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Adaptive management of deep-seabed mining projects: a systems approach

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EDITOR'S NOTE: This article will be part of the IEAM special series entitled: “Implications of Deep-sea Mining on Marine Ecosystems.” The series will comprise the current state of the science regarding deep-sea ocean ecosystems and the likely ecological footprints, risks, and consequences of deep-sea mining. There will be a focus on: impact assessment, policy solutions and practices to aid in the implementation of industry guidance prepared by the International Seabed Authority and other authorities, new monitoring and assessment methods, best management practices, and emerging scientific research related to deep-sea ecosystems.

Abstract

Increasing demand for metals used in clean energy technologies including electric vehicles has led to an increased demand in certain metals such as nickel, cobalt and manganese. This has in turn led to an expanding interest in deep-seabed mining (DSM) of polymetallic nodule deposits that contain these exact metals. The main concerns about DSM relate to the incomplete information available about the environmental risks associated with seabed mineral extraction. Key uncertainties need to be systematically addressed to refine environmental impact predictions and establish effective mitigation measures. Adaptive management is an iterative process for reducing the uncertainty that can be applied by both mining companies and regulatory bodies. This Brief Commentary reviews the key opportunities and challenges to operationalising adaptive management in DSM projects and highlights the need for a framework to move from theory to practice. The discussion proposes a systems approach to adaptive management, which could help to guide the environmental management of deep-sea mineral extraction.

Key Words

Deep-seabed mining, environmental management, adaptive management, participatory modelling, social-ecological systems

Introduction

The metals found in deep-sea mineral deposits - such as nickel, manganese and cobalt - are needed for the global deployment of clean energy technologies (Sovacool et al. 2020; Toro et al. 2020). The polymetallic nodule deposits that reside in the Clarion-Clipperton Zone (CCZ) contain more nickel, manganese and cobalt than all of the known land-based reserves combined (Hein et al. 2020). It has been argued that the quantity of mineral resources located within the CCZ can largely meet the demands of clean energy transitions, potentially with a lower carbon footprint than land-based equivalents (Paulikas et al. 2020). The DSM industry is emerging at a pressing time, during which affordable and clean energy is needed to meet sustainable development goals, while land-based mining is faced with declining ore grades and increasing volumes of waste material that pose environmental concerns. DSM can avoid several key environmental and social impacts traditionally associated with land-based mining, including: acid mine drainage, deforestation, relocation of towns and villages, child labour and tailings dam failures (Hein et al. 2013; Koschinsky et al. 2018). Recycling and reuse of clean energy technologies is understandably a preferred alternative to large-scale DSM; however, even with large increases in recycling rates, there is still likely to be a strong demand for primary minerals (i.e., newly mined material) (Hund et al. 2020). However, the emerging DSM industry faces unique challenges. There is currently a poor understanding of the structure and function of deep-sea ecosystems, the services they provide to humans (i.e., ecosystem services), and the extent to which mining pressures could impact these ecosystem services (Le et al. 2017).

DSM is still mostly in the exploration phase, which is a critical time to learn more about deep-sea ecosystems to inform best environmental practices. Scientists, managers, regulators and industry practitioners must work together to assess the risks posed by deep-sea mineral extraction to the receiving environment and develop practical and robust management measures. The potential environmental effects of deep-sea mineral extraction include: (1) direct removal of sea floor substrate; (2) changes to geochemical and physical properties of the sea floor; (3) dispersal of sediment plumes; (4) changes in water quality; and, (5) increases in sound, vibration and light (Jones et al. 2018; Miller et al. 2018; Kaikkonen et al. 2018; Washburn et al. 2019). From a regulatory perspective, Environmental Impact Assessment (EIA) will be critical to identify the potential impacts of DSM (Durden et al. 2018). However, previous DSM projects have faced criticism during the EIA review, in part due to poor assessment of uncertainty (Clark et al. 2020). Although uncertainty is unavoidable in EIA (Tenney et al. 2006), uncertainty can make decision-making difficult around trade-offs for regulators and managers (Retief et al. 2013). EIAs need to incorporate mechanisms to address uncertainty to sufficiently mitigate potential impacts of DSM (Durden et al. 2018). The lack of precedence for large-scale DSM means that EIAs should explicitly detail uncertainties relating to mining activities for transparent decision-making, and to inform measures to reduce this uncertainty as the industry develops.

