An Exploration of Competition and Cooperation through a Multi-Agent Dynamic-Game Model of Fishery Management

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Abstract: The interaction between economic and ecological dynamic systems is analyzed with a multi-agent dynamic game model of fishery management. Multiple actors (fishermen) harvest multiple fish types and adapt the amount and allocation of their investments to their value functions, which are given as net profits of the fish harvest sold for a market price. We introduce and compare two different decision rules in the competition of fishermen, leading to a decline both of fish stocks and profits for most fishermen. As an alternative, we introduce a cooperative approach to jointly set sustainable limits for total harvest and investment that are then distributed to the fishermen according to distribution rules. As the simulation shows, fish stocks and profits stabilize at significantly higher levels in the cooperative case, leading to a continuous accumulation of capital.

Managing fishery conflicts

The scarcity of natural resources is an expression of the conflicting relationship between mankind and nature. Even though environmental degradation generally may not directly lead to environmental conflicts, it could undermine the economic and societal conditions for the well-being of a growing human population, adding to the various stress factors that contribute to conflict. We discuss here the problem of overfishing in the world's oceans which bears a considerable conflict potential (Charles 1992; Ruseski 1998).

Fisheries build a significant basis for the world's food production and are a major income source in many coastal regions. Due to non-sustainable fishing practices and a growing capacity in fishery technology, many of the fishery resources are declining, despite numerous attempts to improve scientific understanding and management practices.(Meyers and Worm 2003) To stay within ecologically sustainable limits, the focus thus far has been on measuring and controlling the fish stocks, increasingly taking into account the uncertainties inherent in both the ecological and economic systems (Davis and Gartside 2001; Whitmarsh et al. 2000). To include the spatial dimensions, Allen and McGlade (1987) make use of elaborate spatial fisheries models including effort adjustments based on individual fishermen's risk perceptions. Ruth and Hannon (1997) demonstrate a spatial fisheries model that allows detailed spatial resolution and testing of various spatial management strategies on the fish populations, and Hannon and Ruth (2000) develop a fisheries reserve model that shows how much of a given fishery must be reserved as a function of fishing effort.

Growing attention is being paid to the misperceptions and sensitivity of policy analysis in fishery management (Moxnes 2004, 2005). Increasingly the advantages of regulated fishing and enforced cooperation among fishermen are recognized to overcome the problems of competitive fishing. Co-management of marine resources is implemented to increase participation and strengthen compliance with the constraints (Pinkerton 1989; Jentoft et al. 1998; Kearney 2002; Mahon et al. 2003). Game theoretic and agent-based approaches play an important role to understand how individual actors adapt to the ecological necessities via learning and negotiation processes (Dockner et al. 2000; Kaitala and Munro 1995). To deal with a larger number of players who can act and decide on multiple levels, multi-agent models are appropriate (Billari et al. 2006). System dynamics provides a powerful tool to improve public participation in environmental decisions (Stave 2002; Otto and Struben 2004).

To resolve fishery conflicts, we must better understand the dynamics and interactions of the combined ecological-economic system, while respecting viability criteria both for the natural sphere (regeneration capacity) and the socio-economic sphere (profits, employment, social cohesion). We suggest a model approach that facilitates both analytical treatment and computer simulation, building on previous work (Hannon and Ruth 2000; Scheffran 2000; Eisenack et al. 2006; Kropp et al. 2006), and present some new results for different decision rules using the system dynamics methodology.

Ecological and economic viability in fishery management

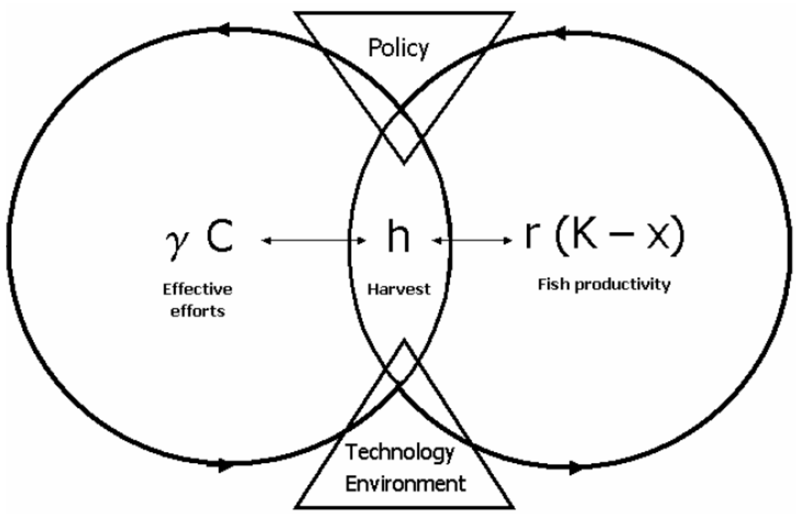
Our modeling approach views fishermen as the key actors, catching fish as a source of income. For a single fisherman the value function $V = q\,h - C$ *is* the net profit from selling the fish catch (harvest) h at a market price q, diminished by the invested costs (efforts) $C = c\,h$ (c is the unit cost of harvest). Market price $q = a - b\,h$ declines with total catch h where a represents the price of the first unit of harvest and b the price elasticity.

