Strategies for integrating scientific evidence in water policy and law in the face of uncertainty

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Science of the Total Environment 931 (2024) 172855

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Review

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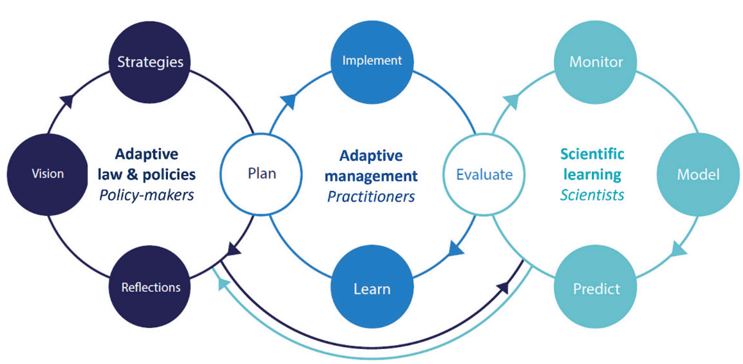
HIGHLIGHTS

- Sustainable decisions need reliable, forward-looking evidence.
- Ecosystem indicators, predictive models and scenarios provide this information.
- Legal certainty complicates use of uncertain scientific data.
- Evolving information can be accommodated by flexible governmental procedures.
- Boosting coherence between scientific and decision-making frameworks is needed.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Jay Gan

ABSTRACT

Understanding how human actions and environmental change affect water resources is crucial for addressing complex water management issues. The scientific tools that can produce the necessary information are *ecological indicators*, referring to measurable properties of the ecosystem state; *environmental monitoring*, the data collection process that is required to evaluate the progress towards reaching water management goals; *mathematical models*,

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https://doi.org/10.1016/j.scitotenv.2024.172855
Received 20 February 2024; Received in revised form 22 April 2024; Accepted 26 April 2024
Available online 29 April 2024

linking human disturbances with the ecosystem state to predict environmental impacts; and *scenarios*, assisting in long-term management and policy implementation. Paradoxically, despite the rapid generation of data, evolving scientific understanding, and recent advancements in systems modeling, there is a striking imbalance between knowledge production and knowledge utilization in decision-making. In this paper, we examine the role and potential capacity of scientific tools in guiding governmental decision-making processes and identify the most critical disparities between water management, policy, law, and science. We demonstrate how the complex, uncertain, and gradually evolving nature of scientific knowledge might not always fit aptly to the legislative and policy processes and structures. We contend that the solution towards increased understanding of socio-ecological systems and reduced uncertainty lies in strengthening the connections between water management theory and practice, among the scientific tools themselves, among different stakeholders, and among the social, economic, and ecological facets of water quality management, law, and policy. We conclude by tying in three knowledge-exchange strategies, namely - adaptive management, Driver-Pressure-Status-Impact-Response (DPSIR) framework, and participatory modeling - that offer complementary perspectives to bridge the gap between science and policy.

1. Introduction

Current water management practices highlight the importance of using scientific knowledge to inform the development of environmental legislation and the design of policies. Biophysical assessments are based on empirical data, mathematical models, and scenario planning, all of which help to understand, characterize, and predict the connections between human activities and ecosystem state (Jakeman and Letcher, 2003; Rekolainen et al., 2003; Turnhout, 2009; White et al., 2010; Schmolke et al., 2010; Verburg et al., 2016). This information is crucial when determining the legal compliance of proposed industrial and other anthropogenic activities that could have a substantial impact on the aquatic environment (Fisher et al., 2010). The boundary between the science and law is 'porous yet substantial' (Paloniitty and Kotamäki, 2021) and there is significant variety in the ways courts in different legal systems deal with scientific uncertainties (Eliantonio et al., 2023).

While scientific knowledge is important for water policy development and implementation, several challenges impede the effective use of empirical evidence. First, there is a persistent problem of disconnection between scientific results, policy analysis, and legislative processes (Ruhl, 2007). Scientific knowledge about the biophysical environment can be challenging to produce in situations where there are different objectives and scales, conflicting interests among stakeholders, and specific requirements associated with water legislation and policy. Second, failure to fully account for the different aspects of aquatic system functioning can lead to poorly informed decision-making. This shortcoming arises from the nonlinearity of ecosystem dynamics, as well as the limited (or contradictory) understanding of the interactions among ecological, economic, social, and technological systems. Third, there seems to be a striking, yet partly unaddressed, imbalance between the scientific uncertainty - that is necessary to be communicated to decision-makers - and the expectations of unambiguous information in designing and implementing water policies and laws (Thorén et al., 2021). The inherent uncertainty associated with scientific knowledge can appear to be contradicting the requirements of predictability and certainty (Karkkainen, 2002), which are fundamental concepts in any established legal framework. However, due to the diversity of legal systems, some have found ways to navigate the reality of scientific uncertainties better than others (Eliantonio et al., 2023). The constitutional and procedural legal norms and ways the legal culture manifests itself in legal practices has at times resulted in elegant juridical solutions to manage the uncertainties (Paloniitty and Kotamäki, 2021), whilst elsewhere no such thing has even been considered (Caine and Broadbent, 2023; Eliantonio et al., 2023).Several decision-support frameworks already exist that aim to overcome the challenges by emphasizing different aspects of the decision-making process. These strategies include (*i*) participatory modeling which highlights the active involvement of public and stakeholders, favours the co-creation of knowledge, makes the decision-making process more transparent and democratic, and is conducive to establishing trust and ownership that ultimately empowers the implementation of the selected environmental policies (Basco-Carrera et al., 2017); (*ii*) the drivers-pressures-status-impacts-response (DPSIR) conceptualization framework that dissects complex environmental problems into simpler cause-effect relationships among anthropogenic disturbances, state of the environment, and societal responses to environmental change (Smeets and Weterings, 1999; Borja et al., 2006; Cvitanovic et al., 2015); and (*iii*) adaptive management, an iterative learning process whereby the management actions are adjusted in conjunction with the emerging evidence and accumulating knowledge (Williams et al., 2009). Adaptive management tries to address the uncertainty arising from our imperfect knowledge and the unexpected responses typically experienced with the management of socio-ecological systems (Allen et al., 2011; Arhonditsis et al., 2019a, 2019b). A common denominator of the three strategies is the support of efficient, science-informed decision-making in complex water management issues, based on the involvement of multiple actors and disciplines as well as the creation of knowledge from multiple – and often diverse – lines of evidence. The three frameworks also complement each other, as one of their pillars is the stakeholder engagement to enhance collaborative learning (Basco-Carrera et al., 2017). The conceptualisation of the pressure-state linkages becomes more policy relevant, when the stakeholders are involved in the process of defining the DPSIR elements, and as such this exercise can be used to inform adaptive management.

