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Dynamic ocean management increases the efficiency and efficacy of fisheries management

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In response to the inherent dynamic nature of the oceans and continuing difficulty in managing ecosystem impacts of fisheries, interest in the concept of dynamic ocean management, or real-time management of ocean resources, has accelerated in the last several years. However, scientists have yet to quantitatively assess the efficiency of dynamic management over static management. Of particular interest is how scale influences effectiveness, both in terms of how it reflects underlying ecological processes and how this relates to potential efficiency gains. Here, we address the empirical evidence gap and further the ecological theory underpinning dynamic management. We illustrate, through the simulation of closures across a range of spatiotemporal scales, that dynamic ocean management can address previously intractable problems at scales associated with coactive and social patterns (e.g., competition, predation, niche partitioning, parasitism, and social aggregations). Furthermore, it can significantly improve the efficiency of management: as the resolution of the closures used increases (i.e., as the closures become more targeted), the percentage of target catch forgone or displaced decreases, the reduction ratio (bycatch/catch) increases, and the total time–area required to achieve the desired bycatch reduction decreases. In the scenario examined, coarser scale management measures (annual time–area closures and monthly full-fishery closures) would displace up to four to five times the target catch and require 100–200 times more square kilometer-days of closure than dynamic measures (grid-based closures and move-on rules). To achieve similar reductions in juvenile bycatch, the fishery would forgo or displace between USD 15–52 million in landings using a static approach over a dynamic management approach.

dynamic ocean management | real-time management | ecosystem-based fisheries management | spatiotemporal | bycatch

Although traditional fisheries management has focused on assessing the health of individual fish stocks, there has been a strong trend over the past two decades toward the incorporation of ecosystem components into fisheries management (1, 2). Ecosystem-based fisheries management (EBFM) seeks to meet multiple, potentially conflicting goals across ecological, economic, and social objectives (3, 4). Meeting these goals is made more complex in marine ecosystems due to the inherent dynamic nature of the oceans. In response to continuing difficulty in managing the ecosystem impacts of fisheries in a highly dynamic environment, including bycatch (i.e., the accidental interaction of fishing gear with nontarget species), interest in the concept of dynamic ocean management (DOM) has accelerated (5–10). Maxwell et al. (8) define dynamic management as "management that changes in space and time in response to the shifting nature of the ocean and its users based on the integration of new biological, oceanographic, social and/or economic data in near real-time" (8). Dynamic management reflects advancement in our ability to manage ocean resources across finer spatial and temporal scales as a result of technological improvements that have paved the way for higher-resolution collection of both fisheries and environmental data (e.g., electronic logbooks, vessel monitoring systems, smartphone technology, remote sensing, and animal tracking) (9). The existing literature has focused on the presumed capacity of dynamic management to increase management efficiency across both ecological and economic objectives (7, 8), and in codifying the different approaches to dynamic management across fisheries and other applications (7, 10). However, little to no empirical research exists to quantify the implied benefits of dynamic management or compare the efficiency of the various spatiotemporal management measures. Additionally, and critically, the benefits of dynamic management hinge on the premise that it is capable of managing resources at scales more aligned with resources and resource users, yet we lack a quantitative assessment of how scale influences the effectiveness of dynamic management—both in terms of how it reflects underlying ecological processes, and how this relates to the efficiency of dynamic management approaches.

