The precursors of governance in the Maine lobster fishery

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Collective action is more likely to occur and to be effective when it is consistent with the self-interest of the affected individuals. The Maine lobster fishery is an instructive example of biological and technological circumstances combining with individual self-interest to create conditions favorable to collective action. The model describes the way social structure emerges from the adaptive behavior of competing fishers. Fishers compete in two ways: in a scramble to find the lobsters first and by directly interfering in other fishers' ability to compete, i.e., by cutting their traps. Both forms of competition lead fishers to interact frequently and to self-organize into relatively small groups. They learn to restrain their competitive behavior toward their neighbors but do not extend that same restraint to nonneighbors. Groups work within well defined boundaries, contact one another frequently, actively exchange information about the resource, and, most importantly, depend on continuing mutual restraint for their economic well-being. These self-organizing, competitive processes lay the foundation for successful collective action, i.e., mutual agreements that create the additional restraint required for conservation. The modeling approach we use is a combined multiagent and classifier systems simulation. The model allows us to simulate the dynamic adaptation (learning) of multiple individuals interacting in a complex, changing environment and, consequently, provides a way to analyze the fine-scale processes that emerge as the broad social–ecological patterns of the fishery. Patterns generated by the model are compared with patterns observed in a large dataset collected by 44 Maine fishers.

agent-based model | classifier system | self-organizing

The Maine lobster fishery is a well studied example of a fishery in which a self-organizing process at a very local level, group territoriality, has created the basis for a rudimentary form of collective action (1). The importance of territoriality is that it restricts the geographic range of fishers. They cannot deplete the resources on their doorstep and expect to repeat the same behavior elsewhere (at least not if their neighbors also practice territoriality). Because they are forced to "stay at home," fishers cannot run away from overfishing; they have to live with the consequences of their actions. Furthermore, when "staying at home," whether they like it or not, they become part of an easily identified, usually fairly small, homogeneous, and stable group, working within well defined geographic boundaries. These social circumstances are almost always associated with well managed common resources (2).

In the lobster fishery, these very local circumstances are the foundation of a relatively stable and effective system of multilevel (local, state, and federal) governance, a reasonably sustained resource,[§] very effective enforcement of conservation rules, and the growth of a personal sense of stewardship among fishers. This kind of outcome is unusual in fisheries. The more common situation is an impersonal, administrative approach that relies on an ecologically restricted set of fishing rules, fails to create biologically effective stewardship incentives, and, too often, leads to the depletion of the resource (3). Consequently, the circumstances that give rise to this form of self-organized governance are of interest because they provide a perspective on the causes of overfishing that is very different from the conventional "technical" or top-down perspective.

We describe here a model used to investigate the factors facilitating the emergence of self-governance in this fishery. The basic premise of the model is that the relatively sedentary behavior of lobsters and the technology of their capture (traps), combined with the self-interested, competitive behavior of individual fishers create circumstances that facilitate collective action. The same people, in the same place, fishing for other species (such as scallops, urchins, groundfish, and shrimp) with mobile fishing gear did not arrive at similar self-organizing arrangements.

The modeling approach is a combination of a multiagent or individual-based simulation and a classifier system (CS) (4). In the typical agent-based simulation, the modeler specifies the rules governing the interactions of self-interested agents with one another and their environment. In recent years, a comparatively large population of these models has appeared (in ecology, see ref. 5; in social sciences, see ref. 6). In a CS model, however, the information pertinent to the decisions of individual agents and the possible actions that they might take are specified by the modeler, but the decision rules that translate that information into action evolve, i.e., are computed, in response to feedback about their value to the agent.

The principal advantage of a CS model is the ability to simulate the evolution of individual behavior in a complex social–ecological environment and to analyze, thereby, the fine-scale competitive dynamics that eventually emerge as broad-scale patterns.[¶] Output from the model is compared with a very large dataset giving the location and catch for 988,000 trap hauls collected by 44 Maine fishers [see supporting information (SI) *Logbook Data*]. The model is specific to the lobster fishery, but in many ways it is a metaphor for the dynamics of more generally competitive and cooperative processes. Presumably, a better understanding of these fine-scale

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Abbreviation: CS, classifier system.

