From Complex Conflicts to Stable Cooperation Cases in Environment and Security[1]

Jürgen Scheffran
Department of Political Science
Department of Atmospheric Sciences
University of Illinois
ACDIS, 505 East Armory Ave.
Champaign, IL 61820
Phone 217-244-0463
Email scheffra@uiuc.edu

Bruce Hannon
Department of Geography
University of Illinois
220 Davenport Hall, MC 150
607 S. Mathews Avenue
Urbana, IL 61801
Phone 217 333-0348 office
Email bhannon@uiuc.edu

Abstract: Conflict is a dynamic and complex form of human interaction, often emerging from incompatible actions, values and goals, and consuming a considerable amount of resources. Conflicts are an expression of and a contribution to system instability and sometimes lead to chaotic escalation between adversaries, causing a breakdown of social and natural systems. To resolve conflicts, the actors can adjust their actions towards cooperatively stabilizing their interaction and form stable coalitions. To study the dynamics of conflict and the evolution of cooperation, we introduce an integrated framework for modeling the interaction of multiple actors who pursue objectives by allocating their resources to various action paths. In repeated learning cycles actors can adjust their targets and resources to those of other actors, thus shifting from conflict to cooperation. Within the general framework it is possible to study the complexity and instability of multi-actor constellations and the transition to cooperation for specific examples in a wide range of fields, including military security and environmental conflicts in fishery management, energy and climate change.

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1 Conflicts in a complex world

Conflicts are an essential part of human life. Much of human history can be described as a history of conflicts, often as armed conflicts which have consumed an enormous amount of resources. Conflict resolution and cooperation, in return, have attracted much less attention. Whether conflicts play a destructive or a constructive role in social change critically depends on the way they are handled by the actors involved. A better understanding of conflict is a prerequisite for resolving it.

After the end of the bi-polar Cold War and as a result of globalization, the international system had been rapidly transforming. Notwithstanding the overwhelming power of the remaining superpower, a multipolar world is emerging in which decisionmaking and conflict are determined by a variety of actors and factors, some of which are coupled in a complex manner (Elhefnawy 2004). Contrary to the world's increasing complexity and diversity, involving a variety of subnational and transnational actors, the concentration of power and the formation of cooperative structures among States has the opposite effect. Changing security conditions can provoke instabilities and the outbreak of violence, as was vividly demonstrated by the destructive, chaos-like dynamics in the Balkan region during the 1990s (e.g. in the violent struggles on Bosnia and Kosovo). The sudden and violent breakup of existing political structures is often associated with an increased ``entropy'' in the fragmented societies of a region, while new stable coalitions evolve only slowly, a problem that the African continent is facing. Not only the arsenals of armament are relevant for security, but also economic and technological interconnections as well as social and ecological factors, on global and regional levels.

2 Conflict modeling and non-linear dynamics

Mathematical methods and models can help to understand the general processes and interactions in conflict and cooperation. The combination of cooperative and dynamic game theory with computational agent-based modeling provides a basis to further develop instruments of decision-support that can be used in international relations and economy as well as in other fields. In our view mathematical modeling and its computer-based implementation can contribute to a deeper understanding and the development of new instruments for conflict-resolution, cooperation and peace building

Complex systems analysis and non-linear dynamics provides a useful framework for conflict analysis. The concept of chaos as a model for arms race and war outbreak was introduced by Saperstein 1984, 1986, to show that even simple nonlinear deterministic arms race models may lead to the breakdown of predictability. The problem of chaotic dynamics in arms race models was further investigated by Grossmann and Mayer-Kress 1989, using nonlinear difference equations based on the arms race model developed by Richardson 1960 but with discrete time and a damping of the growth of expenditure at upper and lower limits. Increasingly the evolution of cooperation and its complexity is being studied.(Axelrod 1984, 1997)

In the following we will introduce our conflict modeling approach and some analysis with regard to stability and complexity. Fields of study will include the arms race between nuclear-armed missiles and missile defenses, fishery conflicts, energy and climate change. We provide a survey of our previous work in this field and new results. The modeling approach is based on a qualitative meaning of conflict which is understood here as a dynamic interaction process involving actors who fail to reduce their conflict potentials to tolerable levels. *Actors* can be any entities that are able to act by using the means they have under their control to change the state of their environment, including individual persons, groups of persons, or institutional actors, such as States, cities or firms. *Conflict potentia*l is described as a continued difference of various factors:

•*Values and goals* are dealing with what actors want, depending on their interests, needs and motivations, objectives and targets, the risks and dangers they are willing to take.
•*Resources and means* concern the instruments and efforts which actors can use to change the state of the environment in pursuing their values and goals. This can be anything with a potential for change, such as cost, investment, information, physical energy and force.
•*System states, options and actions:* Actors observe the state and change of their systems environment and can thus have differences on what the state is and which actions to take, selecting from a range of decision options (e.g. on technology paths and modes of behavior).

For each of these dimensions, actors are able to draw a line between what they are willing to tolerate and what not. As long as a given state of the environment is wanted by some actors and unwanted by other actors, they tend to use their resources to change the difference to their benefit, at the cost of other actors, A conflict potential is a driving force for the emerging conflict dynamics. This is described by the sequence of actions and interactions among actors to pursue their values by transforming their resources into actions. An interaction process that increases rather than decreases the conflict potential contributes to conflict escalation which can result in an unstable dynamics. In many cases an escalation is only finished if one or several of the involved actors reach their resource limits or disappear. If actors succeed in reducing the conflict potential, they are moving towards conflict resolution and a more stable interaction. Through learning and cooperation actors adapt their goals, resources and actions to those of other actors, working together rather than against each other.

With regard to the goals and the allocation of resources, contradictions and conflicts could prevent the successful achievement of objectives for some or even all of the actors. Even though actors might behave individually rational, their collective interaction could become seemingly irrational and the overall benefit-cost ratio negative. Conflict prevention, avoiding destructive conflict escalation, involves a communication and negotiation process aiming at the mediation between contradictory positions and exploring cooperation. Modeling these interdependencies deals on the one hand with the conditions under which conflicting interactions emerge, on the other hand, with the possibility that actors jointly influence the process towards a more cooperative direction.

The individual action sphere and the social and natural environment are closely linked. In regions of a phase transition a change in the value and preference structure on the individual “micro level" can rapidly have an impact on the societal “macro level" if a sufficient number of individuals think and act in a similar direction. This describes a situation which is typical for coordinated and self-organized collective phenomena.

3 A dynamic model of multi-agent interaction

3.1 The individual actor

An essential precondition for analyzing and modeling conflict is to have an understanding of the actions of individual actors. Actions occur in a system environment, characterized by relevant *system variables* which define a current system state $x(t)$ at a given time t. The system state is observed and evaluated by an actor who according to its internal preference structure selects certain system states as more preferable than others. Under certain conditions, the preference order can be represented by a *value function* $V(x)$ and target values V^*. To achieve these targets, the actor decides on investing its *resources* (costs) C into a particular *action* $a(x, C)$ to change the system state by $\Delta x = g(x, a)$ and induce a value change ΔV towards the target value V^*. The value added $\Delta V > 0$ can be consumed, directly reinvested or accumulated to form productive capital K. By observing the outcome of actions and adjusting the invested resources in the next time step, the process can be repeated, which allows for adaptation and learning. In this process, an actor cannot only control the flow of resources applied to system change, but also its direction given by the priority p^x for allocating investment into system variable x. Altogether the relationship between the variables in the value-cost-system (VCX) model can be represented by the following flow diagram (see Figure 1).

