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Synthesis

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ABSTRACT. In social-ecological systems (SES), where social and ecological processes are intertwined, phenomena are usually complex and involve multiple interdependent causes. Figuring out causal relationships is thus challenging but needed to better understand and then affect or manage such systems. One important and widely used tool to identify and communicate causal relationships is visualization. Here, we present several common visualization types: diagrams of objects and arrows, X-Y plots, and X-Y-Z plots, and discuss them in view of the particular challenges of visualizing causation in complex systems such as SES. We use a simple demonstration model to create and compare exemplary visualizations and add more elaborate examples from the literature. This highlights implicit strengths and limitations of widely used visualization types and facilitates adequate choices when visualizing causation in SES. Thereupon, we recommend further suitable ways to account for complex causation, such as figures with multiple panels, or merging different visualization types in one figure. This provides caveats against oversimplifications. Yet, any single figure can rarely capture all relevant causal relationships in an SES. We therefore need to focus on specific questions, phenomena, or subsystems, and often also on specific causes and effects that shall be visualized. Our recommendations allow for selecting and combining visualizations such that they complement each other, support comprehensive understanding, and do justice to the existing complexity in SES. This lets visualizations realize their potential and play an important role in identifying and communicating causation.

Key Words: *causal relationship; complex systems; illustration; visualization*

INTRODUCTION

Science seeks to understand how systems are organized and function. A key element of such understanding is identifying the relationships between causes and effects, also referred to as causation (Woodward 2016, Pearl and Mackenzie 2018). Claiming causal relationships is so commonplace in everyday life that scientists rarely ask themselves what causation actually means and on what basis we make causal claims. The word "because" is omnipresent: we have day and night "because" of the earth's rotation; the plant will not grow "because" it does not get enough water. Such causal claims are simple and direct, and such simple claims are hardwired into our language and thinking.

For explaining phenomena in complex systems, however, simple claims are often not sufficient (Meyfroidt 2016). This is the case for social-ecological systems (SES), which are composed of decision-making interacting agents, such as humans and organisms, and their environment (Ostrom 2009, Ferraro et al. 2018). The key building blocks of these systems, the agents, often behave in elusive ways. Causal relationships between variables in these systems are often nonlinear and can involve more than two variables. Moreover, in SES, social and ecological processes are intertwined. All this leads to complex systems in which single causal relationships are difficult, if not impossible, to disentangle (Schlüter et al. 2019).

The consequences for trying to understand and, thereupon, influence or manage such systems can be dire. Decisions based on erroneously understood causal relationships, or too simple or narrow mental models, can lead to unintended consequences and potentially disasters (Merton 1936, Sterman 2006, Levin et al. 2013). This happened, for example, during the 2008 global financial crisis and the collapse of Atlantic cod stocks (e.g., Frank et al. 2016, Sguotti et al. 2019). Factors complicating the construction of useful models of causation in SES include the diversity of their building blocks, adaptive behavior, positive and negative feedback loops, indirect, delayed or path-dependent effects, stochasticity, and the interaction of processes on different spatial, temporal, and organizational scales (e.g., Meyfroidt 2019, Elsawah et al. 2020).

Being aware that simple causal claims and single, linear causal chains are often insufficient to understand what happens in SES, researchers have sought to identify and communicate more elaborate causal relationships. As the primary sense of humans is the visual one, visualizations play a key role in this endeavor. Their main purpose is to represent complex systems and phenomena with different foci, from different angles, and at different levels of detail. By decomposing and depicting parts of the system and their relationships, visualizations are used to elucidate how these systems function or how the phenomena emerge. This may happen at different stages throughout the research process, from visualizing initial hypotheses to eventually consolidated causal findings (Sheredos et al. 2013). Thus, visualizations are widely used to comprehend and to communicate causal relationships in SES. However, visualizations may also constrain our ability to capture causation, in particular in complex and intertwined systems such as SES. As graphical representations of structures and dynamics, they translate into mental models that may often suggest a level of simplicity in causal relationships that does not mirror reality. Likewise, even if we have better understood complex causation, using, for example, statistical analyses or mechanistic simulation models, our visualizations might not be able to adequately represent this understanding.

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Although visualizations play an important role in exploring and communicating causation in SES, their inherent assumptions, strengths and weaknesses are rarely reflected upon (Spiegelhalter et al. 2011). The way we visualize, and hence conceptualize, complex systems affects our understanding of these systems and the conclusions based on this understanding. For example, the conceptual model of what is known, unknown, or uncertain about an agricultural SES, and how different variables in that SES influence and respond to each other, is virtually inconceivable without visualization, and in turn, shapes the development of climate change mitigation and adaptation strategies (Bentley and Anandhi 2020).

We therefore seek to raise awareness of how widespread types of visualization can shape our ability to properly identify and express causal relationships and provide some ways forward for using visualizations in SES research. We first identify challenges for visualizing complex causation, followed by a presentation of common types of visualization and a discussion of their scope, potential, limitations, and their suitability to address the challenges. We then highlight examples of visualizations in the literature on SES, specifically attempts to visually capture complex causation. Finally, we formulate caveats and recommendations for future use of visualizations. Although comprehensively visualizing causation in a complex SES with a single figure may be impossible, creative solutions for elucidating and communicating this complexity exist and should further be developed.

CHALLENGES FOR VISUALIZATIONS OF COMPLEX CAUSAL RELATIONSHIPS

To systematically analyze the visualization types' potential and limitations for presenting and explaining causal relationships, we identify key challenges for visualizing causal relationships in SES. Although there is overlap with the general obstacles for studying causation in complex systems (e.g., Preiser et al. 2018, Schlüter et al. 2019), we focus on the following challenges that are specific to the task of visualization:

1. Visualizing whether a relationship is causal. This challenge includes separating causation from mere covariance and visualizing confounding. Two variables covary if a change in one of them goes along with a change in the other, but the covariance does not reveal which variable is the cause and which is the effect. Even more important, they may also covary without a direct causal relationship if changes in both are caused by a third variable. These options are not mutually exclusive. Often, there is a causal relationship between two variables, but this relationship is confounded by a third variable, which affects both. This poses a problem for detecting whether two variables are causally related, and for visualizing it (Pearl and Mackenzie 2018).

2. Visualizing the characteristics of causal relationships. This challenge includes discriminating between positive and negative relationships. If two variables are cause and effect, increases in the first variable can increase (positive relationship) or decrease (negative relationship) the second variable. Moreover, the shape of their relationship is often nonlinear or may even change direction. It may also include

discontinuities. Visualizing these characteristics of a causal relationship, especially in a quantitative manner, cannot be achieved by all visualization types.

3. Visualizing reciprocal causal relationships. This challenge includes illustrating that certain variables are causes and effects of each other. This is common in SES, for example, harvesting affects and is affected by the abundance of a target population or the decisions of suppliers affect and are affected by the market price. Such feedback may generate hysteresis or cyclic dynamics. Making these reciprocal relationships perceivable is a frequent demand when visualizing causation in complex systems.

4. Visualizing multiple causes. This challenge includes depicting that two or more factors, actors, processes or events can each lead to the same effect (alternative causes, or equifinality). Moreover, the relationship between a cause and its effect can be moderated by an additional factor or context, or it is the combination of causes that lets a certain effect emerge. The challenge of multiple causes also includes showing causal relationships at different resolutions of system elements. When two variables are causally related, a detailed analysis of their relationship at a higher resolution will often reveal that the relationship is indirect, meaning that the first variable has an effect, which itself is a cause of another effect, and so forth, until the second variable is affected. Visualizing these intermediate variables (mediators) and their relationship (causal chain) is challenging.

5. Visualizing temporal dynamics of causal relationships. This challenge includes showing that and how causal relationships change over time. It may also be that one or several causes lead to an effect with delay. If the temporal sequence of certain actions, processes, events, or the temporal development of a causal variable matter for the resulting effects, then these are legacy effects or path-dependent effects, which can be difficult to visualize. Finally, this challenge also includes displaying the occurrence of temporally discrete events or interventions and the consequences that follow them (Healy and Moody 2014).

6. Visualizing uncertainty about causal relationships. This challenge includes expressing uncertainty about causation and displaying stochastic relationships. Causal relationships between variables are often not deterministic, but changes in one or several variables change the probability of a certain effect to occur. Additionally, it is a challenge to visualize the uncertainty of a causal relationship that is depicted, be it uncertainty whether the relationship is causal at all or about the possible strength of an effect (Spiegelhalter et al. 2011, Hullman 2020).

TYPES OF VISUALIZATION OF CAUSATION

We present an overview of three main types of visualization of causation that are commonly used in the literature on SES and related fields, and we discuss each visualization type's particular characteristics in the light of the challenges introduced above. On this basis, we assess whether a visualization type (1) cannot meet the challenge, (2) can partly meet the challenge, but requires

Table 1. Assessment of the presented visualization types according to the six visualization challenges. o Cannot meet the challenge. ✔ Can partly meet the challenge, requires specific adjustments. ✔✔ Broadly meets the challenge. ✔✔✔ Is especially suited to meet the challenge. The strengths and weaknesses of each visualization type are discussed in the main text. See also Table A1.1 (Append. 1) for further details supporting the assessment.

Visualization challenge	Objects and arrows			X-Y plots	X-Y-Z plots
	Conceptual diagrams	Causal diagrams	Network diagrams		
1 Causal vs. non-causal	✔✔✔	✔✔✔	✔	o	o
2 Characterize relationships	✔	✔	✔	✔✔✔	✔✔
3 Reciprocal relationships	✔	✔✔	✔	✔✔	✔
4 Multiple causes	✔✔	✔	o	o	✔✔
5 Temporal dynamics	✔	o	✔	✔	✔✔
6 Uncertainty	✔	o	o	✔✔	✔

specific adjustments, (3) broadly meets the challenge, or (4) is especially suited to meet the challenge (Table 1). The assignment to these categories is explained below and supported by a detailed consideration of how the different aspects of each challenge can be addressed by the different visualization types (Table A1.1, Append. 1). For illustrative purposes, we use a hypothetical SES as a main example (Box 1) and add examples from the literature where appropriate. It should also be noted that many visualizations mix these main types of visualization of causation and also may contain additional elements that do not fit into any of these types. We refer to examples of such combinations in below in the section "Visualizing Complex Causation in SES Research."

Box 1:

DemoViz: a model of a hypothetical SES. To create exemplary visualizations, we generated data for a hypothetical system with an individual-based simulation model. Here, we provide a short summary of the model. A detailed description following the ODD (overview, design concepts, and details) protocol for standardized descriptions of individual-based and agent-based models (Grimm et al. 2006, 2010, 2020) is given in Append. 2.

The assumed SES comprises a fish population in a river affected by river pollution, temperature, and fishing. Each fish individual is characterized by its body condition and location along the river. Both body condition and location change in time. The individuals' body condition is affected by the environmental variables river pollution level and river temperature, and differs among individuals. The individuals' locations are affected by river temperature only (representing movement to follow shifts of regions with favorable temperature along the river).

The population-level dynamics emerge from stochastic simulations of the individual-level processes according to the individuals' current attributes in each time step (corresponding to 1 year). The ecological processes comprise mortality, which is affected by body condition, and reproduction of individuals, which is affected by body condition and location. Besides natural mortality, the individuals can die through fishing. The social part of the SES is represented in a very simple form via the option to reduce river pollution, and via adapting the fishing pressure to the fish population size. Only above a certain threshold is fishing

carried out, and approximately 20% of the individuals are caught randomly. The simulation is run for 200 time steps, but the population may go extinct before.

Objects and Arrows
One of the most common ways of visualizing and explaining causation in complex systems is a diagram consisting of objects and arrows connecting them (e.g., Fig. 1). It visually represents a phenomenon in a system by its organized parts and relationships, proposing how these interact to bring about the phenomenon (Sheredos et al. 2013). When used for representing causal relationships, an arrow from object A to object B depicts that a change of A causes a change of B. If there is another opposite arrow from B to A (or the arrow is double-headed), the causation is reciprocal: there is a feedback between A and B, as a change of B also causes a change of A. These meanings of objects and arrows are very general and flexible. Yet they require a conceptualization of the system for which the causal relationships are visualized. In particular, the objects must be defined. They can be entities in the system (e.g., agents or other components), but also state variables or processes. It is also possible to connect different kinds of objects in one diagram.

The selection of objects and arrows to be included has important implicit consequences. The objects already determine which claims about causal relationships in the system are possible based on the diagram. The arrows depict which of these relationships are actually considered. Any further causal relationships the objects might be involved in, and any further objects not shown, are ignored. All details within an object are usually ignored too, i.e., the higher-resolution objects it is composed of and the causal relationships between them. This simplified representation of the real complex system (e.g., Fig. 1A) helps to focus only on elements and relationships that are considered essential for a given question (Starfield 1990, Grimm and Railsback 2005). But it is crucial to be aware of these decisions, and they should be made clear. Often they are not explicitly stated, but taken for granted with the diagram of objects and arrows. However, they guide and constrain all subsequent efforts based on this visualization. The diagram represents, so to speak, a certain worldview and leaves out elements that might in fact be important but are ignored in this worldview. This is not only a decision of where to draw the

boundaries and how to choose the resolution of the SES representation. Also, what kind of objects are depicted in a diagram matters. In ecology, a good example is whether ecosystems are perceived either as being composed of organisms or of compartments containing energy and nutrients. This decision strongly influences for which real-world phenomena a causal understanding can be achieved (Grimm et al. 2017).

