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External shocks, agent interactions, and endogenous feedbacks — investigating system resilience with a stylized land use model

Abstract

Dynamics of coupled Social-Ecological Systems (SES) result from the interplay of society and ecology. To assess SES resilience, we constructed an Agent-Based Model (ABM) of a land use system as a stereotypical example of SES and investigated how resilience of the represented system is affected by both external disturbances and internal dynamics. The model explicitly considered different aspects of resilience in a framework derived from literature, which includes "resilience to", "resilience of", "resilience at", "resilience due to", and "indicators of resilience". External disturbances were implemented as shocks in crop yields. Internal dynamics comprised of two types of social interaction between agents (learning and cooperation), an ecological feedback of soil depletion and an economic feedback of agglomeration benefits. We systematically varied these mechanisms and measured indicators that reflected spatial, social, and economic resilience. Results showed that 1) internal mechanisms increased the ability of the system to recover from external shocks, 2) feedbacks resulted in different regimes of crop cultivation, each with a distinctive set of functions, and 3) resilience is not a generic system property, but strongly depends on what system function is considered. We recommend future studies to include internal dynamics, especially feedbacks, and to systematically assess them across different aspects of resilience.

Keywords: Complex Adaptive Systems; Social-Ecological Systems; human-environment interactions; path-dependency; nonlinearity; tipping points

1. Introduction

Resilience, defined here as the ability of the system to maintain certain functions, is a potential Social-Ecological System (SES) property that can contribute to sustainable development under conditions of global environmental change (Folke et al., 2002; Rockström et al., 2009; Turner et al., 2007). Climate change, soil degradation, land use change, and rural depopulation all challenge important functions of SES such as food security (Lambin & Meyfroidt, 2011; Pretty, 2008), biodiversity (Barnes et al., 2014; Brady et al., 2012), and rural livelihoods (Gay et al., 2006). The concept of resilience has been proposed as a new perspective to understand SES (Foley et al., 2005), emphasizing interactions between society and environmental processes within a complex adaptive systems framework (Bohensky et al., 2015; Dearing et al., 2010).

In order to assess resilience of SES, certain typical characteristics of these systems need to be considered. First, Social-Ecological Systems (SES) couple the social sub-system with the ecological sub-system. SES resilience should therefore be considered as a property of the coupled system instead of one that can be independently assessed from one of the sub-systems (Adger, 2000; Carpenter et al., 2001; Folke, 2006). Second, SES processes operate at multiple spatial and temporal scales (Carpenter et al., 2001; Dearing et al., 2010; Gardner et al., 2013), driven by both exogenous factors (Lambin et al., 2001) and endogenous feedbacks (Chen et al., 2016). SES resilience is therefore scale dependent and subject to how the system boundary is defined. Third, macro-level phenomena in SES (e.g. regime shifts, self-organization) emerge from micro-level behaviors and interactions between scale levels. Resilience of a SES should also be considered as an emergent property (Gunderson, 2000). Fourth, with the existence of both external and internal dynamics, SES resilience can be assessed from two perspectives — an 'engineering perspective' focusing on resistance to (or recovery from) external shocks (Holling, 1996), and an 'ecological perspective' focusing on conditions for regime shifts due to changes in the internal dynamics (Gunderson, 2009; Holling, 1973). These characteristics call for approaches in which researchers can better conceptualize, measure, and synthesize SES resilience.

Although agent-based modeling (ABM) has become an operational tool for representing SES (Helbing & Balietti, 2012; Matthews et al., 2007), current models do not fully utilize the potential of ABM to include mechanisms contributing to resilience. In particular, feedbacks between coupled sub-systems and between scale levels are still under way (Filatova et al., 2013; Folke, 2006). With the lack of models that can explain what mechanisms result in resilience, existing resilience studies are found to be mostly descriptive (Janssen et al., 2006; Schlüter & Pahl-Wostl, 2007). This opens up opportunities for ABM to study resilience, as it is process-based and it simulates system-level emergent phenomena from bottom up.

We aim to investigate SES resilience with a stylized land use ABM. Land use takes place at the interface of the social and the ecological sub-system and a land use system can therefore be considered as a stereotypical example of an SES. The model is constructed by explicitly considering different aspects of system resilience in a framework derived from literature. In the framework we distinguish (i) drivers/triggers that may disrupt the system, (ii) system functions to be maintained, (iii) scale of observation, (iv) system characteristics that potentially cause resilience, and (v) resilience indicators. The agents are farmers whose land use activities are affected by external shocks in the form of sudden reductions in crop yield, which is ubiquitous in almost every land use system where perturbations can occur due to e.g. extreme weather conditions or diseases. The system characteristics that potentially cause resilience are represented by agent interactions and endogenous feedbacks. Agent interactions are designed as learning, leading to improvement in production; and cooperation, allowing the transfer of resources (in the form of loans) between farmers. Endogenous feedbacks are designed as a decrease in crop yields due to soil depletion (a negative feedback) and an increase in profitability if many land users grow the same crop due to agglomeration benefits (a positive feedback). Two sets of resilience indicators are quantified, with one set showing system's recovery from shocks and the other set showing the absolute values of state variables. We intend to answer the following research questions: 1) to what extent is system resilience affected by external shocks, 2) to what extent do agent interactions contribute to system resilience, and 3) to what extent is system resilience affected by endogenous feedbacks. The next section describes the resilience framework, the stylized model, and the experimental setup. Model results are presented in section 3. We explain and interpret results and discuss implications and limitations in section 4, followed by conclusions in section 5.

2. Conceptual framework and Methods

2.1 A framework of resilience

A conceptual framework based on existing literature was summarized to guide our modeling investigation (Table 1). As the definition of resilience varies across fields (Adger, 2000; Bennett et al., 2005; Holling, 1973), and resilience assessments are often operationalized based on specific case studies (e.g., see Hostert et al., 2011; Ojima et al., 2014; Reenberg et al., 2013), there is a need to contextualize resilience for better communication and understanding. For example, Carpenter et al. (2001) emphasize that resilience assessments should specify of what system state and to what perturbation the resilience measures are quantified. These two aspects are considered the first step in the approach proposed by Bennett et al (2005) to assess SES resilience, in which they further ask modelers to identify feedback processes, to design a system model that incudes key elements and linkages between them, and to identify resilience measures. Besides, as systems are complex and evolving, resilience measures are only meaningful when temporal and spatial scales are defined (Carpenter et al., 2001). These aspects were summarized into a framework that distinguishes 1) "Resilience to": drivers/triggers that may disrupt the system, 2) "Resilience of": functions of the system that need to be preserved, 3) "Resilience at": the scale levels at which resilience is observed, 4) "Resilience due to": features or mechanisms creating resilience, and 5) "Indicators of resilience": measurements that quantify resilience (Bennett et al., 2005; Carpenter et al., 2001).