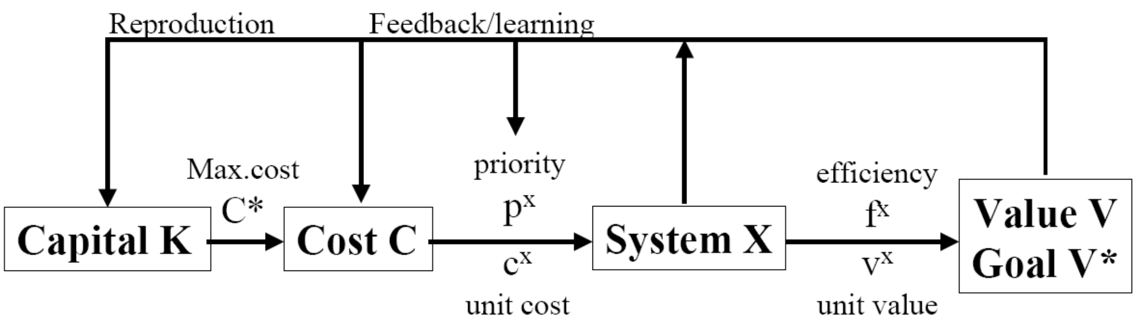

Figure 1: The feedback cycle of single agent action

By use of the resource flow $C(t)$ an actor changes the system state by $\Delta x(t) = C(t)/c(t)$ (with unit cost c), resulting in a value gain $\Delta V(t) = v(t)\, \Delta x(t) = f(t)\, C(t)$ where v is the value per unit of system change Δx and $f = v/c$ is the efficiency of producing value output for a given resource input (benefit-cost ratio). If at a given time t an actor aims at achieving a particular value $V^*(t+1)$ in the following time step $t+1$, value needs to change by $\Delta V^*(t) = V^*(t+1)-V(t)$. The required resources to bridge the gap towards the desired state are given as $C^*(t) = \Delta V^*(t)/f$. Thus the targets in value space have been transferred into targets in resource space.

If at given time t actual resources $C(t)$ differ from target resources $C^*(t)$, the gap can be bridged by an adaptation process for invested resources according to a “decision rule”:

$$\Delta C(t) = C(t+1)-C(t) = \alpha^C D(C) = \alpha^C (C^*(t) - \tau C(t)) = (\alpha^C/f) (\Delta V^*(t) - \tau \Delta V(t)) \quad (1)$$

where α^C is the cost response factor. The parameter τ reflects the required speed of adjustment for value: If the target value is to be reached in τ time steps for the current rate $\Delta V(t)$ (the observed trend), the decision rule is to increase resource flow ($\Delta C(t)>0$) as long as $V(t) + \tau \Delta V(t) < V^*(t)$ and to decrease it if the goal is exceeded, i.e. $V(t) + \tau \Delta V(t) > V^*(t)$. At the threshold $V(t) + \tau \Delta V(t) = V^*(t)$ the resource input remains constant ($\Delta C(t)=0$), which corresponds to an exponential decay $\Delta V(t) = (V^*(t)-V(t))/\tau$ towards the target with decay time τ. In particular, for $\tau=1$ the target is to be reached in one time step, for $\tau>1$ the actor seeks to reach it at a later time and for $\tau<1$ at an earlier time. For $\tau=1$ the speed of adjustment does not matter, only the distance to the target V^*.

In pursuing the objective, an actor has only a limited amount of resources under control, given by an upper limit C^+, such that $0 \le C \le C^+$. In case of $C^+<C^*$ the invested resources are insufficient to achieve the objective. Even with limited resources, an actor can try to improve the action efficiency f which implies that the same objective V^* can be achieved at lower cost C^*. This may be done by switching from an action a^1 to an action a^2 with higher efficiency $f^2 > f^1$ than the first one. Learning is to find such a more preferable "new" action path and to allocate an increasing share p of the resources to this option, at the cost of a lower share $1 – p$ for the established action path. Then the overall efficiency of the mixed action is $f(p) = (1-p) f^1 + p f^2 > f^1$. If actors would behave optimal, they would allocate all their resources to the new path as soon as possible. However, real world actors are bound by the rules they are used to and need time to adjust. We take this into account by a finite speed of adjustment for the action priorities: $\Delta p(t) = \alpha^p D(p)$.

Here $D(p)$ is a decision rule for adapting priority p. If p^* is the priority an actor would find best serving its interests, the optimizing rule would be $D(p) = p^* - p$. For $p^* = 1$ all investment is spent on the second path. Among the many possible decision rules we will consider one that respresents actors pursuing several paths weighted by the expected value gains on each path, given by the partial derivative $V_p = \partial V/\partial p$ of the value function with regard to allocation, thus moving along the gradient.

The speed of adjustment is represented by α^p and α^C which can be either fixed reaction strengths (the inverse of which is a decay time $\tau = 1/\alpha$) or a function of state. In particular, a natural choice is a logistic growth function $\alpha^p = \kappa^p p (1-p)$ which dampens speed near the boundaries, with κ being a constant reaction strength. A similar approach is used in evolutionary game theory.[8] Accordingly, cost adaptation is $\alpha^C(t) = \kappa^C C(t) (C^+(t)-C(t))$. Altogether we achieve value-driven adaptive decision rules which form a set of difference or differential equations for a single actor:

$$\Delta C(t) = \kappa^C C(t)(C^+(t)-C(t))(\Delta V^*(t) - \tau \Delta V(t)) = \alpha^C C(t)(C^+(t)-C(t))(C^*(t) - \tau C(t))$$
$$\Delta p(t) = \kappa^p p(t) (1-p(t)) V_p(t)$$
$$\Delta V(t) = v(t) \Delta x(t) = f(t) C(t)$$

3.2 Multi-agent interaction, stability and conflict

At this point we have a dynamical system describing a single actor who pursues a goal by investing resources to change the environment. If n actors act upon the same system state x, an interaction evolves which is simultaneously controlled by all actors according to their strategies. During the interaction process each actor Ai ($i = 1,..., n$) invests its resources C_i into m system variables x^k ($k = 1,..., m$), and evaluates the outcome of the combined actions according to its own value criteria V_i to derive new actions in the next time step. The players can adapt the amount C_i and allocation p_i^k of resources to variables x^k, leading to an induced change $\Delta x_i^k = (p_i^k / c_i^k)\, C_i$, where the condition $\sum_{k=1}^{m} p_i^k = 1$ is to be satisfied. Important is the learning capability of the actors to adapt resource allocation to achieve the value targets ΔV_i^*. In the linear case the value change

$$\Delta V_i = \sum_j f_{ij}(p)\; C_j + V_i^U \qquad (i = 1,\dots, n)$$

depends on the resources of all actors, weighted by the interaction efficiencies f_{ij} which describe each value change per resource unit of each actor. V_i^U includes external value changes which can be important but are neglected in the following analysis. The target conditions $\Delta V_i = \Delta V_i^*$ depend on actions and resources of others according to

$$C_i^* = (\Delta V_i^* - \sum_{j \neq i} f_{ij}(p)\, C_j) / f_{ii} \qquad (i = 1,\dots, n).$$

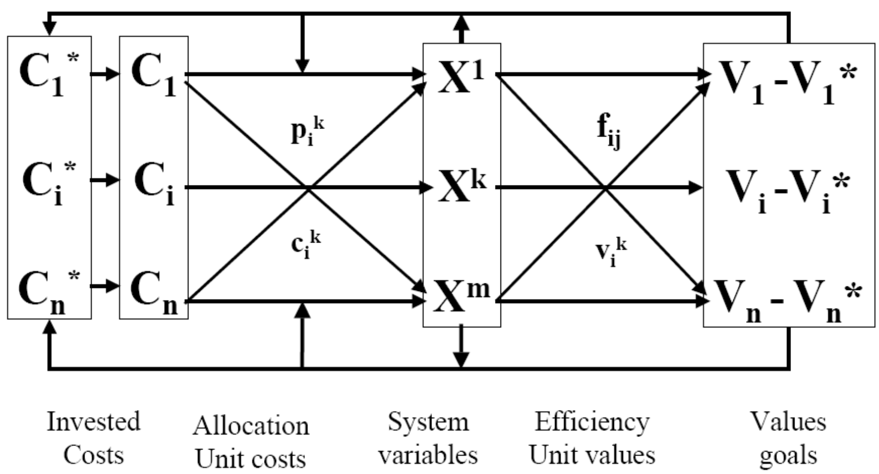

Figure 2: The feedback cycle for interaction of multiple actors in the Value-Cost-System (VCX) modeling process.

