Title: Using Economic Information to Anticipate Transitions in Social-Ecological Systems

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Abstract

A common pattern of environmental crises is a vicious cycle between environmental degradation and socio-economic disturbances. For example, environmental changes may drive fish stocks to a low productive regime that can lead to sudden losses in the livelihoods of coastal communities. This ecological transition in turn erodes social institutions, such as social norms of cooperation, with cascading pressure on the resource base. Here we show that while such feedbacks may give rise to critical transitions in social-ecological systems, at the same time they can offer novel opportunities for anticipating them. We model a community that has joint access to the harvest grounds of a resource that is prone to collapse. Individuals are tempted to overexploit the resource, while a cooperative harvesting norm spreads through the community via interpersonal relations. Both social and ecological collapses can be induced by environmental and socio-economic driving forces. Regardless of the type and cause of collapse we find that upcoming transitions may be detected using simple socio-economic response variables, such as individual profits. At the same time, adaptive behavior of resource users may mask signs of a nearby resource collapse. Our findings suggest that social-ecological systems not only hide vulnerabilities to collapse as changes spread from one system to the other, but

that they may also provide alternative sources of information that can be used to detect upcoming critical transitions.

Introduction

Under present rates of environmental change, earth systems are facing an increased threat of undergoing extreme transitions on a global scale (1, 2). Species extinctions (3), desertification (4), climatic shifts (5) are only few examples of major changes that can have considerable effects on the delivery of ecosystem services and on the livelihood of people who depend upon them. Typically, the fate of ecosystems is highly linked to the practices exercised by the socio-economic system around them (6, 7). For instance, the stability and resilience of common pool resources have been traditionally influenced by whether resource users succeeded in crafting institutional rules facilitating a cooperative sustainable exploitation regime (8-11). However, identifying the causal links between ecosystem stability and social institutions is difficult, because changes in the ecological system have a profound effect on how the socio-economic system will evolve (12, 13). Clearly, transitions of social-ecological systems (SES) are often the result of both natural and socio-economic processes. Indeed, a common pattern of historical crises is the vicious cycle emerging due to positive feedbacks between environmental degradation and socio-economic disturbances (13-15).

Nonetheless, it remains still unclear whether a SES is more prone to collapse if the driving force inducing those feedbacks stems from the socio-economic or the ecological part of the system. Climatic changes, for example, have a major impact on the provisions of ecosystem services with cascading socio-economic effects, such as economic deteriorations and social conflicts (16-18). Technological innovation – a socio-economic driver – makes it profitable to transform mangroves into agricultural land (19), or intensify fishing activity (20) with profound effects on the ecosystem. In order to understand how social-ecological transi-

tions unfold and how we can manage them, it is therefore essential to disentangle how social and ecological transformations mutually influence each other, and to understand to what extent they are mirroring the resilience of the SES as a whole.

In this paper we develop a model of a SES in which gradual changes and sudden transitions can occur both in the ecosystem, and in the social system to which the ecosystem is strongly coupled. We do this, by taking specifically into account feedbacks between social actors and ecological resources of the two subsystems that may give rise to a collapse induced either by socio-economic or environmental drivers. We investigate whether under such a multiple thresholds scenario, a collapse can be anticipated by using generic early warning signals for critical transitions (21-23). Early warning signals indicate the resilience of a system that is approaching a transition, and have been successfully applied to anticipate abrupt systemic changes, like past climate transitions (24, 25), extinctions in experimental systems (4, 26, 27), or lakes shifting to a eutrophic state (28). However, most studies have so-far focused on purely ecological systems (22, 29) neglecting that most ecological systems are part of complex adaptive SES with processes changing over time depending on the state of the system (30). For example, resource users will most likely adapt their exploitation strategy when a resource is increasingly depleted, making it difficult to predict and understand the dynamics of the system.

Here, we develop a model of a SES (Fig 1A), that takes such interactions into account by considering a small community that has joint access to a common pool resource (7-11). Following the literature on cooperation in social dilemma situations, we assume that the community consists of the following two types of individuals: i) *cooperators* and ii) selfish individuals, the so-called *defectors* (31-34). While *cooperators* strive for a sustainable harvesting regime and follow a social norm that gives all community members the highest long-term yield possible, *defectors* do neither take the sustainability of the resource stock, nor the

welfare of other community members into account. Instead, they simply try to maximize their short-term income that can be made by harvesting the resource. The transmission of social norms is assumed to take place via interpersonal interactions, with *cooperators* putting peer pressure on *defectors* to start acting in the community's interest (35-37). While *cooperators* are intrinsically motivated to follow the social norm, they feel also the temptation to become a *defector*, depending on the payoff difference between those two strategies. As the resource is depleted, *cooperators* reduce their harvesting effort in an attempt to recover the resource. However, the cost of restraining effort increases the temptation to defect – and more widespread defection reduces the resource even further. As a result, a spiral of defection unfolds and cooperation can suddenly collapse; see *SI Social Dynamics* for more details and ref. 32 for a detailed mathematical analysis. In addition, an ecological transition may occur, as the resource is prone to collapse as well (Fig. S1). We investigate whether a transition in the SES induced either by ecological or socio-economic drivers may be anticipated by warning signals obtained not only by monitoring directly the ecological system (i.e. resource biomass), but also indirectly using economic information, such as the individual profits of resource users.

Results

In what follows, we describe how external drivers that are either socio-economic (as reflected by changes in technology or the number of users harvesting the resource) or ecological (as reflected by changes in environmental conditions or growth rates of the resource) can cause transitions in the social system (as collapse of cooperation in the community) or in the ecological system (as collapse of the resource itself).

As a starting point, we analyze the situation of a community that adopts over time a more efficient technology (reflected by an increase in parameter q, Fig. 2A). Improved technology caused resource biomass to decrease over time (Fig. 2B). When the biomass level dropped below the level supporting the maximum sustainable yield (MSY) *cooperators* re-

duced their extraction efforts as an attempt to recover the resource. However, these attempts led only to a temporary stabilization of the resource, and ultimately the resource biomass collapsed (Fig. 2B). The temptation to defect increases because *cooperators* – unlike *defectors* – sacrifice profits to save the resource. As a result, cooperation eroded over time (Fig. 2C). Upon resource collapse, neither *cooperators*, nor *defectors* make any profits anymore, so cooperation levels recover. Although cooperation was restored in the community, resource biomass did not, as it shifted to the basin of attraction of the alternative overexploited state. Looking at the time series of the profits did not give any signs of a collapse to come. On the contrary, at the time of collapse, profits of *defectors* were still as high as they were when the resource biomass was at its level supporting the MSY (Fig. 2D).

