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Special Section:
Multi-Sector Dynamics: Advancing Complex Adaptive Human-Earth Systems Science in a World of Interconnected Risks

Key Points:

- Systematic efforts to collect data on impacts across multiple sectors, systems, and years are required
- Methodological pluralism is necessary to fully address the complexity of compound and cascading impacts (CCI) and their underlying risk drivers
- Investigation of the risks of multi-sector impacts should be guided not only by probability but also by plausibility considerations

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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 (CCI) 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 inform effective adaptation planning. This perspective paper aims to bridge this critical gap by presenting methods for assessing the dynamics of the multi-sector 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 or even convergent roles for analyses based on quantitative (e.g., data-mining, systems modeling) and qualitative methods (e.g., mental models, qualitative storylines). 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.

Plain Language Summary Droughts and floods can have significant impacts on both natural and social systems. These impacts are often interconnected, resulting in a complex chain of events. In this perspective paper, we aim to assist researchers in understanding the dynamics of compound and cascading impacts (CCI) caused by hydrological extremes. We provide an overview of various methods that can be utilized to assess and analyze interconnected impacts. To begin, we address the ongoing challenges associated with CCI research, such as the limited availability of comprehensive impact data spanning multiple sectors and over extended periods. Subsequently, we present a range of qualitative and quantitative methods that can be employed to analyze CCI dynamics, supported by case study examples. Finally, we conclude with six recommendations to advance the research in this field.

1. Introduction

Future climate projections show an intensification of 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 data sets can also improve our understanding of risk drivers (Kellermann et al., 2020) and serve as ground truth information for impact-based early warning systems (Hagenlocher et al., 2023; Hobeichi et al., 2022).

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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) (Figure 1 and Box 1). Indeed, natural 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, the 2021 floods in Europe damaged major access routes and bridges in the Ahr Valley, Germany (Schäfer et al., 2021). This led to cascading impacts, such as isolating villages from evacuation routes and disrupting access to medical care (Kreienkamp et al., 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 hazards (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 hazards 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 CCI.

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, low flows in the Rhine impaired shipping during the 2018 drought in Germany (Erfurt et al., 2019). This led to increased fuel prices in Switzerland, which heavily relies on Rhine river imports (Denzler et al., 2019; Niggli et al., 2022).

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 (2021a) 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

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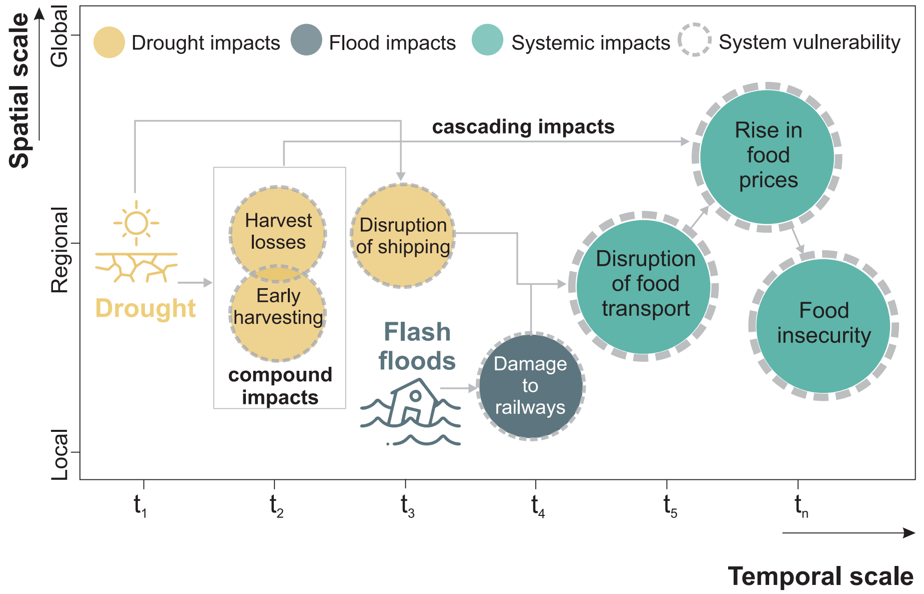

Figure 1. Schematization of compound and cascading impacts (CCI) for a fictitious drought followed by a flood event. The impacts triggered by different hazards interact, compound, and cascade, leading to spillover effects at different spatial and temporal scales. System vulnerabilities underlie all the impacts.

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 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 knowledge-driven, data-driven, and mixed 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 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; Visser-Quinn et al., 2019), the socioeconomic CCI of droughts and floods remain relatively unexplored (Naumann et al., 2021; Ward et al., 2022). 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. Furthermore, impact data are seldom disaggregated by demographics (e.g., gender, income), hampering a nuanced understanding of how some groups are disproportionately affected by the impacts of floods and droughts (Zwarteveen et al., 2017).

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

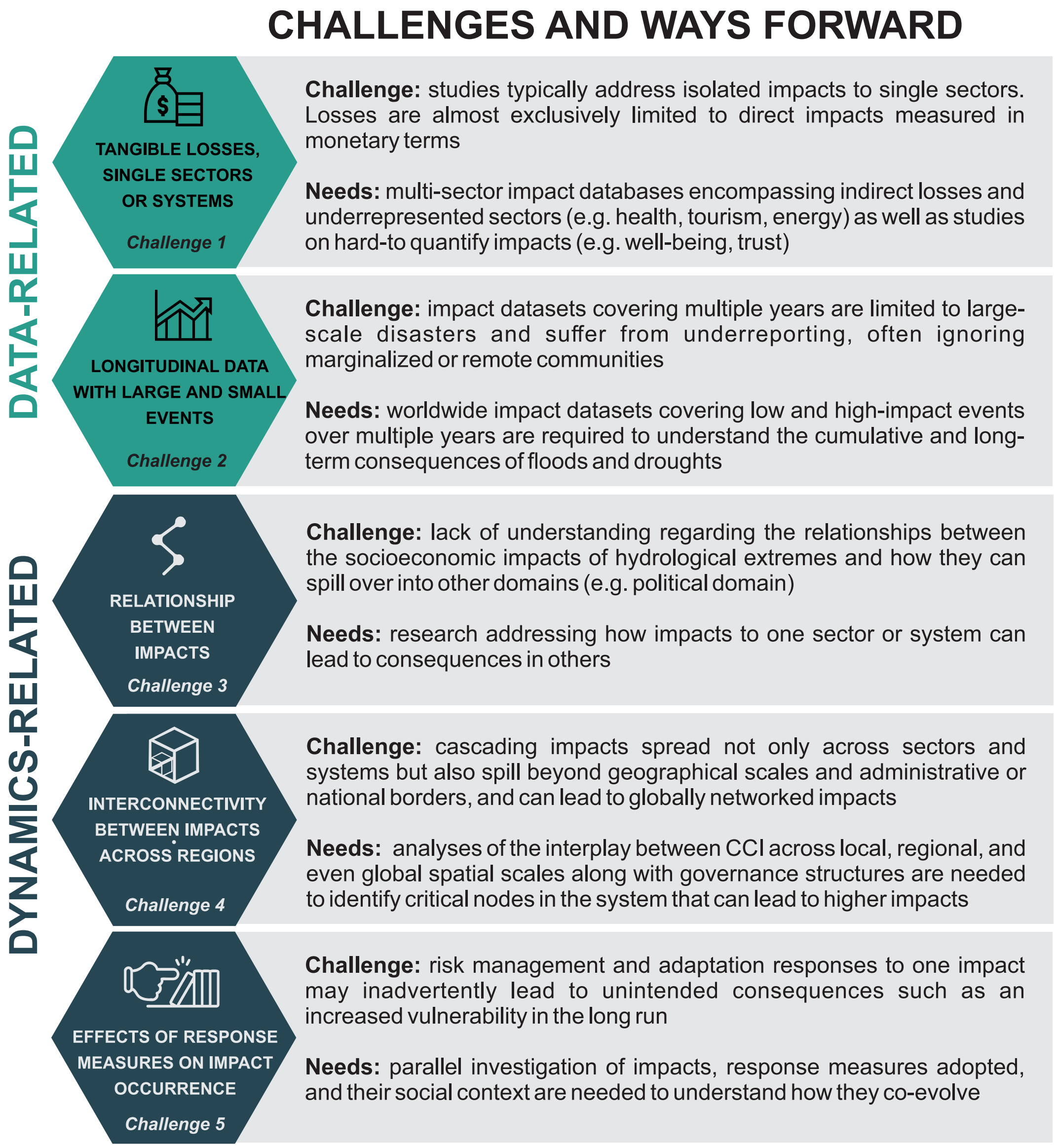

Figure 2. Set of challenges and needs that must be addressed to provide targeted information to understand compound and cascading impacts (CCI). In this study, we focus on methods that can be used to address the needs of challenges 3–5, which are related to dynamic aspects.

Challenge 1 is linked to the focus of existing impact assessments on *tangible losses and single sectors or systems* (Fronzek et al., 2019; Ward et al., 2022). Studies typically address single impact types, including critical infrastructure (Qiang et al., 2020), agriculture (H. Chen et al., 2019; Rahman & Di, 2020; Tapia-Silva et al., 2011), buildings (Gerl et al., 2014; Serpico et al., 2012), and fatalities (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 than intangible losses, such as societal, psychological, and cultural impacts (Allaire, 2018; Walz et al., 2021). 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. Exceptions include initiatives such as the Panta Rhei benchmark data set, which includes impact information on 93 floods and droughts worldwide (Kreibich et al., 2023). Also worth mentioning are the Spatial Hazard Event and Loss Database for the United States (SHEDLUS) (CEMHS, 2023) and the European HOWAS21 database (Kellermann et al., 2020), which includes detailed data on objects affected by 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, and energy, are needed. Moreover, studies addressing hard-to-quantify impacts (e.g., decrease of subjective well-being and growing lack of trust in institutions) are also needed.