These target conditions correspond to reaction curves (which in general are multi-dimensional hyperplanes) which lead to an adaptation of resources (costs) and thus a multi-actor dynamical system. The intersection of the reaction curves is the cost equilibrium vector $C^* = F^{-1}\, \Delta V^*$ (balance of power) where $F = (f_{ij})_{ij=1,\dots,n}$ is the determinant of the interaction matrix:

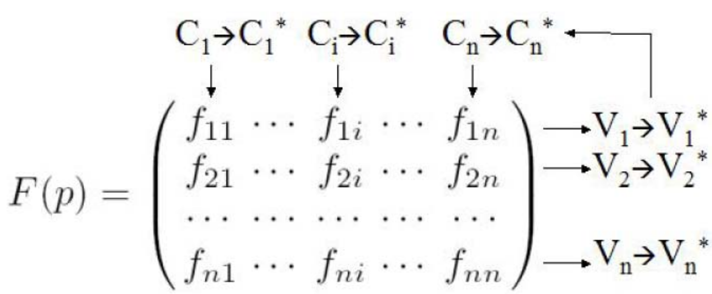

Figure 3: The interaction matrix with cost inputs and value outputs

Since the interaction coefficients $f_{ij}(p)$ between the actors depend on the vector of the allocation priorities $p = (p_1,\dots, p_n)$ of all actors, each of them can control the dynamical system by changing their own priority p_i (which itself can be a vector) to achieve the respective target equilibria and stabilize or destabilize them. If the action priorities p_i are changed towards non-cooperative relations, the equilibrium moves towards higher costs, for a cooperative relation towards lower costs (see the stylized symmetric cases in Figure 4). In asymmetric cases one player may profit from another player, who in return may loose from the interaction, and vice versa. The actors can negotiate on the right choice of their own p_i which can be expressed as a dynamic game problem. They can form coalitions by pooling some of their resources and redistribute gains (or losses) to the individual actors.

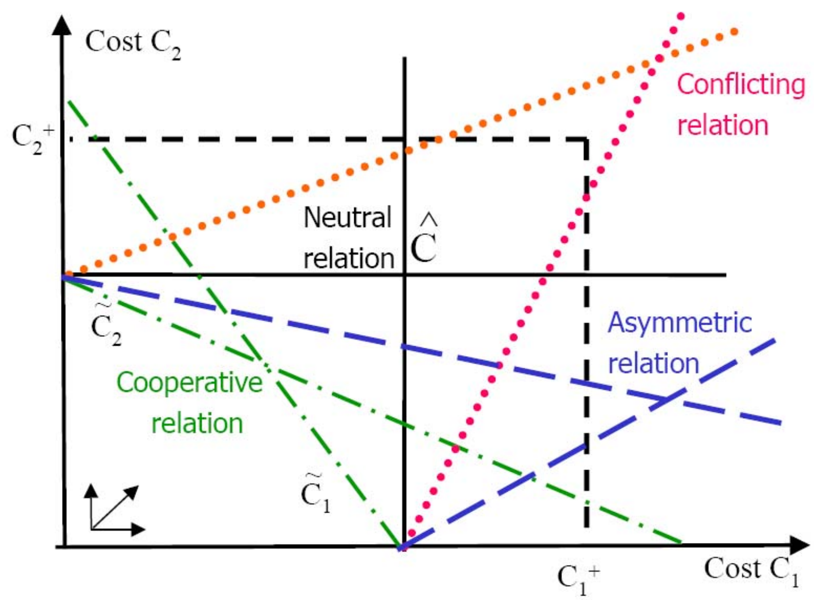

Figure 4. Cost balance for neutral, cooperative and conflicting and asymmetric relations.

A mutually conflicting situation can be contained as long as the adverse investments by other actors can be compensated by own investments, allowing to achieve the target within the budget limits. If the target point is outside of the admissible cost domain for at least one actor, then the conflict potential remains unresolved. If this actor does not want to give up its aim, it may be possible to increase efficiency or acquire resources elsewhere, e.g. by support from other actors who join the same alliance. These “transfer payments” may contribute to keep the conflict under control as long as the resource gap can be bridged but they may also further escalate the conflict if they damage the interests of others.

A conflict tends to escalate if the target cost lines become parallel or their slopes do not permit a joint target set within the positive cost domain. Then the adjustment process fails and the interaction becomes unstable. In this case no cost compensation can help because the conflict is inherently escalatory and exceeds limits: In pursuing their aims, actors generate more harm to other actors’ aims whose reactions in return impose harm on others until one or several actors have used up all their resources or are destroyed if the value losses are existential. Possible measures to resolve or end the conflict are to stop the supply of resources (dry out the conflict), to support those actors that are supposed to be “right” (join an alliance) and attack their “adversaries”. An alternative is to adjust the aims to each other or change the direction of actions towards mutual benefits. While the first two can be applied against the will of actors (e.g. by a blockade or use of force), the other two require mutual adjustment, consent and negotiation.

These qualitative statements about conflict can be translated into mathematical conditions in our model. Of particular interest are stability conditions at a given cost equilibrium. Since we have a dynamical system, we can apply the established approach in stability theory based on the Jacobi-Matrix of the interaction, whose elements f_{ij} are formed by the partial derivatives of each dynamical equation with regard to each of the variables. The general stability condition is that all eigenvalues of this matrix would be negative. For two actors with $f_{ii} > 0$ and $f_{ij} < 0$ the stability condition between two actors boils down to the essential requirement

$$S_{ij} = f_{ii}\, f_{jj} - f_{ij}\, f_{ji} > 0\ . \qquad (2)$$

This reflects the intuitive meaning that the product of the self-imposed (positive) impacts f_{ii} and f_{jj} exceeds the product of the (negative) mutual impacts $f_{ij},$ and f_{ji}. This condition holds as long as other actors do not interfere or their impact on the two actor interaction can be neglected. For a larger number of actors with $f_{ii} > 0$ and $f_{ij} < 0$, a sufficient stability condition is $\Sigma_j f_{ij} > 0$ for each $i = 1,\ldots,n$. A more general condition is given in Scheffran 2001, options for control are studied in Jathe/Krabs/Scheffran 1997; Krabs/Pickl/Scheffran 2000. With the number of actors involved, the complexity of the interaction matrix increases and thus the potential for instability which restrains the formation of large social groups. However, social evolution processes allow for the adjustment of interaction parameters as a result of learning among actors, selecting the more stable interactions while the unstable ones are less “successful”, according to fitness criteria of societal competition. This is an important aspect of institution building, which is related to questions of coalition formation.[11]

3.3 Simulation of the framework model

To understand the basic modes of behavior of the VCX model, we use a specific parameter setting for the initial conditions of value and costs, the upper cost limit C_i*, interaction efficiencies f_{ij} and the reaction parameter κ_i for two players. Results are depicted in Figures 5 and 6 for a situation which is symmetric for two actors, except for the initial conditions in value which are opposite to each other ($V_1(0) = -V_2(0) = -0.3$). For a response time $\tau = 0$ (i.e. the speed of value adaptation does not matter) the actors show periodic oscillations around their target values $V_i^* = 0$. For increasing τ this oscillation is damped until at some τ fluctuations occur around the target which follow the typical bifurcation pattern in chaos theory with τ being the order parameter. The chaos-like behavior is shown for $\tau = 10$ which is anti-symmetric between the two actors (for this model the phenomenon is first described in Scheffran 1989; see also Jathe/Scheffran 1995). Key factors are the logistic response coefficient $\alpha^C = C\,(C^* - C)$ and the decision rule $D(C)$ which regulates the time-discrete logistic growth model used in chaos theory.

