arrangements.

Thrush SF, Hewitt JE, Pilditch CA, Norkko A (2021) Ecology of Coastal Marine Sediments: Form, Function, and Change in the Anthropocene. Oxford University Press

Thrush SF, Lewis N, Le Heron R, Fisher KT, Lundquist CJ, Hewitt J (2016) Addressing surprise and uncertain futures in marine science, marine governance, and society. Ecology and Society 21:44

Turchin P (2003) Phenomenological Time-Series Analysis. Complex Population Dynamics. Princeton University Press

Uusitalo L, Tomczak MT, Müller-Karulis B, Putnis I, Trifonova N, Tucker A (2018) Hidden variables in a Dynamic Bayesian Network identify ecosystem level change. Ecological Informatics 45:9-15

Walker WE, Lempert RJ, Kwakkel JH (2013) Deep Uncertainty. In: Gass SI, Fu MC (eds) Encyclopedia of Operations Research and Management Science. Springer US, Boston, MA

Watters GM, Hill S, Hinke J, Matthews J, Reid K (2013) Decision-making for ecosystem-based management: evaluating options for a krill fishery with an ecosystem dynamics model. Ecological Applications 23:710-725

Waugh SM, Filippi DP, Kirby DS, Abraham E, Walker N (2012) Ecological Risk Assessment for seabird interactions in Western and Central Pacific longline fisheries. Marine Policy 36:933-946

Woodworth-Jefcoats PA, Polovina JJ, Howell EA, Blanchard JL (2015) Two takes on the ecosystem impacts of climate change and fishing: Comparing a size-based and a species-based ecosystem model in the central North Pacific. Progress in Oceanography 138:533-545

Zhou SJ, Daley RM, Fuller M, Bulman CM, Hobday AJ (2019) A data-limited method for assessing cumulative fishing risk on bycatch. ICES J Mar Sci 76:837-847

Zhou SJ, Griffiths SP (2008) Sustainability Assessment for Fishing Effects (SAFE): A new quantitative ecological risk assessment method and its application to elasmobranch bycatch in an Australian trawl fishery. Fish Res 91:56-68

Zhou SJ, Smith ADM, Fuller M (2011) Quantitative ecological risk assessment for fishing effects on diverse data-poor non-target species in a multi-sector and multi-gear fishery. Fish Res 112:168-178

Appendix: Minutes from Sustainable Seas Project 3.1 & 3.2 joint co-developer workshop

Organisers: Joanne Ellis; Fabrice Stephenson; Paula Blackett; Shaun Awatere; Judi Hewitt; Gemma Couzens

When: 3rd November 2020

Meeting Participants: Ben Sharp (MPI), Ben Moginie (EPA), Conrad Pilditch (University of Waikato), David Taylor (Aquaculture NZ), Erica Gregory (EPA - afternoon session), Hannah Jones (Waikato Regional council), Joe Harawira (DOC), June Logie (University of Auckland), Katherine Short (Terra Moana), Komathi Kolandai-Matchett (Auckland University), Kris Ramm (DOC), Maria Armoudian (Auckland University), Martin Cryer (MPI), Megan Carbines (ARC), Paula Blackett (NIWA), Ray Wood (CRP), Rebecca Gladstone-Gallagher (Auckland University), Richard Le Heron (Auckland University), Simon Lamping (MFE), Shaun Awatere (Landcare), Shelton Harley (MPI), Vera Rullens (University of Waikato)

Aims: Building on prior work from Phase I, the first research aim (RA1) of Project 3.2 (*Communicating risk and uncertainty to aid decision-making*) was to assess existing risk assessment frameworks of well documented procedures in the form of a literature review. The aims of the co-developer workshop were to:

Update co-development partners on the results of the literature review and provide consistent terminology and definitions for a participatory survey

Review and discuss the usefulness of the reviewed methods and framework(s) for risk assessment within a Kaupapa Māori (with regards to Māori values and aspirations) and Ecosystem-Based Management (EBM) context. The outcomes of this discussion help to inform the selection of tools / methods that will be used in RA2 and RA3 (case studies).

Note: only information pertaining to Project 3.2 is provided here.

Morning session

The morning session provided an overview of:

- The Sustainable Seas challenge objectives
- Principles of EBM
- Aims of Project 3.1 and 3.2
- Definitions of risk
- Perceptions of risk

Aims of the workshop

A presentation of established risk assessment methods and criteria was provided. During Phase I of the Sustainable Seas Science Challenge and the development phase of this project, workshops were held, and a list of methods used in Aotearoa New Zealand (Aotearoa NZ)for assessing risk in the marine environment were identified by co-developers. The next part of the project aimed to determine the suitability of these existing methodologies for assessing risk in the marine environment in the context of EBM. To do this a set of criteria were developed to help in the assessment of whether the methods/frameworks would be suitable in an EBM framework. During the workshop the usefulness of the methods and framework(s) for risk assessment within a mātauranga Māori and EBM context were reviewed. This included discussion during the workshop as well as completion of a survey. The survey asked results of the criteria and methods in supporting Māori aspirations and EBM are provided below.