Related to this issue is the *lack of longitudinal impact data sets encompassing both large and small-scale events* (Challenge 2) (de Brito et al., 2020; Jones et al., 2022). Existing impact data sets covering multiple years (e.g., EM-DAT, NatCatSERVICE) suffer from underreporting (Jones et al., 2022). As a result, smaller-scale disasters, which disproportionally affect marginalized or remote communities, may remain invisible (Cadag et al., 2017). According to the UNISDR (2015), 99.7% of all disasters between 1990 and 2013 were smaller-scale, 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 (UNDRR, 2021b) and are equally damaging when considering their cumulative occurrence (UNDRR & CRED, 2020). Small-scale events are also neglected for political reasons, as some regions may be deemed more "relevant" than others. In fact, disasters in Europe and the United States receive far more attention than those in the Global South (Joye, 2009; Porter & Evans, 2020). Therefore, worldwide disaggregated impact data sets covering low and high-impact events over multiple years are required to understand the cumulative and long-term consequences of floods and droughts.

Challenge 3 refers to our limited understanding of the *relationships between the socioeconomic impacts* of hydrological extremes (Pescaroli & Alexander, 2016; Simpson et al., 2021; UNDRR, 2021c). These impacts are not isolated; rather, they form an intricate network where impact outputs from one sector or system can become inputs into others depending on existing dependencies and vulnerabilities (Ding et al., 2011). For instance, droughts often lead to ripple effects, starting with crop failures that inflict income losses, especially on smallholder farmers who heavily depend on agriculture for their livelihoods (Quandt, 2021). The ramifications of severe droughts can also spill over into the political domain, where they have been linked to political instability and conflict (von Uexkull et al., 2016). Research addressing how impacts on one sector or system can lead to consequences in others is thus needed to support effective mitigation measures. To this end, a better understanding of the societal drivers of CCI (e.g., water governance, vulnerabilities, politics) is needed.

Challenge 4 is linked to the limited research on the *interconnectivity between impacts across regions, administrative borders, and spatial scales* (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 (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. (Challinor et al., 2018; Hunt et al., 2021). These globally networked impacts are highly influenced by governance practices (Zwarteveen et al., 2017). Hence, analyses of the interplay between CCI across local, regional, and even global scales (e.g., Lawrence et al., 2020; Mishra et al., 2021), along with an understanding of the coordination strategies, are needed to identify critical nodes in the system that can lead to higher impacts.

Finally, research on the *effects of response measures* on the generation or exacerbation of CCI is scarce (Challenge 5). However, 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). Moreover, power relations can significantly shape response measures and foster differential impacts. For instance, increased water tariffs have been shown to further exacerbate the CCI of droughts in already marginalized communities (Savelli et al., 2023). Therefore, it is difficult to measure to which extent adaptation measures reduce impacts or lead to unintended consequences. Thus, a parallel and integrated investigation of impacts, response measures adopted, and their social context 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 3–5 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 qualitative, quantitative and mixed methods that can be used to address challenges 3–5, which are rooted in the complexity of CCI interactions.

We argue that a holistic approach incorporating multiple perspectives, methods, and disciplines is needed to address these challenges. We do not view data-driven quantitative methods as the "ultimate solution," nor do we see knowledge-driven qualitative methods as mere "supplements" (de Brito et al., 2021). Instead, we endorse using both approaches or a combination of them (i.e., mixed methods) in a complementary, compatible, or even convergent manner (Rusca & Di Baldassarre, 2019). While quantitative assessments can support the identification of generalizable patterns, qualitative tools can help contextualize them (Di Baldassarre et al., 2021). For instance, through causal loop diagrams (CLD) and qualitative content analysis, researchers can better examine how adaptation plans help to reduce CCI (Challenge 5). Results can then provide a basis for theory generation and hypothesis testing using quantitative modeling (Biggs et al., 2021).

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 of methods used in CCI research are still missing.

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 methods were selected based on the experience of the co-authors, who 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 3–5 in Figure 2. Besides considering their strengths, the choice for a specific method should be guided by the study's objective (Figure 3), data requirements, and complexity. This assessment is essential for evaluating the trade-offs inherent to each approach. In fact, data-driven methods excel in harnessing empirical evidence and large data sets for robust analyses but may overlook the nuanced contextual understanding that knowledge-driven methods offer. Conversely, knowledge-driven methods promote richer insights through participatory engagement and expert judgment but often have limited transferability between different cultural contexts or locations (Fekete et al., 2021; Moreira et al., 2023). 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 that 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. Here, we focus on methods such as mental models, visual techniques, qualitative scenarios and storylines. 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—a dimension often overlooked in data-driven approaches. They can also act as a trigger for social learning (de Brito et al., 2018). By analyzing CCI in a flexible way, knowledge-driven methods can provide in-depth knowledge of the impact dynamics for specific case studies (Challenges 3–5). However, by their very nature, they fall short of providing certainty and the potential for falsiability (Biggs et al., 2021), posing challenges to achieving comparable and scalable results. Furthermore, they carry the risk of being biased by the interests of powerful stakeholders (Karnieli-Miller et al., 2009).

Table 1
Overview of Methods That Can Be Used to Investigate Compound and Cascading Impacts Dynamics

	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, Hagenlocher, et al., 2023)	Visualize the interplay between CCI (Challenge 3). When built in a participatory way, it enables the inclusion of perspectives of marginalized groups. Some methods allow for a semi-quantitative quantification of relationship strengths, allowing us to explore how adaptation measures interact with impact occurrence (Challenge 5)	Highly dependent on the participants' knowledge. Spatial and temporal dynamics are usually not explicitly addressed (Challenge 4). Merging mental models can be complex as it requires the homogenization of variables used
	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)	Comparability between studies is limited as results are highly context-specific. Are often unsuitable for addressing spatial dynamics (Challenge 4)
	Qualitative storylines and scenarios	- Qualitative storylines (van den Hurk et al., 2023) - (Semi)-qualitative scenarios (Rusca et al., 2021; Rusca, Savelli, 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. Limited predictive power compared to quantitative storylines. Can be time-intensive depending on the number of stakeholders involved
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 data sets 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 (Challenge 3) from high-dimensional and noisy data (e.g., unstructured data). Allow uncovering temporal and spatial dependencies (Challenge 4)	Potential loss of complexity and details when reducing high-dimensional data to lower-dimensional representation. Results can be difficult to interpret
Mixed methods	Systems modeling	- Agent-based modeling (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)	Require comprehensive data coverage of the underlying system. Careful calibration and validation are needed. Models without empirical components run at risk of being "toy" models

Table 1
Continued

Group of methods	Methods and key references	Strengths	Weaknesses
Network analysis	- Network analysis (Naqvi & Monasterolo, 2021)	Intuitive visualization of interconnected systems (Challenges 3 and 5). Enable the identification of key nodes within the network. Allow investigating spatial patterns (Challenge 4)	Require extensive data and knowledge on both impacts and causal relationships between impacts
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

Note. 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.

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. They are typically constructed through stakeholder involvement (Romero-Lankao & Norton, 2018). Since individuals' perspectives differ, mental models can be highly variable. Hence, they have been shown to provide more holistic perspectives when diverse groups are involved (e.g., Aminpour et al., 2021). Due to their flexibility, they are often paired with other methods, such as system dynamics (Perrone et al., 2020).

Several approaches are used to elicit mental models, ranging from *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 (through positive links) or balancing them (through negative links). 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 & 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).

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 & Gaganis, 2016; Mehryar & 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 considering geolocated data on 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). They draw 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 directly link impacts and adaptation strategies (Challenge 5). 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.

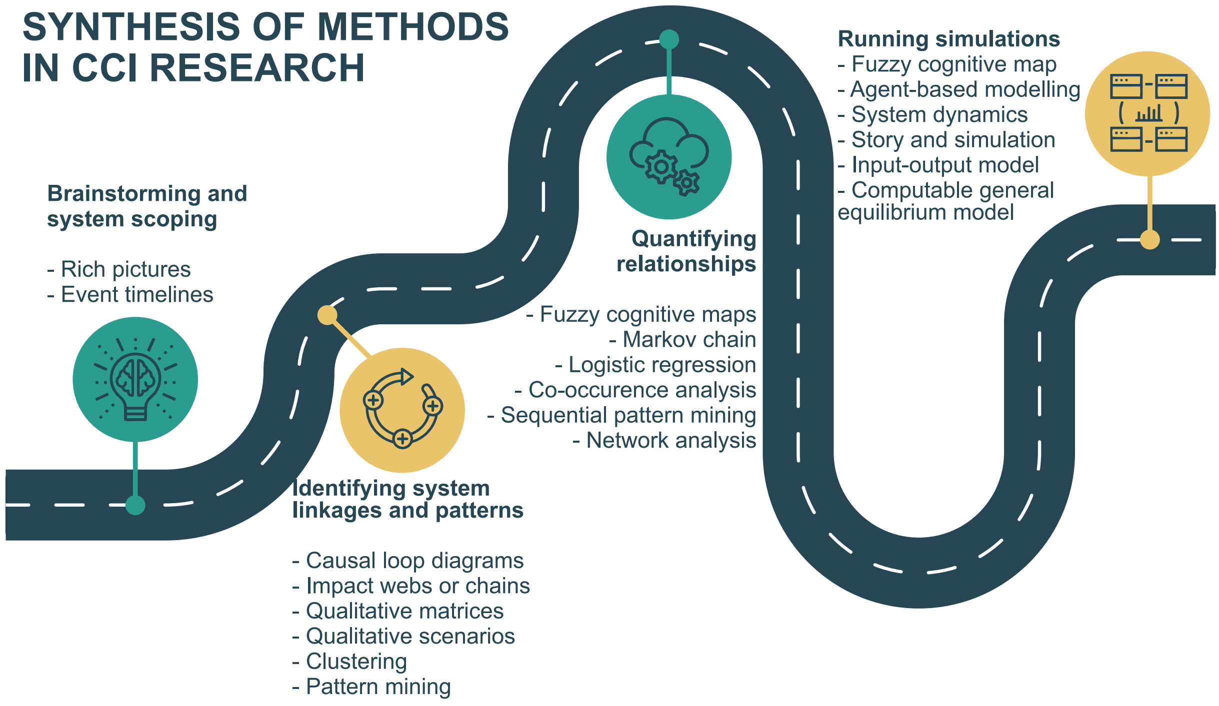

Figure 3. Synthesis of methods used in compound and cascading impacts research to brainstorm, identify system linkages and patterns, quantify relationships, and run simulations. Some methods can be used for multiple purposes.