There are two key approaches to environmental decision-making to address uncertainty - the precautionary approach and science-based adaptive management - both of which could support environmental management of DSM projects. The precautionary approach emphasises proactive decision-making to manage risks and the delaying of potentially-harmful decisions until causal relationships are better understood. Implementation of the precautionary approach could help to prevent actions that might lead to “serious harm” (Levin et al. 2016; Jones et al. 2019); however, precaution can have a paralysing effect if it is applied too strictly due to the focus on risk avoidance (Jaeckel 2017). On the other hand, science-based adaptive management recognises that some causal relationships can only be understood by observing how the system responds to management. The International Seabed Authority (ISA) regulates DSM activities beyond national jurisdiction and has adopted the precautionary approach in their draft exploitation regulations (ISA 2019). In an international workshop convened by Griffith University in collaboration with the ISA, there was agreement that: (1) adaptive management could be appropriate for DSM projects; (2) adaptive management and the precautionary approach are compatible; and, (3) adaptive management can play a part in the implementation of the precautionary approach (ISA 2017). Environmental managers should favour precautionary decisions with adaptive capacity (Quigley et al. 2019), combining the planning necessary for a precautionary approach, with the flexibility of adaptive management. This Brief Commentary: (1) emphasises the value of adaptive management to address uncertainty; and, (2) introduces a systems approach to operationalise adaptive management in DSM projects.

Adaptive management of deep-seaBED mining projects

Adaptive management is a deliberate process of learning by doing to improve management over time and should be applied by both mining companies and regulatory bodies (Jones et al. 2019). Adaptive management is likely to play a crucial role in DSM projects, yet there is a lack of regulatory guidance to move from theory to practice. It is suitable for projects where there is both high uncertainty about system responses to management, and high controllability of management actions (Peterson et al. 2003). The primary goal of adaptive management is to "learn by doing", allowing managers and regulators to remain flexible in response to a changing knowledge environment (Williams et al. 2009). It is a structured, yet flexible, approach that allows managers to make provisional decisions based on the best available science, and later adjust these decisions in response to new knowledge.

Adaptive management is often misinterpreted and/or misapplied as trial and error. Trial and error is problematic because it relies on a surprise for learning, running the risk of unforeseen consequences resulting from management actions (Allen et al. 2011). Unlike trial and error, purposeful adaptive management has an explicit setup phase to conceptualise the resource system and facilitate social learning (Cundill and Rodela 2012; Williams and Brown 2014). Moreover, trial and error requires an error in order to initiate the learning process, and, by definition, lacks precaution. Learning is initiated in the setup phase of adaptive management for planned and focused monitoring to reduce uncertainty. Monitoring is used to measure system responses to management, to facilitate both technical and institutional learning (Williams and Brown 2018). Thus, it is important for mining companies and regulatory bodies to recognise that the setup phase of adaptive management is a critical step to avoiding the perception of trial and error in DSM projects, and to identify and plan processes whereby risk is clearly reduced to acceptable levels for management.