But could the catastrophic transition have been anticipated? When a tipping point is approached, the dominant eigenvalues of the system are expected to approach zero (38). Indeed, this is also what we found in our model (Fig. S3). Unfortunately, estimating eigenvalues directly from data is difficult in the absence of a mechanistic model. In contrast, generic early-warnings do not require any model knowledge and can be derived directly from the data. Indeed, we found that standard deviation and autocorrelation at-lag-1 of resource biomass increased as technological innovation slowly pushed the system close to a transition (Fig. 3A,C). Interestingly, when resource biomass passed the MSY level and *cooperators* reduce their extraction efforts, standard deviation and autocorrelation dropped, picking up the attempts by *cooperators* to save the system. When cooperation fully eroded, the leading indicators increased again signaling the ecological collapse. While these results corroborate earlier findings that early warnings are expected to signal the transitions in models of overexploited resources (39, 40), we show that one can expect similar warnings when the collapse is exogenously induced by drivers of the social part of an SES. More interestingly, this information may not necessarily be extracted only from the ecological part of the system. It might even be

possible to anticipate the resource collapse based solely on socio-economic information. This is especially relevant for cases where it will not be possible to collect biological data (e.g. there is no formal management authority, monitoring is difficult, etc.). Indeed, we found that leading indicators estimated from *defectors*' and *cooperators*' profits responded strongly to technological improvement preceding a collapse (Fig. 3B,D). However, contrary to expectations, standard deviation and autocorrelation did not provide the same information as the transition was approached across the community. At the onset of social erosion, standard deviation rose sharply for *defectors* (Fig. 3B, red line), while it actually decreased (as was the case for biomass) for *cooperators*' profits (Fig. 3B, green line). In contrast, autocorrelation at-lag-1 of profits followed closely the pattern estimated from resource biomass data for profits of both *defectors* and *cooperators* (Fig. 3D).

Similar signals were also extracted from catch per unit effort data (Fig. S5) that may be available even if data on resource biomass is missing (41). The obtained results also carry over to the case where the transition is ecologically-induced, for example because of changes in environmental conditions (Figs. 4A, S4). Furthermore, our results hold for other socio-economic drivers, such as demographic growth, like migration of new agents into the community (Fig. 4B).

While many SES are at least partially governed by communities, there are obviously cases where communities play no role and social norms of cooperation do not guide behavior. In our model, when cooperation and social pressure are absent, transitions can only occur in the resource system. We found that in the absence of social norms leading indicators strictly increased when the ecological transition is approached, regardless from whether the driver is ecological (Fig. 4C) or socio-economic (Fig. 4D). In cases where there are not inherent tipping points in the ecological system, early warning signals also provide reliable information about the fact that the resource is severely depleted (Fig. S6).

Discussion

In this paper we have demonstrated how a transition in an ecosystem can be detected in advance by monitoring the social component to which the ecosystem is strongly coupled. Somewhat unexpectedly, we found that ecological variables contain signals for transitions induced by socio-economic changes, such as technological innovation. Even more striking is our finding that socio-economic variables, such as profits or catch per unit of effort, also can indicate an ecological collapse, no matter whether it is induced by ecological or socio-economic drivers. These results imply that in strongly interacting social-ecological systems, there is an opportunity to identify ecological shifts based on information coming from other sources than monitoring the ecological system itself. These findings may offer an alternative solution to anticipate transitions for systems that are notoriously poorly understood or inadequately monitored (42) .

Despite the fact that our results support, in theory, the suggestion that mechanistic understanding is not necessary for anticipating transitions in complex systems when using early warning signals (21), in practice, we found that the interpretation of the signals requires knowledge of the underlying processes, especially when they are intended to complement management (23). For instance, when *cooperators* try to stabilize the resource by reducing exploitation, the reduction in exploitation is manifested as a decrease in variance and autocorrelation both in the resource biomass and in the *cooperators* profits. This observation would have made one falsely conclude that the system is self-stabilizing and is moving away from a potential tipping point. In reality the signal reflected the attempts of the *cooperators* to save the system *exactly because* the system is so close to collapse.

Although our findings propose a promising alternative towards the practical use of early warnings, important challenges remain. In principle, socio-economic data are more easily

and frequently monitored than ecological data, but resource users may be reluctant to share private information with management authorities (43). Our assumptions on the social interactions are an example of complex dynamics that may characterize SES, but are by no means a complete picture of the real world (10, 44). Important time lags between the components of the social-ecological systems, such as slow feedbacks from the ecological system may have consequences that have yet to be explored. Simulations from individual-based models of SES models can offer opportunities for investigating such limitations (45). Nonetheless, it appears that loss of resilience of a SES can be signaled by generic early-warnings based on both socio-economic or ecological information irrespective of whether the resource is governed by a community or characterized by open access, with or without tipping points in the ecological system.

We believe that the conclusions of this study may open new perspectives and search images for the anticipation and management of tipping points in SES. This is especially the case for applications in fisheries, where catch and effort data are increasingly used to complement biological stock assessments, and the informational value of those data alone is controversially debated (46, 47). Another interesting avenue for further research is to tap the vast amount of data coming from financial markets, such as options prices for natural resources or share prices of companies relying on ecosystem services that are prone to collapse (48, 49). Due to the increased connectivity and strengthening of interactions up to global scales (6, 50), the world's marine ecosystems (51, 52) or tropical forests (53) have become more strongly coupled to socio-economic developments, like trade agreements, energy policies, or land use change. For such social-ecological systems, it may be worthwhile to explore whether patterns in economic information, be it trade flows, commodity prices, energy consumption, or fisheries profits, might reflect the social-ecological resilience of such systems and the likelihood of approaching a critical transition in the ecological part of these systems.

Methods

Harvesting. We assume that a small community consists of n individuals who have joint access to the harvest grounds of a renewable common pool resource. Each individual can either decide to spend time and effort on harvesting the resource or engage in an alternative economic activity. Time is limited, and therefore the effort rate of each individual is constrained by parameter $\hat{e}$. The effort rate that individual i allocates into resource extraction is denoted by e_i and effort that is allocated into the alternative activity is given by $\hat{e}-e_i$. Individual harvests h_i are given by the Gordon-Schaefer model $h_i = qXe_i$, where q is a technology parameter reflecting harvesting efficiency. Harvests can be sold at a constant price P, while the alternative economic activity yields a net revenue of m, which is the opportunity cost of harvesting. Additionally, each unit of effort has a direct cost of w reflecting expenses for fuel, material and equipment. Individual profits π_i are then given by $\pi_i = PqXe_i - we_i + m\left(\hat{e}-e_i\right)$.

Resource dynamics. Following ref. 54, we model a renewable natural resource that grows stochastically and exhibits critical depensation; see Figure S1. Critical depensation tends to be most pronounced in terrestrial systems and to a lesser extent also in aquatic and marine systems (55). While some fish populations exhibit depensatory dynamics, the pattern for most stocks tends to be more ambiguous (56, 57). Instead, recruitment of fish populations is typically affected by biomass levels, but it also tends to shift between alternative regimes of productivity (58). Not surprisingly, fishing at least contributes to a shift towards a less productive or even collapsed regime (59, 60). Here, we use a minimal model that allows for alternative stable states to occur by incorporating reduced reproduction of the resource at low abundances in the natural growth function of the resource. We introduce stochasticity to ac-

count for random disturbances due to environmental or demographic variation following Ito calculus (54, 61). Taking into account the joint harvest activity of all community members $\sum_{i=1}^{n} e_i$ the development of the resource stock in time interval $\mathrm{d}t$ is given as

$\mathrm{d}X = rX\left(X - X_{\mathrm{crit}}\right)\left(1 - \frac{X}{K}\right)\mathrm{d}t - qX\sum_{i=1}^{n} e_i \mathrm{d}t + \sigma_X \mathrm{d}W$. If the resource biomass is below a critical threshold X_{crit} the resource is not viable and will go extinct. The term $\mathrm{d}W$ is an increment of the stochastic Wiener process W, such that $\mathrm{d}W = \varepsilon\sqrt{dt}$, where $\varepsilon(t)$ is a normally distributed error term with zero mean and unit variance. The intensity of the disturbances is scaled by σ_X; see also *SI Resource Dynamics.*

