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Oceans of plenty? Challenges, advancements, and future directions for the provision of evidence-based fisheries management advice

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Oceans of plenty? Challenges, advancements, and future directions for the provision of evidence-based fisheries management advice

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Abstract Marine population modeling, which underpins the scientific advice to support fisheries interventions, is an active research field with recent advancements to address modern challenges (e.g., climate change) and enduring issues (e.g., data limitations). Based on discussions during the 'Land of Plenty' session at the 2021 World Fisheries Congress, we synthesize current challenges, recent advances, and interdisciplinary developments in biological fisheries models (i.e., data-limited, stock assessment, spatial, ecosystem, and climate), management strategy evaluation, and the scientific advice that bridges the science-policy interface. Our review demonstrates that proliferation of interdisciplinary research teams and enhanced data collection protocols have enabled increased integration of spatiotemporal, ecosystem, and socioeconomic dimensions in many fisheries models. However, not all management systems have the resources to implement model-based advice, while protocols for sharing confidential data are lacking and impeding research advances. We recommend that management and modeling frameworks continue to adopt participatory co-management approaches that emphasize wider inclusion of local knowledge and stakeholder input to fill knowledge gaps and promote information sharing. Moreover, fisheries management, by which we mean the end-to-end process of data collection, scientific analysis, and implementation of evidence-informed management actions, must integrate improved communication, engagement, and capacity building, while incorporating feedback loops at each stage. Increasing application of management strategy evaluation is viewed as a critical unifying component, which will bridge fisheries modeling disciplines, aid management decision-making, and better incorporate the array of stakeholders, thereby leading to a more proactive, pragmatic, transparent, and inclusive management framework–ensuring better informed decisions in an uncertain world.

Keywords Stock assessment · Fisheries management · Data-limited methods (DLMs) · Ecosystem and climate models · Spatial modeling · Management strategy evaluation (MSE)

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Extended author information available on the last page of the article

Introduction

Fisheries management broadly encapsulates the end-to-end process of creating fisheries policy based on evidence-informed scientific advice to ensure the sustainable harvest of marine resources, and includes data collection, scientific research and advice, stakeholder engagement, and subsequent implementation of management actions (Cochrane and Garcia 2009).

Ensuring sustainable fisheries and healthy marine ecosystems has been the goal of fisheries management since the turn of the twentieth century, when the limited production of fish species and the potentially detrimental impacts of industrial fishing became widely recognized (Larkin 1978; Quinn 2003; Angelini and Moloney 2007). The ability of management frameworks to maintain healthy populations of fish and the livelihood of fishers has been mixed over the course of the 20th and early 21st centuries (Caddy and Cochrane 2001; Hilborn et al. 2020). However, fisheries successes have proliferated as stewardship of the world's living marine resources has evolved to more thoroughly rely on evidence-based and scientifically-informed management (Hilborn 2012; Melnychuk et al. 2017). Because evidence-based management relies on outputs from a variety of fields, understanding critical challenges across such fields can help illustrate issues facing fisheries management, while highlighting emergent solutions.

Historically, legal mandates and resultant policies have driven the development of the scientific tools needed to inform fisheries management decisions (Hilborn 2012). Concomitantly, the amount, quality, and types of fisheries and biological data have influenced the scientific approaches that advise marine policy (Anderson 2015). Traditionally, the scientific basis for fisheries management actions has been derived from stock assessments, which analyze fishery catch and effort data, fishery-independent survey information, and demographic rates to determine the impacts of fishing on a population and identify sustainable rates of exploitation (Methot 2009). The implementation of total allowable catch quotas based on the outputs of stock assessments were considered a major advance in quantitative fisheries management and a primary factor in rebuilding of many fish stocks globally (Hilborn 2012)—when the scientific advice has been heeded (Galland et al. 2018; Karnauskas et al. 2021). Despite what was heralded as a 'golden age' of fisheries modeling in the 1980s and 1990s, at the turn of the 21st century, Quinn (2003) foresaw several dilemmas to continued advancements. These impediments included: inadequate communication among managers, stakeholders, and scientists; the inability to understand and adequately utilize uncertainty within the management framework; data and computing power limitations preventing implementation of complex integrated analyses; the lack of rigorous testing of multispecies and ecosystem models and replacement of, instead of coevolution with, single-species assessments; and difficulties incorporating spatial structure, habitat relationships, and climate-induced changes into assessment models.

In the intervening two decades since Quinn's (2003) 'clouds on the horizon' outlook, major strides have been made in the collection of data to support fisheries models, the modeling frameworks used to determine marine population health, and the associated management frameworks. In particular, a critical aid to management decision-making has been the development and expansion of simulation-based management strategy evaluation (MSE). MSE enables a priori analysis of tradeoffs in performance metrics associated with potential management strategies (i.e., the combination of data collection, the analyses applied to those data, and the decision rule or harvest control rule, HCR, used to determine management actions based on those data or analyses; note that a fully specified and simulation tested management strategy is referred to as a management procedure, see Supplementary Information Table S1 for definitions of common terms), and exploration of management strategy robustness (i.e., the ability to maintain desired performance across the range of plausible simulated dynamics) to potential system uncertainties (Rademeyer et al. 2007; Punt et al. 2016). Simultaneously, expanded research on data-limited methods (DLMs), which are empirical or analytical approaches to obtain performance indicators of population status in the absence of an integrated stock assessment model, has allowed the provision of quantitative scientific advice for the large diversity of data-limited fisheries.

Despite strides in managing the world's marine resources, several stressors have received renewed attention as potential impediments to sustainable use, including climate change, loss of biological diversity, and socioeconomic inequities. Management bodies worldwide increasingly acknowledge these challenges and are implementing novel approaches to engage stakeholders and citizens in fisheries management (e.g., the inauguration of the United Nation's 'Ocean Decade' in 2021; Pecl et al. 2022). Moreover, recent advances across scientific disciplines and the expansion of modeling tools suggests there are opportunities for synergism to address these challenges. A review of current developments across fisheries modeling disciplines is needed to highlight important research themes, while helping to identify the challenges that remain for the provision of evidence-based fisheries management advice. Based on a multi-session symposium during the 2021 World Fisheries Congress, titled 'Land of Plenty: Advances and Future Directions in Population Dynamics Modeling to Support Fishery Management', we will synthesize the challenges and emerging solutions in fisheries modeling. We will conclude with a perspective on near-term evolutions in the evidence-based scientific advisory process by developing a strategic guide for improving fishery management frameworks (i.e., including data collection, scientific analyses, advice formulation, and stakeholder engagement). While the science and policy used to manage fisheries is often intertwined with the broader complexities of ocean governance and marine spatial planning initiatives in the emerging blue economy, the latter topics are outside the scope of the current manuscript. We focus on quantitative fisheries management advice and the modeling tools used to support decisions related to sustainable harvest of fish populations.

Novel data to stimulate improvements in scientific advice

Scientific understanding of the marine environment, and the ability to realistically model it, requires collection of considerable data. Ever-improving technology has enabled increased collection, better resolution, wider applicability, improved dataset interoperability, and faster collation and dissemination of data. However, the ability of modelers to effectively utilize the increasing number of data streams often lags, because most fisheries models exploit the contrast in long-term time series. Many new data types are only now starting to emerge from experimental collection protocols to be more widely integrated and institutionalized. However, it is expected that there will be rapid incorporation of a variety of 'new' data types within fisheries models in the near future. Given that the collection of data (and associated knowledge gained) is the cornerstone for developing evidence-informed management advice, we begin with a discussion of data advances that are likely to spur improvements in fisheries modeling and management (see Table 1 for a summary of novel data streams and associated potential uses in fisheries models).

Fisheries monitoring data

Robust fisheries-dependent data from a combination of human at-sea observer programs, recently introduced fisheries electronic monitoring (EM) systems, port sampling, and self-reported logbooks can be used to develop indices of abundance, understand species distributions, identify bycatch hotspots, and elucidate age- or size-composition of the population (Gilman et al. 2017). Fisheries EM systems are increasingly being used to complement conventional onboard observer programs and to initiate at-sea monitoring where none had previously existed (van Helmond et al. 2020). While EM systems are not yet able to collect all of the data types collected by conventional observer programs, EM may provide more certain data (van Helmond et al. 2020) because it overcomes sources of statistical sampling bias faced by observer programs (e.g., changes in fishing practices, coercion, or deception when observers are present; Babcock et al. 2003; Benoit and Allard 2009; Gilman et al. 2019b). Unlike observers, EM analysts can view multiple fields of view simultaneously, while continuously monitoring the fishing platform. Thus, increasing implementation of EM systems will help provide more consistent and dedicated sampling programs globally, though overhead costs (e.g., video analysis) may impede application in resource-limited regions. For recreational and small-scale fisheries, EM can take the form of slipway, boat ramp, or dock-based camera systems that can estimate fishing effort and potentially catch (e.g., Powers and Anson 2016). Increasingly, fishing vessel position data can also be obtained, for example, from satellite-based vessel monitoring systems (VMS) or Automated Identification Systems (AIS), which can be used to identify spatiotemporal patterns in the distribution of fisheries. With advancing technology (i.e., continued miniaturization and reduced cost), it is envisioned that similar monitoring of coastal waters will be possible through GPS reporting on small vessels, recreational reporting of precise catch locations from phone-based apps, and even data collected from divers or spear-fishers (e.g., including depth and temperature profiles as from electronic tags attached to fish). As VMS and EM data collection continue to expand, research should focus on identifying fine-scale patterns in resource extraction to enable better understanding of linkages between catch rates and habitat, oceanographic variables, and species distributions (e.g., Gardner et al. 2022). Despite the undeniable benefits of increasingly high resolution data on fishery removals, behavior, and distribution, the ability to utilize the wealth of information from fishery-dependent sources is limited if the data cannot be readily shared or easily accessible by researchers due to increasing confidentiality concerns (Bradley et al. 2019). Therefore, collaboration among scientists, managers, and stakeholders is needed to improve trust, transparency, and sharing of information to ensure development of protocols that enable fishery-dependent data to be fully utilized.