The purpose of this paper is to review the various challenges emerging at the interface between science, policy and law. We are focusing on the implementation of EU's Water Framework Directive (WFD, 2000/60/EC), which is based on river basin level planning. While the Water Framework Directive itself fosters the integration of the scientific strategies listed above, including DPSIR and adaptive management (Soininen and Platjouw, 2018; Paloniitty, 2023), there are considerable challenges during their implementation at various jurisdictional levels. These challenges revolve around the selection of suitable ecosystem indicators, the lack of sufficient data for model groundtruthing, difficulty to select scenarios, and the lack of connection among all the available knowledge-production tools. We further demonstrate that the national environmental permit framework, through which the EU policies are being implemented, is often hindered by the *paradox of certainty*, or the impasse that arises because the law demands a certain level of scientific certainty that is often impossible to meet.

Rather than separately examining the individual features of DPSIR framework, participatory modeling, and adaptive management, we present them as interconnected, complementary cycles and show how this integrative approach could bridge the gaps between science, policy and law, and facilitate the governance of complex water management problems. This paper aims to appeal to both scientists (e.g., modelers, data analysts, environmental practitioners, ecologists) and decision-makers at different governmental levels (policy-analysts, planners, permit authorities, judges) alike. Scientists may benefit from pinpointing their role in the larger socio-ecological context, while decision-makers are expected to improve their understanding of the properties and interlinkages of different decision-support frameworks that are important when addressing water security issues.

The paper is structured as follows: (*i*) Section 2 outlines the context of societal decision-making, which sets the requirements and expectations from the foundational knowledge. Here we use EU's WFD as an example. (*ii*) Section 3 introduces the tools that can produce the required scientific knowledge. The same section also identifies the most pressing challenges that prevent the applicability of these tools. (*iii*) Section 4 identifies several directions for improvement that are conducive to strengthening the links between science and policy, between theory and practice, between knowledge producers and knowledge users, and among the scientific tools used. We use a real-world example from Canada to illustrate how science-based water management and regulation can be effectively implemented in practice.

2. Societal decision-making context

2.1. Water policies and laws

National (e.g., US Clean Water Act), bilateral (e.g., Great Lakes Water Quality Agreement) or multilateral (e.g., EU Water Framework Directive) water management policies require robust knowledge, as they aim at establishing scientifically derived, often numerical, water quality standards/criteria. For example, in the European Union, the surface water management policies, processes, and guidelines are set by the Water Framework Directive (2000/60/EC). The main objective of the WFD is to achieve and maintain good ecological and chemical status of all rivers, lakes, coastal and groundwaters (Art. 4 Water Framework Directive – Environmental objectives), and to prevent the status of waters from further deterioration. The targeted good ecological status in surface waters is assessed against nearly pristine reference conditions on three sets of quality elements: biological, hydro-morphological, and physico-chemical (Annex V). To achieve these goals, the EU member states are obligated to deliver River Basin Management Plans that include monitoring, status assessment, identification of the main pressures, implementation and evaluation of water management measures (Art. 5–7). The WFD also requires the review of permits of existing water-use activities (Art. 11) as well as stakeholder and public participation making stakeholders actively involved in the entire process (Art. 14). The WFD is clearly a science-intensive and collaborative regulatory mechanism to guide water quality management.

2.2. Water management and planning

The WFD planning and management links human actions with environmental impacts using the DPSIR framework (Borja et al., 2006; Song and Frostell, 2012). Scientific tools, such as scenario planning, mathematical models, and ecological indicators, are at the forefront of this process. Global climate and/or socioeconomic scenarios can be downscaled to local drivers (D) of change (Sarkki et al., 2017). Mathematical ecosystem models provide quantitative linkages between pressures (P) and ecosystem state (S) (Pastres and Solidoro, 2012). Ecosystem state (S) is then assessed with a set of ecological indicators. However, the intrinsic complexity of open natural systems poses challenges to build operational models and produce knowledge that can advance our understanding of the human-environment relationships (Blair et al., 2019).