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§Since the late 1980s, the lobster fishery has enjoyed record levels of abundance and harvests (Maine Department of Marine Resources; www.maine.gov/dmr/rm/lobster/lobdata.htm). This period was preceded by ≈40 years of relatively stable harvests. It is not the argument of this paper that the current abundance is attributable to the social organization described here. It is more likely that overfishing removed lobster predators and competitors and, thereby, released the lobster population from restraints that previously contained the population. Management before the current boom, however, did seem to have protected lobsters from the fate of the other major species in the system, but the events in the rest of the ecosystem have turned lobsters into a monoculture that is potentially subject to disease and the instabilities of an eroded system. These problems cannot be addressed by lobster management alone.

¶At least two other models address similar learning questions in fisheries from a very different perspective. Allen and McGlade (7) use a systems-modeling approach; Dreyfus-León (8) uses neural networks.

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dynamics will help avoid reliance on the usual assumptions of uniformity that drive most policy panaceas (9).

The Competitive Problem Faced by Fishers

In the Gulf of Maine, the fishery starts in early summer, when a large number of juvenile lobsters molt and reach the legal minimum size. During and just after the molt, fishing activity tends to concentrate in shallow water and then moves to deeper water as the year progresses. Traps are the only permitted harvest technology in Maine. They are baited with salted fish, placed where lobsters are thought to be, and left, exposed to weather and other fishers, for 1 day to as much as 2 weeks before being hauled. The buoy for each trap is marked with a distinctive color combination that identifies its owner. Lobsters are attracted to traps over only a very short distance (tens of meters). From week to week, month to month, and year to year, lobster density and patchiness can vary significantly but at a rate that is very slow compared with finfish. The catch of lobsters at any particular place varies in response to environmental factors and, especially, the previous activities of other fishers.

A fisher's challenge is to maximize income in this changing natural and human environment. The human environment is especially complex for the fisher because it requires continuous adaptation to the strategically competitive behavior of other fishers. There are two principal modes of competition used by fishers. One is comparable to what ecologists call scramble competition. Fishers need to search out and capture lobsters before other fishers. Each day a fisher might haul several hundred traps and must decide where to put each trap next. That decision is based on information (most of it very imperfect) about the activities and catch rates of other fishers, water temperature, bottom type, and a variety of other indicators about the natural environment and, of course, the fisher's own recent and longer-term experiences. To compete effectively through scramble competition, fishers closely watch and quickly adapt to the changes in the location of their own catch and to the location of the catch of other fishers.

The second mode of competition is comparable to what ecologists call interference competition. In the lobster fishery, interference competition occurs when fishers directly reduce the capabilities of their competitors by destroying, i.e., cutting, their competitors' traps. It is almost as if retailers could compete by burning one another's stores. The benefit of cutting is a reduction in competition, but there is a high risk of reciprocal action by affected competitors. Trap cutting, consequently, can be a very costly form of competition and is one that fishers try their best to avoid. It does not occur frequently; nevertheless, it is possible, and the constant threat of its occurrence is a significant restraint on fishers' activities.

For each fisher, the competitive result over the course of a year is the cumulative outcome from thousands of individual trap-placement and trap-cutting decisions. Fishers make those decisions in the context of ongoing strategic interactions with their competitors. It is this decision process and its aggregate outcomes that the model addresses.

Broad Design of the Model

There are two major components to the model: (*i*) a biophysical model that represents a patchy natural environment and (*ii*) an agent-based classifier model that addresses the learning/competitive behavior of fishers. The harvesting activity of fishers is the link between the two components.

The biophysical model is represented by a spatially explicit map with three spatial scales: a global scale (70 × 70 grid), a broad ecological scale (24 irregular zones), and a very local scale (a 3 × 3 neighborhood around each trap). For each cell in the map, the model records depth, bottom type, wave exposure, seasonal temperatures, and lobster densities (*SI Appendix 1* and Figs. 12–14 therein). There are three temporal scales in the model: (*i*) a daily scale in which the number of lobsters in each cell is reduced by fishing, (*ii*) a seasonal scale marked by changes in water temperature, and (*iii*) an annual scale marked by the recruitment of new lobsters to the population. The annual recruitment of lobsters varies stochastically in each of the 24 ecological zones. The catchability of lobsters changes seasonally as changing water temperatures at different depths induce changes in lobster metabolism. At any time of the year the best catch rates tend to occur in relatively warmer water: shoal in the summer, deep in the winter. The maximum densities of lobsters and traps in each cell are parameters usually set to 100 and 3, respectively. (Greater detail about the biophysical model is provided in *SI Appendix 1*.) This environment generates a continually changing array of information, which is used by individual fishers when they decide where to place their traps. The computation of those decisions takes place in the agent-based part of the model.