Scale in Fisheries Management

Frameworks for dynamic management (e.g., ref. 6) have defined it in contrast to traditional static spatiotemporal management of fisheries (i.e., coordination of fisheries in space and/or time) including monthly or seasonal closures of specific areas (often known as "time–area closures"), and seasonal full-fishery closures. Alternatively, dynamic management operates at smaller scales of space and time, and depends on contemporaneous conditions. Work on dynamic management has focused on three types of measures: grid-based hot-spot closures, real-time closures based on move-on rules, and oceanographic closures. Grid-based closures involve the overlaying of a grid on an area of interest and closing individual grid cells where bycatch has exceeded a threshold level (e.g., refs. 11 and 12); they have been implemented on a daily or weekly basis with cell sizes as small as

Significance

Food security and the economic well-being of millions of people depend on sustainable fisheries, which require innovative approaches to management that can balance ecological, economic, and social objectives. We offer empirical evidence that dynamic ocean management, or real-time ocean management, can increase the efficacy and efficiency of fisheries management over static approaches by better aligning human and ecological scales of use. Furthermore, we show that dynamic management can address critical ecological patterns previously considered to be largely intractable in fisheries management (e.g., competition, niche partitioning, predation, parasitism, or social aggregations) at appropriate scales. The evidence and theory offered supports the use of dynamic ocean management in a range of scenarios to improve the ecological, economic, and social sustainability of fisheries.

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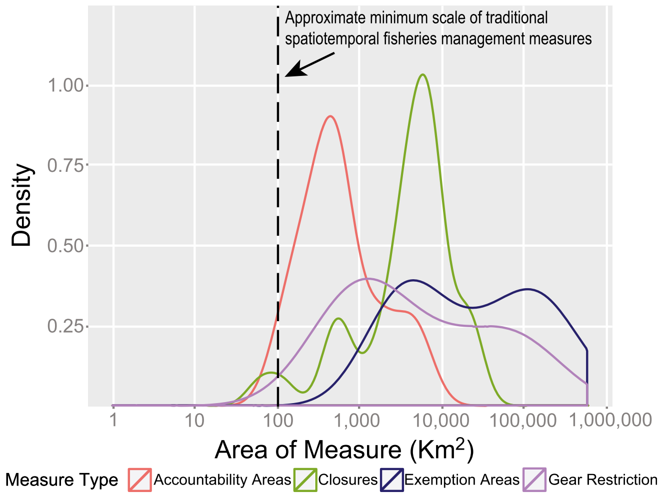

Fig. 1. Density of the area of spatiotemporal management measures in the Northeast Multispecies Fishery. Data abstracted from the Greater Atlantic Region Fisheries Office (www.greateratlantic.fisheries.noaa.gov/educational_resources/gis/data/index.html; downloaded on March 30, 2015). Only one management measure in the fishery, Fippennies Ledge Area, is finer than 100 km^2 (Table S1).

~50 km^2. Move-on rules are similarly triggered by a threshold, but rather than using predefined grid cells, fishermen must move a set distance away from the affected area. Move-on rules have been widely implemented with real-time closures lasting days to weeks over distances as short as 2–10 km in radius (5, 10, 13, 14), with the potential to be implemented on temporal scales of days or hours if higher-resolution catch data are incorporated. Oceanographic closures are areas defined by environmental conditions (e.g., sea surface temperature) and have been implemented on a daily (15) and biweekly (16, 17) basis. In the only compulsory example, the Eastern Australia pelagic longline fishery employs a habitat model to inform a dynamic oceanographic closure to reduce bycatch of southern bluefin tuna (*Thunnus maccoyii*) based on 5-km resolution temperature data, but the oceanographic closure is implemented at a much coarser scale (17).

Although there are active examples of dynamic management, the vast majority of spatiotemporal fisheries management measures are static and occur at much larger scales. The resolution and extent of fisheries management have largely been dictated by logistical, and legal and political constraints, respectively, and secondarily by the geographic range of the species or subpopulation dynamics (18). Management units in developed coastal fisheries are rarely smaller than 1,000 km^2, and management measures are generally larger than 100 km^2. For example, in the Northeast Multispecies Fishery in the United States from which the data for this study are drawn (see *Methods* for further details on the fishery), the mean size of a spatiotemporal management measure is 25,635 km^2 ($n = 74$; range, 61–592,539 km^2; SD, 78,339 km^2; Fig. 1 and Table S1). If we consider only closures, the mean is 6,344 km^2 ($n = 33$; range, 61–23,454 km^2; SD, 6,194 km^2; Table S1). From a temporal perspective, the resolution of management measures is at best a month (e.g., Rolling Closure Areas) and generally a year (Table S1).

