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Opportunities for agent-based modelling in human dimensions of fisheries

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Abstract

Models of human dimensions of fisheries are important to understanding and predicting how fishing industries respond to changes in marine ecosystems and management institutions. Advances in computation have made it possible to construct agent-based models (ABMs)—which explicitly describe the behaviour of individual people, firms or vessels in order to understand and predict their aggregate behaviours. ABMs are widely used for both academic and applied purposes in many settings including finance, urban planning and the military, but are not yet mainstream in fisheries science and management, despite a growing literature. ABMs are well suited to understanding emergent consequences of fisher interactions, heterogeneity and bounded rationality, especially in complex ecological, social and institutional contexts. For these reasons, we argue that ABMs of human behaviour can contribute significantly to human dimensions of fisheries in three areas: (a) understanding interactions between multiple management institutions; (b) incorporating cognitive and behavioural sciences into fisheries science and practice; and (c) understanding and projecting the social consequences of management institutions. We provide simple examples illustrating the potential for ABMs in each of these areas, using conceptual ("toy") versions of the POSEIDON model. We argue that salient strategic advances in these areas could pave the way for increased tactical use of ABMs in fishery management settings. We review common ABM development and application challenges, with the aim of providing guidance to beginning ABM developers and users studying human dimensions of fisheries.

KEYWORDS
complexity, ecosystem-based fishery management, governance, human behaviour, social-ecological systems, sustainability

1 | INTRODUCTION

Fisheries are coupled natural-human systems in which all of the management levers, and many significant sources of uncertainty, reside on the human side (Branch et al., 2006; Fulton, Smith, Smith, & Putten, 2011; van Putten et al., 2012). While fishing patterns—that is, how much fishing occurs, where, when and with what gear—directly determine fishery impacts on ecosystems, fishing patterns are not the direct control levers in fisheries management. The control levers are instead institutions—including formal institutions such as regulations (e.g., gear restrictions), incentives [e.g., individual transferable quotas (ITQs) or landing taxes] and stakeholder decision-making processes (e.g., community-based management) and informal institutions such as social norms. Institutions—as well as other social forces, such as trust, economic well-being, uncertainty about the future and risk preferences—drive fishing patterns via their influence on fisher behaviour, and they can also themselves be influenced by the state of the ecosystem (Gelcich, Edwards-Jones, & Kaiser, 2005). Indeed, there can be feedbacks between fisher behaviour, institutions, other social forces and the ecosystem (Glaser et al., 2014). Gaps in our understanding of these causal relationships and feedbacks create challenges to building effective and resilient fishery management systems (Fulton et al., 2011; van Putten et al., 2012).

Models can play a key role in filling knowledge gaps in the human dimensions of fisheries (Nielsen et al., 2018). Models can serve as "virtual laboratories" for exploring causal hypotheses or potential consequences of novel institutional conditions (Lindkvist et al., 2020). This is useful in management settings, where real-life experiments are often infeasible or unethical, and data-rich natural experiments are also rare. The widespread use of models in ecosystem-based fishery management (EBFM) illustrates models' utility in understanding and managing complex systems (Collie et al., 2016). The experience of EBFM also illustrates the utility of diverse portfolios of modelling tools, spanning varying levels of complexity, to address both strategic ("big picture, direction-setting and contextual") and tactical ("focused on management actions on short timescales") problems (Plagányi et al., 2014). The scientific and management-related challenges in the human dimensions of fisheries demand a similarly diverse portfolio of modelling tools (Gotts et al., 2019).

Here, we focus on the role of agent-based models [ABMs; also sometimes called "individual-based models" (IBMs)] in this portfolio. We highlight opportunities for ABMs to address three important knowledge gaps in the human dimensions of fisheries:

Gap 1: in understanding interactions between multiple management institutions;
Gap 2: in incorporating cognitive and behavioural sciences into fisheries science and practice [i.e., moving beyond the simplifying assumptions of neoclassical economics— e.g., that fishers are perfectly rational profit maximizers with a constant discount rate on future profits (Holland, 2008)—to incorporate bounded rationality (Simon, 1955) and other elements of cognitive realism]; and
Gap 3: in understanding and projecting social consequences of management institutions.

Addressing each of these knowledge gaps would generate insight into how fishers adapt to their institutional, social and ecological environments, in ways that could strategically inform fishery management. Such strategic advances could potentially motivate ABM applications in tactical settings or in management strategy evaluation (MSE). Drawing on illustrative simulations from a new ABM called POSEIDON (Bailey et al., 2018, 2019; Carrella, 2017; Carrella, Bailey, & Madsen, 2019)—as well as examples from previous ABM research in fisheries and other fields—we argue that these three research areas are ripe for important advances. We do not intend our list of knowledge gaps to be exhaustive, but it hopefully offers a useful launch point for future research.

2 | ABM BACKGROUND

ABMs explicitly describe the behaviour of individual agents, which can be individuals, firms or fishing vessels, depending on the context. ABMs typically focus on agent-level decisions, such as where, when and what to fish (Bastardie, Nielsen, Andersen, & Eigaard, 2010; Bastardie, Nielsen, & Miethe, 2013; Cabral, Geronimo, Lim, & Aliño, 2010; Dowling, Wilcox, Mangel, & Pascoe, 2012; Little et al., 2009; Soulié & Thébaud, 2006; Toft, Punt, & Little, 2011; Yu, Wang, & Lai, 2009), and with whom to share information and trust (Barbier & Watson, 2016; Klein, Barbier, & Watson, 2017; Lindkvist, Basurto, & Schlüter, 2017; Tilman, Levin, & Watson, 2018). ABMs also often focus on decision-making processes, such as which objectives to pursue, and what maximization processes, heuristics or decision rules to use (Bailey et al., 2019; Libre et al., 2015). Often, the objective of ABMs is to study how these agent-level behaviours produce emergent properties of the fishery as a whole. Emergent properties are macroscopic patterns arising from agent interactions, which are often observed in the system, motivating the study (Conte & Paolucci, 2014; Heckbert, Baynes, & Reeson, 2010). Box 1 summarizes some terminology and key features of ABMs.

ABMs have uncovered compelling and sometimes counterintuitive links between emergent group behaviours and underlying agent-level decisions in several fields. For instance, urban planners have used ABMs to understand why increasing the number of roadways sometimes increases congestion (Pas & Principio, 1997), and why improvements to arterial roadways sometimes have greater impacts on commute time reliability than improvements to highways (Bonabeau, 2002; Los Alamos National Laboratory, 1998). In economics, ABMs have demonstrated the statistical inevitability of wealth concentration in economies having both stochasticity and inheritance (Fargione, Lehman, & Polasky, 2011), and have shown how individual lenders'

BOX 1 . ABM Taxonomy

What is an "agent"? An agent is a discrete entity with its own goals and behaviours; it is autonomous, with a capability to adapt and modify its behaviours (Grimm & Railsback, 2011). In ABMs of social and ecological systems, agents are typically thought of as individual humans and organisms, respectively, but they can also be aggregations, for example fish schools, fishing vessels, firms or even whole economic sectors.

Emergent properties: ABMs are primarily used to identify emergent patterns at higher levels of organization, from simple rules governing the interaction of agents (Grimm & Railsback, 2011). Often, two levels are studied, where the first level is that of the individual or agent, and the second level is that of the group. However, multiple levels or organization can be studied, for example among individuals, groups and then communities (groups of groups), or even among non-hierarchical groupings.

Pattern-oriented modelling: ABMs often cannot be directly fit to data using statistical approaches. Pattern-oriented modelling is a validation strategy whereby ABMs are calibrated according to empirically observable agent-level properties (e.g., fishing costs), and validated by comparing emergent patterns (e.g., fleet size, spatial distributions of fishing effort or tradable quota prices) against empirical observations (Grimm et al., 2005).