The agent-based model addresses the evolution of the decision rules, the learning process, fishers employ to compete effectively. We describe first the part of the model dealing with scramble competition, or trap placement, and then turn to interference competition, or trap cutting. Fishers are assumed to be boundedly rational, profit maximizers. Each fisher is given a small number of traps,[‖] each of which is hauled and placed each day. Each fisher has fixed and variable costs. The criteria fishers use to select effective decision rules is profitability. Except when long-run sustainability questions are addressed, the model is run with 30 fishers, as if there were a limited number of licenses in the fishery.[**] Depending on the question the model addresses, there is only one harbor with 30 fishers or two harbors with 15 fishers each.

We use a variation of Holland and Holyoak's (4) learning classifier system to model the evolution of a fisher's decision rules. A decision rule is defined as a unique combination of conditions describing a particular state of the environment and a specific action. Decision rules can be very general or very specific. For example, a general rule might be something like, "If it is summer, fish inshore." A more specific rule might be something like, "If it is summer, the bottom is muddy, water temperature is low, the depth is deep, and the catch from the trap is low, move the trap to warmer, shallow, rocky water." The latter rule depends on much more specific information and requires a much more specific action. Both rules, however, can apply to a particular summertime situation. In effect, a classifier system creates a hierarchy of general to specific rules; thus, in any situation, a fisher is likely to have a number of rules of varying degrees of specificity that might apply to that particular situation. Because the biophysical–human environment is complex, fishers require a large, heterogeneous set of decision rules to adapt effectively (the model holds up to 1,200 rules in each fisher's memory).

The basic logic of the decision process is reasonably straightforward. The biophysical model and the agent-based model together provide the fisher with information about the current state of the environment. Each fisher has a memory that consists of a list of decision rules (classifiers) of the form described above; each rule is accompanied by a weight that reflects its performance (profitability) in previous use.

The trap placement decision begins with the fisher's observation of the environment. The fisher then checks his memory to find rules used previously in similar circumstances. One that performed well in the past is chosen (using a "roulette" based on the rule's weight) and implemented. If, once again, the rule performs well, its weight

‖In the real fishery, traps are fished in groups referred to as a string and are located in the same neighborhood. A string may consist of 5–25 traps. Placing a string generally involves a single location decision, at least at the scale employed in the model.

**Entry is driven by average fleet profits. At entry, each fisher is endowed with a bank account that buffers the initial costs of learning or other temporary declines in profitability; the exhaustion of the account at any time is taken as a signal to exit.

Table 1. Environmental information, conditions evaluated, and actions available to fishers in scramble competition

Environmental information	Condition evaluated	Possible actions
Global information	For choice of strategy (CS#1)	Actions for CS#1
Season	Current catch vs. own best	Stay at current location
"Coffee hour"/public information about global	Own best vs. others' best	Go to own current best
catch rate	Current catch vs. others' best	Imitate other best fisher
Change in global catch rate	Change in current catch	Go to an historically productive area; explore
Broad-area information	Change in global catch	Actions for CS#2
Current area (1 of 24 broad locations)	For choice of broad area (CS#2)	Go to a new area (1 of 24)
Orientation of area (compass direction from land)	Season	Actions for CS#3
Historical catch in each area	Current location	Same depth and bottom type as current
Local information	For choice of a particular habitat (CS#3)	Different depth and bottom type
Bottom type of current trap	Current time	
Depth of current trap	Current depth	
Catch rate of current trap	Current bottom type	
Catch rate for other/own traps		
Frequency of encounter with each other fisher		
Imperfect knowledge of other fisher's catch		

is increased still more and, in addition, the rules used just previously are also strengthened (i.e., precursor rules share some of the credit for the success of the current rule).[††] Strengthened rules are more likely to be used again when similar circumstances are encountered. If the rule performs poorly, it and its precursors are weakened and less likely to be used again. If the fisher has no rules that fit a particular circumstance, fairly general new rules appropriate to the circumstance are created and added to the fisher's memory (*SI Appendix 1*). Holland (10) describes the entire process as one of continuous hypothesis creation, testing, and revision. Generally, the information available to fishers varies according to its proximity in time and space. There are three basic classes of information available to the fisher.

