Unified in diversity: Unravelling emerging knowledge on drought impact cascades via participatory modeling

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Abstract

Diverse groups exhibit enhanced capabilities in tackling complex problems compared to individuals. Also, involving diverse stakeholders has been shown to improve the understanding of complex social-ecological systems. Considering this, we investigated how pooling the knowledge of diverse stakeholder crowds can create new, emergent knowledge on cascading drought impacts. We define 'emergent knowledge' as information that only becomes visible when multiple perspectives are combined. Therefore, we used participatory modeling to capture the systemic effects of droughts on diverse socio-economic and environmental systems. We interviewed 25 stakeholders with different expertise to obtain individual causal loop diagrams (CLDs) representing how drought impacts propagate in a case study in Thuringia, Germany. These CLDs were aggregated to develop a collective CLD. We then compared the individual and collective CLDs using graph theory statistics. Our analysis revealed emergent system-level features, such as feedback loops, that only became apparent when combining individual perspectives. Also, variables like 'biodiversity loss', which had minimal influence within the individual CLDs, gained influence in the collective CLD. These findings demonstrate how pooling diverse stakeholder knowledge on cascading drought impacts unveils new insights that may be hidden when considering only individual perspectives. We anticipate these findings to enhance the integration of knowledge from diverse stakeholder crowds when studying complex drought impacts. Furthermore, these findings highlight the need for careful consideration in selecting domain expertise in participatory processes that study drought impact cascades, as the system dynamics can vary substantially.

Keywords: participatory modeling, cascading drought impacts, Thuringia, network analysis

1. Introduction

Droughts trigger a series of cascading and compounding impacts (CCI) due to interdependencies between coupled natural and social systems (1,2). As such, they often cause impacts that transcend sectors (3). For example, the low water availability in European rivers in 2022 had far-reaching consequences for the energy sector, leading to decreased nuclear and hydropower generation (4,5). As a result, electricity prices increased, causing subsequent disruptions in industrial production (6). The effects of droughts can also spill over beyond their initial temporal and spatial domains, impacting areas not directly exposed to the physical hazard (7). Indeed, droughts have been shown to lead to food security crises due to food production shocks in countries other than those where the food is produced (8). Consequently, gaining a deeper understanding of drought cascading impacts is crucial to inform the ex-ante management of systemic risks, as emphasized in the research agenda of the Integrated Research on Disaster Risk 2021-2030 (9) and by several researchers (10,11).

Responding to this need, scholars are investigating the propagation of droughts' impacts and how they interact with society (12,13). Typically, qualitative descriptions and narrative accounts based on observed data are employed to depict how the impacts unfold (14). For example, (13) conducted a literature review, examining scientific articles to identify evidence of cascading consequences of droughts in 8 case studies. Detailed studies focusing on specific economic sectors, such as agriculture, are also prevalent (15). Nevertheless, gaining a holistic understanding of the drought CCI across multiple sectors remains challenging due to the limited availability of impact data (16).

To provide a nuanced and comprehensive understanding of drought CCI, local stakeholders who experience or manage drought-related challenges may play a significant role, as they possess first-hand knowledge regarding the affected systems (17). Such knowledge becomes valuable when data on impact occurrence is incomplete or access restricted (18,19). Furthermore, by involving local stakeholders, researchers can ensure that the study findings reflect the reality of the affected population (20) while at the same time promoting social learning (21).

While including stakeholder perspectives to investigate drought impacts is not a new topic (22–25), few studies have attempted to systematically model the relationship between multi-sector impacts based on the stakeholder inputs (26). Even fewer have explored how group diversity can provide new knowledge on the CCI of droughts. However, as stakeholders hold a partial understanding of complex systems (19) shaped by their experiences and values, relying solely on single perspectives exposes a significant gap in our knowledge of drought CCI patterns. Instead, collective intelligence, that is, the ability of a group to solve problems effectively, can support an improved understanding of drought impact dynamics. Collective intelligence also referred to as the wisdom of crowds, has been shown to lead to an enhanced understanding of complex social-ecological systems (27) or to promote changes in awareness of climate change impacts (28).

In this study, we draw from research on collective intelligence (18) and complex systems theory (29,30) to examine the CCI of droughts. We hypothesize that by combining the perspectives of diverse stakeholders, emergent knowledge about the CCI becomes tangible. By emergent knowledge, we refer to an understanding of CCI that is not apparent within individual stakeholders' perspectives but emerges when combining diverse perspectives. This idea follows the concept of emergent system properties, where the system is more than the sum of its individual parts (30). To address this hypothesis in a real-world context, we employ a participatory modeling approach that leverages causal loop diagrams (CLD) and social network analysis to quantify emergent knowledge. Specifically, we aim to (1) identify the impacts or drivers that most significantly emerge in influencing the impact cascades according to collective insight and (2) determine new knowledge concerning the structural properties (such as feedback loops or other complex structures) of CCI that emerges when pooling diverse stakeholder perspectives.

The participatory process took place in a case study on the German federal state of Thuringia, a region recently affected by severe drought conditions with far-reaching consequences across multiple sectors (14,31). This area experienced drastic forest dieback in 2019 and 2020, during which over a third of all trees were damaged (14). Recent drought events (e.g. 2003, 2018, 2019) exposed the region to Germany's most severe soil moisture deficits (32). Furthermore, Thuringia is particularly prone to future temperature increases according to climate model ensembles considering different greenhouse gas concentration scenarios (33).

2. Methods and data

We engaged in a participatory process with local stakeholders with experience in managing drought-related challenges following a multi-step research design (see Fig 1). First, we generated causal loop diagrams (CLDs) through individual stakeholder interviews. In these CLDs, drought impacts and their drivers are described as variables (i.e. nodes) connected within a network structure to indicate causal relationships. Second, we homogenized the individual CLDs by grouping the variables across all CLDs according to similar terms and concepts. We then created a collective CLD that aggregates all individual CLDs. This collective CLD was then validated by stakeholders within a group workshop to assess whether it depicts the reality of CCI. To identify emergent knowledge resulting from the aggregating of CLDs, we employed network statistics to evaluate the network structure and its properties (e.g. node centrality). The following sections describe these steps in detail.

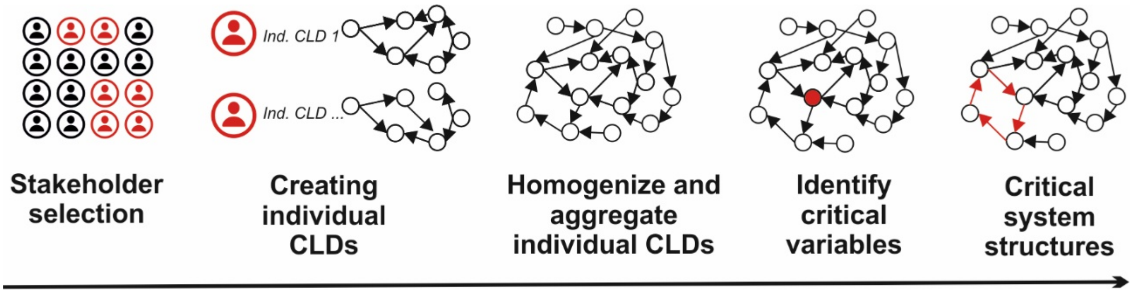

Figure 1: Overview of the research process.