Agent-based models as learning tools: ABMs can be used by both researchers and stakeholders to explore and develop understanding of the major qualitative features of a complex system. The structural realism of explicitly describing individuals makes ABMs relatable and intuitive to users (Lindkvist et al., 2020), even if the ABMs are simple enough to have analytically tractable statistical mechanics (Flierl, Grünbaum, Levins, & Olson, 1999).

Agent-based models as predictive tools: ABMs can be used to make quantitative or qualitative predictions about the future state of a given system (Bastardie et al., 2013). Empirically validating agent-level assumptions—for example through pattern-oriented modelling—is especially important for quantitatively predicting agent responses to novel (i.e., out-of-sample) conditions.

exuberance during market booms and caution during market busts can greatly amplify the boom-and-bust cycle, including during the financial crisis of 2008 (Battiston et al., 2016; Bookstaber, 2012; Geanakoplos et al., 2012). In business, ABMs have been used to understand how weaknesses in organizational structure can compound to promote fraud and excessive risk-taking (Bonabeau, 2002). In politics, ABMs have been used to predict the size distribution of wars (Cederman, 2003). Theme park engineers have used ABMs to design crowd-control systems that reduce congestion and wait times (Bonabeau, 2000, 2002). In ecology, ABMs have illuminated how intelligent group-level navigation among groups of fish, birds and other organisms can emerge from basic individual instincts such as self-orienting towards conspecifics and changing movement speeds based on favourable current conditions (Berdahl, Torney, Ioannou, Faria, & Couzin, 2013; Berdahl, Westley, Levin, Couzin, & Quinn, 2016; Grimm et al., 2005; Railsback & Johnson, 2011; Stillman, Railsback, Giske, Berger, & Grimm, 2015).

In human dimensions of fisheries—and in the larger field of social-ecological systems (SES)—the use of ABMs is becoming increasingly common within the scientific community, but uptake is still relatively limited in management settings (Gotts et al., 2019; Nielsen et al., 2018; Schulze, Müller, Groeneveld, & Grimm, 2017). (There have also been several ABM studies of fish and aquatic ecosystems, as noted above, but these are beyond the scope of our discussion here.) ABMs have attracted scientific interest in these fields because groups of human agents interacting with each other and their environments have many features that ABMs are thought to be well suited to studying (Gotts et al., 2019). Specifically, (a) there are complex interactions between agents that influence the individual behaviour of each agent, and can produce complex aggregate behaviour patterns; (b) there is important heterogeneity among the agents in their decision processes or interactions with each other and their natural/social environments; (c) the agents follow decision rules that do not lend themselves well to analytical aggregation or abstraction (Axtell, 2000; Bonabeau, 2002; Conte & Paolucci, 2014; Gotts et al., 2019; Grimm, 1999; Heckbert et al., 2010; Schulze et al., 2017). Because ABMs are rooted in agent-level decision-making processes, they are flexible in complexity and scale, and provide a natural description of the system (Axtell, 2000; Bonabeau, 2002; Grimm, 1999).

ABMs used to study the human dimensions of fisheries have varied in complexity—some relatively simple and strategically oriented (Cabral et al., 2010), others relatively complex and system-tailored (Bastardie et al., 2013), others moderately complex (Carrella et al., 2020; Toft et al., 2011) and others designed to be scale-flexible (Bailey et al., 2019). ABMs of commercial fisheries have shown how fisher interactions in markets for tradable quotas can alter spatial fishing patterns and by-catch rates (Little et al., 2009; Toft et al., 2011), how information sharing can be incentivized and can affect the risk and returns from fishing (Barbier & Watson, 2016; Klein et al., 2017), and how changes in monitoring and management of fish populations can affect other sectors such as shipping (McDonald et al., 2008). ABMs of small-scale fisheries have shown how diversity in reliability among fishers can promote hierarchical—rather than cooperative—relationships within local fishing industries (Lindkvist et al., 2017); and how social and cultural forces can drive entry and exit decisions, as well as spatial fishing patterns (Libre et al., 2015). ABMs have also been used to study analogous SES settings to fisheries, such as hunting (Iwamura, Lambin, Silvius, Luzar, & Fragoso, 2014; Mathevet, Bousquet, Page, & Antona, 2003) and rangeland management (see Matthews, Gilbert, Roach, Polhill, & Gotts, 2007, for review).

Despite such advances, ABMs are still rarely used in fisheries management, especially in tactical situations (Nielsen et al., 2018). Reasons for this lack of uptake include the facts that ABMs are often complex, not analytically tractable and difficult to empirically validate—especially using statistical metrics of fit common to other types of models (Bousquet & Le Page, 2004; Gotts et al., 2019; Nielsen et al., 2018; Schulze et al., 2017). For these reasons, it can be challenging to communicate to managers how an ABM's assumptions lead to its conclusions, and how to evaluate an ABM's trustworthiness. These challenges potentially become larger as ABMs become more complex, analogous to the more general realism–tractability trade-off that has been the subject of rich discussion recently in the context of ecosystem modelling in fisheries (Collie et al., 2016; Plagányi et al., 2014).

For each of the knowledge gaps we focus on here (Gaps 1–3 above), we argue that there are opportunities for ABMs to produce important strategic insights, which could pave the way for the development and application of more tactical uses of ABM. Strategic insights are often applicable to a wider range of systems, and they can be uncovered by simpler, more mechanistically transparent models. These features of strategic studies could lay foundations of trust for ABMs among managers, upon which tactical applications could be later expanded. Schulze et al. (2017) argue for building out such processes iteratively within modelling frameworks, that is building tactical versions of ABMs that have already generated strategic insights in simpler forms. For an analogy to this process, consider that the tactically rich field of modern stock assessment science has foundations in strategic concepts such as maximum sustainable yield (MSY), derived from much simpler models (Schaefer, 1954). We use POSEIDON here to provide illustrative examples of strategic insights related to each of our focal knowledge gaps, and we discuss future directions. We discuss possible pathways to tactical ABM uptake in our concluding section.

In addition to developing ABMs in strategic areas with low-hanging fruit, ABM utility and uptake can be improved by integrating ABMs into larger ensembles of diverse models and empirical approaches (Gotts et al., 2019), and by following best practices to avoid over-fitting and other technical challenges, and to manage time, capital and data costs. These challenges and best practices in ABMs are the subject of a rich literature [see Müller et al. (2013, 2014), Schulze et al. (2017), and Smajgl and Barreteau (2017), for recent reviews]. We review some of the key insights of this literature—focusing on ABMs of human behaviour in fisheries—in the ABM Challenges section.

3 | POSEIDON MODEL

We use a fisheries ABM called POSEIDON (Bailey et al., 2018, 2019), to provide working examples addressing each of the three knowledge gaps we highlight. POSEIDON has the advantage, for our purposes, of flexible complexity. It can be used as a "toy" model to ask strategic questions in a simplified setting, as we do here, but it can also be made more complex and site specific (Carrella et al., 2020) for more tactical applications. The core component of POSEIDON is an algorithmically flexible agent-based model of fishing-vessel behaviour (Carrella et al., 2019). Full documentation and computer code of POSEIDON are publicly available (Bailey et al., 2018; Carrella, 2017).

Agent-based models of fishing-vessel behaviour, including POSEIDON, often have five basic aspects: vessel objectives, a set of strategies vessels are permitted to pursue (e.g., fishing site choice, gear, information sharing with other vessels, time spent at sea), an ecosystem that vessels interact with (which may be a single species, or multiple species and/or abiotic factors), a set of management institutions and a decision-making algorithm by which vessels choose a strategy in order to pursue their objective (Figure 1).

The decision-making algorithm is the key aspect of ABMs for our purposes here, because simple algorithms can be designed that allow fishing vessels to adaptively pursue any objective in social-ecological environments of any complexity. The model's ability to simulate complex management systems is thus not constrained by mathematical tractability; this is key to addressing Gap 1. The flexibility with which vessel objectives can be defined allows alternative objectives not based on profit or total catch to be considered, and algorithms can be designed to simulate specific mental models of vessel captains; this is key to addressing Gap 2. The flexibility with which vessel strategies can be defined allows ABMs to model social strategies (e.g., whether and with whom to share information) in addition to fishing strategies (e.g., where to fish); this is key to addressing Gap 3. These aspects apply to POSEIDON but are also general properties of most fishery ABMs, making POSEIDON an appropriate model example for highlighting how ABMs can address Gaps 1–3.