The first class is historical information about the location of lobsters and fishing patterns. This information is contained in the fisher's decision rules. It is an imperfect indicator of the current location of the resource because the environment changes both in the long term, due to changing recruitment of lobsters, and in the short term, due to the activities of other fishers. This information is useful to the fisher only to the extent that there are environmental regularities that persist despite these changes.

Observations concerning the immediate biophysical circumstances relevant to the trap the fisher just hauled and his current catch rate make up the second class of information. The fisher is assumed to be fully knowledgeable about this data.

The third class of information is obtained by communications with or observations of other fishers. The fisher knows the current "global," or fleet, average catch rate; however, knowledge of the catch of individual fishers is assumed to be dependent on the frequency of encounters and observations of those fishers in the course of fishing. The more frequent the encounters, the more reliable is his or her knowledge of the other fisher's catch and the more likely he or she is to imitate the other fisher. Because there are only so many encounters that can take place, this formulation is an implicit recognition of the costliness of information, because it leaves the fisher with little or no knowledge of the activities of many other fishers. The patterns of this knowledge are particularly important to the fisher's strategic interactions with other fishers. Fishers who frequently encounter one another are labeled neighbors.

[††]Holland (10) uses the example of a checkers game in which, say, a triple jump is set up by several prior moves. The credit given to the decision that implements the triple jump also has to be shared with the prior decisions that made it possible. The entire strategy has to be learned.

The Hierarchical Decision Process

The complexity of this environment creates a very large decision search space. For each fisher, the possible number of unique decision rules is ≈14 trillion. Clearly, each time a fisher hauls a trap he or she does not search through 14 trillion possibilities. Fishers in the real world and in the model simplify the problem by using a hierarchical decision process. In the model of scramble competition, the hierarchy consists of three steps. Each step in the hierarchy rapidly shaves away irrelevant circumstances, reducing the search space for each decision to several thousand possibilities (the number varies according to the route of the decision through the hierarchy). We model each step in the hierarchy by using the architecture of Stewart Wilson's zeroth-level classifier system (11) (*SI Appendix 1* and Fig. 10 therein).

Table 1 shows the basic elements of the hierarchy for scramble competition. The first column lists the environmental information provided to the fisher. Column 2 lists the analytical conversion of that information into conditions pertinent to the decisions of the individual fisher (e.g., "own current catch vs. other's best") and sorts that information into the three hierarchical components. Column 3 lists the possible actions each fisher might take for each component of the hierarchy.

The first step in the decision hierarchy, CS#1, is the choice of a broad strategy. The fisher's choice is based on the results from the trap just hauled, the current performance of his or her other traps, an estimate of the catch of other fishers, and historical knowledge of the productivity of broad ecological areas. The strategies (actions) are (*i*) stay in the same neighborhood, (*ii*) move to the neighborhood of one's own best-performing trap, (*iii*) imitate another fisher who is doing well, or (*iv*) explore an area that has been productive in the past. The choice of strategy is made by matching the conditions of the environment with rules used previously in the same or similar circumstances. If the fisher chooses actions *i*, *ii*, or *iii*, then the broad ecological area and the local neighborhood are given, and all that remains is to find a spot in that neighborhood where there is room to place the trap. If *iv*, explore, is chosen, then the next step (CS#2) is to choose the broad ecological area where the trap might be placed. The decision to explore is made on the basis of information that does not deteriorate over longer periods of time. A simple general rule in CS#2 is one that says "in the fall of the year it is usually profitable to move to area *x*." Once in the chosen area, the final decision (CS#3) concerns the choice of a bottom type and depth and, then, a particular spot to drop the trap.

The fisher's trap-cutting strategy, interference competition, is implemented as a fourth CS module (always with two harbors).

After each trap is placed, the fisher is paired randomly with another fisher in the same ecological zone and faced with a decision of whether to "cut or ignore" the other fisher's trap. The information available to the fisher is the frequency with which he or she has encountered the other fisher, the ratio of neighbors to nonneighbors in the area, and the value of the catch in the area. Each fisher uses this information to learn a strategy applicable to the cut-or-ignore decision. A simple decision rule might be, "If the other fisher is a neighbor, don't cut (ignore) the trap." The feedback about the effectiveness of each rule depends on the action of the other fisher. We specify four 2×2 feedback matrices. The relevant variables in each matrix are (*i*) the change in competition in the immediate area arising from the decision (slightly less catch if the other trap is ignored, slightly more if it is cut); (*ii*) any change in the benefits of cooperation that might occur as a result of the decision; and (*iii*) the cost of a trap if it is cut. The value of the cells in the four matrices depends on whether the other fisher is a neighbor or not and whether the interaction takes place in an area dominated by fishers from his or her own harbor or the other harbor. (The factors generating the pay-off matrix are illustrated in *SI Appendix 1* and Table 13 therein.)