The WFD implementation is also an iterative process that is conceptually in tune with the key tenets of adaptive management (Borja et al., 2006; Hering et al., 2010; Carvalho et al., 2019). This framework recognizes that even if certain facets of water quality management may change over time, the core issues remain the same. It is thus critical to maintain the continuity in the decision-making process, but also to introduce iterative adjustments that accommodate the extrinsic non-stationarity or intrinsic stochasticity of open environmental systems (Allen et al., 2011). Viewed from this perspective, the WFD establishes a process that not only acts as a hedge against the ubiquitous uncertainty surrounding the management of waters, but also paves the way for advancing our fundamental understanding of the ecosystem functioning (Rist et al., 2013). In the context of adaptive management, it is difficult to delineate the role of scientific knowledge, management decisions, and judicial decision-making (Paloniitty and Eliantonio, 2018; Paloniitty, 2023). This is also more widely a challenge with the design of all legislative and policy frameworks that seek to safeguard the environmental quality (Soininen et al., 2023). Uncertainty in relation to the environmental impacts and most probable ecosystem responses is the primary reason for a widespread reluctance to embrace adaptive management (Karkkainen, 2002). For example, environmental laws do not intentionally include an option for adaptive management, as the idea of iterative planning and learning can potentially lead to “moving targets” and may be misconstrued as promoting a “trial-and-error” mindset (Arhonditsis et al., 2019a).

2.3. Legal requirements and environmental permits

In addition to water planning and management, the EU member states are required to establish permits and other implementation mechanisms that will ensure the ecological objectives of the directive are translated into specific legal requirements for activities intricately linked to water quality impairments (Art. 11). The good status requirements are typically materialized through environmental impact assessment, feeding information into permit proceedings, in which state authorities evaluate whether the potential disturbance brought about by a new industrial or other operation fulfils the legal requirements set by the national legislation of the EU member states and the Water Framework Directive. The Court of Justice of the EU has ruled that the WFD Art. 4 sets a legally binding obligation to not deteriorate the ecological status of waters, and to not hinder the realization of good water quality status (Weser case C-461/13). This obligation applies to the EU member states but also to individual companies and other stakeholders seeking to obtain environmental permits for activities that may alter the biological, hydro-morphological, or physico-chemical characteristics of waters. The latter step of the environmental permit process underscores the need for robust impact assessment frameworks, including the use of models and scenarios (Fisher et al., 2010; Thorén et al., 2021).

While the WFD is built upon the best available ideas characterizing the adaptive management, DPSIR and participatory approaches, the national permit frameworks can find it challenging to put in effect the desired adaptive spirit. This is primarily due to the permit system's demand for a high level of scientific certainty. The inevitable uncertainty associated with any assessment exercise can become a decisive factor when the precautionary principle prevails (Paloniitty and Kotamäki, 2021) and puts greater weight on the degree of confidence in the scientific evidence relative to the potential socioeconomic benefits. The problem of requiring scientific certainty – instead of navigating reality of various sources uncertainties – is most prominent in the realm of EU nature conservation directives (García-Ureta, 2023). In operationalizing the EU Green Deal, and in particular the problem with the critical raw material (COM(2023)160) and renewable energy increase (EU Council Regulation 2022/2577) targets, the environmental permit processes have become a focal point in enabling investments in renewable energy. This has triggered a debate about whether the laws regulating environmental quality set overly high expectations for the required certainty of, for example, mathematical models (Thorén et al., 2021). This could lead to the dismissal of this line of evidence and questioning of model reliability.

3. Scientific tools and knowledge production

3.1. Ecological indicators

Ecological indicators are measurable characteristics reflecting the biological, physical or chemical properties of the ecosystem state (S) (Jackson et al., 2000; Niemi and McDonald, 2004; Heino, 2015). The guidelines for selecting ecosystem indicators are often set by legislation. Ecological indicators must provide information that is relevant and meaningful to societal concerns and can be easily communicated to decision-makers and the public (OECD, 1993). Ecosystem indicators are a prime example of the collaborative relationship between science and policy, as their selection may be influenced not just by scientific understanding but also by political factors and a multitude of socioeconomic priorities (Turnhout et al., 2007).

The criteria and standards of what is regarded as good water condition depend on the designated use of the water resources and management objectives (Reckhow et al., 2005). For example, good ecological status in the EU, as defined by the Water Framework Directive, is based on indicators reflecting the levels of selected biological elements such as phytoplankton, macrophytes, benthic invertebrates, and fish (e.g., Heiskanen et al., 2004). The measurable metrics of these indicators reflect the changes in the ecosystem structure and function and are specifically sensitive to anthropogenic pressures (Oliver et al., 2015). Ecological indicators should ideally offer reliable proxies to assess the status of ecosystem services (Broszeit et al., 2017). Good water quality conditions typically imply that the integrity of ecosystem functioning is not compromised, and the multitude of associated services are maintained (Grizzetti et al., 2019). In their review, Grizzetti et al. (2016) listed ecosystem services and their indicators that are directly related to waterbodies or to land-water interactions. These include metrics of water quality, biodiversity, fish communities, and food-web structure. These elements can be ultimately integrated into the evaluation of the overall ecosystem health and linked to economic indicators to better inform decision-making (Niemi and McDonald, 2004).

There is a growing body in the literature cautioning that if we opt for small/skewed subset of ecological indicators, there is a risk to oversimplify the assessment of the ecosystem status and behaviour, which in turn can lead to poorly informed decision-making and inefficient management practices (Dale and Beyeler, 2001). By contrast, the inclusion of an excessive number of indicators at varying spatial and temporal scales can result in prohibitively high data collection costs and cumbersome analysis of the derived information, in addition to the risk of convoluting the decision-making process with false positive (unjustifiably comforting) or negative (unnecessarily alarming) information (Ovaskainen et al., 2019).