In POSEIDON, fishing vessels can be programmed to pursue a range of possible objectives, using a range of possible fishing strategies and algorithms (see Bailey et al., 2018; Carrella, 2017; Carrella et al., 2019). Under each algorithm, vessels adaptively pursue their objective under any set of biological or policy conditions without requiring vessels solve complex nonlinear optimization problems (Bailey et al., 2019). Thus, POSEIDON projects the behaviour of vessels that results from the assumed vessel objective, and consequently, POSEIDON projects the emergent consequences of this behaviour for the whole system, within any biological and management setting. This flexibility, too, is a general feature of ABMs, not just POSEIDON.

In the examples shown here, vessels' objectives are to maximize utility (we assume utility = profits in the first and third examples, but not in the second example, which focuses on cognitive and behavioural deviations from profit maximizing). Vessels maximize utility using either: (a) an "explore-exploit" (EE) algorithm, where each vessel picks a spot to fish randomly in the first period, and then in subsequent periods either picks the most lucrative previous spot (i.e., exploit) or, with some probability, picks a new fishing spot randomly (i.e., explore); or (b) an "explore-exploit-imitate" (EEI) algorithm, which is similar to EE except exploiting vessels also have information about the locations and profits of other vessels in the fleet when choosing the best spot (i.e., imitate; see Bailey et al., 2018; Carrella, 2017; Carrella et al., 2019 for full details). Explore-exploit models are commonly used in the literature on foraging and environmental management to represent human decision-making (Berger-Tal, Nathan, Meron, & Saltz, 2014; He, Luo, Tan, Wu, & Fan, 2019; Kunz, 2011; Roberts & Goldstone, 2006). Indeed, Carrella et al. (2019) compare several possible algorithms in POSEIDON, finding a trade-off between flexibility and optimization performance, but finding EEI to be among the best on both metrics. However, we note that the specific choice of algorithm the vessels use to pursue utility maximization is not germane to the questions our POSEIDON simulations explore here.

Beyond vessel behaviour, POSEIDON spatially represents a coastline, ocean area, ports and fish biology. Fish biology can be represented as simply as with non-age-structured logistic growth models with diffusion among grid cells, or as complexly as full ecosystem models, such as OSMOSE (Grüss et al., 2015; Shin & Cury, 2001, 2004). Although it is possible to tailor both fleet and biological components of POSEIDON to a specific fishery (Carrella et al., 2020), here we use a simple conceptual version simulating a hypothetical fishery with one port (Figures 2–4), and one or more non-interacting fish species having logistic growth (Schaefer, 1954).

4 | GAP 1: UNDERSTANDING INTERACTIONS BETWEEN MULTIPLE MANAGEMENT INSTITUTIONS

In fisheries, there are often many different management institutions designed to achieve similar outcomes. For example, efforts to reduce overfishing have included formal institutions such as gear restrictions, spatial and temporal closures, catch limits, trip limits, size limits, and individual transferable quotas (ITQs; Hilborn & Ovando, 2014; Hilborn, Punt, & Orensanz, 2004). Informal institutions, such as social norms, can also be important to management, especially in small-scale fisheries and recreational fisheries (Basurto, Gelcich, & Ostrom, 2013; Cooke, Suski, Arlinghaus, & Danylchuk, 2013).

Simple analytical models have had success in predicting the effects of many formal institutions individually. For example, analytical models correctly predicted that fishers would fish close to the boundaries of marine protected areas (MPAs) to capitalize on target species spillover (Kellner, Tetreault, Gaines, & Nisbet, 2007; Murawski, Wigley, Fogarty, Rago, & Mountain, 2005); that fishers might "high-grade" (i.e., discard low value fish) in response to trip or catch limits that were assessed only at port (Branch et al., 2006; Copes, 1986); and that ITQs would reduce fleet capacity and increase fleet-wide profits (Arnason, 2012). Fewer formal, analytical models are used to study informal institutions in fisheries, though there are game theoretic models exploring emergence

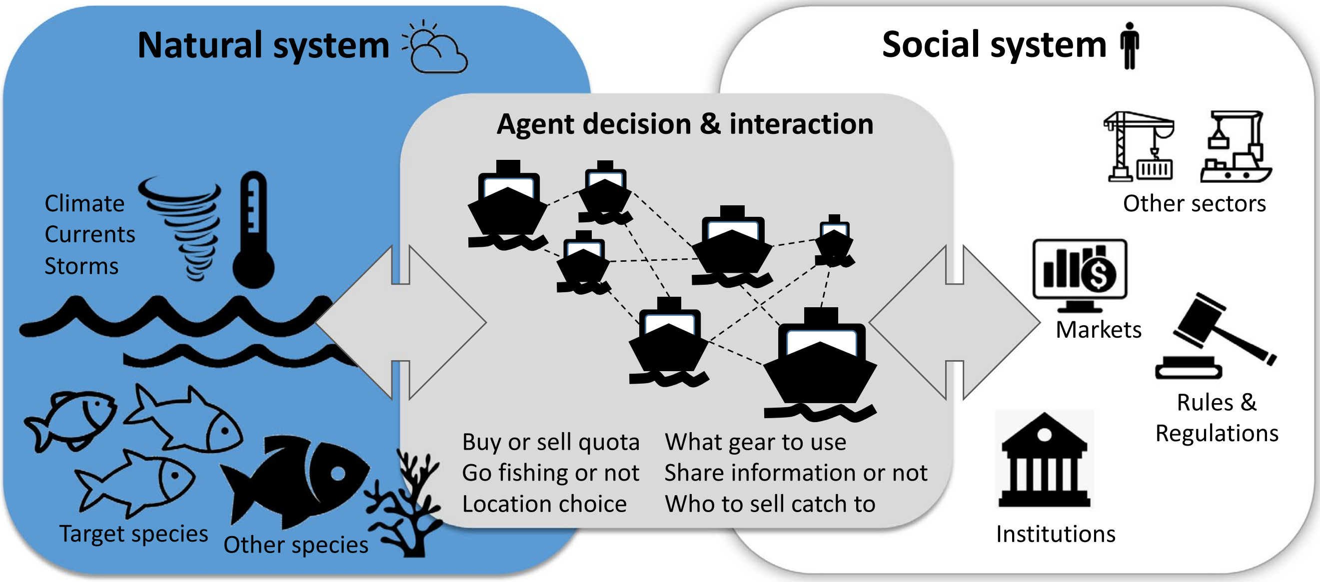

FIGURE 1 ABM schematic. Conceptual schematic of a hypothetical agent-based model (ABM) of fishing vessels. Agents are individual vessels, which make decisions about fishing, information sharing, and buying/selling catch and quota. They make these decisions based on objectives and/or rules that are independent of their social and ecological environments; however, these environments, and their social networks among other vessels (dashed lines), influence the decisions the vessels make in accordance with their objectives and/or rules. Vessels' decisions also impact their social and ecological environments and social networks, allowing the model to explore emergent properties arising from the bidirectional feedbacks between components. Because vessels' decision *processes* do not depend on their environments, the complexity of these environments in the ABM is highly flexible [Colour figure can be viewed at wileyonlinelibrary.com]