Adaptive management requires explicit and measurable management objectives to guide decision-making, and these objectives determine whether the approach is active or passive (Williams 2011a). Active adaptive management applies when management objectives are designed to reduce uncertainty (i.e., learning by doing), and passive adaptive management applies when the reduction of uncertainty is not specified as an objective (i.e., learning while doing). In other words, active adaptive management prioritises learning by deliberately designing and testing management hypotheses to reduce uncertainty, while passive adaptive management prioritises achieving management objectives and learning is a by-product (Walters 1986). Similar to the precautionary approach, active adaptive management prioritises learning about system responses to management in a proactive manner (Figure 1). Active adaptive management will be an important element of the Environmental Management and Monitoring Plan (EMMP) to account for uncertainties that cannot be sufficiently reduced in EIA (i.e., residual impact uncertainty). Active adaptive management can be used to prioritise residual uncertainties to identify suitable monitoring plans. For example, Runge et al. (2011) show how expert elicitation surveys can be used to prioritise monitoring plans based on the expected value of information theory. Hence, monitoring plans can be designed to target important uncertainties that can be sufficiently reduced through monitoring. Adaptive management can support the implementation of EMMP by providing a mechanism to: (1) reduce uncertainties that may limit effective risk assessment; (2) ground-truth mitigation measures; and, (3) monitor residual impacts, providing an information feedback loop to update initial predictions from EIA. A more integrated approach to the EIA-EMMP process may be suitable for DSM whereby the objectives for adaptive management are specified based on initial risk assessment models, and monitoring is designed to target model uncertainties to improve risk assessment and the iterative development of mitigation measures. Table 1 presents several example methods that have already been discussed by scholars to support the implementation of adaptive management in DSM projects. However, to date, no study has presented a framework for adaptive management that is specifically tailored for DSM, or provided measures to enable an “active”, rather than “passive” approach. In the following section, we introduce the conceptual foundations of such a framework, which forms part of a future research agenda to support the development of good industry practice for DSM projects.

SYSTEMIC ADAPTIVE MANAGEMENT

Systems thinking is a problem-solving methodology that takes a holistic lens to the study of complex systems (Sterman 2000). The systems approach involves the development of conceptual models to represent the structure and behaviour of a system to reduce system complexity (Arnold 2015). Adaptive management can be used to ground-truth system models by: (1) designing management experiments to perturb the system; and (2) implementing monitoring to see how the system behaves under stress. Here we present a conceptual framework for Systemic Adaptive Management (SAM) to manage complex social-ecological problems under uncertainty, the situation faced in DSM (Figure 2).

The SAM framework provides a mechanism to manage residual uncertainties in EMMP for DSM projects. SAM can be summarised in six broad steps: (1) define goals and objectives, (2) conceptualise system models (i.e., system conceptualisation), (3) identify management alternatives, (4) implement management actions, (5) monitor system responses, and (6) evaluate management outcomes. The ecological system can be tested using planned "experiments" and monitoring to better understand how the system responds to management. Similarly, the social system can be tested using structured stakeholder interviews, workshops or surveys, and information can be elicited from these stakeholders to identify areas of consensus, resolve disagreements and support decision-making. SAM recognises the importance of managing both social and ecological systems to enable a structured approach to reducing uncertainty.

The SAM framework could be used to manage residual uncertainties from EIA by specifying the reduction of uncertainty as a management objective and designing "experiments" to reduce uncertainty (i.e., active adaptive management). The SAM framework could also be used to develop indicators for monitoring residual impacts from mining operations for compliance against specified thresholds (i.e., passive adaptive management).

Participatory modelling is a method to operationalise SAM by engaging stakeholders to create a formalised and shared representation of the social-ecological system. Participatory modelling provides a structured opportunity for both top-down and bottom-up stakeholder engagement in DSM projects whereby stakeholders co-produce knowledge using professional facilitation and mediation to: (1) provide context for engagement; (2) develop shared goals; (3) manage power dynamics; and, (4) manage scalar fit (Reed et al. 2018). Participatory modelling is a method to make the implicit mental models of stakeholders explicit (Hovmand 2014), which in turn allows for the identification of flawed mental models that could lead to unintended consequences, and the iterative updating of these mental models as more information becomes available from adaptive management measures. In most adaptive management frameworks, both stakeholder engagement and model development are included as explicit steps in the setup phase (Williams 2011b). Crevier and Parrott (2019) argue that adaptive management and participatory modelling are distinct processes with many overlapping components that can proceed at independent rates. Therefore, participatory modelling can be viewed as a way to support SAM by modelling the social-ecological system to inform each decision step (denoted by the bi-directional links in Figure 2). Incorporating participatory modelling into the EMMP process for DSM could help to emphasises an objectives-led approach (rather than a baseline-led approach) to account for deeper forms of uncertainty such as ambiguity and ignorance (Bond et al. 2015). Moreover, participatory modelling can be used to identify ecosystem indicators and conduct risk analyses to build consensus and transfer useful information to resource managers for ecosystem-based assessments (Fletcher et al. 2014). To support the potential uptake of participatory modelling in the EMMP process for DSM projects, we describe some key tools for modelling social-ecological systems under uncertainty (Table 2).