We assume that a fisherman harvests fish stock x (for several fish types we use index $k = 1, \ldots, m$) which grows with the logistic reproduction function, diminished by harvest:

$$\Delta x = r\, x\, (K - x) - h.$$

Here $\Delta x(t) = x(t+1) - x(t)$ is the change of the fish stock from one time step to the next. If harvest $h = C/c = x\, \gamma\, C$ increases proportionate to fish stock x, invested costs C and technical catch efficiency γ, then a steady state for the fish stock x can be maintained for the condition $\Delta x = 0$ which leads to γ C = r (K-x). Figure 1 represents this balance relationship in producing harvest, with the right side being the fish productivity in the ecological system and the left side the efficient investment of the economic system. Keeping the balance is also influenced by political, technical and environmental factors.

Figure 1: Balancing ecological and economic systems in fishery harvesting



Both sides of this equation represent a minimal precondition for sustainability, balancing the societal demand for fish with its ecological supply. The "effective costs" γC combine total invested costs by all fishermen with the catch efficiency γ which is determined by technology and catch method applied. The right hand side indicates the reproduction per fish, which is limited by the reproduction rate r, the current fish stock x and the carrying capacity K of the ecosystem. While in principle limits for γC can be calculated, two problems make its practical implementation difficult:

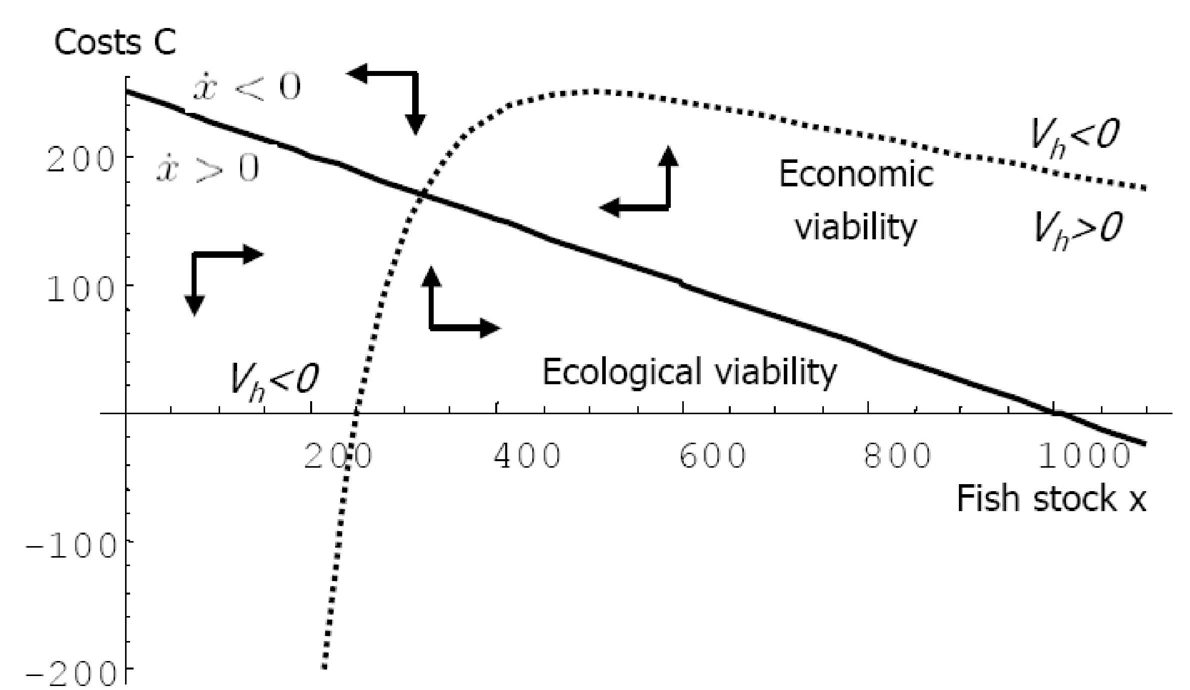
- Each of the three parameters in the ecosystem is bound by uncertainties.
- If each fisherman acts individually to maximize profit, the total effective cost can easily exceed the sustainable limit and thus create the risk of overfishing which adversely affects the interest of all fishermen (tragedy of the commons).

Resolving these problems requires better information gathering and understanding of processes and mechanisms that keep total harvest within boundaries, either by topdown control or by bottom-up cooperation. The best solution would be to find those states that maintain viability of both the ecosystem and the socio-economic system. Such a win-win solution can be derived from the two requirements:

$$x > 0 \text{ and } \Delta x \geq 0$$
$$V > 0 \text{ and } \Delta V \approx V_h \, \Delta h \geq 0.$$

The partial derivative $V_h = \partial V / \partial h$ is used to determine the direction along which value increases with growing harvest ($\Delta h > 0$ for $V_h > 0$, otherwise the signs should be opposite). The boundary conditions define curves along which fish stock or value is constant. Each viability limit divides the (x,C) diagram into a set of states in which these criteria are satisfied or not satisfied. Keeping $\Delta x \geq 0$ implies that costs C should stay below the straight line of ecological viability. Keeping $\Delta V \geq 0$ implies that costs C should stay below the curve of economic viability.

Figure 2: Phase diagram showing compatibility of conditions for economic viability (dotted lines) and ecological viability (solid lines)



Most desirable are those states where viability conditions of both the ecosystem and the socio-economic system are met, and least desirable where neither of them is met. In the mixed cases only one of them holds which implies a conflict on which criteria to prefer. At the intersection of both viability limit curves we have an equilibrium with $\Delta x = \Delta V = 0$ (see Figure 2). The dynamics around the intersection point is circular which implies that the boundaries between viable and non-viable regions are crossed and one of the viability conditions is violated without proper stabilization measures.