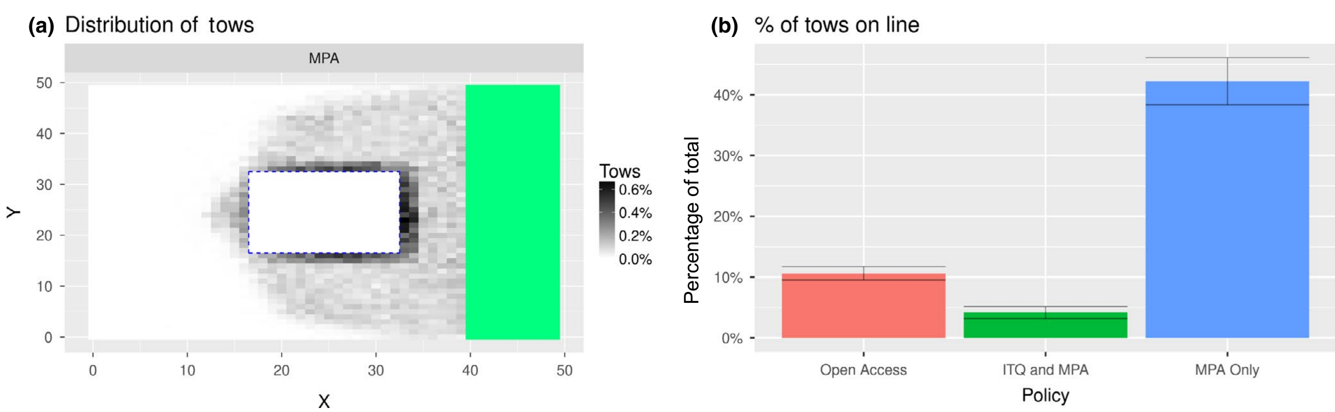

FIGURE 2 Simulating combinations of institutions in POSEIDON. The panels represent fishing patterns in a model with a target species, found throughout the fishing area, and a constraining species located in a smaller area, which is protected by an MPA in some simulations. The fishery can also be managed with ITQs. (a) When the MPA is in effect without ITQs, vessels disproportionately fish close to the MPA boundary ("fishing the line") relative to under open access. (b) With both ITQs and the MPA, vessels avoid the MPA boundary to avoid catching the constraining species, which has an expensive quota [Colour figure can be viewed at wileyonlinelibrary.com]

of cooperation (Klein et al., 2017; Tilman et al., 2018), and many conceptual models exploring informal institutions, in fisheries and other social-ecological systems (Hunt, Sutton, & Arlinghaus, 2013; Kraak, 2011). ABMs are already becoming a common modelling tool for exploring informal institutions (Libre et al., 2015; Lindkvist et al., 2017), likely due to the suitability of ABMs for incorporating objectives and decision processes beyond perfectly rational profit maximization.

While simple analytical models have been useful in understanding fisher responses to single management institutions, it is difficult for them to account for interactions between multiple institutions and remain tractable. Vessels' behavioural responses to multiple institutions may not be additive; indeed, how vessels respond to the introduction of one institution often depends on which other institutions are in place concurrently. In this way, vessel responses to multiple institutions constitute an emergent property of the system. In many jurisdictions—such as the United States, Europe, Canada, New Zealand and Australia—fisheries are predominantly managed by complex combinations of formal management institutions (Emery, Green, Gardner, & Tisdell, 2012).

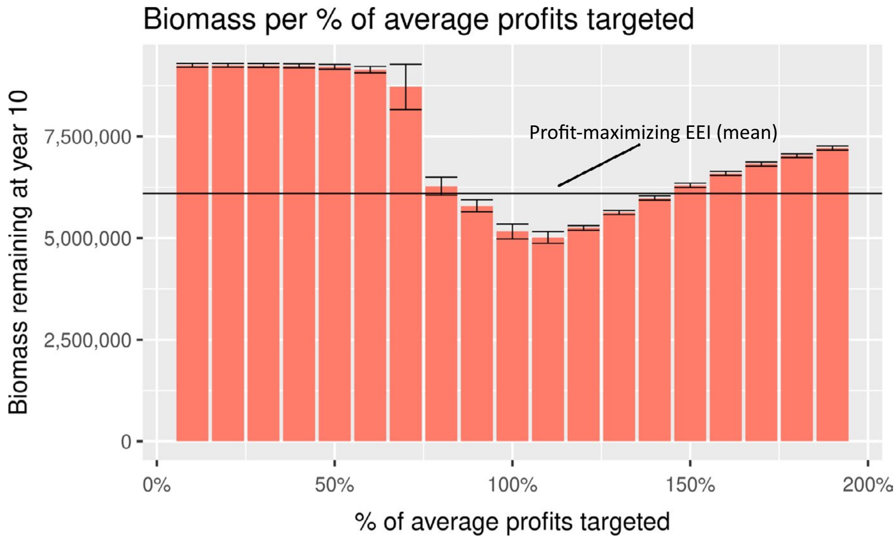

FIGURE 3 Behavioural economics (social annealing) in POSEIDON. Social annealing vessels return to their previous fishing location if they are making at least a certain percentage (x-axis value) of the average profits of their peers, and they explore otherwise. If this threshold is too low, vessels remain too long at unproductive locations and exploit the stock more lightly than profit-maximizing vessels would. If the threshold is too high, they leave productive patches too quickly, and are similarly less efficient. The stock is most heavily exploited when vessels are satisfied with patches that produce slightly above-average profits. Indeed, this type of social annealing exploits the stock more heavily than profit-maximizing EEI (black line). Error bars represent plus-or-minus two standard deviations among 100 model runs [Colour figure can be viewed at wileyonlinelibrary.com]

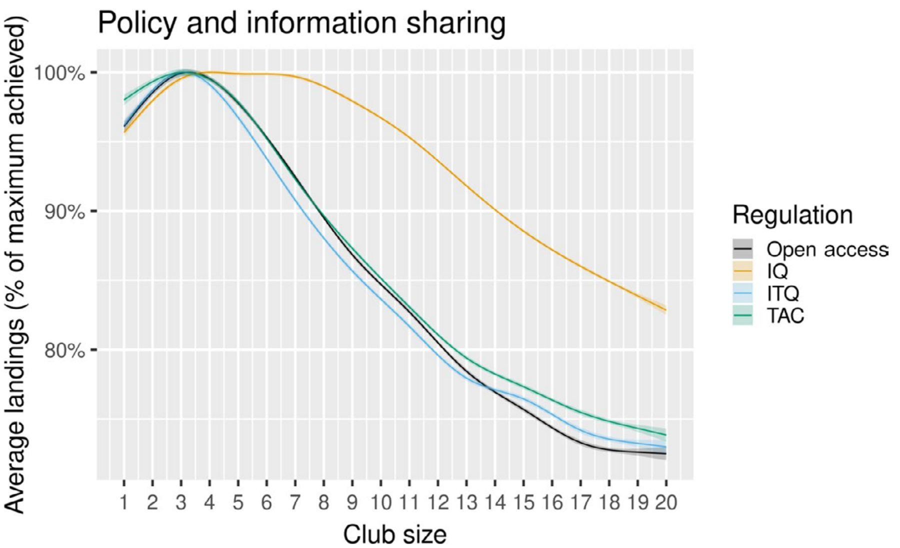

FIGURE 4 Effects of catch limits and property rights on information-sharing incentives in POSEIDON. Lines show LOESS fits of average landings (as a percentage of the maximum achieved) as a function of club size in each scenario. Shaded regions denote the 95% confidence intervals around these fits [Colour figure can be viewed at wileyonlinelibrary.com]

ABMs can be used to understand and project emergent fishery responses to such combinations, as part of or alongside other approaches to MSE (e.g., see Punt, Butterworth, Moor, Oliveira, & Haddon, 2016).

The U.S. West Coast groundfish fishery, for example, has implemented every one of the formal institutions mentioned above since being declared an economic disaster in 2000 and has since significantly reduced overfishing (Miller & Deacon, 2017). Yet, in some cases, the institutions had counterintuitive effects in combination. One such example is the interaction of ITQs on multiple species and MPAs targeting critical habitat for the most overfished rockfish species (*Sebastes* sp.), which produced two counterintuitive emergent patterns, documented empirically by Miller and Deacon (2017). First, the quota lease prices of some rockfish species exceeded their landing prices, because their quota became limiting to vessels' profits from other species they were caught with. The reason why lease prices of constraining species in multispecies ITQs should sometimes exceed landing prices has been described in analytical theory (Arnason, 2014), but this theory requires an abstract representation of fishing technology and thus is not easily applied to predicting lease prices quantitatively in a specific fishery. Second, fishing vessels on average *avoided* the MPA boundaries, rather than fishing close to them, due to the implied cost of catching the constraining rockfish species.