Fig. 1. Visualizations of causal relationships based on the example model DemoViz (Box 1) by objects and arrows. (A) Conceptual diagram broadly visualizing causal relationships in the SES. Humans affect fish by polluting the river and by fishing. They also cause the change of climate, which in turn affects fish via river temperature. The arrows have different meanings, such as processes (e.g., fishing) or mediators (e.g., river temperature), which is expressed by the different arrow labels. The bottom arrow shows two relationships (two labels). The direction of effect of relationships is not specified (e.g., whether high or low temperature is better for the fish). One may interpret that the dashed arrow means that the causal relationship between humans and climate is not part of the analysis. However, this is not explicitly defined and should be explained in the figure caption. (B) Diagram of a causal chain that illustrates how river pollution by humans is mediated to eventually affect the fish population. Note that river pollution, which was a label for the arrow between objects (the relationship between entities) in A, is now an entity itself, as the causal relationship is visualized at a higher resolution.
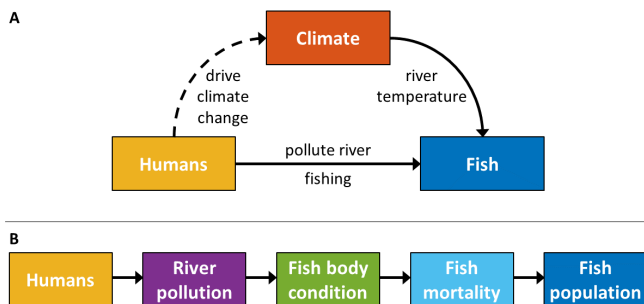
Potential. This visualization type can represent multiple causes by several arrows leading to an object. Thus, it can also indicate that a phenomenon emerges from the influence and interaction of these multiple causes. The visualization can also represent multiple effects by several arrows starting from an object. In addition to direct feedback between two objects (cf. above), indirect loops of causal relationships involving more than two objects can be visualized. An arrow starting from and looping back to an object can represent internal feedback. The causal relationship indicated by an arrow can be used to represent temporal order (i.e., termination of object 1 causes the start of object 2; e.g., in flowcharts). It can also represent flows of energy, matter, or information. The direction and strength of causal relationships can be visualized by using different widths or styles of arrows, or by labeling them. In any case, the absence of an arrow allows for a clear and even quantitative statement: there is no direct causal relationship between objects 1 and 2.

Limitations. Due to their versatility, visualizations with objects and arrows are used in many ways. This freedom can also be a drawback leading to confusion. Any intended meaning of specific shapes and styles of objects and arrows (e.g., Fig. 1A) should therefore be well explained in the figure captions. The meaning of arrows can remain unclear as they do not necessarily represent causal relationships. If they do, the possibilities of expressing different characteristics of these relationships are clearly limited. Even if the specific appearance of arrows can be varied to show differences, all these specifications are not inherent to the visualization. They might root implicitly in a presupposed common understanding of their meaning in the visualized context, for instance because this is established in a specific scientific discipline or methodological community. Preferably, they should be explicitly communicated in addition to the diagram, in particular with regard to the fact that SES research is interdisciplinary. Moreover, a single arrow does not specify the underlying mechanism(s) of causation. Additional objects involved in such mechanisms and any details within objects are not visualized according to the selected resolution or worldview. They are therefore also ignored. However, for showing these detailed objects and their relationships, such as causal chains, the same form of objects and arrows can be used too (e.g., Fig. 1B). This offers an important option for understanding and visualizing causal mechanisms.

Three subtypes of diagrams with objects and arrows are particularly relevant for causation in SES: conceptual diagrams, causal diagrams, and network diagrams.

Conceptual diagrams
Visualization by objects and arrows is very popular for conceptual diagrams, which are highly generic and flexible. They are ubiquitous in use for SES representations, visualizing conceptual models of the systems, but also frameworks and approaches to study them. Conceptual diagrams do not require strict formal rules. They may contain just a few objects and arrows (e.g., Fig. 1A) or many. To take into account the complexity of SES, different kinds of arrows, different kinds of objects (e.g., representing factors, actors, other system components, processes), multiple colors, layers, labels or pictures can be included, and diagrams can be nested (e.g., Lindkvist et al. 2020; Fig. A3.1, Append. 3). However, to be used meaningfully and unambiguously, these differences require careful explanation. Moreover, although very helpful for visualizing multiple causes and discriminating causal from non-causal relationships, the high flexibility comes at the cost of lower potential for conveying more specific or quantitative information, for instance on the shape, strength, or temporal changes of causal relationships (Table 1). As the numbers of objects and arrows increase, it can become difficult to grasp which causal relationships are indicated, and it becomes likely that only selected relationships will be grasped, ignoring how they are embedded and interact with additional system elements. Attempts to reflect the actual complexity of an SES can lead to a conceptual diagram containing plenty of objects and arrows in an almost arbitrary manner (i.e., everything is linked to everything). Although each object and link in such a diagram may be justified and have a meaning, the visualization is then of limited use for specifying and disentangling complex causal relationships. Nonetheless, it can be useful for demonstrating this complexity, showing that phenomena are intertwined and that simple, mono-

Fig. 2. Visualizations of causal relationships based on the example model DemoViz (Box 1) by causal diagrams. (A) Causal diagram of the system in dot and arrow format as it is represented in the simulation model. Each node depicts a specific state variable or process rate, each arrow depicts a causal relationship. The diagram includes instances of mediators (e.g., an indirect path from river pollution to fish mortality via fish body condition, which thus mediates the effect), multiple causes (e.g., two arrows leading to fish body condition), multiple effects (e.g., two arrows from river temperature), and reciprocal relationships (a direct loop between fish reproduction and population visualizing density dependence; an indirect loop involving fishing, fish mortality, and the fish population). This causal diagram is particularly useful for discriminating causal from non-causal relationships. For example, one might think that the fish location affects body condition, and also find them to be correlated. However, the diagram shows that there is no direct causal relationship between them (no arrow), but both are affected by temperature, which is therefore a confounding variable. (B) Causal loop diagram of a part of the system. Two state variable names (fish body condition, fish location) have been converted into clearly interpretable descriptions consistent with the "+" and "-" labeling scheme. This example combines stocks (e.g., fish population) and flows (e.g., fishing), and the loops are additive. The left loop is a balancing loop (one negative sign along the loop), whereas the right loop is a reinforcing loop (no negative sign).
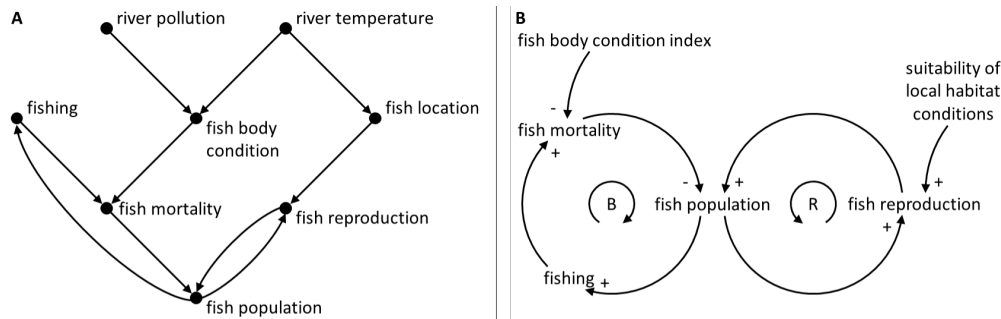
causal thinking is inadequate (e.g., Walker et al. 2009; Fig. A3.2, Append. 3).

Formal causal diagrams
Certain diagrams of objects and arrows follow a more specific formalism to represent causal relationships, for instance the dot and arrow format (e.g., Fig. 2A). Using such causal diagrams to visualize what we assume (or know) about the causal relationships in an SES makes these assumptions about the system more explicit and transparent, and allows inferences about their consequences. Causal diagrams in the dot and arrow format, with dots representing variables and the additional restriction that only unidirectional arrows and no cycles are allowed, can be used as tools for causal inference (Pearl and Mackenzie 2018, Lederer et al. 2019). To this end, the paths between dots can be traced, and common challenges for causal inference can be identified because they go along with characteristic structures in causal diagrams. For example, for a given arrow between two variables, a backdoor path is a path that leads to both of them from a third variable, which is therefore a confounder of the relationship. An indirect path connects the two variables in the same direction as the direct arrow, but via a third variable, which is therefore a mediator (Textor et al. 2016, Lederer et al. 2019). Such paths can be embedded in relationships involving many more than just three variables. Detecting them, as well as more complicated generic structures with specific meaning for causal analysis, is greatly facilitated by causal diagrams. Thus, the visualization serves as a robust and powerful tool that provides the basis for well-justified decisions whether certain variables must or must not be controlled for in causal inference. Without visualization, this would soon become much more difficult with an increasing number of variables and causal relationships between them (Pearl and Mackenzie 2018).

Although causal diagrams can be used for depicting stochastic causal relationships, the stochasticity itself is not visualized (Table 1). This means that it is not clear whether an arrow indicates, for example, that changes in one variable will sometimes, often, or always lead to changes in another variable that is linked by an arrow. Or an arrow connecting two events need not mean that the first event always causes the second. It may just modify the chances for the second event to occur.

Causal diagrams are also used to visualize structural equation models (SEM), a popular method for analyzing statistical associations between variables that then serve for causal interpretation (Shipley 2000, Grace 2006, Asah 2008, Fan et al. 2016). In these diagrams, in addition to arrows showing the direction, path coefficients indicate the strength and sign of relationships between variables (e.g., Palomares et al. 1998; Fig. A3.3, Append. 3). When applying SEM, the relationships that are included (i.e., the structure of the diagram) can be varied to test different models and select the preferred one based on fitting to data. Thus, the causal relationships that form the underlying conceptual model of the system would not be determined a priori but as a result of the system analysis (Eisenhauer et al. 2015). However, it is important to notice that the causal relationships cannot be derived from the associations between variables alone. Rather, these relationships need to be provided to the SEM as causal assumptions, and subsequent findings rely on careful interpretation (Bollen and Pearl 2013).

Causal loop diagrams are another popular type of visualizing causal relationships (e.g., Fig. 2B). They are a key tool in systems dynamics approaches to SES research (Elsawah et al. 2017, Radosavljevic et al. 2020). In these diagrams, arrows are labeled with "+" or "-" signs to indicate positive or negative relationships between the connected variables, respectively. The particular focus

of the diagrams is on closed loops involving two or more variables. If the number of negative signs along a loop is even, the loop is reinforcing, meaning that increases (decreases) in one variable feed back positively through the loop and further increase (decrease) that variable. If the number of negative signs along the loop is odd, the loop is balancing, meaning that increases (decreases) in one variable feed back negatively through the loop and decrease (increase) the variable. These features make causal loop diagrams highly suitable to visualize and characterize reciprocal causal relationships (Table 1).

However, when combining stocks and flows (as variables) in a causal loop diagram, the visualization is prone to misinterpretation because the "+" and "-" labels can have two different meanings: additive or proportional change. An additive arrow denotes that the first variable adds to the second variable (or, for the negative sign, subtracts from that variable). But two variables linked by a positive arrow do not necessarily change in the same direction (and vice versa for a negative arrow). For instance, fish reproduction adds to the fish population (Fig. 2B), but it is possible that fish reproduction decreases whereas the fish population increases (e.g., when the population approaches its maximum capacity). For proportional arrows, the two variables do always change in the same (or opposite) direction and thus are positively (or negatively) correlated (see Richardson 1997, Lane 2008 for details on this ambiguity of causal loop diagrams). Hence, thorough reflection and clarification of these meanings is strongly advocated when using causal loop diagrams.

Network diagrams
Network diagrams visualize objects and their pairwise relations as networks of nodes (objects) and edges (lines linking objects) between them (e.g., Fig. 3). The networks (also called graphs) can be used as abstract descriptions of structural aspects of studied systems, including SES (Borgatti et al. 2009, Dale 2017, Will et al. 2020). The nodes and edges can have flexible meaning. For instance, nodes may represent specific organizational units, such as individuals, populations, species, or spatial areas. Although nodes typically represent elements of the same type, this need not always be the case. For example, actor-network theory focuses on associations between different types of elements to investigate, among other things, how social processes influence a studied phenomenon (Latour 2005, Langley and Tsoukas 2016). Edges in network diagrams may represent proximity, flows, (potential) interactions or any other kind of associations between the elements. They can be undirected (edges only) or directed (edges with arrows), and they can have weights that, for example, express the distance between objects or costs, durations, or intensities of flows or interactions. This flexibility can lead to ambiguity. For example, when visualizing foodwebs with network diagrams, arrows can be used to represent predation (directed from predator to prey), flows of biomass (from prey to predator), or reciprocal causation between predator and prey abundance (bidirectional arrows). Edges without arrows are also common, which can represent any of these options.

Network representations of SES focus on structural aspects of the systems and thereby implicitly assume that interaction structure plays a key role in the systems' causations (Borgatti et al. 2009, Scott 2011, Levine et al. 2017). To analyze this structure, graph theory provides a variety of tools and metrics to assess,

among others, the spatial or functional connectance, density, nestedness, vulnerability, or node centrality of networks (Bollobas 1998, Butts 2009, Thébault and Fontaine 2010). The structure that is visualized in a network diagram often determines the framework for identifying causal relationships, for example, the potential interactions. But it is not equivalent to the actual processes operating in an SES, for example, the realized interactions.