Different from the first case in which all efficiencies are identical, in the second case the positive self impacts f_{ii} are smaller than the negative mutual impacts f_{ij}. This implies that the exchange is harmful for both actors and thus unstable, as is shown in Figure 6. The costs for both go to the maximum costs and both fail to achieve positive values. Interestingly for actor 1 the situation becomes worse because starting from positive values the actor initially reduces its costs while actor A2 increases them, thus both turn positions. Even though actor A1 returns to increasing costs it is too late to compensate for the incremental decline in value when the upper cost limit is reached. Response time τ does not play a significant role here which indicates that instability overrides chaos.

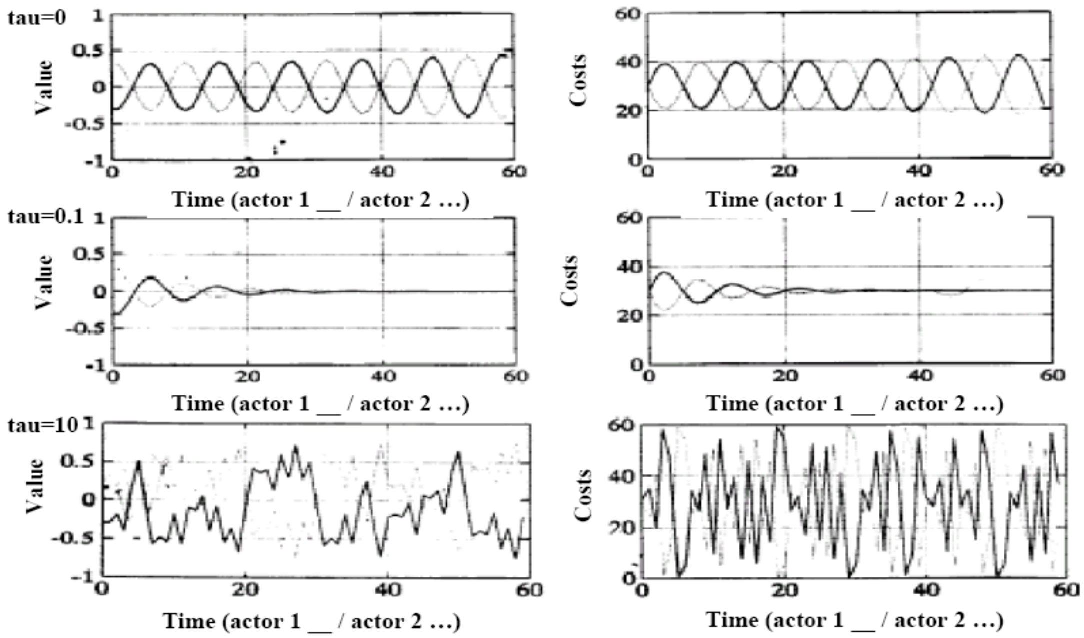

Figure 5: Transition to chaos: Anti-symmetric case as function of response time τ
Parameter setting: V1(0) = -V2(0) = -0.3, C1(0) = C2(0) = 30, f11 = f22 = -f12 = -f21 = 0.01, $\kappa 1 = \kappa 2$ = 0.02, $C1^+ = C2^+$ = 60.

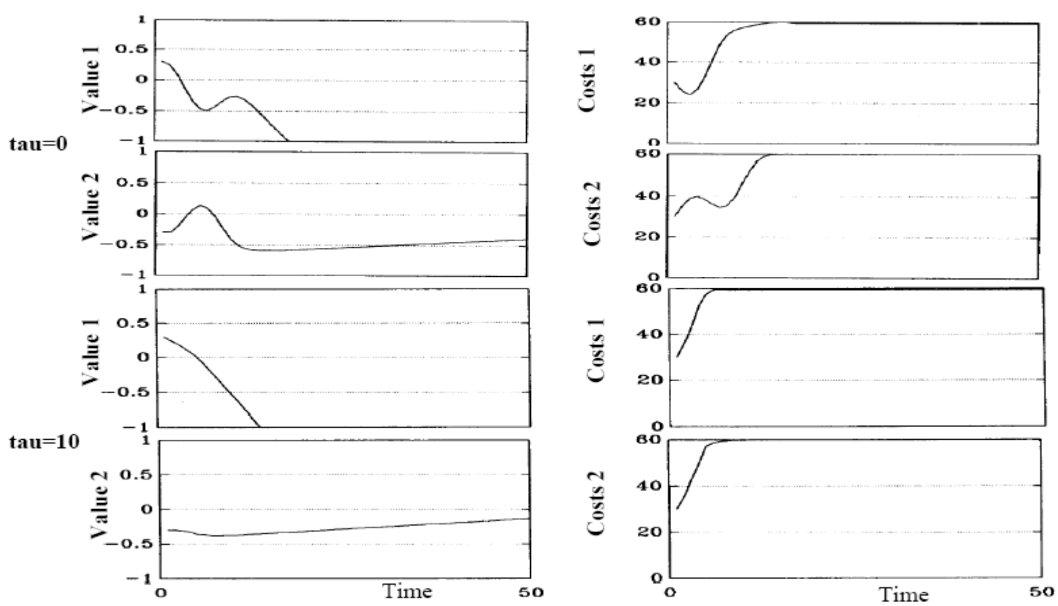

Figure 6: An unstable conflict escalation
Parameter setting: V1(0) = -V2(0) = -0.3, C1(0) = C2(0) = 30, f11= f22 = 0.009, f12 = f21 = -0.011, $\kappa 1 = \kappa 2$ = 0.02, $C1^+ = C2^+$ = 60.

4. Offense, defense and international stability

An important field of application for a dynamic conflict model is the arms race between offenses and defenses which dominated warfare throughout history. A most recent example is the introduction of missile defense systems to counter strategic offensive weapons which during the Cold War were the pillars of nuclear deterrence. Despite attempts to build these systems, technical difficulties, excessive economic costs and the possibility of countermeasures prevented an effective missile defense system.

Referring to previous work[14,12,15] we define security value functions for each actor that include offensive, defensive and anti-defensive capabilities, denoted as O_i, D_i, A_i for each actor, their marginal security impacts o_i, d_i, a_i and unit costs c_i^o, c_i^d, c_i^a, and the military budgets C_i spent on acquiring these capabilities. Essential are the expected damages Y_i in case of a military exchange, in particular those for a first and second strike Y_i^F and Y_i^S. Significant control variables in the model are the priorities p_i^o, p_i^d and p_i^a for allocating the military budget to each of the military capabilities and the expected likelihoods q_i^F, q_i^S, q_i^0 for striking first, second or not at all.

Security is defined here as the expected value of peace, dimished by expected damages for different scenarios of military conflict and weighted by their respective probabilities:

$$V_i = q_i^0\, V_i^+ - q_i^F\, Y_i^F - q_i^S\, Y_i^S - V_i^*$$

Here V_i^* is the threshold below which security is seen as intolerable. For guaranteed retaliation $q_i^S = 1$ *and* $q_i = q_i^F$ the coefficients of mutual efficiency between two actors Ai and Aj are given as (for explanation see Scheffran 1989, 2003):

$$f_{ii} = q_i\, y_i\, d_i^c\, p_i^d, \qquad f_{ij} = -\, q_i\, y_i\, o_j^c\, (1 - p_i^d)$$

which depend on the attack probabilities q_i and allocation priorities p_i as well as on unit damages y_i, offense and defense capabilities per cost unit o_i^c *and* d_i^c (subsuming the anti-defense capability under offense). For an arms race between two opponents, the stability condition $S_{ij} > 0$ in equation (2) defines a boundary condition for probabilities and priorities above which an unstable escalation occurs.

Going beyond the two-actor model, we consider five countries building offensive, defensive and anti-defensive capabilities. The parameter set is intended to match some qualitative patterns of the United States (1), Russia (2), China (3), India (4) and Pakistan (5). Figure 7 shows that the world's dominant power A1 spends a considerable fraction of its budget on defense and thus largely exceeds the capabilities of others, undermining their security. Actor A3 acquires a considerable amount of anti-defense capabilities, in competition with actor A1's defense capabilities. Due to its enormous resources (up to $40 billion per year), A1 can acquire offense, missile defense and security gains that far exceed those of others. Actors A3, A4 and A5 exhaust their resources and stay in the negative security domain while A2 after 30 time steps invests into its strategic arsenal to increases its security value.