Dynamics of fishery competition

For each fisherman the value (net profit) V achieved in each time step is added to or subtracted from the capital C^K from which a fraction κ is used in the following time step as an upper investment limit C^+. Within this limit, the fisherman adjusts the invested costs to generate value. An adaptive approach for the invested costs is

$$\Delta C(t) = \alpha^c D^c(V(t))$$

where $D^c(V)$ is a value-based decision rule that drives cost dynamics based on value considerations, and α^c represents the speed of adaptation. We implement and compare decision rules for cost:

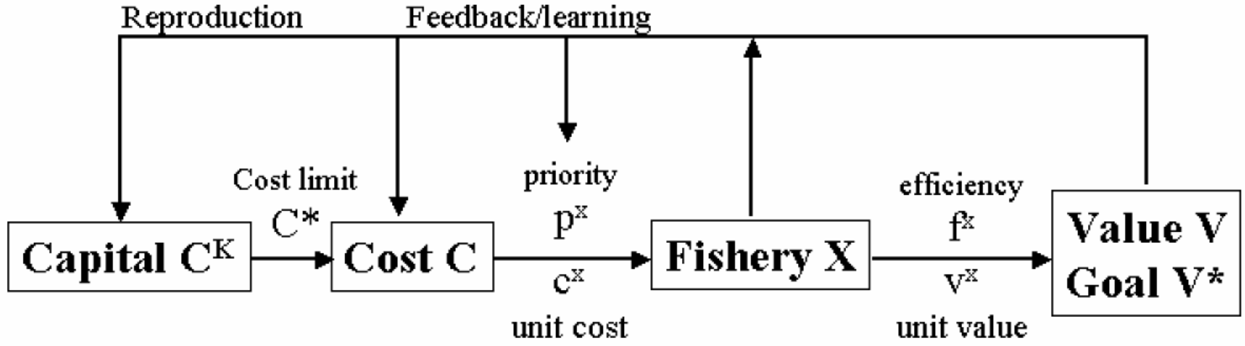
- With the *gradient decision rule* actors increase or decrease costs proportionate to the incremental value impact, measured by the partial derivative $v = \partial V/\partial C$, leading to the rule $D^c(V) = v$.
- The *optimizing decision rule* determines the cost C^* that maximizes value according to the condition $\partial V/\partial C = 0$. Cost is adapted proportionate to the distance from this target according to the decision rule $D^c(V) = C^* - C$.

Both rules describe two different types of human behavior. The gradient approach represents actors who observe their local environment and incrementally move towards increasing value. The optimizer seeks to determine the global value optimum and move towards this target by adjusting costs.

The adaptation process also depends on the response parameter α^c which defines how sensitive and fast cost adaptation responds to the changing environment. For $\alpha^c = 1$, for instance, an optimizer would reach the target C^* in one time step (if nothing else changes) and for $\alpha^c > 1$ would shoot over the target. Rather than having a rapid shutdown at the given limits $C = 0$ and $C = C^+$, we prefer a logistic function $\alpha^c(t) = \kappa^c C(t) (C^+(t)-C(t))$ where κ^c is the logistic response parameter.

In the same manner, we can also describe the adaptation of allocation of investment, given here by the allocation priorities p^k for the fish types x^k $(k = 1, \ldots, m)$ which change according to the decision rules $\Delta p^k(t) = \alpha^k D^k(V)$. The decision functions D^k use partial derivatives $v^k = \partial V / \partial p^k$ to represent the gradient or optimizing approach, where the latter defines targets p^{k*} for allocation priority. For the speed of adaptation we use the logistic approach $\alpha^k(t) = \kappa^k p^k(t) (1 – p^k(t))$, similar to the approach used in evolutionary game theory (Hofbauer and Sigmund 1998). The variables and their interaction are depicted in Figure 3.

Figure 3: The feedback cycle of single actor fishing



We now study the interaction between multiple actors (fishermen) S_i *(i = 1, …, n)* who choose between catching *k= 1,…,m* different fish populations x^k with a catch efficiency γ_i^k and a fraction p_i^k (priority) of their costs allocated to catching this fish with $\sum_k p_i^k = 1$.The actors' value functions

$$V_i = f_i(x,p,C) = \sum_k q^k h_i^k - C_i = \left(u_i - \sum_j w_{ij} C_j \right) C_i$$

are the net profits from harvest h_i^k for a market price q^k, diminished by the invested costs C_i. The value is a bilinear-quadratic function in costs of all actors, with

$$h^k = \sum_j h_i^k \qquad u_i = \sum_k \frac{a^k}{c_i^k} p_i^k - 1 \qquad w_{ij} = \sum_k b^k \frac{p_j^k p_i^k}{c_j^k c_i^k}$$

Simulation of multi-agent and multi-fish interaction

Economic competition

In the following we present simulation results of the multi-actor fishery model for a specific case, describing the competition between fishermen who individually behave either according to the gradient or the optimizing decision rules. We use the STELLA software for simulation and presentation. These models are depicted in Figures 4 and 5 which were created by translating the equations listed above into stock-flow models while utilizing STELLA's array functionality. Because STELLA is currently not able to handle arrays with more than two dimensions, which are required for our multi-agent and multi-fish interactions, we circumvented these limits by explicitly replicating model structures to simulate two different fish populations (shown as 'fishtype 1' and 'fishtype 2'). The two dimensions available for use in arrayed variables are usually used here to simulate individual actor interactions (given subscripts *i* and *j* above). In cases where individual references were made to the interaction matrices (such as the definition of V_i shown above), the arrayed variables are defined for each individual case within the interaction matrix (n x n for n-fisherman case). In other cases, we define an array dimension for fishtype, denoting 'x' and 'y' as individual fish populations in the fish stock.