Fig. 3. Visualization of the spatial connectedness of fish individuals at two points in time by network diagrams. Snapshots from a run of the example model DemoViz. A random subgroup of the fish population is shown, with dots representing individuals. Their number differs because individuals may die, and new ones get born in each time step. Two dots are connected if the two individuals' locations are within a neighborhood (defined by a maximum distance). In the diagrams, dots are placed arbitrarily such that the resulting networks are well displayed. They visualize that individuals are much closer to each other and thus more connected at time step 121 (A) than at time step 122 (B). The underlying, yet invisible cause is that temperature increased between these time steps and affected the individuals' locations (cf. Box 1, Append. 2).
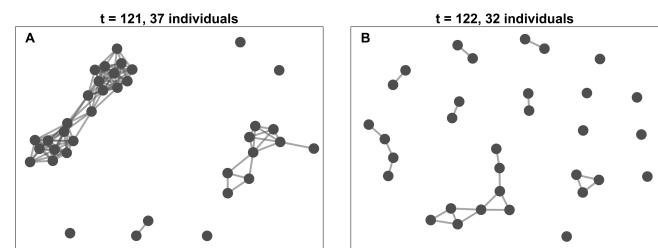

Networks can be used in two ways for deciphering causation in an SES. On the one hand, the structure has certain causes, that is, properties and dynamics of the system elements that led to the structure. On the other hand, the structure also has consequences as it enables, facilitates, or constrains processes in the system. In both cases, the network structure and its metrics can be regarded as patterns, and these patterns hint at the system's causal relationships (Bodin et al. 2019). However, such causal implications of the network structure are not conveyed by the visualization itself. They require interpretation and additional analyses and explanations. Nonetheless, the causal understanding is considerably supported by network diagrams, and its derivation can be straightforward. A network diagram of a foodweb implies that an abundant predator population causes a pressure on its prey population. A weighted network diagram of trading routes makes visible that closing a certain route could cause higher costs for trading partners using that route and higher usage of alternative routes. Here, the weights also serve to characterize the causal relationships.

X-Y Plots
This very common visualization type comprises two-dimensional line, point, bar, or similar plots relating two variables X and Y (e.g., Fig. 4). In this way, an X-Y plot reduces system complexity to just two chosen factors. The plot displays how different values of

X are associated with different values of Y. Given that Y is not constant, this means that changes in X are related to changes in Y. Very often, this visualization type is interpreted as indicating causation, meaning that changes in X cause changes in Y. This suggested causal relationship is mirrored by a common terminology, calling X the independent and Y the dependent variable. X-Y plots are appealing as they convey a simple message, which is easy to grasp and memorize. However, they also strongly evoke mono-causal thinking, ignoring complexity and context. X-Y plots often suggest a simplicity and generality that do not exist in reality.

Fig. 4. Visualization of DemoViz (Box 1) results for one run over 200 time steps by X-Y plots. (A) Line plot showing the number of fished individuals vs. time (often referred to as time series). This number drops to zero during several periods. The (invisible) cause is that fishing is adaptive and stops when the population size falls below a threshold (cf. Box 1). (B) Bar plot comparing the total amount of fished individuals over the whole simulation period for two different scenarios. The visualization suggests that the intervention (reduced river pollution) is the cause for the higher amount of fishing, which is correct. (C) Point plots of the body condition of fish both at the individual and the population level (cf. legend) vs. river pollution. The visualization suggests a causal relationship from river pollution to body condition. This relationship exists, but is not that simple as pollution is not the only factor affecting body condition (cf. Fig. 2A). (D) Point plot of population growth vs. population size of the previous time step. It makes the causal relationship visible that large population sizes do not allow for high reproduction. However, for small population sizes reproduction can also be low, driven by different causes that are not shown.
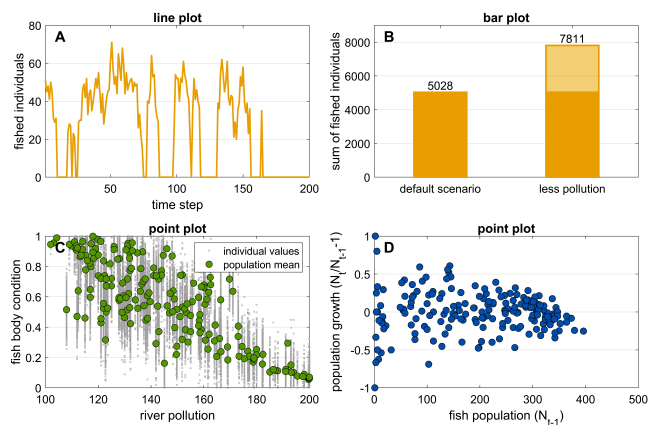
There are exceptions of X-Y plots for which the visualized relationship is clearly not meant to indicate causation. The independent variable may be a mere criterion for discriminating different cases, such as the names of different agents or places, or the ranks of different items according to their associated Y value (e.g., species rank-abundance plots, May et al. 2016; Fig. A3.4, Append. 3). Also time series, plots in which time is the independent variable on the X axis (e.g., Fig. 4A), do not imply that time is the direct cause for change of the dependent variable (although time is usually involved in such change).

Potential. This visualization type is standard and extremely useful for depicting the relationship between one potential cause and one effect. In X-Y plots, the detailed characteristics of such a relationship can be made visible right away, such as its direction, strength, nonlinearity, or non-monotony, and also critical thresholds (Table 1). The relationship can be shown at high resolution of the variables' values. Variations, uncertainty, or confidence can be incorporated, for instance by individual values underlying a mean (Fig. 4C), error bars, intervals around the plotted curve, or symbols and labels for the results of statistical tests (e.g., tests whether data from different treatments have a common mean). In time series, the time points/periods of occurrence of events/treatments/interventions can be highlighted. This facilitates inspection whether those changes, which are not plotted themselves, are related to changes in the plotted Y variable. For the same purpose, one can plot two time series, one for the (potential) causal and one for the effect variable, or even more to consider multiple effects. Generally, using multiple lines/points/bars differing in style or color can overcome the restriction to only one Y variable (sometimes also using two different Y axes). This strategy can be used to visualize different instances of an additional variable (cf. "Multiple Plots of the Same Visualization Type" below). But within one plot, these potentially dependent Y variables all need to be related to the same independent X variable.

Limitations. Apart from depicting the relationship to only one (potential) cause, the most important limitation of X-Y plots is that it is not possible to visually discriminate causation from mere covariance (Table 1). For instance, two variables might show a strong relationship not because X is the cause of Y, but because both are affected by a common cause C that confounds their relationship but is not shown. This is crucial and makes the plot amenable to mis- or over-interpretation. It adds to the problem that depicted relationships, even if they are causal, can be modified in complex systems by additional factors. Information about such factors and context, as well as mechanistic interpretations of causation behind depicted relationships, is not conveyed by the plot itself. These aspects require additional explanation. The same is true for underlying statistical models and assumptions, if uncertainty is included in the visualization.

It is also possible to plot the values of an independent variable X together with the change of that variable (dX/dt as Y variable). This allows visualizing the feedback of a variable X on itself (e. g., Fig. 4D). However, it also separates this self-feedback from its context and suggests ignoring the additional causes for changes of the X variable.

To visualize the reciprocal relationships between two variables, phase space plots can be used. These X-Y plots show the trajectories of combinations of two state variables (value pairs of X and Y), denoting changes over time in the phase space of possible states of a system (e.g., Fig. 5A). They usually imply that X and Y are causally related in both directions. In addition to visualizing possible combinations of X and Y, a trajectory also shows that for a given value of one variable, various values of the other variable are possible.

Fig. 5. Visualization of trajectories of combinations of two variables by X-Y plots. (A) Phase space plot showing observed numbers of Canadian hare and lynx individuals (thousands) from 1875 to 1906. The two populations are prey and predator and thus involved in a reciprocal causal relationship. However, the visualization does not allow clearly discriminating whether this predator–prey relationship, an alternative relationship of disease transmitted from hare to lynx, the relationship between hare and its food, or the relationship from human hunters to both populations is the major cause for the system dynamics. Source and further details: Gilpin (1973). Figure used with permission by the University of Chicago Press. (B) X-Y plot showing hysteresis in a hypothetical dynamic ecosystem with alternative stable states (Y axis). Arrows visualize the temporal development, including abrupt changes (catastrophic shift or restoration) when the environmental conditions (X axis) cross a tipping point (black dots). Ecosystem states between the solid black curves are not stable, they cannot be maintained over time. The dashed curve separates unstable states from which the ecosystem would return to the upper "conserved" stable state (blue area above the dashed curve) and states from which it would return to the lower "degraded" stable state (area below the dashed curve). The blue arrow depicts a disturbance. Source and further details: van den Elsen et al. (2020). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).
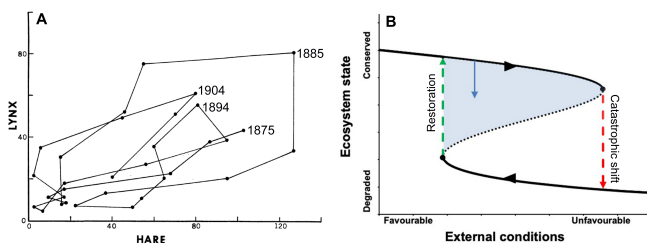

When X depicts an environmental driver and Y depicts a state variable, the effect that the driver has on the system state can depend on the current state of that system (e.g., Fig. 5B). Thus, both X and Y have an effect on changes in Y, leading to alternative stable states for the same value of the driver variable X. There may also be tipping points (Milkoreit et al. 2018), which means that the state variable changes abruptly when the driver exceeds a certain threshold. Even if the driver variable changes back, potentially very far from the threshold, the state variable does not reach the same values as before. It is possible that two tipping points exist, meaning that the state variable changes back (abruptly) only if the driver exceeds another threshold. This phenomenon of path-dependence causing alternative stable states (hysteresis) is common for SES, and X-Y plots are popular for visualizing it (May 1977, Scheffer et al. 2001, Hughes et al. 2013, Sguotti et al. 2019). Typically, the trajectories of the different stable states are connected with dashed or dotted lines to visualize that the corresponding combinations of X and Y values belong to unstable states (cf. Fig. 5B).
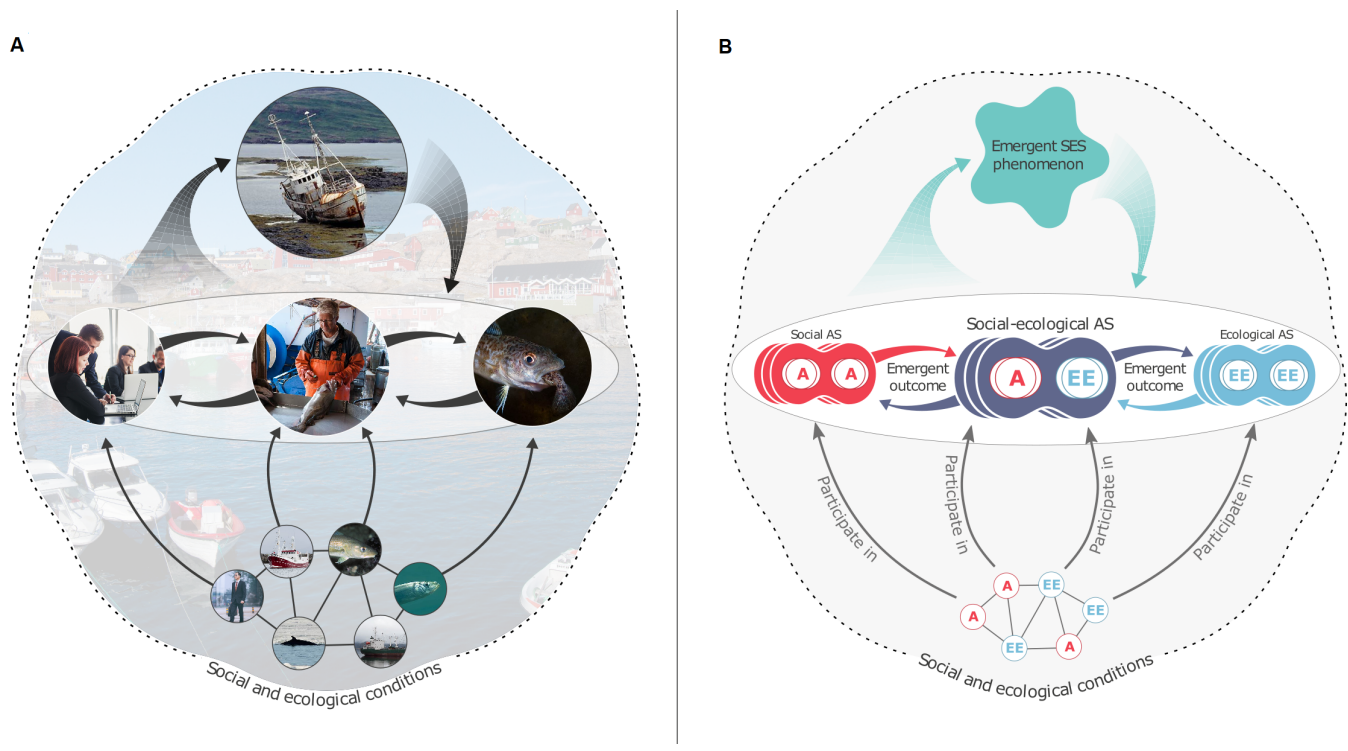
X-Y-Z Plots

This visualization type includes three variables. Here, X and Y are two independent variables, and Z is the dependent variable shown for different combinations of values of X and Y (e.g., Fig. 6). This is realized, for example, by two-dimensional contour or raster plots, or by three-dimensional surface or point plots. Thus, two potential causes and their effects on Z can be visualized together. This is an important step toward visualizing complex relationships in the system represented. The downside of this added complexity is that the plots can be more difficult to grasp compared with X-Y plots. And similar to X-Y plots, there remains the pitfall of perceiving depicted relationships as causal even though this may not be the case (Table 1).