The situation can drastically change if actors who experience continued insecurity from major powers may switch to other forces that may cause high damage at low cost and are hard to protect against, such as nuclear weapons smuggled into a country which is a scenario for terror attack. An effective defense against such a threat may be much harder to achieve and at higher cost, if at all.

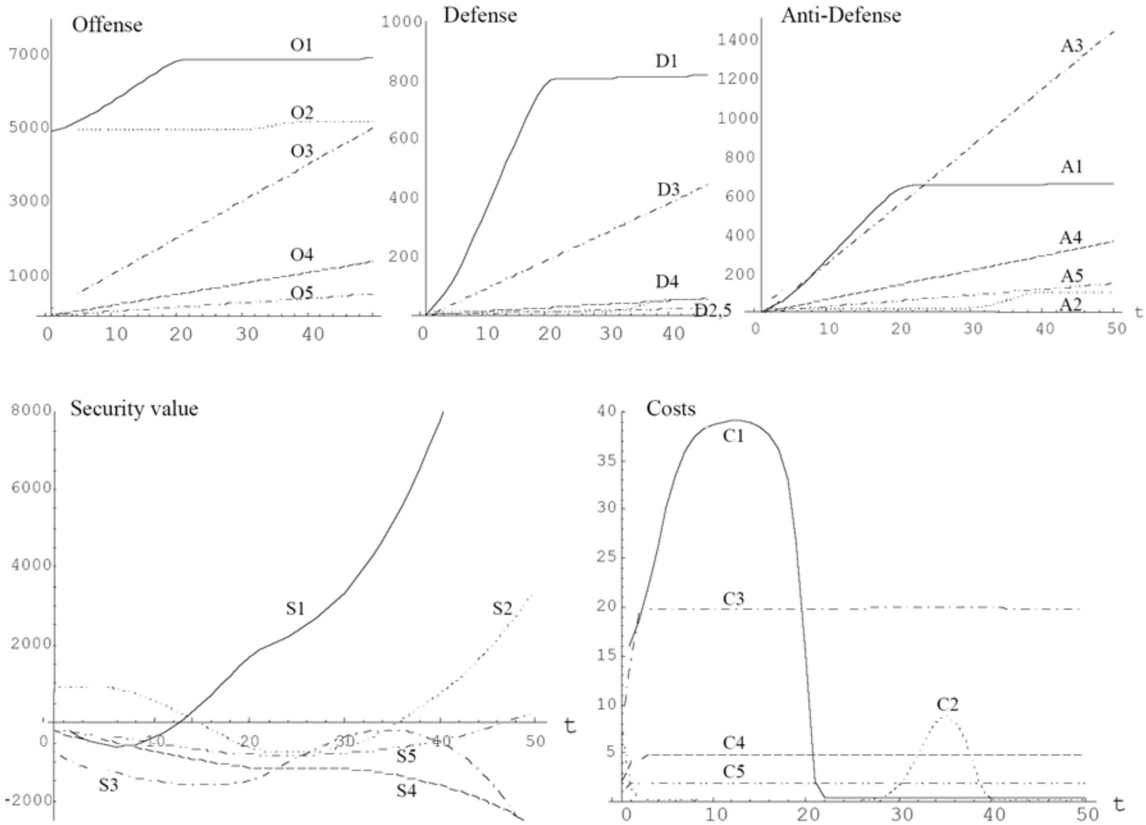

Figure 7: An offense-defense arms race between five countries (explanation in text).

5. Environmental conflicts: The case of fishery

While military conflict is seen as the dominant field of national and international security and attracts much of public attention, environmental conflicts are becoming increasingly significant and begin to shape the international security debate. The scarcity of natural resources, in particular energy use and its pollution of the environment, are two aspects of the conflicting relationship between man and nature. Even though environmental conflicts generally may not directly lead to military conflict, they tend to degrade the economic and societal conditions for survival of the earth's population, adding to the various stress factors that contribute to conflict. We discuss here two cases in particular: the problem of overfishing in the world's oceans, rivers and freshwater reservoirs, and the conflicting relationship between energy use and climate change.

Fishery is a significant source of the world's food production and an 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. To stay within ecologically sustainable limits, the focus in both fields so far has been on measuring and controlling the fish stock, often neglecting the inherent dynamics in the social and economic domain. To resolve the conflict, we must better understand the dynamics on both sides of the ecological-economic equation and their interaction and respect viability conditions for both systems (Scheffran 2000, Eisenack/Scheffran/Kropp 2005).

Our modeling approach uses fishermen as the key actors who catch fish as a source of income. Their value functions $V_i = q_i h_i - C_i$ are the profits from selling the fish catch (harvest) h_i for a market price q_i, diminished by the costs invested. Market price declines with total catch supplied by all competing fishermen. We assume that the fishermen catch fish x (several fish types have an index $k = 1, \ldots, m$) which is growing with the reproduction function, diminished by total harvest:

$$\Delta x = r x (K - x) - \Sigma_i h_i$$

A particular fish stock can be maintained for $\Delta x = 0$ which leads to the limit condition

$$\gamma C = r (K-x)$$

where C is total costs and γ is the average catch efficiency of all actors. 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 combines total investments by all fishermen with average 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. Maintaining a balance of economic and ecological necessities is hampered by two problems:

- Each of the three parameters in the ecosystem is bound by uncertainties.
- If fishermen seek to maximize their individual profits, their total effective costs can exceed the sustainable limit and thus result in 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 top-down 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 generally derived from two requirements:

$$x > 0 \text{ and } \Delta x \geq 0$$
$$V > 0 \text{ and } \Delta V \geq 0.$$

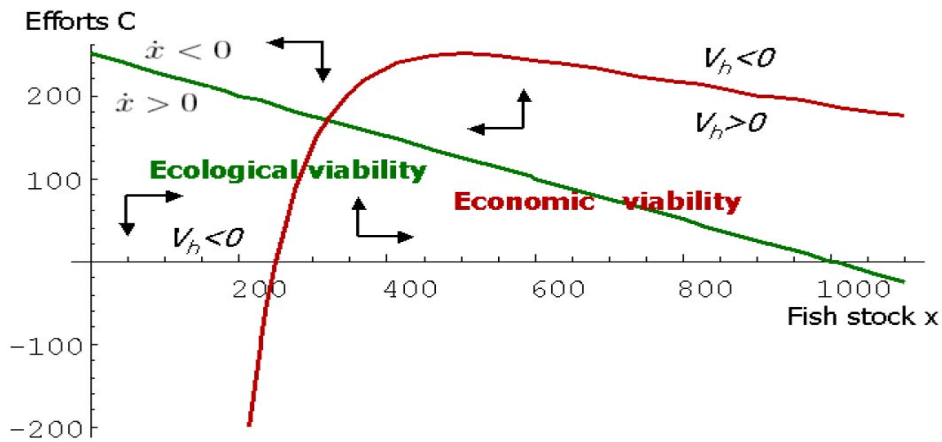

Figure 8: Compatibility of economic and ecological viability conditions

Each viability limit divides the system space into two sets of states, where the respective criteria are satisfied and not satisfied. Most desirable are those where viability conditions of both ecosystems and socio-economic systems are valid (win-win solution), least desirable where neither of them is satisfied. In the mixed cases only one of them holds which implies a conflict on which criteria to prefer. At the intersection of viability limits we have an equilibrium with $\Delta x = 0 = \Delta V$ (see Figure 8). Around the intersection point the dynamics tends to cross the boundaries which contains the risk that one of the viability conditions cannot be maintained in the long run without further stabilization.