The value of participatory modelling is less about making precise predictions, and more about promoting social learning to build a shared understanding of complex systems. Participation in adaptive management can help to focus stakeholder concerns around uncertainties that are important and reducible. Involving stakeholders during model development can help to fill knowledge gaps, manage disagreements and increase buy-in to model results (Henriksen et al. 2007; Brown et al. 2019). Models can be used to test competing hypotheses and develop consensus among stakeholders by clearly representing different management options. Moreover, models can be used to focus stakeholder engagement towards less intimidating means, like the underlying modelling assumptions, rather than broad value judgements (Kelly et al. 2013). Some argue that high uncertainty makes it difficult to build precise models, however, the process of building models with stakeholders can be just as important as the models themselves (Smith et al. 2007). The focus on modelling assumptions enables social learning, since assumptions are tested throughout a project in response to adaptive management measures. In this way, the implementation of participatory modelling as part of the SAM framework can help to update the mental models of stakeholders for social learning throughout DSM projects.

Conclusion

Adaptive management will play a crucial role in DSM projects to account for the high levels of uncertainty in the EIA-EMMP process. In order to sufficiently address uncertainty, the adaptive management approach should be:

- Active: prioritises “learning by doing” to reduce uncertainty;
- Systemic: based on the holistic study of social-ecological systems;
- Participatory: fosters a shared understanding of social-ecological systems; and,
- Integrated: combines multiple approaches to the modelling of social-ecological systems.

The conceptual framework for SAM presented here provides a mechanism for dealing with uncertainty through the holistic study of social-ecological systems. We reframe the standard adaptive management cycle with a systems’ focus and outline several participatory modelling techniques to help managers move from theory to practice. The SAM approach forms part of a future research agenda to support the industry and regulatory development of DSM.

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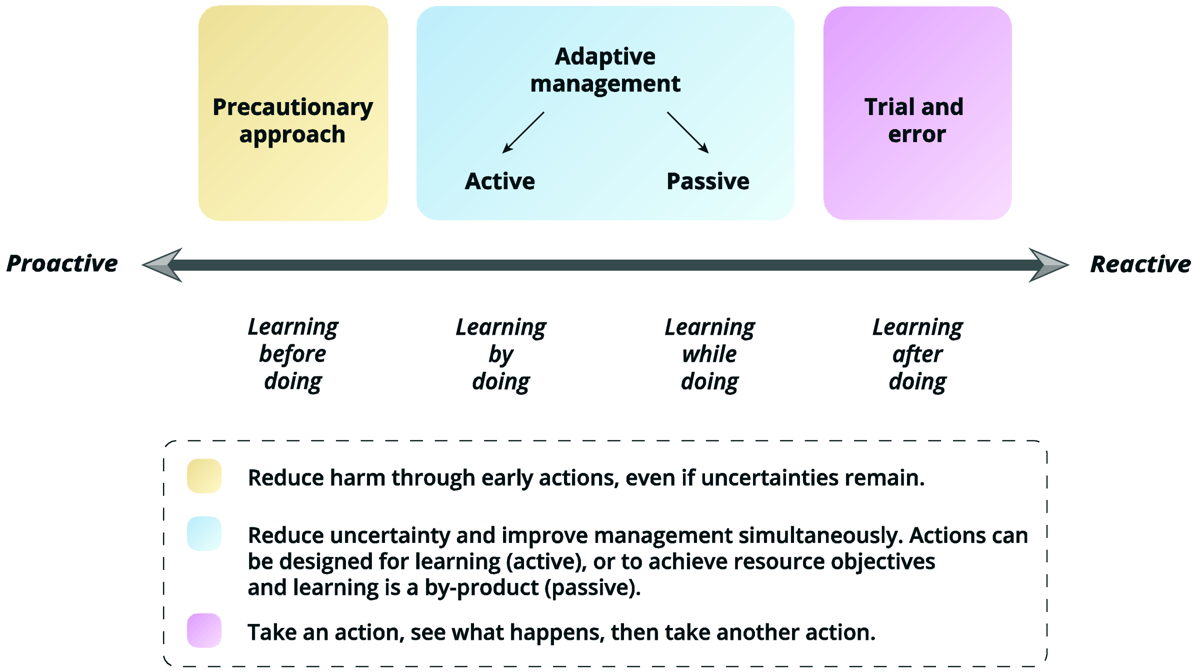

