Uncovering the dynamics of multi-sector impacts of hydrological extremes: a methods overview

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Abstract

Hydrological extremes, such as droughts and floods, can trigger a complex web of compound and cascading impacts due to interdependencies between coupled natural and social systems. However, current decision-making processes typically only consider one impact and disaster event at a time, ignoring causal chains, feedback loops, and conditional dependencies between impacts. Analyses capturing these complex patterns across space and time are thus needed to better inform effective adaptation planning. This perspective paper aims to bridge this critical gap by presenting methods for assessing the dynamics of the multi-sector compound and cascading impacts (CCI) of hydrological extremes. We discuss existing challenges, good practices, and potential ways forward. Rather than pursuing a single methodological approach, we advocate for methodological pluralism. We see complementary roles for analyses building on quantitative (e.g. data-mining, systems modeling) and qualitative methods (e.g. mental models, qualitative storylines). We believe the data-driven and knowledge-driven methods provided here can serve as a useful starting point for understanding the dynamics of both high-frequency CCI and low-likelihood but high-impact CCI. With this perspective, we hope to foster research on CCI to improve the development of adaptation strategies for reducing the risk of hydrological extremes.

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Abstract

Hydrological extremes, such as droughts and floods, can trigger a complex web of compound and cascading impacts due to interdependencies between coupled natural and social systems. However, current decision-making processes typically only consider one impact and disaster event at a time, ignoring causal chains, feedback loops, and conditional dependencies between impacts. Analyses capturing these complex patterns across space and time are thus needed to better inform effective adaptation planning. This perspective paper aims to bridge this critical gap by presenting methods for assessing the dynamics of the multi-sector compound and cascading impacts (CCI) of hydrological extremes. We discuss existing challenges, good practices, and potential ways forward. Rather than pursuing a single methodological approach, we advocate for methodological pluralism. We see complementary roles for analyses building on quantitative (e.g. data-mining, systems modeling) and qualitative methods (e.g. mental models, qualitative storylines). We believe the data-driven and knowledge-driven methods provided here can serve as a useful starting point for understanding the dynamics of both high-frequency CCI and low-likelihood but high-impact CCI. With this perspective, we hope to foster research on CCI to improve the development of adaptation strategies for reducing the risk of hydrological extremes.

1 Introduction

Future climate projections show an intensification of variations in the hydrological cycle, with more droughts and floods expected to occur in many regions (Cook et al., 2020; IPCC, 2021; Merz et al., 2021; Pokhrel et al., 2021; Samaniego et al., 2018; Simpson et al., 2021). In this context, understanding the magnitude and distribution of the impacts of these hydrological extremes becomes crucial to inform adaptation planning. Impact assessments can facilitate the identification of areas that are disproportionately affected, aiming to support the allocation of resources (Hammond et al., 2015). They can further provide baseline information for evaluating whether adaptation measures effectively reduce loss and damage. Spatio-temporal impact datasets can also improve our understanding of risk drivers (Kellermann et al., 2020) and serve as ground truth information for impact-based early warning systems (Hobeichi et al., 2022).

In today's interconnected world, assessing the risks and impacts of floods and droughts has become increasingly complex as these events often have far-reaching consequences that spread throughout various sectors and systems, leading to **'compound and cascading impacts' (CCI)** (Fig. 1 and Box 1). Indeed, natural, technological, and social systems are deeply intertwined, and the adverse outcomes of hydrological extremes heavily depend on how the elements of the affected systems interact with each other (Matanó et al., 2022; Raymond et al., 2020; Ruiter et al., 2020; Zscheischler et al., 2018). For example, during the 2021 flood event in Europe, the flood waters damaged major access routes and destroyed most of the bridges in the flooded area in Ahr valley (Schäfer et al., 2021). This reduced the accessibility for rescue cars and fire brigades, leading to cascading impacts.

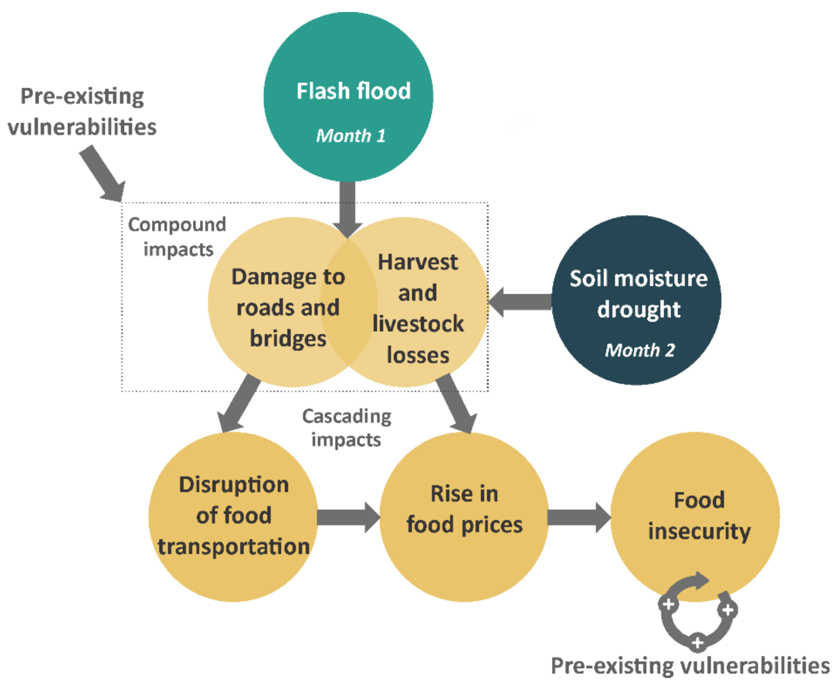

Figure 1 *Schematization of compound and cascading impacts (CCI) for a fictitious flood followed by a drought event. The impacts triggered by different hazards interact, compound, and cascade. Unrelated events or pre-existing vulnerabilities, such as pandemics and conflicts, can also contribute to the impacts.*

Flood and drought impacts can also spill over beyond their initial geographical location through the interconnectivity of socioeconomic sectors and ecosystems (UNDRR, 2021a). As a result, some of the most affected areas can be those not directly affected by the physical hazard (e.g. flood waters). For instance, the extremely low soil moisture values in the summer of 2018 in Germany caused severe crop failures, leading to fodder shortages and the consequent early slaughtering of animals. As a consequence, farmers restrained from investing in fertilizers and machinery, resulting in ripple effects along supply chains (de Brito, 2021).

Box 1 *Defining compound and cascading impacts (CCI)*

‘**Socioeconomic impacts**’ are defined as the adverse effects of floods and droughts on society. They can include but are not limited to casualties, infrastructure collapse, increased demand for water, need for credit, increased commodity prices, migration, food insecurity, conflicts, reduced quality of life, crop yield losses, and mental health problems. Hydrological extremes can, in exceptional cases, lead to positive consequences. For instance, drought combined with heat waves can benefit fruit growers and winemakers depending on the onset of the event, as they can increase the sugar concentration in fruits.

The term ‘**compound impact**’ is used to denote impacts that temporally and spatially coincide. These could be, for instance, a drought that simultaneously impairs the transportation of goods and affects tourism via restrictions on boat cruises. The impacts of hydrological extremes can also compound with the effects of other ‘compounding hazards’ or events (i.e. multi-hazard events) and/or circumstances (e.g. conflicts). Even unrelated events, such as the Covid-19 pandemic, can amplify the impacts of droughts and floods and vice versa (UNDRR, 2021c).

‘**Cascading impact**’ refers to consecutive impacts triggered or amplified by other impacts or processes. For instance, the delay in sowing and transplanting crops caused by droughts can reduce employment in agriculture, which in turn further reduces employment due to the reduced need of labor for harvesting. Similarly, the direct impacts of floods and droughts on ecosystems and their services can lead to cascading impacts on livelihoods. Cascading impacts can also ripple within and across economic sectors. Energy outages very often impact other services, such as healthcare facilities. Upstream and downstream relations also lead to cascading impacts. For instance, low flows can impair shipping and lead to increased commodity prices.

The concept of ‘**systemic impact**’ is based on the notion that the impacts of a hazard can be influenced by how the elements of the affected system interact. These interactions can either increase or decrease the overall impact. The interactions between sectors and systems and associated impacts create mutual dependencies, where actions and outcomes in one sector or system can lead to actions and outcomes in another. The term ‘systemic impact’ encompasses both compound and cascading impacts, therefore, both coincidental and consecutive impacts.

A better understanding of CCI’s characteristics and underlying drivers can, therefore, inform the ex-ante management of systemic risks. The need to investigate CCI has been underscored by the UNDRR (2021) and has recently been included in the research agenda of the Integrated Research on Disaster Risk 2021-2030 (ISC-UNDRR-IRDR, 2021). Likewise, the IPCC is moving from a static understanding of risk to a dynamic framing that considers compounding, cascading, and systemic effects (IPCC, 2022).

Inspired by these calls, research on CCI of floods and droughts is on the rise. In recent years, scientists have addressed CCI to specific sectors and hazard types, especially critical infrastructure (Fekete, 2020; Guimarães et al., 2021; Rohr et al., 2020), water quality (Mishra et al., 2021), agriculture (Christian et al., 2020) as well as cascading impacts linked to the COVID-19 pandemic and its policy responses to it (UNDRR, 2021c). Interactions between hydrological extremes have also been investigated. For instance, Matanó et al. (2022) and Ward et al. (2020) provide examples of interactions between flood and drought impacts. Despite these advances, research on CCI remains highly fragmented, and an overview of available methods to study them is missing.

In this perspective, we discuss key approaches for investigating CCI dynamics within the context of climate change and an increasingly connected world. Our goal is to help researchers navigate the emerging field of CCI by providing a synthesis of existing methods. We first highlight persisting challenges, such as the lack of multi-sector and longitudinal impact data. Then, we present a range of qualitative and quantitative methods that can be used to analyze CCI dynamics, drawing on case study examples. Based on these, we end with six recommendations to advance this field of research. While the set of methods discussed here is not exhaustive, it provides a holistic view of how to tackle CCI and serves as a useful starting point for researchers studying the systemic risks and impacts of droughts and floods on coupled social, technological, and natural systems.

2 Challenges in the understanding of CCI

Due to the complexity of CCI, our ability to identify and understand them is still in its infancy. While there has been notable progress in compound hazards research (e.g. Batibeniz et al., 2023; Bevacqua et al., 2021; Singh et al., 2021; Sutanto et al., 2020), the socioeconomic CCI of droughts and floods remain relatively unexplored (Naumann et al., 2021; Ward et al., 2022; Zscheischler et al., 2020). One of the reasons for the limited exploration of CCI patterns is the scarcity of data on the socioeconomic impacts of floods and droughts, especially in the global South. Impact assessments are often conducted for single hazard types, and standardized, methodologically comparable impact information for multiple disaster types is hardly available.

In this context, we present five challenges that need to be addressed to provide targeted information to understand CCI (Fig. 2). It should be highlighted that the field of CCI research encompasses many more challenges than those depicted in Fig. 2, such as the understanding of the risk drivers of CCI. However, these aspects fall outside the scope of this perspective paper.

Figure 2 *Set of challenges and needs that must be addressed to provide targeted information to understand CCI. In this study, we focus on methods that can be used to address the needs of challenges 3 to 5, which are related to dynamic aspects.*

<u>Challenge 1</u> is linked to the focus of existing impact assessments on **single socioeconomic sectors or systems** and tangible losses (Fronzek et al., 2019; Ward et al., 2022). Studies typically address isolated impacts to single sectors, including damage to critical infrastructure (Qiang et al., 2020), agriculture losses (H. Chen et al., 2019; Rahman & Di, 2020; Tapia-Silva et al., 2011), damage to buildings (Gerl et al., 2014; Serpico et al., 2012), and fatalities (e.g. Papagiannaki et al., 2022). Furthermore, existing databases are almost exclusively limited to impacts measured in monetary terms (Ding et al., 2011), which are more easily quantified compared to intangible losses, such as societal and cultural impacts (e.g. decrease of subjective

well-being and growing lack of trust in institutions) (Ding et al., 2011). However, these intangible losses can be just as severe, if not more so. As a result, a holistic understanding of all sectors and systems affected is missing. This gap is related to difficulties in deriving reliable estimates of indirect or intangible losses such as adverse social, psychological, and environmental consequences (Allaire, 2018; Walz et al., 2021). Exceptions include initiatives such as the HOWAS21 database (Kellermann et al., 2020), which includes detailed data on objects affected by European floods. For drought events, the few existing multi-sector impact databases are based on the analysis of news (e.g. U.S. Drought Impact Recorder (NDMC, 2019), European Drought Impact Inventory – EDII (Stahl et al., 2016), and country specific databases (de Brito et al., 2020)). While these studies represent significant methodological advances, they are currently not widespread. Hence, multi-sector impact databases encompassing underrepresented sectors such as health, tourism, energy and forestry, are needed.

Related to this issue is the **lack of longitudinal impact datasets encompassing both large and small-scale events** <u>(Challenge 2)</u> (de Brito et al., 2020; R. L. Jones et al., 2022). Impact assessments are conducted mostly ad hoc, following a specific disaster (Ding et al., 2011). Existing impact datasets covering multiple years are limited to large-scale disasters (e.g. EM-DAT, NatCatSERVICE) and suffer from underreporting (R. L. Jones et al., 2022). As such, they may overlook the risks posed by smaller, more frequent events that can be equally damaging when considering their cumulative occurrence (UNDRR & CRED, 2020). According to the UNISDR (2015), 99.7% of all disasters between 1990 and 2013 were smaller-scale disasters, with fewer than 30 deaths or less than 5,000 affected buildings. Thousands of these smaller-scale events are unreported as they do not result in high impacts at the national or international levels. Nevertheless, they bring a constant stream of local losses and damages (UNDRR, 2021b) and are thus relevant for understanding local patterns of CCI. Therefore, impact datasets covering low and high-impact events over multiple years are required to understand the cumulative and long-term consequences of floods and droughts.