2.1. Stakeholder selection

Stakeholder selection is a crucial step in participatory processes, as stakeholders directly influence the research outcomes (34). Here, we employed a purposive sampling approach (35) to provide a diverse representation of stakeholders from different types of institutions (NGOs, state or administrative agencies, private persons, or businesses) and sectors (e.g. agriculture, forestry, or water supply). Initially, a list of 44 potential stakeholders was developed based on consulting with local partners in the case study and complementing web research. These stakeholders were categorized based on the sector and type of institution they represent. Of the 44 people contacted between September and November 2022, 25 (56%) agreed to participate in the interviews. The stakeholders who accepted the invitation were ensured with a comprehensive description of the research goals and were informed about their right to withdraw from the study at any time.

2.2 Elicitation of individual causal loop diagrams (CLDs) through interviews

We used CLDs to capture and visualize stakeholders' perspectives on the cascading impacts of droughts. CLDs are widely used in participatory modeling as they allow for an intuitive mapping of causal relationships reflecting individuals' perspectives on particular phenomena (36,37). With a network structure, CLDs represent system variables (e.g. crop yields, precipitation) as nodes, whereas links (directed edges of the network) indicate how the variables are related (see Fig S1). CLDs effectively model complex dynamics by detailing how changes in one variable influence others, either amplifying (via positive links) or reducing (via negative links) their effects (for details on CLDs, see Biggs et al., 2021).

To elucidate the stakeholders' CLD, we conducted 25 semi-structured interviews lasting for 30-45 minutes, either in person or remotely. At the beginning of the interviews, the interviewer introduced the concept of CLDs and the purpose of the research. Stakeholders were then prompted to discuss both current and future drought impacts in Thuringia and the drivers contributing to them. Each of these impacts and drivers was drawn by the interviewer in a collaborative tool (Mental Modeler, see (18)) as a variable (i.e. network node). With each added variable, stakeholders were requested to indicate links to existing ones (i.e. network edge). Also, we asked the stakeholders about how the drought impacts cascaded and other interactions among the drought impacts they considered. All questions were formulated as open questions to not influence the participants' answers. For example, we phrased the question as 'What drought impacts did you perceive' instead of 'Did you perceive any impacts in the agricultural sector'. The interview protocol is provided in supplementary Table S1.

2.3 Homogenization and merging of the individual causal loop diagrams

The interviewed stakeholders often (1) used different terms to convey identical variables (e.g. crop yield and harvest) or (2) explained the drought impacts and their drivers to varying levels of detail (e.g. decreasing hamster population and species loss). Thus, to merge individual CLDs into a unified collective CLD, they must undergo a “homogenization” process. Homogenization involves establishing a shared terminology and detail level to unify comprehension of terms across individual CLDs.

To aggregate all variables and links from the individual CLDs and create a collective CLD that reflects the pooled perspectives of all stakeholders, we followed the approach by (38). Therefore, we homogenized the variables used in each CLD by mapping them to similar concepts. For example, ‘crop yield losses’ and ‘yields in agriculture’ were aggregated to the variable ‘crop yields’. This task was conducted by two team members, who labeled and edited each other’s suggestions to arrive at a homogenization that both agreed to. Disagreements were solved by discussions between them. We removed several variables we identified as describing concepts that were too fuzzy or non-measurable (e.g. “forest management of the past”). After creating a shared terminology, we replaced the original variable names with the homogenized equivalents in each CLD. This process is detailed in File S1 to provide transparency about the decisions taken.

We then aggregated the individual CLDs by starting with the largest one in terms of variables and iteratively added the other CLDs in order of their size, following a similar procedure as (39). As we incorporated each CLD, any variables and links not already present in the aggregated model were added. To investigate knowledge saturation (40,41), a point where further interviews do not yield new variables, we assessed the number of new variables added by each CLD. If this number converges towards 0, it signals that a satisfactory number of interviews have been conducted.

2.4 Visualization of the collective causal loop diagrams

To visualize and describe the collective CLD we applied two visualization techniques from network analysis. First, we conducted a k-core analysis (42) to visualize densely connected and influential variables (i.e. core) and less central ones (i.e. peripheral). This technique identifies central structures by considering the number of connections per variable. As a result, each variable was assigned a *k coreness,* with higher values indicating greater centrality and influence. Variables with the highest *k* can be interpreted as the network's robust core.

Second, we analyzed which socio-economic and environmental systems have been mentioned and how they are related. To this end, we first categorized each variable into one of 7 systems: climate, water system, biodiversity, agriculture, forestry, economy, and water economy. Then, we counted the number of links between different systems to better understand how they are connected by impact cascades. This provided an overview of the interconnected impact patterns in the collective CLD and how impacts propagate through the different socio-economic and environmental systems.

2.4 Validation of the collective causal loop diagram via a workshop

The validity of the collective CLD was assessed through a 2 hours workshop involving 30 participants. These participants were key stakeholders from the case-study area, including researchers working on drought impacts, environmental agencies, and ministry representatives working on drought and water scarcity. They were divided into 5 groups, each comprising six individuals and a moderator. The participants were presented with a simplified version of the aggregated CLD on a large poster (see Fig S2). These simplifications were needed because of the high density of edges, which limited visual comprehension and aimed to provide a visually comprehensible CLD. They involved removing variables mentioned only once and eliminating redundant linkages. Moderators guided each group in examining the CLD and adjusting by adding or correcting links or variables. Following the workshop, we documented the variables and links the participants added or removed, as detailed in Supplementary Table 2.

2.5 Analyzing the significance of each variable

We measured and compared the centrality of variables within the CLDs using graph statistics to identify which specific impacts or drivers emerge as most influential in the CCI impact patterns (see research question 1). Various centrality statistics can identify critical variables in CLD (43). Here, we used betweenness centrality, which is calculated as the number of shortest paths passing through a given variable relative to all shortest paths in the network. For the CCI of droughts, this can be interpreted as identifying the key variables through which drought impacts propagate. We selected this statistic because it effectively pinpoints variables that control information flow within networks (44).

We compared the betweenness centralities of variables between individual and collective CLDs to identify those that emerge as influential when pooling stakeholders' knowledge. For instance, a variable could display low centrality in the individual CLDs while having a high centrality in the collective CLD. This would indicate the strong influence of such variable becomes visible only when pooling diverse knowledge. Therefore, we calculated the betweenness centrality for each variable in the individual CLDs and normalized it based on the maximum and minimum centrality of each CLD. Then, we compared these normalized centrality means of the individual CLD's variables with the respective counterparts in the collective CLD. This allowed us to understand better how aggregating diverse perspectives enhances the identification of variables with significant systemic influence.