4.1 | POSEIDON results

In Figure 2, we demonstrate the emergence of both of these patterns in POSEIDON (see Appendix 1), in a hypothetical fishery with two non-interacting species, having logistic growth within each grid cell, and a constant diffusion rate between adjacent grid cells. Vessels use the EEI strategy. One species (target) is randomly distributed across the shelf, while the other species (constraining) is found only in a certain habitat (where the MPA is located in Figure 2a). Each has the same landing price ($10), but the constraining species is assumed to be of conservation concern. When ITQs are in force, each vessel has a reservation price—a function of past experience and profitability. Vessels are willing to buy quotas priced below their reservation price and sell for offers above it. Market clearing proceeds as a financial order book: all reservation prices are registered and all mutually beneficial trades take place (see Bailey et al., 2018, 2019; Carrella, 2017).

When the constraining species is protected by only an MPA in its habitat, the vessels fish disproportionately close to the MPA boundary, relative to under open-access, to capitalize on the spillover (Figure 2a). However, when a multispecies ITQ is introduced, vessels disproportionately avoid the MPA boundary (Figure 2b), and the lease price of the constraining species quota exceeds its landing price in 16% of trades. Thus, POSEIDON was able to predict both of the theoretically counterintuitive patterns documented by Miller and Deacon (2017) in the vessel data. Previous ABM studies of this and other fisheries have also predicted multispecies ITQ lease prices and resulting spatial behaviour of vessels with some success (Little et al., 2009; Poos, Bogaards, Quirijns, Gillis, & Rijnsdorp, 2010; Toft et al., 2011). These ABMs additionally projected changes in key fishery performance measures, such as profits, catches and biomass.

4.2 | Future directions

We highlight two research avenues in which ABMs can add value regarding interactions between institutions. First, ABMs can explore how suites of formal institutions can be made cheaper and simpler. Many governance- and scientific-capacity-rich fisheries in developed countries—including the West Coast groundfish fishery—have been highly successful at rebuilding overfished species (Hilborn & Ovando, 2014), but have also been exceedingly complex and costly (Arnason, Hannesson, & Schrank, 2000). Therefore, whether and how such successes can be achieved more simply and cost-efficiently is an important unanswered question. The flexibility of ABMs makes them well-suited to performing simulated quasi-experiments of institutional settings of varying complexity. Our POSEIDON example illustrates how such simulations could be done in stylized ABMs for strategic purposes, but detailed site-tailored ABMs similar to DISPLACE (Bastardie et al., 2010, 2013) and/or coupled to relevant models of ecosystems or other sectors (e.g., McDonald et al., 2008) could also explore such questions tactically in MSE-type frameworks.

Second, ABMs are well-suited to exploring interactions between formal and informal institutions (e.g., as illustrated by Libre et al., 2015). Indeed, as we discuss in the following sections, ABMs are well-suited for simulating the effects of social norms and other informal institutions in general (Libre et al., 2015; Lindkvist et al., 2017), given the reliance of such institutions on objectives and cognitive processes other than profit maximization.

5 | GAP 2: INCORPORATING COGNITIVE AND BEHAVIOURAL SCIENCES IN FISHERIES SCIENCE AND PRACTICE

Much of fisheries science and practice is rooted in neoclassical economic assumptions: that fishers are perfectly informed rational profit maximizers who discount future profits (i.e., value them less than current profits) at a constant compounding annual rate (Anderson, 2015; Clark, 2010). Violations of these assumptions are known to have important consequences in many areas (Kahneman, 2011)—for example in the financial sector, irrational exuberance plays a key role in the formation of asset bubbles (Akerlof & Shiller, 2010)—but these consequences are still poorly understood in fisheries (Holland, 2008). Understanding the impacts of violations of neoclassical theory on fishers' responses to management interventions could be important to designing future management.

Research in behavioural economics and behavioural game theory (Camerer, 2003) has uncovered several common violations of neoclassical theory, which may be important in fisheries. These include *income- or yield-targeting* (a.k.a. 'satisficing'; Simon, 1955), whereby fishers allocate fishing effort to achieve fixed targets on a particular timescale (e.g., catch × amount per-day) instead of trying to maximize intertemporal profits (Nguyen & Leung, 2013); *hyperbolic discounting* (Laibson, 1997; Strotz, 1955), whereby fishers would discount all future profits significantly relative to current profits but discount minimally between near- and far-future; this might cause fishers, for example, to be less accepting of rebuilding plans that reduce short-term catches to protect long-term catch potential; *loss aversion* (Tversky & Kahneman, 1991), whereby fishers weigh prospective losses more strongly than prospective gains, which similarly might cause unexpected opposition to short-term costly rebuilding with large potential long-term upsides; *inequity aversion* (Charness & Rabin, 2002), whereby fishers at some level would rather forego some of their own profits in the interest of within-group fairness (Polania-Reyes & Echeverry Perez, 2015); and the *influence of social norms*, for example as an important driver of compliance with regulations separately from (or in place of) formal enforcement measures (such as penalties and monitoring) (Cárdenas, Stranlund, & Willis, 2000; Hatcher, Jaffry, Thébaud, & Bennett, 2000). Research in other human behavioural sciences (e.g., cognitive and evolutionary psychology, ethnography) could shed further light on the motivations and cognitive processes that drive violations of neoclassical theory.

Complex motivations involving multiple fisher objectives (e.g., food, profit, cultural values and safety; see van Putten et al., 2012), mental models (Koralus & Mascarenhas, 2013) and other more realistic representations of fisher decision-making processes are often relatively simple to operationalize at the vessel level, but less tractable when aggregating. Indeed, the relative tractability of neoclassical economic models is one of the reasons they are so commonly used. Because the natural (sensu Bonabeau, 2002) description of cognitively realistic decision-making occurs at the agent (vessel) level, ABMs are well suited to understanding and projecting the consequences of such decision-making processes in fisheries, just as they have been in finance and other fields. Carrella et al. (2020) provide a recent example, showing that assuming vessels use simple heuristics leads to more realistic fishing patterns than assuming vessels perfectly optimize their fishing decisions. ABMs are also well suited to modelling fisheries in which fishers are heterogeneous in their objectives, decision-making processes and other characteristics (e.g., vessel size and available capital). Libre et al. (2015) provide a salient recent example, showing that an ABM incorporating personal (non-rational) motivations to not exit the fishery, cultural norms regarding vessel distribution, and imperfect information can reproduce observed fishing patterns and fleet composition in the Philippine tuna purse seine fishery.

5.1 | POSEIDON results

In Figure 3, we provide a simple demonstration in POSEIDON of a type of income-targeting (satisficing) behaviour, as well as some of its potential consequences for a fishery (see Appendix 1). We refer to this behaviour as “social annealing” (see also Beecham & Engelhard, 2007). Under social annealing, each vessel returns to its previous fishing spot as long as its daily profits are higher than a certain percentage of average fleet-wide profits. Otherwise, they randomly search for a new spot. Behaviours similar to social annealing are common due to humans’ natural tendency to evaluate their success relative to their peers—the “keeping up with the Joneses” phenomenon (Galí, 1994)—and have been raised as a potential concern in a sustainability context (Dasgupta & Ehrlich, 2013). We also simulate profit-maximizing vessels using EEI, for comparison (Figure 3). In each case, we assume that there is a single stock randomly distributed across the fishing area, a single port and no restrictions on fishing.

The consequences of social annealing in fisheries are somewhat counterintuitive. We find that, if the satisfaction threshold is low, the stock is exploited more lightly than under profit maximization, because vessels have little incentive to explore. However, exploitation is also relatively light when the satisfaction threshold is very high because vessels spend most of their time exploring, and miss opportunities to exploit productive areas. The stock is thus most heavily exploited—indeed more heavily exploited than under profit-maximizing EEI behaviour—when vessels each want to do slightly better than average (Figure 3). This is a potentially realistic “keeping up with the Joneses” scenario that merits further investigation.