We study a specific case, the interaction between six fishermen Ai *(n=6)* who choose between catching two different fish populations *x* and *y (k=2)*. Fishermen differ in catchefficiency, where efficiency for fish x increases from A6 to A1 and efficiency for fish y increases from A1 to A6. The results are shown in Figure 9, for a competitive and a cooperative case. In the competitive case fishermen invest into fishing to maximize profit. Even though they behave individually rational they harvest down both fish populations, with fish *y* coming close to extinction. Thus, for most fishermen the initially high net profit values decline to zero or even negative values which implies that they can no longer compete. Fishermen A1 and A2 completely switch to fish type 2, A5 and A6 switch to fish type 1, and A4 and A5 prefer a mix of both (see the diagram of priorities). Fishermen A1 and A6 who are most specialized in catching one of the fish species achieve the highest profits and capital. In the long run, only A6 is able to sustain capital growth from the larger fish population x (Figure 9a). The situation changes with cooperation on keeping a sustainable limit for catch efforts which is distributed according to resource input (Figure 9b). Fish populations stabilize at higher levels which allows for higher sustained harvest and profit which is more evenly distributed. In this case, cooperation serves the viability of the ecological and socio-economic system. Priorities for fish types are not significantly changed compared to the non-cooperative case.

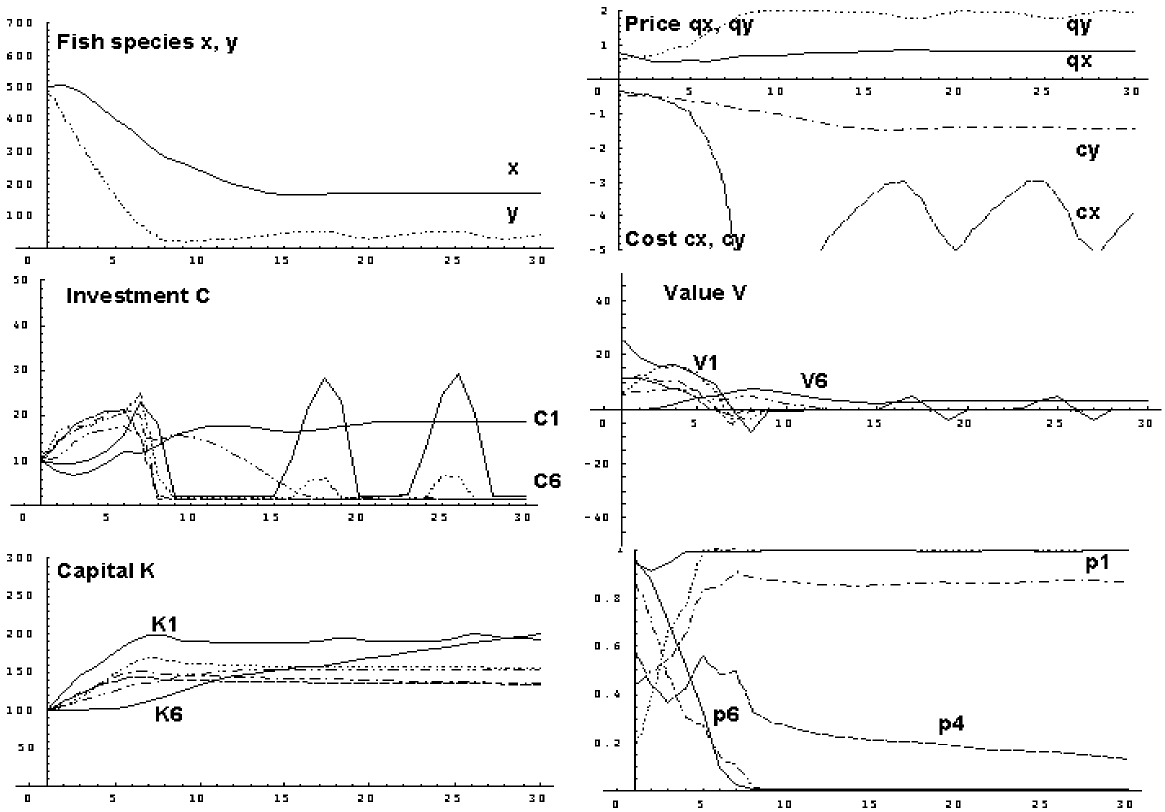

Figure 9a: The competitive fishery case

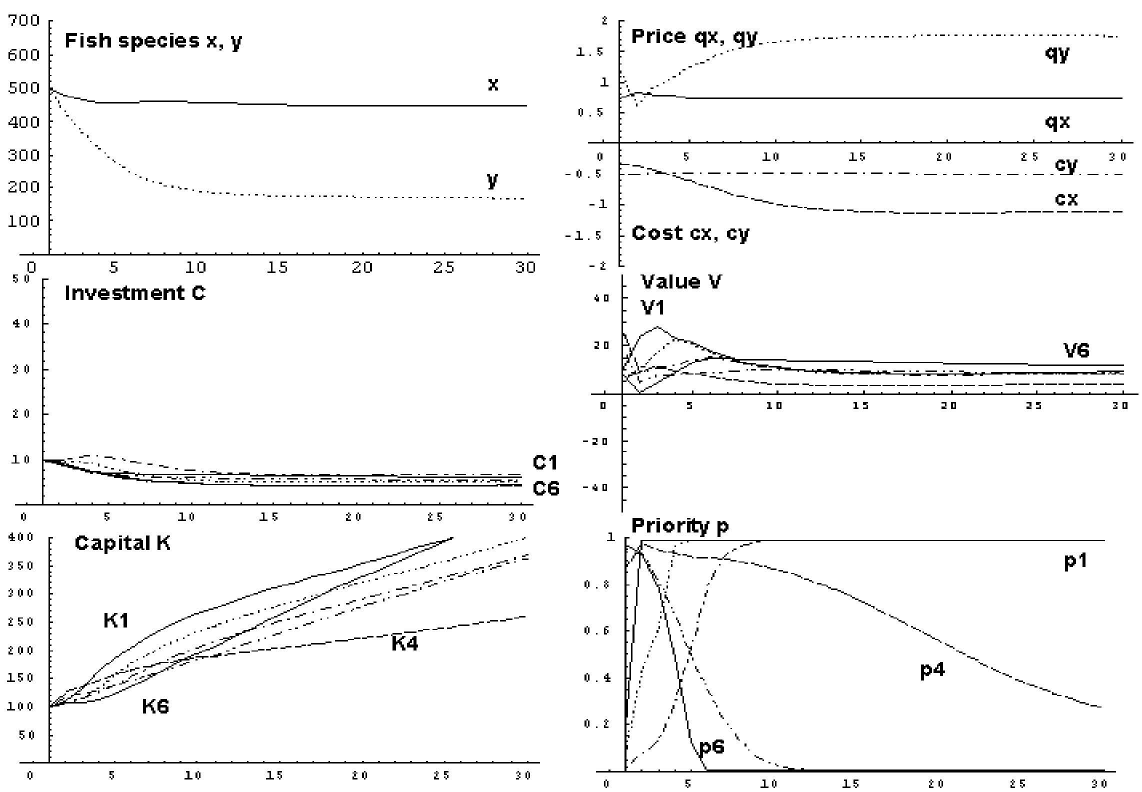

Figure 9b: The cooperative fishery case

Conflicts on energy and climate change

There is a wide range of potential conflicts in the field of energy and climate change, to mention war on oil, the struggle on nuclear power, conflicts over future energy scenarios or conflicts induced by climate change. For an integrated assessment the dynamics of both the climate system and the socio-economic system are taken into account, with energy being a crucial link. Economic models usually optimize a time-discounted global utility function adjusted by climate damage. In our model framework we use a different approach that identifies adaptive control strategies adjusting to the state of and impact on the environment.