Implication of Scale-Dependent Drivers of Ecosystem Structure for Fisheries Management

To understand the need to manage at sub–100-km^2 and 1-mo scales (i.e., the need to use dynamic management) and the efficiency gains potentially afforded by doing so, we need to understand how those scales interact with ecosystem structure and fisheries management. The processes responsible for producing pattern in marine ecological systems vary widely across spatial and temporal scales. At the base of marine ecosystems, the drivers of variability in biomass are scale dependent (19, 20). Plankton abundance is generally a function of highly variable forcing factors influencing growth (light, temperature, and nutrient availability) and distribution at fine scale (e.g., molecular processes, internal waves and tides, and biophysical interactions), mesoscale (e.g., surface tides, fronts, and eddies), and macroscale [e.g., basinal variability, decadal/multidecadal oscillations, and climate change (21–24); reviewed in refs. 25–27]. These patterns are also true for higher trophic level organisms (including fishermen), which are also patchy and forced by diverse scale-dependent drivers, although temporal and spatial lags often exist for higher trophic level organisms because they are not as tightly coupled with physical processes and the distribution of primary productivity (18, 28, 29).

Drivers of ecosystem structure at scales smaller than 100 km^2, however, differ from larger scales by including coactive and social patterns as dominant forces, as opposed to vectorial (i.e., environmental) and reproductive patterns (Fig. 2) (19). Coactive patterns, as defined by Hutchinson (30), arise from interactions between species (e.g., competition, niche partitioning, predation, and parasitism), whereas social patterns are "determined by signalling of various kinds, leading either to spacing or aggregation" (e.g., facilitated foraging, local enhancement, predator avoidance, territoriality). Coactive patterns have been widely described in the marine realm (31–34), and similarly, social patterns are seen within taxa (35, 36), and among them (37, 38). As fishing itself is a predator–prey interaction with strong social pressures among fishermen, patterns of fishing effort within a fishery are also forced by social and coactive processes at sub–100-km^2 scales (39–41). If variability in the distribution and abundance of target species and fishing effort are based on multiple drivers across multiple scales, we can assume that effective fisheries management should also be a multiscale process, capable of addressing drivers at all tractable scales. However, as seen in the example of the size distribution of Northeast Multispecies Fishery measures (Fig. 1), this is rarely the case. Fisheries management is almost entirely a mesoscale activity. As such, attempts to manage processes and patterns at sub–100-km^2, sub–1-mo resolution likely involves some level of spatiotemporal mismatch and some degree of inefficiency.

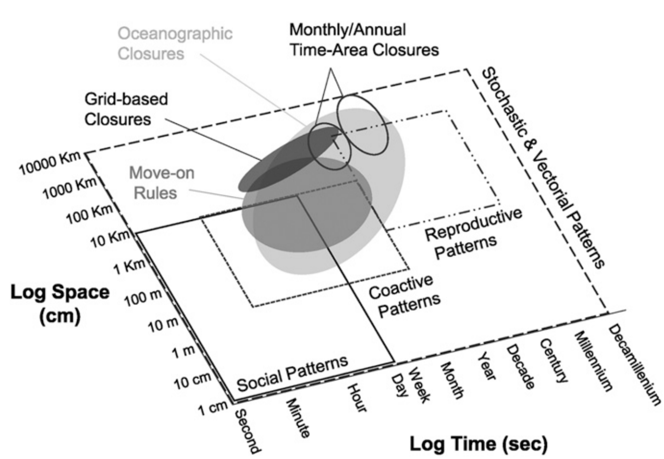

Fig. 2. Spatiotemporal scales of Hutchinson's five patterns and fishery management measures. Traditional spatiotemporal fisheries management measures (i.e., monthly and annual time–area closures) can only address reproductive and some vectorial patterns at appropriate scales. However, dynamic management measures (i.e., closures based on oceanography, grid-based hotspot closures, and real-time closures based on move-on rules) should be able to address social and coactive patterns as well as some vectorial and reproductive patterns.