Figure 4: STELLA model for competition among fishermen with optimizing decision rules

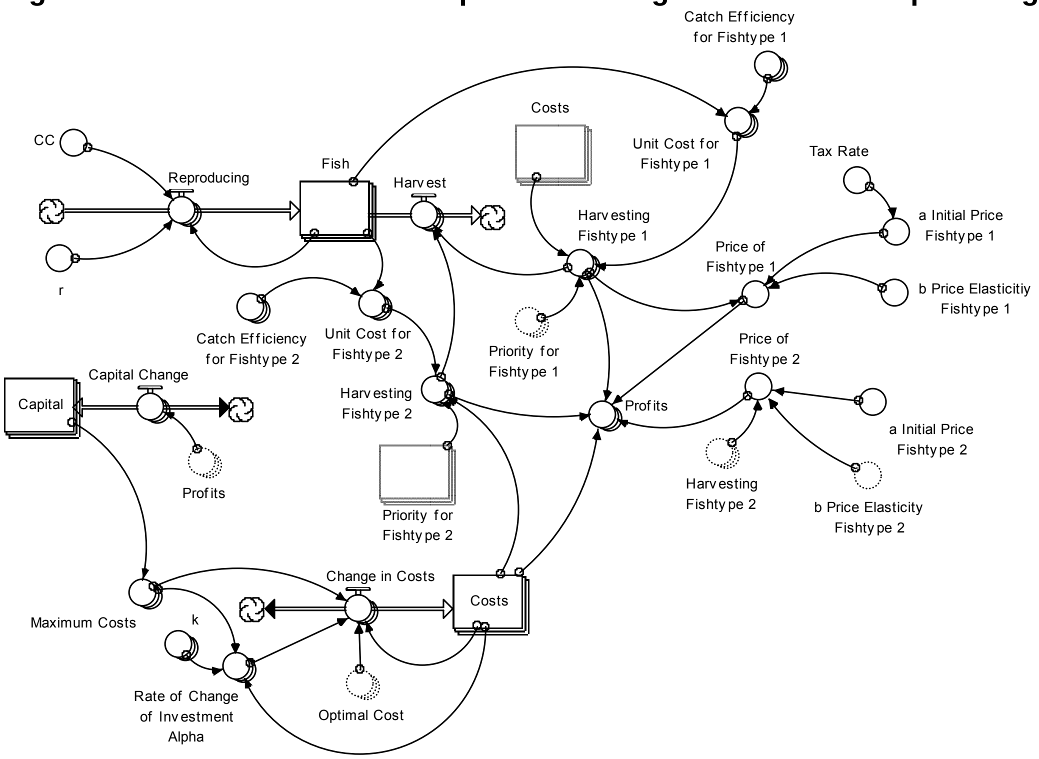
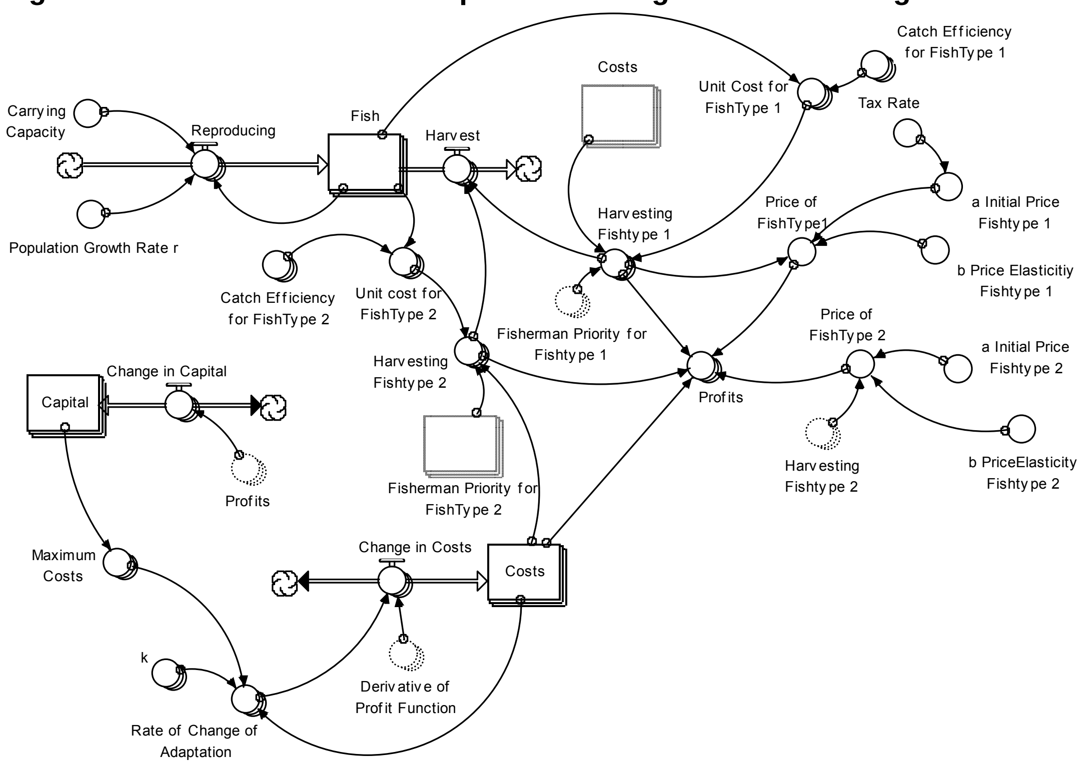