During the presentations feedback was provided on participants experience of working with different risk assessment methods. A summary of the discussion following presentation of the primary risk methods used in Aotearoa NZ is provided below.

Likelihood Consequence (LC)

A number of workshop participants shared their experience of using LC to assess risk across a range of activities including resource consent applications, risks to seabirds from fishing and for applications under the EEZ Act, including offshore mining. The advantages of this method were identified as simplicity, ease of set-up and ease of communicating the outputs. Difficulties included: 1) the need for more nuanced assessments; for example, a ranking that may sit between boundaries within the matrix, 2) that the method is open to personal opinion rather than being data driven, 3) difficulties of combining risk categories, for example to understand the total risk of a fisheries, is problematic and 4) LC does not readily account for cumulative effects or interactions required for ecosystem-based approaches.

ERAEF: SICA/PSA/SAFE

Experiences of the application of these methods in an Aotearoa NZ context that were shared were predominately fisheries based. Advantages included that the methods can be applied to all fisheries target and bycatch species of interest. Disadvantages included that at the lower-level ranking there is no concept of how much risk to too much for a species to sustain. Therefore, the risk of a false negative needs to be low because it is only at a high risk ranking that a full screening or stock assessment is conducted. In general, the methods are sensitive to the quality of the data and feedbacks and indirect effects are not readily assessed. The issue of scale, both temporal and spatial, was raised including the need to consider whether the process is robust to arbitrary decisions about scale (such as quota management areas). It was also noted that management and kaitiaki happens in place and these place-based values are important. An example of the “heat waves” project was provided, which overviews traditional biophysical modelling combined with a Māori case study and work stream. Finally, it was noted that as you move along the continuum from qualitative to quantitative methods, there is an increasing challenge of how to communicate the outcomes to stakeholders.

MSE

Applications of MSE discussed were fisheries-based. This framework was deemed as appropriate if you have good data and for identifying a range of solutions that can be robust over a range of plausible futures. However, it can be difficult to get stakeholders to clearly state objectives, for example what’s important, suitable metrics, and bottom lines. Disadvantages included that its resource intensive in terms of data and can be difficult to communicate; for example, overviewing outcomes related to scenarios of management strategies. This method is potentially similar to physical process-based models used in resource management decisions such as modelling of sedimentation in estuaries under various land development scenarios. In general, a lack of risk assessment frameworks at the regional council level was highlighted as a potential gap.

SEFRA

An advantage of SEFRA that was discussed is that it can be disaggregated or aggregated at various spatial and temporal scales. For example, the relative risk associated by regional (e.g., the west or east coast) or temporally (summer versus winter) can be disaggregated. This enables relative risk to be better understood and has in the past highlighted that a small number of fisheries over relatively localised areas can represent a high level of risk. The method therefore represents an important tool to provide advice to managers in a fisheries context. Uncertainty can also be determined to understand where the greatest variance is and therefore can inform where further research is needed to reduce the uncertainty. It was noted that for offshore applications, where there is limited spatial information, in this case deep sea coral species, producing spatial maps of risks is limited due to the lack of good distribution data.

BN

Examples of Bayesian networks included applications for understanding sediment loadings into Mahurangi estuary and an application in Tasman Golden Bays. In general participants noted that BNs were very useful as a communication tools and for scenario testing. It was also highlighted that BNs provided benefits in being able to communicate relationships beyond the immediate obvious contributors, for example inputs of sediments from non-obvious sources such as unsealed roads. BNs were also useful for highlighting unexpected results and the complexity of systems. It was also noted that the method requires the underpinning information to develop the causal linkages and can reflect "what you already know".

Survey

The survey questionnaire can be found at the end of this appendix.

Afternoon Session

The breakout groups discussed the results of the survey. The following conversations suggested that there was some variability in how the survey questions were interpreted and then answered and that a degree of caution should be applied when using the results.

Key points raised in group discussion included;

Several participants noted the prevalence of fisheries models in the examples discussed in the morning session. These could be used in other contexts and the research team should uncover these other applications.

Model complexity was not considered to be highly ranked in the survey but after general discussion was deemed to be important for EBM to convey various elements of the system in a way that produced useful information. However, simple models are easier to communicate than more complex ones but may be less representative of reality. Either way models must be fit for purpose, and that purpose should dictate the model type; " all models have a niche which depends on the questions being asked". There is no single model to meet all our needs.