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 toward a single risk, impact webs offer a holistic overview of system interactions without directional constraints. While they were 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, Cotti, 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 generalizability 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 & 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, X. 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, this method is 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 that is, through narrative interviews or workshops (Shanahan et al., 2018), document analysis, or modeling. While valuable for exploring the dynamics and narratives within complex systems, these methods possess limited predictive power. This is because they prioritize plausibility and contextual understanding over quantitative precision.

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 regions (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 & 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. These methods allow quantifying interdependencies between impacts and response measures (Challenges 3 and 4), often providing generalizable results. However, a significant challenge lies in their reliance on the quality and quantity of available impact data. Insufficient volumes of data (Challenge 1) can restrict the statistical power of analyses, rendering the detection of subtle patterns difficult. This limitation is particularly pronounced when CCI events are infrequent (e.g., black swan events). At the same time, impact data sets may suffer from inaccuracies and missing values as they tend to focus on high-impact events (Challenge 2). These shortcomings can lead to erroneous insights, potentially compromising the reliability of the results.

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 & 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 data sets 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. Here, we therefore discuss 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 effective in examining temporally successive or spatially co-occurring climate hazards and their impacts (e.g., Ben-Ari et al., 2018; Martius et al., 2016). For example, Ben-Ari et al. (2018) used such a model to identify the climatic drivers behind simultaneous low wheat yields in France. Logistic regression models can also include a time-lagged predictor variable to account, for example, for autocorrelation effects (Mahlstein et al., 2012). However, logistic regressions typically require binarizing data, and may struggle in the presence of many relevant predictor variables. The latter case may require implementing additional analysis steps, which come with their own challenges and limitations (e.g., Vogel et al., 2021). Data-efficient machine-learning models, including random forests, have also been used to link hydro-climatic indicators to environmental and socioeconomic impacts (e.g., Bachmair et al., 2017; Torelló-Sentelles & Franzke, 2022). Again, selecting relevant variables to include in the model can present context-specific challenges (e.g., Goulart et al., 2021). While keeping in mind their limitations, the above approaches could profitably be applied to quantitative socioeconomic impact data. They could, for example, be used to quantify changes in the probability 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). At the same time, the discretization of states implicit in the Markov chain analysis can be problematic in the context of a continuum of hydrological drivers and associated CCIs. Nonetheless, 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 & Liu, 2022)—making their use particularly promising in a CCI context.

The above methods may 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 compound 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, while Tilloy et al. (2022) applied a co-occurrence analysis combined with a clustering algorithm to investigate compound wind and precipitation extremes in Great Britain. Batibeniz et al. (2023) and Velpuri et al. (2023) also present effective concurrence analyses, and further consider numerical simulations of future climates. Similar approaches could be applied to the present and projected impacts of hydrological extremes whenever these can be placed in space and/or time with sufficient precision. 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 data sets. These methods help transform data sets 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 data set's variance using fewer dimensions, thereby maintaining its key characteristics. Principal component analysis, self-organizing maps, and 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 still incipient (e.g., Sodoge, Kuhlicke, Mahecha, et al., 2023). 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 & 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 that describe frequent temporal patterns (e.g., sequences or cascading events) in a data set. Respective algorithms such as SPADE or generalized sequential pattern aim at finding events that occur in predictable orders throughout a given data set. 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 (2021), who detected cascading drought impact patterns for the case of Germany in 2018 and 2019 (Challenge 3). Given data sets of sufficient geographic scope, sequential pattern mining could also investigate interrelationships of CCI spanned between regions (Challenge 4).

3.3. Mixed Methods

Mixed methods refer to approaches that combine both qualitative and quantitative data to understand complex systems. They leverage the strengths of 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, they attempt to offer a more holistic perspective on the phenomenon under study. While mixed methods can mitigate the limitations of individual approaches, careful consideration is needed to avoid simply layering bottom-up onto top-down methods. For instance, using participatory methods solely to validate deductive approaches or failing to adequately showcase participants' input can pose challenges, as observed by Fekete et al. (2021). Additionally, using mixed methods across researchers with diverse disciplinary perspectives can lead to project delays and require extra time for methodological alignment.

3.3.1. Systems Modeling

Systems modeling encompasses a range of methods for understanding complex systems through mathematical and computational models. Here, we focus on two widely used methods—agent-based modeling (ABM) and system dynamics. These methods have gained traction 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 both contextual and quantitative 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. To define these rules, behavioral experiments or survey data are often used (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, different models capturing the interactions of a social and hydrological system have been developed. 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 ABM's capabilities 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 applied in floods and drought research (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 efficiency 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.

3.3.2. 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 many 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 (IO) and Computable general equilibrium (CGE) models. Both models describe our economy through a set of inter-relations between economic actors (e.g., industries, households, and governments) (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 these limitations, economic models are increasingly being used together with noneconomic methods.

Traditional *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 toward 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: (a) firms aim to maximize profits and minimize costs and (b) 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 (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 toward recommendations for advancing the field of CCI research.

(1) Systematic efforts to collect data on impacts across multiple sectors, systems, temporal and spatial scales 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. Recent initiatives that are moving in this direction include the work by CEMHS (2023), Kellermann et al. (2020), and Kreibich et al. (2023). 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, Kuhlicke, & de Brito, 2023). Drones and satellite data can support detailed property and infrastructure damage assessment (e.g., West et al., 2019; Wouters et al., 2021). Citizen science may play a vital role in addressing hard-to-quantify impacts, including well-being (e.g., Smith et al., 2014, 2021). Moreover, digital traces such as credit card transactions and online communications can enable rapid impact assessments (e.g., Jackson & Gunda, 2021; Yuan, Fan, et al., 2022; Yuan, Yang, et al., 2022). Embracing these methods presents valuable opportunities for gathering crucial data to understand CCI, especially in 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 CCI 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, Mazzoleni, et al., 2023; Savelli 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 (See Höllermann et al., 2022; Rusca & Di Baldassarre, 2019; Schlüter et al., 2023; Zwarteveen et al., 2017). Since each method has its 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; Rusca, Mazzoleni, et al., 2023). This can strengthen the research confidence as results that agree across different methods are less likely to be artifacts (Munafò & Davey Smith, 2018). The outcomes from one method can be used as input for others. For instance, information obtained from interviews, questionnaires and focus group discussions can be used to build agent-based models. By using multi and mixed methods, 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 can support knowledge synthesis
Our review has shown that the methods, epistemologies, and temporal and spatial scales used in CCI research vary widely. This heterogeneity among case studies has prevented researchers from engaging in comparative analyses and knowledge synthesis. 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 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 contextual and research design factors (Bodin et al., 2019). A way forward would be combining empirical explanations of observed and/or anticipated phenomena with modeling (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.

(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 be paid to less frequent impact types, whose probability may be lower but with higher consequences, that is, black swans (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.

(6) Ethical and societal implications of CCI research must be considered for informed adaptation

Independent of the method chosen, scientists must consider how CCI research can impact resource allocation, policy equity, and social dynamics. While CCI insights can guide equitable strategies, there is a risk of unintended consequences. For example, existing impact databases often overrepresent Europe and the United States (e.g., Kreibich et al., 2023; Papagiannaki et al., 2022), leading to an incomplete understanding of CCI patterns in the Global South. Likewise, when using impact data sets derived from newspaper articles (e.g., de Brito et al., 2020; Sodoge, Kuhlicke, & de Brito, 2023; Stahl et al., 2016), minority perspectives can be marginalized as media representations often prioritize the concerns of powerful groups (Orgad, 2012). Hence, careful consideration is needed to ensure that strategies to reduce CCI do not exacerbate social inequalities. To address this, impact data disaggregated by demographics (e.g., gender, income) could be instrumental as it enables us to gain a nuanced insight into how different populations are affected by CCI. Moreover, promoting the participation of diverse groups in knowledge production can advance fairness and justice by giving voice to those historically excluded from decision-making (Innes & Booher, 2004).

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.