<u>Challenge 3</u> refers to the lack of understanding regarding the **relationships between the socioeconomic impacts** of hydrological extremes (Pescaroli & Alexander, 2016; Simpson et al., 2021; UNDRR, 2021c). Impact outputs from one sector or system can become inputs into other sectors or systems depending on system/sector dependencies (Ding et al., 2011; UNDRR & UNU-EHS, 2022). For example, droughts can lead to crop failures, food shortages, and increased prices, resulting in ripple effects and social and political instability. Empirical studies investigating CCI relationships have often focused on single and small-scale case studies (e.g. Fekete, 2020; Gonzva et al., 2017; Zeng et al., 2021). Research addressing how impacts to one sector or system can lead to consequences in others is thus needed to support effective mitigation measures.

<u>Challenge 4</u> is linked to the limited research on the **interconnectivity between impacts across regions, borders, and spatial scales** (Andrew J. Challinor et al., 2017; Helbing, 2013). Namely, cascading impacts spread not only across sectors and systems but also spill

beyond geographical scales and administrative or national borders, and can lead to globally networked impacts (UNDRR, 2021a). For instance, drought-related harvest failures in Russia in 2010, combined with an export ban, led to a global spike in cereal prices. This amplified the food security risk in Pakistan and is associated with an increase in the use of food banks in the U.K. (Andy J. Challinor et al., 2018; Hunt et al., 2021). Upstream and downstream relations can also exacerbate the impacts of floods and droughts. For instance, low flows in the Rhine impaired shipping during the 2018 drought in Germany (Erfurt et al., 2019), increasing fuel prices in Switzerland. As such, analyses of the interplay between CCI across local, regional, and even global spatial scales (e.g. Lawrence et al., 2020; Mishra et al., 2021) are needed to identify critical nodes in the system that can lead to higher impacts.

Finally, research on the **effects of response measures** (i.e. impacts linked to risk management or adaptation interventions) on CCI is scarce (Challenge 5). While humans influence the propagation of extreme events, they also respond to their impacts (AghaKouchak et al., 2021). Within this context, risk management and adaptation responses to one impact may inadvertently lead to unintended consequences such as an increased vulnerability in the long run (e.g. Giuliani et al., 2022; Niggli et al., 2022; Schipper, 2022; Simpson et al., 2023). For instance, temporary water abstraction licenses may exacerbate underlying water scarcity as they can be difficult to reverse when the drought ends (Di Baldassarre et al., 2018). Therefore, it is difficult to measure to which extent adaptation measures reduce impacts or lead to unintended consequences. Thus, a parallel investigation of impacts and response measures adopted is crucial to understand how they co-evolve.

Challenges 1 and 2 are closely tied to the quality and availability of socioeconomic impact data, whereas challenges 3 to 5 relate to understanding CCI dynamics. Since significant research has already been conducted on improving impact data collection (Alfieri et al., 2016; Allaire, 2018; Ding et al., 2011; Enenkel et al., 2020; Merz et al., 2020), we focus here on methods that can be used to address challenges 3 to 5, which are rooted in the complexity of CCI interactions.

3 Key methods for investigating CCI patterns and relationships

Several recent studies have provided valuable guidelines on how to assess compound hazard interrelationships (e.g. Bevacqua et al., 2021; Tilloy et al., 2019), the dynamics of risk components (e.g. De Angeli et al., 2022; de Ruiter and van Loon, 2022; Terzi et al., 2019) and multi-sector dynamics (e.g. Reed et al., 2022). However, similar syntheses that incorporate both qualitative and quantitative approaches are still missing for research on CCI.

In the subsequent sections, we present an overview of knowledge-driven, data-driven, and mixed methods that hold the potential to enhance our understanding of the dynamic nature of CCI (Table 1). These were selected based on the experience of the co-authors, which come from different fields, including sociology, engineering, physics, geography and economics. A general description is provided for each method, followed by applications in CCI or related fields and how the method can address challenges 3 to 5 in Fig. 2. Besides considering the strengths of each analytical approach, the choice for a specific method should be guided by the study's objective, data requirements, and complexity level as illustrated in Fig. 3.

Although the examples of applications here focus on drought and flood hazards, these methods can be used for other hazard types (e.g. earthquakes, storms, heatwaves, and landslides). Also, many of these methods can also be applied to understand the relationship between risk drivers (e.g. vulnerability, exposure, and hazard) and their corresponding CCI.

It is worth highlighting that this overview is not intended to encompass all existing methods which can be used to understand complex relationships. Rather, we strive to emphasize key approaches that can aid in comprehending CCI dynamics. Additionally, the articles presented here represent only a fraction of the extensive literature on climate change impacts in a broader sense.

3.1 Knowledge-driven methods

Knowledge-driven methods rely on expert judgment and domain-specific information to analyze complex phenomena. These methods leverage existing knowledge, whether formal or informal, theoretical or practical, to delve into the systemic aspects of CCI. Their foundation lies in recognizing the significance of tacit and explicit knowledge, collective wisdom, and context-specific expertise in generating insights into complex systems (Aminpour et al., 2020). As their development can be done in a co-creation process with relevant actors, they also allow the integration of perspectives of vulnerable and marginalized groups, often overlooked in more data-driven approaches. In this section, we focus on methods such as mental models, visual techniques, and qualitative scenarios and storylines.

Table 1 *Overview of methods that can be used to investigate CCI dynamics. The groups of methods here are, to some extent, subjective, and overlap exists between them. Thus, they should be used as a general guide rather than a definitive categorization.*

	Group of methods	Methods and key references	Strengths	Weaknesses
Knowledge-driven	Mental models	▪ Causal loop diagrams (Groesser & Schaffernicht, 2012; Rest & Hirsch, 2022) ▪ Fuzzy cognitive maps (Ballesteros-Olza et al., 2022; Mehryar & Surminski, 2022) ▪ Impact chains (Hagenlocher et al., 2018; Zebisch et al., 2022) ▪ Impact webs (Sparkes et al., 2023)	Visualize the interplay between CCI (Challenge 3). When built in a participatory way, it enables the inclusion of perspectives of marginalized and vulnerable groups. It also facilitates mapping CCI to responses (Challenge 5)	Criticized as subjective representations of reality. Risk of oversimplification as it is difficult to map the full complexity of a system. Spatial and temporal dynamics are usually not explicitly addressed (Challenge 4)
Knowledge-driven	Visual techniques	▪ Rich pictures (Suriya & Mudgal, 2013) ▪ Event timelines (Matanó et al., 2022; Seebauer et al., 2023) ▪ Qualitative matrices (Gill & Malamud, 2014, 2016; Matanó et al., 2022) ▪ Network diagrams (Gill & Malamud, 2014, 2016)	Simplify complex ideas and enhance their comprehensibility for a wider audience. Visualize relationships between CCI and response measures over time (Challenges 3 and 5)	Can carry ethical risks (e.g. power relations). Comparability between studies is limited. Are often unsuitable for addressing spatial dynamics (Challenge 4)
Knowledge-driven	Qualitative storylines and scenarios	▪ Qualitative storylines (van den Hurk et al., 2023) ▪ (Semi)-qualitative scenarios (Di Baldassarre et al., 2021; Rusca et al., 2023)	Allow to take into account political, cultural, and economic contexts. Give more power to participants to shape the story. Spatial and temporal changes play a key role in these methods (Challenge 4)	Highly context-specific. Risk of making arbitrary assumptions and oversimplification. Limited ability to predict outcomes.
Data- driven	Multivariate statistics	▪ Logistic regression and other machine learning algorithms (Ben-Ari et al., 2018; Martius et al., 2016) ▪ Markov chains (Ronizi et al., 2022) ▪ Co-occurrence analysis (de Brito, 2021)	Capable of capturing non-linear relationships between CCI (Challenges 3 and 5). Can handle large and complex datasets with numerous variables	Data-intensive. Sensitive to data biases and dependency on historical observations, which leads to limitations in a changing climate and/or contexts of under-reporting
Data- driven	Data mining	▪ Dimensionality reduction (Anowar et al., 2021) ▪ Clustering (Lam et al., 2016) ▪ Sequential pattern mining (de Brito, 2021)	Extracting key patterns from high-dimensional and noisy data (Challenge 3) . Allow uncovering hidden dependencies, also spatially (Challenge 4)	Potential loss of complexity and details when reducing high-dimensional data to lower-dimensional representation
Mixed	Systems modelling	▪ Agent-based modelling (ABM) (Wijermans et al., 2022) ▪ System dynamics and multi-sector dynamics models (Savelli et al., 2023; Yoon et al., 2021)	Can portray the temporal dynamics of complex systems (Challenges 3). Allow the assessment of the effects of different adaptation measures (Challenges 5). AMB can account for spatial dynamics (Challenge 4)	Empirical models require comprehensive data coverage of the underlying system. Require careful calibration and validation. Models without empirical components run at risk of being 'toy' models
Mixed	Network analysis	▪ Network analysis (Naqvi & Monasterolo, 2021)	Intuitive visualization of interconnected systems (Challenges 3 and 5). Enable the identification of key nodes within the	Requires data and knowledge on both impacts and causal relationships between impacts

		network. Allow investigating spatial patterns (Challenge 4)	
Economic-based models	▪Input-output analysis (Koks et al., 2019) ▪Computable general equilibrium model (Bachner et al., 2023)	Allow identifying how changes in one sector can propagate through the economy, affecting other sectors and causing cascading effects (Challenge 3). Can analyze cross-sectoral and cross-regional economic impacts (Challenge 4)	Can represent an oversimplistic view of the economy. Data-intensive

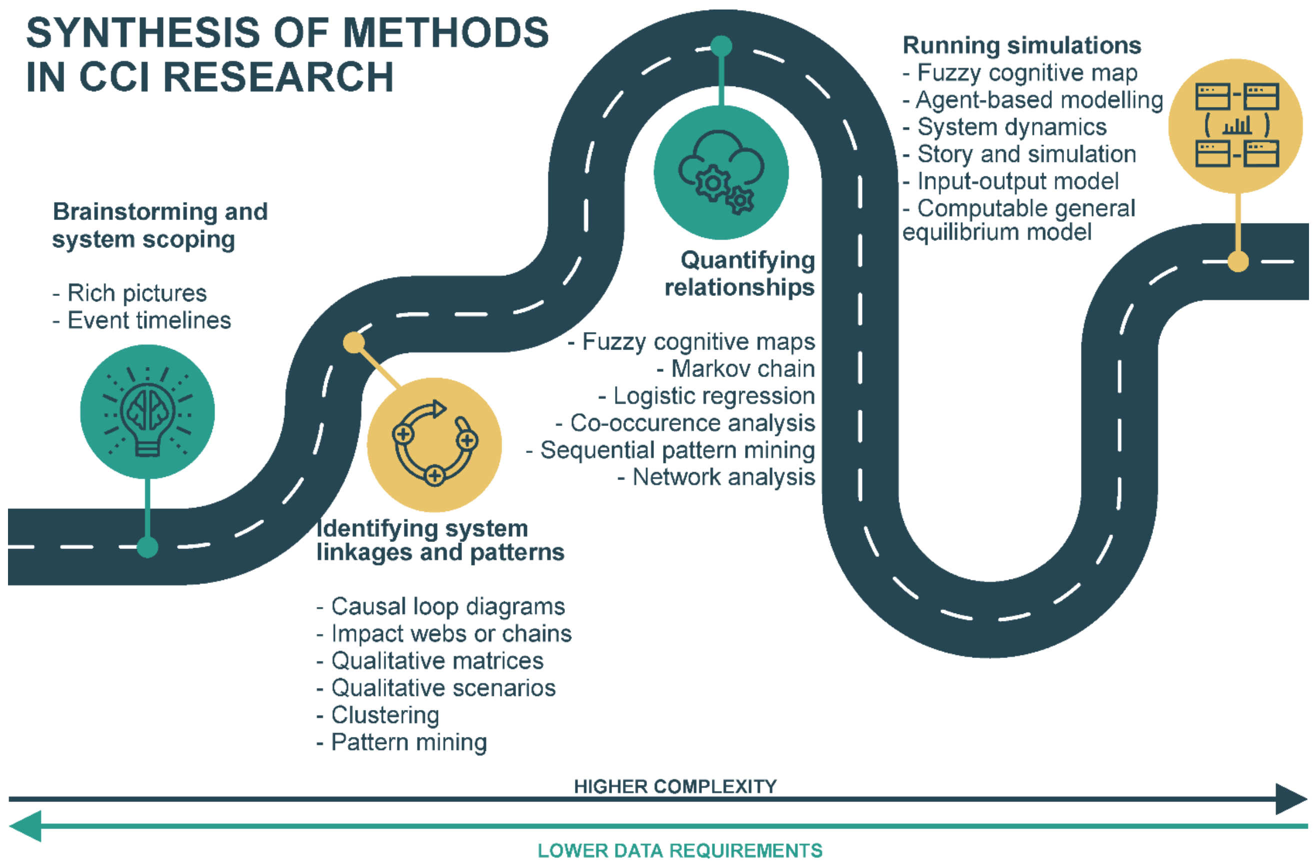

Figure 3 *Synthesis of methods used in CCI research to brainstorm, identify system linkages and patterns, quantify relationships, and run simulations. Some methods can be used for multiple purposes.*

3.1.1. Mental models

Mental models are schematic representations of the world as perceived by humans. By articulating complex relationships between system components (Levy et al., 2018) they aid in comprehending how systems respond to risks and factors such as human activity or environmental changes. However, since individuals' perspectives differ, mental models are subjective depictions of reality (N. A. Jones et al., 2011). They are typically constructed through stakeholder involvement (Romero-Lankao & Norton, 2018) and are often paired with other methods, such as system dynamics (Perrone et al., 2020).