Fig. 6. Visualization of DemoViz (Box 1) results for one run over 200 time steps by X-Y-Z plots. (A) Point plot of fish body condition (population mean of individual values shown) vs. river pollution and temperature. Both pollution and temperature are causally related to fish body condition (cf. Fig. 2A). A linear fit to the relationship is plotted as a gridded plane. It approximately captures the depicted relationship and helps in discerning where the points are. However, the points' exact positions in the X-Y-Z space and how much they deviate from the linear fit are difficult to determine. (B) Raster plot of the linear fit of the same relationship (background colors, constrained to the interval [0, 1]) and single points for values of fish body condition visualized by color (cf. color bar). The background raster plot visualizes the trends of body condition increasing with decreasing river pollution and with increasing temperature. The colored points reveal that the single points approximately follow this trend, but also show considerable deviations. Some deviations are easier to discern than in plot (A) due to the color differences.
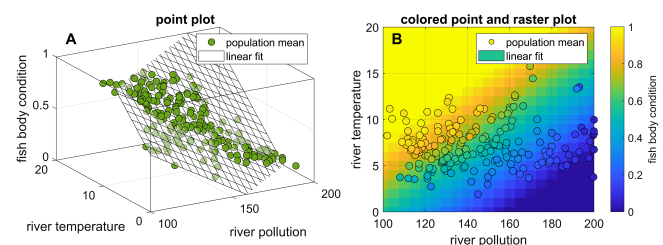
Potential. The visualization of two independent variables enables inspecting and presenting effects that emerge from their interaction. The characteristics of their relationship to the dependent variable get visible, including nonlinearity or critical thresholds. Even highly multifaceted relationships can be quantitatively shown. Similar values of Z for different combinations of X and Y values show that different regimes are similar in terms of their associated effect on Z. This can point to trade-offs between two causes and to options for buffering or compensating for negative effects of one factor by changing a second factor. In particular, the second factor can be a moderator or a variable representing the context and, thus, the dependence of the relationship between X and Z on this second factor Y is visualized. If time is the Y variable, changes of a relationship over time are depicted, although time is not considered a direct cause

Fig. 7. Visualizations of a conceptualization of SES by objects and arrows, illustrating an analytical framework for analyzing emergent social-ecological phenomena. (A) The collapse of a fishery (top object) emerges from and affects "action situations" in which policy makers, fishers, and fish populations interact (middle objects). These diverse action situations affect each other (arrows between middle objects) and they each involve a different network of actors and system components (exemplified by bottom objects). (B) More abstract and generic visualization of the framework, highlighting how an SES phenomenon emerges from and again influences social, social-ecological, and ecological action situations (AS, middle objects). The AS also influence and emerge from their effects on each other (arrows between them). Each of these AS objects involves several instances of participating actors (A) and/or ecological entities (EE) (arrows from bottom objects). An example network of interactions between these A and EE is visualized by lines connecting them. The figure uses different kinds of objects, arrows, colors, labels, layers, and photographs to convey different types of entities and causal relationships that let the SES phenomenon emerge. Frames around the diagrams show that all this is considered in its context of social and ecological conditions. Source and further details: Schlüter et al. (2019). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

for changes of the dependent variable (cf. above). X-Y-Z plots can also be used to visualize the possible combinations of three variables that describe a system state and may all affect each other (e.g., Radosavljevic et al. 2020; Fig. A3.5, Append. 3). Or, comparable to X-Y plots (Fig. 5B), they can visualize that and how the relationship between two variables changes from bistability to a single stable state depending on the value of a third variable (the "cusp" model in catastrophe theory, e.g., Petraitis and Dudgeon 2016, Sguotti et al. 2019; Fig. A3.6, Append. 3).

Limitations. Also in X-Y-Z plots, causation cannot be visually discriminated from mere covariance. Moreover, it can be difficult to accurately discern the characteristics of relationships. Transferring visual differences of colors into quantitative differences of Z values is susceptible to errors (Fig. 6B). Exactly determining the positions of points or a surface in a three-dimensional space, which must nevertheless be plotted as a two-dimensional figure, is not always possible (Fig. 6A). Visualizing uncertainty about relationships is difficult and usually requires an additional plot, for example of the variation of Z values for

different combinations of X and Y values. If time is chosen as the second independent variable Y, the benefit of showing the temporal development of the relationship between X and Z comes at the cost of not showing the interaction with a second potential cause.

VISUALIZING COMPLEX CAUSATION IN SES RESEARCH

The presented characteristics, potentials, and limitations of the different visualization types provide a sound basis for choosing the appropriate visualization of causation in an SES depending on the intended purpose. Nonetheless, this means that a decision needs to be taken as to which—often substantial—aspects of the complexity of the SES will be disregarded and which aspects will be brought into focus. For example, recent advances developed ways to visualize multiple and complex causal relationships that bring about an emergent phenomenon of interest in an SES, such as a fisheries collapse, through elaborate conceptual diagrams with objects and arrows (Fig. 7). A distinctive feature here is that

Fig. 8. Visualizations of a network of action situations that lead to an emergent SES phenomenon by objects and arrows. The diagram follows the approach described by Schlüter et al. (2019, cf. Fig. 7) for the hypothetical SES used in the DemoViz model. The social-ecological (dark blue) and ecological (light blue) action situations can lead to the collapse of the fish population. (Purely social action situations are not included in this example, cf. Box 1.) The action situation "Fish life" comprises fish movement, changes in fish body condition, and fish deaths through natural mortality (cf. Append. 2 for details). How emergent outcomes of one action situation affect another action situation is visualized by labeled arrows between them. For instance, the fish movement in response to the river temperature affects the individuals' locations and, thus, their spatial connectedness (cf. Fig. 3), which affects fish reproduction. Temperature is an external driver of the action situation "Fish life", visualized by a gray dashed arrow.
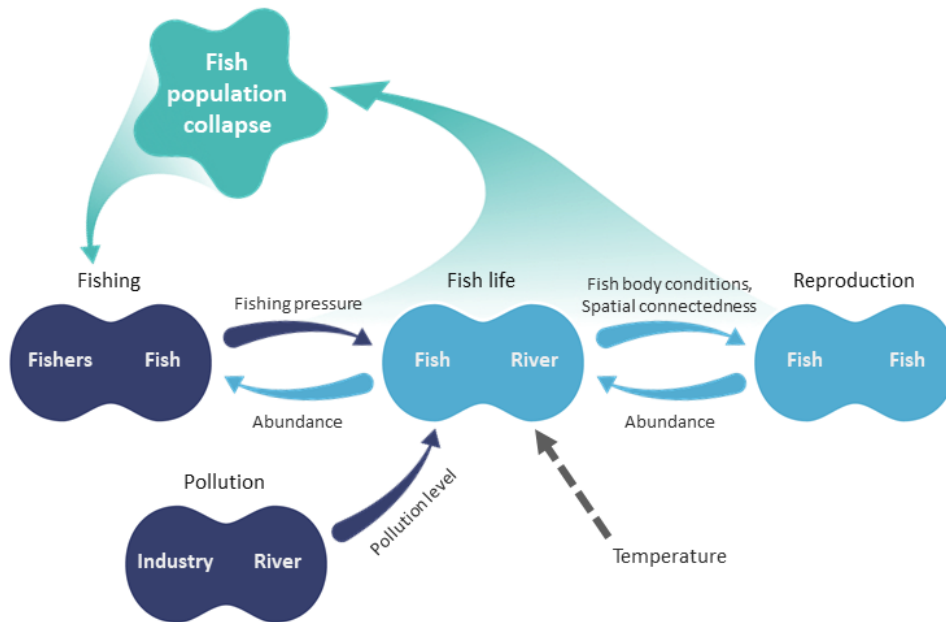
several levels of organization are visualized: from single actors and ecological entities over the action situations they participate in as well as networks of action situations, to the overall emergent phenomenon. Implicitly, such a figure also communicates that (and why) the phenomenon is complex as it is produced by multiple interacting processes. The approach to visualize networks of action situations can be applied to a specific case, for example the hypothetical SES used for the DemoViz model (Fig. 8, cf. Box 1). Based on such visualizations, the analytical framework can be used to develop hypotheses about causal mechanisms that generate SES phenomena (Schlüter et al. 2019, Orach and Schlüter 2021). These possible explanations can then be further examined through empirical research or modeling.

If the focus of a visualization, however, lies in supporting causal inference of relationships between variables in an SES, more formal causal diagrams are often the appropriate choice (Fig. 2). On the other hand, the focus may also lie in presenting specific causal relationships, ignoring the wider SES context they are embedded in for the sake of visualizing the particular shape, tipping points, or reciprocity of a relationship in an X-Y plot (Figs. 4, 5) or, for instance, interactions of two causal variables in an X-Y-Z plot (Fig. 6).

Multiple Plots of the Same Visualization Type
An important option for widening the focus and visualizing complex causation is bringing together several plots of the same

type in one figure. This allows increasing the number of causes to be shown, the number of effects, or both. For example, multiple X-Y plots in one figure depicting the same relationship between one causal and one effect variable for different instances of a second cause (i.e., different contexts) can show how two causes interact (Fig. 9, different columns). At the same time, the precise quantitative visualization of the depicted relationship provided by X-Y plots is maintained. Moreover, depicting the relationships between one causal and several effect variables in multiple X-Y plots further adds complementary information to these relationships, respectively (Fig. 9, different rows). This may, for instance, visualize trade-offs between different effects of changing one cause. The principle of multiple X-Y plots can be extended, for example, by using the X axes, different columns, different rows, and different line colors to show the effects and interactions of four different causal variables (e.g., Banitz 2019; Fig. A3.7, Append. 3). However, it needs to be mentioned that the data needed for such comprehensive visualizations of an effect variable for all combinations of relevant values of the causal variables are rarely available, except for computational models of SES, where conditions can easily be controlled and resulting system state variables obtained (Schulze et al. 2017, Schlüter et al. 2019).

The same principle of multiple plots can also be used with other visualization types. With X-Y-Z plots that already show the interaction of two causes, a third cause or context can be added (Fig. 10). Similarly, this can be achieved by nested rows and

Fig. 9. Visualization of complex causation for a modeled generic agricultural SES by multiple X-Y plots. Rural farmers invest a certain percentage of their assets in individual household activities (X axes) and give the remaining percentage to the community. The single plots show how these investment decisions affect the household- and community-level assets (Y axes) and, thus, poverty. Different columns are used to visualize the effects of a second cause or context, namely the operating poverty trap (column titles). These poverty traps result from mechanisms that involve several additional causes, which are not shown in the figure. Different rows are used to discriminate between two effects. They visualize how farmers' decisions and the operating poverty trap affect the assets of the whole community (top) and of individual households (bottom). Note that, in the single plots, different values of assets are possible for the same values of investments as the modeled dynamical system has multiple stable equilibria (attractors, red line plots). Source and further details: Radosavljevic et al. (2021). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).
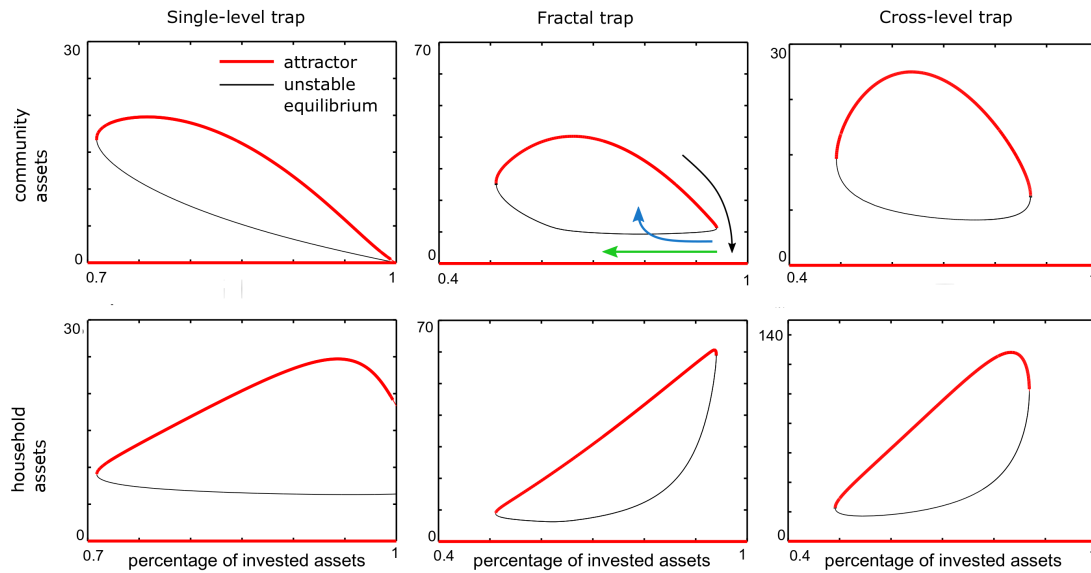

Fig. 10. Visualization of complex causation in a modeled fisheries SES in Northwest Mexico by multiple X-Y-Z plots. The single plots show how the two causal variables "fishing cooperatives' loyalty" (X axes) and "variation of the fishers' reliability" (Y axes) affect the proportion of all fishers that do not directly contract with a fish buyer, but instead become members in a cooperative (visualized by color, cf. color bar). The two causes are varied in three discrete categories (three steps on the X and Y axes). Thus, broad effects are clearly shown, but detailed shapes of the relationships are not in focus. Different columns are used to visualize the effects of a third cause, namely fluctuations in environmental conditions (column titles). Source and further details: Lindkvist et al. (2017). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).
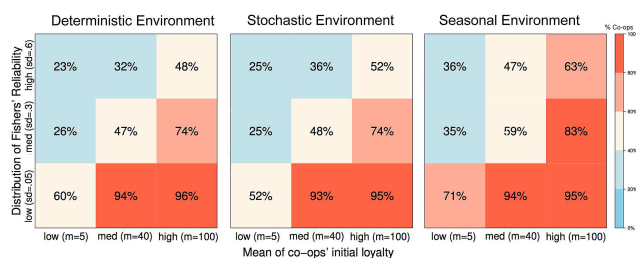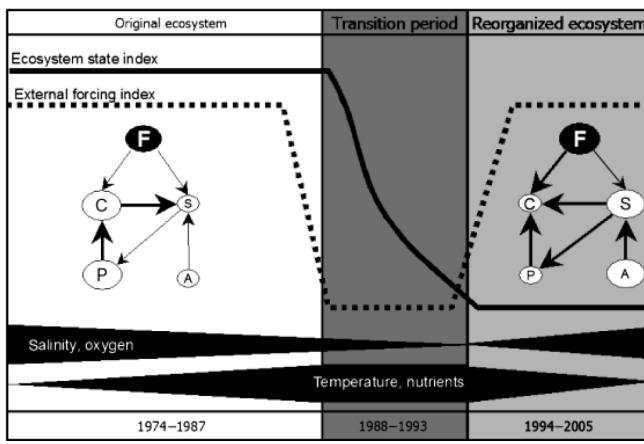

columns for multiple causes in a table and visualizing their combined effects by colors (e.g., Ferguson et al. 2020; Fig. A3.8, Append. 3). Combining multiple network diagrams in one figure can be used to show how networks, and thus their associated causes and effects (cf. "Network Diagrams" above), change in different contexts (Fig. 3; see also Bodin 2017; Fig. A3.9, Append. 3).