To demonstrate our approach, we have built a simple climate model in STELLA, a graphical programming language (Hannon/Ruth 2001). We use the dynamic relationship between carbon emission rate G, accumulated carbon emissions F, atmospheric carbon concentration Ψ above pre-industrial level $\Psi_1 = 280$ ppmv, and global temperature change T beyond pre-industrial level (see Petschel-Held et al. 1999):

$$\Delta F = G$$
$$\Delta\Psi = B F + \beta G - \sigma \Psi$$
$$\Delta T = \mu \ln (1 + \Psi/\Psi_1) - \alpha T$$

where B, β, σ, μ, α are adjustment parameters that fit the model to real-world data. $T_{2C} = \mu/\alpha \ln 2$ is the temperature sensitivity, i.e. the temperature change for a doubling of atmospheric carbon. For this reduced model, we study the problem of global temperature regulation by investment C into emission reductions

$$\Delta G = -C / c < 0 .$$

Here $c = c_0 \ (G/G_0)^{\rho}$ are the unit costs for reduction, with G_0 initial emissions, c_0 being the costs for reducing the first unit and ρ the scaling exponent. Thus, unit costs decline with emissions due to learning. Invested costs are adjusted to a target function $V = T^* - T$ which is the negative excess temperature beyond a temperature target T^* that should not be exceeded in a given time period τ. Thus we have cost adjustment to tolerable temperature T^* and projected temperature change ΔT:

$$\Delta C = - \kappa C (C^+ - C) (T^* - T - \tau \Delta T)$$

where ΔC^+ is the upper limit for cost reduction in a given time unit, κ is the response coefficient in logistic growth and τ is a desired reaction time to bridge the gap.

This model allows to study conditions under which for given initial carbon emissions, concentration, temperature change and for parameters (initial unit cost c_0, maximum cost $C+$, emission trend $\Delta G > 0$, and climate sensitivity T_{2C}) a particular temperature target T^* can be achieved (we use here $T^* = 2^oC$ which is often used as a reference). Our baseline case is given as: $G_0=7.5$ GtC/a, $\Delta G_0=0.2$ GtC/a, $C^*=50\$b$, $c_0=100$ \$/tC (Dollar per ton of carbon), $\alpha=0.017$ ($T_{2C}=3.5^oC$). $\rho=-0.5$, $\kappa=0.001$, $\tau=100$ years. Variation of parameters from this baseline are given in Figure 10. Modifying unit costs c_0 shows that expensive reduction option above somewhere between 50 \$/tC and 100 \$/tC fail to achieve the temperature limit (Figure 10a)

Variation of the maximum reduction costs C^+ shows how relevant total investment is that the world is willing to spend on emission reductions each year (Fig.10b). For baseline unit costs, $100 billion per year may stop temperature growth in about 100 years and reverse it but still misses the target. $200 billion are sufficient to prevent temperature from exceeding the limit and to bring it back below the threshold. Lower investment limits lead to high temperatures where C^+ = $10 billion would result in a temperature increase of *T=10* years in the coming centuries, if the current emission trend continues.

Another critical parameter is climate sensitivity (Figure 10c). In the baseline case the temperature target is missed for $T_{2C} = 3.5$°C and even more for $T_{2C} = 4.5$°C. For a lower sensitivity of $T_{2C} = 2.5$°C however, the given investment limit allows to reverse the temperature increase below the threshold after a temporary overshooting. A lower sensitivity keeps the overshooting smaller but results in oscillations due to the interaction with the response of investment.

Finally, we modify the initial trend for emission increase which is the main driver of global warming (Figure 10d). While the baseline trend of $\Delta G = 0.2$ GtC/a results in a missed target, lower trends can indeed be compensated within the investment threshold, while higher trends lead to strong temperature increases.

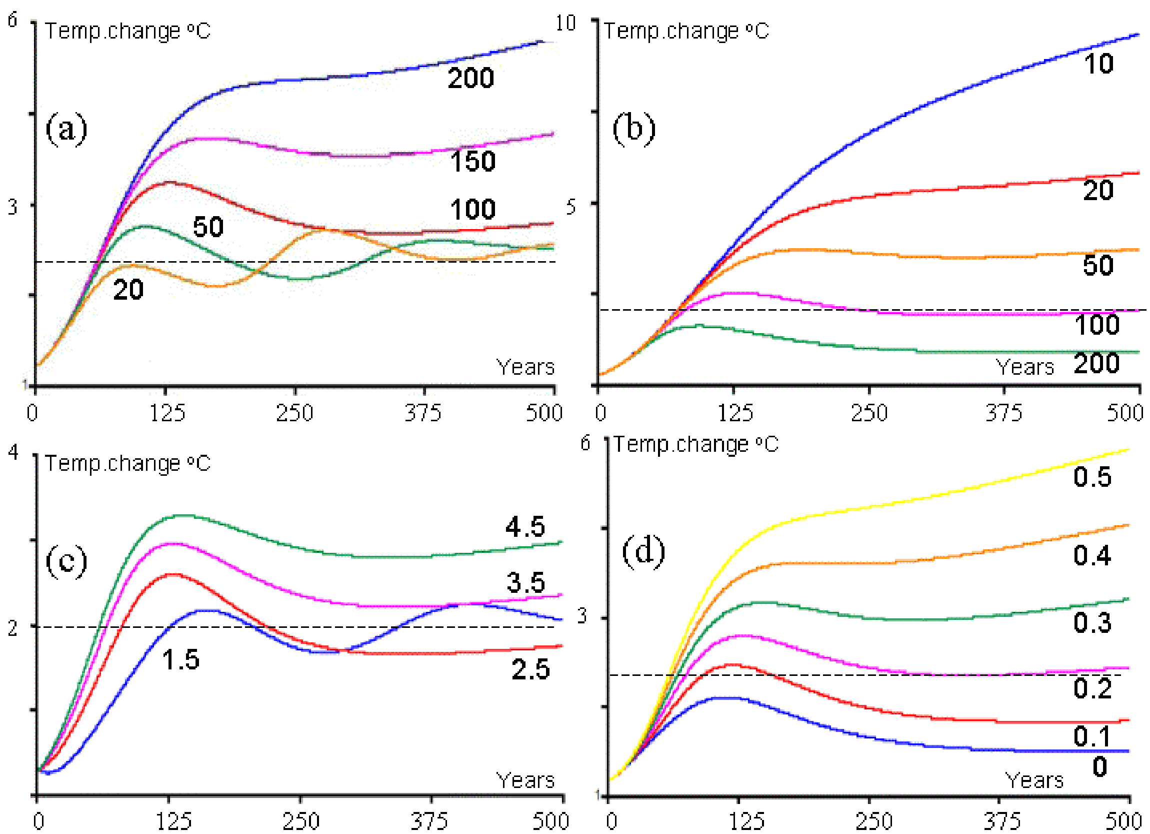

Figure 10: Temperature change for parameter variations: a) Unit costs in $/tC, b) maximum costs in billion $, c) climate sensitivity in °C, d) Initial emission trend in GtC

Now we assume that the world does not act as a single actor but as two independent actors, the region of the developed (industrialized) countries and the developing region. Together both regions have the same total emissions as in the previous case ($G_{10}=6$

GtC/a, G_{20}*=1.5 GtC/a*), total emission increase ($\Delta G_{10} = \Delta G_{20} = 0.1$ GtC/a), total maximum investment $C_1^* = \$40b$ $C_2^* = \$10b$. The main difference is that both regions act according to different temperature targets. In the first case, region 1 pursues a higher target $T_1^* = 2.5$ °C and region 2 a lower target $T_2^* = 1.5$ °C, in the second case it is the other way round. In both cases, by acting independently both actors show a slower reaction than acting as one single actor (in particular the developing region) and consequently they exceed the average temperature threshold $T^* = 2$ °C significantly more, in the first case by about 1°C in the long run, in the second case by about 1.5 °C (Figure 11).

This points to the problem that with conflicting targets and each actor following only its own behavioral rules, the combined uncoordinated actions fail to achieve targets for both regions. This might change with merging of forces, producing gains from cooperation.