Data Availability Statement

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

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References

Alfieri, L., Feyen, L., Salamon, P., Thielen, J., Bianchi, A., Dottori, F., & Burek, P. (2016). Modelling the socio-economic impact of river floods in Europe. *Natural Hazards and Earth System Sciences*, *16*(6), 1401–1411. https://doi.org/10.5194/nhess-16-1401-2016

Allaire, M. (2018). Socio-economic impacts of flooding: A review of the empirical literature. *Water Security*, *3*, 18–26. https://doi.org/10.1016/j.wasec.2018.09.002

Aminpour, P., Gray, S. A., Jetter, A. J., Introne, J. E., Singer, A., & Arlinghaus, R. (2020). Wisdom of stakeholder crowds in complex social–ecological systems. *Nature Sustainability*, *3*(3), 191–199. https://doi.org/10.1038/s41893-019-0467-z

Aminpour, P., Gray, S. A., Singer, A., Scyphers, S. B., Jetter, A. J., Jordan, R., et al. (2021). The diversity bonus in pooling local knowledge about complex problems. *Proceedings of the National Academy of Sciences*, *118*(5), e2016887118. https://doi.org/10.1073/pnas.2016887118

Andrews, M., Squire, C., & Tamboukou, M. (2013). *Doing narrative research. 1 Oliver's Yard, 55 City Road London EC1Y 1SP*. SAGE Publications, Ltd. https://doi.org/10.4135/9781526402271

Anowar, F., Sadaoui, S., & Selim, B. (2021). Conceptual and empirical comparison of dimensionality reduction algorithms (PCA, KPCA, LDA, MDS, SVD, LLE, ISOMAP, LE, ICA, t-SNE). *Computer Science Review*, *40*, 100378. https://doi.org/10.1016/j.cosrev.2021.100378

Armah, F. A., Yawson, D. O., Yengoh, G. T., Odoi, J. O., & Afrifa, E. K. A. (2010). Impact of floods on livelihoods and vulnerability of natural resource dependent communities in Northern Ghana. *Water*, *2*(2), 120–139. https://doi.org/10.3390/w2020120

Bachmair, S., Svensson, C., Prosdocimi, I., Hannaford, J., & Stahl, K. (2017). Developing drought impact functions for drought risk management. *Natural Hazards and Earth System Sciences*, *17*(11), 1947–1960. https://doi.org/10.5194/nhess-17-1947-2017

Bachner, G., Knittel, N., Poledna, S., Hochrainer-Stigler, S., & Reiter, K. (2023). Revealing indirect risks in complex socioeconomic systems: A highly detailed multi-model analysis of flood events in Austria. *Risk Analysis*, *44*, 229–243. https://doi.org/10.1111/risa.14144

Ballesteros-Olza, M., Blanco-Gutiérrez, I., Esteve, P., Gómez-Ramos, A., & Bolinches, A. (2022). Using reclaimed water to cope with water scarcity: An alternative for agricultural irrigation in Spain. *Environmental Research Letters*, *17*(12), 125002. https://doi.org/10.1088/1748-9326/aca3bb

Barbrook-Johnson, P., & Penn, A. S. (2022). *Systems mapping*. Springer International Publishing. https://doi.org/10.1007/978-3-031-01919-7

Batibeniz, F., Hauser, M., & Seneviratne, S. I. (2023). Countries most exposed to individual and concurrent extremes and near-permanent extreme conditions at different global warming levels. *Earth System Dynamics*, *14*(2), 485–505. https://doi.org/10.5194/esd-14-485-2023

Bell, S., Berg, T., & Morse, S. (2019). Towards an understanding of rich picture interpretation. *Systemic Practice and Action Research*, *32*(6), 601–614. https://doi.org/10.1007/s11213-018-9476-5

Ben-Ari, T., Boé, J., Ciais, P., Lecerf, R., Van der Velde, M., & Makowski, D. (2018). Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. *Nature Communications*, *9*(1), 1627. https://doi.org/10.1038/s41467-018-04087-x

Berariu, R., Fikar, C., Gronalt, M., & Hirsch, P. (2015). Understanding the impact of cascade effects of natural disasters on disaster relief operations. *International Journal of Disaster Risk Reduction*, *12*, 350–356. https://doi.org/10.1016/j.ijdrr.2015.03.005

Bevacqua, E., De Michele, C., Manning, C., Couasnon, A., Ribeiro, A. F. S., Ramos, A. M., et al. (2021). Guidelines for studying diverse types of compound weather and climate events. *Earth's Future*, *9*(11), e2021EF002340. https://doi.org/10.1029/2021EF002340

Bevacqua, E., Zappa, G., Lehner, F., & Zscheischler, J. (2022). Precipitation trends determine future occurrences of compound hot–dry events. *Nature Climate Change*, *12*(4), 350–355. https://doi.org/10.1038/s41558-022-01309-5

Biggs, R., Preiser, R., de Vos, A., Schlüter, M., Maciejewski, K., & Clements, H. (2021). *The Routledge handbook of research methods for social-ecological systems*. Routledge. https://doi.org/10.4324/9781003021339

Bodin, Ö., Alexander, S. M., Baggio, J., Barnes, M. L., Berardo, R., Cumming, G. S., et al. (2019). Improving network approaches to the study of complex social–ecological interdependencies. *Nature Sustainability*, *2*(7), 551–559. https://doi.org/10.1038/s41893-019-0308-0

Brunner, M. I., & Stahl, K. (2023). Temporal hydrological drought clustering varies with climate and land-surface processes. *Environmental Research Letters*, *18*(3), 034011. https://doi.org/10.1088/1748-9326/acb8ca

Bunch, M. J. (2003). Soft systems methodology and the ecosystem approach: A system study of the Cooum River and Environs in Chennai, India. *Environmental Management*, *31*(2), 182–197. https://doi.org/10.1007/s00267-002-2721-8

Cadag, J. R. D., Petal, M., Luna, E., Gaillard, J. C., Pambid, L., & Santos, G. V. (2017). Hidden disasters: Recurrent flooding impacts on educational continuity in the Philippines. *International Journal of Disaster Risk Reduction*, *25*, 72–81. https://doi.org/10.1016/j.ijdrr.2017.07.016

Carter, T. R., Benzie, M., Campiglio, E., Carlsen, H., Fronzek, S., Hildén, M., et al. (2021). A conceptual framework for cross-border impacts of climate change. *Global Environmental Change*, *69*, 102307. https://doi.org/10.1016/j.gloenvcha.2021.102307

CEMHS. (2023). *Spatial hazard events and losses database for the United States Version 21.0* [Online Database]. Center for Emergency Management and Homeland Security, Arizona State University.

Challinor, A. J., Adger, W. N., & Benton, T. G. (2017). Climate risks across borders and scales. *Nature Climate Change*, *7*(9), 621–623. https://doi.org/10.1038/nclimate3380

Challinor, A. J., Adger, W. N., Benton, T. G., Conway, D., Joshi, M., & Frame, D. (2018). Transmission of climate risks across sectors and borders. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *376*(2121), 20170301. https://doi.org/10.1098/rsta.2017.0301

Chandra, A., & Gaganis, P. (2016). Deconstructing vulnerability and adaptation in a coastal river basin ecosystem: A participatory analysis of flood risk in Nadi, Fiji Islands. *Climate & Development*, *8*(3), 256–269. https://doi.org/10.1080/17565529.2015.1016884

Chen, H., Liang, Q., Liang, Z., Liu, Y., & Xie, S. (2019). Remote-sensing disturbance detection index to identify spatio-temporal varying flood impact on crop production. *Agricultural and Forest Meteorology*, *269*(270), 180–191. https://doi.org/10.1016/j.agrformet.2019.02.002

Chen, X., Tian, F., & Su, Y. (2022). How did the late 1920s drought affect northern Chinese society? *Weather and Climate Extremes*, *36*, 100451. https://doi.org/10.1016/j.wace.2022.100451

Christian, J. I., Basara, J. B., Hunt, E. D., Otkin, J. A., & Xiao, X. (2020). Flash drought development and cascading impacts associated with the 2010 Russian heatwave. *Environmental Research Letters*, *15*(9), 094078. https://doi.org/10.1088/1748-9326/ab9faf

Clark-Ginsberg, A. (2017). Participatory risk network analysis: A tool for disaster reduction practitioners. *International Journal of Disaster Risk Reduction*, *21*, 430–437. https://doi.org/10.1016/j.ijdrr.2017.01.006

Cook, B. I., Mankin, J. S., Marvel, K., Williams, A. P., Smerdon, J. E., & Anchukaitis, K. J. (2020). Twenty-first century drought projections in the CMIP6 forcing scenarios. *Earth's Future*, *8*(6), e2019EF001461. https://doi.org/10.1029/2019EF001461

Cotti, D., Siemons, A. S., Naumann, G., Wens, M., Moel, H. D., Blauhut, V., et al. (2023). Conceptual models of drought risks for Europe: A step towards a systemic perspective on drought. (May).

D'Agostino, D., Borg, M., Hallett, S. H., Sakrabani, R. S., Thompson, A., Papadimitriou, L., & Knox, J. W. (2020). Multi-stakeholder analysis to improve agricultural water management policy and practice in Malta. *Agricultural Water Management*, *229*, 105920. https://doi.org/10.1016/j.agwat.2019.105920

De Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., & Rudari, R. (2022). A multi-hazard framework for spatial-temporal impact analysis. *International Journal of Disaster Risk Reduction*, *73*, 102829. https://doi.org/10.1016/j.ijdrr.2022.102829

de Brito, M. M. (2021). Compound and cascading drought impacts do not happen by chance: A proposal to quantify their relationships. *Science of the Total Environment*, *778*, 146236. https://doi.org/10.1016/j.scitotenv.2021.146236

de Brito, M. M. (2023). Cities dried up by few. *Nature Sustainability*, *6*, 883–884. https://doi.org/10.1038/s41893-023-01097-6

de Brito, M. M., Evers, M., & Almoradie, A. D. S. (2018). Participatory flood vulnerability assessment: A multi-criteria approach. *Hydrology and Earth System Sciences*, *22*(1), 373–390. https://doi.org/10.5194/hess-22-373-2018

de Brito, M. M., Kuhlicke, C., & Marx, A. (2020). Near-real-time drought impact assessment: A text mining approach on the 2018/19 drought in Germany. *Environmental Research Letters*, *15*, 1040a9. https://doi.org/10.1088/1748-9326/aba4ca

de Brito, M. M., Otto, D., & Kuhlicke, C. (2021). Tracking topics and frames regarding sustainability transformations during the onset of the COVID-19 crisis. *Sustainability*, *13*(19), 11095. https://doi.org/10.3390/su131911095