Table 1. A framework to study SES resilience — key aspects and their implementations in the model, based on (Bennett et al., 2005; Carpenter et al., 2001).

Aspects of resilience	Example or explanation	Implementation in the model
"Resilience to" Drivers/triggers that may disrupt the system	• External shocks (Folke et al., 2002; Holling, 1973): a sudden disruption that is not controlled by the system but has impact on the functions of the system	Sudden drops in the yield of crops (at random time steps)
"Resilience of" Function and identity of the system	• Using land for agricultural production and/or other ecosystem services (Grashof-Bokdam et al., 2017; Jarvis et al., 2008) • Economic viability of farmers (Rasch et al., 2016)	Three functions of the system are monitored as system states: Spatial resilience — the ability of the system to maintain the use of land for both crops and the evenness between crops • Multi-culture system index; with only two land use options A and B, it is calculated as:

	• Continuity of farming (Bernués et al., 2011)	[(1 - | Area_A – Area_B | / (Area_A + Area_B)] * 100 Social resilience — the ability of the system to maintain social integrity of the rural community • Number of fully active agents Economic resilience — the ability of the system to sustain the economic viability of agents • Average wealth (€)
"Resilience at" Scales at which the system is observed	• Over what period of time, or at certain point of time (Cumming et al., 2016; Rogers et al., 2012) • At individual, group/network, sub-system or system level (Milestad & Darnhofer, 2003)	Temporal: Average of the last ten years from each simulation (100 years); Spatial: resilience measures are taken at system level
"Resilience due to" System characteristics that potentially cause resilience	• Buffer capacity to cope with loss (Groot et al., 2016; Speranza, 2013) • Adaptive capacity to learn from experience (Cohen et al., 2016) • Innovative capacity to develop new strategy (Holling, 2001; Milestad & Darnhofer, 2003) • Interaction between individuals (Cumming et al., 2005) • Feedbacks that govern the internal dynamics of the system (Folke et al., 2010; Walker et al., 2004)	Two buffer capacities: i) Agents' own financial resources ii) Agents' social network (via social interaction) Agent interactions: i) Learning: agents learn from their social network to improve their production when they suffer from external shocks; ii) Cooperation: agents who lack buffer capacity ask within their social network for help Two feedbacks: i) Soil Depletion Feedback (SDF): soil fertility for crops decreases when land use intensity increases; ii) Agglomeration Benefits Feedback (ABF): the production cost of a crop for each agent is reduced when area of this crop increases
"Indicators of resilience" Variables that are chosen to measure resilience	• Value of a state variable (Carpenter et al., 2001) • The ratio of the improved performance over the degraded performance due to a disturbance (Groot et al., 2016) • Recovery speed and persistence (Donohue et al., 2016) • Distance to identified threshold of a variable (Bennett et al., 2005)	• Recovery from shocks — ratios of state variables with shocks to functions without shocks • To what values do the system functions recover — absolute values of state variables

2.2 Description of the model

Following this framework, we designed an ABM for evaluating resilience in a simple SES. We represented a land use system, which we consider to be a typical example of an SES, as land use is a social-economic activity that is dependent on but also affects the ecological sub-system. For "Resilience to", we designed sudden drops in crop yields. For "Resilience of", we took the system's ability to maintain spatial resilience (the use of land for both crops, thus a so-called multi-culture system, as opposed to a monoculture system), social resilience (number of farmers who are fully active in agricultural production), and economic resilience (the maintenance of wealth). For "Resilience at", system states were observed by the end of each model run. For "Resilience due to", the model captured social interactions of learning (to improve production) and cooperation (to increase financial buffer capacity), a negative feedback between crop productions and soil fertility, and a positive feedback between the area used for one crop type and reduced production costs (agglomeration benefits). For "Indicators of resilience", we first quantified recovery from shocks. In addition, we quantified the absolute values of state variables.

The represented SES has a number of key properties as identified in scientific literature, see Box 1. Figure 1 displays relationships between the elements in the SES. Due to the Soil Depletion Feedback (SDF), farmers' intensive use of land for one crop results in fertility loss, which requires their adaptation in their land use activities to maintain the soil fertility. Due to the Agglomeration Benefits Feedback (ABF), the increasing use of land for one crop results in reduction in production cost, which further encourages the others to produce this crop. Interactions between agents include learning and cooperation. The learning mechanism describes that farmers learn from their social network to improve crop production. The cooperation mechanism affects the system via farmers' financial resources. When farmers suffer from financial loss, they can borrow money within their social network. Such social interactions increase the buffer capacity within a farming community. Loss in financial resources and soil fertility can result in a change of the farmer's state depending on how many of his/her land parcels can be used for production. Each farmer is in one of the three states — fully active, using all their land parcels for agricultural production; partially active, using part of their land for production; and bankrupted/forced out, leaving their land abandoned and unmanaged. However, farmers' land ownership is a static property and therefore land parcels cannot be overtaken by others in this model.

Box 1. Theoretical principles of land use systems and their implementation in the model