How important is uncertainty in models? Uncertainly is often misunderstood, but models do need to be able to stand up to scrutiny, as we need to be confident, they are telling you something useful that you can trust. How important uncertainty is in any given situation is linked to the problem, for example where the potential impacts of an action is high (e.g., human health) uncertainty plays a more important role than when the potential impact is low. Cases of high uncertainty and high impacts provide room for the application of the precautionary principle. Additionally, there are examples of groups that have used uncertainty as a means to achieve their own objectives.

Several challenges for models with regard to including Mātauranga Māori in particular: There needs to be a general move away from presenting an extractive perspective in models towards a well-being-oriented perspective that restores mauri. This will require re-orienting models to incorporate different world views in ways that support the inclusion of Mātauranga Māori in the decision-making process. Further support for additional Māori models and evolution of the decision-making process to include Māori worldviews will be needed. Most participants were not very comfortable making judgments regarding the applicability of different models in including Mātauranga Māori, they felt it was not something they were able to judge.

Somethings are important but very difficult to quantify (e.g., ecosystem values, mauri, social return on investment) and often get left out or extrapolated out from existing models.

Working with temporal and spatial scales - Models operate at different temporal and spatial scales which need to be considered in their application or up-scaled and or downscaled in a useful but valid way. The components of the models themselves also have a spatial and temporal component.

National SCIENCE Challenges | SUSTAINABLE SEAS | Ko ngā moana whakauka

Risk & uncertainty workshop

1. Defining the most important **criteria**

The aim for this section is to define which criteria are most important to support Māori needs and EBM.

1. **Based on your knowledge, which criteria do you think are most important for methods to support Māori needs and aspirations?**

You have been provided with 20 votes. Please assign any number of votes to the below criteria. You can assign more than one vote to a single criterion, or you could assign none.

	1	2	3	4	5	6	7	8	9	10
Incorporation of risk to multiple ecosystem components	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Ability to estimate uncertainty	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Ability to incorporate indirect effects	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

	1	2	3	4	5	6	7	8	9	10
Ability to accommodate different knowledge types	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Includes risks to social, cultural, economic values	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Ability to incorporate interactions between ecosystem components	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Ability to incorporate feedbacks	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Model complexity	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Production of spatial outputs	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Production of temporal outputs	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Not applicable	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Please include any criteria that you think are important and were not presented in the question above. In addition, any comments and/or discussion points are also welcome (optional).

2. **Based on your knowledge, which criteria do you think are most important for methods to be fit for purpose for EBM?**

You have been provided with 20 votes. Please assign any number of votes to the below criteria. You can assign more than one vote to a single criterion, or you could assign none.

	1	2	3	4	5	6	7	8	9	10
Incorporation of risk to multiple ecosystem components										
Ability to estimate uncertainty										
Ability to incorporate indirect effects										
Ability to accommodate different knowledge types										
Includes risks to social, cultural, economic values										
Ability to incorporate interactions between ecosystem components										
Ability to incorporate feedbacks										
Model complexity										
Production of spatial outputs										
Production of temporal outputs										
Not applicable										

Please include any criteria that you think are important and were not presented in the question above. In addition, any comments and/or discussion points are also welcome (optional).

1 / 2 50%

National SCIENCE Challenges
SUSTAINABLE SEAS
Ko ngā moana whakauka

Risk & uncertainty workshop

2. Defining the best fit for purpose **methods**

The aim for this section is to define which methods are best able to support Māori needs and EBM.

3. **Based on your knowledge, which methods are best able to able to support Māori needs and aspirations?**

You have been provided with 10 votes. Please assign any number of votes to the below methods. You can assign more than one vote to a single method, or you could assign none.

	1	2	3	4	5	6	7	8	9	10
Generalised Likelihood Consequence (GLC)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

	1	2	3	4	5	6	7	8	9	10
Ecological Risk Assessment for the Effects of Fishing (ERAEF)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Management Strategy Evaluation (MSE)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Spatially Explicit Risk Assessment Framework (SEFRA)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Bayesian Networks (BNs)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Not applicable	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Please include any methods that you think are important and were not presented in the question above. In addition, any comments and/or discussion points are also welcome (optional).

4. **Based on your knowledge, which methods may be best fit for informing Ecosystem Based Management (EBM)?**

You have been provided with 10 votes. Please assign any number of votes to the below methods. You can assign more than one vote to a single method, or you could assign none.

	1	2	3	4	5	6	7	8	9	10
Generalised Likelihood Consequence (GLC)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Ecological Risk Assessment for the Effects of Fishing (ERAEF)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Management Strategy Evaluation (MSE)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Spatially Explicit Risk Assessment Framework (SEFRA)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Bayesian Networks (BNs)	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Not applicable	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Please include any methods that you think are important and were not presented in the question above. In addition, any comments and/or discussion points are also welcome (optional).

2 / 2 100%

Prev Done