Local ecological knowledge, crowdsourcing, and self-reported socioeconomic data

Understanding ecological functioning and socioeconomic dynamics often requires first-hand observation and adequate sample sizes, both of which are costly and difficult to obtain from scientific platforms. In particular, socioeconomic data can be elusive for all harvest sectors and fisheries and may not be accessible even when collected due to confidentiality concerns, despite being imperative for developing biosocioeconomic models, understanding fishermen behavior, and developing appropriate economic performance measures. It is increasingly being recognized that commercial, recreational, indigenous, and traditional stakeholders hold a wealth of ecological and systems knowledge, given their first-hand observations and experiences (Beaudreau and Levin 2014). In particular, local ecological knowledge (LEK) can be useful to develop hypotheses about ecosystem functioning (e.g., Duplisea 2018), map resource and fishing effort distributions (Hall-Arber et al. 2009), fill in spatiotemporal data gaps (Lopes et al. 2019), establish population or ecosystem baselines, and help understand the broader bio-socioeconomic system (Rosellon-Druker et al. 2019), particularly when such data are not formally reported in logbooks. Similarly, the increasing use of crowdsourced or cooperative research collection programs, through either citizen science collected or fishermen self-reported data (e.g., in the form of app-based reporting or voluntary submission of samples), is proving to be a cost-effective way to improve sample sizes and spatiotemporal data coverage (Fairclough et al. 2014; Thorson et al. 2014; Bonney et al. 2021; Russo et al. 2021). App-based self-reporting approaches have been particularly useful for collecting socioeconomic data and may help improve stakeholder engagement and willingness to share otherwise confidential information (Skov et al. 2021). In the future, the ability to data-mine and analyze the increasing quantity of digital fisheries data (e.g., social media posts and search trends) will further enable rapid collation of baselines and subsequent patterns in both socioeconomic and ecological factors (Lennox et al. 2022). However, self-reported data can sometimes be unrepresentative when economic or social factors exist and each of these data sources is associated with potential sampling biases. Thus, self-reported data must be carefully vetted to ensure data quality and avoid the pitfalls of anecdotal evidence and non-representative samples, which can bias model outputs and increase scientific uncertainty (Balazs et al. 2021). Although methods exist to address many types of biases associated with self-reported data (e.g., Fairclough et al. 2014), further emphasis should be placed on similar research (i.e., to overcome sampling limitations) to ensure wider utilization of the plethora of fishery- and citizen-dependent data becoming available. Moreover, further expansion of participatory modeling initiatives would promote increased sharing of socioeconomic data, while developing pathways for increased accessibility (i.e., across research groups and government organizations) and subsequent analysis of otherwise confidential data streams.

Autonomous sampling

Although fishery-independent surveys are desirable, many situations exist that make surveys infeasible due to large survey areas (e.g., entire oceanic basins for tuna species), limited manpower, dangerous conditions, or areas that are inaccessible to the survey gear (e.g., high-relief habitat). The ability to conduct acoustic surveys from uncrewed platforms could help replace or augment expensive vessel-based surveys (e.g., De Robertis et al. 2021), thereby addressing many of these concerns using a more cost-effective approach, though lack of age- or size-composition data from acoustic surveys remains problematic. Remote video surveys can provide indices of abundance and length composition (e.g., Thompson et al. 2022), though application may be limited to sessile species or species with

Table 1 A summary of novel data sources and how they can be utilized in fisheries models

Data source	Types of data collected	Model use
Electronic Monitoring (EM)	Catch estimates CPUE Bycatch Discards	Index of abundance for empirical management strategies and model fitting Spatiotemporal models of distribution, bycatch hotspots, and habitat affinity Inform stock assessment development and model fitting Inform technical interactions for ecosystem models
Vessel Monitoring System (VMS)	Georeferenced vessel, catch, and bycatch locations	Spatiotemporal models of species distribution, bycatch hotspots, and habitat affinity Impacts of area-based management tools (ABMTs) on effort redistribution
Local Ecological Knowledge (LEK) and Community Data	Spatiotemporal distribution maps Self-reported catch, effort, bycatch, and socioeconomic data Personal ecological observations	Compare and ground-truth model outputs Fill spatiotemporal data gaps Develop baselines of abundance or ecosystem health Identify model assumptions or hypotheses
Crowdsourced Citizen Science Data	Observations of presence or absence Self-collected samples (e.g., report or release tagged fish, biological samples, eDNA)	Improve stock assessment sample sizes for biological data Spatiotemporal models of distribution, bycatch hotspots, habitat affinity, and range shifts Develop indices of abundance Fill spatiotemporal data gaps
Socioeconomic Surveys (e.g., App-based Self-Reporting or Digital Fisheries Data)	Ex-vessel prices and costs Drivers of fishermen behavior Social dynamics Non-harvest use valuations Self-reported catch, effort, bycatch, and socioeconomic data (e.g., recreational fishery statistics)	Data to estimate parameters of bioeconomic models Develop performance measures for MSE Develop integrated ecosystem assessments More precise recreational catch and effort estimates for stock assessment
Fishery-Independent Surveys	Biomass estimates Age and length frequency Biological samples eDNA Stomach contents Genetic structure	Develop indices of abundance and estimates of total abundance Improve sample sizes for age and length composition inputs to stock assessments along with maturity, growth, and fecundity estimates Spatiotemporal models of species distribution and range expansion or contraction Index of abundance for empirical management strategies Inform stock assessment development and model fitting Identify population structure for spatial stock assessments Data to inform multispecies interactions (e.g., predation)
Uncrewed Survey Platforms	Acoustic or video survey biomass estimates Length frequency distributions from cameras Oceanographic and environmental data eDNA	Indices of abundance for stock assessment or empirical management strategies Improved sample sizes for length composition inputs to stock assessments Spatiotemporal models of species distribution and range shifts Inform ecosystem and habitat linkages

Table 1 (continued)

Data source	Types of data collected	Model use
Biohybrid Systems (e.g., FishBots)	Oceanographic and environmental data Behavior (e.g., feeding, predator–prey, habitat use) Movement	Inform environmental linkages Inform assumptions regarding connectivity patterns and habitat use Test hypotheses and develop mechanistic understanding
Tagging Data	Biologging (e.g., acoustic telemetry, archival tags, satellite tags) Mark-recapture Oceanographic data (from tag sensors) Gene-tagging Close-kin mark-recapture (CKMR)	Inform assumptions regarding connectivity patterns and habitat use Estimate movement and mortality in tagging, assessment, spatial, or ecosystem models Spatiotemporal models of species distribution, habitat affinity, and range shifts Develop indices of abundance and estimates of total abundance Operational biophysical models
Integrated Ocean Monitoring	Remote sensing Synoptic, real-time oceanography	Operational biophysical models (e.g., larval individual-based models) Environmental and ecosystem linkages to population processes
Natural Markers	Otolith microchemistry Parasite infestation	Catch composition to assign input data to population of origin Inform assumptions regarding connectivity patterns and habitat use Estimate movement and mortality in tagging, assessment, spatial, or ecosystem models

strong habitat affinity (e.g., reef fish). Similarly, passive acoustic networks are available at basin scales to track phenology and distribution for mobile protected species (Davis et al. 2020), allowing improved inference about the seasonal overlap between populations and conventional surveys. Biohybrid systems (e.g., 'FishBots' that can mimic biological counterparts) also show promise for enabling in situ data collection (Schmickl et al. 2021). Future autonomous sampling research should focus on the evolution of joint survey platforms that combine multiple collection methods without substantially increasing vessel days or labor requirements (e.g., simultaneous collection of acoustic, video, oceanographic, and environmental DNA, eDNA, data). For example, recent pilot studies demonstrate promise for combining eDNA and acoustic-midwater trawl sampling (Shelton et al. 2022).

Integrated ocean monitoring networks

Improved technology has led to a proliferation in bio-logging data via satellite tags, archival tags, and acoustic telemetry, which provide information on movement, distribution, abundance, and mortality (e.g., direct estimates of natural mortality, which is a problematic parameter for population models; Sippel et al. 2015; Block et al. 2019). As these data become better integrated into ocean monitoring systems, the ability to track animals globally and across regional sensor arrays (e.g., for telemetry data) will continue to improve the ability to link animal movements with biophysical variables (Lowerre-Barbieri et al. 2019). Moreover, marine animals can themselves become autonomous oceanographic samplers when fit with electronic tags and associated ocean sensors, thereby providing data from historically undersampled locations (e.g., ice covered polar seas and remote tropical coastal regions; McMahon et al. 2021). Similarly, remote sensing and in situ measurement systems now allow synoptic, near real-time information on an array of oceanographic variables (e.g., temperature, chlorophyll concentrations, velocity fields, habitat data, etc.; Davidson et al. 2019). Operational oceanography data have greatly improved oceanographic models critical to understanding fish early life history, dispersal, ecosystem dynamics, and potential environmental linkages (Hidalgo et al. 2016), while enhancing the ability to inform dynamic ocean management (Maxwell et al. 2015). Resources to ensure long-term maintenance and yearly updates of oceanographic models should be a priority, especially as biophysical models are further integrated into scientific advice.

Natural markers and omics

The recent and rapid advancements in the 'omics' sciences, particularly the ability to perform high throughput genetic sequencing, allows cost-effective, often non-lethal, monitoring of species population structure and genetic composition of catch (Papa et al. 2021), presence-absence (e.g., eDNA; Wang et al. 2021), and absolute abundance (e.g., gene-tagging or close-kin mark-recapture, CKMR; Preece et al. 2015; Bravington et al. 2016). Additionally, by analyzing the DNA of stomach contents, genetic analyses can provide insight into diet and predator–prey interactions (e.g., Paquin et al. 2014). Genetic data can also be combined with analysis of natural markers (e.g., parasite infestation or otolith microchemistry) to more fully understand population structure, migration patterns, and habitat usage throughout the entire life cycle, including natal birth locations, larval drift, juvenile nursery areas, adult feeding areas, and spawning migrations (e.g., Hussy et al. 2022). Perhaps most revolutionary, though, is the ability to estimate absolute abundance using CKMR or gene tagging, which represents a potential sea-change in monitoring marine population trends and may powerfully augment age-structured stock assessment approaches (Preece et al. 2015; Bravington et al. 2016; Conn et al. 2020). Continued research to address potential bias associated with analyzing CKMR data (e.g., due to spatial sampling limitations and the need for additional demographic information; Conn et al. 2020; Trenkel et al. 2022) should be a high priority, because there is an undeniable utility of CKMR data for supporting fisheries management (e.g. Hillary et al. 2016, 2019).

A key future direction: hypothesis-driven data collection

Historically, data collectors and modelers did not often collaborate during data collection study design phases. The result has been that not all collected data are able to be effectively utilized within modeling or management frameworks. However, emphasis is increasingly being placed on conducting hypothesis-driven data collection and research, which requires careful communication among observationists and modelers. Through clear communication across disciplines, experimental designs for data collection can be tailored to the needs of management, while also supporting development of robust scientific advice. Stakeholder input and LEK, along with increased utilization of cooperative research and crowdsourcing, can be particularly helpful for implementing collection protocols that are both feasible and cost-effective. By tailoring and tuning data collection, while also developing clear pathways for communication and knowledge sharing, there is likely to be a synergistic effect leading to development of more mechanistic models of environmental and climate drivers based on first principles. In addition, simulation analyses (e.g., MSE) can be used to prioritize data types and identify data collection experimental designs that are most likely to result in cost-effective and robust management outcomes. However, given species redistributions due to climate change, careful consideration must be given to optimizing sampling locations. For example, data collection protocols need to be adequately augmented to ensure that sampling occurs at distributional fringes enabling detection of range shifts, which may require increased utilization of non-traditional (e.g., citizen science or eDNA) data (Karp et al. 2019; Melbourne-Thomas et al. 2022). Ultimately, CKMR calibrated visual surveys, which provide direct estimates of fish abundance, are a quantum leap forward over historical survey methods that provide only an indicator of abundance trends, and should help greatly improve scientific advice in coming years.