Evaluation of Static vs. Dynamic Management Measures

Studies comparing static and dynamic measures are lacking despite the potential to increase efficiency through the use of dynamic measures to align the scales of resource variability, resource use, and resource management (7, 8). In a precursor to the recent work on dynamic management, Grantham et al. (42) looked at the efficiency of closures to reduce bycatch by examining permanent full-fishery closures, seasonal full-fishery closures, and a series of temporary (monthly) time–area closures. Although this effort represented a major step forward in considering the utility of dynamic management measures, it did not incorporate many of the aspects of what it might mean for a closure to be "dynamic" (e.g., near real-time closures based on contemporaneous conditions). A study comparing dynamic and static measures by O'Keefe et al. (43) evaluates the effectiveness of time/area closures, quotas/caps, and fleet communication to reduce fisheries bycatch against a set of five criteria. Evaluation criteria include "(1) reduced identified bycatch or discards, (2) no or minimal negative effect on the catch of target species, (3) no or minimal negative effect on the catch of other nontarget species or sizes, (4) no or minimal spatial or temporal displacement of bycatch, and (5) economically viable for the fisher." Their results indicated that four of the five static time–area closures studied failed to meet even two of the criteria, whereas all of the more dynamic measures used were able to meet at least three criteria (mean, ∼4.125 of the criteria). However, no statistical tests were run to show significant differences between the two types of measures. Clearly, broader, quantitative evaluations of dynamic management are necessary, particularly using scenarios capable of comparing across multiple types of static and dynamic management to understand how efficiency differs between them, and within dynamic management approaches themselves.

Here, we highlight the importance of scale for dynamic management and the potential efficacy of dynamic management across both ecological objectives (through reduction of bycatch) and economic objectives (through decreased target catch affected and time–area closed) in the US Northeast Multispecies Fishery. Specifically, we use simulation modeling to compare the ability of closures across a range of spatial and temporal scales to meet a common management goal: the reduction of regulatory discards of undersized (juvenile) target species (Atlantic cod; *Gadus morhua*) while minimizing affected marketable catch and the time–area closed. We compare the efficacy and efficiency of dynamic measures (grid-based "hot-spot" measures and move-on rules) to optimized static monthly and annual closures developed through the use of a spatial conservation prioritization tool (i.e., Marxan) (44, 45). In doing so, we attempt to address both the empirical evidence gap for the increased efficiency of dynamic management over static management, as well as attempt to further the ecological theory underpinning dynamic management.

Results

Using fishery observer data, we simulated six types of closures: (*i*) seasonal full-fishery closures; (*ii*) static annual time–area closures; (*iii*) monthly time–area closures; (*iv* and *v*) daily and weekly grid-based hot-spot closures; and (*vi*) real-time closures based on move-on rules (Fig. S1). Oceanographic closures were not considered due to limitations in the resolution and accuracy of currently available models of bottom temperature for the study area. To compare the six types of closures, we examined (*i*) the percent bycatch reduction achieved by weight; (*ii*) the percent target catch affected by weight (i.e., target catch forgone or displaced); (*iii*) the bycatch reduction efficiency; and (*iv*) the percentage of the time and area closed to fishing required to achieve the bycatch reduction (i.e., the spatiotemporal efficiency of the closure); see *Supporting Information* for details on how individual metrics were calculated for each closure type. We also developed a summary metric, the spatiotemporal utility metric (SUM), to integrate the other metrics and convey the overall utility of the measures.