Figure 1. Proactive and reactive approaches to environmental decision-making under uncertainty

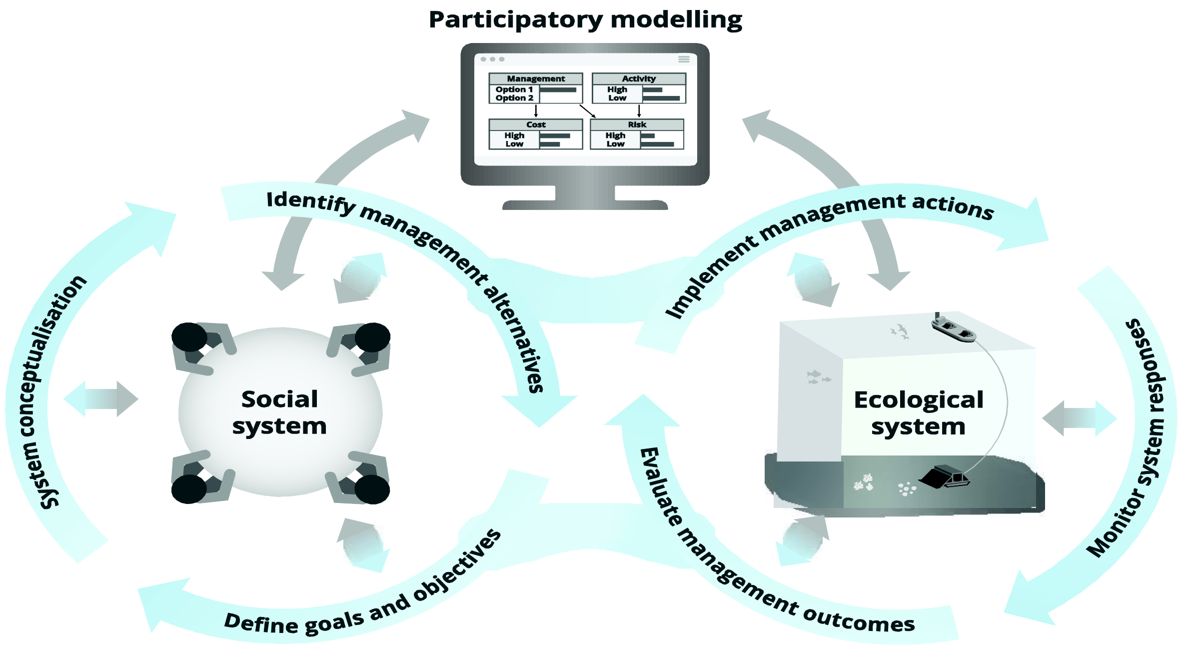

Figure 2. A conceptual framework for SAM

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Table 1. Example methods to operationalise adaptive management in DSM projects