Several approaches are used to elicit mental models, ranging from **causal loop diagrams (CLD)** to free drawing (see Doyle et al., 2022 for a review). CLD are a popular method that demonstrates how changes in one variable can influence others by reinforcing (positive link) or balancing them (negative link). CLD have been widely applied to understand the relationships between socioeconomic impacts (Challenge 3), including the investigation of cascading impacts of hydrological extremes on transport infrastructure, electricity, and healthcare systems (e.g. Berariu et al., 2015; Rest and Hirsch, 2022), as well as multi-sectoral impacts (e.g. Montgomery et al., 2012; Perrone et al., 2020). CLD have also been used to analyze coping and adaptation strategies and their effectiveness in mitigating impacts (Challenge 5) (e.g. Armah et al., 2010; Sanga et al., 2021; Song et al., 2018). While CLD can represent temporal dynamics adequately, spatial aspects are usually not explicitly addressed (Challenge 4). Furthermore, due to their reliance on human interpretation may, their ability to capture the nuances of real-world CCI is compromised, potentially leading to oversimplification.

Fuzzy cognitive maps (FCM) are CLD that account for uncertainty by using weights to define relationship strengths (Challenge 3). FCM have been employed to study drought and flood adaptation solutions and their effect on socioeconomic impacts (e.g. Ballesteros-Olza et al., 2022; Chandra and Gaganis, 2016; Mehryar and Surminski, 2022) (Challenge 5). They have been used to examine past disasters as well as to simulate plausible CCI futures (e.g. D'Agostino et al., 2020). Vanwindekens et al. (2018) incorporated spatial dynamics into the FCM by coupling it with geolocated data to analyze crops' vulnerability to soil moisture drought. Recently, FCM have also been used to address CCI interactions across neighborhood, city, and regional scales (e.g. White et al., 2021) (Challenge 4).

Impact chains are conceptual models used to capture the interplay of hazard, vulnerability, and exposure factors that lead to a specific risk or impact (Menk et al., 2022). This mixed-methods approach draws on elements of CLD and network analysis to investigate complex systems. Impact chains have been applied in various contexts and settings (e.g. Fritzsche et al., 2014; Hagenlocher et al., 2018; Zebisch et al., 2022). For instance, Kabisch et al. (2014) used impact chains to identify the relationships between direct and indirect impacts on multiple sectors resulting from heatwaves, floods, and storm surges (Challenge 3). One of the strengths of impact chains is their ability to link impacts and adaptation strategies (Challenge 5) directly.

However, it is important to note that impact chains often neglect or overly simplify complex systemic interrelations, including transboundary relationships (Menk et al., 2022), which poses a challenge in addressing Challenge 4.

More recently, an approach called **impact webs** was explicitly designed to tackle the complex nature of CCI risks (UNDRR, 2021c). Drawing on the foundations of CLD, impact chains, and network analysis, impact webs provide a comprehensive framework for characterizing the interconnected components of multiple systems, capturing their underlying risk drivers, and visualizing the dynamics of cascading effects (Challenge 3). Unlike impact chains, which often converge towards a single risk, impact webs offer a holistic overview of system interactions without directional constraints. While they have been initially used to understand CCI linked to the COVID-19 pandemic and responses to it, impact webs are now finding application in the study of CCI related to droughts and their compounding hazards, along with exploring potential adaptation options (Challenge 5) (Cotti et al., 2023; Sparkes et al., 2023).

3.1.2. Visual techniques

In addition to mental models, visualization techniques, such as rich pictures, event timelines, and qualitative matrices, are used for visually capturing the elements of a system. They are often part of brainstorming processes and aim to simplify complex ideas and enhance their comprehensibility for a wider audience. However, while these tools help synthesize information at a high level, they may not provide a detailed understanding of the underlying dynamics of CCI. Another concern pertains to the transferability and generalisability of results. While visual techniques facilitate a deep qualitative understanding of a given CCI event, the challenge lies in identifying comparable and scalable results that can be applied more broadly.

Rich pictures are visual depictions of a system, portraying elements and actors involved in a problematic situation (Barbrook-Johnson & Penn, 2022). When used in a participatory setting, this technique enables participants to share experiences about a certain problem and learn from each other (Bell et al., 2019). For instance, Suriya and Mudgal (2013) used the rich pictures method to examine the factors contributing to toxic floods and how their effects cascade downstream (Challenge 4). Similarly, Bunch (2003) used it to investigate the interactions between drought and flood impacts (Challenge 3). In both cases, this brainstorming exercise facilitated the development of a shared understanding of the situation. Although rich pictures are a useful visual aid, comparing their results is challenging since they are typically created without a structured approach.

Event timelines or timelining are another visualization method for representing the sequence of events over time. This approach involves plotting events related to a problem on a graph by considering participants' storytelling as a means to document past experiences (Sheridan et al., 2011), present, or project possible futures. Timelining has been successfully used in group settings to examine climate change impacts (e.g. Dolan and Walker, 2006; Schmook et al., 2023) and to understand the impact of recovery measures on disaster occurrence (e.g. Sword-Daniels et al., 2015) (Challenge 5). Timelines can also be developed using document analysis. For instance, Matanó et al. (2022) conducted an extensive literature review to develop event timelines exploring the temporal interactions between floods and droughts (Challenge 3). Similarly, Seebauer et al. (2023) combined document analysis and interviews to create a timeline depicting the sequence of flood events and adaptation measures from 1980 to 2020 in Austria (Challenge 5). While timelines are an effective tool for visualizing cascades of events, they are constrained by their linearity and, thus, unsuitable for depicting interactions across regions (Challenge 4).

Qualitative matrices and network diagrams offer another approach to studying CCI. Originally proposed by Gill and Malamud (2016, 2014) for visualizing hazard interactions, these tools were later adapted to investigate disaster impacts. The matrices illustrate how a primary impact can trigger and increase the probability of a secondary impact, thus revealing the strength of these relationships. Clark-Ginsberg (2017) used these tools in a participatory setting to examine how multi-hazard events can lead to multiple socioeconomic impacts (Challenge 3). Meanwhile, Chen et al. (2022) reconstructed how the 1920 drought in China affected multiple socioeconomic sectors building qualitative matrices based on newspaper articles. Multiple hazards can also be considered. For instance, Matanó et al. (2022) developed matrices of floods and droughts CCI using stakeholder interviews and a literature review. The matrix results can serve as input for network diagrams, which present the same information in a network format. Since spatial dynamics are usually not addressed in qualitative matrices and their resulting diagrams, they are often unsuitable for addressing Challenge 4.

3.1.3. Qualitative storylines and scenarios

Qualitative storylines and scenarios are commonly used in social sciences to understand the temporal dynamics of systems (Shanahan et al., 2018). These methods have recently gained popularity in climate change science as an alternative approach to studying human-environmental dynamics when information is scarce (van den Hurk et al., 2023; Shepherd et al., 2018). They are often derived in participatory settings i.e. through narrative interviews or workshops (Shanahan et al., 2018), document analysis, or modeling.

Qualitative storylines are temporal accounts of a series of interrelated events, often presented in a storytelling format (Andrews et al., 2013). They provide descriptive narratives of CCI developments without specific quantification, emphasizing plausibility and contextual understanding (Rounsevell & Metzger, 2010). They allow exploring how impacts have occurred in the past or can unfold in the future, highlighting the causality and temporal dimensions. Through qualitative storylines, participants can describe the trickle-down effects and propagation of impacts to one sector through a system (Challenge 3) and between regions – or even across borders (Challenge 4) (e.g. Carter et al., 2021; Liguori et al., 2021; van Delden and Hagen-Zanker, 2009). The synthesis of a collection of storylines enables the extraction of generic principles and can inform the definition of both qualitative and quantitative scenarios (e.g.

Lottering et al., 2021; Rounsevell and Metzger, 2010), as well as conceptual system dynamic models. A protocol for constructing storylines in the field of CCI is provided by van den Hurk et al. (2023).

Findings from qualitative storylines can be used to feed into (semi)-**qualitative scenarios**, which are alternative representations of plausible futures. Scenarios can encompass qualitative or quantitative elements, involve structured assumptions and models, and offer a broader range of possible future trajectories for analysis (Rounsevell & Metzger, 2010; Wiebe et al., 2018). They can be instrumental in developing descriptions of how CCI can succeed through the cross-scale interaction of actors and networks in a system (Challenge 4). Qualitative scenarios are recently gaining momentum in CCI research. For example, Rusca et al. (2021) developed qualitative scenarios of unprecedented flood events and societal recovery trajectories for them (Challenge 5). To this end, the authors relied on a series of qualitative and quantitative data from interviews, focus groups, and empirical analysis. Similarly, Liguori et al. (2021) developed qualitative scenarios to imagine future adaptation scenarios (Challenge 5).

3.2 Data-driven methods

Data-driven methods rely on analyzing and extracting insights from large amounts of data to understand complex systems. Their foundation lies in the principle that data contains valuable insights that can be harnessed to uncover hidden relationships and patterns. In this section, we focus on multivariate statistics and data mining approaches, but many others exist. These methods allow quantifying interdependencies between impacts and response measures, enabling a comprehensive understanding of CCI dynamics (Challenges 3 and 4). However, a significant challenge of these methods lies in their reliance on the quality and quantity of available impact data.

3.2.1. Multivariate statistics

A broad range of tools are available to study multivariate statistics in climate data (e.g. Bevacqua et al., 2022; Jane et al., 2020), many targeted specifically at extreme events (e.g. Salvadori and De Michele, 2013). Recent years have also seen the rapid growth of machine learning applications (e.g. Feng et al., 2021). However, the above approaches are often data-intensive, especially when both temporal and spatial components need to be accounted for (Liu et al., 2021; Messori & Faranda, 2021). The lack of impact datasets covering multiple sectors and over many years (Challenges 1 and 2) and the difficulty of accounting for the effect of response measures (Challenge 5) in past data in practice means that many of these approaches have limited applicability for analyzing CCI. We, therefore, propose here simple statistical methods that may be used to investigate CCI in data-limited contexts and that can be applied to multiple types of data and spatial and temporal scales.

Regression models, specifically **logistic regressions**, have proven to be effective in examining temporally successive or spatially co-occurring climate hazards (e.g. Ben-Ari et al., 2018;

Martius et al., 2016). Data-efficient machine-learning models, including random forests, have also been used to link hydroclimatic indicators to socioeconomic impacts (e.g. Bachmair et al., 2017; Torelló-Sentelles and Franzke, 2022). These same models could profitably be applied to quantitative socioeconomic impact data, for example, to quantify changes in the odds of a given impact occurring prior to, concurrently, or after another impact (Challenge 3). A further application could be to investigate the spatial propagation of impacts (Challenge 4).

In a similar vein, **Markov chains** can be used to describe systems that transition between different states over time. This method has proven effective in examining the succession of interactions between multiple climate drivers and events (e.g. Sedlmeier et al., 2016) and could be directly ported to the analysis of CCI (Challenge 3). For example, Markov chains have recently been used to predict the impact of drought changes on water and soil quality (Ronizi et al., 2022). Markov chains offer particular advantages in addressing spatial changes (Challenge 4) and generating scenarios with different response measures (Challenge 5), as has been demonstrated in neighboring fields (e.g. Rifat and Liu, 2022).

The above methods may still struggle in extremely data-limited contexts, and in such cases, even simpler **co-occurrence analyses** may be favored. These provide a statistical indication of whether the spatial or temporal concurrence of specific impacts is larger than one may expect by random, helping to address Challenge 3. A number of co-occurrence indicators have been developed explicitly for extreme events, exactly by virtue of their effectiveness, even when applied to small data samples. For example, Kornhuber and Messori (2023) used co-occurrence statistics to identify regions of significant concurrence of climate extremes in Europe and North America, and a similar approach could be applied to their impacts. In CCI research, de Brito (2021) conducted a co-occurrence analysis to identify drought impact types often reported together by the media. While this method is useful for identifying relationships between two variables, it has limitations when dealing with patterns that emerge from multiple variables.

3.2.2. Data mining

Data mining methods such as dimensionality reduction, clustering, and sequential pattern mining are well-suited for identifying patterns in complex and high-dimensional datasets. These methods help transform datasets with many variables into interpretable information, making it easier to understand relationships among multiple observations (Challenge 3). However, the data transformation may lead to the loss of relevant information. Similar to other data-driven methods (see section 3.2.1), the application of data mining in CCI research is constrained by the availability of multi-sector and longitudinal data (Challenges 1 and 2).

Dimensionality reduction methods allow for simplifying the analysis of high-dimensional data by transforming them into lower-dimensional representations while retaining the most informative aspects (Anowar et al., 2021). These transformations enable to capture a high share of the original dataset's variance using fewer dimensions, thereby maintaining its key characteristics. Principal component analysis, self-organizing maps, and t-SNE (t-distributed stochastic neighbor embedding) are a few examples of such techniques. By leveraging these methods, researchers can better understand the relationships between multiple socio-economic impacts (Challenge 3). Although dimensionality reduction methods have been successfully applied to identify underlying risk patterns (e.g. hazard, vulnerability) that drive impact occurrence (e.g. Johnson et al., 2020; Maity et al., 2013), their application in the field of CCI is yet to be explored. Adopting dimensionality reduction approaches in CCI research holds promise for gaining a comprehensive perspective on the relationships between different multi-sector impacts (Challenge 3) as well as across different regions (Challenge 4). Furthermore, indicators developed through dimensionality reduction could act as holistic measures for tracking developments through time and space or evaluating the effects of response measures (Challenge 5).