5.2 | Future directions

There are innumerable ways in which ABMs could be further used to add cognitive and behavioural realism to fishery models, and to explore the consequences of this realism, of which our POSEIDON model results provide one example. Indeed, Nielsen et al.’s (2018) recent review of 35 major integrated ecological-economic fishery models found most focus on technical interactions, and only one—an ABM (Bastardie et al., 2013)—incorporates behavioural realism beyond profit maximization. Given the breadth of this potential, we suggest two guiding principles, both aimed at important strategic questions.

First, ABM research should focus on topics for which it has greatest comparative advantage over other types of modelling approaches. We posit that such topics are likely to include exploring the consequences of either socially relative fisher objectives [i.e., when vessels define their success in relation to other vessels, such as in the social annealing example above; or as in the case of the social norm explored by Libre et al. (2015) regarding spatial distribution of vessels] or cognitively realistic decision-making processes (in contrast to fishers performing explicit optimizations). These behavioural phenomena may be more difficult to aggregate using equation-based approaches than other types of behavioural realism. For instance, objectives other than profits that are not socially relative could potentially be analysed using simple equation-based utility maximization frameworks.

Second, ABM research on a particular cognitive or behavioural phenomenon should focus on (a) identifying conditions under which the phenomenon in question would change the fishery management outcome in an important respect, compared to when assuming neoclassical fisher behaviour; and (b) identifying empirical tests for the behavioural phenomenon in question. Our above predictions, comparing the stock-depletion potential of social annealing fishers and profit-maximizing fishers, provide an example of (a).

6 | GAP 3: UNDERSTANDING AND PROJECTING THE SOCIAL CONSEQUENCES OF MANAGEMENT INSTITUTIONS

In fisheries, there is increasing concern for the effects of policies and other institutions on social equity, cohesion, public trust and cooperation (Chan, Satterfield, & Goldstein, 2012; Gelcich et al., 2010, 2014; Jentoft, McCay, & Wilson, 1998; Klein, McKinnon, Wright, Possingham, & Halpern, 2015). Especially in small-scale fisheries, social forces—such as the existence of prominent community leaders (Gutiérrez, Hilborn, & Defeo, 2011)—have been found to be important drivers of management success or failure. Understanding the interactions between these bottom-up social forces and other top-down social forces (e.g., policies, regulations) is therefore important to designing effective management. Because ABMs can simulate the behaviour of strategic agents (i.e., agents that pursue objectives and learn) in environments of wide-ranging complexity (Axtell, 2000;

Bonabeau, 2002), they would be useful in understanding and projecting the social consequences of management institutions, as well as how these effects propagate and feedback on other components of the system.

One area in which ABMs have already shown promise is in studying the effects of institutions and ecosystems on social network structure (who interacts with, and shares information and resources with, whom). For instance, Klein et al. (2017) showed how information-sharing incentives vary with species mobility, heterogeneity in fisher skill and property rights. Other studies have asked analogous questions in the context of predators (Barbier & Watson, 2016). Little et al. (2004) and Little and McDonald (2007) projected that information sharing would affect exploitation rates on fishery resources. Social network structures have been shown to be important in successes and failures at overcoming common problems (see Nowak, Tarnita, & Antal, 2010; Rand & Nowak, 2013, for reviews)—both theoretically (see Macy & Flache, 2009; Nowak, 2006; Nowak & Sigmund, 1993) and empirically in fisheries contexts (Barnes, Lynham, Kalberg, & Leung, 2016; Grafton, 2005; Ostrom, Gardner, & Walker, 1994).

6.1 | POSEIDON results

In Figure 4, we use POSEIDON to provide a simple demonstration of how fishing limits, property rights and tradability of property rights affect fishers' incentives to share information (see Appendix 1). We re-use the scenario from Figure 3 (one species, one port, 100 fishers), but we modify the social network such that fishers are split into clubs of random size between 0 and 20. All fishers share information freely within their club (i.e., each member knows location and profits of all other members).

All agents use EEI within the new social network. The fishery is either open access, managed with a simple catch limit (TAC) without property rights, managed with an individual (non-tradable) quota (IQ) or managed with an individual transferable quota (ITQ). For each of these scenarios, we run 100 simulations and collect average profit per member for each club; Figure 4 shows the average (normalized) profit made per club size. As Klein et al. (2017) also found, information sharing initially increases average member profitability while decreasing variance. However, large clubs are inefficient as congestion lowers profitability to levels below those achieved by lone fishers.

Under open access, TAC and ITQ fisheries, the optimal club size is 3 boats; for IQ fisheries, the optimal club size is between 4 and 7 boats. Open access penalizes large club sizes because sharing knowledge about a good fishing spot will see many imitators converge upon it and consume it quickly. A TAC lowers the biological cost of congestion (as only a limited amount of fishing is allowed) but creates a regulatory congestion problem as now imitators consume from the same quota pool. Perhaps counterintuitively, we find that making quota individual and also tradable does not alter the optimal club size: while nominally individual, the tradability merely shifts the common-pool information problem to the market. Whenever an agent shares the location of a good fishing spot with too many others, the quota prices will consequently rise penalizing the original discoverer. Only individual non-tradable quotas (IQs) incentivize larger club sizes (Figure 4). While a few previous studies suggested property rights and their tradability could affect information-sharing incentives (Costello & Deacon, 2007; Deacon, Parker, & Costello, 2013; Evans & Weninger, 2014), the flexibility of ABMs adds to this literature by facilitating the study of these incentives across a rich range of social and ecological conditions (e.g. as Klein et al., 2017 also demonstrates).

6.2 | Future directions

Looking ahead, ABMs like POSEIDON could be modified to permit vessels to adaptively adjust their social connections throughout the simulation (e.g., see Tilman et al., 2018). Researchers could use such models to study the emergence of the social network structures, as well as how network self-assembly processes interact with other fishery components. In other fields, even simple ABMs with agents that can adapt their interaction frequencies and information flows (in response to past successes and failures) have uncovered important emergent social network properties. Gray et al. (2014) found “Us versus. Them” clustering (where agents cooperate within their clusters and defect out-of-cluster) to emerge from simple reciprocity and transitivity behaviours. Given that ecosystem properties are already known to affect social interaction incentives, and social interactions are already known to impact ecosystem properties, feedbacks between social network structure and ecosystem properties are virtually guaranteed to exist. Tilman et al. (2018) found that variability in fishing resources can create conditions for fishing cooperatives to emerge, with positive effects on resource management. Understanding other such emergent social phenomena in fisheries is likely to yield important management insights.

ABMs can also study emergent feedbacks between adaptive agents and adaptive management (e.g., a strategic management council trying to manage the behaviour of strategic fishers). Such feedbacks can have important and counterintuitive consequences. For example, much of the modern economic theory of single-species management and EBFM uses control theory to derive the optimal time path of fishing pressures on fish stocks; the stocks' dynamics are impacted by fishing, but the fish do not strategically respond to fishing strategies (Clark, 2010). Of course, fishers (and other human agents) do respond strategically to management. In their Nobel-winning research, Kydland and Prescott (1977) demonstrated that such strategic responses result in time inconsistency in an adaptive manager's preferred management strategy, meaning that standard control theory does not apply; this is also closely related to the famous “Lucas Critique” in macroeconomics (Lucas, 1976). For a fisheries example (from Clark, Munro, & Sumaila, 2005), managers typically prefer both to limit over-capacity in the fleet and to avoid buying back vessels, but they often prefer to buy back vessels if over-capacity already exists. Anticipating such buybacks, strategic fishers might enter the fishery who would not have had the incentive to enter otherwise, exacerbating over-capacity. The 2008 financial crisis exposed an analogous situation in banking, where governments have incentives to bail out big banks facing bankruptcy in order to avoid economic calamities, but big banks therefore have incentives to engage in risky lending—the type that promotes economic calamities—anticipating that the government would bail them out (Stern & Feldman, 2004). One of the proposed management solutions for the time inconsistency problem is pre-specifying management rules that cannot be easily revised (Kydland & Prescott, 1977), and ABMs can be useful in designing and testing such rules in complex systems. For instance, Geanakoplos et al. (2012) used an ABM to design simple leverage limits to avoid housing bubbles. Fishery ABMs might be used, for example, to design rules limiting entry, buybacks or harvests in response to ecological conditions.

