PERSPECTIVE

Risk assessment for marine ecosystem-based management (EBM)

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Abstract

Ecosystem-based management (EBM) is a holistic way to manage the marine environment, involving partnerships between people and the recognition of ecological complexity. As we progress towards EBM, risk assessments must move beyond an evaluation of the direct impacts of a single stressor on a species or habitat. Here, we propose 12 risk assessment criteria that explicitly reflect the principles of EBM. These criteria include the need to assess risk to multiple ecosystem components and values, evaluate place and time-specific ecological complexity, evaluate recovery, accommodate different knowledge types and communicate uncertainty. Contemporary risk assessment approaches rarely meet all 12 criteria and whilst many approaches could be adapted to do so, some are more easily modified than others. Risk assessment approaches that meet our criteria have the greatest potential to support decision-making in an EBM context and thereby safeguard our marine environments and their values for future generations.

KEYWORDS

Bayesian networks, coupled natural-human systems, cumulative effects assessments, decision support, ecosystem integrity, Indigenous knowledge, multiple stressors, New Zealand, risk analysis, uncertainty

1 | INTRODUCTION

Globally, ecosystem-based management (EBM) has been advocated as a holistic and inclusive way to manage the multiple human activities that impact coastal and marine ecosystems (Leslie, 2018; Ruckelshaus et al., 2008). In marine systems, uncertainty associated with the direct and indirect ecological responses to stressors and

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activities is often very high, highlighting a primary role for risk assessment in decision making. It is imperative, therefore, that decision makers can assess the utility of present and developing risk assessment approaches for EBM.

EBM is an integrated approach to management that considers the entire ecosystem, including humans (McLeod et al., 2005). It moves away from a single-sector or single-species approach to consider the cumulative effects of multiple human activities on multiple ecosystem components. The key principles defining EBM differ

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between frameworks but typically focus on ecological integrity and complexity, the inclusion of humans in the ecosystem, and sustainability (see Table 1 for the EBM principles developed for Aotearoa New Zealand; Hewitt et al., 2018). Effective implementation of EBM and its principles relies on an estimation of how ecosystems respond to cumulative stressors generated by human activities. However, in marine systems, difficulties in collecting baseline information and in understanding how effects accumulate from multiple, potentially interacting, stressors against a background of environmental variability and climate change generates high levels of uncertainty (e.g., Hewitt et al., 2016). For EBM, this uncertainty is heightened by a lack of understanding of how direct effects propagate through ecological and social systems to create indirect effects on ecological and economic health, and social and cultural values (Holsman et al., 2017).

Making decisions in the face of uncertainty is challenging because realized outcomes may differ from predicted outcomes, leading to management failures or decision paralysis (Foley et al., 2019; Link et al., 2012). Decision-making about uncertain events and their consequences is often informed by a risk assessment process.

TABLE 1 Ecosystem-based management (EBM) principles developed for Aotearoa New Zealand (Hewitt et al., 2018)

EBM principle
1. Humans, along with their multiple uses and values for the marine environment, are considered as part of the ecosystem
2. Decisions are based on science and *mātauranga Māori* (*Māori* knowledge) and are informed by community values and priorities
3. Place and time-specific ecological complexities and connectedness and present cumulative and multiple stressors, as well as those that might occur with new uses, are considered
4. Collaborative, co-designed and participatory decision-making processes are used, involving all interested parties from agencies, *iwi* (tribes), industries, *whānau* (families), *hapū* (subtribes), and local communities
5. Governance structures provide for Treaty of Waitangi partnerships, *tikanga* (customs) and *mātauranga Māori* (*Māori* knowledge)
6. Healthy marine environments, and their values and uses, are safeguarded for future generations
7. Flexible, adaptive management, appropriate monitoring, and acknowledgement of uncertainty

Note: These principles generally align with those applied internationally (Long et al., 2015). Included in these principles is reference to practices that provide for the interests and knowledge of *Māori* as Indigenous people.