Clustering methods are another powerful tool for discovering underlying patterns in high-dimensional data. Unlike dimensionality reduction methods, clustering seeks to group similar data points based on their characteristics. Popular clustering methods include k-means, hierarchical clustering, or density-based clustering. Although hardly applied in CCI research, inspiration for application to CCI can be drawn from other fields, especially hazard research (e.g. Brunner and Stahl, 2023). For example, a study by Lam et al. (2016) leveraged clustering analysis to assess resilience to climate-related hazards for U.S. counties based on 28 variables. For CCI, similar research designs could allow researchers to better understand how CCI impacts affect regions in complex ways and whether these impacts occur in similar patterns across time and space (Challenge 4).

Sequential pattern mining methods are effective for identifying rules which describe frequent temporal patterns (e.g. sequences or cascading events) in a dataset. Respective algorithms such as SPADE or generalized sequential pattern aim at finding events that occur in predictable orders throughout a given dataset. By leveraging these methods, researchers can uncover important temporal relationships and dependencies. Indeed, the application of sequential pattern mining to CCI of hydrological extremes has been demonstrated by de Brito (2022), who detected cascading drought impact patterns for the case of Germany in 2018 and 2019 (Challenge 3). Given datasets of sufficient geographic scope, sequential pattern mining could also investigate interrelationships of CCI spanned between regions (Challenge 4).

3.3 Mixed approaches

Mixed approaches refer to methods that combine both qualitative and quantitative data to understand complex systems. These approaches leverage the strengths of both data-driven methods, which rely on patterns and insights derived directly from the data, and knowledge-driven methods, which incorporate domain knowledge, rules, or expert opinions. By doing so, these approaches offer a holistic perspective on the phenomenon under study.

3.3.1. Systems modelling

Systems modeling encompasses a range of methods for understanding complex systems through mathematical and computational models. Here, we focus on two widely used methods: system dynamics and agent-based modeling (ABM). These methods have gained popularity due to their capacity to incorporate the interplay between social and natural system components (de Brito, 2023). A limitation, however, is that they often require large amounts of data to be effective (Challenges 1 and 2). In such cases, the accuracy and reliability of the models may be compromised.

Agent-based modeling (AMB) is used to study the behavior of individuals or agents within a social system. The agent's behavior is described by a set of rules implemented by the researcher to fit the system under investigation. They often combine data from behavioural experiments or survey data (Wijermans et al., 2022). ABM can help to answer questions on how and why social systems react in response to different stimuli compared to counterfactuals. ABMs represent a well-established method for studying social-ecological systems (Biggs et al., 2021). For CCI research, models for varying purposes have been developed which capture the interactions of a social and hydrological system. For example, Michaelis et al. (2020) developed an ABM to capture processes between floods, impacts, and vulnerability. Galán et al. (2009) investigated domestic water demand using an ABM that reflects individual households. The model allowed the testing of different what-if scenarios concerning varying socioeconomic indicators and urban dynamics. Both applications highlight the capabilities of ABM to reflect on spatial interconnectivity (Challenge 4) and its effectiveness in evaluating policy measures (Challenge 5).

Systems dynamics and **multi-sector dynamic models** focus on studying the complexity of a system through understanding causal relationships and feedback patterns (Yoon et al., 2022). Gaining such understanding is beneficial for predicting future system behavior, identifying detrimental or supportive system components, and evaluating the likely impact of policy strategies. System dynamic models are typically based on a set of mathematical equations and can incorporate various data types to derive model-specific parameters as well as qualitative data from surveys. Integrative models based on both qualitative and quantitative data are increasingly being applied in the context of floods and drought impacts (e.g. Savelli et al., 2023; Yoon et al., 2021). For example, water supply and demand dynamics have been studied for varying climate change scenarios and management decisions (ElSawah et al., 2015). For CCI, these models can help identify how cascades propagate and how impacts across different sectors are connected through complex causal structures (Challenge 3). Additionally, integrated system dynamics models excel in evaluating response measures across different social-ecological systems (Challenge 5) and have already been used to evaluate the efficience of future adaptation strategies (e.g. Giuliani et al., 2022). The development of system dynamics models is, however, often constrained by the availability of data to sufficiently parametrize all model components and their causal relationships.

3.2.2. Network analysis

Network analysis is a frequently employed method for examining the connections between variables. It involves representing network structures using nodes and links, which help reveal the relationships between variables in a system and capture their associations (Bodin et al., 2019). These structures can be derived from various methods such as CLDs, FCM, co-occurrence analysis, or observational data. In flood and drought research, network analysis can provide insights into the interrelationships among individual actors or the flows between impacts, response measures, and risk drivers. While the conceptual (and metaphorical) idea of thinking of CCI as a network is widely adopted throughout CCI studies, few have adopted network analysis as an empirical approach.

In CCI research, network analysis metrics can be leveraged for understanding cascading patterns among manifold socio-economic impacts of hydrological extremes (Challenge 3). Graph theory measures can reveal highly central, relevant, or influential variables in these mental models (Olazabal & Pascual, 2016). For example, de Brito (2021) used network structures to capture and visualize the cascading impacts of drought, while graph theory measures were used to identify highly central variables. Network analysis can also help to understand the spatial interconnectivity of CCI, particularly when networks represent a spatial dimension through which impacts cascade (Naqvi & Monasterolo, 2021) (Challenge 4).

3.3.3. Economic-based models

Macro-economic models have been widely applied to identify and quantify the cross-sectoral and cross-regional economic impacts due to hydrological extremes. The most commonly applied models are input-output and computable general equilibrium models. Both models describe our economy through a set of inter-relations between economic actors (e.g. industries, households, and governments) (E. E. Koks et al., 2016). These models are particularly helpful in identifying potential spillover effects across regions (Challenge 4). However, a key limitation is that they may rely on assumptions that do not always hold in reality (e.g. either no or full substitution between production inputs). Additionally, they may not fully capture intangible impacts, such as the psychological distress experienced by individuals affected by extreme events. To cope with some of these limitations, economic models are increasingly being used together with noneconomic methods.

Traditional **input-output (IO) models** are static linear models in which substitution between products is not possible, and price effects are disregarded. Due to these characteristics, IO models often overestimate the economic losses due to their linearity and lack of substitution. In general, they are considered to best represent the economic situation in the short term, in which the economy is generally inflexible to large changes. While there are no clear examples of applications within CCI, IO models have been used to, for example, assess the cascading effects of flooding towards business disruptions and economy-wide impacts (e.g. Koks et al., 2019) and to analyze global supply-chain effects due to COVID-19 (Guan et al., 2020).

Computable general equilibrium (CGE) models mostly assume a market with perfect competition and are generally built around the rationale that: (i) firms aim to maximize profits and minimize costs and (ii) households aim to maximize their utility within their budget constraint. As such, CGE models may underestimate the economic losses due to 'over'-optimizing the economic situation (E. E. Koks et al., 2016). They are thus most suitable for assessing the long-term impacts of droughts and floods on a national economy and the potential of welfare impacts. For example, García-León et al. (2021) assessed the impacts of droughts on the Italian economy, and Bachner et al. (2023) applied a CGE model to highlight the cross-sectoral impacts of flood events within Austria.

Capturing CCI of hydrological extremes requires economic-based models capable of coupling a physical footprint of the event to disruptions within our economy. This means that CGE and IO models should be extended to convert physical asset damages and employment reductions (i.e., because of casualties and/or displacement) into a 'shock' affecting economic activity. This could either mean disruptions on the supply side of our economy (i.e., reduction in production output) or disruption on the demand side of our economy (i.e., reduction in demand for goods and services). Moreover, capturing cross-regional economic impacts (Challenge 4) requires using multi-regional economic trade data. Finally, a time dimension should be included to assess the effects of cascading events.

4 Pathways for future research

The above synthesis highlights the diversity of methods used to study CCI dynamics. In general, while methods supporting the identification of patterns between impacts (Challenge 3) are well-represented and widely applied, progress in measuring the strength of the causal relationships between socioeconomic impacts has been limited. Furthermore, while most methods are used to study interactions within one geographical scale, relatively few methods support the analysis of cross-scale dynamics (Challenge 4), as shown in Table 1. Also, the majority of the reviewed applications primarily address past or present CCI (e.g. de Brito, 2021; Matanó et al., 2022), with few examining plausible futures (e.g. D'Agostino et al., 2020; Liguori et al., 2021). The analysis of interactions between the impacts of hydrological extremes and response measures is also in its early stages (Challenge 5). Considering these gaps, we point towards recommendations for advancing the field of CCI research.

(1) Systematic efforts to collect data on impacts across multiple sectors, systems, and years are needed

The quality and quantity of longitudinal and multi-sector impact data constrain our understanding of CCI dynamics. Although a wide range of approaches exists to study complex systems, CCI research tends to rely on simple methods due to data availability limitations. Thus, systematic efforts must be made to collect drought and flood impact data. Emerging impact assessment methods that use text, digital traces, new sensors, and citizen science data are potential ways forward. For instance, newspaper and social media data can provide a fine-scale mapping of socioeconomic impacts across sectors (e.g. de Brito et al., 2020; Erfurt et al., 2020; Sodoge et al., 2023). Drones and satellite data can support detailed property and infrastructure damage assessment (e.g. West et al., 2019; Wouters et al., 2021). Moreover, digital traces such as credit card transactions and online communications can enable rapid impact assessments (e.g. Jackson and Gunda, 2021; Yuan et al., 2022b, 2022a). The adoption of these new methods presents valuable opportunities for gathering crucial data to address CCI, especially in currently underrepresented regions.

(2) Disciplinary diversity should be promoted to foster innovation

To better understand the complexity of CCI, engaging in interdisciplinary collaboration among scientists from different fields, such as ecology, economics, engineering, geography, hydrology, law, political sciences, and social sciences, is crucial. Although interdisciplinary research positively correlates with research impact and innovation (Okamura, 2019), evidence suggests that researchers in natural hazards research often work within their own disciplinary silos (Vanelli et al., 2022). This may limit the scope of their analyses, overlooking crucial interdependencies and multi-sectoral impacts. By breaking down these barriers and collaborating across disciplines, CCI research can be decompartmentalized and offer a more comprehensive explanation of how droughts and floods impact critical infrastructure, people, and assets, reducing the potential for disciplinary bias in findings. By working together, interdisciplinary teams can thus advance the understanding of compound and cascading impacts of hydrological extremes. Numerous of the applications highlighted in this paper are already moving in this direction, showcasing the positive outcomes of embracing interdisciplinary collaboration (e.g. Matanó et al., 2022; Rusca et al., 2023).

(3) Methodological pluralism is necessary to fully address the complexity of CCI and their underlying risk drivers

Data and knowledge-driven approaches are commonly used separately in CCI research, and integration of methods is limited. However, no single method can by itself capture all aspects of the intertwined nature of CCI and its underlying risk drivers. We, thus, advocate for epistemological and methodological pluralism to consider the different aspects of CCI. Since each method has its own assumptions, strengths, and weaknesses (Table 1), combining different methods can help reveal various facets of CCI and compensate for the limitations of individual methods. For instance, while quantitative assessments allow us to identify generalizable patterns and dynamics, qualitative analyses help to contextualize and interpret them (Di Baldassarre et al., 2021; Rusca et al., 2021). Hence, by triangulating the outcomes of these approaches, several lines of evidence can be delivered (Raymond et al., 2020). This can strengthen the research confidence as results that agree across different methods are less likely to be artefacts (Munafò & Davey Smith, 2018). The outcomes from one method can be used as input for others. For instance, information obtained from questionnaires and focus group discussions can be used to build agent-based models. By using multi and mixed method approaches, researchers can be more flexible and take advantage of the strengths of particular methods while still grounding the research in biophysical and socioeconomic realities. The examples of methodological pluralism discussed in our paper suggest the feasibility and added value of this approach (e.g. Savelli et al., 2023; Yoon et al., 2021).

(4) Generalizable theories of how socioeconomic impacts compound, cascade, and interact with response measures are required

Studies expressing an explicit ambition to develop theories about the dynamics of drought and flood socioeconomic impacts and their response measures with an understanding of CCI as described above, are still needed. The heterogeneity among case studies has prevented researchers from engaging in comparative analyses. Therefore, we advocate for building a corpus of empirical data on the dynamics of droughts and floods CCI with the specific aim of seeking generalizations across multiple case studies. This effort will support the development of a generalizable theory about CCI dynamics and their interactions with response measures. To achieve this, the findings of multiple case studies could be synthesized, aiming to identify common patterns and draw conclusions that can be applied across a broader range of contexts (Kuhlicke et al., 2023). This task involves disentangling the idiosyncrasies of case-specific findings by considering various contextual and research design factors (Bodin et al., 2019). A way forward would be combining empirical explanations of observed and/or anticipated phenomena with modelling (e.g. ABM or FCM) to test and explore possible explanations. Developing such theories can help overcome the limitations of individual case studies and provide a more comprehensive and nuanced understanding of causality and dynamic interactions in droughts and floods CCI research.

(5) Investigation of the risks of future CCI should be guided not only by probability but also by plausibility considerations

When investigating the risks of CCI and their root causes, attention should also be paid to less frequent impact types, whose probability may be lower but with higher consequences (Shepherd et al., 2018; Sillmann et al., 2021). In an increasingly interconnected world, the complexity of coupled natural-technological-social systems can make probability calculations futile (Engels & Marotzke, 2023). Therefore, understanding CCI entails recognizing that they cannot be fully predicted and that uncertainty is inherent. Instead, we can explore different possibilities for the evolution of CCI under different conditions. This also requires a deep understanding of the underlying risk drivers of different sectors and systems and their interlinkages. To address the plausibility question and better prepare for potential CCI, knowledge-driven tools can be instrumental. They enable us to explore the range of possible outcomes and the associated uncertainty while also offering explanations of why CCI might occur. For instance, mental models and qualitative storylines can be coupled with theories about transformative social change, disruptive change, social inertia, and path dependency. This can help us identify key drivers that can lead to high impacts in a given future scenario as well as adaptation measures that can support risk reduction.