3.2. Environmental monitoring

Environmental monitoring refers to the data collection procedures, i.e., observations, measurements, or experimental work required to calculate the values of ecosystem indicators. On-going technical progress of data collection methods (e.g., online sensors, remote sensing, eDNA, citizen science) has provided new cost-effective ways to monitor the environment and increased considerably the amount/diversity of available data (Bush et al., 2017). With the operationalization of fusion techniques, the new environmental data can be effectively combined with data produced by traditional protocols and become mainstream information to support the decision-making process (Gunia et al., 2022). Monitoring the successes and failures of management actions is an integral part of the adaptive management cycles (Williams, 2011). It is thus important to design monitoring programs that can detect the expected impacts of management actions and assess the cost-effectiveness of policy implementation (Lovett et al., 2007). This means careful evaluation of what, where, when, and how often to measure (Gitzen et al., 2012). It also requires the need to verify that the management questions can be answered with sufficient certainty and with optimal use of monitoring resources (Carstensen et al., 2012).

Like the selection of ecosystem indicators, environmental monitoring is driven by the statutory requirements (Waylen et al., 2019). All too often these monitoring programs are constrained by the available resources (time and funds), and consequently the monitoring efforts gravitate towards traditional sampling methods (e.g., collecting water samples for laboratory analysis) at fixed sampling frequency and locations (e.g., offshore samples solely collected during the growing season). This approach provides long-term data time series that might be useful when stationary conditions prevail, but in light of the non-stationary nature of the pressure exerted by different environmental stressors, the design of more flexible monitoring programs rapidly becomes an emerging imperative (Lindenmayer and Likens, 2009; Schmolke et al., 2010). In addition, there is often a mismatch between the scales where environmental goals are being set and the spatiotemporal domain that predominantly influences the perception of the public (Arhonditsis et al., 2019b). The rigidity of policy-driven monitoring may not always be suitable to meet the needs of iterative learning and impartial evaluation of the degree of success of adaptive management (Waylen et al., 2019).

3.3. Predictive models

Linking human pressures (P) to aquatic ecosystem states (S) requires information about the hydrology and biogeochemical processes in the surrounding catchment, weather variability, and ecological indicators in the receiving waterbody. This complex interplay can be reproduced with models, which offer a methodological strategy to elucidate causal mechanisms, complex interrelationships, direct and indirect ecological paths that shape ecosystem functioning. These models serve as heuristic tools for developing testable hypotheses, advancing our conceptual understanding, and articulating ecological theories. They can also serve as a substitute for performing experiments that are technologically or economically unattainable in real-world settings (Janssen et al., 2015). In the context of water management and policy planning, models offer a way to assess ecosystem response to different external stressors and communicate the potential repercussions/preferred options to managers and politicians who must make decisions but lack scientific expertise (Arhonditsis et al., 2019a).

A variety of data-oriented (statistical) and process-based (mechanistic) models have been used in water quality policy analysis and decision-making, where they assist with the examination of "*what-if*?" scenarios representing management alternatives. The data-oriented models typically reflect steady-state conditions and aim to predict e.g., lake nutrient concentrations as a function of lake morphometric/hydraulic characteristics, such as the areal nutrient or hydraulic loading rate, mean depth, fractional nutrient retention, which are then associated with the chlorophyll *a* or hypolimnetic dissolved oxygen concentrations (Malve, 2007; Kotamäki et al., 2015). An alternative to empirical/statistical relationships are process-based models, which generally comprise a set of ordinary or partial differential equations to describe key physical, chemical, and biological processes with site-specific parameters, initial conditions, and forcing functions. Process-based models can be used to understand ecological processes, to predict aquatic ecosystem responses to external conditions (e.g., nutrient enrichment, climate change), and to evaluate the performance of management alternatives in the near or distant future that can support the policy-making process (Sutherland, 2006; Trolle et al., 2012; Dietze et al., 2018). Statistical and process-based models can be collectively used to maximize the information gained from both the analysis of empirical data and the characterization of system mechanisms (Kotamäki et al., 2015).

Using multiple models to address the same problem (ensemble modeling) can support holistic ecosystem response assessments and comprehensive uncertainty evaluation (Janssen et al., 2015). Ensemble modeling offers a promising strategy to view problems and data from different conceptual and operational perspectives, findings are stronger when multiple lines of evidence are available, information from multiple models can help quantify uncertainty, multiple models can expand opportunities for stakeholders to participate, reconciling differences among models provides insights on key sources and processes, and thus its broader adoption is essential to strengthen adaptive management (Scavia et al., 2017; Arhonditsis et al., 2019a; Kaikkonen et al., 2021).

When used as decision support tools, mathematical models should include information about the uncertainty related to the different management outcomes to help evaluating the trade-offs between human benefits and the harm caused to nature (Williams and Brown, 2014; Uusitalo et al., 2015). In this vein, Hipsey et al. (2020) introduced a hierarchical assessment framework to more comprehensively assess when a model is "fit for purpose", comprising four types of model assessment: *conceptual validation* to ensure that model structure is consistent with ecological theory and valid over a wide range of domains, *state validation* through which simulated state variables are compared against observed properties, *process validation* that confirms simulated energy and mass fluxes are on par with measured process rates; and *system validation* whereby system-scale emergent properties, patterns and relationships match observed phenomena.

In the operational context of water policies (either in EU, US/Canada or anywhere else), models are necessary to produce the knowledge that is needed for water quality management and planning. However, unlike the practices introduced with ecological indicators and monitoring, there are no regulatory or statutory requirements for the modeling practises followed. This has led to a situation where the harmonisation of model assessment practices is not well established, and different countries or even regions have their own, often quite distinct, ways of utilizing models.

3.4. Management alternatives and scenario planning

In water management, scenarios can be perceived in multiple ways, depending on the scale and objectives of their intended use. Scenarios can refer to projections of future conditions in order to showcase possible long-term pathways or may involve the evaluation of management alternatives and selection of the optimal one. Future-oriented scenarios are well suited to guide medium- and long-term planning and to stimulate strategic thinking. They allow the analysts to envision the likely "futures" and to prepare contingency plans for mitigation and adaptation. Uncertainty related to long-term future scenarios is usually high and often unavoidable (Marchau, 2019), because social and economic processes as well as technological development are largely unpredictable.