Figure 5: STELLA model for competition among fishermen with gradient decision rules



As a specific case we use six fishermen, competing for two fish resources *x* and *y*. Both fish species have the same carrying capacity K^x=K^x=1000, the same growth rate r^x=r^y=200/*K* and the same initial density *x(0)=y(0)=500*. For *y* the initial price a^y=2a^x=2 and the price elasticity b^y=2b^x=0.001 are twice as high as for *x*, the technical catch efficiency γ^y=0.006 is higher (γ^x=0.004) in the baseline case of symmetric behavior. In the asymmetric case we assume that catch efficiencies vary between the minimum of half and the maximum of twice of these baseline values such that player 6 is most efficient and player 1 least efficient in harvesting *x*, while for fish *y* it is the other way round. The initial allocation priorities p_i^k=0.5 for both fishes are the same, the initial available capital is C_i^K(0)=100 cost units, the initial investment C_i(0)=10 units for all players. The maximum investment C_i^+ is 50% of the available capital C_i^K which is increased or decreased according to the net value gain (profit) or net value loss V_i. The initial allocation priorities are equal for both fish ($p^x = p^y = 0.5$). Model runs are depicted for 30 years, in different diagrams: (a) fish stocks *x* and *y*, and harvest rates h_i^x,h_i^y ; (b) prices q^x and q^y; (c) accumulated capital C_i^K; (d) invested costs C_i; (e) value V_i (net profit); (f) priorities p_i^k. Additionally, we show the optimal cost as it occurs under the optimizing decision rule as (g) in Figure 7.

As the simulations show, in both the gradient and the optimizing approach initial harvest is around 100 fish units per year. Since this exceeds the reproduction rate per year, both fish types decline and fish *y* - which is caught more efficiently - comes close to extinction. Because of the declining fish stocks, the price goes up (factor 2 for *y*) and the harvest goes down until it equals the reproduction rate and both fish stocks stabilize. The initially high profits decline, more rapidly for the optimizers who seek to switch to the high optimal costs in the beginning but then because of fish scarcity and competition seek to switch to small or even negative optimal costs to avoid negative profits (losses). Their capital stabilizes at a level that is higher than in the beginning (Figure 7).

Initially, the gradient decision rule exhibits a smoother response. Here, all fishermen gradually increase their investment while some experience increasing profits. However, after approximately seven years, fishermen slowly begin to reduce their invested costs in response to the declining or even negative profits which contribute to major capital declines. After 30 years most fishermen have small invested costs and profits close to zero (positive or negative) which implies that they can no longer compete. Remarkable are the exceptions. Fishermen S_1 and S_6, who are most specialized in one of the two fishes, achieve the highest profits and capital. While S_1 initially profits from overfishing y, only S_6 sustains capital growth from the larger fish population x (Figure 6). The allocation priorities are also interesting. For the gradient rule, starting from the same priority for both fish types, four fishermen (S_1-S_4) initially increase priority towards fish *y* because of high catch efficiency, but in the long run only fishermen S_1 and S_2 (being specialized in y) continue this, while S_4 to S_6 prefer fish x. S_3 returns to equal priority (Figure 6). A similar behavior is reproduced in the interaction among optimizers, even though the changes are more rapid (Figure 7). Even though the fishermen exhibit individual rationality using both decision rules, they deplete both fish populations and thus the economic basis upon which they rely.