- **Land use is a spatial variable** (Ricardo, 1817; Veldkamp & Lambin, 2001; von Thünen et al., 1966). The system is initialized with 676 farmer agents, who are randomly assigned to 676 (26 by 26) farms with a total land area of 10506 hectares (10.2 km * 10.3 km), represented by 10506 patches (100-meter resolution).
- **Land use is an economic activity**, and so the decisions are driven — to at least some extent — by profit optimization mechanisms (Ricardo, 1817). Farmers make a living by selling their harvests at market prices. Farmers' decisions on land use activities at each step are driven by profit-maximization — they choose the amount of land parcels to be used for each crop that potentially results in the highest return.
- **Land uses compete for scarce resources**, such as land, labor, and other inputs (Ricardo, 1817). Decisions are constrained by factors such as potential yields, production costs, and labor supply (Lambin et al., 2000; Simon, 1957). Farmers choose between two land use options (A and B) every year. Farmers differ in their costs to produce these two crops, which have different labor requirement. The less labor-intensive crop is therefore more attractive to farmers with less amount of labor. The profit-maximization process is constrained by the amount of their land-, labor-, and financial resources, and takes into account changes in crops yields and production costs.
- **Land users are heterogeneous** in terms of personal preferences, economic leeway, demographic properties, etc., which affects their decisions (Parker et al., 2003; Valbuena et al., 2008a). Farmers differ in their land, labor, and production costs for each land use and their initial financial resources.
- **Land use is affected by past decisions** such as tradition, sunk costs, lock-in, and pathway (Brown et al., 2005; Ellis et al., 2013). Land use activities result in profits or deficits. At each time step, profits (or deficits) are added to (deducted from) their financial resources, which can affect future decision making.
- **Land use activities are susceptible to environmental shocks** (Lambin & Meyfroidt, 2010) such as extreme weather conditions and outbreak of diseases (Rosenzweig et al., 2001). Shocks are implemented to affect the system, by reducing the yields of crops by 80% at a random time step, after which yields recover.
- **Land use has an effect on the factors** (e.g., soil quality, crop price, climate, policies, and production costs) **that determine its profitability** (Foley et al., 2005; Lambin & Meyfroidt, 2011; Turner et al., 2007). Harvests are continually updated by the Soil Depletion Feedback (SDF) — the intensive use of the land for one crop over time results in reduction in soil fertility and therefore the crop yield. Soil fertility can be recovered by letting the land fallow instead of continuously using it. Production costs, though individually different, are continuously modified by the Agglomeration Benefits Feedback (ABF) — as the area of one land use agglomerates, agents' production costs are lowered.
- **Land users are social beings** who share information, social norms, and common resources (Conley & Udry, 2001; Manson et al., 2016) among their social network (Wasserman & Faust, 1994), which is often formed based on spatial proximity. Each farmer is connected to their nearest five other farmers to form a local social network. When farmers face an external shock, they learn from their network to improve their production; when farmers suffer from financial loss, they can borrow money within their social network. A transfer of financial resources takes place when one can and is willing to provide the loan.

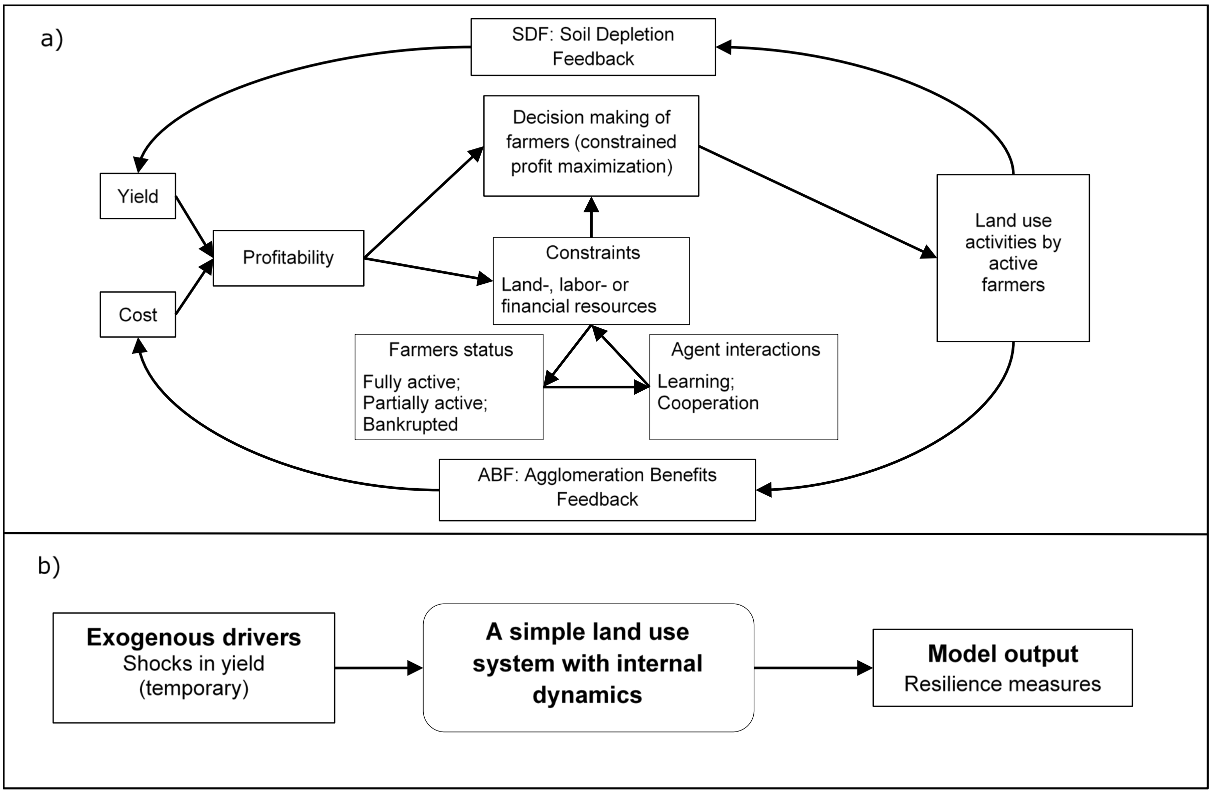


Figure 1. A stylized land use system with internal dynamics. The system evolves due to the existence of exogenous drivers and endogenous dynamics (interaction between agents and feedbacks) under which heterogeneous farmer agents choose between land use options (A, B, and uncultivated) to maximize their profits on a yearly base. Processes illustrating the main endogenous dynamics are depicted in (a), with all arrows indicating causal relationships. Descriptions of each process can be found in the supplementary material. In (b), an overview on input-process-output is provided.

The model was implemented in NetLogo 5.0.4 (Wilensky, 1999). Each step of a model run represents a cycle of crop production, see Figure 2. A complete and detailed description of the model following an ODD protocol (Grimm et al., 2006; Grimm et al., 2010) can be found in the supplementary materials.