Current challenges and emerging solutions for provision of evidence-informed fisheries management advice

A review across five interrelated fields of fisheries modeling, including data-limited methods, stock assessment, spatial modeling, ecosystem modeling, and MSE, is undertaken to highlight existing challenges and evolving methodology in the development of scientifically-informed fisheries management advice. We conclude with a summary of the primary impediments occurring at the science-policy interface (see Table 2 for a summary of these primary challenges and emergent solutions).

Data-limited assessment and management methods

The majority of fisheries (by volume) do not possess the data needed to support traditional assessment methods nor the resource capacity to develop model-based management advice (e.g., Alabsi and Komatus 2014; Geromont and Butterworth 2015). The term 'data-limited' continues to be the catch-all phrase for fisheries or stocks that have data deficiencies, but it can also refer to situations that lack technical or managerial resources (Cope et al. In Press; Dowling et al. 2015). The obvious issue for these data-limited cases is low quality or lack of data, which necessitates maximizing information content from existing data sources (e.g., trends in catch data; McGarvey et al. 2005), borrowing information from similar data-rich species (e.g., Jiao et al. 2011), exploring low-cost monitoring methods (e.g., eDNA; Lacoursiére-Roussel et al. 2016), or collecting LEK (e.g., Machado et al. 2021) to monitor population trends. The methods used to assess stocks with data-limitations have grown, particularly over the past two decades (see Dowling et al. 2008, 2019), largely due to mandates in areas with strong governance to maintain sustainable stock levels through management of all species (Newman et al. 2014, 2015). However, questions remain on how best to inform managerial decisions given the growth of DLMs and the multitude of stocks that are categorized as 'data-limited'. Each data-limited case presents unique challenges and no single solution or generic best practice exists (Dowling et al. 2019).

Generic DLMs result in model misapplication

Assessment practitioners feel pressure to undertake formal stock assessments even when extreme data limitations exist, which often results in model misapplication as practitioners seek generic solutions or blanket application of a single analytical approach to many stocks (e.g., as an efficient way to simultaneously assess and manage multiple data-limited stocks). Although DLMs are often presented as 'simple' and can be technically easy to apply, practitioners can fail to appreciate their limitations and simplifying assumptions, while best practices for DLM use are complex and dynamic. Blindly applying a suite of DLMs without understanding how the data were collected or the underlying model assumptions can lead to unreliable assessments and inappropriate management advice (Dowling et al. 2019). Likewise, increased uncertainty is expected in DLMs due to the need for simplifying model assumptions, sharing biological data across regions or species, mis-identification of similar species, and low or haphazard sampling intensity. Given the proliferation of DLMs, tools are warranted to guide practitioners in identification of appropriate DLMs to utilize, while also highlighting critical assumptions of chosen DLMs (e.g., FishPath; Dowling et al. 2016; Crosman et al. 2020). Indeed, robust and effective management strategies can still be implemented using DLMs when the limitations of the data collection, fishery, and management frameworks are adequately considered and addressed. This can be accomplished through tailored MSEs (e.g., Carruthers et al. 2014, 2016a), which are able to test whether management strategies are robust to modeling limitations, and can be guided through dedicated digital tools (e.g., www.merafish.org). Initiatives to incorporate existing DLMs within a few easily accessible tools should remain a priority, with a focus on flexibility to incorporate new data types (Cope 2013; Cope et al. 2015; Carruthers and Hordyk 2018).

Difficulties monitoring and managing multispecies fisheries

Many stocks worldwide are caught in multispecies fisheries, but lack the data or resources to adequately monitor each stock individually. Approaches to assess and manage data-limited multispecies fisheries include selecting indicator species to represent stocks not assessed using quantitative stock assessment or aggregating stocks into a group (i.e., a species complex). The indicator species approach assumes that the chosen species are representative of other unassessed species. The species selected, however, should generally have higher risk levels (i.e., be more vulnerable to external pressures) compared to the other non-indicator species (Landres et al. 1988; Newman et al. 2018). Conversely, monitoring and assessing a stock complex relies on appropriately

Table 2 Current challenges for the development of evidence-informed management advice and recommendations to help overcome these issues

Category	Challenge	Recommendation
Data	Data limitations	Better incorporation of novel data streams Institutionalize novel data collection with permanent funding Increased utilization of cooperative research opportunities Emphasize data collection over modeling in data and capacity limited regions Focus on collection of community data to establish baselines in artisanal fisheries
	Data integration	Better communication between data collectors and modelers to understand sampling bias and non-independence Expansion of the integrated modeling framework to explicitly account for sampling issues within observation and likelihood components Increased utilization of spatial models to fit data at scale of collection Incorporate random effects and spatial autocorrelation to reduce effective parameters in models Utilize hybrid and multiscalar modeling frameworks to fit varying scales of data Use MSE to optimize data collection programs to support the needs of management
Models	Inadequate assumptions	Improved communication across disciplines, better stakeholder engagement, and use of LEK to develop hypotheses and assumptions Focus on hypothesis-driven data collection to help develop mechanistic understanding of processes Interdisciplinary research teams to adequately account for system processes and acknowledge process error Use MSE to determine robustness of assessment models to specification error Continued development of good practices to aid model building decisions
	Parameter non-stationarity	Interdisciplinary research teams to better identify regime shifts and causes Process studies to identify causal mechanisms that link population processes to environmental drivers Simultaneous and parallel development of single species and ecosystem models to aid synergistic understanding of system and reference points Utilize random effects to address variability
	Appropriate diagnostics	Continued development of good practices Increased training opportunities to disseminate good practices Communication among disciplines and regions to share approaches
	Conveying realistic uncertainty	Improved communication between scientists, stakeholders, and managers Development of intuitive and interactive graphical outputs along with digital applications to aid understanding of model assumptions on results Clear acknowledgement of model limitations and uncertainty Development of multiple models and model ensembles to address structural uncertainty
	Developing sustainable catch targets	Focus on developing baselines through community initiatives and social learning in data and capacity limited situations Apply meta-analytic techniques to borrow life history parameters (across regions and species) when data is limited or models are unstable Use simple management strategies and make management objectives more intuitive Develop reference points from single species and multispecies models simultaneously to help identify appropriate bounds on harvest

Table 2 (continued)

Category	Challenge	Recommendation
Policy Formation	Ill-defined objectives, poor transparency, limited legitimacy	Facilitated communication among stakeholders, managers, and scientists to ensure all participants understand the goals of management Use MSE to formalize co-management, encourage participatory modeling, and aid clear communication of trade-offs in performance measures Explore more intuitive, empirical harvest control rules Training to aid stakeholders in better understanding the management process, how to effectively participate, and to help manage expectations Define tangible and quantifiable management goals (e.g., for ABMTs) before implementation to enable measuring performance Better integrate interdisciplinary research into management advice to ensure stakeholder needs are being measured and addressed
	Institutional inertia	MSE to clearly demonstrate the robustness and improved performance of new management strategies Clear acknowledgement and communication of uncertainty Improved and facilitated communication Emphasize pragmatism and a focus on data collection (over inaction) when data are limited Training and exposure to alternate model and management approaches to aid acceptance of new methods (e.g., empirical management strategies, spatial assessments, and MICE) Increasing application of spatiotemporal models to inform adaptive fine-scale area based management tools (ABMTs)
	Weak governance	Implement social learning initiatives to communicate importance of self-governance Use community driven data to establish baselines and develop sustainable harvest approaches Emphasize pragmatism and local stewardship for artisanal fisheries
	Marine spatial planning	Account for non-harvest use in MSE management objectives and performance metrics Expand participation in management to include non-fishery stakeholders associated with the blue economy Integrate social science models and data to better address broader socioeconomic objectives Utilize spatially explicit models to better account for partitioning of the marine realm (e.g., when developing MSE operating models)
	Adapting to climate change	Use MSE to explore management strategy robustness to climate impacts (e.g., species redistribution) Improve communication across regional and institutional boundaries to address species on the move Implement more flexible and adaptable management utilizing high resolution spatiotemporal models as species move across boundaries Improve data collection at the fringes of a species' range to ensure ability to identify changing distributions Increasingly explore stakeholder collected data to improve sample sizes and identify changes in distribution

assigning stocks to a complex assuming that grouped species will have similar life history traits and functional responses to ecosystem and anthropogenic perturbations (e.g., Cope et al. 2011; Omori et al. 2021). As the trend towards ecosystem-based fisheries management (EBFM) continues, increased emphasis will be placed on simultaneously managing across species, which should aid in developing management advice that transcends technical interactions across multiple species (Fulton et al. 2019). However, monitoring data will still be required to inform decision-making. Therefore, further work is recommended on developing tools to assess and manage species complexes (e.g., using multispecies spatiotemporal models; Omori and Thorson 2022), but pragmatic management solutions should emphasize increased data collection on all species associated with complexes.

A key future direction: empirical management strategies

Data- and capacity-limited fisheries face resource limitations, perceived uniqueness of circumstances, and a broad universe of assessment and management options that is difficult to navigate. Rather than aiming for a 'gold standard' with respect to formal stock assessment, and thus delaying management action until an improved assessment option is available, emphasis on local stewardship is required. For management of data-limited fisheries, increased pragmatism is likely to become a more widely recognized priority, where managers accept the current limitations and aim to work within these constraints to achieve sustainable, rather than optimal, management of the resource. Thus, the emphasis will be placed on improved, targeted data collection that addresses priority management objectives (as opposed to data collection that are not directly applicable for assessing and managing these fisheries). Incremental and adaptive management approaches should be emphasized, given that it is unrealistic to readily overcome data and capacity limitations to move from no analytical assessment to a model-based approach. For instance, when a measure of relative abundance, yield-per-recruit, egg-per-recruit, or an indicator based on a representative length-frequency sample can be developed, it provides the minimum requirement for an HCR to regulate exploitation levels (Hordyk et al. 2015; Jardim et al. 2015; Wakefield et al. 2020). Multiple empirical indicators can be used in indicator-based decision frameworks, wherein greater insight into stock status is provided by considering indicators in combination (Harford et al. 2021). Empirical and data-limited methods should be embedded within management strategies that are robust to the higher levels of uncertainty in assessment output by including precautionary management measures or buffers (Dowling et al. 2019). Achieving general consensus and buy-in from stakeholders to implement a management strategy that adjusts levels of exploitation in response to observable indicator changes can greatly improve management decision-making for data-limited fisheries (Dichmont and Brown 2010; Plagányi et al. 2020), especially when tested through MSE. By adopting an adaptive approach tailored to existing limitations and starting with what is practical, fisheries can access the lower rungs of the formal management 'ladder'. Eventually, resource and context permitting, management can be refined through consideration of the risk-cost-catch incentives (i.e., the trade-offs between risks of overfishing or not achieving objectives, costs to sustainably manage the fishery, and the associated amount of catch that is allowed to be removed; Dichmont et. al. 2016). Similarly, where information or knowledge exists regarding broader ecosystem dynamics that may impact a data-limited species or fishery, such information can still be considered, even if qualitatively, within management advice (e.g., through the use of risk tables; Dorn and Zador 2020).