Combining Visualization Types
Combining different visualization types in one plot is another common and useful option for visualizing complex causation in SES. This strategy allows benefiting from the respective strengths of each visualization type (cf. "Types of Visualization of Causation" above). For example, X-Y plots showing the temporal development of an SES state and of underlying causal variables can be amended by objects and arrows diagrams showing the internal SES organization for different points in time (Fig. 11). Thus, the state of system entities and the causal relationships between them are integrated into the visualization and support causal understanding of the depicted temporal developments. Vice versa, X-Y plots can be inserted in a diagram of objects and arrows to illustrate the specific shape of the visualized relationships between different system variables (e.g., Banitz et al. 2020; Fig. A3.10, Append. 3). In another example from the SES literature, the combination of X-Y plots with objects and arrows visualizes causal relationships between trophic groups in a

Fig. 11. Visualization of complex causation in a modeled fisheries SES in the Baltic Sea by combining an X-Y plot and network diagrams. The time series show the temporal development of several environmental variables (labeled black areas) and an index aggregating them (dashed line). Although the environmental conditions are similar in the first and third period shown, the ecosystem state (straight line) is very different. This is explained by network diagrams that show the biomass of different species populations (white node sizes, C – cod, S – herring, P, A – zooplankton species *Pseudocalanus acuspes* and *Acartia* spp.), the extent of fishing pressure (black node size), and the direction and strength of causal relationships between these SES entities (black arrows). Through the network diagrams, the figure aims to visualize that the changing environmental conditions during the second period have (together with fishing pressure) caused a transition to a different system state, which is difficult to reverse despite favorable environmental conditions. Source and further details: Möllmann et al. (2009). Figure used with permission by John Wiley and Sons.

Fig. 12. Visualization of complex causation in a fisheries SES in the North Atlantic by combining different X-Y-Z plots. The three-dimensional surface plot depicts the effects of two causal variables (fishing mortality and sea surface temperature) on cod biomass according to a theoretical "cusp" model. The "cusp" shape of the surface visualizes the interaction of both causes: depending on temperature, the relationship between fishing and cod biomass is either continuous or discontinuous (hysteresis, cf. surface edges). Dots on the surface depict particular empirical values of cod biomass over time, whereby dot size is used to visualize biomass and dot color to separate two periods (cf. legend). The plot is mapped onto an X-Y plane (bottom), and a section of it visualized by a two-dimensional plot (left). This is again an X-Y-Z plot with the two causal variables on the axes and their effects on cod biomass visualized by the position and size of the dots. The dots are connected to visualize their sequence in time. The background blue area depicts the combinations of values of the two causal variables for which the model is discontinuous, as visualized in the surface plot. Source and further details: Sguotti et al. (2019). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).
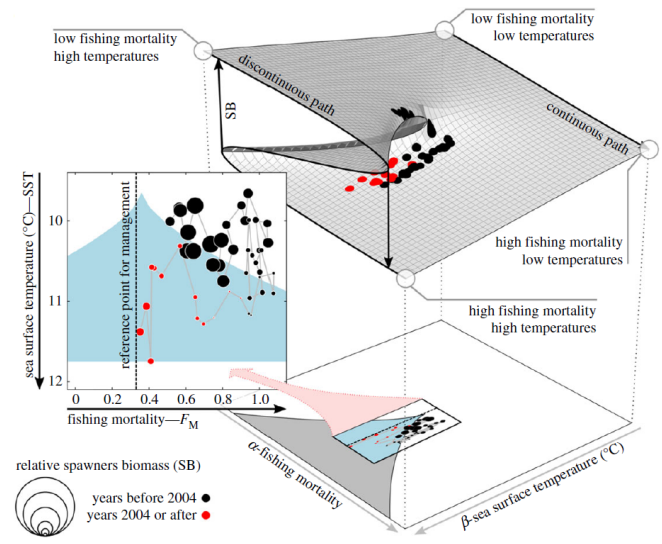

modeled marine ecosystem and quantitatively shows certain preconditions for these trophic interactions to occur as well as certain effects they have (van Leeuwen et al. 2013; Fig. A3.11, Append. 3).

It is also possible to combine different X-Y-Z plots and thus visualize the interaction of two causes both in three dimensions and—in a more precise quantitative manner—in two dimensions (Fig. 12). However, a disadvantage of such nonstandard multifaceted visualizations is that they may easily get very complicated. They require extensive explanation, and grasping the depicted causal relationships is not always intuitive. If used, readers should therefore always be guided through the visualizations in order to fully explain the intended causal claims.

The visualizations presented so far can also be combined with additional types. One example are set diagrams that visualize sets by closed areas (e.g., circles). Set diagrams are widely and flexibly used, for instance, to visualize an SES conceptualization for studying poverty traps, according to which economy is part of a society, and this society is part of the biosphere (e.g., Lade et al. 2017; Fig. A3.12, Append. 3; see also Folke et al. 2016). In Venn

diagrams, overlap of two areas represents overlap of sets, that is, elements that belong to both sets. The same principle works for more than two sets. Integrating a Venn diagram in an objects and arrows visualization can be used to illustrate complex causation in an SES, for instance, the contribution of different causes to an effect. A typical situation is that different factors alone are insufficient to cause an effect. However, they necessarily belong to a particular combination of factors that causes the effect. As this combination is not the only way to bring about the effect, it is sufficient but unnecessary (e.g., Fig. 13A). Such "insufficient but necessary parts of unnecessary but sufficient" (INUS) conditions were defined by Mackie (1965) and are employed to disentangle complex causation in social and social-ecological research (Mahoney 2008, Morgan 2013, Meyfroidt 2016, Carlson et al. 2018). The combination of a Venn diagram with a network diagram can also be used to integrate visualizing subsets of

Fig. 13. Visualization of complex causation by combining Venn diagrams with objects and arrows. (A) The institutional collapse in Brazil in 1964 (Y) was hypothesized to be caused by three characteristics of the Brazilian state and society (X1-3). Labeled arrows visualize that each of these factors is an INUS condition, and their combination (i.e., a Brazilian state and society with all three characteristics) is a sufficient condition causing the collapse. Additionally, the size of the areas is used to indicate the strength of each factor. Source and further details: Amorim Neto and Rodriguez (2016, adapted from Santos 1986). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/). (B) Visualization of potentially relevant elements (white circles) of a fisheries SES in northern Australia. The elements are assigned to different SES components by placing them in boxed areas A–E. Gray areas visualize the overlap of these elements with a subset that is included in a particular model analysis. Only these selected components and their interactions can cause the modeled dynamics. For the ecological SES component, causal relationships in terms of species interactions are visualized by a network diagram. This includes relationships with species outside the gray area, showing that these are neglected in the model. Source and further details: Plagányi et al. (2014). Figure used with permission by John Wiley and Sons.
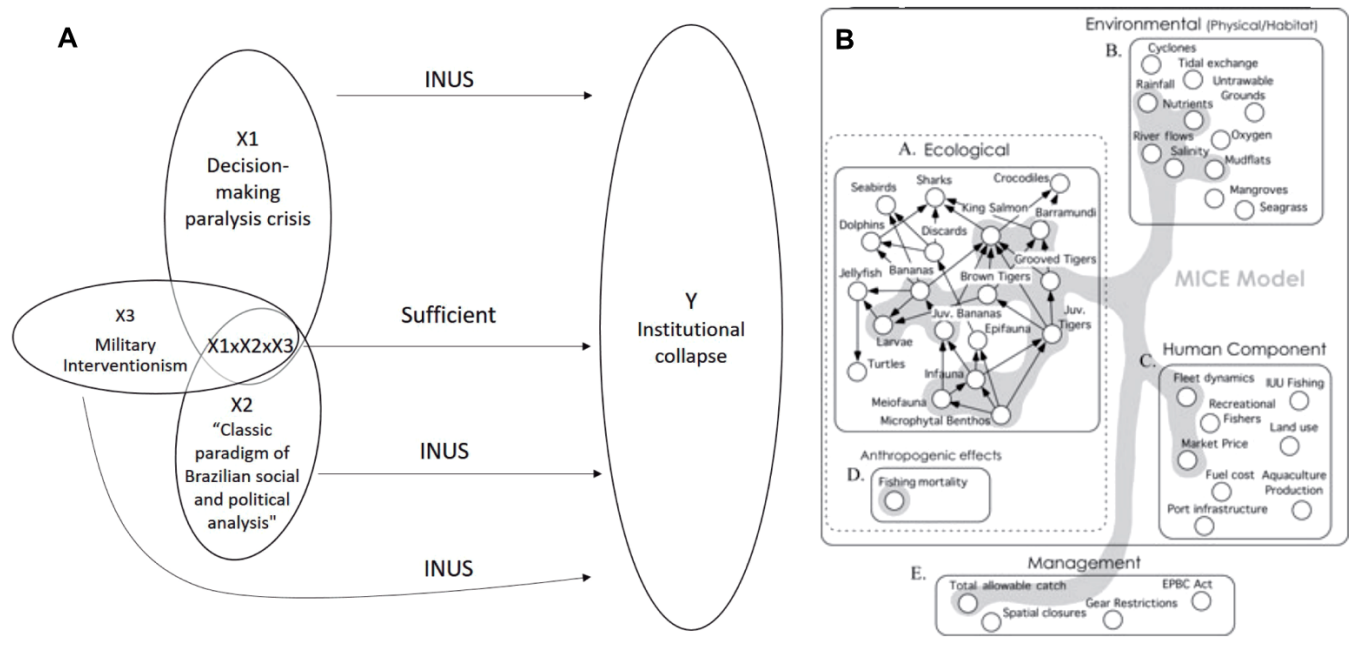
potential factors that are included in an analysis and visualizing causal relationships between these factors (e.g., Fig. 13B).

CONCLUSION
We have highlighted that visualizing causation in SES poses significant challenges, but there are promising ways to overcome them. A prerequisite for using visualizations to present and explain complex SES phenomena is to be aware of the key visualization challenges ("Challenges for Visualizations of Complex Causal Relationships" above) and the strengths and weaknesses of the different types ("Types of Visualization of Causation" above). In summary, the high flexibility of diagrams of objects and arrows is excellent for visualizing complex causation, but can easily lead to ambiguities, so consistency and explanation are critical. Moreover, the biggest limitations of these diagrams are their poor capability to show the characteristics of singular causal relationships and to visualize temporal dynamics and uncertainty. X-Y plots and X-Y-Z plots are more suitable for these challenges, but strongly limited in discriminating causal from noncausal relationships and visualizing multiple causes (Tablea 1, A1.1). Our assessment enables the informed selection of the appropriate visualization type depending on the research question, the purpose (e.g., visualizing assumptions, visualizing

results, or visualizing a conceptual framework of a causal analysis), the knowledge about causal relationships in the SES, and the properties and part(s) of the system that shall be the focus of a figure (cf. specific exemplary recommendations at the beginning of "Visualizing Complex Causation in SES Research" above).

Ideally, figures speak for themselves and their messages are straightforward and fully comprehensible. But a correct and complete understanding of a figure may also rely on certain implicit assumptions. These may be familiar to researchers with a common scientific background. However, tacitly assuming specific knowledge and interpretation along with a visualization risks confusing readers who are unfamiliar with them, even more so because SES research is highly interdisciplinary. For these reasons, information that is needed to correctly understand a figure, or that is needed to communicate an aspect of causal analysis not conveyed by the figure, should be explicitly added with explanatory text. The respective caption should aim at clearly guiding readers through a figure, almost as one would do in presentations. This guidance can be critical to get the meaning and causal implications of a visualization unambiguously understood. One practical option to support this is to use

numbered labels and, in the figure caption, make readers grasp the figure sequentially by "walking" from element to element (e. g. Lindkvist et al. 2020; Fig. A3.1, Append. 3).

For diagrams of objects and arrows, such guidance can also help readers to mentally animate visualizations and, thereby, comprehend how an SES phenomenon is caused by the operation of several processes. This works particularly well for sequential processes. But also in the case of simultaneous processes that let a complex phenomenon emerge, the visual summary of these processes can support causal reasoning and provide a sound basis for the design of analytical tools such as computational models (Jones and Wolkenhauer 2012, Sheredos et al. 2013).

Besides relying on mental animation, a recent additional option is to create actual animations of visualizations (e.g., Anderson 2013, Grossman et al. 2016). Similar to their use during a presentation, animations can be used to visually tell a story about how an SES is organized and functions, in other words, to develop a causal narrative (cf. Shepherd and Suddaby 2017). This option can be appropriate for all three main types of visualization presented. Applied to X-Y and X-Y-Z plots, animations can also be used to visualize the changes of relationships over time, overcoming the challenge of visualizing temporal dynamics while retaining other strengths, such as the precise characterization of relationships (cf. Table 1). Most journals allow for animated visualizations in the supplement, whereas including them in the main manuscript is rarely possible. However, there are attempts to encourage the latter and keep the manuscript still comprehensible when printed on paper (e.g., with additional static figures as placeholders; Grossman et al. 2016).

Most visualizations used in science aim for simplicity so that the key message of a figure is easy to grasp and memorize. For complex causation, however, this design principle can be counterproductive as it suggests a level of simplicity that plainly does not exist. We therefore see a particularly promising way for overcoming the challenges of visualizing complex causation in SES ("Challenges for Visualizations of Complex Causal Relationships" above) in the combination of multiple visualizations in one figure.