In summary, the overview of methods and linked recommendations for future research described here can contribute to an improved characterization and understanding of CCI dynamics and hence support the reduction of CCI risks linked to hydrological extremes. In doing so, this perspective aims to enable researchers to make informed decisions about the choice of methods (or the combination of them) to be used.

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Data availability statement

No new data were created or analysed during this study. Data sharing is not applicable to this article.

CRediT statement

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Uncovering the dynamics of multi-sector impacts of hydrological extremes: a methods overview

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Abstract

Hydrological extremes, such as droughts and floods, can trigger a complex web of compound and cascading impacts due to interdependencies between coupled natural and social systems. However, current decision-making processes typically only consider one impact and disaster event at a time, ignoring causal chains, feedback loops, and conditional dependencies between impacts. Analyses capturing these complex patterns across space and time are thus needed to better inform effective adaptation planning. This perspective paper aims to bridge this critical gap by presenting methods for assessing the dynamics of the multi-sector compound and cascading impacts (CCI) of hydrological extremes. We discuss existing challenges, good practices, and potential ways forward. Rather than pursuing a single methodological approach, we advocate for methodological pluralism. We see complementary roles for analyses building on quantitative (e.g. data-mining, systems modeling) and qualitative methods (e.g. mental models, qualitative storylines). We believe the data-driven and knowledge-driven methods provided here can serve as a useful starting point for understanding the dynamics of both high-frequency CCI and low-likelihood but high-impact CCI. With this perspective, we hope to foster research on CCI to improve the development of adaptation strategies for reducing the risk of hydrological extremes.

1 Introduction

Future climate projections show an intensification of variations in the hydrological cycle, with more droughts and floods expected to occur in many regions (Cook et al., 2020; IPCC, 2021; Merz et al., 2021; Pokhrel et al., 2021; Samaniego et al., 2018; Simpson et al., 2021). In this context, understanding the magnitude and distribution of the impacts of these hydrological extremes becomes crucial to inform adaptation planning. Impact assessments can facilitate the identification of areas that are disproportionately affected, aiming to support the allocation of resources (Hammond et al., 2015). They can further provide baseline information for evaluating whether adaptation measures effectively reduce loss and damage. Spatio-temporal impact datasets can also improve our understanding of risk drivers (Kellermann et al., 2020) and serve as ground truth information for impact-based early warning systems (Hobeichi et al., 2022).

In today's interconnected world, assessing the risks and impacts of floods and droughts has become increasingly complex as these events often have far-reaching consequences that spread throughout various sectors and systems, leading to **'compound and cascading impacts' (CCI)** (Fig. 1 and Box 1). Indeed, natural, technological, and social systems are deeply intertwined, and the adverse outcomes of hydrological extremes heavily depend on how the elements of the affected systems interact with each other (Matanó et al., 2022; Raymond et al., 2020; Ruiter et al., 2020; Zscheischler et al., 2018). For example, during the 2021 flood event in Europe, the flood waters damaged major access routes and destroyed most of the bridges in the flooded area in Ahr valley (Schäfer et al., 2021). This reduced the accessibility for rescue cars and fire brigades, leading to cascading impacts.

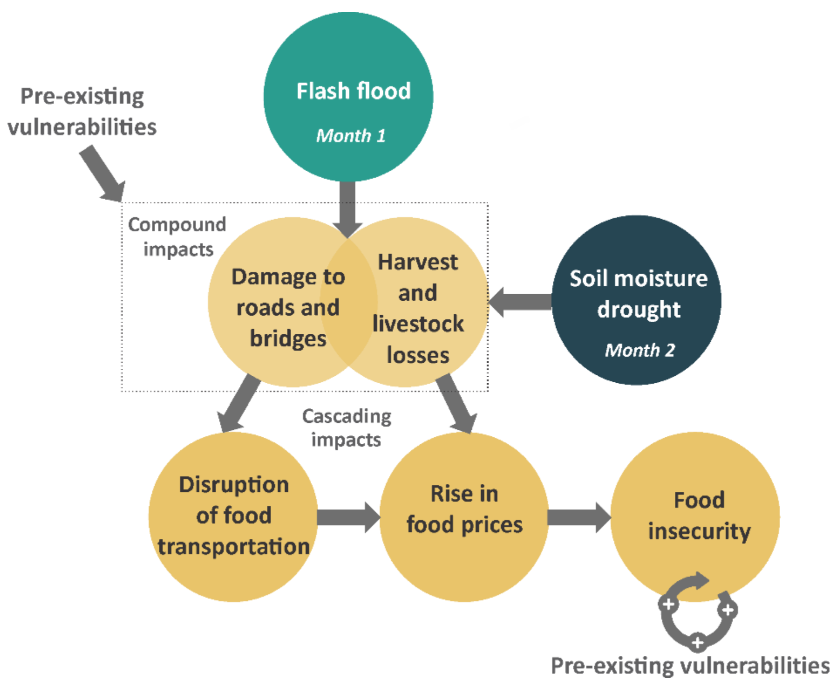

Figure 1 *Schematization of compound and cascading impacts (CCI) for a fictitious flood followed by a drought event. The impacts triggered by different hazards interact, compound, and cascade. Unrelated events or pre-existing vulnerabilities, such as pandemics and conflicts, can also contribute to the impacts.*

Flood and drought impacts can also spill over beyond their initial geographical location through the interconnectivity of socioeconomic sectors and ecosystems (UNDRR, 2021a). As a result, some of the most affected areas can be those not directly affected by the physical hazard (e.g. flood waters). For instance, the extremely low soil moisture values in the summer of 2018 in Germany caused severe crop failures, leading to fodder shortages and the consequent early slaughtering of animals. As a consequence, farmers restrained from investing in fertilizers and machinery, resulting in ripple effects along supply chains (de Brito, 2021).

Box 1 *Defining compound and cascading impacts (CCI)*

'**Socioeconomic impacts**' are defined as the adverse effects of floods and droughts on society. They can include but are not limited to casualties, infrastructure collapse, increased demand for water, need for credit, increased commodity prices, migration, food insecurity, conflicts, reduced quality of life, crop yield losses, and mental health problems. Hydrological extremes can, in exceptional cases, lead to positive consequences. For instance, drought combined with heat waves can benefit fruit growers and winemakers depending on the onset of the event, as they can increase the sugar concentration in fruits.

The term '**compound impact**' is used to denote impacts that temporally and spatially coincide. These could be, for instance, a drought that simultaneously impairs the transportation of goods and affects tourism via restrictions on boat cruises. The impacts of hydrological extremes can also compound with the effects of other 'compounding hazards' or events (i.e. multi-hazard events) and/or circumstances (e.g. conflicts). Even unrelated events, such as the Covid-19 pandemic, can amplify the impacts of droughts and floods and vice versa (UNDRR, 2021c).

'**Cascading impact**' refers to consecutive impacts triggered or amplified by other impacts or processes. For instance, the delay in sowing and transplanting crops caused by droughts can reduce employment in agriculture, which in turn further reduces employment due to the reduced need of labor for harvesting. Similarly, the direct impacts of floods and droughts on ecosystems and their services can lead to cascading impacts on livelihoods. Cascading impacts can also ripple within and across economic sectors. Energy outages very often impact other services, such as healthcare facilities. Upstream and downstream relations also lead to cascading impacts. For instance, low flows can impair shipping and lead to increased commodity prices.

The concept of '**systemic impact**' is based on the notion that the impacts of a hazard can be influenced by how the elements of the affected system interact. These interactions can either increase or decrease the overall impact. The interactions between sectors and systems and associated impacts create mutual dependencies, where actions and outcomes in one sector or system can lead to actions and outcomes in another. The term 'systemic impact' encompasses both compound and cascading impacts, therefore, both coincidental and consecutive impacts.

A better understanding of CCI's characteristics and underlying drivers can, therefore, inform the ex-ante management of systemic risks. The need to investigate CCI has been underscored by the UNDRR (2021) and has recently been included in the research agenda of the Integrated Research on Disaster Risk 2021-2030 (ISC-UNDRR-IRDR, 2021). Likewise, the IPCC is moving from a static understanding of risk to a dynamic framing that considers compounding, cascading, and systemic effects (IPCC, 2022).

Inspired by these calls, research on CCI of floods and droughts is on the rise. In recent years, scientists have addressed CCI to specific sectors and hazard types, especially critical infrastructure (Fekete, 2020; Guimarães et al., 2021; Rohr et al., 2020), water quality (Mishra et al., 2021), agriculture (Christian et al., 2020) as well as cascading impacts linked to the COVID-19 pandemic and its policy responses to it (UNDRR, 2021c). Interactions between hydrological extremes have also been investigated. For instance, Matanó et al. (2022) and Ward et al. (2020) provide examples of interactions between flood and drought impacts. Despite these advances, research on CCI remains highly fragmented, and an overview of available methods to study them is missing.

In this perspective, we discuss key approaches for investigating CCI dynamics within the context of climate change and an increasingly connected world. Our goal is to help researchers navigate the emerging field of CCI by providing a synthesis of existing methods. We first highlight persisting challenges, such as the lack of multi-sector and longitudinal impact data. Then, we present a range of qualitative and quantitative methods that can be used to analyze CCI dynamics, drawing on case study examples. Based on these, we end with six recommendations to advance this field of research. While the set of methods discussed here is not exhaustive, it provides a holistic view of how to tackle CCI and serves as a useful starting point for researchers studying the systemic risks and impacts of droughts and floods on coupled social, technological, and natural systems.

2 Challenges in the understanding of CCI

Due to the complexity of CCI, our ability to identify and understand them is still in its infancy. While there has been notable progress in compound hazards research (e.g. Batibeniz et al., 2023; Bevacqua et al., 2021; Singh et al., 2021; Sutanto et al., 2020), the socioeconomic CCI of droughts and floods remain relatively unexplored (Naumann et al., 2021; Ward et al., 2022; Zscheischler et al., 2020). One of the reasons for the limited exploration of CCI patterns is the scarcity of data on the socioeconomic impacts of floods and droughts, especially in the global South. Impact assessments are often conducted for single hazard types, and standardized, methodologically comparable impact information for multiple disaster types is hardly available.

In this context, we present five challenges that need to be addressed to provide targeted information to understand CCI (Fig. 2). It should be highlighted that the field of CCI research encompasses many more challenges than those depicted in Fig. 2, such as the understanding of the risk drivers of CCI. However, these aspects fall outside the scope of this perspective paper.

Figure 2 *Set of challenges and needs that must be addressed to provide targeted information to understand CCI. In this study, we focus on methods that can be used to address the needs of challenges 3 to 5, which are related to dynamic aspects.*

Challenge 1 is linked to the focus of existing impact assessments on **single socioeconomic sectors or systems** and tangible losses (Fronzek et al., 2019; Ward et al., 2022). Studies typically address isolated impacts to single sectors, including damage to critical infrastructure (Qiang et al., 2020), agriculture losses (H. Chen et al., 2019; Rahman & Di, 2020; Tapia-Silva et al., 2011), damage to buildings (Gerl et al., 2014; Serpico et al., 2012), and fatalities (e.g. Papagiannaki et al., 2022). Furthermore, existing databases are almost exclusively limited to impacts measured in monetary terms (Ding et al., 2011), which are more easily quantified compared to intangible losses, such as societal and cultural impacts (e.g. decrease of subjective well-being and growing lack of trust in institutions) (Ding et al., 2011). However, these intangible losses can be just as severe, if not more so. As a result, a holistic understanding of all sectors and systems affected is missing. This gap is related to difficulties in deriving reliable estimates of indirect or intangible losses such as adverse social, psychological, and environmental consequences (Allaire, 2018; Walz et al., 2021). Exceptions include initiatives such as the HOWAS21 database (Kellermann et al., 2020), which includes detailed data on objects affected by European floods. For drought events, the few existing multi-sector impact databases are based on the analysis of news (e.g. U.S. Drought Impact Recorder (NDMC, 2019), European Drought Impact Inventory – EDII (Stahl et al., 2016), and country specific databases (de Brito et al., 2020)). While these studies represent significant methodological advances, they are currently not widespread. Hence, multi-sector impact databases encompassing underrepresented sectors such as health, tourism, energy and forestry, are needed.

Related to this issue is the **lack of longitudinal impact datasets encompassing both large and small-scale events** <u>(Challenge 2)</u> (de Brito et al., 2020; R. L. Jones et al., 2022). Impact assessments are conducted mostly ad hoc, following a specific disaster (Ding et al., 2011). Existing impact datasets covering multiple years are limited to large-scale disasters (e.g. EM-DAT, NatCatSERVICE) and suffer from underreporting (R. L. Jones et al., 2022). As such, they may overlook the risks posed by smaller, more frequent events that can be equally damaging when considering their cumulative occurrence (UNDRR & CRED, 2020). According to the UNISDR (2015), 99.7% of all disasters between 1990 and 2013 were smaller-scale disasters, with fewer than 30 deaths or less than 5,000 affected buildings. Thousands of these smaller-scale events are unreported as they do not result in high impacts at the national or international levels. Nevertheless, they bring a constant stream of local losses and damages (UNDRR, 2021b) and are thus relevant for understanding local patterns of CCI. Therefore, impact datasets covering low and high-impact events over multiple years are required to understand the cumulative and long-term consequences of floods and droughts.