Denzler, L., Hohmann, R., & Kleppek, S. (2019). *Hitze und Trockenheit im Sommer 2018: Auswirkungen auf Mensch und Umwelt*. Bern.

de Ruiter, M. C., & van Loon, A. F. (2022). The challenges of dynamic vulnerability and how to assess it. *iScience*, *25*(8), 104720. https://doi.org/10.1016/j.isci.2022.104720

Di Baldassarre, G., Cloke, H., Lindersson, S., Mazzoleni, M., Mondino, E., Mård, J., et al. (2021). Integrating multiple research methods to unravel the complexity of human-water systems. *AGU Advances*, *2*(3), e2021AV000473. https://doi.org/10.1029/2021AV000473

Di Baldassarre, G., Nohrstedt, D., Mård, J., Burchardt, S., Albin, C., Bondesson, S., et al. (2018). An integrative research framework to unravel the interplay of natural hazards and vulnerabilities. *Earth's Future*, *6*(3), 305–310. https://doi.org/10.1002/2017EF000764

Ding, Y., Hayes, M. J., & Widhalm, M. (2011). Measuring economic impacts of drought: A review and discussion. *Disaster Prevention and Management: An International Journal*, *20*(4), 434–446. https://doi.org/10.1108/09653561111161752

Dolan, A. H., & Walker, I. J. (2006). Understanding vulnerability of coastal communities to climate change related risks. *Journal of Coastal Research, Proceedings of the 8th International Coastal Symposium (ICS 2004)*, *III*(39), 1316–1323.

Doyle, E. E. H., Harrison, S. E., Hill, S. R., Williams, M., Paton, D., & Bostrom, A. (2022). Eliciting mental models of science and risk for disaster communication: A scoping review of methodologies. *International Journal of Disaster Risk Reduction*, *77*, 103084. https://doi.org/10.1016/j.ijdrr.2022.103084

ElSawah, S., McLucas, A., & Mazanov, J. (2015). Communicating about water issues in Australia. *Simulation & Gaming*, *46*(6), 713–741. https://doi.org/10.1177/1046878115580410

Enenkel, M., Brown, M. E., Vogt, J. V., McCarty, J. L., Reid Bell, A., Guha-Sapir, D., et al. (2020). Why predict climate hazards if we need to understand impacts? Putting humans back into the drought equation. *Climatic Change*, *162*(3), 1161–1176. https://doi.org/10.1007/s10584-020-02878-0

Engels, A., & Marotzke, J. (2023). Assessing the plausibility of climate futures. *Environmental Research Letters*, *18*(1), 011006. https://doi.org/10.1088/1748-9326/acaf90

Erfurt, M., Glaser, R., & Blauhut, V. (2019). Changing impacts and societal responses to drought in southwestern Germany since 1800. *Regional Environmental Change*, *19*(8), 2311–2323. https://doi.org/10.1007/s10113-019-01522-7

Erfurt, M., Skiadaresis, G., Tijdeman, E., Blauhut, V., Bauhus, J., Glaser, R., et al. (2020). A multidisciplinary drought catalogue for southwestern Germany dating back to 1801. *Natural Hazards and Earth System Sciences*, *20*(11), 2979–2995. https://doi.org/10.5194/nhess-20-2979-2020

Fekete, A. (2020). Critical infrastructure cascading effects. Disaster resilience assessment for floods affecting city of Cologne and Rhein-Erft-Kreis. *Journal of Flood Risk Management*, *13*(November 2019), 1–9. https://doi.org/10.1111/jfr3.12600

Fekete, A., Aslam, A. B., de Brito, M. M., Dominguez, I., Fernando, N., Illing, C. J., et al. (2021). Increasing flood risk awareness and warning readiness by participation – But who understands what under "participation"? *International Journal of Disaster Risk Reduction*, *57*, 102157. https://doi.org/10.1016/j.ijdrr.2021.102157

Feng, Y., Maulik, R., Wang, J., Balaprakash, P., Huang, W., Rao, V., et al. (2021). *Characterization of Extremes and compound impacts: Applications of machine learning and interpretable neural networks*. Oak Ridge National Laboratory (ORNL). https://doi.org/10.2172/1769686

Fritzsche, K., Schneiderbauer, S., Bubeck, P., Kienberger, S., Buth, M., Zebisch, M., & Kahlenborn, M. (2014). The vulnerability sourcebook (p. 180).

Fronzek, S., Carter, T. R., Pirttioja, N., Alkemade, R., Audsley, E., Bugmann, H., et al. (2019). Determining sectoral and regional sensitivity to climate and socio-economic change in Europe using impact response surfaces. *Regional Environmental Change*, *19*(3), 679–693. https://doi.org/10.1007/s10113-018-1421-8

Galán, J. M., López-Paredes, A., & del Olmo, R. (2009). An agent-based model for domestic water management in Valladolid metropolitan area. *Water Resources Research*, *45*(5), W05401. https://doi.org/10.1029/2007WR006536

García-León, D., Standardi, G., & Staccione, A. (2021). An integrated approach for the estimation of agricultural drought costs. *Land Use Policy*, *100*, 104923. https://doi.org/10.1016/j.landusepol.2020.104923

Gerl, T., Bochow, M., & Kreibich, H. (2014). Flood damage modeling on the basis of urban structure mapping using high-resolution remote sensing data. *Water*, *6*(8), 2367–2393. https://doi.org/10.3390/w6082367

Gill, J. C., & Malamud, B. D. (2014). Reviewing and visualizing the interactions of natural hazards. *Reviews of Geophysics*, *52*(4), 680–722. https://doi.org/10.1002/2013RG000445

Gill, J. C., & Malamud, B. D. (2016). Hazard interactions and interaction networks (cascades) within multi-hazard methodologies. *Earth System Dynamics*, *7*(3), 659–679. https://doi.org/10.5194/esd-7-659-2016

Giuliani, M., Lamontagne, J. R., Hejazi, M. I., Reed, P. M., & Castelletti, A. (2022). Unintended consequences of climate change mitigation for African river basins. *Nature Climate Change*, *12*(2), 187–192. https://doi.org/10.1038/s41558-021-01262-9

Goulart, H. M. D., van der Wiel, K., Folberth, C., Balkovic, J., & van den Hurk, B. (2021). Storylines of weather-induced crop failure events under climate change. *Earth System Dynamics*, *12*(4), 1503–1527. https://doi.org/10.5194/esd-12-1503-2021

Groesser, S. N., & Schaffernicht, M. (2012). Mental models of dynamic systems: Taking stock and looking ahead. *System Dynamics Review*, *28*(1), 46–68. https://doi.org/10.1002/sdr.476

Guan, D., Wang, D., Hallegatte, S., Davis, S. J., Huo, J., Li, S., et al. (2020). Global supply-chain effects of COVID-19 control measures. *Nature Human Behaviour*, *4*(6), 577–587. https://doi.org/10.1038/s41562-020-0896-8

Guimarães, L. F., Battemarco, B. P., Oliveira, A. K. B., & Miguez, M. G. (2021). A new approach to assess cascading effects of urban floods. *Energy Reports*, *7*, 8357–8367. https://doi.org/10.1016/j.egyr.2021.07.047

Hagenlocher, M., Naumann, G., Meza, I., Blauhut, V., Cotti, D., Döll, P., et al. (2023). Tackling growing drought risks—The need for a systemic perspective. *Earth's Future*, *11*(9), e2023EF003857. https://doi.org/10.1029/2023EF003857

Hagenlocher, M., Schneiderbauer, S., Sebesvari, Z., Bertram, M., Renner, K., Renaud, F., et al. (2018). Climate risk assessment for ecosystem-based adaptation (pp. 1–116). Retrieved from https://www.adaptationcommunity.net/?wpfb_dl=203

Hammond, M. J., Chen, A. S., Djordjević, S., Butler, D., & Mark, O. (2015). Urban flood impact assessment: A state-of-the-art review. *Urban Water Journal*, *12*(1), 14–29. https://doi.org/10.1080/1573062X.2013.857421

Helbing, D. (2013). Globally networked risks and how to respond. *Nature*, *497*(7447), 51–59. https://doi.org/10.1038/nature12047

Hobeichi, S., Abramowitz, G., Evans, J. P., & Ukkola, A. (2022). Toward a robust, impact-based, predictive drought metric. *Water Resources Research*, *58*(2), e2021WR031829. https://doi.org/10.1029/2021WR031829

Höllermann, B., Rangecroft, S., Rohse, M., Banks, E. W., Day, R., Di Baldassarre, G., et al. (2022). Go together, to go further! Reply to "Human–water research: Discussion of 'Guiding principles for hydrologists conducting interdisciplinary research and fieldwork with participants.'". *Hydrological Sciences Journal*, *67*(14), 2211–2213. https://doi.org/10.1080/02626667.2022.2128804

Hunt, E., Femia, F., Werrell, C., Christian, J. I., Otkin, J. A., Basara, J., et al. (2021). Agricultural and food security impacts from the 2010 Russia flash drought. *Weather and Climate Extremes*, *34*, 100383. https://doi.org/10.1016/j.wace.2021.100383

Innes, J. E., & Booher, D. E. (2004). Reframing public participation: Strategies for the 21st century. *Planning Theory & Practice*, *5*(4), 419–436. https://doi.org/10.1080/1464935042000293170

IPCC. (2021). Climate change 2021: The physical science basis - summary for the policymakers (Working Group I).

IPCC. (2022). Climate change 2022: Impacts, adaptation and vulnerability. Working Group II contribution to the sixth assessment report of the Intergovernmental Panel on Climate Change. https://doi.org/10.1017/9781009325844.Front

ISC-UNDRR-IRDR. (2021). A framework for global science in support of risk informed sustainable development and planetary health.