Multiple plots of the same visualization type ("Multiple plots of the same visualization type" above) can be used to show specific causal relationships between variables in different contexts or for different values of additional variables. Thus, they visualize interactions and common emergent effects of multiple causes. The approach can also be used to visualize multiple effects of the same cause(s) within one figure (e.g., Fig. 9). As this principle of adding causes and effects by multiple instances of the same visualization works for all types, their specific potential for visualizing different aspects of complex causation in SES can nonetheless be exploited.

An alternative way to exploit this potential are well-designed combinations of different visualization types in one plot ("Combining visualization types" above). If one is careful not to overcomplicate these combinations, they can provide otherwise impossible comprehensive pictures that simultaneously tackle several of the presented visualization challenges. This considerably helps to disclose the complexity of SES phenomena and prevents unduly simple causal interpretations. However, especially when using creative and less common ways of combining different visualization types, careful and consistent design and thorough guidance in accompanying captions are crucial. Otherwise, they risk being of little value: although containing a large amount of heterogeneous information, they do not serve their main purpose of conveying causal insights to a broad interdisciplinary readership.

Thus, we assert that visualizing causation in complex SES remains an often difficult task and simultaneously addressing many, let alone all, of the identified challenges is virtually unfeasible. A single figure will not capture and characterize all causal relationships that are relevant for the fate and functioning of an SES. Simple figures remain important and useful, for example when putting the visualization focus on subsystems, on specific aspects of complex phenomena, on selected causes and effects. But they should be complemented by figures with combinations of visualizations to remind ourselves that causation in SES is more complex than our common way of thinking in terms of simple causal relationships and linear causal chains—and more complex than common visualization types may suggest. By being aware of this pitfall, and of the strengths and weaknesses of the different types of visualization, we will be well equipped to use visualizations to do justice to the complexity of SES and support a better and more comprehensive causal understanding.

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Data Availability:

Data/code sharing is not applicable to this article because no data/ code were analyzed in this study.

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Appendix 1. Table on visualization challenges

Table A1.1. Details supporting the assessment of visualization types according to the specific aspects of the challenges presented and explained in Section 2 in the main text. No entries denote that the visualization type is, to our knowledge, typically not used to address the respective aspect of the challenge. Categories for overall assessment: **o** Cannot meet the challenge. ✓ Can partly meet the challenge, requires specific adjustments. ✓✓ Broadly meets the challenge. ✓✓✓ Is especially suited to meet the challenge (cf. Table 1).

Visualization challenge	Specific aspect of the challenge	Objects and arrows			X-Y-plots	X-Y-Z-plots
		Conceptual diagrams	Causal diagrams	Network diagrams		
1 Visualizing whether a relationship is causal	Discriminating causation from mere covariance	suitable	suitable	possible (only for potential causal relation-ships, excludes causation when no connection)		
	Confounding	suitable	suitable	conceivable (for potential confounding)		
Overall assessment		✓✓✓	✓✓✓	✓	o	o
2 Visualizing the characteristics of causal relationships	Discriminating positive from negative relationships	possible (arrow labels)	suitable (e.g. +/- labels)		suitable	suitable
	Strength of relationships	possible (arrow styles)	possible (e.g. SEM path coefficients)	possible (weighted edges)	suitable	suitable
	Shape of relationships (incl. nonlinearity, discontinuities)				suitable	suitable (discerning exact shapes can be difficult)
Overall assessment		✓	✓	✓	✓✓✓	✓✓

Visualization challenge	Specific aspect of the challenge	Objects and arrows			X-Y-plots	X-Y-Z-plots
		Conceptual diagrams	Causal diagrams	Network diagrams		
3 Visualizing reciprocal causal relationships	Feedback	suitable	suitable	possible (only for potential feedback)	possible (phase space plot)	possible (phase space plot)
	Hysteresis				possible	possible
	Cyclic dynamics		possible (e.g. causal loop diagrams)		possible (e.g. phase space plot)	possible (e.g. phase space plot)
Overall assessment		✓	✓✓	✓	✓✓	✓
4 Visualizing multiple causes	Equifinality	suitable	suitable			suitable (two causes)
	Moderation, context-dependence	conceivable (e.g. arrows pointing at arrows)				suitable
	Emergence	possible (e.g. arrow labels)				suitable (for emergence from interactions of two causes)
	Discriminating direct from indirect relationships, different resolutions of system elements	suitable	suitable	possible (only for potential relationships)		
Overall assessment		✓✓	✓	o	o	✓✓

Visualization challenge	Specific aspect of the challenge	Objects and arrows			X-Y-plots	X-Y-Z-plots
		Conceptual diagrams	Causal diagrams	Network diagrams		
5 Visualizing temporal dynamics of causal relationships	Change of relationships over time					possible (time as one axis)
	Path dependence, legacy effects	conceivable (diagram of potential system states)		conceivable (network of potential system states)	possible (phase space plot)	
	Delayed effects				possible (events marked in time series)	possible (time as one axis)
	Effects of events and interventions	possible (temporal sequence of events, e.g. flowcharts)	conceivable (events as objects)		possible (e.g. marked in time series)	possible (time as one axis)
	Overall assessment	✓	o	✓	✓	✓✓
6 Visualizing uncertainty about causal relationships	Uncertainty about causation	conceivable (e.g. arrow styles, labels)				
	Stochastic relationships	possible (e.g. arrow styles, labels)	possible (strength of statistical relationship for SEM)		suitable (e.g. error bars, intervals, labels for statistical test results)	possible (e.g. point clouds, labels for statistical test results)
	Overall assessment	✓	o	o	✓✓	✓

Appendix 2. DemoViz model description (ODD)

The following model description complies with the ODD (Overview, Design concepts, and Details) protocol for standardized descriptions of individual-based and agent-based models (Grimm et al. 2006, 2010, 2020).

1 Purpose

The purpose of the DemoViz model is to create example visualizations of causation in a hypothetical SES. The hypothetical research purpose of the model could be to predict the effects of different pollution, fishing or climate scenarios on the dynamics of a river fish population and the catch from this population, and to understand causal mechanisms that lead to these dynamics.

2 Entities, state variables and scales

The model environment comprises a river of 60 km length and individuals belonging to a fish population within this river. The river is characterized by its state variables pollution level P, temperature T, and capacity C. P (unitless value between 100 and 200) and T (in °C) do not vary along the river, but change in time. The capacity C determines the maximum number of fish individuals that can live in the river. It changes in time too. Each fish individual is characterized by its state variables body condition B and location L along the river. Both B (unitless value between 0 and 1) and L (position between 0 and 60 km) change in time depending on the environmental conditions P and T (cf. 7 Submodels). Each time step represents one year. Simulations were run for 200 years.

3 Process overview and scheduling

Each time step includes the following processes: fish movement, fish reproduction, fish mortality, fishing. After fish movement, the remaining processes are scheduled synchronously. This means that new born individuals cannot die in the same time step. If both mortality and fishing happen to cause death of the same individual, the information is stored and at the end of the time step half of these death events are assigned to mortality and to fishing, respectively. The rationale for this is to approximate synchronous dynamics since the temporal order of events within one time step is not explicitly modeled.

4 Design concepts

Emergence. All process rules and the individuals' state variables' responses to environmental conditions are imposed. The population abundance and the fishing catch emerge from the interplay of all modeled processes.

Adaptation. Fishing is adaptive to the fish population abundance. Only if the abundance was above a certain threshold (here set to 150 individuals) in the previous time step, fishing is carried out (cf. 7 Submodels – Fishing).

Objectives. The objective of adaptive fishing is not to exert additional pressure on the fish population when it has a low abundance, thus reducing the risk of extinction.

Sensing. The model uses one overall temperature value for the whole river (cf. 2 Entities, state variables and scales). However, we assume that in reality the local temperature actually varies along the river, the individuals sense this local temperature and move to a location with their preferred temperature range. This is implicitly considered in a simple manner as the fish individuals change their location in response to the overall river temperature (cf. 7 Submodels – Fish movement).

Interaction. Fish individuals' competition for resources is modeled implicitly via limiting the maximum population abundance to the capacity of the river. Humans, who are not explicitly modeled, interact with the fish via altering the level of river pollution and via fishing.

Stochasticity. The creation of environmental input data contains stochastic elements. The individuals' state variable's responses to environmental conditions are partly stochastic. The model processes contain stochastic elements, i.e. random movement, random death and reproduction events, and random fishing mortality (cf. 7 Submodels). These stochastic elements represent variability that is potentially essential for the modeled dynamics, but without explicitly including the causes of this variability.

Observation. The fish population abundance and the fishing catch rate over time are the main observations. Each state variable of the individuals as well as emergent process variables (e.g. population mortality rate, population reproduction rate) can be observed (Fig. A2.1).
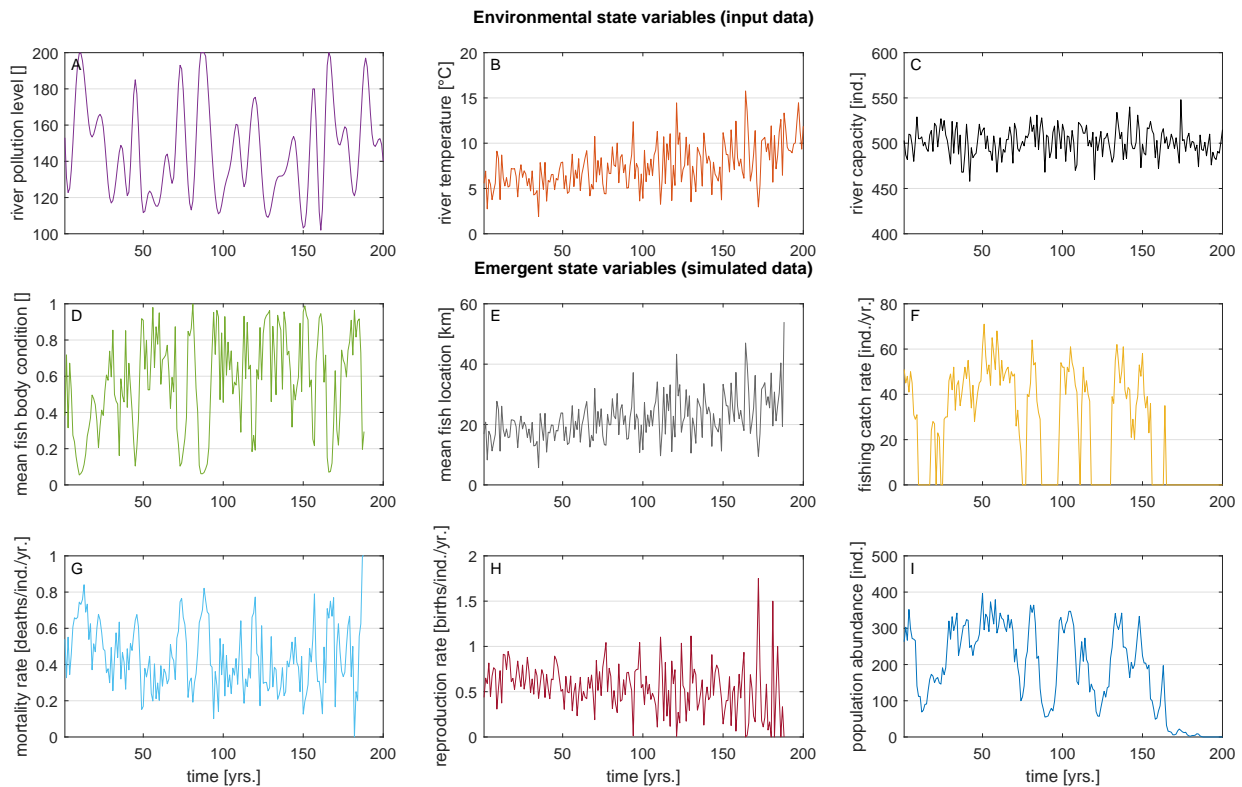
Fig. A2.1. Example time series from the DemoViz model for 200 years (X-axes). **A-C** Environmental state variables used as input data (cf. Y-axes for variable names and units). **D-I** Emergent state variables obtained in one stochastic simulation run with the model (cf. Y-axes for variable names and units). The mortality rate (G) refers to mortality apart from deaths due to fishing (F). In this example run, the fish population collapsed (went extinct) after 189 years (I).

5 Initialization

The fish population is initialized with 350 individuals. Their state variable values are not initialized separately as they depend on current environmental conditions in each time step and, thus, get assigned during the submodels Fish movement and Fish mortality (cf. 7 Submodels).

6 Input data

The model uses input data to represent time series of river pollution level, temperature and capacity over the simulation time of 200 years (Fig. A2.1A-C). These hypothetical input data were randomly generated to represent reasonable variability in the environmental conditions.

7 Submodels

Fish movement. Changes in river temperature T cause the fish to change their locations. The rationale for this relationship is that we assume that the real temperature varies along the river (decreasing from position 0 to position 60 km). This means that when the whole river gets warmer (colder), areas with the temperature range preferred by the fish shift to higher (lower) positions along the river. We additionally assumed that these areas get larger when the overall river temperature T increases. Thus, we implicitly take the movement of fish in response to local temperature changes into account (cf. 4 Design concepts – Sensing). For each individual, the new location is randomly sampled from a normal distribution with mean value 60km * T/20°C and standard deviation 0.125 * 60km * T/20°C. With increasing temperature, the locations change to higher values and the variation among individual locations increases too (cf. Fig. 3 in the main text).

Fish reproduction. Different locations cause different chances for reproductive success. For each individual, the reproduction rate R depends on location L via R = 1.5 - L/24, and the number of new born individuals is randomly sampled from a Poisson distribution with the rate parameter R. New borns are added to the population up to the current capacity C, which cannot be exceeded. This constraint leads to a dependence of the population reproduction rate on population size, but no functional form of this density dependence is explicitly assumed. (Assigning location and body condition to new individuals is not necessary as they are not affected by further processes and these variables get assigned in the submodels Fish movement and Fish mortality during the next time step.)