Scenarios are meant to operate at the boundary of science and policy, as they link social and natural sciences, similar to the way drivers (D) causing pressures (P) and subsequently changes in the ecosystem state (S) (Sarkki et al., 2017). It is important to make a distinction between *baseline* or *business-as-usual* scenarios that depict a plausible future development as a consequence of a scenario narrative, and the *policy* scenario, which is a normative scenario aiming to lead socio-ecological systems to the desired state over the course of time. The comparison between baseline and policy scenarios can – in principle – reveal the implementation gaps or the urgency of mitigation and adaptation measures.

As scenarios are tools to build logical sequences of events that lead to some plausible future state, one challenge is to select scenarios that best serve the purpose of the analysis. The recent challenges to mitigate the impacts and to adapt to a changing climate have led the climate-research community to develop a new scenario architecture. The new framework consists of four Representative Concentration Pathways (RCPs) that describe different future climates until the year 2100, based on a possible range of radiative forcing values (van Vuuren et al., 2014) as well as five Shared Socioeconomic Pathways (SSPs) that describe schematized narratives for plausible alternative evolutions of society at the global level (O'Neill et al., 2014; O'Neill et al., 2020). RCPs and SSPs have been applied as tools in climate impact, assessment and vulnerability literature that examines the risks and opportunities presented by climate change for human or natural systems. This scenario architecture has also been extended to study the cascading effects of climate change on aquatic ecosystems (Mora et al., 2013; Saraiva et al., 2019), and the impacts of global societal changes on sectors operating close to, or directly polluting, aquatic environments (Zandersen et al., 2019; Pihlainen et al., 2020). Inputting numerical projections from scenarios to mathematical models enables to quantitatively assess the future human impact on ecosystems under realistic or largely hypothetical socio-economic and climate conditions (Bunnefeld et al., 2011; Kok et al., 2014; Houet et al., 2016; Huttunen et al., 2021). Short-sighted decisions that ignore potential future changes can hamper the successful implementation of adaptive management (Craig et al., 2017). For example, the 6-year assessment cycles in EU's Water Framework Directive are not well-suited for incorporating longer planning and their use is not required nor regulated. It is therefore important to include "long-term vision" in exercises where analysis of scenarios is used to track the potential long-standing ecosystem changes, as the recovery times of water bodies can vary and may stretch over perennial scales.

4. Strengthening the coherence of scientific and decision-making frameworks

4.1. Linking governmental processes, adaptive management, and scientific learning

The iterative cycles of governmental decision-making, the adaptive management process, and scientific learning represent the backbone of well-functioning science-policy-law interactions (Fig. 1). The triad of these learning processes are interconnected and require close collaboration among scientists, policymakers, water managers, and other stakeholders. The first cycle, i.e., the adaptive policy and law, provide the *vision* (e.g., sustainable use of waters), *strategies* (laws and institutions) to reach these goals, and *plans* for policy and management alternatives. *Reflections* of the decisions made at each step can take the form of evaluation of past policies based on evidence gathering of their performance. The process of adaptive management is represented as iterative steps of *planning*, *implementation*, *evaluation*, and *learning* (Fig. 1 middle circle, e.g., Stankey et al., 2005). The evaluation phase of adaptive management links to the cycle of scientific learning. The steps of *monitoring* and *modeling* enable *predictions* of the currently implemented policy vis-à-vis any plausible management alternatives (Fig. 1 right-hand circle).

4.2. Connecting theory and practice by linking DPSIR and adaptive management

We next demonstrate how the conceptual, theory-driven DPSIR framework and the practice of adaptive management can be interlinked (Fig. 2). We employ the D**A**PSI(**W**)R(**M**) framework (Fig. 2 outer circle), which is an extended version of the DPSIR framework. The additions highlight more concretely the role of human **A**ctivities, referring to impacts on human **W**elfare rather than on the environment, and include human responses as implementation of **M**anagement and policy measures (Elliott et al., 2017). In the DAPSI(*W*)R(M) framework, the *Drivers* are the basic human needs (e.g., food, energy), and they cause humans to take *Actions* (e.g., agriculture, fisheries, offshore wind power) that address their needs. These activities lead to *Pressures* (e.g., increased nutrient runoff) that influence the *State* of the aquatic ecosystem. Changes in the physical, chemical and biological properties, and collectively in ecosystem functioning, are also synonymous with losses of the associated services. Changes in the ecosystem state inevitably have *Impacts* on human societal and economic welfare. The *Responses* are manifested through regulative actions, legislation, and policies which aim to secure ecosystem health. The policy implementation process again drives the actions (i.e., through regulations) and the cycle continues iteratively.