The time–area required for an individual closure can be considered the resolution of the management measure. For instance, each closure based on move-on rules had an area of ∼20 km^2 and was closed for 1 d, resulting in a 20 km^2·d/closure resolution. Seen this way, the measures can be ordered by resolution: high-resolution (move-on rules, 20 km^2·d per closure; grid-based closures, 50 km^2·d per closure), medium-resolution (weekly grid-based closures, 350 km^2·d per closure; monthly time–area closures, 3,000 km^2·d per closure), and low-resolution closures (annual time–area closures, 36,500 km^2·d per closure; and monthly total closures, 78,000 km^2·d per closure). Results of the closure simulations are shown in Table 1 and Fig. 3 ordered from high to low resolution of the individual closure.

A previous study showed real-time closures based on move-on rules could theoretically reduce juvenile cod bycatch 62.17% by weight (5). To draw comparisons between the real-time closures and less dynamic monthly and annual time–area closures, a general target of 60% reduction in bycatch biomass was set for all closures. Trends in the best results from each closure type based on achieving this bycatch reduction target were monotonic (Table 1 and Fig. 3). Percent target catch affected increased linearly as the resolution of the management measure decreased (slope = 8.40; R^2 = 0.869). Consequently, the bycatch reduction efficiency (generally inversely related to the percent catch affected) decreased linearly with resolution (slope = −1.16; R^2 = 0.716). The total kilometer-days used to achieve the target displayed a log-linear increase as resolution decreased (R^2 = 0.923). The mean SUM of dynamic measures (i.e., move-on rules, daily grid-based closures, and weekly grid-based closures) was significantly higher than static measures (independent two-group Mann–Whitney U test, $P < 0.05$).

Discussion

The results of this simulation study clearly depict how the use of more dynamic measures should reduce the negative costs associated with spatiotemporal fisheries management (i.e., lost catch or increased operational costs when effort is displaced). As the spatial and temporal resolution of the closures used increases (i.e., as more targeted closures are used), (*i*) the percentage of target catch affected decreases, (*ii*) the reduction ratio (bycatch/catch) increases, (*iii*) the total time–area required to achieve the target bycatch reduction decreases, and (*iv*) the overall SUM increases.

The coarser scale management measures (annual time–area closures and monthly full-fishery closures) affected up to four to five times the target catch and required 100–200 times the time–area of the dynamic measures (grid-based closures and move-on rules). A simple extrapolation using the value of cod landings in New England for the time period of this study ($1.524/lb*), suggests that the hypothetical difference in potential value of landings affected across the whole fishery (via displaced or forgone target catch) of using the most static measure vs. the most dynamic measure to reduce juvenile cod catch by 60% would be over US$52,750,000, or approximately a third of the value of the all of the cod landed.* The difference between real-time move-on rules and commonly used monthly time–area closures would be more than US$15,500,000. Considered as a group, dynamic measures were significantly more efficient than static measures. Higher-resolution measures had a higher SUM than lower-resolution measures across almost all scenarios [i.e., across changes in boundary length modifier (BLM) and threshold weights; Table 1

*Average price of cod for the years 2005–2010 derived by dividing the total value of cod landed ($152,013,619) in New England by total landings (99,713,856 lb). Data were downloaded from the National Marine Fisheries Service Annual Commercial Landing Statistics website (https://www.st.nmfs.noaa.gov/commercial-fisheries/commercial-landings/annual-landings/index).

Table 1. Results from the simulation of six different closures type spanning a range of spatial and temporal scales

Closure type	BLM or weight threshold, lb	Percent bycatch reduction	Percent target catch affected	Bycatch reduction efficiency	No. of closures	Area of closure; resolution, km^2	Days closed	Log km^2·d of closure	Spatiotemporal efficiency, /1,000	SUM
Move-on rules	NA	62.17	8.57	7.25	48	19.63	1	2.97	0.2	4.64
Daily grid-based closures	10	61.66	17.39	3.55	30	50	1	3.18	0.3	4.13
Weekly grid-based closures	10	61.66	18.27	3.37	30	50	7	4.02	1.8	3.26
Monthly time–area closures	0.0001	60.01	18.77	3.20	5	100	30	4.18	2.6	3.08
Annual time–area closures	0.001	68.72	37.47	1.83	2	100	365	4.86	12.8	2.16
Monthly total closures	NA	68.54	43.28	1.58	4	2,600	30	5.49	54.8	1.46