Risk can be defined in numerous ways (Haimes, 2009) but generally refers to the likelihood that an undesirable event will take place and the potential consequences that may arise as a result. As we progress towards EBM, there is a need for risk assessment approaches to move beyond an evaluation of the direct impacts of a single stressor on a species or habitat (e.g., Georgeson et al., 2020). Rather, they should consider the cumulative, and often indirect, effects that multiple human activities have on various components of social-ecological systems (Hodgson et al., 2019; Holsman et al., 2017).

Here we propose 12 criteria (Table 2) that we believe risk assessment approaches need to meet to be fit for purpose in a marine EBM context. These criteria were informed by international literature on marine EBM and workshops with representatives from marine science, industry, regulatory and community sectors. We discuss the 12 criteria in the context of the EBM principles that they support (Table 1), and we briefly explore the type of risk assessment approaches that could be adapted to meet our criteria and, therefore, be useful for EBM. Although we focus on marine ecosystems in this paper, the criteria that we propose could also be used to ensure that risk assessments applied in other ecosystems (e.g., freshwater, terrestrial) are fit for purpose for EBM.

2 | INFORMING EBM: FIT FOR PURPOSE RISK ASSESSMENTS

2.1 | Assess risk to multiple interacting ecological components and values

One of the aspects of EBM that sets it apart from other management approaches is that it explicitly includes humans as both drivers of change through their behavior, and as holders of values that will be affected by those changes (EBM Principle 1; Table 1). Not only do humans exert pressure on ecosystem components (e.g., species, habitats) through their multiple uses of the marine environment, they also value the ocean in different ways. Accordingly, risk assessment approaches must be able to assess how human activities influence both the ecological response of *multiple components* (C1, Table 2) and the *social, cultural and economic values* (C2, Table 2) that will be affected by these changes (e.g., employment, profit, sustainability; Subagadis et al., 2014). Integrating social and ecological risk into the same assessment helps to understand the *interactions* (C3, Table 2) and *feedbacks* (C4, Table 2) between ecological components, as well as coupled natural-human systems (Holsman et al., 2017). Risk assessment

TABLE 2 Criteria that risk assessments need to meet to support the ecosystem-based management (EBM) principles in Table 1

EBM risk assessment criteria	Principles supported (from Table 1)
C1: 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 behavioral 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)?	1, 3, 6
C2: Includes risks to social, cultural and economic values Can the risk assessment provide outputs of values other than biophysical ones (e.g., ecosystem services, social and cultural values, economic cost)?	1, 2, 4, 5, 6
C3: Interactions Can the risk assessment model interactions between different stressors or different ecosystem components?	3, 6, 7
C4: Feedbacks Can the risk assessment incorporate temporal feedbacks between ecosystem components?	3, 6, 7
C5: Indirect effects Can the risk assessment include indirect effects on the variable of interest?	3, 6, 7
C6: Threshold responses Can the risk assessment explore threshold responses in the outputs?	3, 6, 7
C7: Production of spatial outputs Can the risk assessment produce spatially explicit outputs (e.g., maps of risk)?	3, 4, 5, 6
C8: Production of temporal outputs Can the risk assessment produce temporally explicit outputs (e.g., changes in risk through time, where outputs from one time period affect the assessment for the next time period)?	3, 4, 5, 6
C9: Locational context Can the risk assessment incorporate location specific contexts?	1, 2, 3, 4, 5, 6
C10: Recovery should be explicitly and separately evaluated 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 categorization are confounded.	3, 6
C11: Ability to accommodate different knowledge types Can the risk assessments incorporate different types of knowledge (non-numeric, narrative information, e.g., expert opinion, Indigenous or 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?	1, 2, 4, 5, 6
C12: Estimates of uncertainty Can the risk assessment estimate uncertainty? If so, is uncertainty quantified and is it only related to data limitations?	4, 5, 6, 7

methods that can evaluate risk to diverse values will also facilitate management approaches that are informed by community values and priorities and based on science and Indigenous knowledge (EBM Principle 2; Table 1; Nursery-Bray & Jacobson, 2014; Alexander & Haward, 2019).