Social dynamics. We assume that the community comprises cooperatively minded individuals –*cooperators* (*C*)– and selfish individuals, the so-called *defectors* (*D*), who simply maximize their instantaneous profits, potentially taking advantage of the cooperative efforts made by other community members. We assume that *cooperators* strive for a harvesting strategy that delivers the largest harvests that can be obtained in equilibrium – the maximum sustainable yield (MSY). Out of equilibrium, *cooperators* adopt a linear stock-dependent harvest strategy (62). The derivation of the MSY, stock-dependent harvest strategy and the optimal effort rates is given in *SI Harvesting*. Regarding social dynamics, we follow ref. 32 in which *cooperators* are assumed to put peer pressure on *defectors* to act cooperatively; see also *SI Social dynamics.* At a given point in time, there are *n* community members and therefore the probability of a *cooperator* meeting a *defector* is given by CD/n, while the success rate of peer pressure is given by α. At the same time, *cooperators* are tempted to become *defectors* with strength β. It is assumed that individuals are more likely to defect the larger the relative payoff difference of *cooperators* π_C and *defectors* π_D, as given by $\beta\left(1 - \pi_C / \pi_D\right)$. Combining the effects of

peer pressure and temptation, cooperation evolves over time following $\mathrm{d}C/\mathrm{d}t = C\left(\alpha D/n - \beta\left(1-\pi_C/\pi_D\right)\right)$.

Early warning signals. In the model, a systemic collapse can be driven by gradual changes in parameters that govern the ecological part or in parameters that determine the dynamics of the socio-economic subsystem. We performed ecologically induced transitions by changing carrying capacity K and intrinsic growth rate r, while we performed socio-economically induced transitions by changing technology coefficient q and number of individuals n. To simulate a collapse, we started with an intact system where a relatively moderate pressure is present on the resource stock and the social system and we gradually increased the control parameter until the resource collapsed. We estimated early-warnings in the time series preceding both ecologically and socially induced transitions. In particular, we measured autocorrelation at-lag-1 and standard deviation of resource biomass (the ecological response variable), and individual profits and catch per unit of effort (CPUE) (our socio-economic variables). To estimate the indicators, we increased control parameters in 50 steps till the collapse. At each step we simulated the model for 1,000 time steps after discarding transients, and we used the 50 last points to compute the indicators. We report results from 200 Monte Carlo iterated time series as 5, 50 and 95 percentiles. Model and statistical analyses were performed in MATLAB (Mathworks Inc.).

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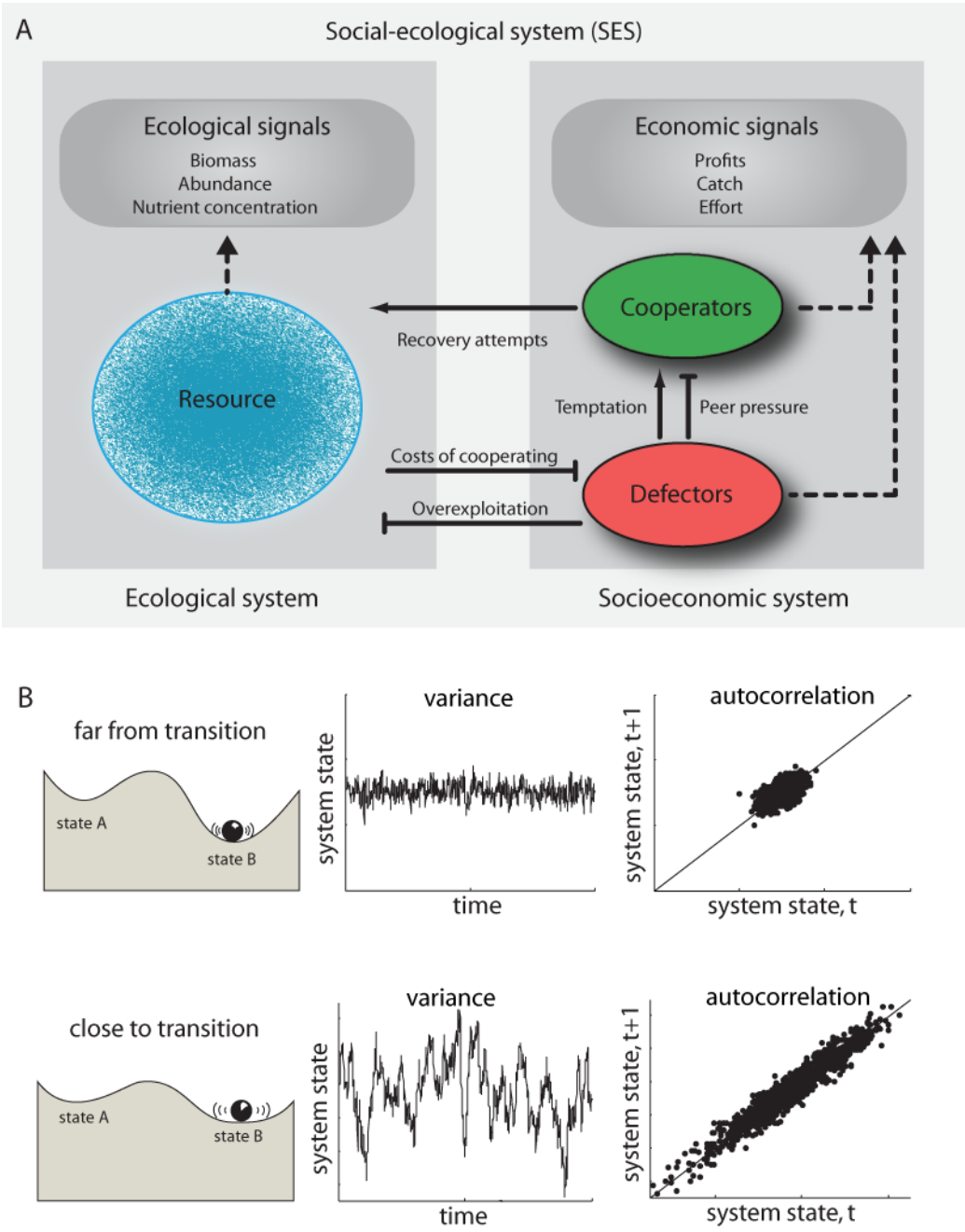


Fig. 1. A conceptual framework for our modeled coupled SES (A). The model feedbacks are depicted by solid lines, while information flow is indicated by dashed lines. If the social norm to cooperate is more widespread, this implies stronger peer pressure which reduces defection, while it tempts agents to take advantage of cooperative efforts undertaken by peers, and therefore increases defection. Alternative stable states occur because of feedbacks between the social and the ecological system. More *defectors* imply higher exploitation, which encourages *cooperators* to undertake recovery attempts, bearing a higher cost of being a *cooperator*. As a result, more individuals defect, creating a vicious cycle of higher defection and lower resource levels. A transition could be anticipated by investigating ecological and economic signals. When the system moves closer to a tipping point, it loses resilience and does not return as swiftly to its equilibrium (B). Therefore, a gradual approach to a transition is reflected in increased variance and autocorrelation of monitored state variables.