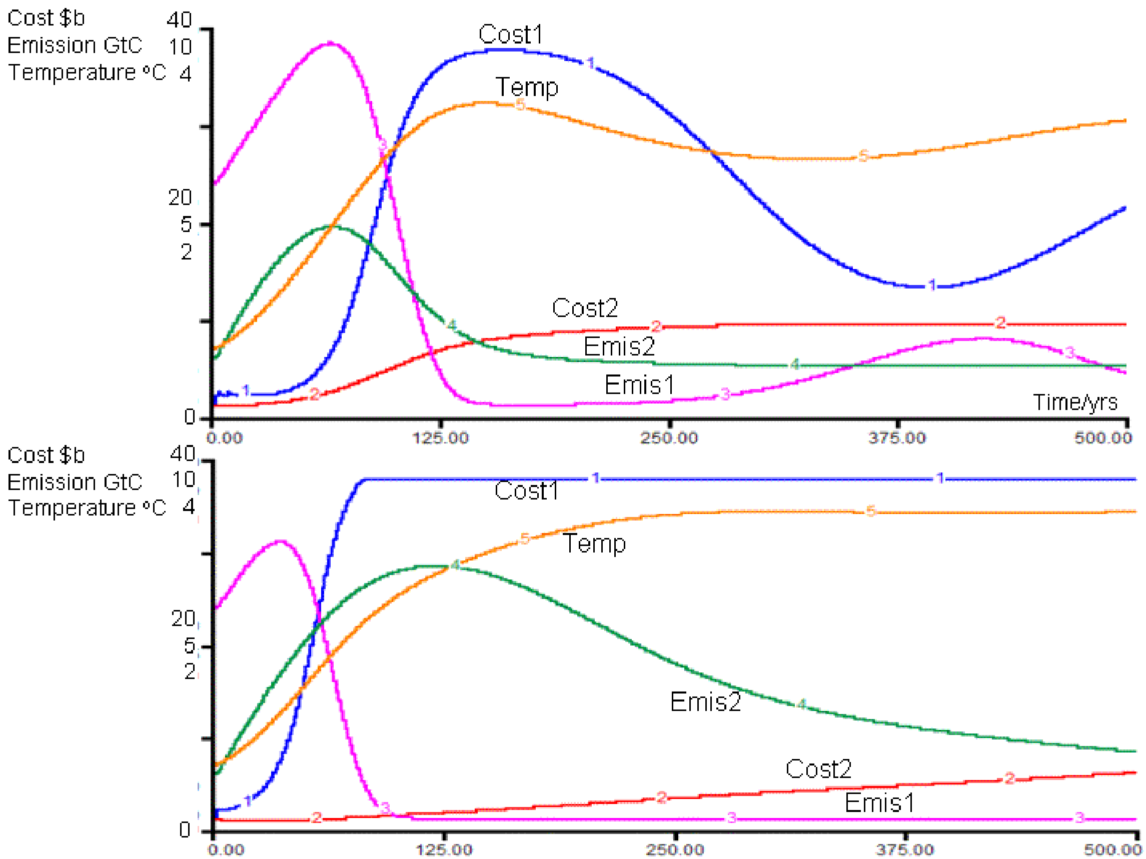

Figure 11: Two actor model with different temperature guardrails, above $T_1^* = 2.5$°C, $T_2^* = 1.5$°C; below $T_1^* = 1.5$°C, $T_2^* = 2.5$°C (for explanations see text)

While this approach allows us to determine costs for adaptive control of temperature, a major issue is to identify incentives to actually invest these costs into new low-emission energy technologies. In general, a variety of economic and policy instruments exist, including legal regulations, taxes, emissions trading, subsidies, cooperative approaches, and coalition formation.

For firms as economic actors the value function turns into a profit functions, with energy as a production factor and products sold on a market. Each firm can choose from two energy paths, a high-emission low cost path and a low-emission high cost path through allocation of investment. To induce a change from high to low emissions, governments can impose a tax on emissions which would increase the cost for the established path and thus create incentives for switching (Scheffran 2002).

Similar to the tragedy of the commons in fishery conflicts, climate policy deals with translating the natural limits on temperature and carbon, derived from climate modeling into admissible global emission paths. Within these restraints there is a collective bargaining problem, given by

$$G(t) = \Sigma_i G_i(t)(1 - r_i(t)) < G^*(t)$$

with $G(t)$ the greenhouse-gas emissions at time t, $G^*(t)$ the global emission limit, $G_i(t)$ the baseline emissions path of actor Ai and $r_i(t)$ the emission reductions from baseline. The Kyoto Protocol limits emissions and establishes cooperative instruments such as Joint Implementation and the Clean Development Mechanism which allow industrialized countries to get credit for investments in developing countries that facilitate emission reductions. Some of the benefits can only be achieved cooperatively, by mechanisms that leave the non-cooperative Nash equilibrium (Ipsen/Rösch/Scheffran 2001).

Coalition formation in energy use

While the previous analysis has studied interactions among individual actors, it is possible that they take joint actions by allocating resources to coalitions that produce joint values. An example describes coalition formation in energy production and consumption. Each coalition of energy producers receives resources from individual consumers to supply energy through different energy paths to produce value for the consumers. Thus we have a triple decision problem: allocation of resources from consumers to producers, allocation of investment from producers to energy paths, and distribution of value to consumers (Scheffran 2006). Each of the decision variables follows adjustment rules, such as those outlined in the first chapter.

Figure 12 provides an example for a simulation of coalition formation among six actors (energy consumers) and six competing coalitions (energy providers) which have the choice between two energy paths: the old one comes with high emissions and low costs, the new one cuts emissions by up to 50%, while unit costs are up to 50% higher. The competing energy paths of coalitions are different with regard to their efficiency, unit costs and emissions, and the consumers vary with regard to their value functions. In the upper case 1 there is diversity in terms of coalition membership among the actors and the coalition actions. In case 2, some parameters have changed (energy path 2 is more efficient and less costly and is favored by a carbon tax). Now there is a faster adjustment of coalition membership and a clearer transition of energy providers towards the low-emission path (energy option 2) while path 1 is phased out.

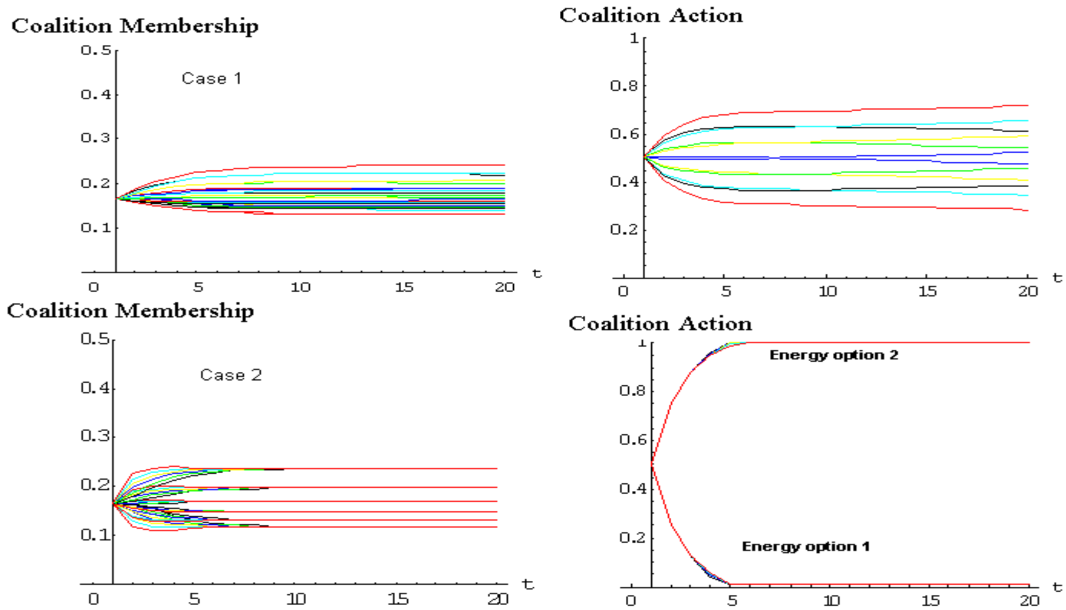

Figure 12: The formation of energy coalitions towards low-emission technology

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