2.2 | Integrate complexity

EBM acknowledges the complexity and interconnectedness of ecosystems and the cumulative and multiple stressors that affect them (EBM Principle 3; Table 1). Ecosystems by nature are complex adaptive systems whose functions and

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responses are underpinned by networks of *interactions* (C3, Table 2) and *feedbacks* (C4, Table 2) between *multiple ecosystem components* (C1, Table 2). Interactions between species, habitats, cultural values, processes, functions and economics mean that assessing risk to one component in isolation is likely to miss risks that arise from the *indirect effects* (C5, Table 2) of an activity on the ecological network. Cultural and social complexities and management actions also create indirect effects and feedbacks that should be considered when evaluating risk (McDonald et al., 2008). These indirect effects, interactions and feedbacks can be incorporated into risk assessments by evaluating risk to multiple ecosystem components using approaches that are underpinned by networks (e.g., Bayesian Networks; Graham et al., 2019), rather than those that assess multiple components in parallel (e.g., Hobday et al., 2011).

Ecological responses to stress are often non-linear, particularly those arising from the cumulative effects of multiple stressors (Hunsicker et al., 2016; Large et al., 2015). Risk assessments need to be able to explore the existence of non-linear *threshold responses* (C6, Table 2) and non-additive *interactions* (C3, Table 2). Threshold and non-additive (i.e., synergistic or antagonistic) responses can be difficult to account for due to the complexity of interactions among stressors. However, risk assessment approaches that have the capacity to explore, through scenario testing (e.g., Pham et al., 2021), the existence of these phenomena will be fundamental in preparing for and preventing tipping points (i.e., rapid ecosystem shifts in response to slow changes in envionmental conditions; Selkoe et al., 2015). Understanding these system dynamics can also help to identify long transient states (i.e., rapid ecosystem shifts in a seemingly constant environment; Hastings et al., 2018). Threshold responses can also influence social, cultural, and economic aspects of risk.

2.3 | Place and time specific

The relative importance of different ecosystem components, processes and their connections differ in space and time, as do the disturbance/stressor regimes that affect them (EBM Principle 3; Table 1). From a risk assessment perspective this means methods need to be able to incorporate spatial and temporal variability in both stressors and ecological processes and produce *spatial and temporal outputs* (e.g., spatial risk maps or graphs of risk through time; C7 and C8, Table 2) that effectively communicate the risk posed to the location of interest and how this varies through time. These outputs support collaborative, co-designed and participatory decision-making processes and co-governance arrangements (EBM Principles 4 and 5; Table 1) by aiding knowledge-transfer.

Biological, ecological, chemical and physical processes interacting over different space and time scales, interwoven with social and economic factors influencing risk, also create *locational contexts* (C9, Table 2). Identification of important locational contexts increases the ability to tailor risk assessments to a specific time and place (EBM Principle 3; Table 1), while understanding how risk will change in other places, at other times or even at other scales. For example, a location dominated by suspension-feeding shellfish or sponges may be more susceptible to increased suspended sediment than one dominated by infaunal polychaetes or burrowing crabs (Thrush et al., 2004). The influence that governance structures, policies and social, economic and cultural values have on risk may also differ between locations (Macpherson et al., 2021; EBM Principles 1, 2, 4, 5). Although the production of spatial outputs often lends itself to the incorporation of locational context information, risk assessment approaches do not always meet both criteria (i.e., a map of risk could be produced without accounting for spatially variable processes influencing risk across that area).