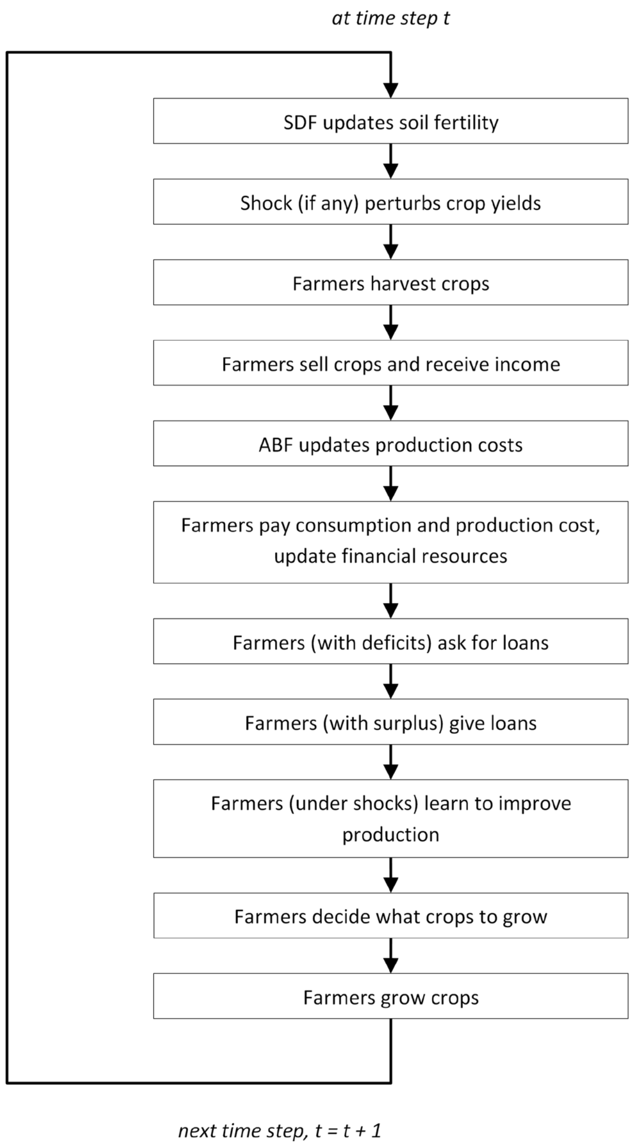


Figure 2. Flowchart of procedures in a time step. SDF is Soil Depletion Feedback and ABF is Agglomeration Benefits Feedback.

2.3 Experimental design

External shocks were implemented as three shocks in a row to disturb the system, with the onset of these shocks determined by a random seed. A shock represented 80% reduction in crop yields, which returned to their original values in the next time step. For internal dynamics, we implemented two types of agent interactions and two types of feedbacks, and defined strength levels for each of them, see Table 2. Each scenario (i.e. unique combination of external shocks and internal mechanism) was run 10 times, to account for stochasticity in timing of shocks and in assigning initial properties to the agent population.

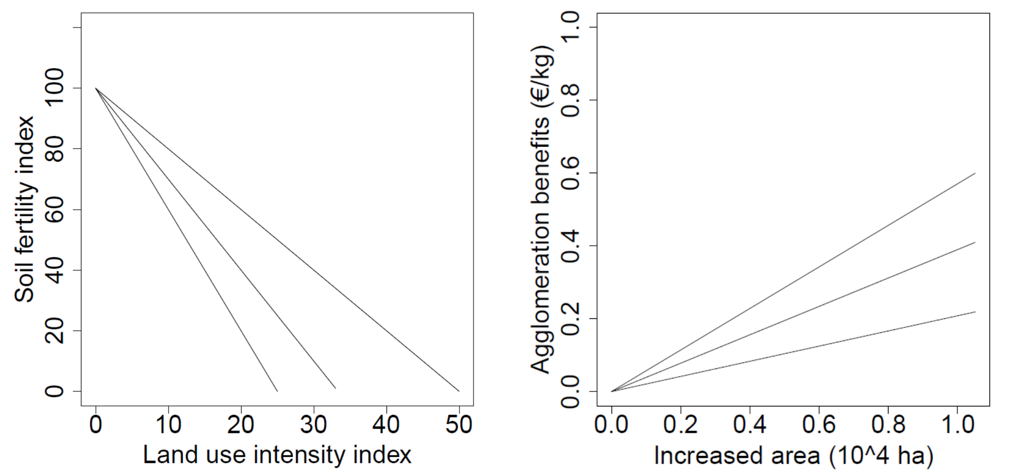
Table 2. Experimental design on the internal dynamics. SDF is Soil Depletion Feedback and ABF is Agglomeration Benefits Feedback.

Mechanism	How the mechanism is varied	Number of variations
Agent interactions	No interaction	9
	Learning (type: random or target)	
	Cooperation (type: likelihood or always)	

	Both learning and cooperation (and the combination of their types)	
Feedbacks	No feedback	16
	SDF (Low, medium, or high strength level)	
	ABF (Low, medium, or high strength level)	
	Both feedbacks (and the combination of their strength levels)	

For agent interactions, we implemented learning and cooperation within a farmer's social network. Learning was implemented as farmers improving production by interacting with other famers after they were affected by an external shock. We distinguished two types: 1) random learning, each farmer compared production costs against another farmer randomly selected from the social network and learned to achieve the same production costs if the other farmer performed better; and 2) target learning, each farmer first searched for the best performer in the social network, and then learned to achieve the same production costs as the best performer. Cooperation was implemented as the transfer (as a loan) of financial resources to an agent with insufficient resources. A farmer with deficit asked another farmer who had the largest amount of resources. Two types of cooperation were considered: 1) farmers had heterogeneous likelihoods to provide help, and 2) farmers were always willing to provide help if they were able to.

For feedbacks, we implemented Soil Depletion Feedback (SDF) and Agglomeration Benefits Feedback (ABF). We considered the following scenarios: 1) the system was not affected by neither feedback, therefore having fixed soil fertility and unchanged individual production costs, 2) soil fertility was regulated by the SDF but production costs remained unchanged, 3) individual production costs were regulated by ABF but crop yields remained fixed; and 4) the system was affected by both feedbacks. Each feedback was implemented with three levels of strength: low, medium, or high (see Figure 3).



a. Soil Depletion Feedback (SDF)

b. Agglomeration Benefits Feedback (ABF)

Figure 3. The implementation of SDF and ABF in the model. For a), land use intensity index is the accumulated time of continuous production of one crop on the same land; soil fertility index is the percentage of the original fertility. As SDF strength increases from low to high, the slope decreases — an increase in land use intensity for one crop results in more reduction in soil fertility. For b), the benefit of increase in the area of one land use is the amount of production cost that can be reduced. As ABF strength level increases from low to high, the slope increases — an increase in the area of a land use results in more benefits for individual farmers.