General stock assessment

Conversely, when data permit, full model-based stock assessments are often implemented to determine stock status. Much of modern "data-rich" stock assessment science is based on the 'integrated analysis' paradigm in which the development of the modeled population dynamics is based on knowledge of the system under consideration, the available data, and how the assessment will be used for management purposes. The basic techniques for conducting stock assessments are well developed for age-structured and size-structured assessment models (e.g., Maunder and Punt 2013; Punt et al. 2013), but many challenges remain.

Inconsistent use of model diagnostics

A core step when conducting any stock assessment is to evaluate whether the model provides an adequate fit to the data. However, there remains inconsistency regarding which diagnostics to use and what constitutes evidence for model rejection. Most assessments examine multiple diagnostics, all of which have on occasion led to rejection of assessments for management purposes (Punt et al. 2020a). Ultimately, the aim of applying model diagnostics is to find a model configuration for which there is no evidence for model mis-specification and that provides plausible results. Some progress has been made on identifying threshold values for these diagnostics (e.g., Hurtado et al. 2015; Carvalho et al. 2017) and simulations have evaluated the ability of some of the proposed diagnostics to detect model mis-specification (e.g., Carvalho et al. 2017). How to deal with retrospective patterns remains a key challenge, because adoption of an assessment with clear evidence of retrospective issues can lead to inappropriate harvest recommendations and a loss of stakeholder confidence in the results of the assessment (Szuwalski et al. 2018). Future work to identify best diagnostics and when an assessment should be rejected (or modified) remains a key research topic.

One model is good but are multiple models better?

There is not a single assessment framework that can include all hypothesized relationships as nested submodels. Thus, researchers are increasingly advocating that assessments include an ensemble of models (e.g., Jardim et al. 2021). Building an ensemble involves a priori decisions about the set of models to include, their relative weighting, and how outputs are combined to generate a representative distribution or point-estimate. Here we emphasize two strong arguments for building ensemble models relative to building a single model that includes alternative hypotheses via estimated parameters (i.e., continuous-model expansion):

1. *Mitigate known biases*: Stock assessment models may result in biased estimates of key parameters (e.g., Lee et al. 2012), and in these cases a pre-weighted model ensemble defined by alternative parameter values may perform better than estimation using a Bayesian prior (i.e., particularly in data-limited situations; Rudd et al. 2019).
2. *Management-relevant weighting*: Ensemble models allow for models to be weighted based on metrics that might be more relevant than fit to historical data. For example, ensembles might be weighted based on retrospective performance for a key variable (Stewart and Hicks 2018), stakeholder and reviewer feedback (Thompson et al. 2021), or hypotheses that are indistinguishable given available data but consequential for management purposes.

Although the machinery for conducting assessments based on multiple models exists, the weighting scheme can influence the final management advice, which often makes choosing appropriate weighting controversial. Future research to understand how to select the models to include in an ensemble and how to weight them, including automatic weighting methods, is warranted.

Reference point subjectiveness

Fisheries management typically involves comparing a measured population or fishery variable (e.g., current biomass or fishing mortality) against a target or limit reference point (Methot et al. 2014; ICES 2022). Calculating reference points often requires defining values for parameters that are difficult to estimate (e.g., stock-recruit parameters; Goethel et al. 2018). For this reason, reference points are often developed using generalized simulations and, in turn, based on prior meta-analysis (e.g., Clark 1991). However, differences among stocks are not adequately acknowledged leading to inappropriate or subjective reference points, which can hinder management performance (Harford et al. 2019). Moreover, inconsistent definitions and methods for calculation of limit reference points (i.e., population levels below which sustainability of the resource is likely to be impaired) creates further management uncertainty, inconsistent application across regions or agencies, and confusion among stakeholders and the public as to the risks to a stock when limits are approached (van Deurs et al. 2021). Robust evidence synthesis using meta-analytic approaches could provide an objective basis for reference points (or proxies that capture the intent of the reference points), yet there is surprisingly little life-history and meta-analytic research to support evidence-informed reference point estimation. For instance, thoroughly analyzing how life history relationships or demographic rates vary across species or taxonomic groups using meta-analysis can help identify specific parameters that warrant monitoring (e.g., Thorson 2020). Similarly, meta-analysis is necessary to identify plausible combinations of demographic rates for simulation testing, and to identify whether tests have been conducted across an appropriately wide range of species. A resurgence of research regarding fish life-histories, emphasizing data-limited and climate-linked contexts, and involving both theoretical and comparative (meta-analytic) methods is needed to identify objective reference points.

Difficulties addressing reference point nonstationarity

Time-variation in biological parameters, such as growth, natural mortality, and recruitment is widely recognized and accounted for within integrated assessment models, but how to address resulting time-variation in reference points is more controversial. Some assessments utilize dynamic reference points (MacCall et al. 1985; Berger 2019) or allow for regime-shift-like changes (e.g., Wayte 2013). Best practice guidelines for selecting when to invoke a regime-shift have been developed (Klaer et al. 2015), but accounting for regime-shifts and the use of dynamic reference points remains rare in practice, and the willingness to allow for these factors differs across jurisdictions. One major impediment is the breakdown of an observed or hypothesized environmental relationship, which is used to model the time-varying parameter, as new data are collected. Moreover, it may take decades of observation and modeling to develop confidence in predictive relationships (e.g., Hollowed et al. 2020). Although it is desirable to account for changes in population parameters over time, the implications for target and limit reference points are often controversial. For instance, reductions in productivity can lead to lower reference point targets and a lack of management action in the face of declining biomass (e.g., Edgar et al. 2019). There is a need to extend previous work (e.g., Berger 2019; Bessel Browne et al. 2022) to examine the costs and benefits of adopting time-varying parameters and reference points and to refine best practice guidelines in this regard.

A key future direction: increased use of random effects

The complexity of a population dynamics model, as well as its ability to emulate temporal and spatial variation in processes such as recruitment, selectivity, and growth, depends on how many parameters it estimates. Traditionally, stock assessments and the associated supporting analyses treated all of the model parameters as fixed effects, perhaps with a prior to constrain their estimation to plausible values. When time-, spatial-, or age-variation in a process was accounted for in a stock assessment, it was done so using 'penalized likelihood' with the parameters defining the variation treated as fixed effects and subject to a penalty. Moreover, the parameter determining the extent of variation was pre-specified or tuned and was often subsequently found to be substantially biased. However, in the statistical literature, such variation would be treated by modelling the associated parameters as random effects. It is now recognized that 'penalized likelihood' is only a rudimentary approximation to random effects (Methot and Taylor 2011; Thorson 2019a), and is generally limited to allowing only one process to be time-varying owing to computational constraints.

Random effects are a unifying statistical framework for otherwise disparate research fields in fisheries biology (Thorson and Minto 2015). The use of random effects in ecology was previously restricted to linear models owing to the computational demands of approximating the marginal likelihood maximized for parameter estimation. However, access to automatic differentiation software (e.g., Template Model Builder; Kristensen et al. 2016) has substantially aided the adoption of random effects.

The methods on which stock assessments are based now use random effects in multiple ways. For example, random effects have allowed population dynamics models to be formulated as state-space models, allowing the extent of observation and process error to be estimated simultaneously (e.g., Berg and Nielsen 2016; Winker et al. 2020; Stock and Miller 2021). Additionally, random effects are now used in stock assessment methods to represent (a) time- and age-varying selectivity and catchability (Xu et al. 2019), (b) uncertainty in population-dynamics arising from immigration, emigration, and natural mortality (Stock et al. 2021; Clark 2022), (c) spatial variation in population density within a stock domain, which would otherwise result in variable stock-level selectivity (Sampson and Scott 2011; Cao et al. 2020), (d) excess variation in age- and length-composition data (Thorson et al. 2017), and (e) otherwise unexplained variation about the stock-recruit function (Brooks et al. 2018).

Random effects are also central to hierarchical models, which provide some of the auxiliary analyses that support specification of stock assessments. These analyses include comparison of the explanatory power of environmental covariates for predicting demographic rates (Miller et al. 2016; O'Leary et al. 2020), evaluation of correlations in demography among multiple species in the same region (Stawitz et al. 2015) or adjacent stocks in a single species (Minto et al. 2014), and estimation of spatial variation in survey data (Berg and Kristensen 2012; Thorson et al. 2015).

It is expected that random effects will continue to gain popularity across fisheries modeling disciplines and aid the development of more biologically realistic models.

Spatial models

Population spatial structure is influenced by the marine biophysical environment (e.g., currents, temperature, prey, and predators), fish behavior (e.g., habitat preferences, dispersal, and movement), and fishing patterns, which can manifest in an array of biogeographic patterns (Cadrin 2020). Spatiotemporal (including species distribution) models can elucidate local and broad-scale distributions, while linking population dynamics to environment or habitat variables (Thorson 2019b; Thorson et al. 2021). On the other hand, spatially-stratified models can account for population structure and broad-scale spatial dynamics (Goethel et al. 2011; Sippel et al. 2015). As a relatively new (i.e., within the last few decades) approach for fisheries models, spatial applications encounter many data and methodological impediments.

Data impediments

There is an inherent trade-off between data quantity and spatial model precision, because sample sizes decrease with increased model resolution (Cope and Punt 2011). Accounting for spatial autocorrelation and random effects, as is done in spatiotemporal models, can help overcome these data limitations by sharing information across the model domain and reducing the effective number of parameters that need to be estimated (Thorson 2019b). Although most fishery-dependent and -independent data collection programs now routinely collect precise spatial coordinates, historical data collected prior to the widespread availability of GPS or VMS were typically only reported by large scale management areas (Goethel and Cadrin 2021). Thus, historical analysis of fine-scale spatial patterns is often precluded, baselines are difficult to establish, and the spatial resolution for models that use the full time series is forced to be coarser than desired. Information regarding the population structure (i.e., stock identification information) is also a prerequisite for spatial assessments, but it can be expensive and time consuming to collect and analyze (Cadrin 2020). Continued research on how best to integrate the myriad new georeferenced data sources, including how to handle potential sampling bias, is needed to ensure wider application of spatial models.