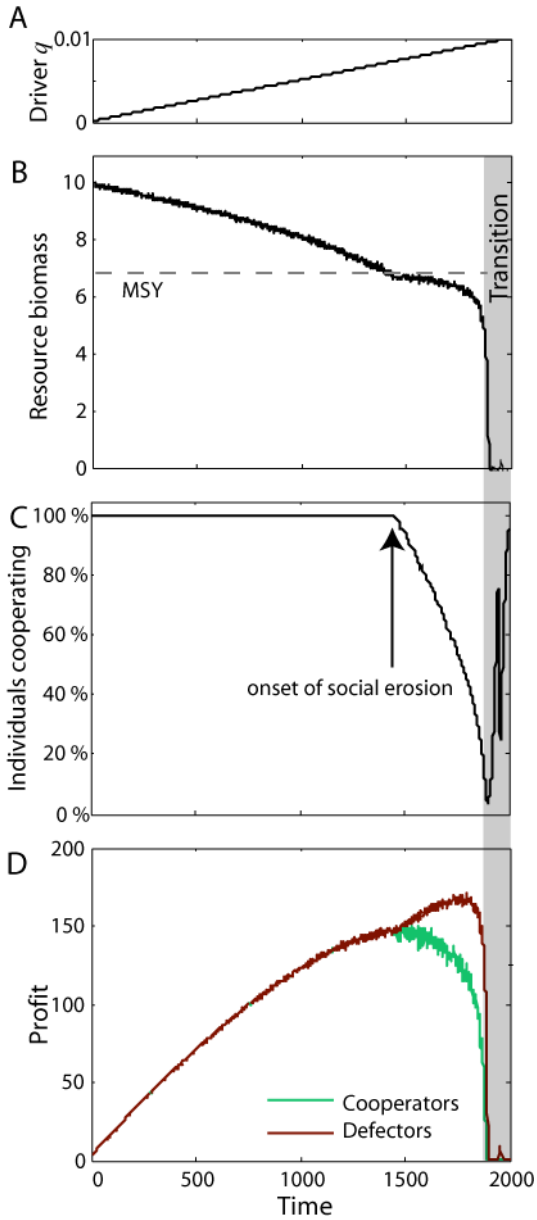


Fig. 2. A scenario of a socioeconomically induced transition. A slowly improving technology (q), which implies an increase in harvesting efficiency, leads ultimately to the collapse of the resource (B). After the resource drops below the level supporting the maximum sustainable yield (MSY), *cooperators* lower their harvests in an attempt to restore the system. This increases the temptation to defect, leading to social erosion in the form of increased defection (C). Inspecting profits alone gives no direct indication of the resource collapse (D).

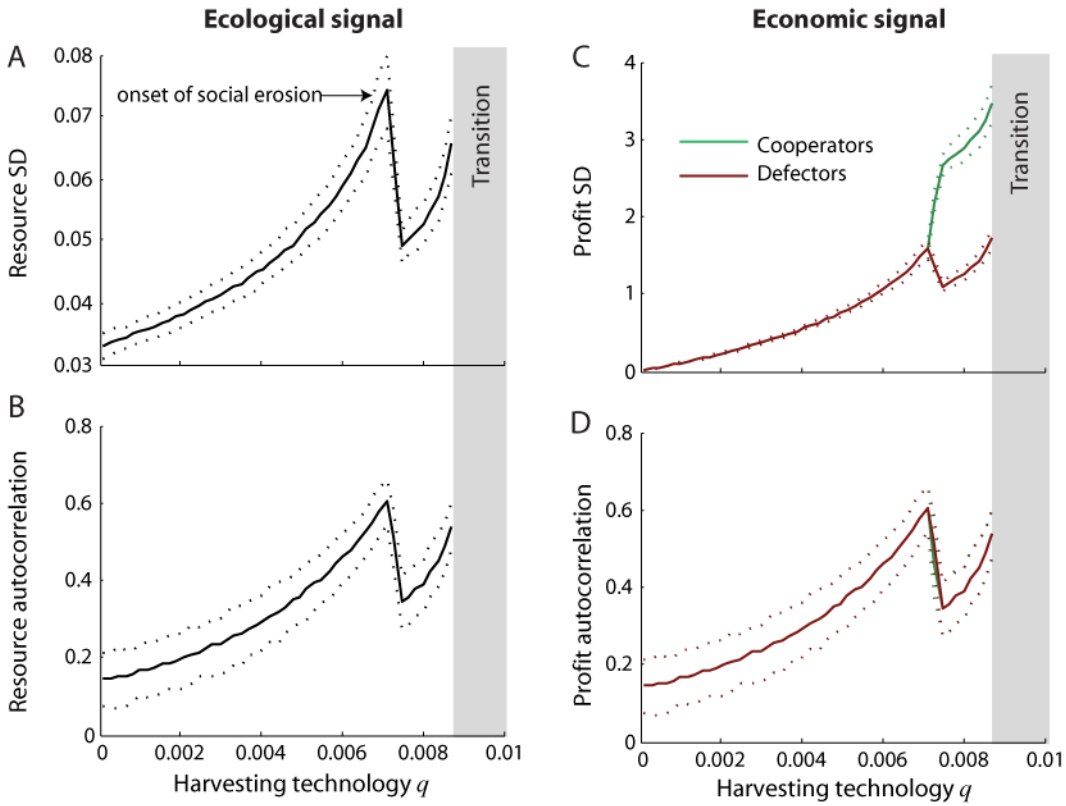
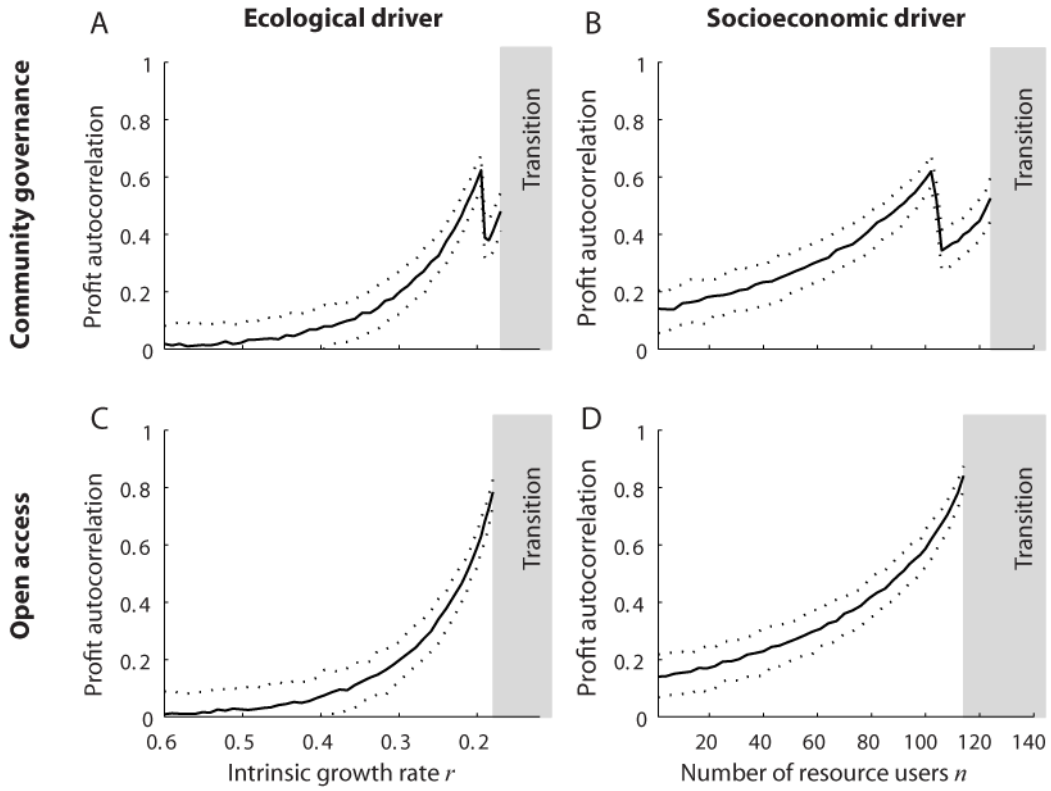


Fig. 3. Early warning signals prior to resource collapse driven by an increase in technology. A socio-economically induced transition is preceded by an increase in standard deviation (SD) (A) and in autocorrelation (B) of the resource biomass. At the onset of social erosion the SD sharply drops before increasing at the vicinity of the critical transition. The same pattern can be observed when using SD (C) and autocorrelation (D) of profits. Note that SD for *defectors* does not have this sharp drop, providing a different signal. The dotted lines show 5 and 95 percentiles of the Monte Carlo Simulations.