BLM, boundary length modifier (see *Supporting Information*); SUM, spatiotemporal utility metric that provides a summary across all metrics.

and Table S2]. However, no attempt to test for significant differences between individual measures was performed due to the small sample sizes. Allowing the BLM to vary in the Marxan runs predictably led to lower "cost" (i.e., the percent target catch affected) but also decreased the spatiotemporal efficiency of the closures.

The various metrics used suggest that the results of this study are not artifacts of the way the SUM is formulated. The spatiotemporal efficiency component likely has an outsized effect on the SUM because the range of spatiotemporal efficiency values across all closure types (spanning three orders of magnitude) is greater than the range in the bycatch reduction efficiency (less than one order of magnitude). Despite this, the three independent metrics that make up the SUM (target catch affected, bycatch reduction efficiency, and the log of spatiotemporal efficiency) all displayed the same strong trends ($R^2 > 0.7$) with little overlap in the SUM as measures became more dynamic. Thus, although further consideration should be given to ensuring the formulation of the SUM is weighted appropriately for the context it is applied in, the general results of this study are not sensitive to changes in how the SUM is formulated.

Furthermore, the methods used to identify optimal closures for the coarser-scale spatiotemporal closures (monthly and annual time–area closures and monthly full-fishery closures) are a best-case scenario based on perfect knowledge of where the juvenile bycatch hot spots were located. That is, they were chosen after fishing occurred and the bycatch was known. The grid-based closures and real-time move-on rules are based on a trigger (i.e., bycatch in a given set exceeding a threshold) that affected sets in the future with no knowledge of where or when the future bycatch events occurred. This assumption of perfect hindsight strongly biases the results of the study in favor of the more static measures, making our conclusions regarding the utility of dynamic measures conservative.

It is important to note that DOM is made possible by the speed at which information is transferred or by defining management measures against conditions on the ground that fishermen may respond to directly. Based on technology and processes that are already in place in a number of fisheries (46), this study assumes immediate transfer of knowledge to all other fishermen in the sector. For example, mobile apps like eCatch (https://www.ecatch.org/), Digital Deck (pointnineseven.com/resources/display/digital_deck), and Deckhand (deckhandapp.com) are used by fishermen to transfer catch data in real time and can or could transmit DOM products back to fishermen. Although these tools allow for operational implementation of DOM, there is a larger question of how DOM fits within current fisheries management regimes. Previous studies have shown that DOM does not seek to supplant existing adaptive management processes but falls within the implementation component of that framework (7, 8). For example, move-on rules as they are currently implemented in numerous fisheries do not occur at a predetermined time or location and do not require management council review for each application of the measure (5, 10); rather, the distance which fishermen must move following a bycatch event is determined during the council review process and the move-on rule is applied in near real time on the ground. The potential legal constraints on the various stages encountered in implementing DOM have also been enumerated including appropriate legal notice of changes in closure location (e.g., for grid-based closures and oceanographic closures), and addressing permits that confer absolute property rights (9). In these cases, dynamic closures may violate such property rights by restricting access, although exceptions to absolute property rights already exist in a fisheries context (e.g., emergency closures due to maximum take of protected species). Moreover, this study indicates that dynamic management has less impact on fishermen (i.e., it affects less target catch and time–area) than static management. Thus, it may not be necessary to develop DOM regulations, but rather offer information to fishermen to use voluntarily to meet already legally established management goals (e.g., bycatch reduction) or improve their economic efficiency (e.g., by avoiding the need to lease more quota). In such scenarios (e.g., as implemented in the US East Coast Scallop Fishery) (12), DOM amounts to information sharing and is only limited by the aforementioned speed of content delivery.