For example, if a fisher encounters a neighbor in an area dominated by his or her neighbors, the outcome of the cut-or-ignore decision is likely to be very different from a situation in which the fisher is not among neighbors and encounters a nonneighbor. In both instances, the important consideration is the way other fishers are likely to reinforce their or the other fisher's actions. Among neighbors, actions are likely to be reinforced by similar decisions by the neighbors. Among nonneighbors, the other fisher's actions are likely to be reinforced by that other fisher's neighbors. After fishers learn the context, the result is a "boring game" in which the outcome is ambiguous usually only in areas of low abundance that are fished relatively infrequently. In these areas, it is often the case that paired fishers are from the same harbor and never encounter trap cutting, even though at some times of the year fishers from the other harbor may be present. This feedback is also sent to CS#2, the scramble competition module where fishers decide what new areas to explore. As the model progresses, feedback gives the fisher a history of the "trap-cutting status" of the areas he or she fishes and informs decisions about where to fish in the future. Thus, fishers can make the strategic decision about whether to defect or cooperate, and can also adjust the areas they fish. The latter gives them the valuable ability to avoid future interactions that might involve trap cutting.

This four-stage decision process is modeled with 30 fishers operating simultaneously. Each day each fisher hauls and relocates all of his or her traps and decides whether to cut or ignore the traps of other fishers. Each year the fisher makes several thousand decisions of each type (depending on how many traps are fished). Both the biophysical and the agent-based parts of the model are modified daily as a result of these decisions and, as described above, some of that information is transmitted to fishers for their use the following day (Table 1, column 1). There are 240 days in the fishing year. At the end of each year, a new year-class of lobsters is recruited and distributed around the map. The model is usually run for 50 years.

Gaining Confidence in the Model

The insights we wish to gain from the model concern the fine-scale behavioral dynamics that generate the aggregate spatial, temporal, and social patterns observed in the fishery. In the model, there are five basic patterns that lead to the social conditions that facilitate collective action. They are described below. These patterns tend to be relatively robust so long as resources are patchily distributed and fishers have the ability to communicate with one another.

To better understand these patterns and because the model is complicated, there are a number of steps we have taken to make sure the outcome from the model is not simply an artifact of the model itself. First, we have, as much as possible, subjected the assumptions and the behavioral outputs to an informal comparison with the experience of consulting fishers and project members. Second, we have tested the patterns generated by the model against the patterns observed in the fishery, specifically those observed in the Maine Department of Marine Resources data. Finally, we explored the model to find its limits. We changed its specifications so we can better understand how resource patchiness and communication among fishers affect the dynamic patterns we observe. These tests and explorations are reported below and in greater detail in *SI Appendix 2*. Our confidence in the model is based on the consistency of results from all these tests, even though no single test might be offered as conclusive proof of the model's validity.

Compared with the Conventional Bioeconomic Model

First, we wanted to know whether the modeling approach generated results that were consistent with those of conventional bioeconomic models of fisheries. We modified the model so that its circumstances approximated those found in a typical Gordon–Schaefer bioeconomic model of a fishery (12). We used a logistic function to calculate the recruitment of lobsters, placed them randomly on the map, gave fishers a single fishing rule to fish at random locations,[‡‡] and used profit-driven entry and exit processes. Given these assumptions, fishers have nothing to learn; the dynamics of the model are limited to the long-term adjustment of fishing effort to recruitment, and the model closely replicates the broad qualitative patterns generated by the Gordon–Schaefer model (SI Table 2).