455 **Fig. 4.** The autocorrelation of *defectors*' profits for different parameter values of the intrinsic growth rate of the resource *r* and number of individuals harvesting the resource *n*. Community governance portrays the case where some *cooperators* are guided by social norms (A,B), while open access refers to the situation where all individuals act selfishly (C,D). The dotted lines show 5 and 95 percentiles of the Monte Carlo Simulations.

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Supporting Information

Using Economic Information to Anticipate Transitions in Social-Ecological Systems

Andries Richter and Vasilis Dakos

SI text

The Supporting Information provides a supplementary description of the biological growth model and the harvesting decisions taken by the individuals provided in *SI Resource dynamics* and *SI Harvesting strategies.* Figure S1 plots the biological growth functions that are assumed in the model. Furthermore, we provide a supplementary description on the mechanisms operating in the social model and an intuitive explanation why they give rise to a sudden collapse of cooperative harvesting norms, as described in *SI Social Dynamics.* We also provide a bifurcation plot S2 showing the steady states of the system for different parameters.

In what follows, we present additional results that corroborate the main findings in the section *SI Results.* Fig. S3 shows that the dominant eigenvalues of the system go to zero, as the transition is approached. Fig. S4 presents the case where the transition is ecologically induced and transmitted through a loss of carrying capacity. Fig. S5 turns to the case where neither biomass data, nor profit data is available and early warning signals are derived with simulated data on catch per unit of effort. Finally, Fig. S6 shows that early warning signals can provide valuable information even if a system does not exhibit a minimum viable population and alternative stable states, but the resource dynamics are determined by the simpler logistic growth function. All model parameter values are summarized in Table S1.

SI Resource dynamics

The ecological part of our model is given by a minimal model that allows for alternative stable states to occur by incorporating an Allee effect in the natural growth function of the resource as

$$G(X) = rX(X - X_{\text{crit}})\left(1 - \frac{X}{K}\right), \tag{S1}$$

where X denotes the biomass of the natural resource, r is the intrinsic growth rate, K is the carrying capacity, and X_{crit} is the critical resource biomass, below which the population is unable to recover and will go extinct. This implies that the growth function is convex at low biomass levels, and concave at high biomass levels, while the per capita growth is dome-shaped (Fig. S1). The results obtained in Fig. S6 employ the simpler standard logistic growth function, which is given by

$$G(X) = rX\left(1 - \frac{X}{K}\right). \tag{S2}$$

Logistic growth implies that the growth function is dome-shaped, while the per capita growth function is linearly decreasing (Fig. S1). Incorporating stochasticty and harvesting gives the full resource dynamics for the model that uses eq. S1 as

$$\mathrm{d}X = rX(X - X_{\text{crit}})\left(1 - \frac{X}{K}\right)\mathrm{d}t - qX\sum_{i=1}^{n} e_i \mathrm{d}t + \sigma_X \mathrm{d}W, \tag{S3}$$

where e_i is the effort rate of individual i of a community comprising n resource users. The term $\mathrm{d}W$ is an increment of the stochastic Wiener process W, such that $\mathrm{d}W = \varepsilon\sqrt{dt}$, where $\varepsilon(t)$ is a normally distributed error term with zero mean and unit variance. The intensity of the disturbances is scaled by σ_X. The stochastic version of the standard logistic growth function (given in eq. S2 and used in Fig. S6) is given by

$$\mathrm{d}X = rX\left(1 - \frac{X}{K}\right)\mathrm{d}t - qX\sum_{i=1}^{n} e_i \mathrm{d}t + \sigma_X \mathrm{d}W. \tag{S4}$$

SI Harvesting strategies

We assume that cooperators try to harvest the resource sustainably with the goal to maximize the yield accruing from the resource. The maximum sustainable yield (MSY) of the resource is the largest harvests that can be obtained in equilibrium with a joint effort rate E_{MSY}.[1] The fair share of the socially optimal effort rate for a single individual is given by $e_{\mathrm{MSY}} = E_{\mathrm{MSY}} / n$. The MSY can be obtained by maximizing the growth function given in eq. (S1) with respect to *X*. This gives

$$X_{\mathrm{MSY}} = \frac{\sqrt{K^2 - KX_{\mathrm{crit}} + X_{\mathrm{crit}}^2} + K + X_{\mathrm{crit}}}{3}, \tag{S5}$$

while the corresponding effort rate is given by

$$e_{\mathrm{MSY}} = \frac{r\left(\left(K + X_{\mathrm{crit}}\right)\sqrt{K^2 - KX_{\mathrm{crit}} + X_{\mathrm{crit}}^2} + K^2 - 4KX_{\mathrm{crit}} + X_{\mathrm{crit}}^2\right)}{9qKn} \tag{S6}$$

The logistic growth model (S2) has $X_{\mathrm{MSY}} = K/2$ and $e_{\mathrm{MSY}} = r/(2qn)$. We assume that cooperators engage in adaptive management (2) to approach the equilibrium smoothly with a linear harvest control rule of the type $e = a + bX$, where *a* and *b* are set such that cooperators invest e_{MSY} if $X = X_{\mathrm{MSY}}$. Furthermore, we assume that the harvest control rule parameters are aimed at steering the system towards the optimal steady state (so that $a < 0$ and $b > 0$). Obviously effort cannot be negative, and the harvest control rule used by cooperators is given by $e^C = \max\{a + bX, 0\}$.

Unlike cooperators, defecting individuals are assumed to be purely selfish and try to maximize their own private welfare without taking into account the negative consequences of their extraction effort on the welfare of all other agents in the community, or the fact that any

[1] Assuming that cooperators aim for a strategy that maximizes profits rather than yields will complicate the mathematical expressions, while yielding qualitatively similar results; see ref. 1.

harvesting decision today will squander potential harvest revenues in the future. The effort rate that maximizes instantaneous private welfare is given by maximizing the profit function $\pi_i = PqXe_i - we_i + m(\hat{e} - e_i)$ with respect to e_i. Since the maximization problem is linear in effort, it is either profitable to exploit the resource maximally at rate $\hat{e}$ or not at all. The effort rate of defectors is the given by $e^D = \begin{cases} 0 \text{ if } X < (w+m)/(Pq) \\ \hat{e} \text{ if } X \geq (w+m)/(Pq) \end{cases}$.

SI Social dynamics

Thanks to the pioneering work of Elinor Ostrom, it is now well established that self-regulation of communities can be effective in reducing overextraction of resources (3-10). Laboratory studies have shown that several self–regulatory instruments can be successful, such as peer–to–peer punishments (11-13), peer–to–peer rewards (14), verbal expressions of discontent (15), and also excluding individuals from other activities (16, 17), and ostracism (18). In many cases these mechanisms are combined, and the mere threat of using them is often sufficient to create the necessary peer pressure that induces cooperative behavior (19-22).