The best scientific knowledge available is an overarching element

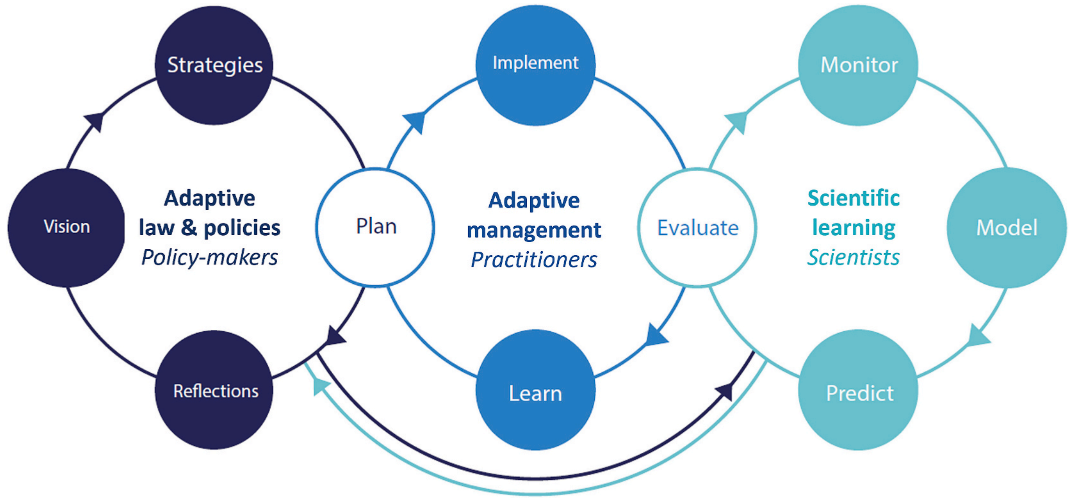

Fig. 1. Simplified interconnected cycles of adaptive policy and law (*strategic level*), adaptive management (*implementation level*) and scientific learning (*knowledge base*). Figure modified and combined from Boyle et al., 2001 and Stankey et al., 2005.

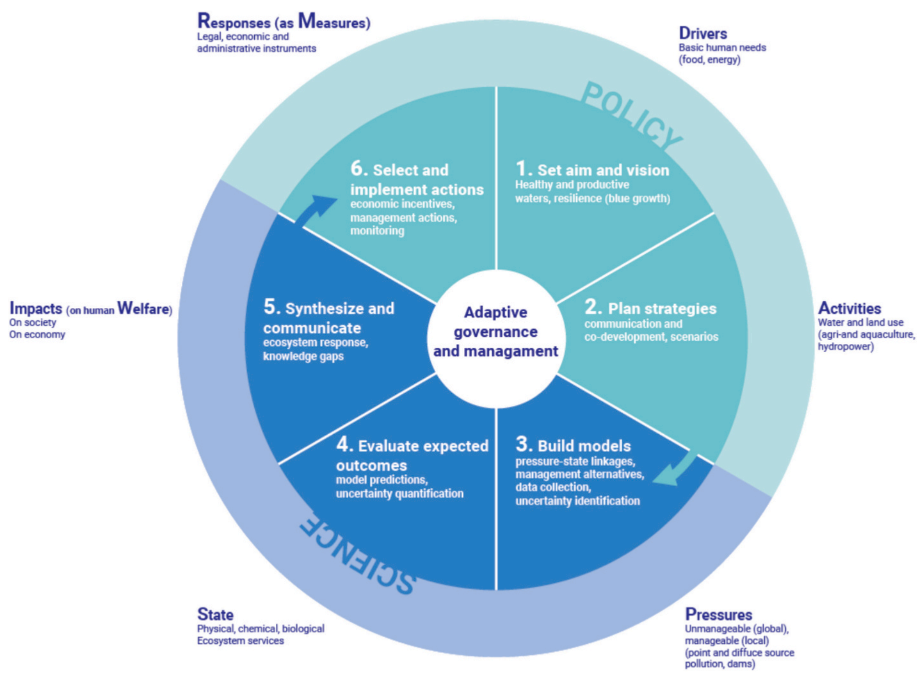

Fig. 2. A simplified presentation of the science-policy linkages. The DAPSI(*W*)R(M) framework (*outer circle*) sets the theoretical context of the science-policy interface. The practical implementation steps 1–6 describe the iterative loop of adaptive management, laws, and policies that are informed by model predictions and scenario planning. Figure modified from multiple sources (e.g., Elliott et al., 2017; Arhonditsis et al., 2019a).

that drives the implementation of the adaptive management process (Fig. 2 inner circle). The process of adaptive management starts by framing the environmental problem (*Step 1* in Fig. 2). In our governmental context, the goal is to achieve and maintain good water quality. To do so, the management and policy actions are identified and strategies to reach the environmental goals are set (*Step 2*). Scenarios of alternative "futures", such as changes in climate, society or environmental policies are selected together with the stakeholders in order to identify the core drivers of the ecosystem-state change. The global scenarios are downscaled and quantified as pressure projections. To quantitatively link the human pressures with the ecosystem state, suitable ecosystem indicators and models are selected or developed (*Step 3*). Next, the model predictions for the planned strategies and scenarios are evaluated, and the uncertainties are quantified (*Step 4*). Results of the modeling exercise(s) are then synthesized and communicated to the administrative institutions (*Step 5*). This iterative process collectively leads to learning from scientific knowledge, implementing the best management actions at any given time, updating the monitoring programs accordingly, and providing suitable policy recommendations (*Step 6*).

A real-life demonstration of a successful science-based water management, reflecting the ideal framework of adaptive management and policy implementation, is the Lake Erie case that follows the spirit of the binational (Canada-USA) Great Lakes Water Quality Agreement (Box 1).

4.3. Linking monitoring and modeling

In theory, the iterative management cycles produce incremental learning that should advance our scientific understanding and reduce the uncertainty (Fig. 2). To achieve this goal in practice, emphasis needs

Box 1
Adaptive management and integrated modeling in Lake Erie

Lake Erie, the shallowest of the Great Lakes, has been severely impacted by eutrophication-related problems including excessive harmful algal blooms (Stumpf et al., 2012; Bertani et al., 2016), dissolved oxygen depletion (Zhou et al., 2013; Rucinski et al., 2010), and excessive growth of macroalgae in the eastern basin (Higgins et al., 2008; Depew et al., 2011; Watson et al., 2016). To ameliorate the severity of these eutrophication phenomena, the reduction of nutrient loading has been regarded as the primary and most effective mitigation strategy (Maccoux et al., 2016).