2.6 Analyzing the structural properties of the causal loop diagrams

To answer research question 2 and provide evidence on structural system properties of the CCI that emerge when pooling individual stakeholder perspectives, we leveraged network-level statistics that can measure different structural features. We compared individual and collective CLDs using network-level statistics (i.e. average path length, diameter, centralization, transitivity), which we interpreted as indicators of CCI complexity. Network-level statistics describe the overall structural features of the CLD rather than focusing on individual variables. The selected statistics enabled us to evaluate the complexity of the cascading impact patterns, the level of interconnectedness among variables, and the degree of centralization of impact cascade patterns towards individual variables. A detailed description of each statistic is provided in Table 1. For instance, average path length measures the average distance between all nodes in the CLD. This can be interpreted as how tightly connected variables are and how nuanced cascading patterns are described. Complementing, the diameter of a CLD represents the maximum length of the longest causal chain in the CLD. A larger diameter signifies more extended and indirect causal pathways between variables. Network centralization determines if a CLD is centered around a few highly central variables or has a more decentralized structure. Network transitivity assesses the likelihood in networks that connections between three variables form a closed loop. Specifically, if node A is connected to node B, and node B to node C, there is a high probability of a direct link between node A and C. For CLDs, we interpret these triangular formations as indicators of complex, non-linear interdependencies among variables.

Table 1: Overview of network-analysis statistics used in this study. Variable-level statistics concern individual nodes, while network-level statistics concern characteristics that describe the entire network.

	Statistic	**Definition**	**Interpretation**
Variable -level	In-degree centrality	The sum of links incoming to a particular node in the network	Level of influence received from other variables, how many factors directly affect it within the system
	Out-degree centrality	The sum of links outgoing to a particular node in the network	The extent of its influence on other variables factors it directly impacts within the system
	Betweenness centrality	Importance of a particular node based on its role as a bridge	Role as an intermediary in the interactions between variables
Network -level	Average path length	Average distance between all pairs of nodes in the network	The average number of causal steps or links that connect variables in the system
	Diameter	The maximum shortest distance between any two nodes in a net	Maximum distance across which a causal effect travels within the system
	Centralization	Measure of how centralized a network is towards a particular node	High centralization suggests that a small number of variables have a significant number of connections
	Transitivity	A measure of tendency for interconnectedness or clustering in a network	The extent of causal effects in the system to form closed loops or chains of influence
	Feedback loop	Closed-directed cycle in a network	Structural elements that either drive escalating or balancing dynamics in the reflected system

We specifically analyzed emerging feedback loops as these are a common structural feature contributing to the non-linear dynamics of complex social-ecological systems (45–47). In CLDs, a feedback loop is defined as a set of variables that are connected by edges in a closed cycle. This allows for the continuous flow of an impulse created by the change of one variable within the loop, which can either be self-reinforcing or self-regulating. In self-reinforcing feedback loops, all variables change in the same direction, thereby creating a snowball effect where an initial impulse is continuously amplified. A reinforcing feedback loop could drive the escalation of a particular impact, such as increasing water scarcity. For example, increased agricultural water demand can lead to over-extraction of groundwater, limiting water availability and resulting in even more aggressive groundwater extraction. Instead, balancing feedback loops prevents the escalation of a particular effect. For example, water conservation measures that respond to decreasing groundwater levels can lead to reduced water usage and thereby stabilize groundwater levels.

3. Results

3.1. Individual interviews and CLDs of drought-society interactions

We conducted 25 interviews, resulting in 21 individual CLDs, which could be further processed. Reasons for interviews that failed to produce a CLD are declined usage for research purposes (n=1), technical failure of the modeling software during the interview (n=1), and stakeholders preferring traditional interviews over CLD development (n=2). The organizational types of the selected stakeholders (i.e. NGOs, government bodies, research, and industry) exhibit equal presence across organizational types, with scientists being an exception, being featured only twice. Each sector type is ensured representation by at least one expert, although certain sectors are disproportionately emphasized, particularly in the case of nature conservation and industry (Table 2).

The CLDs resulting from the individual interviews vary in the number of variables yet share a strong degree of cross-sectoral impact patterns. Stakeholders used a median of 9 variables with high variance (minimum: 3, maximum: 22, standard deviation: 5.4). Overall, the variables in the individual CLDs are linked to an average of 5 socio-economic and environmental systems.

Table 2: Overview of represented sectors and organizational type.

	Class	N
Represented expertise	Nature conservation	5
	Industry	4
	Water supply	3
	Agriculture	3
	Science	2
	Water ecosystems	2
	Forestry	1
	Fishing	1
	Water management	1
	Environmental ecosystems	1
Organization type	NGO	9
	Governmental body	8
	Industry	6
	Research center	2

3.2. Collective CLD of drought-society interactions

The aggregation of the 21 individual CLDs led to a collective CLD consisting of 76 variables, summarizing those 345 originally mentioned by the stakeholders. We remove 42 variables that do not describe measurable concepts (File S1). During the aggregation of the CLDs, we observed a saturation point concerning the introduced variables (Fig 2). This indicates that a satisfactory number of interviews have been conducted. Here, the 3 largest CLDs already introduce 52% of all variables to the collective CLD, while the last 5 CLDs only add 2.2%. Thus, it can be argued that the collective CLD fully covers the CCI system under investigation and that conducting additional interviews would only add a few new information.

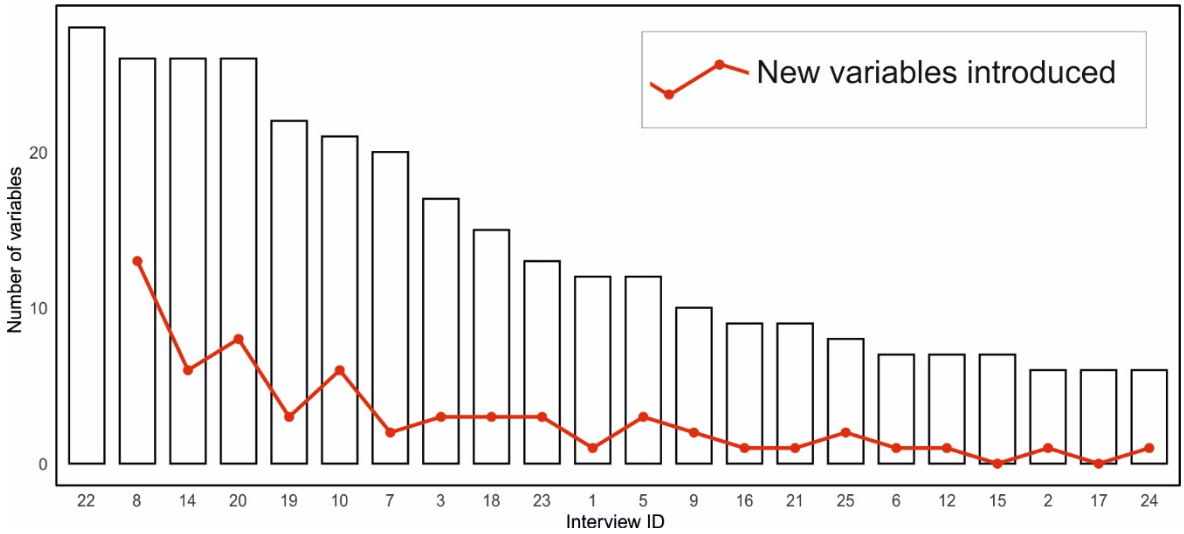

Figure 2: Aggregation of individual CLDs. Bars represent the number of variables included in each individual CLD. The red line indicates the number of new variables introduced in each step of the aggregation.