Implications for Ecosystem-Based Fisheries Management. This study highlights the increases in efficiency that can be obtained by using finer-scale management measures than traditionally used in fisheries management, which generally occurs at mesoscale spatial resolutions and monthly or annual timescales. That is not to say that the understanding and integration of mesoscale, macroscale, and megascale processes and patterns into fisheries management is not critical. Mesoscale and macroscale are, have been, and will continue to be the dominant scales of strategic fisheries management. However, managers must develop finer-scale (1–10 km) management measures to ensure that the tactical implementation of those strategies is done as efficiently as possible.

The gap in fisheries management at scales less than 10 km also raises some doubt as to whether, and at what cost due to the inefficiency of the measures, we can meet commitments to implement ecosystem-based fisheries management with spatiotemporal measures that may be fundamentally mismatched in space and time to address important drivers of ecosystem structure (i.e., coactive and social patterns). Since its inception, calls for EBFM have contained requirements to protect ecosystem structure, stock structure, and

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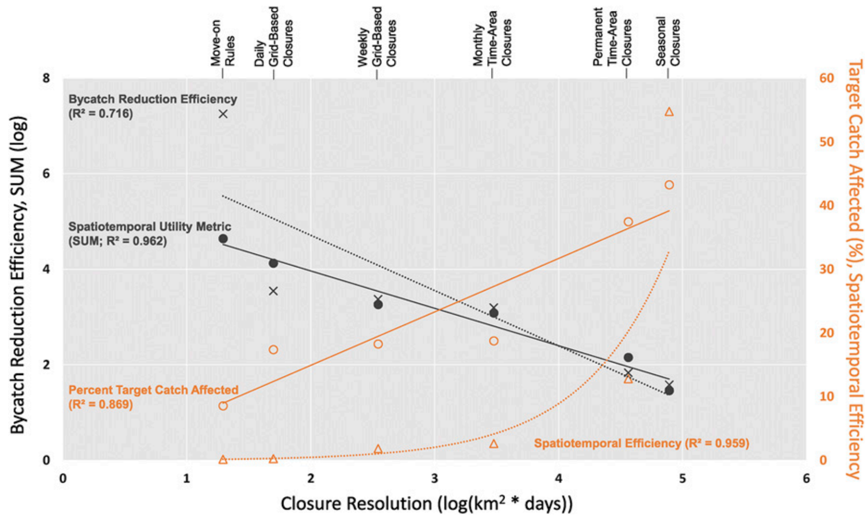

Fig. 3. Comparison of the efficacy and efficiency of the simulated static and dynamic closure. As closure resolution decreases (i.e., as individual closures get bigger), percent catch affected and the log of the time–area required to meet the bycatch reduction target increase monotonically. Consequently, and conversely, the bycatch reduction ratio and the log of the SUM decline linearly.

trophic interactions (3, 47, 48). More generally, key elements of ecosystem-based management include the use of "appropriate spatial and temporal scales" and "accounting for the dynamic nature of ecosystems" (44, 49). It is critical that managers recognize ecological processes exist below 10 km and that the marine realm is a complex adaptive system where large-scale dynamics can be driven by fine-scale interactions (45, 50).

Does Dynamic Management Only Benefit Highly Mobile Species? Beyond the question of scale, there are a number of other important ecological factors to consider as we move forward with DOM. Two recent articles (7, 8) make the argument that, as the vagility of an organism or process increases, the amount of space required to encapsulate it within a management scheme is inversely proportional to the temporal resolution used. This implies that dynamic management may be more useful for the management of highly mobile pelagic species or processes (e.g., sea turtles and tuna, or fronts and eddies), and limits the consideration of dynamic management of less mobile species. However, the work in this study shows that dynamic management can more efficiently meet management targets in demersal species as well. Considered together with other recent work (5, 10, 12, 51), a trend begins to appear indicating that the utility of dynamic management to more sedentary, demersal fisheries may be the norm, not an anomaly. Further work needs to be done to examine how dynamic management fares against a continuum of species life-histories (benthic vs. pelagic, central place foragers vs. wanderers, migratory vs. local populations, etc.). It is critical that we develop a better idea of whether, and to what degree, the use of dynamic management will reduce bycatch, decrease the time and area required to address management problems, and decrease the economic burden placed on fishermen by inefficient static management. This can be done only through the production of more example analyses examining the efficiency of spatiotemporal management measures under various scenarios.