2.4 Measuring resilience

For each model run, we took the mean value of each state variable (multi-culture system index, fully active farmers, and wealth) from the last ten steps to represent various system functions. Specifically, multi-culture system index represented spatial resilience, fully active farmers represented social resilience, and wealth represented economic resilience. The effect of external shocks was quantified by comparing each state variable under shocks to those in absence of shocks. Such comparison revealed the extent to which each function recovered, hence the 'engineering perspective' of resilience. The effect of internal mechanisms was investigated by quantifying the absolute values of state variables over these mechanisms and their strengths. We hypothesized that differences in these internal mechanisms result in regime shifts and therefore allowed us to gain insights into the 'ecological perspective' of resilience. Statistical analyses were performed to test if internal mechanisms resulted in significantly different resilience measures in comparison to model runs without these internal mechanisms, using t-test. To better explain model results and understand the relationships between model inputs and model outputs (Schulze et al., 2017), we measured the sensitivity to a model input as the proportion of the output variance that can be explained by changes in the model input (ten Broeke et al., 2016), using the effect size measure eta squared (Richardson, 2011).

3. Results

Resilience was assessed as the recovery of state variables from external shocks (Table 3) as well as the absolute values of state variables (Table 4). The systematic investigation following Table 2 resulted in thousands of model runs in which the effects of each mechanism and their interactions were explored. To avoid unnecessary complexity, we only presented the results from each individual mechanism, and the interaction between the two feedbacks. A complete overview of results that accounted for the complex interactions effects between various mechanisms can be found in Figure 4. We found that (1) overall the presence of internal mechanisms increased the ability of the system to recover from external shocks, and that (2) these internal mechanisms resulted in different regimes, each with a distinctive set of functions. Details of these two findings are presented below.

Table 3. Resilience as recovery from shocks. Results are average values. Recovery is a relative term, with values < 1 indicating a lack of recovery and values > 1 indicating improvement. Recovery was calculated as the ratio of the absolute values of the state variable with shocks to those without. ABF is Agglomeration Benefits Feedback and SDF is Soil Depletion Feedback. ABF x SDF represents interaction between feedbacks. Indicators from the 2nd row onwards were compared against the indicators in the 1st row using t-test. Significant difference on the mean was marked by * (0.05 < p.value < 0.1) or ** (p.value < 0.05).

Internal mechanism	**Recovery of spatial resilience** (multi-culture system index)	**Recovery of social resilience** (fully active farmers)	**Recovery of economic resilience** (wealth)
No internal mechanism	0.87	0.94	0.91
Learning (random)	0.95**	0.97**	0.91*
Learning (target)	0.93*	0.98**	0.91*
Cooperation (likelihood)	0.96**	0.94*	0.90*
Cooperation (always)	0.96**	0.93*	0.89**
ABF Low	1.14**	1.00**	0.93
ABF Medium	NA	1.00**	0.95**
ABF High	NA	1.00**	0.95**
SDF Low	0.98**	1.46**	0.91*
SDF Medium	1.00**	1.10*	1.14*
SDF High	0.98**	1.77**	1.70**
ABF x SDF (average of all strength levels)	1.06**	2.60**	0.84**

We observed the following effects concerning recovery from shocks. (1) Without any internal mechanism, external shocks resulted an overall decrease of resilience — all functions showed a lack of recovery. (2) Learning resulted in significant increases on the recovery of multi-culture system index (for random learning) and fully active farmers (for both learning types) but had no significant effect on the recovery of wealth. (3) Cooperation resulted in a significant increase on the recovery of multi-culture system index (for both cooperation types), no significant effect on the recovery of fully active farmers, and a significant decrease in the recovery of wealth (for always cooperation). (4) The positive feedback ABF resulted in a complete recovery on fully active farmers (for all ABF strengths) and a significant increase on the recovery of wealth (for ABF Medium and High). The recovery of multi-culture system index could not be calculated for ABF Medium and High. This was because the multi-culture system totally disappeared in these cases. (5) The negative feedback SDF resulted in significant increases on the recovery of multi-culture system index, fully active farmers (for SDF Low and High), and the recovery of wealth (for SDF High). (6) Under both feedbacks, there were improvements on the recovery of multi-culture system index and fully active farmers, but the recovery of wealth was significantly lower. (7) Due to ABF (Medium and High), monoculture was observed without external disturbance, resulting in a multi-culture index of 0. Consequently the recovery of this state variable cannot be calculated, see "NA" in Table 3.

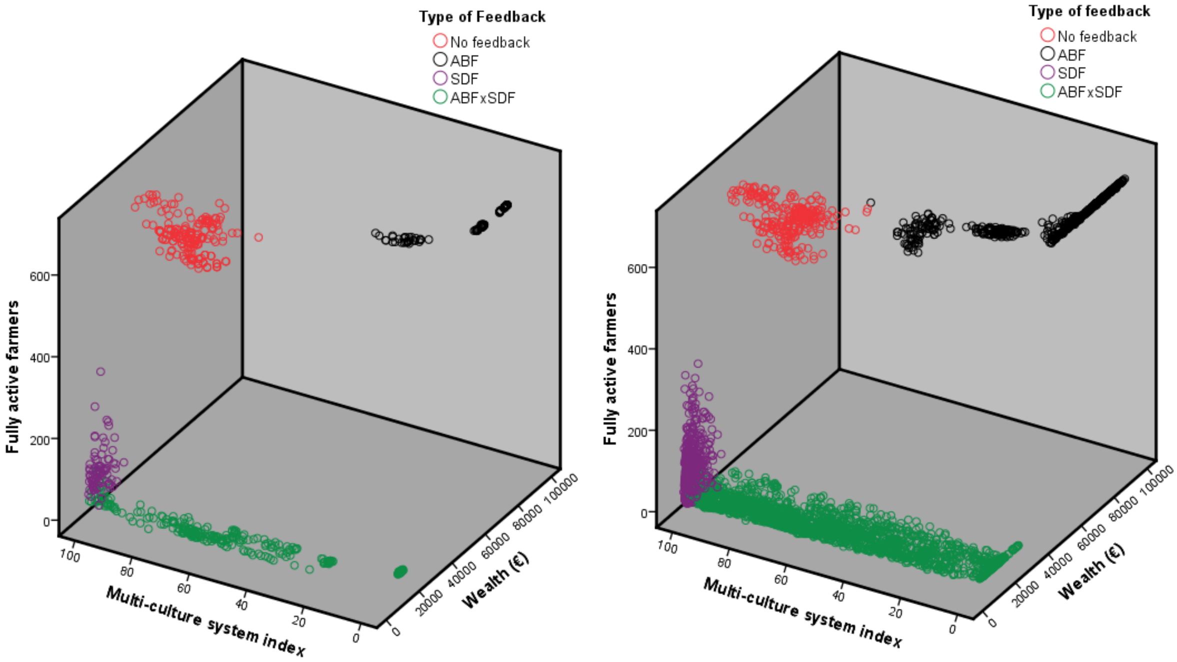
Cases exist in which external shocks resulted in improvements on certain functions, indicated by a recovery value greater than 1. For example, when the internal mechanism was set as ABF Low, external shocks improved the multi-culture system index. This was because the positive feedback favored the agglomeration of one land use, which moved the system towards a mono-culture. However, external shocks reduced the favorable conditions for the dominant land use, which made room for the alternative land use to grow and therefore improved the multi-culture system index. We also found that external shocks improved social resilience and economic resilience when the system was controlled by SDF. This was because SDF required farmers to put aside land to recover soil fertility, which hampered their ability to fully use their land and gain profits. However, external shocks resulted in many farmers putting aside a lot of land, the resulting recovery of soil fertility benefited farmers' wealth and allowed more of them to be fully active.