K-core analysis results showed that the collective CLD consists of a densely connected core and a less well-connected peripheral structure (Fig 3a). In the center, variables with a high k-core centrality engage in a dynamic interplay, impacting and being impacted by others. Variables in the peripheral structure with lower k-core centrality either influence the core structure or are influenced by it.

The collective CLD displays high interconnectivity among the different systems (see Table S1 for the definition of all systems). Particularly, there are many connections between variables associated with 'climate' (e.g. precipitation) and 'water' systems (e.g. surface water level) (Fig 3b). These two densely interconnected systems facilitate the propagation of climatic trends to bio-physical drought conditions and consequent impacts. Variables in the 'water' system hold connections to all those systems where impacts are felt, such as 'agriculture', 'forestry', and 'economy'. Among the systems impacted by drought, we observe differences in the number of ties to other systems. For instance, dense interconnections exist between the 'forestry' and 'biodiversity' systems, reflecting upon the ecosystem services provided by forests. Instead, stakeholders included few links between 'forestry' and 'agriculture', which matches expectations.

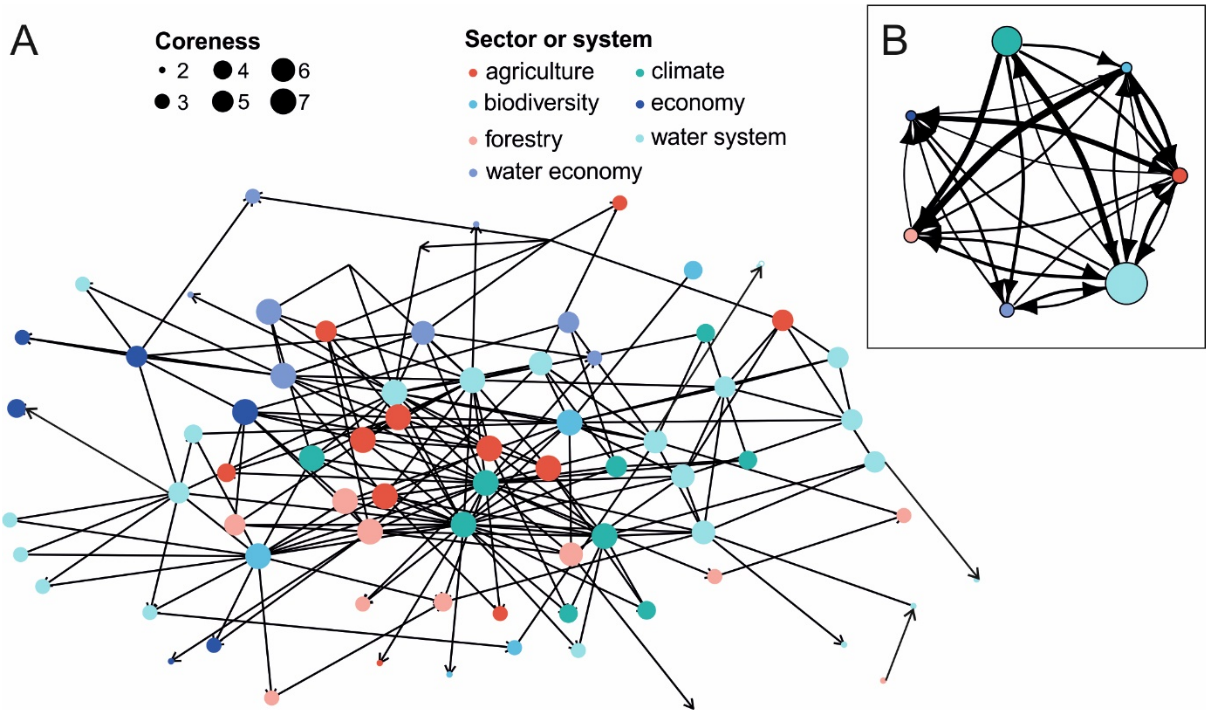

Figure 3: Visualization of collective CLD and cross-sectoral linkages. A) k-coreness visualization of the collective CLD. High coreness values indicate a higher level of centrality and influence in the overall system dynamics. B) Connections in the collective CLD between the individual socio-economic and environmental systems. The size of an edge corresponds to the number of variables in each system, and the size of ties corresponds to the number of connections between two systems.

During the validation workshop, stakeholders suggested 20 additional variables and mildly questioned existing links. However, only five of these were not part of the collective CLD already. The suggested 15 variables were only removed in the simplified version of the CLD presented to the workshop participants yet contained in the collective CLD we analyze in the subsequent sections. Each group questioned an average of five existing links and added an average of 5.8 links. Similarly, a large share of the added links is part of the collective CLD already, yet had been removed for simplification. The validation highlights the logical consistency of the CLD and the convergence toward a complete representation of the system under investigation. Even though the workshop participants come from highly diverse backgrounds (e.g. public sector, science), the CLDs were effective in instigating discussions. This emphasizes the applicability of CLDs in providing a neutral communication technique (48).

3.3 Emerging critical variables in CCI drought propagation patterns

The betweenness centralities of each variable reveal influential impacts and drivers within individual and collective CLDs. These can be regarded as variables with a higher importance in influencing the CCI patterns. Overall, the betweenness centrality scores of variables in the individual CLDs vary significantly (see Fig 4). For instance, 'water use restrictions' stands out as the most central variable in one but ranks least central in another CLD (median: 0.35, sd: 0.36). These variances occur across most variables and highlight the differences in their perceived centrality depending on the stakeholders' viewpoints. Conversely, variables with lower variance are either variables positioned at: (i) the beginning of CCI patterns, thus possessing a low centrality (e.g. climate change), (ii) the end of CCI patterns, thus possessing a high centrality (e.g. biodiversity losses), (iii) the middle of CCI patterns, thus possessing medium to high centrality (e.g. industrial production). Yet, it is important to state that the variation across models displayed here depends on the number of times a variable is mentioned in individual CLDs.