The social model used here does not focus on a specific instrument, but assumes that cooperators put peer pressure on defectors, and therefore, cooperation spreads through social encounters between defectors and cooperators (1). This setup is consistent with the instruments mentioned above, and also with the combination of several instruments. The main mechanisms of the model and the feedbacks leading to social erosion and a collapse of cooperation are shown in Fig. 1. Peer pressure is stronger if there are more cooperators, but so is the temptation to defect – because defectors can take advantage of any rents accruing from conservation efforts by cooperatively-minded community members. Therefore, the social dynamics as such are inherently self-stabilizing. In our model, alternative stable states material-

ize because of a positive feedback between the size of the resource stock and the number of defectors. Such feedback arises because cooperators reduce their harvesting efforts if the resource stock declines, while defectors do not. This increases the gap between profits of defectors and cooperators, raising the temptation to defect. As a result, more cooperators decide to defect, putting even more pressure on the resource stock. This causes a spiral of resource depletion and defection that may eventually lead to a catastrophic transition. A bifurcation plot is shown in Fig. S2A for different values of the technology parameter q and equilibrium values for the state of the resource. Indeed, there are two alternative stable states, separated by an unstable equilibrium. A similar pattern can be observed for an increase in the number of individuals having access to the harvest grounds (Fig. S2C). Furthermore, we find that a collapse does not necessarily have to be socio-economically induced. Ecological changes, such as a decrease in carrying capacity K (Fig. S2B), or intrinsic growth rate r lead also to alternative stable states (Fig. S2D).

SI Results

As expected, we find that as the system moves towards a tipping point, the dominant eigenvalues approach zero (Fig. S3). However, such information is difficult to obtain for real systems, which is why one has to rely on early warning signals. While Fig. 3 in the main text shows the early warning signals for a socio-economically induced transition, here we show that the same pattern can be observed if the transition is ecologically induced. If a loss of carrying capacity – for example a result of climatic changes – occurs, the early warning signals derived from biomass data and profit data follow the same pattern as if the transition was socio-economically induced (Fig. S4). This shows that economic and ecological data can be used to anticipate a collapse – irrespective of whether the driver is coming from the socio-economic or ecological part of the system.

However, a practical limitation is often the lack of adequate biomass data and resource users are often not revealing their profits to management authorities. For that case, we analyze whether data on catch per unit of effort (CPUE) can be used as EWS. Catch and effort data is typically easier to obtain than biomass data, which often has to come with expensive surveys or virtual population analysis, which also involves high uncertainty. With changing technology, the correlation between abundance and CPUE is not necessarily proportional (23). Therefore, it is not a priori clear whether one can derive statistical properties in the form of EWS to derive information about the state of the stock. We show that EWS in the form of standard deviation and autocorrelation at-lag-1 used on CPUE, based on simulated catch and effort data, can detect a systemic collapse. These results hold when the transition is driven by ecological (Fig. S5A,C), as well as socio-economic forces (Fig. S5B,D). Similar to the EWS estimated from biomass time series, the indicators dropped after cooperators started to reduce effort in order to restore the resource stock to MSY levels.

Finally, we analyze to what extent EWS provide reliable information if the resource dynamics are determined by the much simpler logistic growth function (S4), that does not allow for alternative stable states. Instead, the equilibrium where the resource is fully extinct is typically unstable, even though it can also become the only stable state in the system if the costs of harvesting are constant and very small (24). We find that even when using the simple biological model, the EWS provide reliable information about the fact that the biomass is severely depleted (Fig. S6). This happens because it is not the presence of alternative stable states that makes EWS work, but the fact that an unstable equilibrium is approached, which is also the case for the logistic growth model (25).

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Symbol	Description	Value
Model variables		
X	Resource stock	
C	Number of cooperators	
D	Number of defectors	
Model parameters		
r	Intrinsic growth rate	0.2
K	Carrying capacity	10
X_{crit}	Critical resource stock	0.1
σ_X	Standard deviation X	0.075
n	Number of agents	100
p	Resource sales price	5000
q	Technology coefficient	0.007
w	Unit cost of effort	1
m	Wage alternative sector	1
$\hat{e}$	Effort endowment	0.6
α	strength of moral persuasion	0.1
β	Strength of temptation	0.2
a	Precautionary reference point	−0.3

Table S1. Key variables and default values of the parameters with their economic denotation.

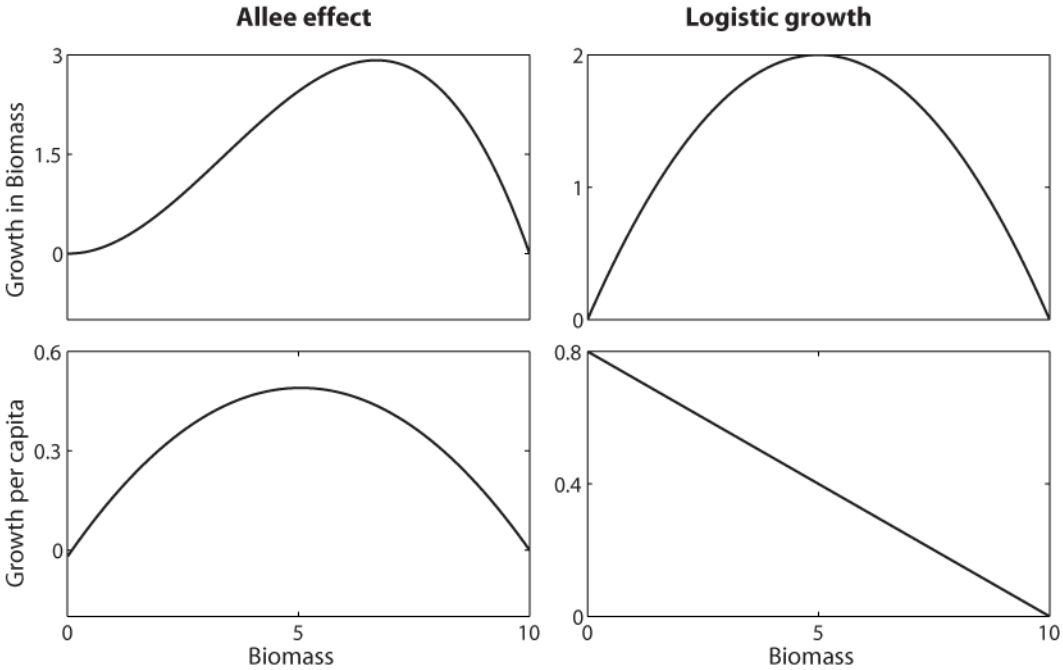

Fig. S1. The growth function for the biological model that features the Allee effect in comparison to the logistic growth model. The upper panels show the growth in total biomass, while the lower panels show per capita growth.