Methodological constraints

Overparameterization is a routine concern for spatial models, because the number of parameters increases with the number of spatial units modeled, whereas the associated data sample sizes decrease (Cope and Punt 2011; Goethel et al. 2011) unless random effects are introduced. Identifying the appropriate or feasible spatial and temporal structure, which is influenced by the data, computing power, and management goals, often requires balancing competing objectives (i.e., resolution, realism, accuracy, precision, run time, and cost) and influences all subsequent model assumptions (Punt 2019; Thorson 2019b). Though the desired spatiotemporal resolution is seldom achieved, management goals can still be met with models of intermediate complexity, and sub-optimal resolution should be weighed against the alternative of using spatially aggregated approaches. Various methods exist for validating spatial model assumptions and robustness, including direct observation (e.g., for sessile species; Anderson et al. 2016), cross-validation, and retrospective model skill testing for spatiotemporal applications (Thorson 2019b). Increased application of spatially explicit MSE (e.g., Carruthers et al. 2016b; Punt et al. 2017; Jacobson et al. 2022) is necessary to identify the types of spatial processes (e.g., movement, population structure, and/or demographic variation) that need to be explicitly modeled to develop robust management strategies, while highlighting tradeoffs between model resolution and data requirements. Additionally, best practices for calculating spatially explicit biological reference points remains an open-ended research question (Bosley et al. 2019; Kapur et al. 2021).

A key future direction: model hybridization

Multiscalar, modular, and hybrid (i.e., cross-framework) modeling approaches will continue to gain traction as facets of each framework are borrowed and shared. For example, by using hybrid modeling approaches, the multiscalar nature of common data sources (e.g., fine-scale biologging data and broad-scale historical fishery data) and population processes can be explicitly addressed, while also adjusting to the scale of management (e.g., by embedding spatiotemporal sub-models within coarser resolution spatially stratified assessments; Thorson et al. 2021). Similarly, wider incorporation of state-space frameworks that utilize spatial and temporal random effects and spatial autocorrelation will aid implementation of spatially explicit assessment approaches by reducing the number of effective parameters (e.g., Cao et al. 2020). As habitat usage becomes better understood, increased sophistication and validation of habitat preference functions to define movement and connectivity dynamics (e.g., Marsh et al. 2015) will further enable finer resolution models (e.g., the spatial population model, SPM; Dunn et al. 2015). Given the need to better understand spatial processes during early life history stages (i.e., the reproductive resilience paradigm; Lowerre-Barbieri et al. 2017), spatially explicit full life cycle models that imbed larval bio-physical individual-based models (IBMs) within coarser resolution models of adult dynamics will also be more widely implemented (e.g., Goethel et al. 2011; Archambault et al. 2016). Habitat preference and utilization across life stages (i.e., spatial ecology) represent a natural segue for incorporating ecosystem components into management advice (Lowerre-Barbieri et al. 2019). Thus, as fine-scale spatial models are increasingly implemented as operational assessments, they will provide a step towards EBFM (and easier incremental addition of ecosystem processes in single species assessment), while also being particularly useful as conditioned operating models for MSE.

Ecosystem modeling

There has been increased sophistication in ecosystem models as EBFM has begun to be implemented worldwide and climate-induced impacts on marine resources have been more broadly acknowledged. In many jurisdictions, Models of Intermediate Complexity for Ecosystem Assessment (MICE) fit to observed data (e.g., Plaganyi et al. 2014) and whole of ecosystem models (e.g., the Atlantis model; Fulton et al. 2011) are now used to provide a holistic understanding of potential management actions on ecosystem functioning (Perryman et al. 2021). Yet, integrating ecosystem model outputs into quantitative management advice remains elusive.

Difficulty integrating ecosystem and assessment frameworks

Because most fishery management processes are structured at the stock level, a reasonable first step towards EBFM is to integrate key climate and ecosystem effects into existing stock assessments (Lynch et al. 2018). However, difficulties arise with ecosystem-linked stock assessments due to attempts to model complex relationships between population dynamics processes and environmental variables using relatively simple linkages based on correlations (Skern-Mauritzen et al. 2016). Correlative approaches have often explained limited variance in population dynamics parameters, such as annual recruitment, likely because the actual ecosystem linkage remains poorly understood. Additionally, correlations often weaken or fail over time, which emphasizes the need to develop mechanistic understanding of stock productivity drivers at the ecosystem level (Skern-Mauritzen et al. 2016). Overall, we envision a tiered approach for identifying and eventually incorporating ecosystem information in stock assessments and MSEs:

1. *Explore Common Impacts Across Species*: Common trends in fish condition or productivity across species can point to ecosystem level changes in productivity regimes and highlight potential drivers or regime shifts that should be addressed in an assessment (Gaichas et al. 2018).
2. *Develop Conceptual Network Models*: The models can identify and integrate pertinent ecosystem drivers and can help determine the processes most likely to have significant impacts on population dynamics that should be incorporated into a stock assessment (Rosellon-Druker et al. 2021).

3. *Perform Systematic Hypothesis Testing*: The conceptual model or multispecies investigations can then be used to develop specific hypotheses regarding environmental drivers at each life stage, which can be systematically tested within the assessment framework to elucidate mechanistic linkages (e.g., Tolimieri et al. 2018; Haltuch et al. 2019). Adding ecosystem processes in assessment models potentially increases estimation uncertainty, which should be offset by decreased process uncertainty.

Currently, there are two common ways through which ecosystem knowledge and stock assessment models can be effectively linked: natural mortality and spatial dynamics. Scaling the natural mortality parameter (e.g., based on output from an ecosystem model; Plagányi et al. 2022) to account for predation, multispecies interactions, or environmental drivers (e.g., increased mortality due to red tide; Sagarese and Harford 2022) is the most common method. Multispecies interactions can also be addressed implicitly by adjusting target harvest levels to account for the needs of other species (e.g., using multispecies reference points from MICE; Essington and Plagányi 2013; Free et al. 2021). Similarly, dynamic B_0 approaches, which calculate non-stationary reference points in the absence of fishing, can be utilized to implicitly account for changes in the relative abundances of predators and prey (Haltuch et al. 2009; Pecl et al. 2014; Maunder and Thorson 2019). Multispecies assessment approaches (e.g., multispecies virtual population analysis, MSVPA) can also be implemented, using fish stomach-content data, to explicitly estimate mortality due to predation within an assessment framework (Whipple et al. 2000; Jurado-Molina and Livingston 2002; Holsman et al. 2016). However, predation modeling requires intricate knowledge of food web dynamics along with large quantities of reliable spatiotemporally resolved diet data (Marshall et al. 2019), though, in coming years, data demands may be addressed with high throughput genetic sequencing to analyze stomach contents. Accounting for spatial dynamics also represents a potential intersection between single-species and ecosystem models, given the shared importance of accounting for spatial processes. Future research should focus on interdisciplinary collaborations to aid hybridization across assessment and MICE frameworks, with a focus on spatial dynamics.

Can MICE be systematically reviewed for operationalization?

Many ecosystem models such as MICE are formally fitted to data in an analogous manner to stock assessment models. However, there is little guidance on how to address ecosystem model robustness and adequacy for management decision-making (Kaplan and Marshall 2016). Building on the guidelines recommended by Plaganyi et al. (2022), development of tactical ecosystem models should begin with consideration of stakeholder inputs and LEK and be built in a stepwise manner starting with well-understood or proven dynamics. Focus should be placed on the main system drivers and additional complexity should only be added if it is supported by the data. As complexity increases, multiple model structures should be maintained to enable thorough exploration of sensitivity to key assumptions, especially where limited data or information exist to inform plausible trophic or environmental relationships, or to allow development of ensemble approaches (Spence et al. 2018; Reum et al. 2021). Systematic review should follow best practices (e.g., analysis of fits to observed data and exploration of model sensitivities), but it should also include in-person review panels (e.g., typical of stock assessments) that are more in-depth (Rose and Cowan 2003; Kaplan and Marshall 2016). Future emphasis on developing common guidelines for reviewing the goodness of fit, adequacy, and robustness of ecosystem models would help aid the acceptance and adoption of MICE within management frameworks.

A key future direction: modeling ecosystem regime transitions

Identifying and incorporating regime shifts or drifts into management frameworks remains a critical challenge, because ignorance of changing biological, ecosystem, or climatic conditions can lead to unsustainable harvest recommendations. Developing consensus regarding the timing and impact of a regime transition is extremely difficult, especially considering that environmental changes are likely to differentially influence (i.e., in terms of degree of impact, population processes impacted, and timing of impact) each species in the ecosystem. Similarly, fishing and associated management measures also play a role in regime changes and the potential contribution of anthropogenic activities must also be considered (Bakun and Weeks 2006; Litzow et al. 2014). Moreover, attempting to address non-stationarity for individual species in isolation (e.g., within single-species assessment models) may lead to spurious correlations or result in mismatched regimes across species. Thus, unified approaches for identifying and accounting for climatic regime transitions across all species within an ecosystem is required (e.g., Perretti et al. 2017). We envision increasing use of MICE to identify ecosystem regime changes and associated drivers, while allowing simultaneous accounting of impacts on sustainable catch for all modeled species (e.g., through the use of ecosystem reference points). Development of regionally standardized ocean and climate model projections would further help determine impacts of regime transitions, which could then be incorporated into MICE for more realistic projections of short-term management advice.

Management strategy evaluation

MSE uses a simulated biological-fishery system to determine management strategies that are likely to be robust to real-world data, model, management, and ecosystem uncertainty (Punt et al. 2016; ICES 2020). The operating model simulates the implementation of the management advice (including feedback between the management strategy and the operating model), the biology of the underlying resource(s) dynamics, how the fisheries harvest those resources, and data sampling. MSE has led to a paradigm shift in quantitative fisheries management advice by moving fisheries modeling into the realm of policy formation. There are an array of potential applications for MSE across fisheries modeling and management (e.g., data collection optimization, model robustness testing, and exploration of management strategy performance), which has been demonstrated by the extensive reference to its use in each of the preceding sections. Despite many successful applications of MSE for operational fisheries management, broad adoption within management frameworks has only been undertaken in a few regions globally due to a handful of critical challenges.