Spatial, Temporal, and Social Patterns from Scramble Competition

In the model of scramble competition (i.e., no trap cutting), fishers start off on the first day of the first year with no decision rules, i.e., no skills or memory. They place their traps randomly near their harbor. The next day, they haul their traps and evaluate their performance. On the basis of the limited information gathered that first day, they place their traps in the same or another location on the second day. This process continues day after day. At the start of a model run, fishing success is rather poor even though there is a large population of lobsters. After a while, however, fishers begin to associate good and bad results with particular conditions in the combined biophysical and human environment. Fishers' decision rules evolve following the procedures in the classifier system described above. They also communicate with and learn from one another, i.e., they acquire new decision rules by imitating. As the run progresses, the decision rules that produce good results are strengthened and those that do not are weakened. Individual and fleet performances improve dramatically over the course of a few years (SI Fig. 3).

Scramble competition generates four robust patterns. By a robust pattern we mean one that persists in the face of large changes in important model variables, e.g., numbers of fishers, traps, and lobsters, the variability of lobsters from year to year, and so on (*SI Appendix 2*). Two attributes of the model, the patchiness of the resource and the ability of fishers to communicate, are especially important for an understanding of these patterns. When the model is modified to remove either resource patchiness or communication among fishers, almost all patterns described below tend to disappear.

[‡‡]In the CS model, as long as the environment is uniform, fishers evolve multiple rules. However, each rule yields exactly the same feedback and, consequently, there is no preference for one over the other. Each has an equal probability of being chosen at any time, and together they function as if there were a single random rule (*SI Appendix 2*).

Individual Search. The spatial patterns generated by individual search are generally characterized by a move to a new location, one to several days spent fishing down the resource at that location (or the immediate vicinity), and then a move to another location (SI Table 3). The pattern is a function of the changing patchiness of the resource and the fisher's knowledge of both current and historical catch rates in particular areas. Long-term, fairly regular patterns of lobster distribution occur at the scale of the ecological zone. However, at the level of the individual cell, that regularity is disrupted by the daily harvests of the fleet, creating a premium for knowledge of the current, fine-scale distribution of the resource.

A trap is moved when the fisher learns that his or her catch rate at that location is below (*i*) the catch rate of one of his or her own traps at another location or (*ii*) the catch rate of another fisher at another location or (*iii*) the global average catch rate or (*iv*) historical catches at that same time of year at another location. The new location for the trap depends on the information that prompted the move; e.g., the fisher moves to the location of his or her best-performing trap if that information is what prompted the move. This process continually moves traps to neighborhoods where higher catch rates are expected (SI Movie 1). Usually, these moves raise the catch rate of newly placed traps but also reduce the catch rate of the traps already in those locations. Then, as the immediate neighborhood is fished down, other locations appear better; traps are moved again, and the innovate-and-exploit dynamic starts on another loop. There is no equilibrium. (SI Fig. 4). Without resource patchiness, the innovate-and-exploit pattern disappears (SI Movie 2). Without communication, the pattern is similar, but a change in location occurs less frequently (SI Table 4).

Group Formation. The trap technology of the fishery and the relatively sedentary nature of lobsters facilitate observation and learning about the fishing patterns of other fishers. But knowledge of the activities of other fishers is not free; it is limited by the time available for observation. Consequently, fishers have better knowledge about the fishing patterns of other fishers whom they encounter frequently. They tend to imitate fishers who are doing well. Imitation leads to still more encounters, which further improves their knowledge of the other fishers and leads to still more imitation. This positive feedback leads to the formation of very persistent groups of fishers (SI Movie 3 and SI Fig. 5). When we disable fishers' ability to communicate with one another, groups do not form, but fishers are still able to acquire useful knowledge of the resource, only at a much slower rate (SI Fig. 3, *SI Appendix 2*, and SI Movie 4). With no patchiness, groups still form but confer no advantage to the individual fisher (*SI Appendix 2* and SI Movie 5).

Diversity. Fishers within groups tend to enjoy the benefits of the knowledge gained by other members of the group, but there are limits to the collective benefit that results. As more fishers join groups, collective knowledge of the current distribution of the resource declines because there is less exploration taking place. This decline raises the value of individual exploration and tends to draw fishers away from fishing as part of a group. As a result, a diverse population of fishers engaged in both group and autonomous behaviors tends to evolve; this better fits their collective activities to the patchy spatial and temporal distribution of the resource (SI Fig. 5 *f–j* and SI Table 5). The collective effect of this diversity is greater efficiency.