Fish mortality. The current river pollution level P and temperature T both affect the body condition B of fish (cf. Fig. 6 in the main text). For each individual, the new value of B is randomly sampled from a normal distribution with mean value (6 - 3 * P/100) * T/20°C and standard deviation 0.1. Thus, body condition decreases with pollution and increases with temperature. The random sampling may yield values for B below 0 or above 1. Such values are replaced by uniform random values between 0 and 0.1 or 0.9 and 1, respectively, to keep B in the allowed range (cf. 2 Entities, state variables and scales). The individuals' mortality rate M depends on B via M = 0.84 - 0.64 * B + *err* (where *err* is a common error for the whole population randomly sampled from a normal distribution with mean value 0 and standard deviation 0.05). Individuals die randomly with a probability equal to their mortality rate M. (If the

population happens to exceed the current capacity C at the end of the time step after all processes have been realized, additional randomly selected individuals die until C is reached.)

Fishing. Fishing is adaptive. It takes place only if the population abundance was above a threshold of 150 individuals at the end of the previous time step. In this case, individuals get fished randomly with a probability of 0.2. This means that higher population abundances cause higher annual catch rates (cf. Fig. A2.1).

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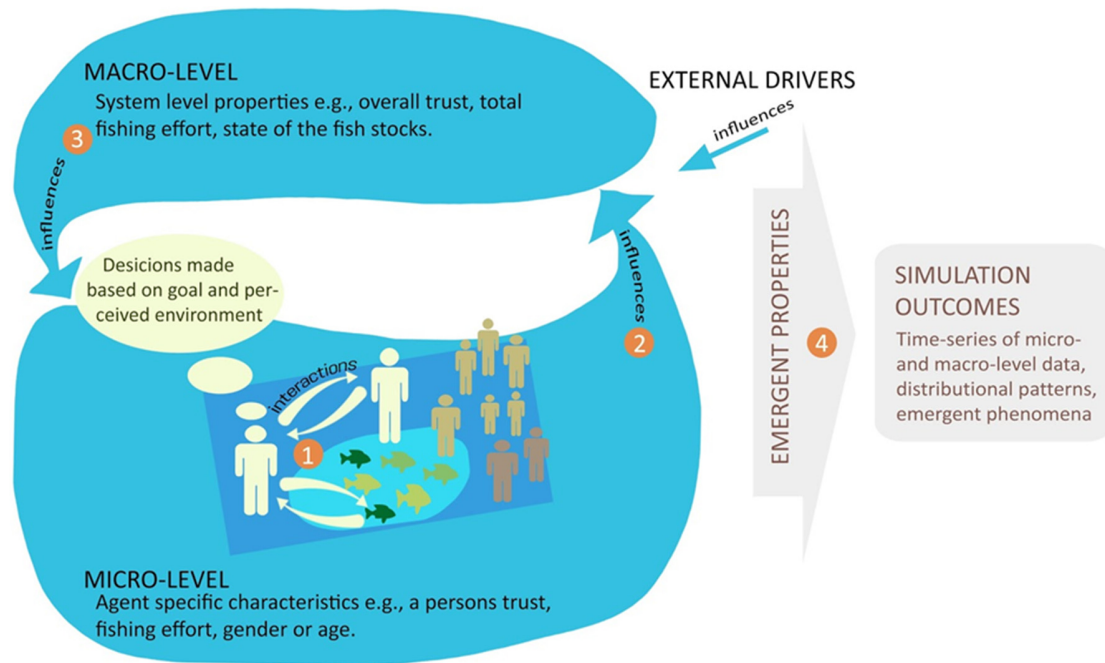**Appendix 3.** Additional example figures

Fig. A3.1. Visualization of an agent-based fisheries SES model by a conceptual diagram. The focus is put on the interplay (reciprocal causal relationships) between agents' characteristics and (inter)actions (the micro-level) and system properties (the macro-level). This interplay is affected by environmental drivers and it causes emergent properties of the modeled system, both at the macro- and micro-level. Numbered markers are used to visually guide readers through the steps of micro- and macro-level changes affecting each other during the simulation. Different kinds of objects and arrows as well as labels and additional illustrations show and discriminate the processes operating during the simulation (left) and the emergent simulation outcomes (right). Source and further details: Lindkvist et al. (2020). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).
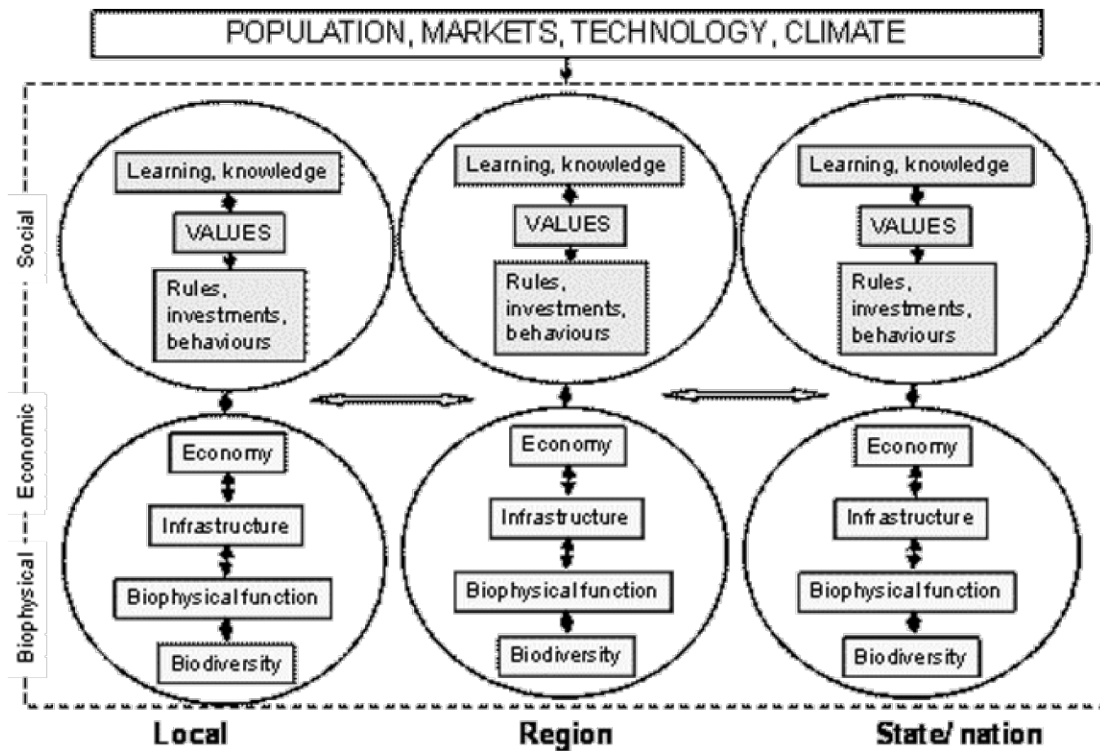
Fig. A3.2. Visualization of a framework for assessing the social-ecological resilience of a study region, using a large number of objects and arrows to represent complex causation. Resilience is assessed for multiple biophysical, economic and social values (left labels) and multiple spatial scales (bottom labels). Different variables driving the system's state are visualized by boxes, grouped in circles, and their multiple interactions shown by many arrows. Exogenous drivers of the SES state are visualized as an additional box linked by an arrow (top). Source and further details: Walker et al. (2009). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).
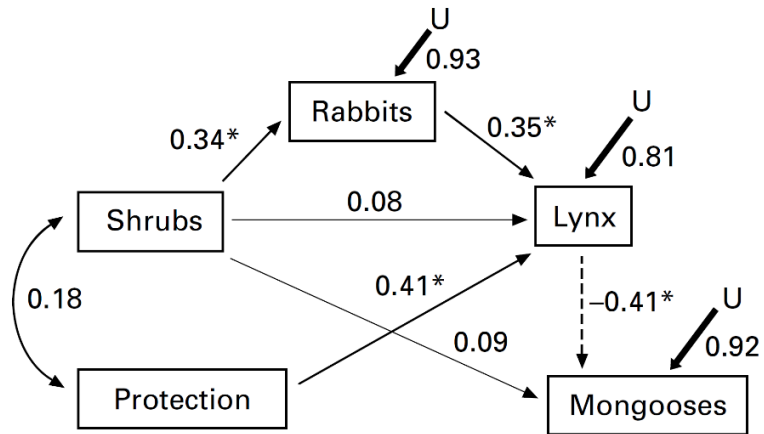
Fig. A3.3. Visualization of structural equation modeling (SEM) results for a Mediterranean ecosystem in south-western Spain by a causal diagram with a standard formalism. Path coefficients provide the strength and sign of statistical relationships between variables (additionally visualized by the thickness and line style of arrows, dashed for negative relationship). Relationships significantly different from zero are marked with an asterisk. Arrows pointing to a variable that do not start from another variable (marked with 'U') represent error terms in the SEM, which account for variance in those variables due to unmeasured causal factors or stochasticity. The additional curved arrow between two variables visualizes that no hypothesis on their causal relationship was included in the model. Their correlation might represent a causal relationship in any direction or effects of a common, unmeasured causal factor. Source and further details: Palomares et al. (1998). Figure used with permission by John Wiley and Sons.
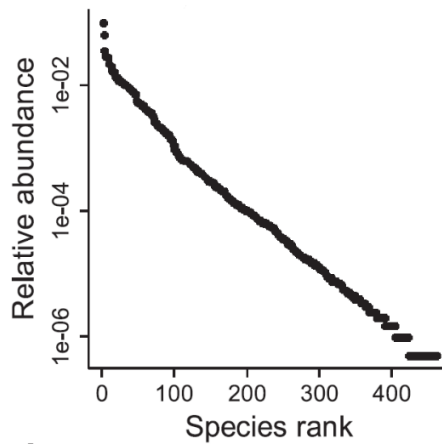
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Fig. A3.4. Visualization of a simulated abundance distribution of tropical tree species by an X-Y-plot. The species are ranked (X-axis) according to their abundance, which is plotted relative to the total abundance of the community (Y-axis, logarithmic scale). The species ranks are the plain result of sorting and do not imply to be the cause for the depicted abundances. Source and further details: May et al. (2016). Figure used with permission by John Wiley and Sons.
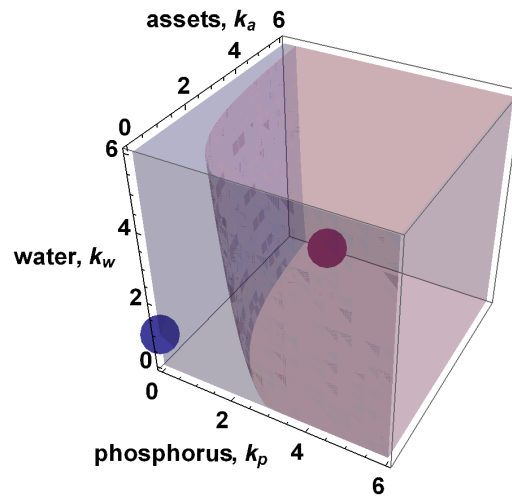
Fig. A3.5. Visualization of the state space of an agricultural SES by an X-Y-Z-plot. Three SES state variables are depicted that are all causally related to each other in a dynamical systems model: phosphorous in the environment (X-axis), household assets (Y-axis) and water level (Z-axis). Two colored circles visualize two different stable states the system can approach over time (attractors) and the transparent colored volumes separate the initial states that cause one or the other attractor to be reached (basins of attraction). Source and further details: Radosavljevic et al. (2020). Figure used in accordance with the authors' right to reuse own material (https://www.elsevier.com/about/policies/copyright).
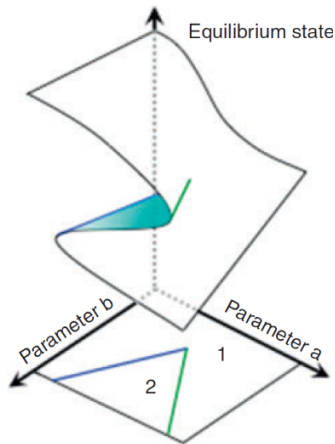
Fig. A3.6. Visualization of the so-called "cusp" model from catastrophe theory by an X-Y-Z-plot. The causal relationship between one variable (parameter a, X-axis) and the system's equilibrium state (Z-axis) changes qualitatively depending on a second variable (parameter b, Y-axis). The bottom areas visualize the combinations of values of a and b with either one corresponding stable state (area 1) or two alternative stable states (area 2, i.e. hysteresis in the relationship between parameter a and the system state, cf. Fig. 5B in the main text). The transparent fold shows the possible system states, the cyan fold shows states that cannot be reached. Source and further details: Petraitis and Dudgeon (2016). Figure used with permission by CSIRO Publishing.
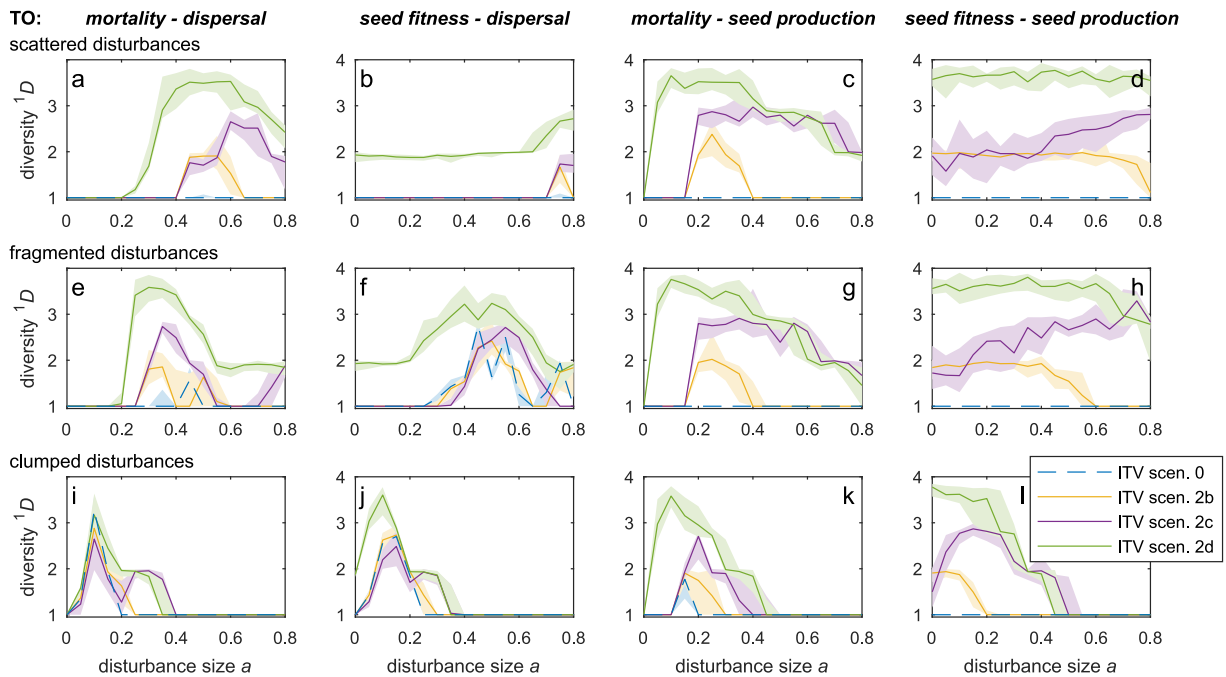
Fig. A3.7. Visualization of the effects of multiple factors on biodiversity in a modeled ecosystem by multiple X-Y-plots. In each subplot, the quantitative relationships between disturbance size (X-axes) and species diversity (Y-axes) are shown, with shaded areas visualizing the variation among multiple stochastic simulation runs. The additional factors causally related to diversity are the actual trade-off in species traits (TO, different columns), the spatial configuration of disturbances (different rows), and the applied scenario of intraspecific trait variation (ITV, different colors). Source and further details: Banitz (2019). Figure used in accordance with the authors' right to reuse own material (https://onlinelibrary.wiley.com/page/journal/16000706/homepage/Permissions.html).