<u>Challenge 3</u> refers to the lack of understanding regarding the **relationships between the socioeconomic impacts** of hydrological extremes (Pescaroli & Alexander, 2016; Simpson et al., 2021; UNDRR, 2021c). Impact outputs from one sector or system can become inputs into other sectors or systems depending on system/sector dependencies (Ding et al., 2011; UNDRR & UNU-EHS, 2022). For example, droughts can lead to crop failures, food shortages, and increased prices, resulting in ripple effects and social and political instability. Empirical studies investigating CCI relationships have often focused on single and small-scale case studies (e.g. Fekete, 2020; Gonzva et al., 2017; Zeng et al., 2021). Research addressing how impacts to one sector or system can lead to consequences in others is thus needed to support effective mitigation measures.

<u>Challenge 4</u> is linked to the limited research on the **interconnectivity between impacts across regions, borders, and spatial scales** (Andrew J. Challinor et al., 2017; Helbing, 2013). Namely, cascading impacts spread not only across sectors and systems but also spill

beyond geographical scales and administrative or national borders, and can lead to globally networked impacts (UNDRR, 2021a). For instance, drought-related harvest failures in Russia in 2010, combined with an export ban, led to a global spike in cereal prices. This amplified the food security risk in Pakistan and is associated with an increase in the use of food banks in the U.K. (Andy J. Challinor et al., 2018; Hunt et al., 2021). Upstream and downstream relations can also exacerbate the impacts of floods and droughts. For instance, low flows in the Rhine impaired shipping during the 2018 drought in Germany (Erfurt et al., 2019), increasing fuel prices in Switzerland. As such, analyses of the interplay between CCI across local, regional, and even global spatial scales (e.g. Lawrence et al., 2020; Mishra et al., 2021) are needed to identify critical nodes in the system that can lead to higher impacts.

Finally, research on the **effects of response measures** (i.e. impacts linked to risk management or adaptation interventions) on CCI is scarce (Challenge 5). While humans influence the propagation of extreme events, they also respond to their impacts (AghaKouchak et al., 2021). Within this context, risk management and adaptation responses to one impact may inadvertently lead to unintended consequences such as an increased vulnerability in the long run (e.g. Giuliani et al., 2022; Niggli et al., 2022; Schipper, 2022; Simpson et al., 2023). For instance, temporary water abstraction licenses may exacerbate underlying water scarcity as they can be difficult to reverse when the drought ends (Di Baldassarre et al., 2018). Therefore, it is difficult to measure to which extent adaptation measures reduce impacts or lead to unintended consequences. Thus, a parallel investigation of impacts and response measures adopted is crucial to understand how they co-evolve.

Challenges 1 and 2 are closely tied to the quality and availability of socioeconomic impact data, whereas challenges 3 to 5 relate to understanding CCI dynamics. Since significant research has already been conducted on improving impact data collection (Alfieri et al., 2016; Allaire, 2018; Ding et al., 2011; Enenkel et al., 2020; Merz et al., 2020), we focus here on methods that can be used to address challenges 3 to 5, which are rooted in the complexity of CCI interactions.

3 Key methods for investigating CCI patterns and relationships

Several recent studies have provided valuable guidelines on how to assess compound hazard interrelationships (e.g. Bevacqua et al., 2021; Tilloy et al., 2019), the dynamics of risk components (e.g. De Angeli et al., 2022; de Ruiter and van Loon, 2022; Terzi et al., 2019) and multi-sector dynamics (e.g. Reed et al., 2022). However, similar syntheses that incorporate both qualitative and quantitative approaches are still missing for research on CCI.

In the subsequent sections, we present an overview of knowledge-driven, data-driven, and mixed methods that hold the potential to enhance our understanding of the dynamic nature of CCI (Table 1). These were selected based on the experience of the co-authors, which come from different fields, including sociology, engineering, physics, geography and economics. A general description is provided for each method, followed by applications in CCI or related fields and how the method can address challenges 3 to 5 in Fig. 2. Besides considering the strengths of each analytical approach, the choice for a specific method should be guided by the study's objective, data requirements, and complexity level as illustrated in Fig. 3.

Although the examples of applications here focus on drought and flood hazards, these methods can be used for other hazard types (e.g. earthquakes, storms, heatwaves, and landslides). Also, many of these methods can also be applied to understand the relationship between risk drivers (e.g. vulnerability, exposure, and hazard) and their corresponding CCI.

It is worth highlighting that this overview is not intended to encompass all existing methods which can be used to understand complex relationships. Rather, we strive to emphasize key approaches that can aid in comprehending CCI dynamics. Additionally, the articles presented here represent only a fraction of the extensive literature on climate change impacts in a broader sense.

3.1 Knowledge-driven methods

Knowledge-driven methods rely on expert judgment and domain-specific information to analyze complex phenomena. These methods leverage existing knowledge, whether formal or informal, theoretical or practical, to delve into the systemic aspects of CCI. Their foundation lies in recognizing the significance of tacit and explicit knowledge, collective wisdom, and context-specific expertise in generating insights into complex systems (Aminpour et al., 2020). As their development can be done in a co-creation process with relevant actors, they also allow the integration of perspectives of vulnerable and marginalized groups, often overlooked in more data-driven approaches. In this section, we focus on methods such as mental models, visual techniques, and qualitative scenarios and storylines.

Table 1 *Overview of methods that can be used to investigate CCI dynamics. The groups of methods here are, to some extent, subjective, and overlap exists between them. Thus, they should be used as a general guide rather than a definitive categorization.*

	Group of methods	Methods and key references	Strengths	Weaknesses
Knowledge-driven	Mental models	▪ Causal loop diagrams (Groesser & Schaffernicht, 2012; Rest & Hirsch, 2022) ▪ Fuzzy cognitive maps (Ballesteros-Olza et al., 2022; Mehryar & Surminski, 2022) ▪ Impact chains (Hagenlocher et al., 2018; Zebisch et al., 2022) ▪ Impact webs (Sparkes et al., 2023)	Visualize the interplay between CCI (Challenge 3). When built in a participatory way, it enables the inclusion of perspectives of marginalized and vulnerable groups. It also facilitates mapping CCI to responses (Challenge 5)	Criticized as subjective representations of reality. Risk of oversimplification as it is difficult to map the full complexity of a system. Spatial and temporal dynamics are usually not explicitly addressed (Challenge 4)
	Visual techniques	▪ Rich pictures (Suriya & Mudgal, 2013) ▪ Event timelines (Matanó et al., 2022; Seebauer et al., 2023) ▪ Qualitative matrices (Gill & Malamud, 2014, 2016; Matanó et al., 2022) ▪ Network diagrams (Gill & Malamud, 2014, 2016)	Simplify complex ideas and enhance their comprehensibility for a wider audience. Visualize relationships between CCI and response measures over time (Challenges 3 and 5)	Can carry ethical risks (e.g. power relations). Comparability between studies is limited. Are often unsuitable for addressing spatial dynamics (Challenge 4)
	Qualitative storylines and scenarios	▪ Qualitative storylines (van den Hurk et al., 2023) ▪ (Semi)-qualitative scenarios (Di Baldassarre et al., 2021; Rusca et al., 2023)	Allow to take into account political, cultural, and economic contexts. Give more power to participants to shape the story. Spatial and temporal changes play a key role in these methods (Challenge 4)	Highly context-specific. Risk of making arbitrary assumptions and oversimplification. Limited ability to predict outcomes.
Data- driven	Multivariate statistics	▪ Logistic regression and other machine learning algorithms (Ben-Ari et al., 2018; Martius et al., 2016) ▪ Markov chains (Ronizi et al., 2022) ▪ Co-occurrence analysis (de Brito, 2021)	Capable of capturing non-linear relationships between CCI (Challenges 3 and 5). Can handle large and complex datasets with numerous variables	Data-intensive. Sensitive to data biases and dependency on historical observations, which leads to limitations in a changing climate and/or contexts of under-reporting
	Data mining	▪ Dimensionality reduction (Anowar et al., 2021) ▪ Clustering (Lam et al., 2016) ▪ Sequential pattern mining (de Brito, 2021)	Extracting key patterns from high-dimensional and noisy data (Challenge 3) . Allow uncovering hidden dependencies, also spatially (Challenge 4)	Potential loss of complexity and details when reducing high-dimensional data to lower-dimensional representation
Mixed	Systems modelling	▪ Agent-based modelling (ABM) (Wijermans et al., 2022) ▪ System dynamics and multi-sector dynamics models (Savelli et al., 2023; Yoon et al., 2021)	Can portray the temporal dynamics of complex systems (Challenges 3). Allow the assessment of the effects of different adaptation measures (Challenges 5). AMB can account for spatial dynamics (Challenge 4)	Empirical models require comprehensive data coverage of the underlying system. Require careful calibration and validation. Models without empirical components run at risk of being 'toy' models
	Network analysis	▪ Network analysis (Naqvi & Monasterolo, 2021)	Intuitive visualization of interconnected systems (Challenges 3 and 5). Enable the identification of key nodes within the	Requires data and knowledge on both impacts and causal relationships between impacts

		network. Allow investigating spatial patterns (Challenge 4)	
Economic-based models	▪ Input-output analysis (Koks et al., 2019) ▪ Computable general equilibrium model (Bachner et al., 2023)	Allow identifying how changes in one sector can propagate through the economy, affecting other sectors and causing cascading effects (Challenge 3). Can analyze cross-sectoral and cross-regional economic impacts (Challenge 4)	Can represent an oversimplistic view of the economy. Data-intensive

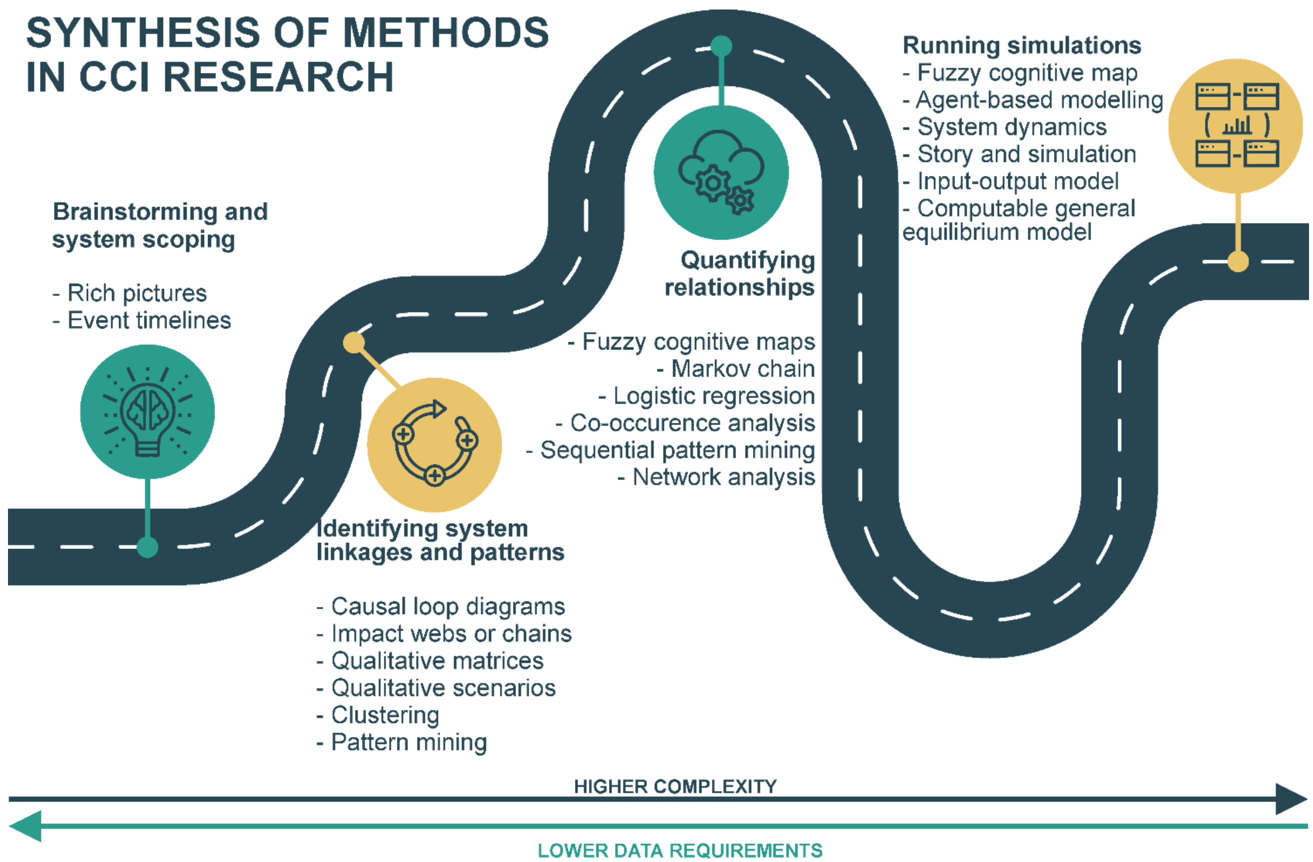

Figure 3 *Synthesis of methods used in CCI research to brainstorm, identify system linkages and patterns, quantify relationships, and run simulations. Some methods can be used for multiple purposes.*

3.1.1. Mental models

Mental models are schematic representations of the world as perceived by humans. By articulating complex relationships between system components (Levy et al., 2018) they aid in comprehending how systems respond to risks and factors such as human activity or environmental changes. However, since individuals' perspectives differ, mental models are subjective depictions of reality (N. A. Jones et al., 2011). They are typically constructed through stakeholder involvement (Romero-Lankao & Norton, 2018) and are often paired with other methods, such as system dynamics (Perrone et al., 2020).