Though resilience was reflected by recovery of each state variable from shocks, such a relative indicator did not show at what absolute values these states recover to and weather these values are distinctive due to different internal mechanisms. These absolute values of state variables were shown in Table 4. We found they changed significantly with feedbacks. This became more apparent as we plotted model results in 3-dimensional graphs, labelled by the type of feedback, see Figure 4. In Figure 4a (graphical illustration of Table 4), four clusters of system states emerged. Conveniently, we refer to these clusters as regimes, which change with feedbacks. The system was under regime I with no internal mechanism, with learning, and with cooperating (see the red circles in Figure 4a): there was a high level of multi-culture system index, the majority of farmers were fully active, and farmers' wealth was abundant. Within regime I, learning significantly increased resilience, as the system showed higher multi-culture index (for target learning), more fully active farmers and wealth (for both learning types) as compared to the scenario with no internal mechanism; cooperation was found to significantly increase the multi-culture system index (for both cooperation types), but to reduce wealth (when agents always liked to help).

Table 4. Resilience as the absolute values of state variables. Results are average values. The multi-culture system index is dimensionless (highest value as 100, a multi-culture with even crop compositions, and lowest value as 0, a monoculture). The fully active farmers is a count (highest value as 676, and lowest value as 0). Wealth takes the unit of euro. ABF is Agglomeration Benefits Feedback and SDF is Soil Depletion Feedback. ABF x SDF represents interaction between feedbacks. Indicators from the 2nd row onwards were compared against the indicators in the 1st row using t-test. Significant difference on the mean was marked by * (0.05 < p.value < 0.1) or ** (p.value < 0.05).

Internal mechanism	**Spatial resilience (multi-culture system index)**		**Social resilience (fully active farmers)**		**Economic resilience (wealth)**		**Regime**
	No shocks	With shocks	No shocks	With shocks	No shocks	With shocks	
No internal mechanism	82	71	633	594	27620	25255	**I**

Learning (random)	74^{**}	70	669^{**}	651^{**}	30909^{**}	28177^{**}	
Learning (target)	91^{**}	85^{**}	674^{**}	663^{**}	33307^{**}	29930^{**}	
Cooperation (likelihood)	82	79^{**}	638	594	27599	24654^{*}	
Cooperation (always)	83	79^{**}	634^{*}	593	27418	24557^{**}	
ABF Low	16^{**}	17^{**}	674^{**}	672^{**}	51378^{**}	47831^{**}	
ABF Medium	0^{**}	0^{**}	674^{**}	675^{**}	68875^{**}	65213^{**}	**II**
ABF High	0^{**}	0^{**}	675^{**}	675^{**}	82814^{**}	78680^{**}	
SDF Low	98^{**}	96^{**}	71^{**}	103^{**}	2056^{**}	1864^{**}	
SDF Medium	95^{**}	95^{**}	121^{**}	133^{**}	2066^{**}	2351^{**}	**III**
SDF High	96^{**}	95^{**}	86^{**}	153^{**}	2333^{**}	3950^{**}	
ABF x SDF (average of all strength levels)	52^{**}	58^{**}	5^{**}	13^{**}	10408^{**}	8760^{**}	**IV**

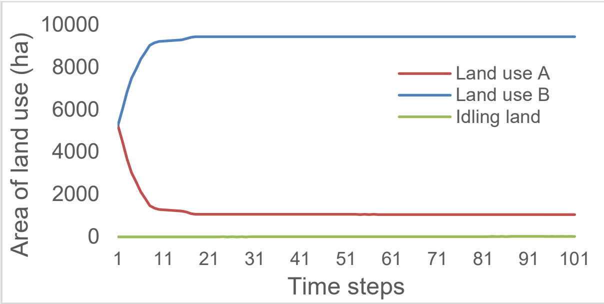


(a) Excluding model runs with between-mechanism interactions, except for ABF x SDF

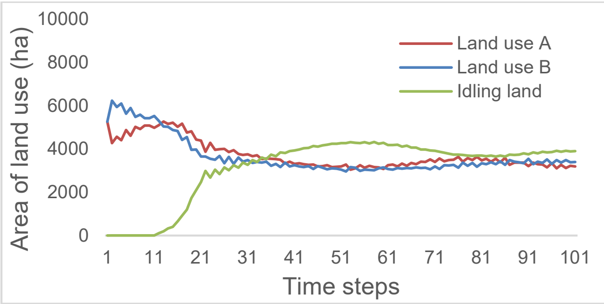
(b) All model runs, including between-mechanism interactions

Figure 4. Resilience indicators (absolute values of each state variable) under different types of feedback. The change of feedback suggested that the system changed its functions distinctively. In (a), the graph contains model simulations in which between-mechanism interactions are not considered. Therefore, (a) corresponds to results in Table 4: the red cluster is regime I, the black cluster is regime II, the purple cluster is regime III, and the green cluster is regime IV. In (b), the graph contains all model simulations, including all types of between-mechanism interactions, e.g. between learning/cooperation and the feedbacks.