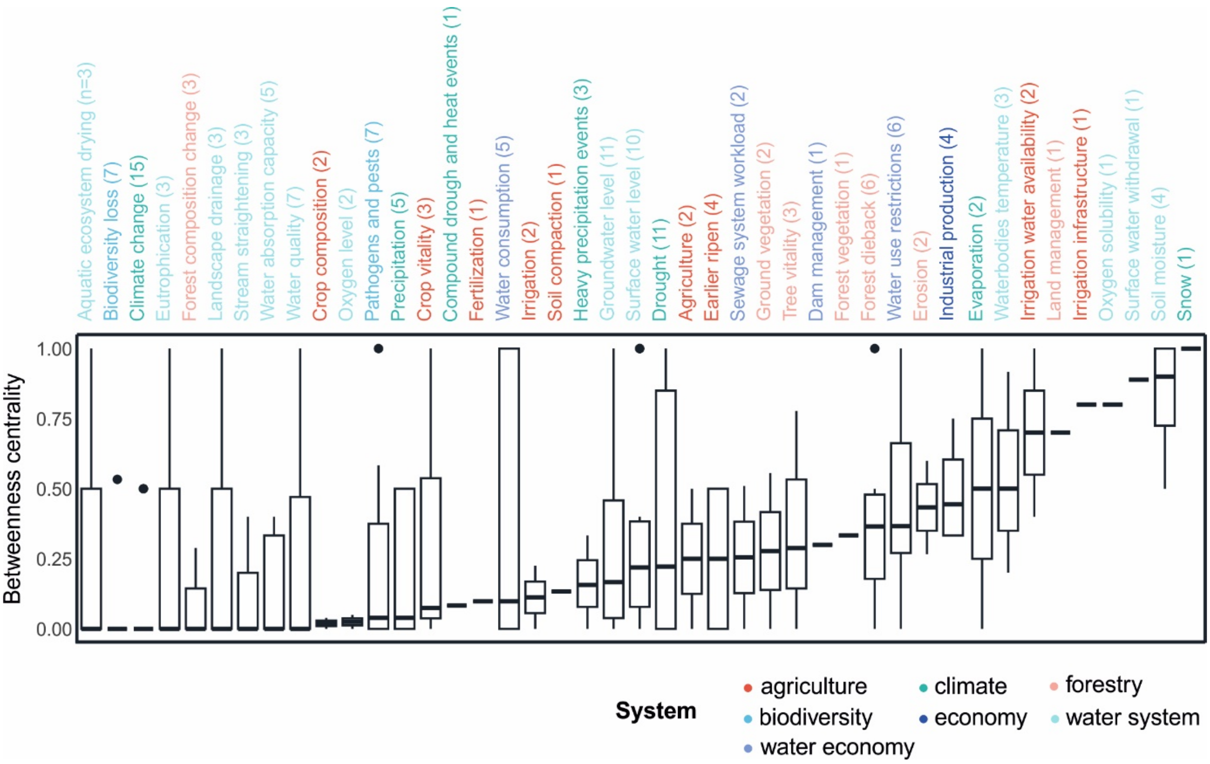

Figure 4: Betweenness centralities of individual variables in the individual CLDs. Higher values indicate variables with a greater impact on the overall dynamics of the system, as they are positioned at key junctures in the causal relationships. The centralities are normalized to 1 for each CLD individually to allow for comparisons using the CLD's maximum and minimum betweenness centrality values. Boxplots represent median, 0.25 and 0.75 quantiles. Circles represent outliers.

This picture changes drastically when considering the collective CLD: our results show that several variables transition from low centrality in the individual CLDs to high scores in the collective one (Fig 5A, green marking). As a result of the aggregation process, these variables become strongly embedded in the collective CLD, thus gaining prominence. For example, 'biodiversity loss' holds low centrality in the individual CLDs as it functions predominantly as an outcome variable (13 links from other variables, 3 links to other variables). However, when aggregating both ingoing and outgoing links, the 'biodiversity loss' becomes more embedded in the CCI patterns. This example shows how variables can emerge as central only when aggregating diverse stakeholder perspectives.