R_0	On Trigger	Total deaths			
		Do nothing	CI_HQ_SD	PC_CI_SD	PC_CI_HQ_SD
2	60	410,000	47,000	6,400	5,600
	100	410,000	47,000	9,900	8,300
	200	410,000	46,000	17,000	14,000
	300	410,000	45,000	24,000	21,000
	400	410,000	44,000	30,000	26,000
2.2	60	460,000	62,000	9,700	6,900
	100	460,000	61,000	13,000	10,000
	200	460,000	64,000	23,000	17,000
	300	460,000	65,000	32,000	26,000
	400	460,000	68,000	39,000	31,000
2.4	60	510,000	85,000	12,000	8,700
	100	510,000	87,000	19,000	13,000
	200	510,000	90,000	30,000	24,000
	300	510,000	94,000	43,000	34,000
	400	510,000	98,000	53,000	39,000
2.6	60	550,000	110,000	20,000	12,000
	100	550,000	110,000	26,000	16,000
	200	550,000	120,000	39,000	30,000
	300	550,000	120,000	56,000	40,000
	400	550,000	120,000	71,000	48,000

Fig. A3.8. Visualization of the effects of multiple factors on death tolls in a human pandemic model by a colored table, which yields a nested raster plot in a simple manner. It shows the effects of the three causal factors intervention strategy (X-axis, different column labels), number of intensive care unit cases needed to trigger the intervention (inner Y-axis, range 60-400), and virus reproduction number R_0 (outer Y-axis, range 2-2.6) on the simulated number of total deaths (cell entries, visualized by color). Source and further details: Ferguson et al. (2020). Figure used without modification under the CC BY-NC-ND 4.0 license (https://creativecommons.org/licenses/by-nc-nd/4.0/).
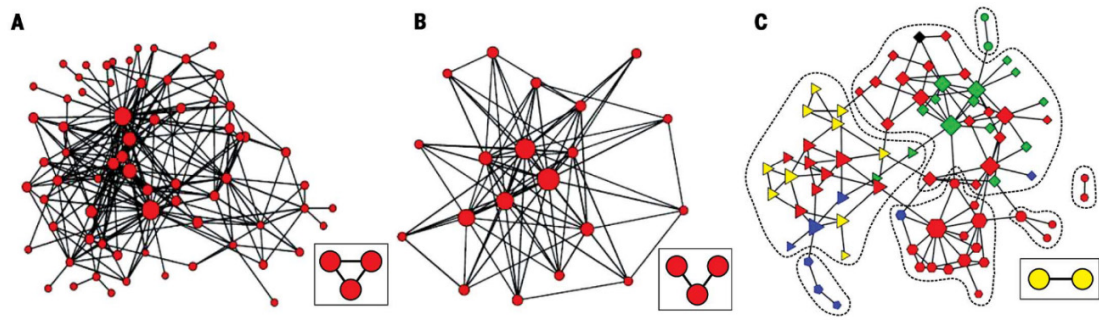
Fig. A3.9. Visualization of human collaboration in different SES by multiple network diagrams. The nodes depict human actors and the edges connect collaborating actors in (A) coastal ecosystem management in Sweden, (B) biosphere reserve management in Canada, and (C) small-scale coastal fishery in Kenya. In network C, different colors visualize different types of gear used by the fishers and dashed lines show different subgroups of fishers with many connections between them. The combination of multiple network diagrams in one figure facilitates comparison of the different networks' structural characteristics and causal interpretation of these structures (cf. Section 3.1.3 in the main text). Insets in the bottom right of each subplot show frequent structural building blocks of the visualized network, respectively. Source and further details: Bodin (2017). Figure used with permission by The American Association for the Advancement of Science.
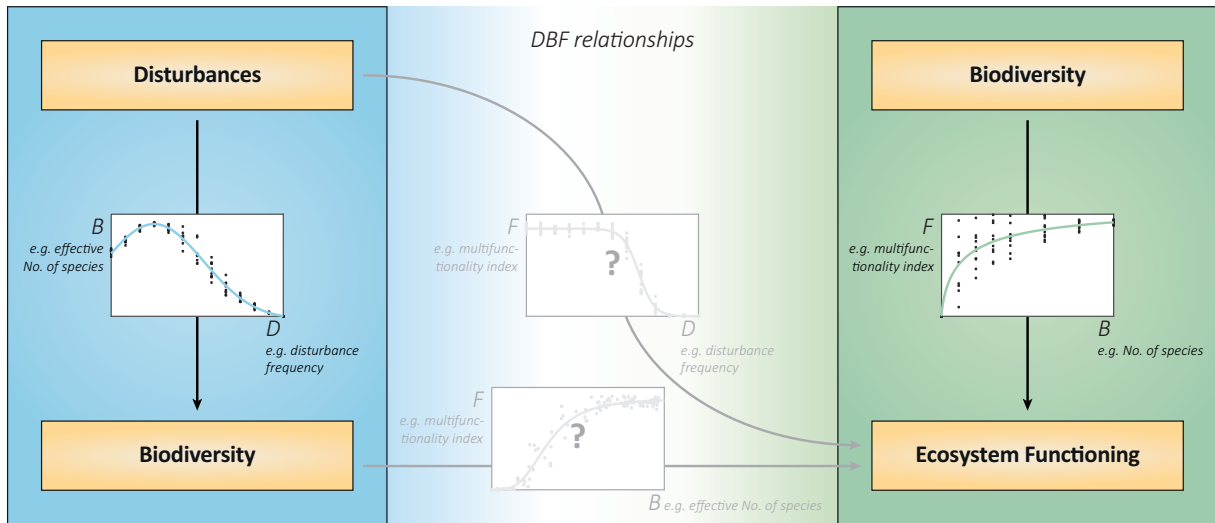
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Fig. A3.10. Visualization of complex causation in a conceptual ecosystem model by combining a diagram of objects and arrows with X-Y-plots. The objects and arrows visualize causal relationships between disturbances D, biodiversity B and ecosystem functioning F (biodiversity is shown twice to illustrate that its relationship to ecosystem functioning is often studied separately from disturbances). The X-Y-plots inserted visualize observable relationships between variables representing the connected objects, respectively (axis labels). These emergent DBF relationships are affected by the underlying causal relationship between these variables, and by additional variables (either shown or not shown). For example, the relationship between the effective number of species and the multifunctionality index (bottom X-Y-plot) is confounded by the disturbance frequency which is causally related to both variables (visually detectable by a backdoor path between them, cf. Section 3.2.1 in the main text). Source and further details: Banitz et al. (2020). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).
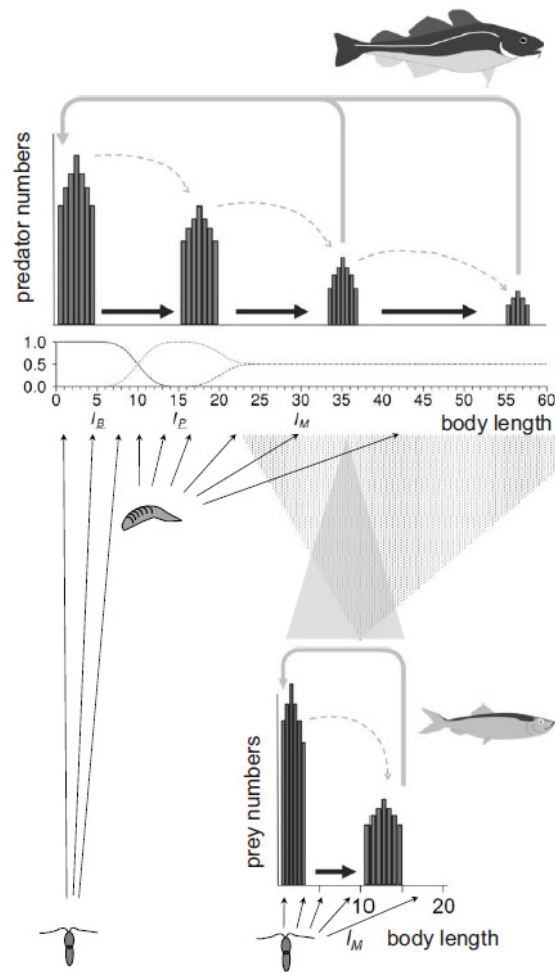
Fig. A3.11. Visualization of complex trophic relationships between different species in a marine ecosystem model by combining X-Y-plots with diagrams of objects and arrows. The two bar plots (X-Y-plots) visualize frequency distributions of body length (X-axes) of two fish species (the predator cod and the prey sprat, cf. Y-axes, also visualized by icons). They show that the populations are structured in cohorts. In these bar plots, arrows between cohorts visually indicate the model processes growth (black arrows), reproduction (gray arrows) and mortality (dashed gray arrows). Another line plot (X-Y-plot) visualizes the switching of cod prey preference throughout its life-stages. Additional prey species are visualized by icons (zooplankton at the bottom, benthic organisms in the middle), and thin arrows represent biomass flows from these prey species to the different life-stages of the two fish species. Similarly, the gray areas visualize the predator-prey relationship between the two fish species, but here the dotted area shows the size range of predators that can feed on a prey individual of a certain size (11 cm), and the shaded area shows the size range of prey a predator individual of a certain size (35 cm) can feed on. The figure requires detailed explanation, but helps understanding the model rules and processes that let the population dynamics emerge in simulations. Source and further details: van Leeuwen et al. (2013). Figure used with permission by the University of Chicago Press.
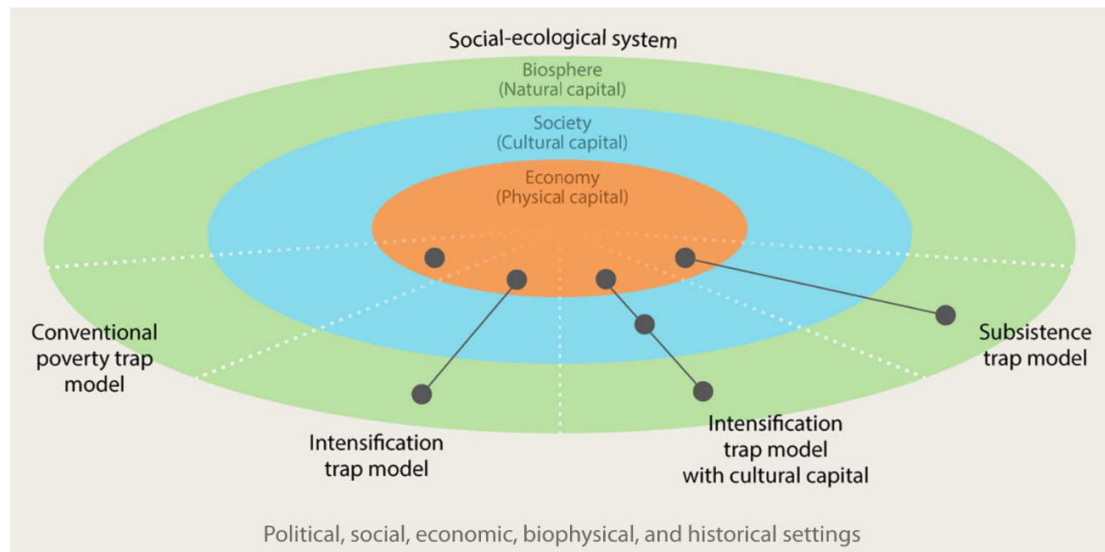
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Fig. A3.12. Visualization of an SES conceptualization by a set diagram. The colored areas visualize that economy is considered a part of society and this society is considered a part of the biosphere (cf. Folke et al. 2016). Gray lines and circles depict different poverty trap models, which explicitly take into account different subsets of the complex SES. Source and further details: Lade et al. (2017). Figure used without modification under the CC BY 4.0 license (https://creativecommons.org/licenses/by/4.0/).

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