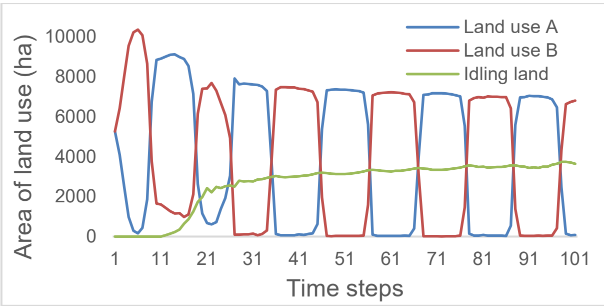
With the presence of feedbacks, the system showed very different land use dynamics, which we illustrated in Figure 5. The positive feedbacks ABF resulted in regime II (see the black circles in Figure 4a): the system was found to have a dominant crop (very low multi-culture system index) or even to be a monoculture (multi-culture system index at 0), see Figure 5a; almost all of the farmers were fully active; and their wealth was substantially increased compared to regime I. Within regime II, increase in ABF strength resulted in increase of social and economic resilience but at the cost of a complete loss of spatial resilience (Table 4). The reason why land use B became dominant was because it required less labor input than land use A.



(a) ABF Low. The system shows: dominance of crop B over crop A over space and time



(b) SDF Low. The system shows: co-existence of crops over space and time



(c) ABF x SDF, both at low strength level. The system shows: each crop takes turns to dominate the space for about 9 time steps

Figure 5. Land use dynamics under the control of different feedbacks. ABF is Agglomeration Benefits Feedback and SDF is Soil Depletion Feedback. ABF x SDF represents interaction between feedbacks.

The negative feedback SDF resulted in regime III (see the purple circles in Figure 4a): land use activities resulted in a very high level of multi-culture system index due to the coexistence of both crops (Figure 5b), only a small amount of farmers were fully active, and farmers' wealth was substantially reduced compared to regime I and II. Within this regime, an increase in SDF strength led to increase of fully active farmers and wealth. One may find this counter-intuitive as stronger soil depletion should result in less wealth. However, farmers adapted to soil depletion by constantly putting aside some land to recover soil fertility and by changing between crops. A stronger SDF resulted in a faster response of farmers and therefore a quicker adaptation.

Finally, the system entered regime IV when both feedbacks were present (see the green circles in Figure 4a): multi-culture system index can take any value within the full range (higher when SDF controls the system, and lower when ABF controls the system), very few farmers were fully active, and accumulated limited amount of wealth. This was because under this regime, crops were found to rotate (Figure 5c).

Agglomeration benefits allowed one crop to dominate for a while, then taken over by the other crop due to the soil depletion. Even for the dominance period, farmers had to put aside land for fertility recovery.

These four regimes (clusters of state variables) persist, even when we included all types of between-mechanism interactions, see Figure 4b. However, the range of the different regimes increases when between-mechanism interactions are included. As each cluster grew in size from Figure 4a to Figure 4b, it shows that system functions were affected by between-mechanism interactions. These effects were nevertheless much smaller, comparing to the effect of feedback. The change of feedback was the most important cause: as we found feedbacks to have an average effect size of 89% in explaining the variance in state variables.

4. Discussion

4.1 Engineering perspective vs. Ecological perspective

We assessed resilience both in relative and absolute terms. The relative term corresponds to the 'engineering perspective' of resilience, for which we calculated resilience as recovery from shocks. Other indicators exist such as the ratio of system performance before and after disturbance (Groot et al., 2016), stability (whether a system returns asymptotically to its equilibrium), variability (coefficient of variation of a variable over time or across space), persistence (length of the time a system maintains the same state), resistance (similar to Groot et al), and speed of recovery (Donohue et al., 2016). These measures add more dimensions to resilience particularly by capturing different aspects of how a system responds to external shocks. Many of these indicators are based on the 'engineering perspective', they usually focus on stability near equilibrium (Holling, 1996) and ignore how internal dynamics change system behavior. By systematically combining disturbances and internal dynamics we identified different regimes, which allowed us to explore the more holistic 'ecological perspective' of resilience (Gunderson, 2009) focusing on behavior change and regime shifts (Holling, 1973). We found that recovery from external shocks can change due to internal mechanisms (Table 3), but the interpretation of a system being more or less resilient is limited. For example, the recovery of wealth was found the same for both learning and SDF Low (all were 0.91 in Table 3), however, the maintenance of wealth was totally different given these two internal mechanisms, by looking at the absolute values on this state variable. The difference in the absolute values of the state variable resulted from the change of internal dynamics. By showing the absolute values, we demonstrated that different regimes existed due to various internal mechanisms. A typical 'ecological perspective' of resilience investigates the amount of disturbance to shift regimes, where the internal dynamics change as well. We implemented the change of internal dynamics in different model runs instead of changing it within a model run, as this remains challenging (Polhill et al., 2016).

4.2 Resilience-causing mechanisms

Our model included two types of agent interactions and two feedbacks as the internal dynamics of the system. Through agent interactions farmers were able to share or transfer resources which can increase their capacity to cope with change. We found that both learning and cooperation increased the ability of the system to recover from shocks (Table 3) and increased the absolute values (Table 4) of state variables that represented different system functions. Specifically, target learning showed more profound effects on each state variable (Table 4), compared to random learning, indicating the importance of information within the social network. There was not much difference between the two cooperation types. This was because cooperation required not only willingness but also ability. With extra analysis, we found the number of transfers (loans) was constrained by their ability for both cooperation types. In other land system studies, agent interactions are usually implemented as farmers imitating the behavior of others depending on spatial proximity (Bert et al., 2011) or social-economic similarity (Le et al., 2012). However, the effect of agent interactions on system resilience is mostly unreported (Rindfuss et al., 2008). A recent study (this special issue) aims at bridging the gap in the context of common-pool resource systems (ten Broeke et al., 2018). We also found that the effects due to agent interactions (both learning and cooperation) were less pronounced compared to the effects due to feedbacks — regimes changed with feedbacks but not with agent interactions (Table 4). This can be explained by how they affected the system. Learning took place when the system was under shocks and it allowed farmers to reduce their production costs by learning from a better performing farmer; cooperation took place when agents were not financially viable and it allowed them to increase their resources by asking a loan from a richer farmer. However, neither interaction was able to change land use dynamics when feedbacks were present — under the control of ABF, one land use became more and more economically attractive and the system shifted to the monoculture, agglomeration benefits resulted in wealth growth and farmers did not need help from others; under the control of SDF, farmers had to put aside land and rotate between crops, regardless of conditions in their production costs and financial resources. More importantly, feedbacks continuously affected the system over the entire model run. Their effects were accumulated over time. As a result, the extent to which system functions were maintained is more determined by feedbacks than by agent interactions in this study. Real-world examples can be found for the implemented feedbacks. The positive correlation between farm size, productivity, and cost reduction in the US corn belt between 1982 and 2012 (Key, 2018) reflects the Agglomeration Benefits Feedback; while the existence of Soil Degradation Feedback is well observed across the world (Barão et al., 2019; Parihar et al., 2018; Wiesmeier et al., 2018), with crop rotation as one of the adaptive farming strategy.