When the model is modified so fishers can imitate but are not able to explore, a single, large, inefficient group forms. Search is limited to incremental movements into cells adjacent to current fishing spots, and profits decline (SI Movie 6 and SI Fig. 6). Similarly, when fishers cannot imitate but can explore, there is a comparable decline in collective profits (SI Fig. 3). We conclude from this that a pattern of diverse individual behavior, i.e., a combination of mutual imitation and autonomous activity, best adapts the fleet to searching out the resource.

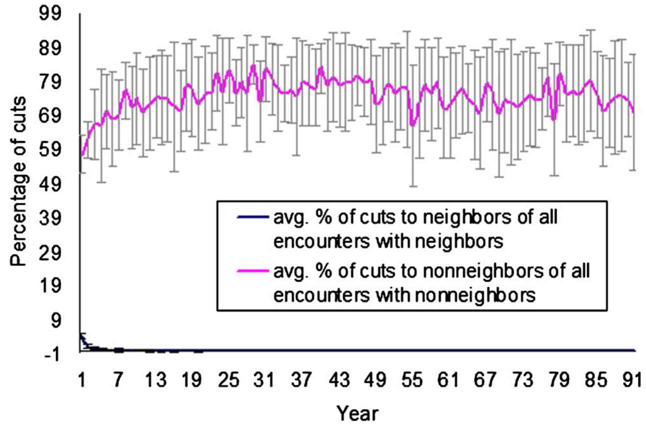

Fig. 1. Trap cutting of neighbors and nonneighbors. On the first day, the choice of trap-cutting actions is random, and 50% of all traps are cut. Eventually fishers cut only nonneighbors. That rate is ≈75% of encounters with nonneighbors. The decline is due to learning about the costs of cutting and to the relocation of traps so that they are not placed in areas dominated by nonneighbors.

The Spatial Allocation of Effort. All three patterns, individual search, the formation of groups, and diversity, contribute to a fourth pattern that closely mimics the spatial patterns observed in the real fishery. In both the real fishery and our model fishery, the entire fleet tends to allocate its fishing effort to particular areas and/or depths in almost strict proportion to the available catch (SI Fig. 7). The result is a remarkable and close-to-optimal allocation that occurs with no coordination of individuals' activities. However, with scramble competition alone, the spatial and temporal patterns of fishing by both individuals and groups are best described as those of roving bandits (ref. 13 and SI Movie 7). Fishers compete with all other fishers over the entire map, and the resource boundaries necessary for effective collective action do not emerge (SI Fig. 8*a*).

Interference Competition: Trap Cutting

When competition takes place through trap cutting, the stakes can be very high. In the model, a lost trap (a string in the real fishery) is equivalent to the profits from several typical days of fishing. Episodes of reciprocal trap cutting can be very expensive. However, under some circumstances there are competitive advantages that accrue to a trap cutter, so the temptation to cut is often present. Consequently, the decision about when, where, and whose trap to cut is very selective. It depends critically on the personal relationships that arise from scramble competition. The groups that form strongly influence each fisher's expectations about the benefits and costs that are likely to emerge from strategic interactions with other fishers.

The trap-cutting version of the model has two harbors with 15 fishers each. Global information about catch rates is restricted to people from the same harbor. Trap cutting does not begin until the 11th year. The first 10 years give fishers a chance to establish the groups and the spatial fishing patterns that form through scramble competition. They know their neighbors and the areas their neighbors dominate. As a result, when trap cutting begins, the circumstances created by these patterns in most areas of the map give fishers strong and unambiguous feedback from their ignore–cut decisions (see pay-off matrix in *SI Appendix 1*). Fishers learn that cutting a neighbor's trap can be very costly, so after several years the incidence of trap cutting among neighbors falls to zero (Fig. 1).

Fishers also reduce the number of times they cut the traps of nonneighbors to a very low level, ≈1–2% of all trap hauls (Fig. 1). However, when fishers do encounter nonneighbors, they cut their traps ≈75% of the time (SI Fig. 9); in other words, they learn to actively defect from cooperation with nonneighbors.