Jackson, N. D., & Gunda, T. (2021). Evaluation of extreme weather impacts on utility-scale photovoltaic plant performance in the United States. *Applied Energy*, *302*, 117508. https://doi.org/10.1016/j.apenergy.2021.117508
Jane, R., Cadavid, L., Obeysekera, J., & Wahl, T. (2020). Multivariate statistical modelling of the drivers of compound flood events in south Florida. *Natural Hazards and Earth System Sciences*, *20*(10), 2681–2699. https://doi.org/10.5194/nhess-20-2681-2020
Johnson, P. M., Brady, C. E., Philip, C., Baroud, H., Camp, J. V., & Abkowitz, M. (2020). A factor analysis approach toward reconciling community vulnerability and resilience indices for natural hazards. *Risk Analysis*, *40*(9), 1795–1810. https://doi.org/10.1111/risa.13508
Jones, R. L., Guha-Sapir, D., & Tubeuf, S. (2022). Human and economic impacts of natural disasters: Can we trust the global data? *Scientific Data*, *9*(1), 572. https://doi.org/10.1038/s41597-022-01667-x
Joye, S. (2009). The hierarchy of global suffering. *Journal of International Communication*, *15*(2), 45–61. https://doi.org/10.1080/13216597.2009.9674750
Kabisch, S., Chakrabarti, R., Wolf, T., Kiewitt, W., Gorman, T., Chaturvedi, A., & Arora, R. (2014). Climate change impact chains in the water sector: Observations from projects on the East India coast. *Journal of Water and Climate Change*, *5*(2), 216–232. https://doi.org/10.2166/wcc.2013.118
Karnieli-Miller, O., Strier, R., & Pessach, L. (2009). Power relations in qualitative research. *Qualitative Health Research*, *19*(2), 279–289. https://doi.org/10.1177/1049732308329306
Kellermann, P., Schröter, K., Thieken, A. H., Haubrock, S.-N., & Kreibich, H. (2020). The object-specific flood damage database HOWAS 21. *Natural Hazards and Earth System Sciences*, *20*(9), 2503–2519. https://doi.org/10.5194/nhess-20-2503-2020
Koks, E. E., Carrera, L., Jonkeren, O., Aerts, J. C. J. H., Husby, T. G., Thissen, M., et al. (2016). Regional disaster impact analysis: Comparing input–output and computable general equilibrium models. *Natural Hazards and Earth System Sciences*, *16*(8), 1911–1924. https://doi.org/10.5194/nhess-16-1911-2016
Koks, E. E., Pant, R., Thacker, S., & Hall, J. W. (2019). Understanding business disruption and economic losses due to electricity failures and flooding. *International Journal of Disaster Risk Science*, *10*(4), 421–438. https://doi.org/10.1007/s13753-019-00236-y
Kornhuber, K., & Messori, G. (2023). Recent increase in a recurrent Pan-Atlantic wave pattern driving concurrent wintertime extremes. *Bulletin of the American Meteorological Society*, *104*(9), E1694–E1708. https://doi.org/10.1175/BAMS-D-21-0295.1
Kreibich, H., Schröter, K., Di Baldassarre, G., Van Loon, A. F., Mazzoleni, M., Abeshu, G. W., et al. (2023). Panta Rhei benchmark dataset: Socio-hydrological data of paired events of floods and droughts. *Earth System Science Data*, *15*(5), 2009–2023. https://doi.org/10.5194/essd-15-2009-2023
Kreienkamp, F., Philip, S. Y., Tradowsky, J. S., Kew, S. F., Lorenz, P., Arrighi, J., et al. (2021). *Rapid attribution of heavy rainfall events leading to the severe flooding in Western Europe during July 2021* (Vol. 13). Royal Netherlands Meteorological Institute (KNMI). Retrieved from https://www.meteo.be/fr/infos/actualite/ce-que-lon-sait-sur-les-pluies-
Kuhlicke, C., de Brito, M. M., Bartkowski, B., Botzen, W., Doğulu, C., Han, S., et al. (2023). Spinning in circles? A systematic review on the role of theory in social vulnerability, resilience and adaptation research. *Global Environmental Change*, *80*, 102672. https://doi.org/10.1016/j.gloenvcha.2023.102672
Lam, N. N. S., Reams, M., Li, K., Li, C., & Mata, L. P. (2016). Measuring community resilience to coastal hazards along the Northern Gulf of Mexico. *Natural Hazards Review*, *17*(1), 04015013. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000193
Lawrence, J., Blackett, P., & Cradock-Henry, N. A. (2020). Cascading climate change impacts and implications. *Climate Risk Management*, *29*(August 2019), 100234. https://doi.org/10.1016/j.crm.2020.100234
Levy, M. A., Lubell, M. N., & McRoberts, N. (2018). The structure of mental models of sustainable agriculture. *Nature Sustainability*, *1*(8), 413–420. https://doi.org/10.1038/s41893-018-0116-y
Liguori, A., McEwen, L., Blake, J., & Wilson, M. (2021). Towards 'creative participatory science': Exploring future scenarios through specialist drought science and community storytelling. *Frontiers in Environmental Science*, *8*, 589856. https://doi.org/10.3389/fenvs.2020.589856
Liu, Y. R., Li, Y. P., Yang, X., Huang, G. H., & Li, Y. F. (2021). Development of an integrated multivariate trend-frequency analysis method: Spatial-temporal characteristics of climate extremes under global warming for Central Asia. *Environmental Research*, *195*, 110859. https://doi.org/10.1016/j.envres.2021.110859
Lottering, S. J., Mafongoya, P., & Lottering, R. T. (2021). Assessing the social vulnerability of small-scale farmer's to drought in uMsinga, KwaZulu-Natal. *International Journal of Disaster Risk Reduction*, *65*, 102568. https://doi.org/10.1016/j.ijdrr.2021.102568
Mahlstein, I., Martius, O., Chevalier, C., & Ginsbourger, D. (2012). Changes in the odds of extreme events in the Atlantic basin depending on the position of the extratropical jet. *Geophysical Research Letters*, *39*(22), n/a. https://doi.org/10.1029/2012GL053993
Maity, R., Ramadas, M., & Govindaraju, R. S. (2013). Identification of hydrologic drought triggers from hydroclimatic predictor variables. *Water Resources Research*, *49*(7), 4476–4492. https://doi.org/10.1002/wrcr.20346
Martius, O., Pfahl, S., & Chevalier, C. (2016). A global quantification of compound precipitation and wind extremes. *Geophysical Research Letters*, *43*(14), 7709–7717. https://doi.org/10.1002/2016GL070017
Matanó, A., de Ruiter, M. C., Koehler, J., Ward, P. J., & Van Loon, A. F. (2022). Caught between extremes: Understanding human-water interactions during drought-to-flood events in the horn of Africa. *Earth's Future*, *10*(9), e2022EF002747. https://doi.org/10.1029/2022EF002747
Mehryar, S., & Surminski, S. (2022). Investigating flood resilience perceptions and supporting collective decision-making through fuzzy cognitive mapping. *Science of the Total Environment*, *837*, 155854. https://doi.org/10.1016/j.scitotenv.2022.155854
Menk, L., Terzi, S., Zebisch, M., Rome, E., Lückerath, D., Milde, K., & Kienberger, S. (2022). Climate change impact chains: A review of applications, challenges, and opportunities for climate risk and vulnerability assessments. *Weather, Climate, and Society*, *14*(2), 619–636. https://doi.org/10.1175/WCAS-D-21-0014.1
Merz, B., Blöschl, G., Vorogushyn, S., Dottori, F., Aerts, J. C. J. H., Bates, P., et al. (2021). Causes, impacts and patterns of disastrous river floods. *Nature Reviews Earth & Environment*, *2*(9), 592–609. https://doi.org/10.1038/s43017-021-00195-3
Merz, B., Kuhlicke, C., Kunz, M., Pittore, M., Babeyko, A., Bresch, D. N., et al. (2020). Impact forecasting to support emergency management of natural hazards. *Reviews of Geophysics*, *58*(4), e2020RG000704. https://doi.org/10.1029/2020RG000704
Messori, G., & Faranda, D. (2021). Technical note: Characterising and comparing different palaeoclimates with dynamical systems theory. *Climate of the Past*, *17*(1), 545–563. https://doi.org/10.5194/cp-17-545-2021
Michaelis, T., Brandimarte, L., & Mazzoleni, M. (2020). Capturing flood-risk dynamics with a coupled agent-based and hydraulic modelling framework. *Hydrological Sciences Journal*, *65*(9), 1458–1473. https://doi.org/10.1080/02626667.2020.1750617
Mishra, A., Alnahit, A., & Campbell, B. (2021). Impact of land uses, drought, flood, wildfire, and cascading events on water quality and microbial communities: A review and analysis. *Journal of Hydrology*, *596*, 125707. https://doi.org/10.1016/j.jhydrol.2020.125707
Montgomery, M., Broyd, T., Cornell, S., Pearce, O., Pocock, D., & Young, K. (2012). An innovative approach for improving infrastructure resilience. *Proceedings of the Institution of Civil Engineers - Civil Engineering*, *165*(6), 27–32. https://doi.org/10.1680/cien.11.00062

Moreira, L. L., Vanelli, F. M., Schwamback, D., Kobiyama, M., & de Brito, M. M. (2023). Sensitivity analysis of indicator weights for the construction of flood vulnerability indexes: A participatory approach. *Frontiers in Water*, *5*, 970469. https://doi.org/10.3389/frwa.2023.970469

Munafò, M. R., & Davey Smith, G. (2018). Robust research needs many lines of evidence. *Nature*, *553*(7689), 399–401. https://doi.org/10.1038/d41586-018-01023-3

Naqvi, A., & Monasterolo, I. (2021). Assessing the cascading impacts of natural disasters in a multi-layer behavioral network framework. *Scientific Reports*, *11*(1), 20146. https://doi.org/10.1038/s41598-021-99343-4

Naumann, G., Cammalleri, C., Mentaschi, L., & Feyen, L. (2021). Increased economic drought impacts in Europe with anthropogenic warming. *Nature Climate Change*, *11*(6), 485–491. https://doi.org/10.1038/s41558-021-01044-3

NDMC. (2019). National drought mitigation center: Drought Impact Reporter (DIR). Retrieved from https://droughtreporter.unl.edu

Niggli, L., Huggel, C., Muccione, V., Neukom, R., & Salzmann, N. (2022). Towards improved understanding of cascading and interconnected risks from concurrent weather extremes: Analysis of historical heat and drought extreme events. *PLoS Climate*, *1*(8), e0000057. https://doi.org/10.1371/journal.pclm.0000057

Okamura, K. (2019). Interdisciplinarity revisited: Evidence for research impact and dynamism. *Palgrave Communications*, *5*(1), 141. https://doi.org/10.1057/s41599-019-0352-4

Olazabal, M., & Pascual, U. (2016). Use of fuzzy cognitive maps to study urban resilience and transformation. *Environmental Innovation and Societal Transitions*, *18*, 18–40. https://doi.org/10.1016/j.eist.2015.06.006

Orgad, S. (2012). Media representation and the global imagination.