Methods

The potential efficiency and efficacy of various static and dynamic closures were examined using observer data produced by the Northeast Fisheries Observer Program related to the Northeast Multispecies Fishery. The Northeast Multispecies Fishery management plan contains 16 species, including the iconic Atlantic cod. The Atlantic cod population has continued to decrease despite repeated attempts over decades by management to address overfishing and habitat concerns. One consistent issue across many fisheries including the Northeast Multispecies Fishery is the catch and discarding of target species smaller than the minimum size length allowed under the fishery management plan. The discarding of such juveniles or "small" fish has led to numerous regulations including gear modifications and time–area closures (5, 52). In this study, we model how time–area closures across a range of spatial and temporal scales could hypothetically decrease juvenile discards of cod in the Northeast Multispecies Fishery using high-resolution fishery-dependent data from a sector within the fishery.

Details of the method used to develop and optimize the simulated closures are provided in *Supporting Information*. We consider four metrics to compare static and dynamic closures (acronyms given in parentheses relate to the algorithm for calculating the SUM provided below): bycatch reduction (BR), target catch affected (TCA), bycatch reduction efficiency (BR/TCA), and spatiotemporal efficiency (STE). Bycatch reduction is the percentage (by weight) of the bycatch species that might have been avoided by using the given closure. Similarly, target catch affected is the percentage of the target catch that would be forgone or displaced if the given closure had been implemented. Bycatch reduction efficiency is the ratio of percent bycatch reduced to the percent target catch affected. Spatiotemporal efficiency refers to the percent of the total time–area available in the study that would have been closed to achieve the bycatch reduction.

Each of the metrics separately has information useful to managers, but none conveys the overall utility of the measure by themselves. As such, we also provide a summary metric, the SUM:

$$\text{Spatiotemporal Utility Metric} = \begin{cases} \text{N. A.} & \text{for BR } < \text{Reduction Target} \\ \log\left(\dfrac{\text{BR/TCA}}{\text{STE}}\right) & \text{for BR } \geq \text{Reduction Target.} \end{cases} \quad [1]$$

The SUM is a hurdle metric that requires that the bycatch reduction target be met before allowing further comparison of the spatiotemporal efficiency of the measures. The hurdle is applied to ensure that consideration of conservation (i.e., bycatch reduction) is not lost to either catch affected or space-time efficiency. When the bycatch reduction target is not met (i.e., BR < Reduction Target), the SUM is not applicable. The metric conveys information about efficacy and efficiency of the management measures. As the ratio of bycatch reduced to catch affected increases, the numerator goes to infinity. Alternatively, as bycatch reduction efficiency decreases, it goes to zero. The denominator [i.e., the spatiotemporal efficiency metric (STE)] is a proxy for impact on fishermen. The actual effect of a closure on an individual fisherman will vary greatly based on physical, fiscal, and social factors that are far beyond the scope of this paper to incorporate. However, the metric operates under the assumption that fishermen prefer fewer restrictions on their ability to fish, particularly to the time and area in which they are permitted to fish. As the percentage of the fishery (in time and space) required to reach the bycatch reduction goal decreases (i.e., as the spatiotemporally efficiency of the measure increases), the denominator approaches 0 and the SUM approaches infinity. Thus, the metric increases with bycatch reduction efficiency and spatiotemporal efficiency.

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