Lack of standardized MSE methodology

One barrier to wider implementation and adoption of MSE has been the proliferation of disparate MSE approaches, which creates confusion among managers and stakeholders as to the potential benefits of adopting or engaging in MSE initiatives. While many MSEs are used to develop and implement a management strategy for a specific fishery (e.g. Geromont et al. 1999; Plaganyi et al. 2007; Hillary et al. 2016) or to identify generic management strategies that are applicable to an array of fisheries (e.g., for data-limited fisheries; Geromont and Butterworth 2015; Fischer et al. 2020), 'desktop MSEs' can also be used to explore research questions (e.g., the value of information and the relative economic return under different classes of a management regime; McGarvey et al. 2015). Similarly, the development of short-cuts to MSE, which simplify aspects of the simulated system or management strategy (e.g., by replacing a full stock assessment with random error around the true population status), leads to a framework that differs from the standard definition of MSE (ICES 2020). The result is often confusion regarding the distinction between MSE and the 'best assessment' paradigm as well as the role of a stock assessment when a model-based management strategy is implemented. The adoption of a standardized terminology (e.g., Rademeyer et al. 2007; Miller et al. 2019) and further work to clearly define MSE (and associated methodology) would help reduce confusion regarding the goals and capabilities of different MSE initiatives.

Overlooking meta-rules for long-term MSE implementation

A common impediment to successful implementation of MSE for the provision of management advice is a lack of well-defined rules that define: the timing and conditions for a review of the management strategy; the review frequency of potential exceptional circumstances (i.e., realized system states that are outside the bounds of simulated conditions; Carruthers and Hordyk 2019); and the specification of the process that follows if exceptional circumstances are identified (de Moor et al. 2022). Collectively, such directives are referred to as ‘meta-rules’ (Butterworth 2008; Rademeyer et al. 2008; Preece et al. 2021). Meta-rules can additionally specify the frequency for implementing the management strategy along with the distinct role and timing of a full stock assessment (Preece et al. 2022; CCSBT, 2020). Despite the importance of meta-rules, they are often overlooked when management strategies are being developed. Thus, increased emphasis on meta-rules should be undertaken early on in MSEs.

No best practices on adequate levels of robustness testing

There is no general consensus regarding the breadth of testing required to identify a robust management strategy within an MSE. Robustness tests are used to evaluate performance of the management strategy for meeting the primary management objectives or goals under alternate plausible, but less likely, states of nature (e.g., regime shifts) or sampling conditions (e.g., loss of data sources or reduced sampling intensity). Even if performance under a robustness test is not optimal, a management strategy could still be adequate if it demonstrates a sufficiently rapid feedback response to the changed conditions. Conversely, if robustness tests are too broad or speculative, all candidate management strategies will fail (Butterworth 2008). General best practices for determining adequate and sufficient levels of robustness testing are needed, though these will be difficult to generically define due to the context-dependent nature of MSE applications (de Moor et al. 2022). In particular, guidance is needed regarding operating model complexity (e.g., the biological processes to include, such as spatial and ecosystem dynamics) and adequate levels of measurement error to simulate.

A key future direction: optimizing data collection

A primary goal in developing evidence-informed advice for natural resource management is how to best use and cost-effectively collect data to support robust management strategies. MSE can be utilized to identify whether data collection experimental designs can provide feedback responsiveness within a given management strategy. Thus, it is expected that MSE will increasingly be implemented to simulate the tradeoffs between the benefits of collecting various data, in terms of management improvements, compared with associated data collection costs. Concomitantly, there will likely be an increase in the exploration (through MSE) of empirical and hybrid (i.e., with both empirical and model-based components, such as using CKMR absolute abundance estimates) management strategies (e.g., Carruthers et al. 2016a; Hillary et al. 2019). Moreover, as the breadth of bio-socioeconomic performance measures increases, more complex operating models will be required. In particular, it is expected that advances in spatial modeling and application of MICE will enable conditioning spatially explicit ecosystem operating models, thereby enhancing robustness testing and leading to tangible steps towards implementing EBFM. As generic MSE software packages are refined and become more user-friendly, the ability to efficiently apply MSE should improve, thereby increasing the worldwide utilization of MSE.

Translating scientific advice into management action

Although there are many challenges encountered when developing evidence-informed management advice, an oft-overlooked impediment lies in ensuring that scientific outputs are adequately interpreted and utilized to make informed management decisions. In modern fisheries management, crossing of the science-policy interface often takes the form of an HCR. The HCR is the technical basis for translating evidence-based scientific advice (i.e., estimates of stock status, whether based on empirical evaluations or model-based outputs) into management responses (i.e., catch advice) based on a pre-determined relationship that is designed to achieve specific performance measures (Punt 2010). The HCR is the algorithm in a management strategy that prescribes the final management action to be taken and is often the critical component being tested for robustness in applied MSEs. Although HCRs are now common (Hilborn 2012), the transition from scientific advice to management action is often impeded by scientific uncertainty and imperfect management implementation.

Scientific and management inertia

There are many benefits to a stable approach to providing management advice, but institutional inertia can lead to the 'curse of the status-quo'. Inertia in fisheries management can take many forms starting with stagnating scientific advice when scientists lack the time or motivation to learn new skills or adopt new methodology. Similarly, management and review bodies tend to prefer assessments based on existing, commonly utilized data and methods, and novel approaches are often only adopted if resulting advice is consistent with previous methods (i.e., the 'anchoring' effect where previous results or information is overemphasized in decision-making; Schuch and Richter 2022). Thus, there is hesitancy to move away from the traditional 'best assessment' (or 'no assessment', in the case of data-limited fisheries) framework (i.e., utilizing a single assessment model upon which catch advice is based, as opposed to MSE) or to explore alternate (e.g., empirical) management strategies. Despite stock assessment science relying on continued development of new approaches that challenge existing paradigms, the burden of proof for demonstrating that a new method improves management advice can be onerous. For instance, institutional inertia can prevent the adoption of new assessment approaches due to time constraints, lack of motivation by scientists to apply new methods, costs associated with adapting to a new assessment-management framework, poor communication, and difficulty comprehending multidimensional outputs of more complex models (Berger et al. 2017). Similarly, although recommended guidelines for implementing EBFM exist (e.g., Garcia and Cochrane 2005; Cowan et al. 2012; Link et al. 2020), most countries and jurisdictions still lack a formal process for converting ecosystem model outputs into management advice. Incorporating new assessment or ecosystem approaches within management frameworks benefits from paradigms accepting iterative, incremental improvements and valuing scientific innovation. For instance, data conditioned spatial or ecosystem models can form the basis of operating models in MSE, which for jurisdictions where MSE is widely used, will allow seamless merging into the management framework. Eventually, management advice will become more flexible and adaptive, once there is increased exposure to new modeling approaches or management strategies, wider dissemination of best practices, and improved access to training opportunities.

Poorly defined scientific advice and management goals

All fisheries management interventions require specific, measurable, and time-bound objectives to enable evaluation of performance, as well as to inform the design of monitoring programs (Bjerke and Renger 2017; Gilman et al. 2020). However, many management actions are reactive, ad hoc approaches, which often preclude direct model-based advice or quantitative performance assessments (Gilman et al. 2019a). For example, in the case of area-based management tools (ABMTs; e.g., marine protected areas), site selection can be opportunistic and not based on ecological or quantitative criteria. Analytical tools can be developed to retrospectively analyze and infer the actual impacts and performance of management measures, such as the counterfactual prediction-based synthetic control modeling approach used to understand the impacts of ABMTs (Gilman et al. 2020; see Hilborn et al. 2021 for a comprehensive review). However, there is a need to explicitly define management objectives prior to policy implementation to support prospective evaluation of the possible performance of a proposed action (e.g., through MSE-type frameworks). Moreover, even if management objectives are clear, scientific advice may be poorly communicated, imprecise, or inadequately consider uncertainty. Thus, decision-makers may make risk-prone decisions, despite believing that resulting policy will be sustainable and in line with the scientific advice (Galland et al. 2018). The onus lies with scientists to ensure there is no ambiguity when drafting advice and that uncertainty is thoroughly explored and resulting implications adequately conveyed to managers and stakeholders. Improved communication training for scientists along with generic graphical outputs, which are readily understandable by non-scientists, would help improve the clarity of model results when conveying scientific advice. Similarly, as fisheries management moves towards EBFM and tries to develop climate-ready policies, it is increasingly imperative that clear communication occurs amongst scientists, managers, and stakeholders. New ecosystem-based management objectives need to be clearly defined and methods to measure and operationalize their use must be feasible, given the current state of the science, to ensure they can be adequately incorporated into the scientific advice.

Confusion regarding uncertainty

Fisheries management decisions strive to be as robust as possible given scientific understanding of the human-ecological system. Yet, the traditional treatment of scientific uncertainty in the 'best assessment paradigm' (i.e., equivalence to the statistical error around model outputs) limits the ability of management bodies to adequately incorporate risk in decision-making, because model and system structural uncertainty is typically ignored in stock assessment advice. Moreover, myriad approaches exist for conveying uncertainty, which may impact managers' understanding of risk levels, and acknowledgement of reasonable levels of uncertainty is often inconsistent among scientists (Privitera-Johnson and Punt 2020). Increased emphasis on consistent and adequate characterizations of uncertainty by scientists is needed to ensure evaluations of management strategy robustness are adequate, which should include a broader consideration of socioeconomic and ecosystem tradeoffs. However, increased acknowledgement of uncertainty should not be used to question the validity of the associated advice.

Communication barriers and limited operational capacity

Poor understanding of scientific products by stakeholders and managers is a significant barrier to achieving sustainable outcomes. For instance, stakeholder hesitancy to pursue pre-agreed science-based decision rules for managing fisheries is often due to poor understanding of MSE and the benefits of the process. The knowledge gap is partly due to scientists lacking adequate communication training, which can hinder the ability to convey complex technical topics to stakeholders. The inclusion of trained facilitators and boundary organizations can improve communication and help develop knowledge sharing pathways (Goethel et al. 2019), whereas dedicated professional development for scientists to improve their communication skills is also warranted. Similarly, capacity building through improved training opportunities can help bridge the knowledge gap between scientists, managers, and stakeholders. However, traditional capacity building usually relies on in-person training, which can be difficult in some regions and has been exacerbated by the COVID-19 pandemic. Online training platforms and digital decision-support tools have proliferated rapidly and can help expand access to learning opportunities for oft-overlooked or isolated stakeholder groups. Ultimately, resource limitations often drive capacity limitations and neither are likely to improve in many regions, which emphasizes the need for pragmatic and novel solutions in the future.