7 | ABM Challenges

Though we have highlighted several opportunities for ABMs to aid in solving important problems in human dimensions of fisheries, there are also important challenges in developing and using ABMs, which new ABM users in particular should be aware of. Below, we briefly discuss best practices for addressing challenges regarding scope; calibration, sensitivity analysis and validation (and related data needs); how best to balance the proper degree of realism and complexity in agent behaviour and model dynamics; and the necessary resource and time investments (Gotts et al., 2019; Schulze et al., 2017). We focus our discussion on ABMs of human behaviour, with specific emphasis on the three knowledge gaps identified here.

7.1 | Scope

It is important to match the scope of ABMs to the research questions of interest, the data available for validation and calibration, and the capital and time available to design and implement the model. Common pitfalls often involve setting the scope too large and/or complex, and thereby risking over-fitting the data, obscuring the model's key insights, exceeding the capacity of the research team and time constraints, or a combination of these (Gotts et al., 2019). As our POSEIDON examples here demonstrate, quite simple "toy" ABMs can address many strategic questions. Other site-specific applications of POSEIDON (Carrella et al., 2020) illustrate how these simple ABMs can be expanded within the same modelling framework to address more complex questions moving in the tactical direction. The ODD + D protocol (Müller et al., 2013) and the TRACE framework (Grimm et al., 2014) provide useful sets of guiding questions and principles for model design, as well as documentation.

7.2 | Calibration and validation

Unlike many other types of models, ABMs are often not fit directly to data through, for example, optimizing a likelihood function. This means that parameter values and model rigour often cannot be evaluated using typical statistical fitting metrics such as likelihood ratio tests or the Akaike information criterion (AIC). Instead, a best practice for calibrating and validating ABMs is a framework called "pattern-oriented modelling" (see Grimm et al., 2005). The strategy is to identify empirically observable agent-level and emergent patterns that the model should be able to reproduce, and then to distinguish among successful models using additional empirically falsifiable hypotheses generated by each one.

For ABMs of fisher behaviour, calibration might use information on vessel cost structures and constraints, and then, the models might be validated by comparing emergent patterns of fishing location, target species, timing and gear choice to empirical observations of these patterns in the study system. Carrella et al. (2020), for instance, use fleet-level economic data to calibrate their POSEIDON model of the U.S. West Coast groundfish fishery. Libre et al. (2015) validate their model by comparing the numbers of vessels and firms remaining in the fishery in their model and in reality. For tactical applications—for example to quantitatively project impacts of multiple management institutions (Gap 1)—either pattern matching would have to be quantitative (e.g., one could compare parameter estimates of discrete-choice models fit separately to ABM output, and to logbook data from the real vessels, the ABM is meant to simulate) or pattern matching would have to be combined with other validation approaches.

Validating candidate fisher decision rules or processes will be important for ABMs addressing each of the knowledge gaps we focus on—perhaps especially Gap 2 (cognitive and behavioural realism). Candidate fisher decision rules should be contrasted in their abilities to reproduce the observed emergent behaviours, and, where possible, validated using information (e.g., from surveys or experiments) on the decision rules themselves. Smajgl and Barreteau (2017) review strategies for such agent-level validation. Thorough sensitivity tests on all ABM assumptions should be performed to determine the importance of each assumption to each result (David, 2013; Galán et al., 2013), similarly to how controlled experiments are used to infer causality in the real world. However, we note that even thorough sensitivity analyses have the limitation of retaining the bedrock structural assumptions of the ABM as a premise, and thus cannot be used to test these assumptions.

Another challenge in adding cognitive and behavioural realism (Gap 2) to ABMs is that, often, few data are available to directly support assumptions about the seemingly intangible elements of human decision-making. Individual motivations beliefs, and learning behaviours are difficult to characterize quantitatively despite their significance to process-based approaches to understanding human dimensions. There is thus a clear need for integration between ABM research and the branches of social science (including assessing expert knowledge; Fulton et al., 2011; Haapasaari & Karjalainen, 2010) currently studying these human intangibles in quantitative and qualitative ways (Smajgl & Barreteau, 2017). For example, ethnographic research may be useful in understanding fisher motivations (especially non-economic motivations; Chan et al., 2012); cognitive and behavioural research may be useful in understanding the heuristics fishers (and other agents within the system) use to make decisions (Kahneman, 2011). On the other hand, these data gaps also present opportunities for ABMs to add insight, by comparing emergent patterns (e.g., fishing patterns, social network structures) arising from a wide range of possible fisher decision-making processes, and observing either which patterns most accurately reflect the data (e.g., as in Carrella et al., 2020), or to what extent the patterns differ in ways that are meaningful to management, across decision-making assumptions.

Importantly, any pattern used for validation (via pattern-oriented modelling) should be emergent as a result of lower-level assumptions rather than assumed directly, or "baked in" through ad hoc assumptions aimed at reproducing the pattern to be validated instead of capturing an underlying process. For example, some fisher ABMs (Saul, 2012) directly specify fishing patterns (e.g., where, when to fish) by fitting discrete-choice models to data, rather than specifying a lower-level motivation and resulting decision-making process. Such discrete-choice models would not be appropriate for predicting fishing patterns in novel policy contexts, in contrast to process-oriented models, which have had some success in predicting responses to such novel conditions (Toft et al., 2011). Additionally, conclusions from model projections should be drawn at scales matching the scales of validation. For example, Toft et al. (2011) study the impacts of policies in a stylized two-species version of a fishery that targets dozens of species in reality, and therefore, they appropriately focus their discussion on high-level qualitative predictions rather than fine-scale quantitative ones.

7.3 | Balancing realism and complexity

As the computational constraints on model sophistication have continued to shrink, complex-system models have become increasingly common in fisheries science [e.g., Atlantis (Fulton, Smith, & Johnson, 2004; 2010)] and elsewhere. Like other computational simulation models, many of the features making ABMs useful—their versatility, sophistication and complexity, for example—also pose challenges (Grimm, 1999). In a complex world, model realism necessarily trades off with parameter uncertainty (Collie et al., 2016), mechanistic transparency (our ability to interpret the meaning of a modelled result) and error propagation. Over-fitting can be a concern (Collie et al., 2016). Minimum realistic models (MRMs) have emerged, which are of intermediate complexity and aim to include only the necessary set of parameters yet are still able to capture complex ecological and social processes (Plagányi et al., 2014). Given the limited parameter space and the ability to quantify uncertainty, MRMs can provide tactical advice, but need to be tailored to individual questions. For instance, when modelling the effects of cognitive realism (Gap 2) or the emergence of social networks (Gap 3), highly simplified ecological models may be appropriate in many cases. When modelling the effects of multiple management institutions (Gap 1), forming specific hypotheses about interactions could be useful in motivating simplifications. In all cases, extensive stakeholder consultation in both defining the questions and developing the model will increase the likelihood of tactical uptake (Plagányi et al., 2014).

Beyond individual studies, the fields addressing these knowledge gaps will benefit from a portfolio approach—combining high-, intermediate- and low-complexity models, as well as non-ABM approaches and widely sampling the efficiency frontier of the realism–tractability trade-off [Gotts et al. (2019) make a similar argument]. As much as possible, new counterintuitive emergent results in complex models should be carefully distilled down to their mechanistic essence using simpler mechanistic models, mean-field approximations, moment expansions or closures, equation-free reductions of the ABM (Kevrekidis et al., 2003) and/or experiments (where possible) and empirical validations. Conversely, mechanistic predictions from simple models should be tested for robustness in more complex frameworks. Multi-model comparison and model-ensemble forecasting approaches are applied widely in other fields (e.g., climate science; Tebaldi & Knutti, 2007) and hold promise in quantifying model uncertainty for a system (Gotts et al., 2019).