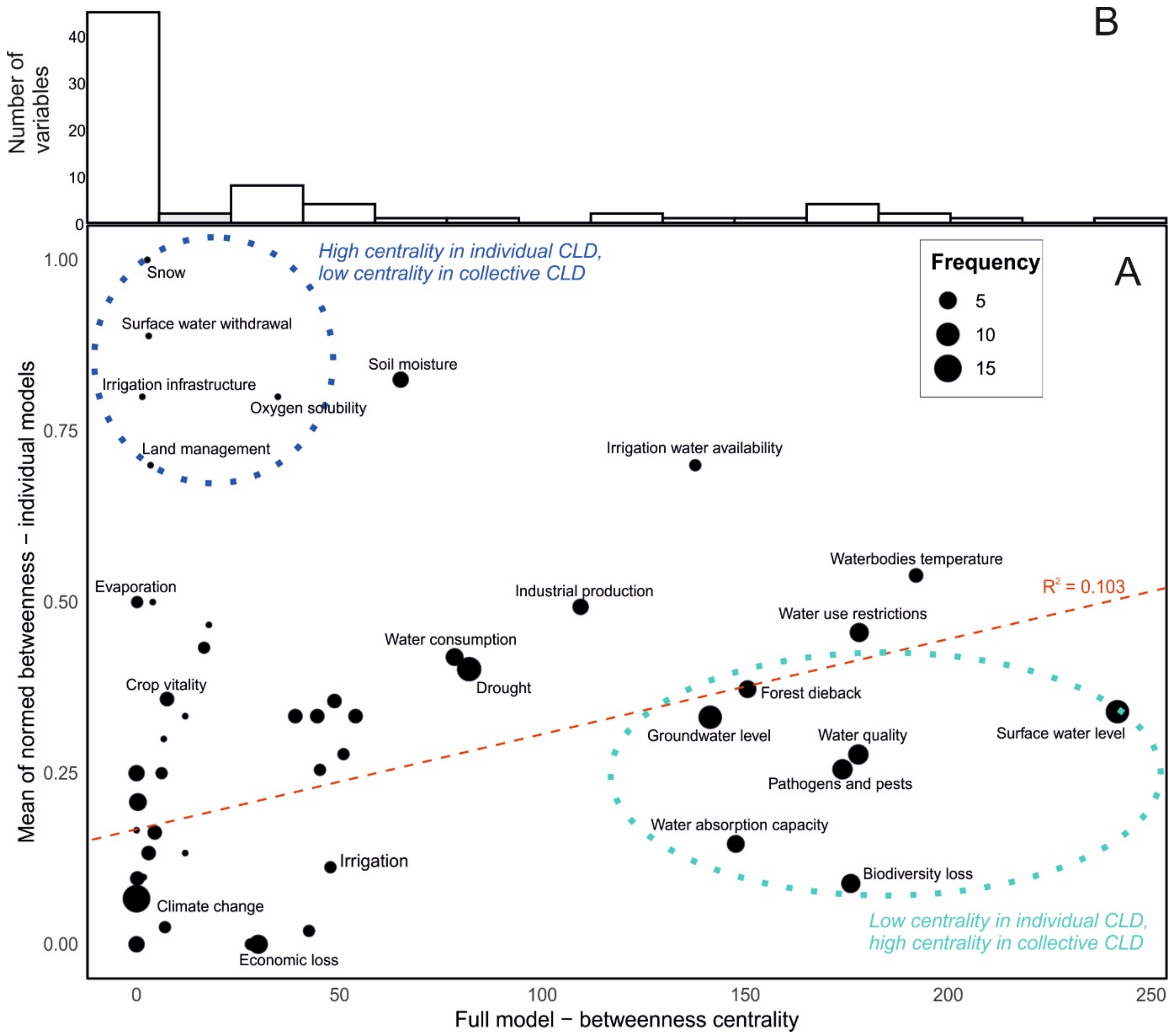

Figure 5: A Betweenness centrality of variables in the individual CLDs and collective CLD. For the individual CLDs, betweenness centrality was calculated and normalized by the CLD's respective minimum and maximum betweenness centrality. Then, for each variable, the mean betweenness centrality was computed across all individual CLDs. B histogram with the distribution of betweenness centralities in the collective CLD.

At the same time, we identify variables with high centrality in the individual CLDs but with low centrality in the collective CLD (Fig 5A, blue marking). For example, 'snow' emerges as the most central variable in the individual CLDs while featuring low centrality in the collective CLD. These variables typically are mentioned by only one stakeholder, resulting in a lack of emergent effects that could elevate their centrality in the collective CLD. Essentially, these variables can be perceived as outliers that are not part of a collective understanding shared by multiple stakeholders.

The disparity between the collective and individual CLDs is supported by their weak correlation (Fig 4a). Although there is a positive correlation (R2 = 0.1), its low value suggests that many variables that are central in the individual CLDs are not influential in the collective CLD and that many variables influential in individual CLDs lack influence in the collective CLD.

3.4 Emergent-system-level properties

The structure of the collective CLD is decentralized and less dependent on single variables (Fig 6b). Overall, the pooling of diverse knowledge leads to more complex CCI patterns, as indicated by the average path length, network diameter, and network transitivity. The average path length in the collective CLD (2.6) is higher than in most individual CLDs (median 2.1). Similarly, the network diameter of the collective CLD is larger, indicating a more detailed depiction of cascading impacts. Additionally, the network transitivity of the collective CLD (0.26) exceeds the median of the individual CLDs (0.11). This highlights the emergence of transitive structures in the collective CLD, implying higher complexity levels in the described CCI drought patterns.

The decentralized structure in the collective CLD is reflected by its moderate network centralization (0.14). While there is still a core-peripheral structure, the core comprises multiple, equally central variables. In contrast, the individual CLDs show strong variation in centralization (median 0.14, sd: 0.1). This decentralization stems from varying stakeholder prioritizations, which are reconciled through aggregation. These findings were as expected since the number of variables in a CLD significantly influences these network statistics, and the collective CLD has more variables.

We find an increase in the number of feedback loops when aggregating randomly sampled individual CLDs. While only 2 of 21 stakeholders described a total of 7 feedback loops in the individual CLDs, the collective CLD features 108 feedback loops. This trend is highlighted when a varying number of individual CLDs is gradually combined (see Fig 6b). Our results show that the number of feedback loops increases exponentially. For instance, aggregating 8 CLDs results in a median of 6 feedback loops, whereas combining 15 CLDs leads to 26 feedback loops. Also, outliers for each boxplot show that the number of apparent feedback loops resulting from these aggregations depends on which CLDs are sampled.

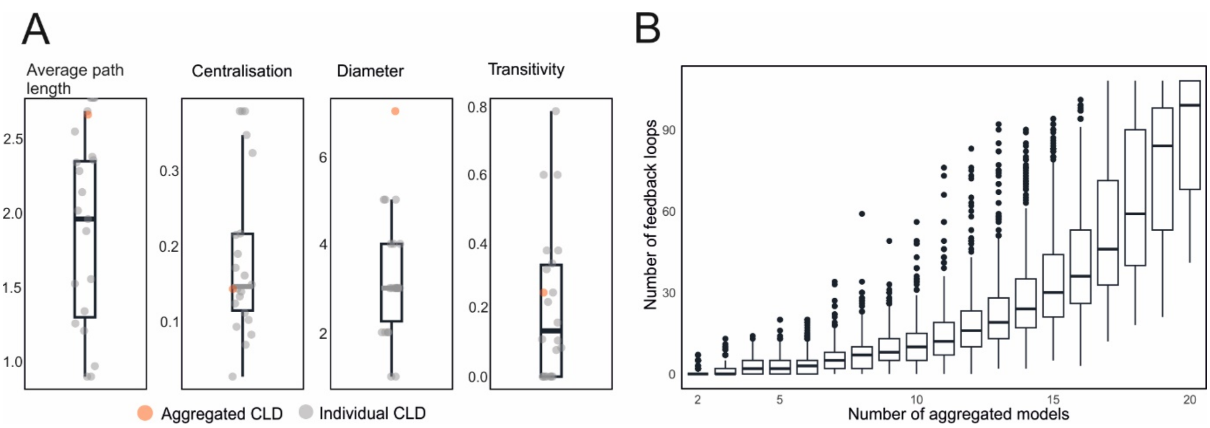

Figure 6: A: Number of emergent feedback loops when aggregating multiple individual CLDs. B: Network-level statistics measuring characteristic features of both individual and collective CLDs.

In the collective CLD, we identify both balancing and self-reinforcing feedback loops that underscore the CCI patterns' interconnected nature and the system's non-linear behavior. While seemingly intuitive, these feedback loops only emerge upon aggregating individual CLDs. For example, several balancing feedback loops center around 'water use restrictions', which stabilize both ground- and surface-water levels within industrial water withdrawal, agricultural irrigation, and general water consumption (see Fig 7a). The implementation of water use restrictions leads to reduced water withdrawal and, subsequently, a decline in industrial production. In turn, this eases the presence of water use restrictions. According to the participating stakeholders, these restrictions prompt a decrease in overall water consumption, raising groundwater and surface water levels, thus prompting a reduction in water-use restrictions. In the ‘agriculture’ system, water use restrictions lower the available irrigation water, thereby contributing to an increasing ground- and surface water level, again reducing the water-use restrictions in place.

Self-reinforcing feedback loops emerge in the collective CLD, implying escalating effects on water quality and biodiversity (see Fig 7b). In this example, water quality and biodiversity losses are coupled with drought impacts. For example, a decline in water quality leads to a reduction in biodiversity, which amplifies the drying out of ecosystems. Consequently, ecosystems lose their natural water absorption capacities, and the overall water quality further deteriorates. Additionally, water quality and eutrophication form a self-reinforcing feedback loop. As water quality declines due to increased eutrophication, a diminishing water quality, in turn, accelerates eutrophication.