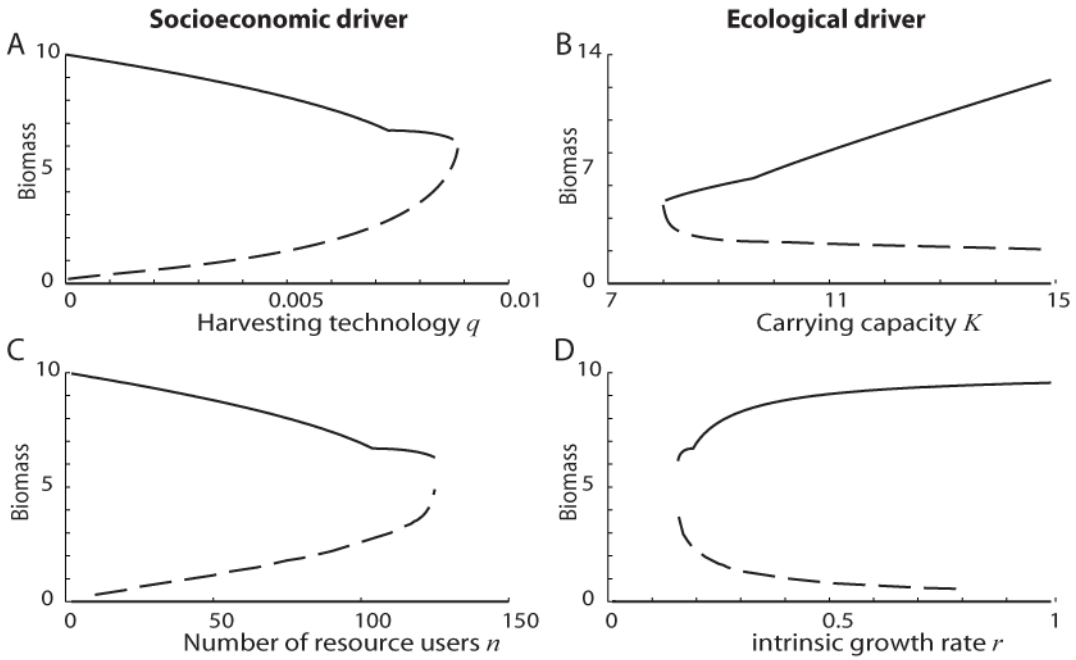

Fig. S2. Bifurcation plot showing equilibrium values of the resource biomass for different values of the technology parameter q (A), the carrying capacity K (B), the number of individuals harvesting the resource n (C), and the intrinsic growth rate of the resource r (D). Solid lines show stable equilibria, while unstable equilibria are depicted by dashed lines.

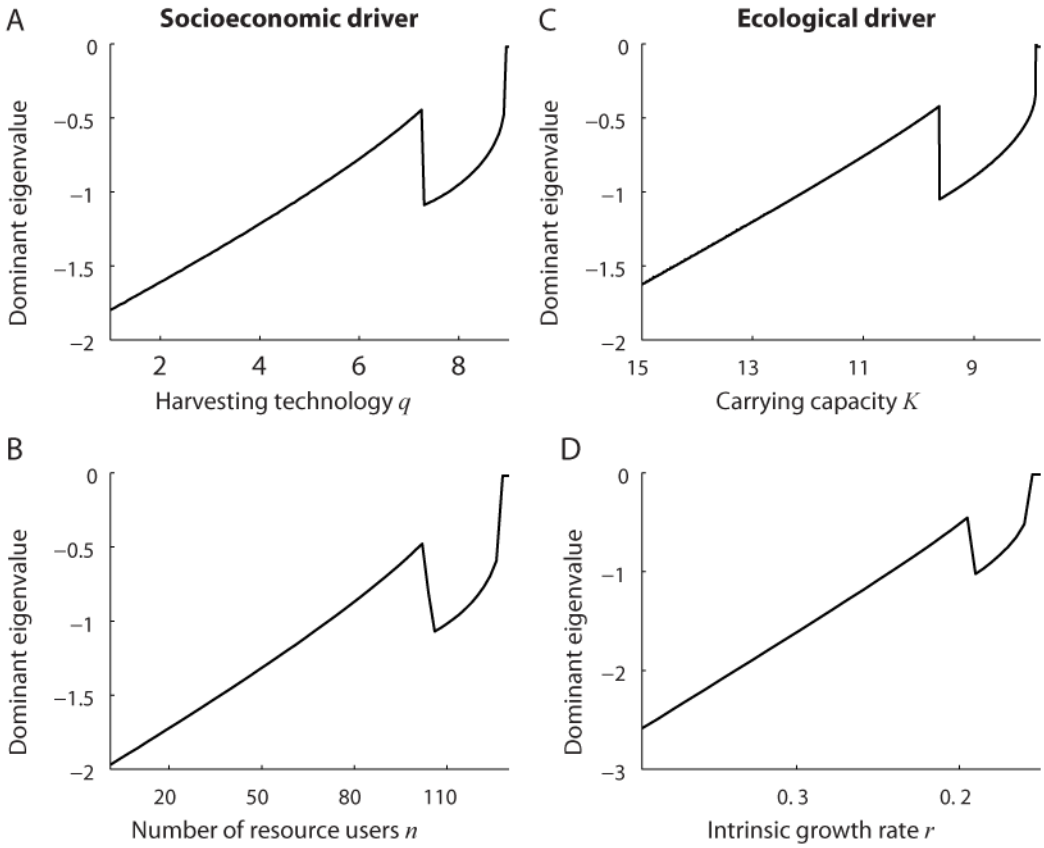

Fig. S3. The dominant eigenvalues of the system tend towards zero as a transition is approached. Plot showing the dominant eigenvalues for different values of the technology parameter q (A), the carrying capacity K (B), the number of individuals harvesting the resource n (C), and the intrinsic growth rate of the resource r (D).

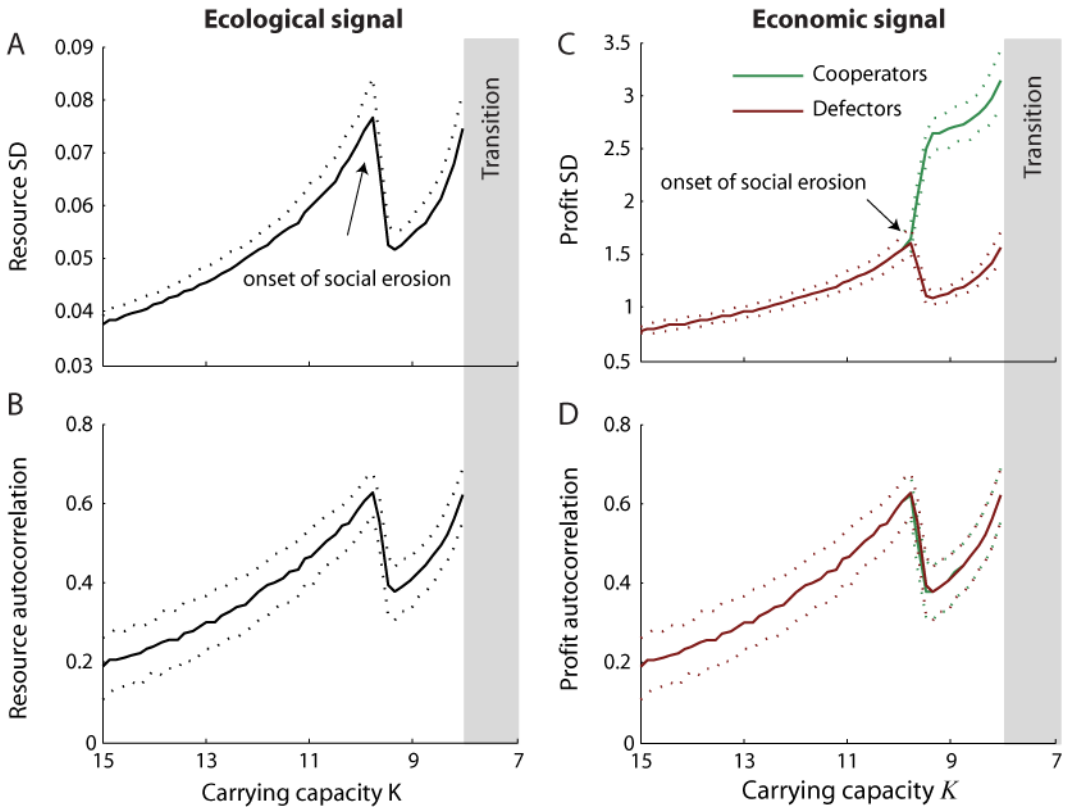

Fig. S4. Early warning signals for different parameter values of the carrying capacity *K*. A transition is preceded by an increase in standard deviation (SD) (A) and in autocorrelation (B) of the resource biomass and of the profits of cooperators and defectors (C,D). The dotted lines show 5 and 95 percentiles of the Monte Carlo Simulations.