Several approaches are used to elicit mental models, ranging from **causal loop diagrams (CLD)** to free drawing (see Doyle et al., 2022 for a review). CLD are a popular method that demonstrates how changes in one variable can influence others by reinforcing (positive link) or balancing them (negative link). CLD have been widely applied to understand the relationships between socioeconomic impacts (Challenge 3), including the investigation of cascading impacts of hydrological extremes on transport infrastructure, electricity, and healthcare systems (e.g. Berariu et al., 2015; Rest and Hirsch, 2022), as well as multi-sectoral impacts (e.g. Montgomery et al., 2012; Perrone et al., 2020). CLD have also been used to analyze coping and adaptation strategies and their effectiveness in mitigating impacts (Challenge 5) (e.g. Armah et al., 2010; Sanga et al., 2021; Song et al., 2018). While CLD can represent temporal dynamics adequately, spatial aspects are usually not explicitly addressed (Challenge 4). Furthermore, due to their reliance on human interpretation may, their ability to capture the nuances of real-world CCI is compromised, potentially leading to oversimplification.

Fuzzy cognitive maps (FCM) are CLD that account for uncertainty by using weights to define relationship strengths (Challenge 3). FCM have been employed to study drought and flood adaptation solutions and their effect on socioeconomic impacts (e.g. Ballesteros-Olza et al., 2022; Chandra and Gaganis, 2016; Mehryar and Surminski, 2022) (Challenge 5). They have been used to examine past disasters as well as to simulate plausible CCI futures (e.g. D'Agostino et al., 2020). Vanwindekens et al. (2018) incorporated spatial dynamics into the FCM by coupling it with geolocated data to analyze crops' vulnerability to soil moisture drought. Recently, FCM have also been used to address CCI interactions across neighborhood, city, and regional scales (e.g. White et al., 2021) (Challenge 4).

Impact chains are conceptual models used to capture the interplay of hazard, vulnerability, and exposure factors that lead to a specific risk or impact (Menk et al., 2022). This mixed-methods approach draws on elements of CLD and network analysis to investigate complex systems. Impact chains have been applied in various contexts and settings (e.g. Fritzsche et al., 2014; Hagenlocher et al., 2018; Zebisch et al., 2022). For instance, Kabisch et al. (2014) used impact chains to identify the relationships between direct and indirect impacts on multiple sectors resulting from heatwaves, floods, and storm surges (Challenge 3). One of the strengths of impact chains is their ability to link impacts and adaptation strategies (Challenge 5) directly.

However, it is important to note that impact chains often neglect or overly simplify complex systemic interrelations, including transboundary relationships (Menk et al., 2022), which poses a challenge in addressing Challenge 4.

More recently, an approach called **impact webs** was explicitly designed to tackle the complex nature of CCI risks (UNDRR, 2021c). Drawing on the foundations of CLD, impact chains, and network analysis, impact webs provide a comprehensive framework for characterizing the interconnected components of multiple systems, capturing their underlying risk drivers, and visualizing the dynamics of cascading effects (Challenge 3). Unlike impact chains, which often converge towards a single risk, impact webs offer a holistic overview of system interactions without directional constraints. While they have been initially used to understand CCI linked to the COVID-19 pandemic and responses to it, impact webs are now finding application in the study of CCI related to droughts and their compounding hazards, along with exploring potential adaptation options (Challenge 5) (Cotti et al., 2023; Sparkes et al., 2023).

3.1.2. Visual techniques

In addition to mental models, visualization techniques, such as rich pictures, event timelines, and qualitative matrices, are used for visually capturing the elements of a system. They are often part of brainstorming processes and aim to simplify complex ideas and enhance their comprehensibility for a wider audience. However, while these tools help synthesize information at a high level, they may not provide a detailed understanding of the underlying dynamics of CCI. Another concern pertains to the transferability and generalisability of results. While visual techniques facilitate a deep qualitative understanding of a given CCI event, the challenge lies in identifying comparable and scalable results that can be applied more broadly.

Rich pictures are visual depictions of a system, portraying elements and actors involved in a problematic situation (Barbrook-Johnson & Penn, 2022). When used in a participatory setting, this technique enables participants to share experiences about a certain problem and learn from each other (Bell et al., 2019). For instance, Suriya and Mudgal (2013) used the rich pictures method to examine the factors contributing to toxic floods and how their effects cascade downstream (Challenge 4). Similarly, Bunch (2003) used it to investigate the interactions between drought and flood impacts (Challenge 3). In both cases, this brainstorming exercise facilitated the development of a shared understanding of the situation. Although rich pictures are a useful visual aid, comparing their results is challenging since they are typically created without a structured approach.

Event timelines or timelining are another visualization method for representing the sequence of events over time. This approach involves plotting events related to a problem on a graph by considering participants' storytelling as a means to document past experiences (Sheridan et al., 2011), present, or project possible futures. Timelining has been successfully used in group settings to examine climate change impacts (e.g. Dolan and Walker, 2006; Schmook et al., 2023) and to understand the impact of recovery measures on disaster occurrence (e.g. Sword-Daniels et al., 2015) (Challenge 5). Timelines can also be developed using document analysis. For instance, Matanó et al. (2022) conducted an extensive literature review to develop event timelines exploring the temporal interactions between floods and droughts (Challenge 3). Similarly, Seebauer et al. (2023) combined document analysis and interviews to create a timeline depicting the sequence of flood events and adaptation measures from 1980 to 2020 in Austria (Challenge 5). While timelines are an effective tool for visualizing cascades of events, they are constrained by their linearity and, thus, unsuitable for depicting interactions across regions (Challenge 4).

Qualitative matrices and network diagrams offer another approach to studying CCI. Originally proposed by Gill and Malamud (2016, 2014) for visualizing hazard interactions, these tools were later adapted to investigate disaster impacts. The matrices illustrate how a primary impact can trigger and increase the probability of a secondary impact, thus revealing the strength of these relationships. Clark-Ginsberg (2017) used these tools in a participatory setting to examine how multi-hazard events can lead to multiple socioeconomic impacts (Challenge 3). Meanwhile, Chen et al. (2022) reconstructed how the 1920 drought in China affected multiple socioeconomic sectors building qualitative matrices based on newspaper articles. Multiple hazards can also be considered. For instance, Matanó et al. (2022) developed matrices of floods and droughts CCI using stakeholder interviews and a literature review. The matrix results can serve as input for network diagrams, which present the same information in a network format. Since spatial dynamics are usually not addressed in qualitative matrices and their resulting diagrams, they are often unsuitable for addressing Challenge 4.

3.1.3. Qualitative storylines and scenarios

Qualitative storylines and scenarios are commonly used in social sciences to understand the temporal dynamics of systems (Shanahan et al., 2018). These methods have recently gained popularity in climate change science as an alternative approach to studying human-environmental dynamics when information is scarce (van den Hurk et al., 2023; Shepherd et al., 2018). They are often derived in participatory settings i.e. through narrative interviews or workshops (Shanahan et al., 2018), document analysis, or modeling.

Qualitative storylines are temporal accounts of a series of interrelated events, often presented in a storytelling format (Andrews et al., 2013). They provide descriptive narratives of CCI developments without specific quantification, emphasizing plausibility and contextual understanding (Rounsevell & Metzger, 2010). They allow exploring how impacts have occurred in the past or can unfold in the future, highlighting the causality and temporal dimensions. Through qualitative storylines, participants can describe the trickle-down effects and propagation of impacts to one sector through a system (Challenge 3) and between regions – or even across borders (Challenge 4) (e.g. Carter et al., 2021; Liguori et al., 2021; van Delden and Hagen-Zanker, 2009). The synthesis of a collection of storylines enables the extraction of generic principles and can inform the definition of both qualitative and quantitative scenarios (e.g.

Lottering et al., 2021; Rounsevell and Metzger, 2010), as well as conceptual system dynamic models. A protocol for constructing storylines in the field of CCI is provided by van den Hurk et al. (2023).

Findings from qualitative storylines can be used to feed into (semi)-**qualitative scenarios**, which are alternative representations of plausible futures. Scenarios can encompass qualitative or quantitative elements, involve structured assumptions and models, and offer a broader range of possible future trajectories for analysis (Rounsevell & Metzger, 2010; Wiebe et al., 2018). They can be instrumental in developing descriptions of how CCI can succeed through the cross-scale interaction of actors and networks in a system (Challenge 4). Qualitative scenarios are recently gaining momentum in CCI research. For example, Rusca et al. (2021) developed qualitative scenarios of unprecedented flood events and societal recovery trajectories for them (Challenge 5). To this end, the authors relied on a series of qualitative and quantitative data from interviews, focus groups, and empirical analysis. Similarly, Liguori et al. (2021) developed qualitative scenarios to imagine future adaptation scenarios (Challenge 5).

3.2 Data-driven methods

Data-driven methods rely on analyzing and extracting insights from large amounts of data to understand complex systems. Their foundation lies in the principle that data contains valuable insights that can be harnessed to uncover hidden relationships and patterns. In this section, we focus on multivariate statistics and data mining approaches, but many others exist. These methods allow quantifying interdependencies between impacts and response measures, enabling a comprehensive understanding of CCI dynamics (Challenges 3 and 4). However, a significant challenge of these methods lies in their reliance on the quality and quantity of available impact data.

3.2.1. Multivariate statistics

A broad range of tools are available to study multivariate statistics in climate data (e.g. Bevacqua et al., 2022; Jane et al., 2020), many targeted specifically at extreme events (e.g. Salvadori and De Michele, 2013). Recent years have also seen the rapid growth of machine learning applications (e.g. Feng et al., 2021). However, the above approaches are often data-intensive, especially when both temporal and spatial components need to be accounted for (Liu et al., 2021; Messori & Faranda, 2021). The lack of impact datasets covering multiple sectors and over many years (Challenges 1 and 2) and the difficulty of accounting for the effect of response measures (Challenge 5) in past data in practice means that many of these approaches have limited applicability for analyzing CCI. We, therefore, propose here simple statistical methods that may be used to investigate CCI in data-limited contexts and that can be applied to multiple types of data and spatial and temporal scales.

Regression models, specifically **logistic regressions**, have proven to be effective in examining temporally successive or spatially co-occurring climate hazards (e.g. Ben-Ari et al., 2018;

Martius et al., 2016). Data-efficient machine-learning models, including random forests, have also been used to link hydroclimatic indicators to socioeconomic impacts (e.g. Bachmair et al., 2017; Torelló-Sentelles and Franzke, 2022). These same models could profitably be applied to quantitative socioeconomic impact data, for example, to quantify changes in the odds of a given impact occurring prior to, concurrently, or after another impact (Challenge 3). A further application could be to investigate the spatial propagation of impacts (Challenge 4).

In a similar vein, **Markov chains** can be used to describe systems that transition between different states over time. This method has proven effective in examining the succession of interactions between multiple climate drivers and events (e.g. Sedlmeier et al., 2016) and could be directly ported to the analysis of CCI (Challenge 3). For example, Markov chains have recently been used to predict the impact of drought changes on water and soil quality (Ronizi et al., 2022). Markov chains offer particular advantages in addressing spatial changes (Challenge 4) and generating scenarios with different response measures (Challenge 5), as has been demonstrated in neighboring fields (e.g. Rifat and Liu, 2022).

The above methods may still struggle in extremely data-limited contexts, and in such cases, even simpler **co-occurrence analyses** may be favored. These provide a statistical indication of whether the spatial or temporal concurrence of specific impacts is larger than one may expect by random, helping to address Challenge 3. A number of co-occurrence indicators have been developed explicitly for extreme events, exactly by virtue of their effectiveness, even when applied to small data samples. For example, Kornhuber and Messori (2023) used co-occurrence statistics to identify regions of significant concurrence of climate extremes in Europe and North America, and a similar approach could be applied to their impacts. In CCI research, de Brito (2021) conducted a co-occurrence analysis to identify drought impact types often reported together by the media. While this method is useful for identifying relationships between two variables, it has limitations when dealing with patterns that emerge from multiple variables.

3.2.2. Data mining

Data mining methods such as dimensionality reduction, clustering, and sequential pattern mining are well-suited for identifying patterns in complex and high-dimensional datasets. These methods help transform datasets with many variables into interpretable information, making it easier to understand relationships among multiple observations (Challenge 3). However, the data transformation may lead to the loss of relevant information. Similar to other data-driven methods (see section 3.2.1), the application of data mining in CCI research is constrained by the availability of multi-sector and longitudinal data (Challenges 1 and 2).

Dimensionality reduction methods allow for simplifying the analysis of high-dimensional data by transforming them into lower-dimensional representations while retaining the most informative aspects (Anowar et al., 2021). These transformations enable to capture a high share of the original dataset's variance using fewer dimensions, thereby maintaining its key characteristics. Principal component analysis, self-organizing maps, and t-SNE (t-distributed stochastic neighbor embedding) are a few examples of such techniques. By leveraging these methods, researchers can better understand the relationships between multiple socio-economic impacts (Challenge 3). Although dimensionality reduction methods have been successfully applied to identify underlying risk patterns (e.g. hazard, vulnerability) that drive impact occurrence (e.g. Johnson et al., 2020; Maity et al., 2013), their application in the field of CCI is yet to be explored. Adopting dimensionality reduction approaches in CCI research holds promise for gaining a comprehensive perspective on the relationships between different multi-sector impacts (Challenge 3) as well as across different regions (Challenge 4). Furthermore, indicators developed through dimensionality reduction could act as holistic measures for tracking developments through time and space or evaluating the effects of response measures (Challenge 5).

Clustering methods are another powerful tool for discovering underlying patterns in high-dimensional data. Unlike dimensionality reduction methods, clustering seeks to group similar data points based on their characteristics. Popular clustering methods include k-means, hierarchical clustering, or density-based clustering. Although hardly applied in CCI research, inspiration for application to CCI can be drawn from other fields, especially hazard research (e.g. Brunner and Stahl, 2023). For example, a study by Lam et al. (2016) leveraged clustering analysis to assess resilience to climate-related hazards for U.S. counties based on 28 variables. For CCI, similar research designs could allow researchers to better understand how CCI impacts affect regions in complex ways and whether these impacts occur in similar patterns across time and space (Challenge 4).