A key future direction: synergism in management advice through interdisciplinary collaborations

Robust fisheries management advice requires interdisciplinary knowledge that spans and integrates a diversity of fishery fields, including biology, ecology, social science, and economics (Phillipson and Symes 2013). Historically, fisheries disciplines have been siloed and segregated. Increasingly, though, research teams are becoming interdisciplinary, including data collectors, biologists, assessment scientists, ecosystem modelers, social scientists, and often stakeholders. Increased collaboration across disciplines leads to important parallel and synergistic developments, and the EBFM paradigm explicitly acknowledges the importance of interdisciplinary research (Marasco et al. 2007). In moving towards increasing use of interdisciplinary scientific outputs in the provision of *quantitative* management advice (see Table 3), a first practical step is the collation of qualitative metrics and quantitative indices (when feasible) of ecosystem health and socioeconomic performance. Simultaneous consideration of these factors in the form of a risk table aids dialogue amongst disciplines, while allowing managers to understand ecosystem impacts and anthropogenic factors that may affect management performance and warrant consideration for adjusting harvest recommendations (e.g., as is done in the North Pacific region of the United States to adjust catch quotas; Dorn and Zador 2020). A next step is participatory modeling initiatives to develop conceptual network models (i.e., the Integrated Ecosystem

Approach, IEA), which describe functional relationships across the entire marine system (i.e., biological, human, and ecosystem components; Rosellon-Druker et al. 2019; Spooner et al. 2021). Conceptual network models can then be translated into ecosystem models, the outputs of which can be used to inform assessment model parameters (e.g., natural mortality; Marshall et al. 2019; Plagányi et al. 2022) or for adjusting target fishing mortality to account for ecological processes (Bentley et al. 2020; Howell et al. 2021). The simultaneous development of assessment and bio-socioeconomic ecosystem models, within the context of the science advisory process, can then help managers to better understand ecosystem interactions and system uncertainty (e.g., Drew et al. 2021). Eventually MICE can form the basis of management advice or MSEs can be implemented where realistic accounting of system uncertainty can be achieved through bio-socioeconomic operating models (e.g., Plagányi et al. 2013). Bio-socioeconomic ecosystem models that are able to be conditioned on observed data with fine spatial granularity, can account for climate-driven dynamics, and are able to address a range of system complexities (and associated model assumptions), such as SEAPODYM (Lehodey et al. 2008, 2014), will be ideal candidates for MSE operating models, and currently represent the upper rung of the interdisciplinary scientific advice ladder. Despite stepwise progression, incomplete understanding and inability to directly model many aspects of marine systems emphasizes the importance of iterative progress and feedback, where the results of IEA-type initiatives can be progressively incorporated into MSEs as data, knowledge, and modeling advances allow. To ensure cross-discipline collaborations do not stagnate, wider access to professional development opportunities (e.g., ICES training courses) can aid understanding of interdisciplinary concepts, whereas workshops, such as those developed by the Center for the Advancement of Population Assessment Methodology (CAPAM), can bring together scientists across disciplines to develop good practices. Additionally, collaboration across regions and disciplines should aid in sharing of expertise and developing a common lexicon (e.g., developing common definitions for widely used, but ambiguous, terminology), scientific currency (e.g., model diagnostics and visualization techniques), and generic modular modeling platforms (Punt et al. 2020b).

Recommended refinements to the science advisory framework

For stakeholders and communities directly impacted by scientific and management failures, thorough reevaluation of management approaches is critical for economic and social well-being. Thus, aspects of the current science advisory and fisheries management paradigm require iterative refinements.

A strategic guide for improving fisheries management advice

Given the multipronged challenges, but also rapid advancements, in the scientific advice that forms the basis of fisheries management decisions, several pertinent questions arise about the future of the science advisory process, including:

1. What aspects of these recent advances in fisheries modeling will become critical to the development of fisheries management advice in the future?
2. How will fisheries management processes evolve to utilize new sources of scientific information?
3. Aside from better data and improved models, how can fisheries management frameworks be revised to become more transparent, inclusive, and flexible?

To address these questions, we envision and describe an integrated fisheries management framework, which can be viewed as a strategic guide for developing iterative, participatory fisheries management advice (Fig. 1).

Engagement, communication, and capacity building

The development of traditional fisheries management advice using the 'best assessment' paradigm has followed a three-step loop involving data collection, assessment of population status and projection of recommended catch, and translation of scientific advice into management actions. However, management agencies recognize the need for more interactive, iterative, and transparent processes (Lynch et al. 2018; ICES 2021). Thus, the management advice framework needs to be reenvisioned as a spoked wheel, where well-defined stakeholder engagement activities, clear communication by trained facilitators, and

Table 3 Synergistic interdisciplinary approaches to enhance the science advisory process, with examples listed by increasing integration of ecosystem and socioeconomic knowledge into *quantitative* management advice

Interdisciplinary approach	Aid to management advice	Limitation
Qualitative interdisciplinary input during assessment process	Incorporate ecosystem and socioeconomic factors in management decision-making (e.g., qualitative risk tables; Dorn and Zador 2020)	Marginalizes non-assessment disciplines
Integrated Ecosystem Assessment (IEA)	Develop holistic understanding of system to inform management, improve communication, and engage stakeholders (e.g., Spooner et al. 2021)	Less explicit than direct quantitative catch advice
Bio-socioeconomic model output utilized as stock assessment input	Least complex, ecosystem-informed assessment advice (e.g., use MICE to estimate natural mortality and input to assessment; Plagányi et al. 2022)	Ignores critical ecosystem processes
Adjust catch advice for ecosystem dynamics	Account for ecosystem considerations and ecosystem model outputs directly in projections of sustainable catch (e.g., Howell et al. 2021)	Limited utilization of ecosystem models
Simultaneous development of assessments and MICE	Improved understanding of interactions between complexity, uncertainty, data needs, and assumptions, while incorporating ecosystem dynamics into catch advice (e.g., Drew et al. 2021)	Uncertainty regarding how to amalgamate single species and ecosystem model catch advice
Management advice based on MICE	Integrated interdisciplinary research teams to ensure knowledge sharing and avoid marginalization, integration across system processes, tools that directly support management (i.e., avoid 'ivory tower' isolation), and direct incorporation of ecosystem dynamics into projection of quantitative catch advice (Plagányi et al. 2014, 2022)	Increased data requirements, tractability issues, and longer timelines given model complexity and number of participants
Bio-socioeconomic ecosystem models as MSE operating models	Address management strategy robustness to system uncertainty, identify ability to achieve EBFM objectives, incorporate quantitative social and economic performance measures (e.g., Kaplan et al. 2021)	Conditioning models on data, informing assumptions, and development time

progressive capacity building initiatives are key components of the central hub that interact with each step of advice development (Fig. 1). Similarly, each stage should be iterative with ingrained feedback loops along the spokes as well as with other stages across the larger loop. Moreover, interdisciplinary, mutual knowledge exchange among all participants (i.e., data collectors, scientists, managers, and stakeholders) is emphasized at each stage.

Under the post-normal science paradigm, stakeholder engagement at each step will become a formal aspect of the management process, which will help move management systems away from a client-oriented bureaucratic approach towards a co-management paradigm (Bax et al. 2021; Haas et al. 2022). As participatory modeling initiatives are adopted, stakeholder LEK will help elucidate important biological processes, whereas input on desired socioeconomic outcomes will help determine adequacy and tradeoffs in management performance. Increased usage and improvements in virtual meeting platforms (i.e., due to the COVID-19 pandemic) can support increased participation in the management process, but virtual forums cannot fully replace in-person meetings (e.g., for conveying and discussing technical details) and meeting fatigue must be carefully monitored. By ensuring engagement throughout the management process, stakeholder input will be ingrained and help to foster a sense of ownership in resulting scientific and management products. Thereby, a sense of inclusion, transparency, and legitimacy will be established.

We envision that trained facilitators and boundary organizations (i.e., institutions that act as intermediaries) will become key participants within the management process to aid dialogue, develop clear communication pathways, and encourage knowledge sharing (Feeney et al. 2019; Goethel et al. 2019), thereby infusing trust, credibility, saliency, and legitimacy in the resulting scientific advice (Cash et al. 2003; Heink et al. 2015; Galland et al. 2018). The communication gap between scientists and stakeholders, though, is bidirectional, because stakeholders must also learn to communicate their knowledge base and management preferences in a way that scientists can understand and translate into quantitative metrics. Thus, increased stakeholder training opportunities (e.g., the Marine Resource Education Program in the United States and the FarFish project funded by the EU) are warranted to aid understanding of the science-management process and how stakeholder expertise and time can be maximized within it (Goethel et al. 2019; Miller et al. 2019).

Digital decision-support tools can be another aid to capacity building and communication, while supporting participatory processes when resources are limited. This new generation of apps (e.g., FishPath, https://www.fishpath.org/, and MERA, https://www.merafish.org/) is aimed at making fishery analytics and management science more easily understood, interactive, automated, and accessible through a user-friendly, cost-effective approach. The dynamic visualizations utilized help convey modeling concepts by illustrating them 'live', providing a shared experience that improves understanding and supports stakeholder buy-in (Miller et al. 2019). However, digital tools do not replace the need for critical review of input choices or hidden assumptions nor careful interpretation and vetting of results. Use of digital tools during initial phases of policy development will improve management capacity by aiding quick exploration of alternate management options. Implementation of final management advice, though, must utilize carefully tailored application of digital tools with the help of trained regional experts, while thoroughly incorporating stakeholder input.

Data collection

Advanced data collection technology will result in dedicated, consistent, and novel sampling for a wider array of species, enabling increased implementation of basic assessments (e.g., DLMs) along with higher resolution and better conditioned spatial and ecosystem models (Table 1). Though, given the breadth of dimensions that must be addressed in management advice, sampling efforts will need to be more carefully targeted to maximize resources. Feedback from subsequent steps (i.e., fisheries modeling and MSE) will help improve sampling experimental designs by highlighting the data sources with the highest value of information or that most effectively support management strategies. Yet, the limits of any modeling initiative must be acknowledged, as no model can incorporate the entire suite of complexities of the real world system being emulated. Thus, when using MSE or other fisheries models to guide data collection, it is important that recommendations are not too narrowly focused as to become overly restrictive (i.e., do not