2.4 | Explicitly and separately evaluate recovery

Ecological *feedback* (C4, Table 2) loops between ecosystem components are fundamental for how the ecosystem functions (e.g., the feedback between the recruitment of juveniles and the state of the adult population; Gillanders, 2002) and determine whether the ecosystem is resilient to state changes (e.g., feedbacks that preclude ecosystem recovery such as biotic interactions; Zajac et al., 1998). In the context of EBM, an ability to incorporate these feedbacks enables identification of the aspects of the ecosystem that may prevent management interventions from working. This is particularly true in the context of ecosystem recovery because ecological feedbacks can create hysteresis and recovery lags that hinder recovery, even when stressors are reduced (e.g., population recruitment failure from Allee effects; Lundquist & Botsford, 2011). Decades of research on the complexities of ecosystem recovery dynamics (e.g., Sousa, 1984; Thrush et al., 1998; White & Jentsch, 2001) suggest that it is important that *recovery is explicitly and separately evaluated* (C10, Table 2), rather than combined with impact in a risk assessment. For example, the Productivity-Susceptibility Analysis used to assess risks of fishing to bycatch species and habitats amalgamates initial decreases with the potential to recover (e.g., Georgeson et al., 2020). It also often ignores the ecological variables that are involved in recovery or hysteresis (e.g., habitat quality, species occupancy, biotic interactions) and instead assumes recovery based on population traits such as fecundity and time to maturity.

2.5 | Accommodate different knowledge types

In addition to evaluating risk to diverse values (e.g., ecological, social, economic, cultural), risk assessments must be able to accommodate *different knowledge types* (e.g., non-numeric narrative information as well as quantitative data; C11, Table 2). Information to support decision-making does not always come in the form of quantitative data, either because such data does not exist or because knowledge is captured in an alternative manner. Some forms of knowledge are primarily narrative, for example, Indigenous knowledge derived from oral histories, beliefs or experiences, or local (expert) knowledge borne from long periods of observation or experimentation in a specific place. This narrative information can be useful to assess the cumulative impacts of multiple stressors on ecosystem health (e.g., Mantyka-Pringle et al., 2017). Expert judgment can also be used to bridge data gaps in data poor situations (e.g., Halpern et al., 2008). These non-numeric forms of knowledge are essential to fill quantitative data gaps, widen our evidence-base and ensure that EBM objectives align with the values of multiple sectors of society.

Risk assessments that *accommodate different knowledge types* (C11, Table 2) also support co-governance structures and collaborative decision-making processes (EBM Principles 4 and 5; Table 1). Co-governance refers to the sharing of power and responsibility between government and local resource users (Berkes, 2009). It can be as simple as the informal sharing of information, but more formalized arrangements to honor treaty settlements are increasingly common worldwide (e.g., Canada, Australia; Hill et al., 2012; Notzke, 1995). Collaborative decision-making is a process whereby interested parties collectively make decisions and co-design management strategies. In a risk assessment context, collaborative processes increase stakeholder understanding of the structure and assumptions of risk assessment models, promote open discussion and acceptance of model results and help to ensure model outputs meet the diverse needs of end-users, who often have differing values and knowledge sets (Laurila-Pant et al., 2019).