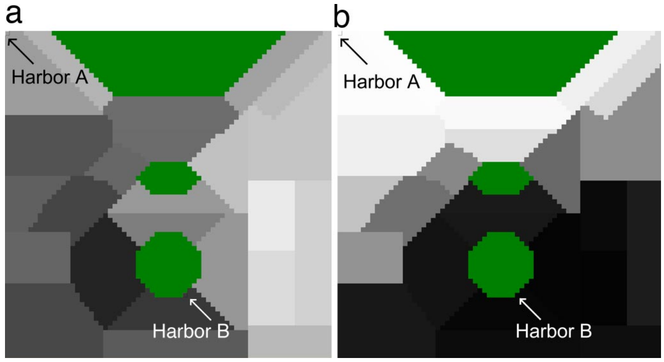

Fig. 2. Areas fished with no trap cutting (*a*) and with trap cutting (*b*). The map records the percent of visits of fishers from Harbor B (bottom of the island, lower center) to areas of the map: black, 100%; gray, contested area; white, 0%; green, land. Contested areas can change from run to run, depending on the spatial patterns of fishing established in the first few years of the run, but territories always develop. SI Fig. 8 shows the evolution of the groups forming these territories in a typical run of the model.

Consequently, the most important reason for the overall reduction in the cuts of nonneighbor's traps is that fishers know where their traps have been cut in the past and tend to avoid fishing in those areas. This avoidance is a response to the feedback about trap cutting (*SI Appendix 1*) that is sent to CS#2; it effectively segregates fishers into two territories separated by contested areas. These contested areas tend to be, but are not always, less productive and visited less often by fishers. When fishers do visit these areas, they are usually in the company of their neighbors. As a result, random pairing produces fewer encounters with nonneighbors, and fishers do not learn to avoid trap cutting in these areas. Thus, trap cutting segregates fishers into territorial groups because (*i*) fishers learn not to cut the traps of their neighbors, and (*ii*) they learn especially to avoid fishing in areas where their traps might be cut (Fig. 2 and SI Movie 8). (SI Fig. 8 shows the evolution of territories and contested areas.) Each group operates within fairly well defined social and spatial boundaries; members of each group tend to encounter one another and communicate frequently, and they learn to restrain the way they compete with one another. These circumstances facilitate effective collective action.

Summary

Collective action is more likely to occur and to be effective when it is consistent with the self-interest of the affected individuals. The particular circumstances of the natural and social environment are an important determinant of the way self-interest is played out. The Maine lobster fishery is an instructive and, in fisheries, an unusual example of biological and technological circumstances combining with individual self-interest to create conditions favorable to collective action. The model described here emphasizes the way the particulars of the biology and technology of the fishery affect the self-organizing, competitive interactions among fishers.

We describe two kinds of competition: scramble competition, in which fishers race to find the patchy resource, and interference competition, in which fishers destroy traps used by other fishers. In a patchy, changing environment, knowledge of the location of the resource is the key to competitive success. Fishers acquire this knowledge through costly individual search and communications with limited numbers of other fishers. The resulting patterns of information availability are the principal determinant of the social relationships developed by individual fishers and by groups of fishers.

Individual search tends to follow a pattern in which there is an initial move to a location; the resource at that location is fished down until the rate of catch is below what is perceived available elsewhere, and another move is made. As fishers search, they encounter one another. The more frequent the encounters, the more they learn about one another's fishing patterns and, consequently, the more likely they are to imitate one another. Imitation, of course, increases the frequency of contact and eventually leads to the formation of persistent groups of fishers. As members of a group, fishers gain significant knowledge of the resource; however, as more fishers rely on imitation, the advantages of being a member of a group decline because less new information is acquired. This leads to circumstances in which individuals often find it advantageous to fish away from the group. Consequently, when the group as a whole is considered, a mix of group-oriented behavior, imitation, and autonomous behavior, exploration, tends to occur. The balance between group and autonomous behavior is driven by the self-interested actions of individual fishers and is an important determinant of fleet efficiency. The groups that form as a result of scramble competition are the beginning of the social relationships important for governance. However, the activities of these groups overlap in space and, consequently, do not generate the boundaries necessary for effective collective action.

Trap fishing opens the door for fishers to compete with one another by direct and costly interference, i.e., trap cutting. Fishers adapt to the threat of trap cutting by learning to restrain the way they compete with others they encounter often, i.e., members of their own group, and by rearranging the spatial patterns of their fishing to minimize their contact with fishers whose restraint they cannot trust. The result is territories occupied by groups of fishers who work within well-defined boundaries, contact one another frequently, actively exchange information about the resource and, most importantly, depend on continuing mutual restraint for their economic well-being. These circumstances lay the foundation for successful collective action (2), i.e., explicit mutual agreements that create the additional restraint required for conservation.

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