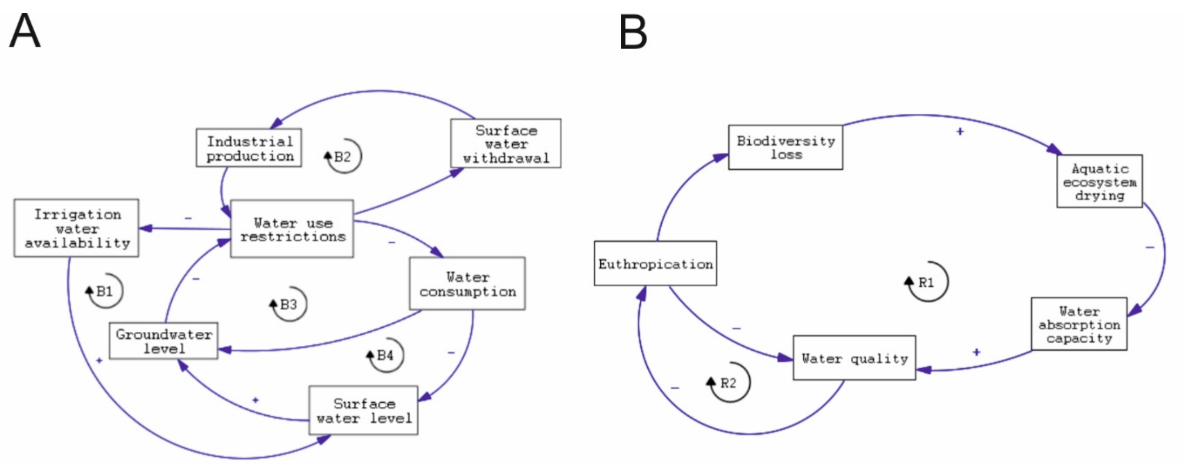

Figure 7: Example feedback loops that emerge in the collective CLD. A) balancing loops involving water use restrictions. B) reinforcing loops on water quality and biodiversity losses.

4. Discussion

Collective intelligence has been shown to provide improved estimates and knowledge compared to individuals in various domains (18,19,49). Against this background, our findings confirmed that aggregating individual stakeholder knowledge on CCI of drought can indeed lead to new knowledge on certain system elements. Using CLDs and network statistics, our study provides insights into critical variables and system properties that only emerge when pooling diverse stakeholder knowledge and perspectives.

Our findings illustrate the applicability of CLDs for analyzing complex patterns of drought-induced CCI from diverse perspectives. Prior work has leveraged CLDs to capture the complex dynamics imposed by drought impacts while focusing on the system complexity (24,50). However, the added value of stakeholders and participatory research designs remains unexplored for studying CCI patterns of droughts. Thus, our study contributes by highlighting the suitability of CLDs for integrating different, unique perspectives on CCI and providing a series of statistics and analyses for drawing new knowledge from these. Particularly, the aggregation process of the CLDs shows if a knowledge “saturation” is reached, where all relevant impacts and drivers within the studied system are considered. Thereby, the system’s boundaries (i.e. the variables relevant to understanding a system) can be clearly defined (40,51). As saturation was achieved after around 17 interviews (Fig 2), we can reason that the most relevant drivers and impacts of droughts have been mapped in the interview process.

By comparing the betweenness centrality of variables between the individual CLDs and the collective CLDs, we identified multiple variables that emerged as influential in the CCI patterns only when combining stakeholder perspectives. For example, ‘biodiversity losses’ was not central within individual CLDs. It becomes highly central only when aggregating the individual CLDs, reflecting its positioning within key CCI impact patterns of drought (52,53). This observation points to the benefits of explicitly combining diverse stakeholder perspectives to reveal critical system components. For future research, our results stress the importance of considering individual system components in CCI patterns from different perspectives to assess their total influence.

The emerging knowledge concerning structural features of CCI drought impacts became evident when considering feedback loops within the models. While the individual models held mostly no feedback loops, their number drastically increased in the collective CLD. For instance, it became the collective insight of stakeholders that highlighted the balancing role of water use restrictions in emerging feedback loops. The resulting balancing feedback loops thereby contributed to a more stable water withdrawal. Prior research has emphasized the critical role of feedback loops in understanding complex system dynamics, as these loops introduce key non-linear elements, such as escalating or balancing behaviors (29,30,50). While previous work on drought impacts has underscored their relevance (50,54), our research contributes by stressing how the knowledge of feedback loops might only be visible when combining knowledge from stakeholders with different expertise.

The participatory design of this research enhanced stakeholder engagement and contributed to instigating discussions. The interviews and workshop facilitated a stronger sense of interaction and intuitive access to the study subject. Also, the intuitive network visualizations of the CLD allowed stakeholders with different levels of expertise to reflect on CCI patterns and quickly understand the aggregate CLD. Multiple studies have shown such positive effects of participatory research using CLDs across other domains (48,55,56). Therefore, we advocate for more widespread use of participatory modeling approaches for communicating CCI of droughts as their multi-sectoral nature requires the involvement of diverse stakeholders (without knowledge of modeling techniques required) to understand such complex systems better

Our study has certain limitations that warrant consideration. First, our findings concern a single case study and thus constrain their generalizability. Future research should thus compare such findings across regions exhibiting different CCI patterns. Second, the qualitative nature of the CLDs can limit the practical use of such models e.g. for policy-making. Therefore, we suggest using e.g. fuzzy-cognitive maps or system dynamics modeling for a (semi-) quantitative modeling of such impact cascades for future research (16). These could be used to test different scenarios, such as unintended consequences of adaptation measures. However, it's essential to note that these methods tend to be more cognitively demanding, requiring thorough understanding and expertise in their application.

5. Conclusion

In this study, we analyzed how pooling the knowledge of individual stakeholders on CCI drought impacts can lead to new knowledge about the system. We found that this pooling uncovered emergent system-level features, such as feedback loops, and variable-level characteristics. Indeed, variables that hold little importance in individual mental models became more significant in collective ones. This includes variables such as biodiversity loss and the role of water use restrictions, which only became apparent through the synthesis of individual perspectives. These findings underscore the unique value of integrating diverse stakeholder knowledge in understanding complex drought impacts. The study underscores the necessity of considering a variety of expert opinions to capture the complexity of drought-society interactions, emphasizing that the dynamics of drought impacts can significantly vary based on the diversity of knowledge integrated into the model. For future research, these findings are essential for designing assessments and modeling complex, multi-sectoral drought impacts as they highlight the role collective intelligence can play in revealing otherwise ignored aspects of environmental phenomena.