2.6 | Quantify and communicate uncertainty

EBM requires flexibility and an ability to adapt in the face of uncertainty (EBM Principle 7; Table 1). Various types of uncertainty are inherent in decision-making associated with EBM (Marcot, 2020). These include epistemic uncertainty (i.e., uncertainly arising from incomplete knowledge or the inherent variability in natural and human systems), linguistic uncertainty (i.e., uncertainty arising from vagueness, ambiguity, under specificity) and human decision uncertainty (i.e., uncertainty arising from subjective human preferences, judgments, and world views; Kujala et al., 2013). The ability to quantify and communicate these sources of *uncertainty* (C12, Table 2) is an important aspect of decision-making (Ascough et al., 2008). While various methods exist to quantify and/or reduce epistemic uncertainty (e.g., adaptive management, scenario testing, sensitivity analysis, multi-model approaches, use of probability distributions; Regan et al., 2002; Labiosa et al., 2005; Francis et al., 2018), communicating the uncertainty associated with human factors remains a challenge (Ascough et al., 2008; Kujala et al., 2013). Participatory processes that involve interested parties in all phases of model development can be used to reduce linguistic uncertainty by promoting shared understanding (e.g., Henriksen et al., 2012). Methods that account for the uncertainties associated with human input (e.g., Multi-Criteria Decision Analysis; Linkov et al., 2006) can be used in conjunction with probabilistic approaches (e.g., Bayesian Networks; Kaikkonen et al., 2020) to quantify the uncertainty arising from group consensus among a diverse set of participants (e.g., Laurila-Pant et al., 2019). Progress has also been made towards integrated frameworks that comprehensively address different aspects of uncertainty in environmental decision-making (Ascough et al., 2008).

3 | SUITABILITY OF CONTEMPORARY RISK ASSESSMENT APPROACHES FOR EBM

Whilst there are many robust approaches to risk assessment that show promise for meeting the criteria set out in this paper, it is rare that all 12 criteria are met in their application. Many risk assessment approaches could be adapted to reflect these criteria in this paper, however, some approaches will be more easily modified than others. For example, although risk assessments underpinned by complex process-based models (e.g., those reviewed by Fulton et al., 2003) might appear to be more suited to answering the multifaceted management questions arising from EBM, these approaches are often limited by their considerable numeric data requirements and the high effort and cost associated with their development (Perryman et al., 2021). Increasing model complexity also comes at the cost of increasing uncertainty (Ascough et al., 2008). Simple models, conversely, are

cost effective, easy to communicate, quick to implement and can, if components are carefully selected, reflect the intricacies of natural systems. Risk assessment approaches that are easy to set up, run and understand also lend themselves to the collaborative decision-making that underpins EBM.

Multi-model approaches have been suggested for use in EBM to counteract the uncertainties and limitations of using a single approach (Francis et al., 2018) and may also help risk assessments meet more of the criteria suggested here (i.e., the shortfalls of one model are picked up by the strengths of another). Further, coupled models enable feedbacks between human and natural systems to be assessed (e.g., Liu et al., 2007) and are, therefore, particularly useful for EBM. Ultimately, the more formal and quantitative the modeling behind the risk assessment approach, the more difficult it is to incorporate all of the criteria proposed in this paper, suggesting that approaches that are underpinned by simple likelihood-consequence matrices (e.g., Campbell & Hewitt, 2013), flexible agent based methods (e.g., McDonald et al., 2008; Sun et al., 2016), or network type models that can be built with a range of data types (e.g., Bayesian Networks, qualitative network modeling and loop analysis; Martone et al., 2017; Bulmer et al., 2022) are likely to be the most appropriate for use in an EBM context. These modeling approaches are all flexible and can incorporate complex information from a variety of data sources.

4 | CONCLUSION

The area of risk assessment is under development, with no standard approaches yet completely useful for EBM. Here, we present a set of criteria to verify that risk assessment approaches are fit for purpose when EBM is being pursued. We argue that risk assessment approaches that meet our criteria have the greatest potential to support decision-making in an EBM context and thereby safeguard our marine environments and their values for future generations (EBM Principle 6; Table 1).

CONFLICT OF INTEREST
The authors declare no conflicts of interest.

AUTHOR CONTRIBUTIONS
The concept for the paper was developed by all the authors. Dana E. Clark and Rebecca V. Gladstone-Gallagher led the literature review that underpinned the paper and wrote the original draft. All authors reviewed and edited the paper. Judi E. Hewitt, Fabrice Stephenson and Joanne I. Ellis provided project administration and funding acquisition.

DATA AVAILABILITY STATEMENT
No new data were collected for this perspective piece.

ETHICS STATEMENT
All ethical guidelines were followed in the conduct of this research.

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