A novel multi-model ensemble strategy was developed aiming to capitalize upon the wide variety of both statistical and mathematical models of variant complexity available in Lake Erie (Arhonditsis et al., 2019a, 2019b). This multi-model framework was used to examine the achievability of the ecosystem indicator targets under various external nutrient loading conditions (Arhonditsis et al., 2019a, 2019b). In terms of model diversity, the local watershed modeling work has been based on five independent applications of the same Soil and Water Assessment Tool (SWAT) model. These models collectively captured some of the uncertainty in watershed attributes and functioning (Scavia et al., 2017). Analysis of scenarios for best management practices were designed after considering issues related to their practical implementation and policy feasibility. The degree of divergence of the individual model forecasts for a given management scenario examined offered insights that can meaningfully inform the environmental policy analysis process.

The nutrient loading targets and ecosystem response indicators were based on the offshore waters of Lake Erie, and were thus unable to capture the water quality conditions in nearshore areas of high public exposure (e.g., beaches) (Arhonditsis et al., 2019b). This practice was criticized as being neither reflective of the range of spatiotemporal dynamics typically experienced in the system nor suitable to evaluate the progress with ecosystem services at the degree of granularity required to assess the public sentiment. Generally, this outdated limnological practice to basing the water quality assessment on the offshore zone with a coarse time scale has two major flaws: (*i*) offshore waters cannot effectively track the progress with the response of the system, as it is not clear to what extent an incremental improvement in the open waters is translated into distinct changes in the nearshore; and (*ii*) the environment targets and decisions are implicitly disconnected with our aspiration to protect ecosystem services and gauge public satisfaction at the appropriate resolution.

to be placed on the interfaces between the data produced from monitoring and available models. A closer link between monitoring and modeling aids the validation of process-based models and advances the construction of empirical, data-driven models (Rykiel, 1996; Nichols et al., 2011). As data and models go hand in hand, inadequate or poorly designed water quality monitoring poses constraints to the predictive power of models (Rode et al., 2010; Robson, 2014). Therefore, if we strive to maximize the benefits from adaptive management, monitoring should be – at least partly – "model-driven" and provide data that better match the resolution and parameters of process-based models (Robson, 2014). In turn, as the cycles of adaptive management progress, a well-fitted model can be used to optimize monitoring programs by offering insights into points in time, locations, or facets of the ecosystem functioning, where more information is needed (Dabrowski and Berry, 2009; Filgueira et al., 2013).

Regarding the latter prospect, there are several recent studies illustrating how the Bayesian inference methods can improve model forecasts and management actions over space and time (Arhonditsis et al., 2007, 2018). The Bayesian approach provides a posterior predictive distribution that explicitly consider model residual variability, measurement error, parameter uncertainty, natural variability, and other sources of error. The Bayesian (iterative) nature of the presented modeling frameworks is conceptually similar to the policy practice of adaptive management, as well as to the scientific process of progressive learning by offering a natural mechanism to sequentially update our knowledge on model inputs and structure every time as new data are collected from the impaired system. Importantly, the probabilistic statements provided from the Bayesian parameter estimation techniques can indicate where the limited monitoring resources should focus on (Arhonditsis et al., 2018). Specifically, additional data collection efforts can target "hot spots" or "hot moments", where the predictive distributions are suggestive of a high probability of non-attaining water quality goals or, alternatively, an unacceptably high variance. Thus, the uncertainty of a model coupled with the rigorous assessment of the value of information provided by past and present datasets can guide additional monitoring efforts by optimizing the sampling designs.

4.4. *Linking economic aspects with environmental monitoring and assessment*

The fact that environmental monitoring is a fundamental component of any adaptive management framework can offer "ammunition" to allocate more resources that would improve our sampling efforts and learning capacity (Williams et al. 2009, Kotamäki et al., 2019). Monitoring itself should adapt to changes in management targets, evolving knowledge and new technologies (Lindenmayer and Likens, 2009). Bearing in mind that sampling campaigns are far less expensive compared to the value of the resources they are intended to protect and the policies they inform (Lovett et al., 2007), the funds used for monitoring can be seen as a "much-needed" investment to improve management decisions (Nygård et al., 2016; Koski et al., 2020). The concept of value of information has been identified as a means to assess the benefits gained by improving our knowledge of the studied system and understand the role of uncertainty (or lack knowledge) in management decisions (Williams and Johnson, 2015a, 2015b).

When ecological model predictions and data suggest high uncertainties about the management outcomes, the concrete economic benefits might be easier for the decision-makers to grasp when weighting the risks of our actions to the environment (Yang et al., 2020). The latter assertion underscores the need of introducing models that account for the economic facets of environmental management problems and the importance of expressing the benefits of a well-functioning ecosystem in monetary terms (Hjerppe et al., 2016). Ecosystem services and their monetary valuation can be used as indicators when assessing the impacts of environmental degradation on human welfare. Combining impact assessments with information on the socioeconomic costs of alternative measures enables an analyst to weigh both costs and gains of proposed policy reforms (Hyytiäinen et al., 2015; Keiser et al., 2019). The advent of ecological economics has led to the development of optimization tools that collectively use cost functions and ecological processes to develop cost-efficient management strategies (Ahlvik et al., 2014; Wulff, 2014; Hansen et al., 2021).