Papagiannaki, K., Petrucci, O., Diakakis, M., Kotroni, V., Aceto, L., Bianchi, C., et al. (2022). Developing a large-scale dataset of flood fatalities for territories in the Euro-Mediterranean region, FFEM-DB. *Scientific Data*, *9*(1), 166. https://doi.org/10.1038/s41597-022-01273-x

Perrone, A., Inam, A., Albano, R., Adamowski, J., & Sole, A. (2020). A participatory system dynamics modeling approach to facilitate collaborative flood risk management: A case study in the Bradano River (Italy). *Journal of Hydrology*, *580*, 124354. https://doi.org/10.1016/j.jhydrol.2019.124354

Pescaroli, G., & Alexander, D. (2016). Critical infrastructure, panarchies and the vulnerability paths of cascading disasters. *Natural Hazards*, *82*(1), 175–192. https://doi.org/10.1007/s11069-016-2186-3

Pokhrel, Y., Felfelani, F., Satoh, Y., Boulange, J., Burek, P., Gädeke, A., et al. (2021). Global terrestrial water storage and drought severity under climate change. *Nature Climate Change*, *11*(3), 226–233. https://doi.org/10.1038/s41558-020-00972-w

Porter, J. J., & Evans, G. (2020). Unreported world: A critical analysis of UK newspaper coverage of post-disaster events. *The Geographical Journal*, *186*(3), 327–338. https://doi.org/10.1111/geoj.12353

Qiang, Y., Huang, Q., & Xu, J. (2020). Observing community resilience from space: Using nighttime lights to model economic disturbance and recovery pattern in natural disaster. *Sustainable Cities and Society*, *57*, 102115. https://doi.org/10.1016/j.scs.2020.102115

Quandt, A. (2021). Coping with drought: Narratives from smallholder farmers in semi-arid Kenya. *International Journal of Disaster Risk Reduction*, *57*, 102168. https://doi.org/10.1016/j.ijdrr.2021.102168

Rahman, M. S., & Di, L. (2020). A systematic review on case studies of remote-sensing-based flood crop loss assessment. *Agriculture*, *10*(4), 131. https://doi.org/10.3390/agriculture10040131

Raymond, C., Horton, R. M., Zscheischler, J., Martius, O., AghaKouchak, A., Balch, J., et al. (2020). Understanding and managing connected extreme events. *Nature Climate Change*, *10*(7), 611–621. https://doi.org/10.1038/s41558-020-0790-4

Reed, P. M., Hadjimichael, A., Moss, R. H., Brelsford, C., Burleyson, C. D., Cohen, S., et al. (2022). Multisector dynamics: Advancing the science of complex adaptive human-earth systems. *Earth's Future*, *10*(3), e2021EF002621. https://doi.org/10.1029/2021EF002621

Rest, K.-D., & Hirsch, P. (2022). Insights and decision support for home health care services in times of disasters. *Central European Journal of Operations Research*, *30*(1), 133–157. https://doi.org/10.1007/s10100-021-00770-5

Rifat, S. A. A., & Liu, W. (2022). Predicting future urban growth scenarios and potential urban flood exposure using Artificial Neural Network-Markov Chain model in Miami Metropolitan Area. *Land Use Policy*, *114*, 105994. https://doi.org/10.1016/j.landusepol.2022.105994

Rohr, A., Priesmeier, P., Tzavella, K., & Fekete, A. (2020). System criticality of road network areas for emergency management services—Spatial assessment using a tessellation approach. *Infrastructures*, *5*(11), 99. https://doi.org/10.3390/infrastructures5110099

Romero-Lankao, P., & Norton, R. (2018). Interdependencies and risk to people and critical food, energy, and water systems: 2013 Flood, Boulder, Colorado, USA. *Earth's Future*, *6*(11), 1616–1629. https://doi.org/10.1029/2018EF000984

Ronizi, S. R. A., Negahban, S., & Mokarram, M. (2022). Investigation of land use changes in rural areas using MCDM and CA-Markov chain and their effects on water quality and soil fertility in south of Iran. *Environmental Science and Pollution Research*, *29*(59), 88644–88662. https://doi.org/10.1007/s11356-022-21951-y

Rounsevell, M. D. A., & Metzger, M. J. (2010). Developing qualitative scenario storylines for environmental change assessment. *WIREs Climate Change*, *1*(4), 606–619. https://doi.org/10.1002/wcc.63

Ruiter, M. C., Couasnon, A., Homberg, M. J. C., Daniell, J. E., Gill, J. C., & Ward, P. J. (2020). Why we can no longer ignore consecutive disasters. *Earth's Future*, *8*(3), e2019EF001425. https://doi.org/10.1029/2019EF001425

Rusca, M., & Di Baldassarre, G. (2019). Interdisciplinary critical geographies of water: Capturing the mutual shaping of society and hydrological flows. *Water*, *11*(10), 1973. https://doi.org/10.3390/w11101973

Rusca, M., Mazzoleni, M., Barcena, A., Savelli, E., & Messori, G. (2023). Speculative political ecologies: (Re)imagining urban futures of climate extremes. *Journal of Political Ecology*, *30*(1). https://doi.org/10.2458/jpe.4827

Rusca, M., Messori, G., & Di Baldassarre, G. (2021). Scenarios of human responses to unprecedented social-environmental extreme events. *Earth's Future*, *9*(4), 1973. https://doi.org/10.1029/2020EF001911

Rusca, M., Savelli, E., Di Baldassarre, G., Biza, A., & Messori, G. (2023). Unprecedented droughts are expected to exacerbate urban inequalities in Southern Africa. *Nature Climate Change*, *13*(1), 98–105. https://doi.org/10.1038/s41558-022-01546-8

Salvadori, G., & De Michele, C. (2013). Multivariate extreme value methods (pp. 115–162). https://doi.org/10.1007/978-94-007-4479-0_5

Samaniego, L., Thober, S., Kumar, R., Wanders, N., Rakovec, O., Pan, M., et al. (2018). Anthropogenic warming exacerbates European soil moisture droughts. *Nature Climate Change*, *8*(5), 421–426. https://doi.org/10.1038/s41558-018-0138-5

Sanga, U., Sidibé, A., & Olabisi, L. S. (2021). Dynamic pathways of barriers and opportunities for food security and climate adaptation in Southern Mali. *World Development*, *148*, 105663. https://doi.org/10.1016/j.worlddev.2021.105663

Savelli, E., Mazzoleni, M., Di Baldassarre, G., Cloke, H., & Rusca, M. (2023). Urban water crises driven by elites' unsustainable consumption. *Nature Sustainability*, *6*(8), 929–940. https://doi.org/10.1038/s41893-023-01100-0

Schäfer, A., Mühr, B., Daniell, J., Ehret, U., Ehmele, F., Brand, J., et al. (2021). Hochwasser Mitteleuropa, Juli 2021 (Deutschland) (Vol. *2021*). https://doi.org/10.5445/IR/1000135730.CEDIM

Schipper, E. L. F. (2022). Catching maladaptation before it happens. *Nature Climate Change*, *12*(7), 617–618. https://doi.org/10.1038/s41558-022-01409-2

Schlüter, M., Brelsford, C., Ferraro, P. J., Orach, K., Qiu, M., & Smith, M. D. (2023). Unraveling complex causal processes that affect sustainability requires more integration between empirical and modeling approaches. *Proceedings of the National Academy of Sciences*, *120*(41), e2215676120. https://doi.org/10.1073/pnas.2215676120

Schmook, B., Radel, C., Carte, L., & Johnson, R. L. (2023). In the shadow of the green revolution: Constrained spatial imaginaries and smallholder farming in Guatemala's Pacific Lowlands. *The Professional Geographer*, *75*(2), 305–315. https://doi.org/10.1080/00330124.2021.2014907

Sedlmeier, K., Mieruch, S., Schädler, G., & Kottmeier, C. (2016). Compound extremes in a changing climate – A Markov chain approach. *Nonlinear Processes in Geophysics*, *23*(6), 375–390. https://doi.org/10.5194/npg-23-375-2016

Seebauer, S., Thaler, T., Hanger-Kopp, S., & Schinko, T. (2023). How path dependency manifests in flood risk management: Observations from four decades in the Ennstal and Aist catchments in Austria. *Regional Environmental Change*, *23*(1), 31. https://doi.org/10.1007/s10113-023-02029-y