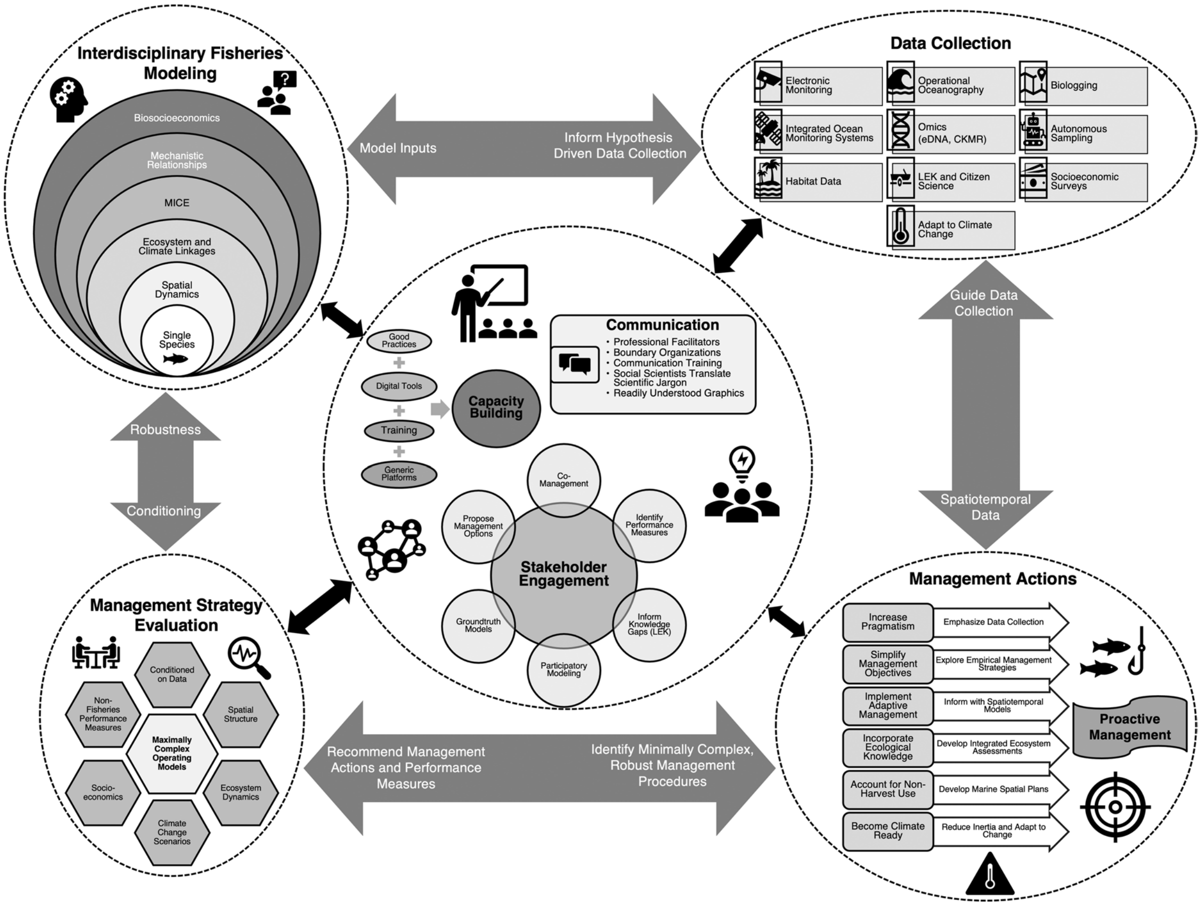

Fig. 1 A strategic guide for implementing an integrated, evidence-informed fisheries management framework. The management process is reformulated as a spoked wheel that emphasizes the importance of engagement, communication, and capacity building at its central hub. Additionally, the development of management advice, which in regions with strong governance has historically involved three primary stages (i.e., data collection, assessment of population abundance through fisheries models, and translation of scientific advice into management actions), is expanded to more thoroughly institutionalize management strategy evaluation (MSE). The entire management advice process is envisioned as iterative and interactive, emphasizing feedback within and among components to ensure continual improvement and optimization of scientific tools and resulting advice

preclude collection of data that might be of importance to research initiatives not directly associated with developing management advice). Overall, the data collection enterprise is expected to become more cost effective, synergistic, and better able to support management objectives.

Fisheries modeling

Diverse, interdisciplinary research teams will help ensure consistent knowledge exchange across disparate disciplines, allow better incorporation of a systems view for modeling the marine environment, and improve the ability to more broadly acknowledge system uncertainty (Phillipson and Symes 2013). With increasing, often georeferenced, data availability, there will be a continued trend away from spatially aggregated single-species modeling efforts towards spatially explicit assessment approaches and data-conditioned MICE, where random effects act as a unifying statistical tool utilized across disciplines. Ensemble and multi-model approaches will become more commonplace, allowing an improved recognition of ecosystem functioning and associated uncertainty in model recommendations (e.g., Drew et al. 2021; Howell et al. 2021; Reum et al. 2021). Bio-socioeconomic modeling initiatives will also continue to advance, helping to elucidate the processes driving harvest patterns and technical interactions in multispecies fisheries (e.g., Russo et al. 2019).

MSE

The wider incorporation of MSE as a tool for developing operational scientific advice within management frameworks will be one of the more impactful refinements. MSE can improve management legitimacy, enhance communication, and spur inventive management solutions through consultative development (Punt et al. 2016; Goethel et al. 2019; Deith et al. 2021). Additionally, MSE provides a unifying paradigm to mesh interdisciplinary fisheries modeling through development of maximally complex, spatially explicit, bio-socioeconomic ecosystem operating models conditioned on real world data that are then used to identify robust, minimally complex management strategies. Therefore, it is envisioned that MSE applications will help pioneer tangible steps towards implementation of EBFM and more thorough evaluation of the ability of management strategies to achieve socioeconomic objectives (Table 3). Moreover, there is likely to be an increasing trend towards simultaneous evaluation of empirical and model-based (i.e., assessment-based) management strategies (Rademeyer et al. 2007; Hillary et al. 2016) as well as hybrid management strategies (e.g., that incorporate absolute abundance estimates from CKMR; Hillary et al. 2019; Trenkel et al. 2022), through MSE. As generic MSE software packages and associated digital tools continue to become more sophisticated, development of MSE applications will gain efficiency enabling increased usage worldwide.

Pragmatic, adaptive, and proactive management

Integrating MSE, more formally adopting co-management approaches that thoroughly assimilate all stakeholders (i.e., through appropriate representation), and developing pre-agreed management strategies (via the MSE process) should help to reduce stakeholder disputes, eliminate TAC negotiations, and generally result in science-based management advice that is pragmatic and proactive. Thus, there will be fewer surprises, and the process will inherently gain legitimacy, assuming that adopted management strategies that have been evaluated via MSE are strictly adhered to, stakeholders have been adequately incorporated in the process, and no exceptional circumstances (e.g., unanticipated stock distribution shifts driven by climate change) invalidate the implementation of the management strategy as defined in the meta-rules. Additionally, utilization of bio-socioeconomic operating models will enable quantitatively addressing ecosystem and socioeconomic (i.e., including non-harvest use associated with emerging blue economy sectors) objectives and tradeoffs.

Adapting to climate change will require further flexibility, as species redistribute across management areas. Thus, cross-boundary and cross-institution (i.e., intra- and inter-national) coordination and communication will be critical. However, ecosystem dynamics are ever-changing and management advice and decision-making will always be subject to unforeseen perturbations. Thus, the distinction between proactive and reactive management remains subtle, where the former relies on management framework flexibility to allow quick adaptation to changing ecosystem knowledge and conditions. For example, progressive incorporation of spatiotemporal models will enable implementation of near real-time, high resolution dynamic and adaptive ABMTs (Maxwell et al. 2015), which allow nimble management measures that can rapidly adjust to changing species distributions. By more thoroughly adopting and utilizing technical tools such as MSE and spatiotemporal models and ensuring clear communication and stakeholder engagement, we foresee that refined management frameworks will eventually lead to fisheries policy that is more pragmatic, adaptive, and, ultimately, proactive instead of reactive.

Our outlook, though, is inherently prejudiced towards regions that invest heavily in fisheries management, and will be harder to implement in areas where funding is limited and governance is weak. Thus, despite ever advancing data collection technology, it needs to be emphasized that basic data (e.g., life history or even reliable catch data) have yet to be collected in many data-limited situations. Of course, focusing on moving species out of the data-limited category is often less glamorous than developing more complex modeling approaches for data-rich species. Therefore, an emphasis on pragmatism is needed for management in capacity-limited situations with a focus on collecting data (Haas et al. 2022). Moreover, social learning initiatives with community stakeholders and scientists should be integrated to promote local stewardship, help elucidate available data, and instigate the collection of voluntary fishery-dependent data that can be used as a baseline for assessing future trends (e.g., Prince 2010; Berkström et al. 2019).

Conclusions

We have attempted to portray a broad spectrum of quantitative tools to guide the management of fishery removals. The suite of tools designed for data-limited situations provide a starting place for a quantitative conversation about fishery management by providing first estimates of basic stock trends. When data allow, age- and length-structured integrated analysis models can then be implemented to track long-term trends, evaluate stock status, and project sustainable catch levels. Stock assessment models are becoming adept at incorporating random effects to track environmentally driven perturbations and avoid bias due to inadequate model flexibility. However, assessment models remain essentially empirical, describing historical and recent patterns due almost solely to fishing effects. A more holistic understanding of the causal and mechanistic relationships that beget population trends can only be achieved through multispecies ecosystem models, integrating spatial structure, and directly accounting for climate and socio-economic drivers of the biological and fishing processes. Interdisciplinary fisheries modeling research teams are now bringing these pieces together through MSEs within co-management settings. Thus, it is becoming increasingly feasible to provide quantitative advice that incorporates the probability of myriad potential outcomes and associated tradeoffs when implementing a management strategy, given improving knowledge of marine systems.

Although fisheries management is a ‘wicked’ problem, because there is no terminal solution that satisfies all competing interests (Jentoft and Chuenpagdee 2009; Jentoft and Knoll 2014), incremental improvements to the current management paradigm are likely to lead to more robust fisheries policy and progressively more sustainable harvest. However, given the rapid expansion of the blue economy, existing fisheries management and ocean governance frameworks are likely to be taxed in unforeseen ways (Collie et al. 2013). As the demand for marine ‘real estate’ expands in the blue economy, managers will be increasingly tasked with weighing the desires of fisheries stakeholders against shifts or expansion in the needs of non-fishery interest groups (e.g., wind energy, oil extraction, and marine tourism; Cohen et al. 2019; Lombard et al. 2021). Even if an optimal, scientifically informed fisheries management process could be identified and implemented, the overall biological, social, and economic objectives are unlikely to be met if the system is not adequately embedded in a holistic marine spatial plan.

Fisheries management will never be perfect, yet we believe that the trend towards evidence-informed management advice will continue. However, recommended refinements based on our idealized integrated fisheries management framework (Fig. 1) are likely to filter into management processes at variable rates across jurisdictions. It is meant as a strategic guide from which individual management needs and aspirations can be linked to support synergism within and among components of evolving management processes based on available budgets and capacity. Despite new challenges and the pessimistic predictions of Quinn (2003), we are cautiously optimistic that novel data sources will continue to spur developments across progressively more interdisciplinary fisheries modeling initiatives, and that the fisheries management paradigm will become increasingly robust. Thus, we believe that the production of evidence-informed management advice will continue to be an ‘ocean of plenty’, despite enduring pitfalls associated with the ‘wicked’ problem of ocean governance.

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