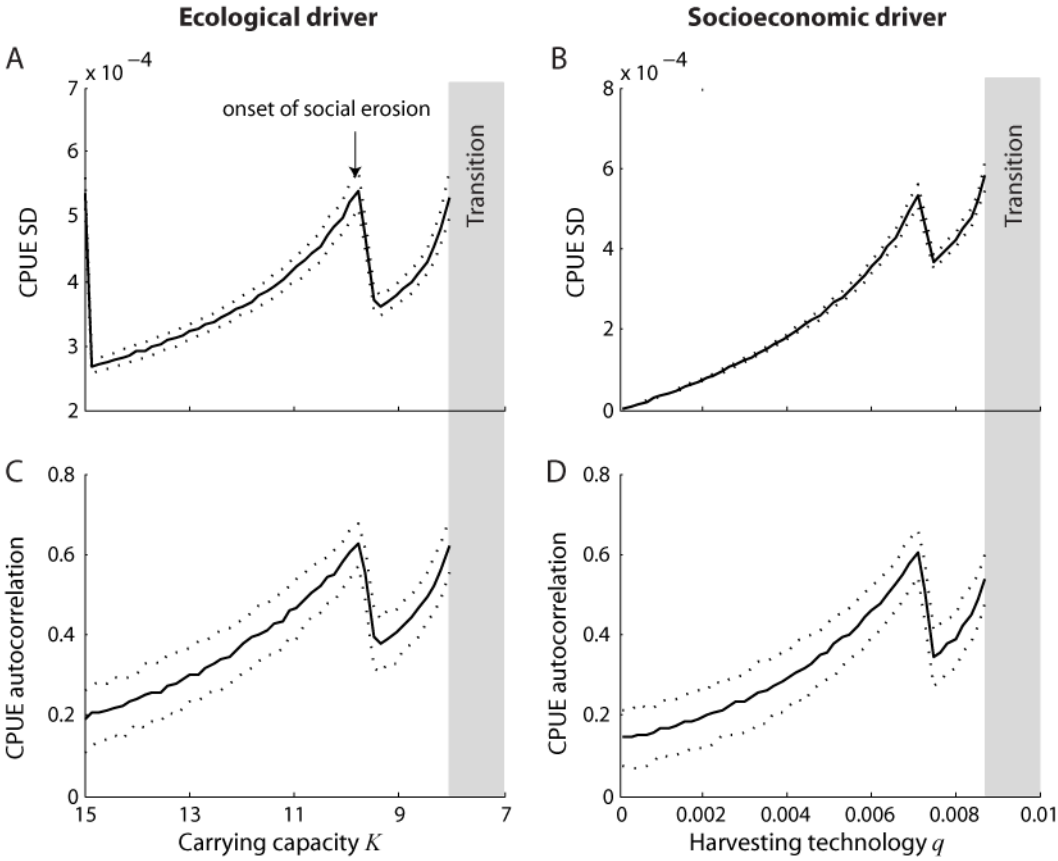

Fig. S5. Early warning signals measured from the resource biomass in the form of standard deviation (SD) (A,B) and autocorrelation (C,D) for different parameter values of the socio-economic variable CPUE. The dotted lines show 5 and 95 percentiles of the Monte Carlo Simulations.

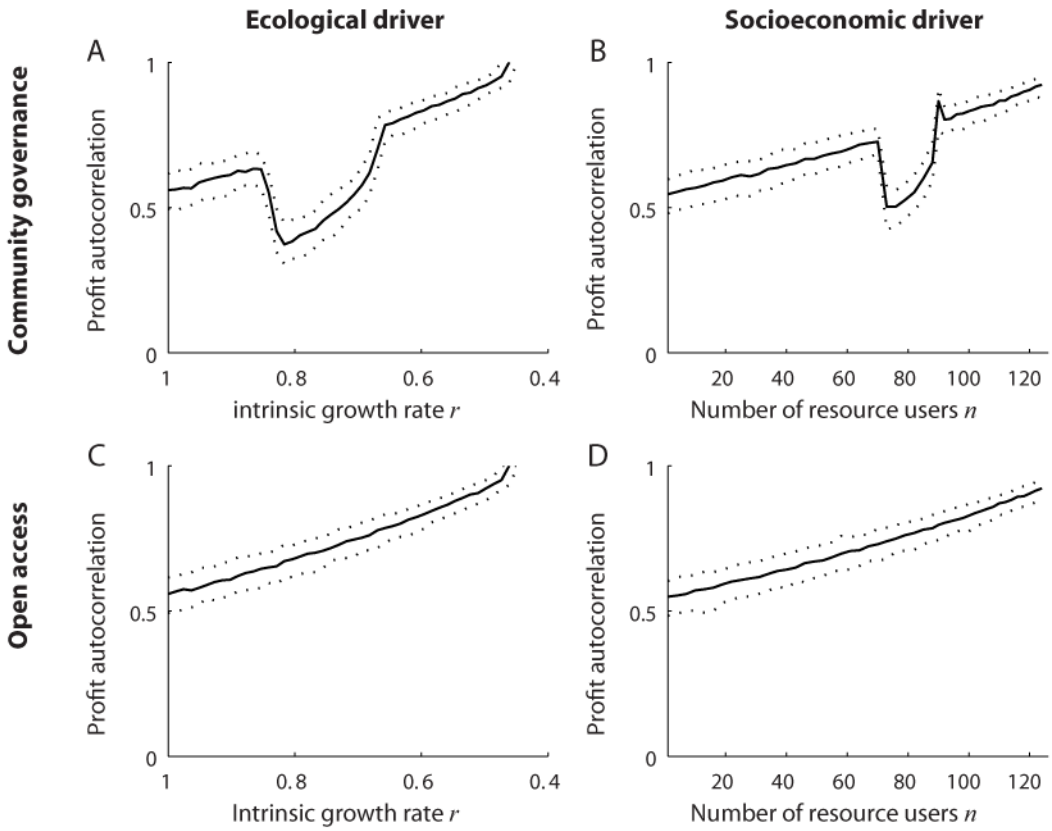

Fig. S6. Early warning signals for the case that the resource dynamics are determined by the logistic growth model (r = 0.6). We show autocorrelation of defectors' profits for different parameter values of the intrinsic growth rate of the resource r and number of individuals harvesting the resource n. Community governance portrays the case where some cooperators are guided by social norms (A,B), while open access refers to the situation where all individuals act selfishly (C,D). The dotted lines show 5 and 95 percentiles of the Monte Carlo Simulations.