Methods	Description	Refs
Conceptual modelling	A conceptual model is a procedural mechanism that mining companies can use to update project-specific information at each project phase. Conceptual models can be used to synthesise evidence, engage stakeholders, express causal relationships, identify knowledge gaps and facilitate decision-making. Models are particularly useful for scenario-based planning to design management "experiments" that will yield valuable information to fill critical knowledge gaps.	Durden et al. 2017
Expert elicitation surveys	Where there is a lack of quantitative data, expert knowledge can be used to fill critical knowledge gaps to support decision-making under uncertainty. Structured surveys and/or workshops can be used to elicit expert knowledge to develop suitable indicators for monitoring, identify pressures from mining activities and prioritise potential risks to ecosystem services.	Washburn et al. 2019
Integrated ecosystem assessments	Integrated ecosystem assessments (IEAs) are a formal approach to synthesising ecological and socioeconomic information to determine the probability of exceeding acceptable limits as defined by management objectives. Mining companies can conduct IEAs to engage diverse scientists and stakeholders to explore ecosystem service trade-offs, identify management alternatives, and transfer useful information to managers and regulators.	Levin et al. 2009
Disturbance experiments	In situ "experiments" allow scientists to observe the recovery of deep-sea biological systems at a local-scale by monitoring these systems over time as compared to baseline conditions. These "experiments" can provide a basis to estimate the impacts of commercial-scale mining and provide opportunities to refine mining equipment and monitoring technologies.	Jones et al. 2017
Integrated monitoring	State-of-the-art monitoring such as integrative DNA taxonomy and ecosystem observatories are increasingly being used to monitor deep-sea ecosystem services. For example, seabed imaging is being complemented by environmental DNA sequencing technologies to improve the identification and traceability of deep-sea organisms.	Glover et al. 2015; Aguzzi et al. 2019
Staged	Staged (or scaled) approaches allows DSM projects to proceed at a small scale or for a short duration to facilitate the monitoring of	Craik

mining	impacts prior to subsequent stages. A staged approach would allow mining companies to operationalise mining equipment and refine monitoring technologies to facilitate "learning by doing", while maintaining a precautionary approach by limiting the scale or timing activities to reduce harmful effects from seabed mineral extraction.	2020

Table 2. Participatory modelling techniques for effective SAM

Techniques	**Description**	**Refs**
Systems Thinking (ST) / System Dynamics (SD)	ST studies the interactions within systems, and how these interactions form dynamic causal relationships. The goal of ST is to reduce complexity by modelling the system conceptually, often with input from diverse stakeholders. A shared understanding of the system can emerge to identify systemic issues and aid decision-making. A Causal Loop Diagram (CLD) is a tool for visualising system interactions, using nodes as system variables and links as positive or negative causal relationships. Stakeholders can interrogate CLDs to identify common system archetypes, such as “tragedy of the commons” or “fixed that fail”, to identify behaviours that may lead to negative consequences. SD is a quantitative modelling approach used primarily for policy analysis and design. It builds upon systems thinking through a quantitative assessment approach to explicitly represent the dynamics of a system as a stock and flow diagram. SD software uses an interactive graphical interface to simulate system behaviour over time.	Sterman 2001; Dhirasasna and Sahin 2019; Salim et al. 2020
Bayesian Network (BN)	BNs are directed acyclic graphs that explicitly represent system uncertainty using a probabilistic graphical interface that can be parameterised using both empirical data and expert opinion. BN allow for a flexible modelling approach that is well-suited to adaptive management since they can be easily updated in light of new information from expert surveys and monitoring programs. BN software can perform scenario analysis to make systemic predictions and diagnose systemic issues under uncertainty. BNs for the most part lack support for feedback loops, which is an important consideration when modelling complex systems.	Nyberg et al. 2006; Howes et al. 2010; Argent et al. 2016
Digital Twin (DT)	DTs are a digital representation of a physical system, often supported with 2D/3D interactive simulations fed by real-time or close to real-time monitoring data using Internet of Things (IOT) technology. DT monitoring data can be derived from a high-technology ecosystem observatories to provide rapid information to update models for live	Aguzzi et al. 2019; Kaur et

	monitoring of impacts, agile decision-making and faster iterations of adaptive management. Digital twins allow for activities to be adjusted in real-time to avoid potential unforeseen issues that may arise during operations.	al. 2020
Integrated modelling	Integrated models can account for known shortfalls of individual models by combining multiple modelling approaches. For example, BNs can be integrated with SD to allow for the integration of empirical data and expert opinion (feature of BN) and represent system dynamics via feedback relationships (feature of SD). Systems modelling approaches can also be complemented with other techniques including but not limited to: geographical information systems, multi-criteria decision-making, agent-based models, fuzzy cognitive mapping and driver-pressure-state-impact-response (DPSIR) frameworks.	Hafezi et al. 2020; Kelly et al. 2013; Marcot and Penman 2019