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Data availability

The data for the individual models, the homogenization process, and the collective model, as well as the code for performing the outlined analyses, are publicly available: github.com/jansodoge/participatory_cci_impacts_data

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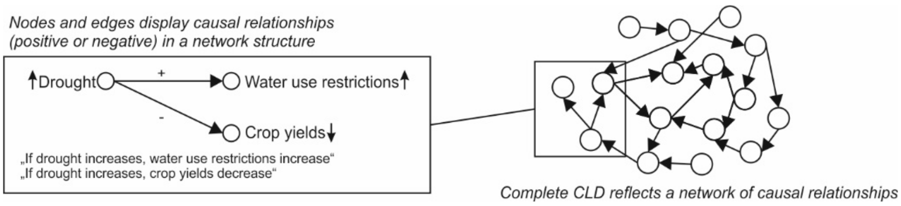
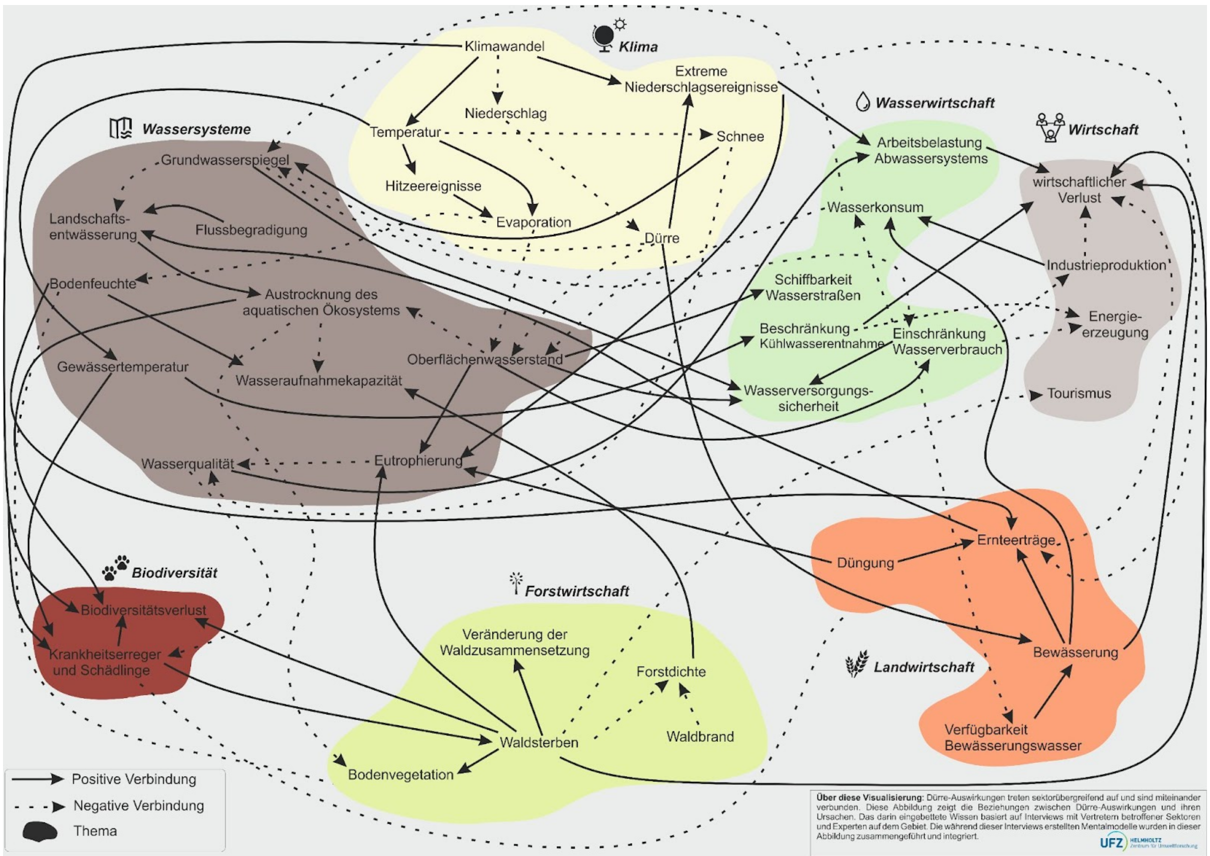
Supporting information



S1 Fig. Illustration of CLD composition and functionality. CLDs consist of a set of nodes and edges where nodes represent variables and edges the causal relationships between them. Relationships can be positive or negative, referring to whether a change in one variable leads to an increase or decrease in the state of the second variable.



S2 Fig. Simplified collective CLD that was presented to stakeholders during the validation group workshop.

S1 Table: Definition of systems into which variables in the CLDs are categorized.

System	Description
Agriculture	Involves the cultivation of crops and the rearing of livestock for food production
Biodiversity	Includes the variety of plant and animal life within a particular habitat or ecosystem
Water economy	This system focuses on the management and distribution of water resources for various human activities
Forestry	Forestry involves the management and conservation of forests
Economy	The economic system encompasses the production, distribution, and consumption of goods and services
Climate	Encompasses the long-term patterns of temperature, precipitation, wind, and other atmospheric conditions in a particular region
Water system	Comprises the interconnected network of water bodies, including rivers, lakes, and groundwater

S2 Table. Interview guideline

Introductory questions
1. Describe your position 2. What are your areas of focus and responsibilities? 3. How long have you been working in this position? 4. How would you assess your knowledge of droughts and low water levels in Thuringia? (Low, Moderate, High)
Sector-specific impacts
1. What specific impacts of drought and water scarcity have been observed in your sector in the past? 2. Are there geographic hotspots in Thuringia for the outlined impacts? 3. What are the possible causes of these impacts, such as socio-economic or climatic factors? 4. In your opinion, what impacts of drought and water scarcity can be expected in your sector in the future? Can you think of impacts that have not yet occurred but could occur (plausible impacts)?
Cascading, interconnected, and other cross-sectoral impact relationships
1. What cascading and interdependencies exist between the outlined drought consequences? 2. Apart from cascading impacts, where have you experienced overlaps (e.g., conflicts, compromises, or collaborations) with other sectors? What caused these situations, and do they occur only during specific drought events or regularly?
Coping and adaptation measures
1. To what extent does your organization engage in preparations and activities to address the impacts of drought and water scarcity? 2. What coping and adaptation measures has your institution already taken in the past to address the impacts of drought and water scarcity in your sector? Have the effects of these measures been evaluated, and if so, what was the assessment? 3. How urgently do you consider coping and adaptation measures in terms of future impacts of drought and water scarcity in your sector? 4. In addition to the existing coping and adaptation measures, are there any further measures that your institution considers for future implementation? Under what circumstances are these measures being considered? 5. What measures should be implemented to avoid future cross-sector conflicts arising from drought and water scarcity (e.g., agreement on compromises, collaborations, etc.)?

S1 File. Documentation of model aggregation.