7.4 | Resource and time investment

Complex models of coupled natural-human systems require significant investment in data collection and organization, model development, validation and review before they can play a key role in decision-making. If starting from scratch, this process can take decades and millions of dollars of capital, as the experience of other sophisticated modelling approaches shows [e.g., the Atlantis model of the California Current (Kaplan, Horne, & Levin, 2012) or Earth system models to generate global emission targets (Intergovernmental Panel on Climate Change, 2014)]. ABMs of coupled marine systems are no different. Indeed, the POSEIDON model—a multi-institution, multiyear effort, which has developed site-specific applications (Carrella et al., 2020), but is still working towards tactical uptake—is illustrative of this challenge.

However, many start-up costs are one-time. Existing models or modelling platforms can often be adapted or leveraged on a much shorter term and smaller budget, as demonstrated by the widespread use of large global climate models by research groups of all sizes, for instance. Moreover, simple ABMs used for strategic purposes can be constructed at widely varying levels of complexity and cost, including very cheaply (Gray et al., 2014). Thus, we advise groups undertaking ABM development to carefully match the scope and complexity of their model—or of their modification of an existing model—to both the scope of their chosen research question, and to the available time and capital for development.

7.5 | Documentation and reproducibility

Finally, we note the importance of including careful and accessible documentation in an agent-based model, to enhance reproducibility, transparency, user-friendliness (and therefore uptake) and debugging. Ideally, this should be done both at the publication/release stage (e.g., in a supplement, paper or online read-me) and throughout the process of building the model, by inserting comments explaining each step of the code into the code itself. The ODD + D protocol (Müller et al., 2013) is designed specifically for ABMs with human agents, aimed at this purpose (see Bailey et al., 2018 for POSEIDON's ODD + D protocol). Wilson et al. (2014) review of best coding practices for scientists.

8 | CONCLUSION: FROM STRATEGIC TO TACTICAL ABMS

We have reviewed some of the literature and best practices for designing and implementing ABMs, and we identified three knowledge gaps in the human dimensions of fisheries, listed above, that ABMs can offer useful contributions in addressing. Each of these research areas holds potential for strategic advances, which could be important to fishery science in their own right and could also inspire tactical applications. However, as the experience of ecosystem modelling shows—reviewed by Plagányi et al. (2014)—moving from strategic to tactical model applications takes time and often requires a deliberate and consultative socialization process for the models.

Drawing on the experience of ecosystem models, we hypothesize an approximately three-stage process leading to tactical uptake of ABMs of human dimensions in fisheries. First, strategic ABM studies need to produce insights that saliently demonstrate a potential tactical value of ABMs for a question of importance to a specific fishery. For instance (related to Gap 2), Carrella et al.'s (2020) ABM study of the U.S. West Coast groundfish fishery suggests that economic models which assume exact profit-maximizing vessel behaviour (in contrast to simple heuristics) might underestimate the challenge of quota balancing across target and constraining species. Quota balancing is a challenge at the front of mind for managers of this fishery (Kuriyama, Branch, Bellman, & Rutherford, 2016) and likely many others. Carrella et al.'s (2020) results may suggest that ABMs would be useful to managers in understanding and designing solutions to address this challenge. Libre et al. (2015) provide another possible example (related to Gaps 1 and 2): their results suggest that management institutions such as ITQs could have different effects on fleet consolidation and spatial effort patterns in the Philippines than they do in western fisheries, due to Philippine social norms and resistance to exit. Other strategic insights revealing, for example, important interactions between formal and informal institutions such as information-sharing networks (related to Gaps 1 and 3), could speak similarly saliently to specific management challenges.

Second, inspired by results of strategic ABMs, one-off tactical applications of ABMs could arise through consultative co-production processes generating questions and model designs—using best practices described above for validation and documentation. Though not an ABM, the California Marine Life Protection Act (MLPA) provides an analogous example for bioeconomic models, which also have had limited tactical uptake (as noted by Plagányi et al., 2014). The MLPA created an MPA network in California, which was designed through a stakeholder-engagement process guided by two bioeconomic models (White et al., 2013). The inclusion of bioeconomic models in this process was likely inspired by the previous bioeconomic modelling work of several of the modellers invited to participate [e.g., Steven Gaines, Christopher Costello and Ray Hilborn were all on the Scientific Advisory Team; California Department of Fish and Wildlife (CDFW), 2008], which had produced a wide range of strategic insights, in the California region and elsewhere. Plagányi et al. (2014) provide other examples from ecosystem modelling. For ABMs, one possible entry point to early tactical application could be in management strategy evaluation (MSE).

Third, the success of one-off tactical applications of ABMs could inspire tactical applications in other fisheries and/or the institutionalizing of the tactical ABM application in the original fishery. Here again—although there is no precedent, we are aware of in ABMs of human dimensions in fisheries—there are some examples of analogous successes in ecosystem models. For instance, some U.S. fish stock assessments have begun to use multispecies models to refine natural mortality estimates as a function of changes in predation (Plagányi et al., 2014). Widespread use of ecosystem models such as Ecopath with Ecosim (Christensen & Walters, 2004)—though often not tactical—illustrates successes of models in spreading laterally among systems, following insightful initial uses.

Whether or not the progression of ABM-use from strategic to tactical follows this path, salient management-relevant advances from strategic ABM studies, best practices for validation and documentation, and co-production of tactical models with stakeholders, are likely to be key to success. The three knowledge gaps highlighted in this paper are ripe for such strategic advances.

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DATA AVAILABILITY STATEMENT

Full documentation and code for POSEIDON are publicly available from Carrella (2017) and Bailey et al. (2018).

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APPENDIX 1

Simulation details

Full details of POSEIDON are available in Bailey et al. (2018, 2019), Carrella (2017) and Carrella et al. (2019). Parameter values for the simulations shown in Figures 2–4 are given below in Tables A1–A4.Table A1 The baseline parameter settings in POSEIDON [appendix section 2.1.2 in Bailey et al. (2019)] are replicated here

Parameters	Value	Meaning
Biology	Logistic	
K	5,000	Max units of fish per cell
m	0.001	Fish speed
r	0.7	Malthusian growth parameter
Fisher	Explore-exploit-imitate	
Rest hours	12	Rest at ports in hours
ϵ	0.2	Exploration rate
δ	~U[1,10]	Exploration area size
Fishers	100	Number of fishers
Friendships	2	Number of friends each fisher has
Max days at sea	5	Time after which boats must come home
Map		
Width	50	Map size horizontally
Height	50	Map size vertically
Port position	40,25	Location of port
Cell width	10	Width (and height) of each cell map
Market		
Market price	10	$ per unit of fish sold
Gas price	0.01	$ per litre of gas
Gear		
Catchability	0.01	% biomass caught per tow hour
Speed	5.0	Distance/h of boat
Hold size	100	Max units of fish storable in boat
Litres per unit of distance	10	Litres consumed per distance travelled
Litres per trawling hour	5	Litres consumed per hour trawled

Table A2 Parameter values for Figure 2

Parameters	Value	Baseline value
Biology	2 species logistic	1 species logistic
Kred	5,000	5,000
Kblue	5,000 if $15 \leq x \leq 35$ and $15 \leq y \leq 35$; 0 otherwise	0 everywhere

Table A3 Baseline parameters except for using simulated annealing algorithm: exploration is 100% whenever agent is making <δ

Parameters	Value	Baseline value
Fisher	Social annealing	Explore-exploit-imitate
δ	from 0.1 to 2	–

Table A4 Baseline parameters except for network structure and degree

Parameters	Value	Baseline value
Friendships	0 to 19	2
Network structure	Independent clusters/clubs	Random network