Figure 6: Scenario with competitive gradient decision rules

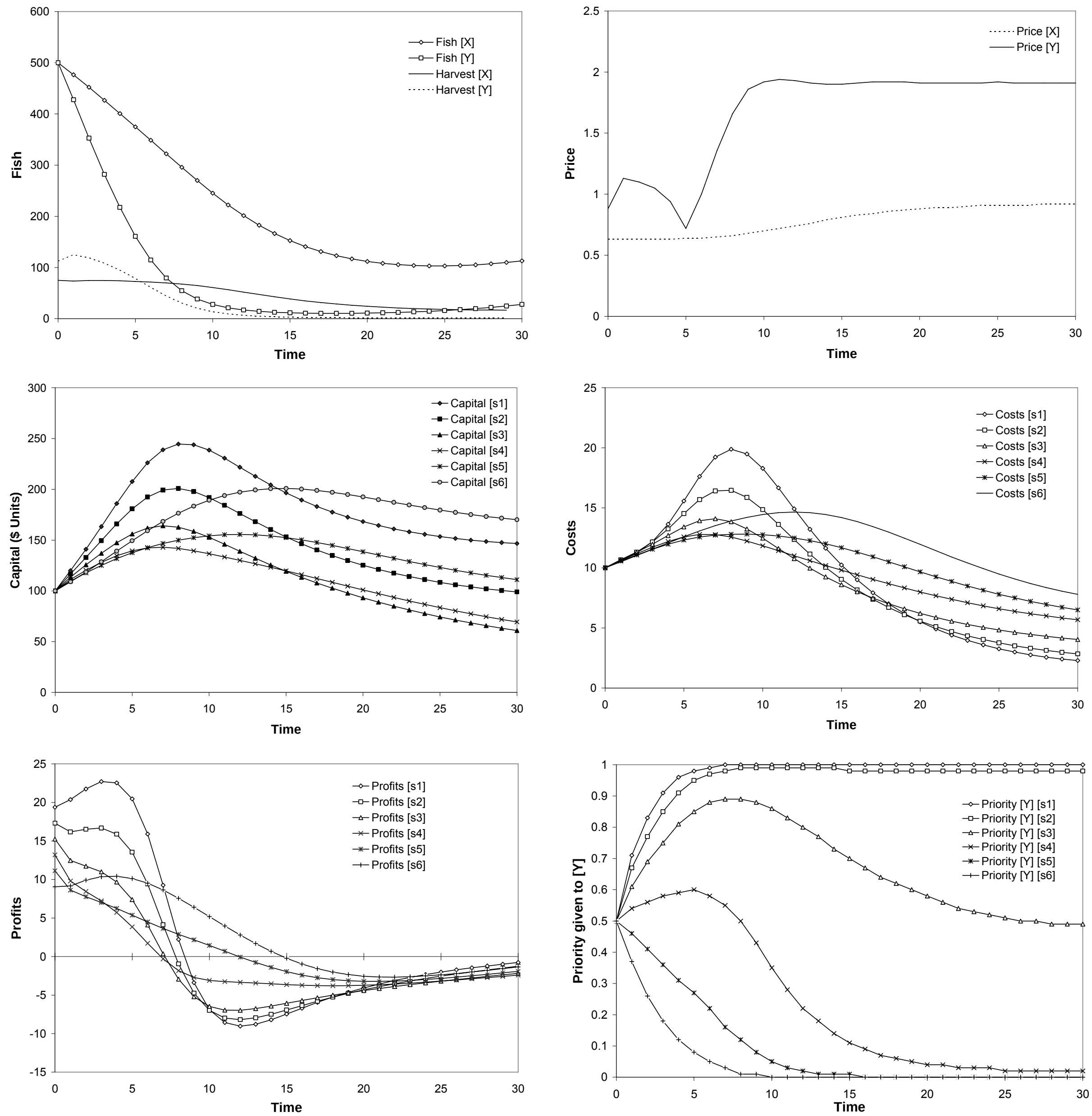
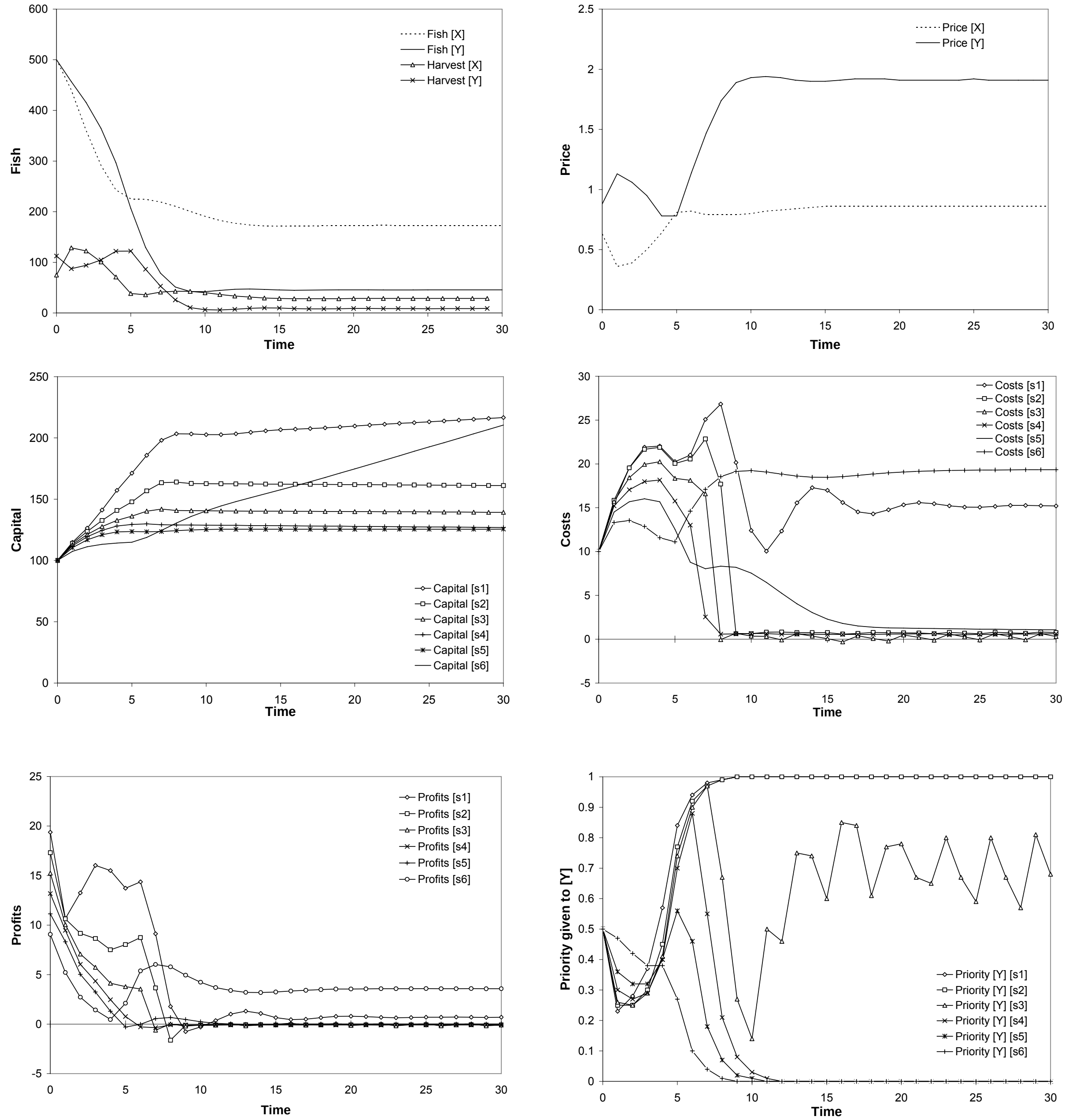
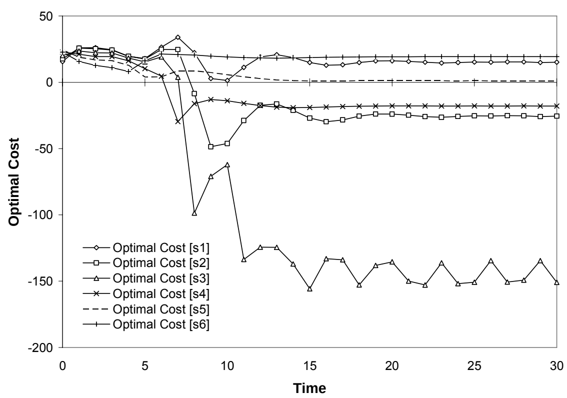