4.3 Resilience is not generic but specific to each function

Resilience assessment should be specific on the function of the system (Bennett et al., 2005; Carpenter et al., 2001). One may reach different conclusions when multiple functions (Fleskens et al., 2009; Jacobi et al., 2015; Wilson, 2010) are under concern. To illustrate this argument, we make use of the absolute values of state variables presented in Table 4. If we focus on the economic resilience of the system, we found the system more resilient when it was under the control of ABF. However, ABF resulted in a shift of the system to a monoculture regime, in which spatial resilience decreased. The system showed higher spatial resilience (with very high multi-culture system index) when it was under the control of SDF. Such dichotomy suggests that one function can conflict with another (Wiggering et al., 2003; Willemen et al., 2010). Therefore, it becomes very important to identify and assess the key functions of a system ("resilience of" in the framework) as they might result in different interpretations of system resilience. Moreover, the detection of trade-offs between functions implies the need for a multidimensional view to evaluate and optimize objectives in SES management (Donohue et al., 2016). For example, an agricultural land use system as a SES provides not only food and income security but also other non-marketed ecosystem services such as soil fertility and biodiversity (Deguines et al., 2014; Swinton et al., 2007). The monoculture regime (resulting from ABF in our model result) may be providing economic benefits at the expense of hampering the ecological objective such as to maintain biodiversity (Deguines et al., 2014). Real-world SES management therefore requires the know-how to balance between production and conservation.

4.4 Design choices and limitations

The exploration of resilience was based on the stylized land use model. Obviously, real-world land use systems are also affected by factors that are not included in the model. They include, amongst others, technological development (Ellis et al., 2013), market dynamics (Lambin et al., 2003), and policy interventions (van Zanten et al., 2014). Whether or not such factors function as an external driver or endogenous feedbacks (Lambin & Meyfroidt, 2010; Meyfroidt, 2013) can greatly affect the underlying system resilience. Agent interactions can take other forms such as the formation of norms (Matthews et al., 2007) and coordination (Lansing & Kremer, 1993). Modelers still face the challenge to identify possible interactions and emphasize on the most relevant ones, as little knowledge exists on their relative importance in models (Rindfuss et al., 2008). Besides, the model does not include the process in which new agents enter the system. This process can greatly affect system resilience as measured by us and even how we should define resilience, as the replacement of existing or forced out agents by new ones directly increases the resilience of the system.

System resilience can also be affected by characteristics such as diversity (or heterogeneity), including diversity in human decisions (Leslie & McCabe, 2013) and diversity in landscape (Schippers et al., 2015). Though diversity was captured in this study by implementing agents as heterogeneous in many aspects such as available labor, financial resources, production costs, the effect of diversity on system resilience was not explored. Also, diversity follows different distributions. Real-world systems can be composed of agents whose characteristics are far from the normal distributions, which were assumed in the model. The assumptions that decision-making is profit-oriented and that agents produce crops for a market ignore other goals of agents and lack the consideration on the topology of farmer agents (Bakker & van Doorn, 2009; Valbuena et al., 2008b). For example, short-term profit maximization is more often seen among land tenants while ecologically beneficial land use is found typical for land owners (Bert et al., 2011). Though in the model profit-maximization was assumed for individual decision-making, in reality farmers can be risk averse (Aka et al., 2018) and opt for cost minimization (Zereyesus & Featherstone, 2017), for example through optimized crop allocation.

The scale at which resilience is measured is also important to be defined (Cumming et al., 2016). In this study the resilience indicators were measured at the system level and by the end of each model run. One can reach different results by e.g. looking at an individual level and by e.g. assessing resilience right after a shock. This is because measurements at individual level may neglect how individuals interact with each other and how they are affecting and being affected by system properties. However, measuring resilience right after shocks runs the risk of overlooking if the measures represent stable states. Due to the large amount of model runs used in this study, we did not show how resilience indicators change over time, which may improve our understanding on the temporal dynamics of resilience (Rogers et al., 2012). Instead, we calculated each state variable as the mean of the last 10 steps from 100-step model runs. Such measures were only representative if there were no strong spatial-temporal nonlinearities within these 10 steps. We found that the positive feedback resulted in rapid transition, and by the time the mean values were taken, the system already reached extreme states and stayed there with no change in spatial distribution of crops (Figure 5a); and that the negative feedback resulted in dynamic equilibrium (Figure 5b). Therefore, our measures in both cases represented the states of the system. However, it became more complex when the system was under the influence of both feedbacks, as we found different spatial-temporal dynamics (Figure 5c). These model runs require measuring windows of different lengths to capture the 'true' state of each system function, which would make the experimental design much more complex. We addressed this issue by repeating the model runs for many times to avoid measuring the system at a specific phase.

Despite the limitations, model results imply the importance of including both external disturbances and internal dynamics in studying resilience. Particularly for the internal dynamics, feedback mechanisms should be considered and well designed. Future studies may also consider to extend the types of agent behaviors and their interactions, to include other important processes in SES, and to consider the effects of initial conditions and path-dependency on resilience (Brown et al., 2005).

5. Conclusions

Resilience is better assessed by considering both external disturbances and internal dynamics. Our model represents a simple land use system as a coupled SES since both ecological and economic feedbacks are incorporated to affect socially interacting farmer agents. By comparing resilience indicators under different internal mechanisms, we found that (1) the presence of internal mechanisms increased the ability of the system to recover from external shocks, (2) these internal mechanisms, particularly feedbacks, resulted in different regimes, each with a distinctive set of functions, and (3) resilience of one system function may be at the cost of the resilience of another function. The first finding corresponds to the 'engineering perspective' of resilience — how does the system recover from external shocks. The second finding suggests the need to further explore the 'ecological perspective' of resilience — the maintenance of functions is affected by internal dynamics. It also implies the importance to design and assess feedbacks carefully. The last finding implies the risk of a partial understanding of system resilience, e.g., by only looking at one specific function of the system.

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