4.5. Connecting knowledge producers and knowledge users

Scientific knowledge is important for sustainable water resources management, but our thesis is that this knowledge is more useful when actively co-produced with stakeholders (Cvitanovic et al., 2015; Malve et al., 2016), and truly connected with actions aiming at fostering environmental sustainability (van Kerkhoff and Lebel, 2006). Prime examples of concrete science-policy interfaces are the global expert panels or platforms such as the Intergovernmental Panel on Climate Change (IPCC) and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). Similar national-scale expert groups are important in increasing the accessibility, understanding, and appreciation of scientific knowledge and in engaging policy-makers and public to explore new or alternative environmental policies (Beck et al., 2014).

The robustness of the scientific information, its relevance to the policy and societal needs as well as the stakeholders' divergent values determine the effectiveness of the information used in decision making (Cash et al., 2003). The criteria of effective knowledge exchange also hold for any results produced by environmental models and decision-support tools. Model quality checklists have traditionally focused on their technical aspects, but model relevance and credibility should also be explicitly considered through deeper stakeholder engagement (van Voorn et al., 2016). Interactions between modelers and stakeholders and co-creation of operational tools enhance insights and mutual understanding (Carmona Mora et al., 2013, Malve et al., 2016). Increasing model acceptability requires collaborative development of guidelines and standards of model quality (Fisher et al., 2015).

Predictability is a critical part of the functionality of environmental legislation, even when the mechanisms of balancing socioeconomic values and environmental concerns are employed. The reluctance of legislators to adapt legal requirements according to the evolvement of scientific knowledge can create a situation that appears to be difficult to circumvent at the outset (Chalmers et al., 2006; Ebbesson, 2010, Paloniitty and Eliantonio, 2018, Soininen et al., 2019). Legal systems in democratic societies are multi-actor entities, comprising not only legislators but also the executive branches and administrative and judicial decision-makers, each vested with their own powers. There is a diverse landscape in how the administrative and judicial decision-makers deal with scientific knowledge and scientific uncertainties in the context of EU nature conservation law, where the legislative requirement on scientific certainty is even stricter than in the EU water management realm (Eliantonio et al., 2023). As the EU legal system consists of multiple levels, norms established at the EU level are implemented at the Member States' administrative-legal systems. However, the judicial decision-makers in individual Member States do not follow the strict requirements for scientific certainty established at the EU level. Instead, they have found their own ways to negotiate the rigid expectation calling for scientific certainty over the likelihood of a detrimental environmental impact (Eliantonio et al., 2023). The diversity of legal systems and their multilevel structure have rendered the precaution versus certainty dichotomy largely theoretical. From the perspective of comparative juridical review research, the legal landscape appears to be much more diverse.

The most constructive way forward has been the collaboration between courts and environmental agencies, working together to develop a mutually agreed policy-making process (Fisher et al., 2015). Modelers should transparently communicate the uncertainties and limitations associated with their assessments. Additionally, modelers should enhance their understanding of legal criteria to better meet the requirements set by the law for the models (Thorén et al., 2021), and actively participate in the "science-and-law" discourses together with legal decision-makers. The legal community, on the other hand, must be clear on the various ways they navigate the uncertainty landscape and openly express the decisions they take therein (Paloniitty, 2023). Last but not least, regulators must do their best to build regulatory instruments that facilitate open decisions on the model selection and uncertainty communication (Paloniitty and Kotamäki, 2021; Thorén et al., 2021, Eliantonio et al., 2023).

5. Conclusions

Decision-making aiming at sustainability requires reliable, timely, and forward-looking scientific evidence. This applies especially to lakes, rivers and coastal waters, which are sentinels of climate change and human activity, and their protection requires systematic long-term planning. Ecological indicators, predictive models, monitoring data, and scenario design can increase the understanding of complex socio-ecological linkages and provide essential information to guide decision-making. However, the information produced from these different strategies is inherently uncertain and can change significantly over time. It is critical to treat these lines of evidence as mere decision-support tools to moderate the unreasonable expectations of a high degree of confidence in the information produced. This is particularly true with the design of environmental laws, where the legal criterion of certainty complicates the use of information generated by models and scenarios. It is important to recognize that when the law does not allow the use of uncertain but still scientifically defensible evidence, valuable information may be completely disregarded in the long-run.

In conclusion, the following strategies are proposed to address these issues in future:

- Flexibility and room for learning should be formally built-in the governmental procedures to allow policies and actions, including the legally binding decisions, adapt to evolving scientific knowledge.
- Efforts should be made to translate theory-oriented frameworks to practical challenges of water management implementation; to strengthen connections between data, models, and scenarios; and to bring the scientific community and political decision-makers into a bilateral, mutually beneficial, dialogue.
- The determination of appropriate metrics and scales of expression along with the design of a monitoring program are critical steps to effectively track the progress of the system in both time and space.
- Of equal importance is the development of rigorous frameworks that quantify the socioeconomic benefits from a well-functioning ecosystem. Viewing ecosystems as providers of economically valuable benefits to humans, the concept of ecosystem services effectively links their structural and functional integrity with human welfare.

CRediT authorship contribution statement

Niina Kotamäki: Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **George Arhonditsis:** Writing – review & editing, Conceptualization. **Turo Hjerppe:** Writing – review & editing. **Kari Hyytiäinen:** Writing – review & editing. **Olli Malve:** Writing – review & editing, Conceptualization. **Otso Ovaskainen:** Writing – review & editing. **Tiina Paloniitty:** Writing – review & editing. **Jukka Similä:** Writing – review & editing. **Niko Soininen:** Writing – review & editing. **Benjamin Weigel:** Writing – review & editing. **Anna-Stiina Heiskanen:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

This work was funded by the Strategic Research Council of Academy of Finland (Contract No. 312650 BlueAdapt). OO was supported by the Academy of Finland grant 309581 and the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program; grant agreement No 856506; ERC-synergy project LIFEPLAN. We thank Katri Haatainen and Luukas Myller for helping with the visualizations.

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