Figure 7: Scenario with competitive optimal decision rules





Economic cooperation for sustainable fishery management

The situation considerably changes with cooperation among fishermen who try to keep a sustainable limit for catch investments to avoid overfishing and subsequent ecological and economic decline. Under competition, fishermen define their investments based on their individual evaluation and profit seeking goals. This contrasts with the cooperative case, where a sustainable collective target is defined and used to determine the individual harvests and investments based on distribution rules.

Using $C\gamma_i = \gamma_i C_i$ to denote the effective costs for actor S_i (weighted with the catch efficiency) and

$$C_\gamma = \sum_i \gamma_i C_i$$

as the total effective cost, then the steady-state condition for fish stock k is given as $C\gamma^{k*} = r^k (K^k - x^k)$. If all agents jointly try to aim for this sustainable target, an adequate algorithm to adapt effective cost is

$$\Delta C\gamma^k = \beta^k (C\gamma^{k*} - C\gamma^k),$$

where $k = 1,\dots,m$ and β^k is the reaction strength. A relevant question is which share φ_i^k of $\Delta C\gamma^k$ is assigned to each fisherman S_i for each fish type k. One plausible distribution rule would be to assign everyone a fraction proportionate to their actual effective costs

$$\varphi_i^k = \gamma_i^k C_i^k / C\gamma^k.$$

This distribution implies that those with higher effective investment costs receive a high share of increases (and reductions). Here, allocation priorities are the result of the distribution mechanism and cannot be freely chosen.

When implemented in STELLA (Figure 8), the simulated dynamics completely differ from the competitive case (Figure 9). The STELLA model for the cooperative dynamics case is significantly simpler than the competitive scenarios. This is largely due to the simplified model structures for calculating priority for allocating investment (costs) to a given fish species. Moreover, it is no longer necessary to perform the complex calculations needed for determining changes in individual agent investment (either locally or globally optimizing) in a competitive atmosphere. Here, the diagram is also significantly simplified as we are no longer reliant on the competitive decision mechanisms that require array usage to calculate decision matrices between different fishermen. As a result, we can condense quite a few of the formerly un-arrayed variables into arrays, thereby demonstrating the simplicity of the cooperative decision mechanisms.

Here, both fish populations stabilize at considerably higher levels, allowing for higher sustained harvests and profits, which are distributed in proportion to effective investment, thus sustaining capital growth for all fishermen. The price for *y* again increases by almost a factor 2 while the priority for *x* increases compared to *y*. In this case, cooperation serves the viability of both the ecological and the socio-economic system but it requires a mechanism of target setting and distribution which needs to be implemented through institutional procedures that may include a negotiation framework, a management authority and input from scientific institutions (see Eisenack et al. 2006).