Sequential pattern mining methods are effective for identifying rules which describe frequent temporal patterns (e.g. sequences or cascading events) in a dataset. Respective algorithms such as SPADE or generalized sequential pattern aim at finding events that occur in predictable orders throughout a given dataset. By leveraging these methods, researchers can uncover important temporal relationships and dependencies. Indeed, the application of sequential pattern mining to CCI of hydrological extremes has been demonstrated by de Brito (2022), who detected cascading drought impact patterns for the case of Germany in 2018 and 2019 (Challenge 3). Given datasets of sufficient geographic scope, sequential pattern mining could also investigate interrelationships of CCI spanned between regions (Challenge 4).

3.3 Mixed approaches

Mixed approaches refer to methods that combine both qualitative and quantitative data to understand complex systems. These approaches leverage the strengths of both data-driven methods, which rely on patterns and insights derived directly from the data, and knowledge-driven methods, which incorporate domain knowledge, rules, or expert opinions. By doing so, these approaches offer a holistic perspective on the phenomenon under study.

3.3.1. Systems modelling

Systems modeling encompasses a range of methods for understanding complex systems through mathematical and computational models. Here, we focus on two widely used methods: system dynamics and agent-based modeling (ABM). These methods have gained popularity due to their capacity to incorporate the interplay between social and natural system components (de Brito, 2023). A limitation, however, is that they often require large amounts of data to be effective (Challenges 1 and 2). In such cases, the accuracy and reliability of the models may be compromised.

Agent-based modeling (AMB) is used to study the behavior of individuals or agents within a social system. The agent's behavior is described by a set of rules implemented by the researcher to fit the system under investigation. They often combine data from behavioural experiments or survey data (Wijermans et al., 2022). ABM can help to answer questions on how and why social systems react in response to different stimuli compared to counterfactuals. ABMs represent a well-established method for studying social-ecological systems (Biggs et al., 2021). For CCI research, models for varying purposes have been developed which capture the interactions of a social and hydrological system. For example, Michaelis et al. (2020) developed an ABM to capture processes between floods, impacts, and vulnerability. Galán et al. (2009) investigated domestic water demand using an ABM that reflects individual households. The model allowed the testing of different what-if scenarios concerning varying socioeconomic indicators and urban dynamics. Both applications highlight the capabilities of ABM to reflect on spatial interconnectivity (Challenge 4) and its effectiveness in evaluating policy measures (Challenge 5).

Systems dynamics and **multi-sector dynamic models** focus on studying the complexity of a system through understanding causal relationships and feedback patterns (Yoon et al., 2022). Gaining such understanding is beneficial for predicting future system behavior, identifying detrimental or supportive system components, and evaluating the likely impact of policy strategies. System dynamic models are typically based on a set of mathematical equations and can incorporate various data types to derive model-specific parameters as well as qualitative data from surveys. Integrative models based on both qualitative and quantitative data are increasingly being applied in the context of floods and drought impacts (e.g. Savelli et al., 2023; Yoon et al., 2021). For example, water supply and demand dynamics have been studied for varying climate change scenarios and management decisions (ElSawah et al., 2015). For CCI, these models can help identify how cascades propagate and how impacts across different sectors are connected through complex causal structures (Challenge 3). Additionally, integrated system dynamics models excel in evaluating response measures across different social-ecological systems (Challenge 5) and have already been used to evaluate the efficience of future adaptation strategies (e.g. Giuliani et al., 2022). The development of system dynamics models is, however, often constrained by the availability of data to sufficiently parametrize all model components and their causal relationships.

3.2.2. Network analysis

Network analysis is a frequently employed method for examining the connections between variables. It involves representing network structures using nodes and links, which help reveal the relationships between variables in a system and capture their associations (Bodin et al., 2019). These structures can be derived from various methods such as CLDs, FCM, co-occurrence analysis, or observational data. In flood and drought research, network analysis can provide insights into the interrelationships among individual actors or the flows between impacts, response measures, and risk drivers. While the conceptual (and metaphorical) idea of thinking of CCI as a network is widely adopted throughout CCI studies, few have adopted network analysis as an empirical approach.

In CCI research, network analysis metrics can be leveraged for understanding cascading patterns among manifold socio-economic impacts of hydrological extremes (Challenge 3). Graph theory measures can reveal highly central, relevant, or influential variables in these mental models (Olazabal & Pascual, 2016). For example, de Brito (2021) used network structures to capture and visualize the cascading impacts of drought, while graph theory measures were used to identify highly central variables. Network analysis can also help to understand the spatial interconnectivity of CCI, particularly when networks represent a spatial dimension through which impacts cascade (Naqvi & Monasterolo, 2021) (Challenge 4).

3.3.3. Economic-based models

Macro-economic models have been widely applied to identify and quantify the cross-sectoral and cross-regional economic impacts due to hydrological extremes. The most commonly applied models are input-output and computable general equilibrium models. Both models describe our economy through a set of inter-relations between economic actors (e.g. industries, households, and governments) (E. E. Koks et al., 2016). These models are particularly helpful in identifying potential spillover effects across regions (Challenge 4). However, a key limitation is that they may rely on assumptions that do not always hold in reality (e.g. either no or full substitution between production inputs). Additionally, they may not fully capture intangible impacts, such as the psychological distress experienced by individuals affected by extreme events. To cope with some of these limitations, economic models are increasingly being used together with noneconomic methods.

Traditional **input-output (IO) models** are static linear models in which substitution between products is not possible, and price effects are disregarded. Due to these characteristics, IO models often overestimate the economic losses due to their linearity and lack of substitution. In general, they are considered to best represent the economic situation in the short term, in which the economy is generally inflexible to large changes. While there are no clear examples of applications within CCI, IO models have been used to, for example, assess the cascading effects of flooding towards business disruptions and economy-wide impacts (e.g. Koks et al., 2019) and to analyze global supply-chain effects due to COVID-19 (Guan et al., 2020).

Computable general equilibrium (CGE) models mostly assume a market with perfect competition and are generally built around the rationale that: (i) firms aim to maximize profits and minimize costs and (ii) households aim to maximize their utility within their budget constraint. As such, CGE models may underestimate the economic losses due to 'over'-optimizing the economic situation (E. E. Koks et al., 2016). They are thus most suitable for assessing the long-term impacts of droughts and floods on a national economy and the potential of welfare impacts. For example, García-León et al. (2021) assessed the impacts of droughts on the Italian economy, and Bachner et al. (2023) applied a CGE model to highlight the cross-sectoral impacts of flood events within Austria.

Capturing CCI of hydrological extremes requires economic-based models capable of coupling a physical footprint of the event to disruptions within our economy. This means that CGE and IO models should be extended to convert physical asset damages and employment reductions (i.e., because of casualties and/or displacement) into a 'shock' affecting economic activity. This could either mean disruptions on the supply side of our economy (i.e., reduction in production output) or disruption on the demand side of our economy (i.e., reduction in demand for goods and services). Moreover, capturing cross-regional economic impacts (Challenge 4) requires using multi-regional economic trade data. Finally, a time dimension should be included to assess the effects of cascading events.

4 Pathways for future research

The above synthesis highlights the diversity of methods used to study CCI dynamics. In general, while methods supporting the identification of patterns between impacts (Challenge 3) are well-represented and widely applied, progress in measuring the strength of the causal relationships between socioeconomic impacts has been limited. Furthermore, while most methods are used to study interactions within one geographical scale, relatively few methods support the analysis of cross-scale dynamics (Challenge 4), as shown in Table 1. Also, the majority of the reviewed applications primarily address past or present CCI (e.g. de Brito, 2021; Matanó et al., 2022), with few examining plausible futures (e.g. D'Agostino et al., 2020; Liguori et al., 2021). The analysis of interactions between the impacts of hydrological extremes and response measures is also in its early stages (Challenge 5). Considering these gaps, we point towards recommendations for advancing the field of CCI research.

(1) Systematic efforts to collect data on impacts across multiple sectors, systems, and years are needed

The quality and quantity of longitudinal and multi-sector impact data constrain our understanding of CCI dynamics. Although a wide range of approaches exists to study complex systems, CCI research tends to rely on simple methods due to data availability limitations. Thus, systematic efforts must be made to collect drought and flood impact data. Emerging impact assessment methods that use text, digital traces, new sensors, and citizen science data are potential ways forward. For instance, newspaper and social media data can provide a fine-scale mapping of socioeconomic impacts across sectors (e.g. de Brito et al., 2020; Erfurt et al., 2020; Sodoge et al., 2023). Drones and satellite data can support detailed property and infrastructure damage assessment (e.g. West et al., 2019; Wouters et al., 2021). Moreover, digital traces such as credit card transactions and online communications can enable rapid impact assessments (e.g. Jackson and Gunda, 2021; Yuan et al., 2022b, 2022a). The adoption of these new methods presents valuable opportunities for gathering crucial data to address CCI, especially in currently underrepresented regions.

(2) Disciplinary diversity should be promoted to foster innovation

To better understand the complexity of CCI, engaging in interdisciplinary collaboration among scientists from different fields, such as ecology, economics, engineering, geography, hydrology, law, political sciences, and social sciences, is crucial. Although interdisciplinary research positively correlates with research impact and innovation (Okamura, 2019), evidence suggests that researchers in natural hazards research often work within their own disciplinary silos (Vanelli et al., 2022). This may limit the scope of their analyses, overlooking crucial interdependencies and multi-sectoral impacts. By breaking down these barriers and collaborating across disciplines, CCI research can be decompartmentalized and offer a more comprehensive explanation of how droughts and floods impact critical infrastructure, people, and assets, reducing the potential for disciplinary bias in findings. By working together, interdisciplinary teams can thus advance the understanding of compound and cascading impacts of hydrological extremes. Numerous of the applications highlighted in this paper are already moving in this direction, showcasing the positive outcomes of embracing interdisciplinary collaboration (e.g. Matanó et al., 2022; Rusca et al., 2023).

(3) Methodological pluralism is necessary to fully address the complexity of CCI and their underlying risk drivers

Data and knowledge-driven approaches are commonly used separately in CCI research, and integration of methods is limited. However, no single method can by itself capture all aspects of the intertwined nature of CCI and its underlying risk drivers. We, thus, advocate for epistemological and methodological pluralism to consider the different aspects of CCI. Since each method has its own assumptions, strengths, and weaknesses (Table 1), combining different methods can help reveal various facets of CCI and compensate for the limitations of individual methods. For instance, while quantitative assessments allow us to identify generalizable patterns and dynamics, qualitative analyses help to contextualize and interpret them (Di Baldassarre et al., 2021; Rusca et al., 2021). Hence, by triangulating the outcomes of these approaches, several lines of evidence can be delivered (Raymond et al., 2020). This can strengthen the research confidence as results that agree across different methods are less likely to be artefacts (Munafò & Davey Smith, 2018). The outcomes from one method can be used as input for others. For instance, information obtained from questionnaires and focus group discussions can be used to build agent-based models. By using multi and mixed method approaches, researchers can be more flexible and take advantage of the strengths of particular methods while still grounding the research in biophysical and socioeconomic realities. The examples of methodological pluralism discussed in our paper suggest the feasibility and added value of this approach (e.g. Savelli et al., 2023; Yoon et al., 2021).

(4) Generalizable theories of how socioeconomic impacts compound, cascade, and interact with response measures are required

Studies expressing an explicit ambition to develop theories about the dynamics of drought and flood socioeconomic impacts and their response measures with an understanding of CCI as described above, are still needed. The heterogeneity among case studies has prevented researchers from engaging in comparative analyses. Therefore, we advocate for building a corpus of empirical data on the dynamics of droughts and floods CCI with the specific aim of seeking generalizations across multiple case studies. This effort will support the development of a generalizable theory about CCI dynamics and their interactions with response measures. To achieve this, the findings of multiple case studies could be synthesized, aiming to identify common patterns and draw conclusions that can be applied across a broader range of contexts (Kuhlicke et al., 2023). This task involves disentangling the idiosyncrasies of case-specific findings by considering various contextual and research design factors (Bodin et al., 2019). A way forward would be combining empirical explanations of observed and/or anticipated phenomena with modelling (e.g. ABM or FCM) to test and explore possible explanations. Developing such theories can help overcome the limitations of individual case studies and provide a more comprehensive and nuanced understanding of causality and dynamic interactions in droughts and floods CCI research.

(5) Investigation of the risks of future CCI should be guided not only by probability but also by plausibility considerations

When investigating the risks of CCI and their root causes, attention should also be paid to less frequent impact types, whose probability may be lower but with higher consequences (Shepherd et al., 2018; Sillmann et al., 2021). In an increasingly interconnected world, the complexity of coupled natural-technological-social systems can make probability calculations futile (Engels & Marotzke, 2023). Therefore, understanding CCI entails recognizing that they cannot be fully predicted and that uncertainty is inherent. Instead, we can explore different possibilities for the evolution of CCI under different conditions. This also requires a deep understanding of the underlying risk drivers of different sectors and systems and their interlinkages. To address the plausibility question and better prepare for potential CCI, knowledge-driven tools can be instrumental. They enable us to explore the range of possible outcomes and the associated uncertainty while also offering explanations of why CCI might occur. For instance, mental models and qualitative storylines can be coupled with theories about transformative social change, disruptive change, social inertia, and path dependency. This can help us identify key drivers that can lead to high impacts in a given future scenario as well as adaptation measures that can support risk reduction.

In summary, the overview of methods and linked recommendations for future research described here can contribute to an improved characterization and understanding of CCI dynamics and hence support the reduction of CCI risks linked to hydrological extremes. In doing so, this perspective aims to enable researchers to make informed decisions about the choice of methods (or the combination of them) to be used.

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Data availability statement

No new data were created or analysed during this study. Data sharing is not applicable to this article.

CRediT statement

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