Figure 8: STELLA model for cooperation among fishermen

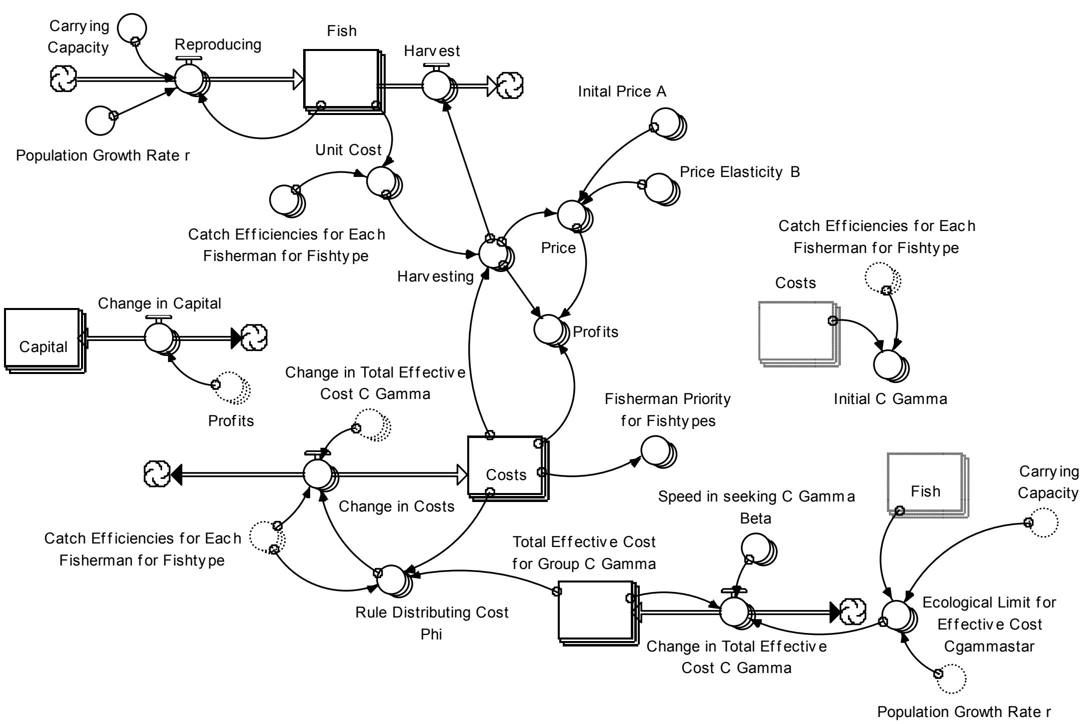
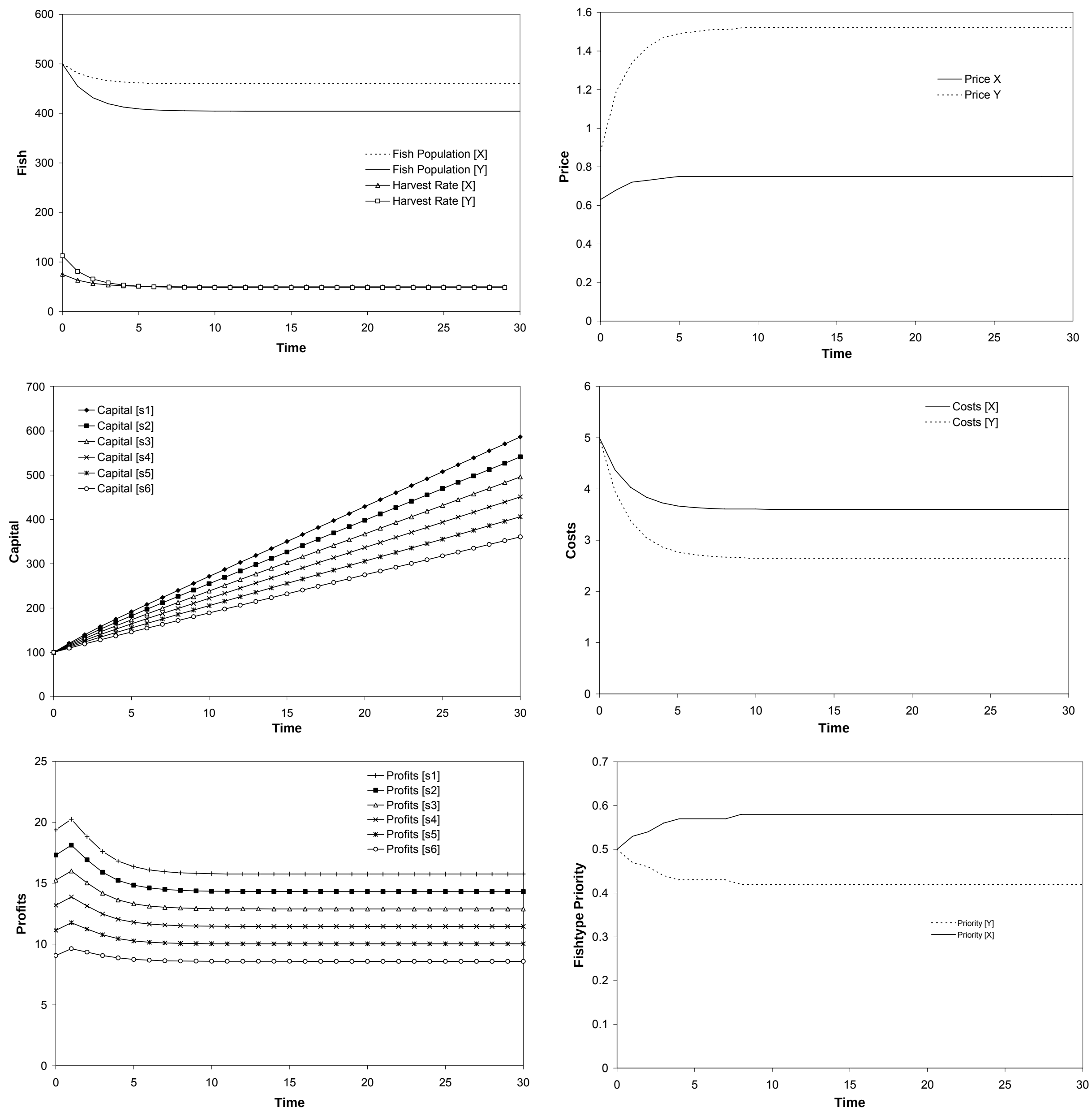


Figure 9: Scenario with cooperative sustainable decision rules



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