Serpico, S. B., Dellepiane, S., Boni, G., Moser, G., Angiati, E., & Rudari, R. (2012). Information extraction from remote sensing images for flood monitoring and damage evaluation. *Proceedings of the IEEE*, *100*(10), 2946–2970. https://doi.org/10.1109/JPROC.2012.2198030

Shanahan, E. A., Jones, M. D., McBeth, M. K., & Radaelli, C. M. (2018). The narrative policy framework. In *Theories of the policy process* (4th ed.). https://doi.org/10.4324/9780429494284-5

Shepherd, T. G., Boyd, E., Calel, R. A., Chapman, S. C., Dessai, S., Dima-West, I. M., et al. (2018). Storylines: An alternative approach to representing uncertainty in physical aspects of climate change. *Climatic Change*, *151*(3–4), 555–571. https://doi.org/10.1007/s10584-018-2317-9

Sheridan, J., Chamberlain, K., & Dupuis, A. (2011). Timelining: Visualizing experience. *Qualitative Research*, *11*(5), 552–569. https://doi.org/10.1177/1468794111413235

Sillmann, J., Shepherd, T. G., van den Hurk, B., Hazeleger, W., Martius, O., Slingo, J., & Zscheischler, J. (2021). Event-based storylines to address climate risk. *Earth's Future*, *9*(2), e2020EF001783. https://doi.org/10.1029/2020EF001783

Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., et al. (2021). A framework for complex climate change risk assessment. *One Earth*, *4*(4), 489–501. https://doi.org/10.1016/j.oneear.2021.03.005

Simpson, N. P., Williams, P. A., Mach, K. J., Berrang-Ford, L., Biesbroek, R., Haasnoot, M., et al. (2023). Adaptation to compound climate risks: A systematic global stocktake. *iScience*, *26*(2), 105926. https://doi.org/10.1016/j.isci.2023.105926

Singh, J., Ashfaq, M., Skinner, C. B., Anderson, W. B., & Singh, D. (2021). Amplified risk of spatially compounding droughts during co-occurrences of modes of natural ocean variability. *Npj Climate and Atmospheric Science*, *4*(1), 7. https://doi.org/10.1038/s41612-021-00161-2

Smith, K. H., Burbach, M. E., Hayes, M. J., Guinan, P. E., Tyre, A. J., Fuchs, B., et al. (2021). Whose ground truth is it? Harvesting lessons from Missouri's 2018 bumper crop of drought observations. *Weather, Climate, and Society*, *13*(2), 227–244. https://doi.org/10.1175/WCAS-D-19-0140.1

Smith, K. H., Svoboda, M., Hayes, M., Reges, H., Doesken, N., Lackstrom, K., et al. (2014). Local observers fill in the details on drought impact reporter maps. *Bulletin of the American Meteorological Society*, *95*(11), 1659–1662. https://doi.org/10.1175/1520-0477-95.11.1659

Sodoge, J., Kuhlicke, C., & de Brito, M. M. (2023). Automatized spatio-temporal detection of drought impacts from newspaper articles using natural language processing and machine learning. *Weather and Climate Extremes*, *41*, 100574. https://doi.org/10.1016/j.wace.2023.100574

Sodoge, J., Kuhlicke, C., Mahecha, M. D., & de Brito, M. M. (2023). Text-mining uncovers the unique dynamics of socio-economic impacts during multi-year drought. *Natural Hazards and Earth System Sciences Discussions*, *2023*, 1–25.

Song, K., You, S., & Chon, J. (2018). Simulation modeling for a resilience improvement plan for natural disasters in a coastal area. *Environmental Pollution*, *242*, 1970–1980. https://doi.org/10.1016/j.envpol.2018.07.057

Sparkes, E., Cotti, D., Shekhar, H., Werners, S. E., Valdiviezo-ajila, A. A., Banerjee, S., et al. (2023). Impact webs: A novel approach for characterising and assessing multi-risk in complex systems. (May).

Sparkes., E., Hagenlocher, M., Cotti, D., Banerjee, S., Masys, A. J., Rana, S., et al. (2023). Understanding and characterizing complex risks with Impact Webs: A guidance document. UNU-EHS. Retrieved from https://collections.unu.edu/view/UNU:9266

Stahl, K., Kohn, I., Blauhut, V., Urquijo, J., De Stefano, L., Acácio, V., et al. (2016). Impacts of European drought events: Insights from an international database of text-based reports. *Natural Hazards and Earth System Sciences*, *16*(3), 801–819. https://doi.org/10.5194/nhess-16-801-2016

Suriya, S., & Mudgal, B. V. (2013). Soft systems methodology and integrated flood management: A study of the Adayar watershed, Chennai, India. *Water and Environment Journal*, *27*(4), 462–473. https://doi.org/10.1111/j.1747-6593.2012.00365.x

Sutanto, S. J., Vitolo, C., Di Napoli, C., D'Andrea, M., & Van Lanen, H. A. J. (2020). Heatwaves, droughts, and fires: Exploring compound and cascading dry hazards at the pan-European scale. *Environment International*, *134*(October 2019), 105276. https://doi.org/10.1016/j.envint.2019.105276

Sword-Daniels, V. L., Twigg, J., & Loughlin, S. C. (2015). Time for change? Applying an inductive timeline tool for a retrospective study of disaster recovery in Montserrat, West Indies. *International Journal of Disaster Risk Reduction*, *12*, 125–133. https://doi.org/10.1016/j.ijdrr.2014.12.006

Tapia-Silva, F.-O., Itzerott, S., Foerster, S., Kuhlmann, B., & Kreibich, H. (2011). Estimation of flood losses to agricultural crops using remote sensing. *Physics and Chemistry of the Earth, Parts A/B/C*, *36*(7–8), 253–265. https://doi.org/10.1016/j.pce.2011.03.005

Terzi, S., Torresan, S., Schneiderbauer, S., Critto, A., Zebisch, M., & Marcomini, A. (2019). Multi-risk assessment in mountain regions: A review of modelling approaches for climate change adaptation. *Journal of Environmental Management*, *232*, 759–771. https://doi.org/10.1016/j.jenvman.2018.11.100

Tilloy, A., Malamud, B. D., & Joly-Laugel, A. (2022). A methodology for the spatiotemporal identification of compound hazards: Wind and precipitation extremes in Great Britain (1979–2019). *Earth System Dynamics*, *13*(2), 993–1020. https://doi.org/10.5194/esd-13-993-2022

Tilloy, A., Malamud, B. D., Winter, H., & Joly-Laugel, A. (2019). A review of quantification methodologies for multi-hazard interrelationships. *Earth-Science Reviews*, *196*, 102881. https://doi.org/10.1016/j.earscirev.2019.102881

Torelló-Sentelles, H., & Franzke, C. L. E. (2022). Drought impact links to meteorological drought indicators and predictability in Spain. *Hydrology and Earth System Sciences*, *26*(7), 1821–1844. https://doi.org/10.5194/hess-26-1821-2022

UNDRR. (2021a). GAR special report on drought 2021.

UNDRR. (2021b). Regional assessment report on disaster risk in Latin America and the Caribbean.

UNDRR. (2021c). Understanding and managing cascading and systemic risks: Lessons from COVID-19. Retrieved from www.undrr.org

UNDRR, & CRED. (2020). Human cost of disasters: An overview of the last 20 years 2000–2019. https://doi.org/10.18356/79b92774-en

UNISDR. (2015). Making development sustainable: The future of disaster risk management. In *Global assessment report on disaster risk reduction. Geneva*. Retrieved from https://www.preventionweb.net/english/hyogo/gar/2015/en/gar-pdf/GAR2015_EN.pdf

van den Hurk, B. J. J. M., Baldissera Pacchetti, M., Boere, E., Ciullo, A., Coulter, L., Dessai, S., et al. (2023). Climate impact storylines for assessing socio-economic responses to remote events. *Climate Risk Management*, *40*, 100500. https://doi.org/10.1016/j.crm.2023.100500

van Delden, H., & Hagen-Zanker, A. (2009). New ways of supporting decision making: Linking qualitative storylines with quantitative modelling (pp. 347–367). https://doi.org/10.1007/978-1-4020-8952-7_17
Vanelli, F. M., Kobiyama, M., & de Brito, M. M. (2022). To which extent are socio-hydrology studies truly integrative? The case of natural hazards and disaster research. *Hydrology and Earth System Sciences*, *26*(8), 2301–2317. https://doi.org/10.5194/hess-26-2301-2022
Vanwindekens, F. M., Gobin, A., Curnel, Y., & Planchon, V. (2018). New approach for mapping the vulnerability of agroecosystems based on expert knowledge. *Mathematical Geosciences*, *50*(6), 679–696. https://doi.org/10.1007/s11004-018-9730-5
Velpuri, M., Das, J., & Umamahesh, N. V. (2023). Spatio-temporal compounding of connected extreme events: Projection and hotspot identification. *Environmental Research*, *235*, 116615. https://doi.org/10.1016/j.envres.2023.116615
Visser-Quinn, A., Beevers, L., Collet, L., Formetta, G., Smith, K., Wanders, N., et al. (2019). Spatio-temporal analysis of compound hydro-hazard extremes across the UK. *Advances in Water Resources*, *130*, 77–90. https://doi.org/10.1016/j.advwatres.2019.05.019
Vogel, J., Rivoire, P., Deidda, C., Rahimi, L., Sauter, C. A., Tschumi, E., et al. (2021). Identifying meteorological drivers of extreme impacts: An application to simulated crop yields. *Earth System Dynamics*, *12*(1), 151–172. https://doi.org/10.5194/esd-12-151-2021
von Uexkull, N., Croicu, M., Fjelde, H., & Buhaug, H. (2016). Civil conflict sensitivity to growing-season drought. *Proceedings of the National Academy of Sciences*, *113*(44), 12391–12396. https://doi.org/10.1073/pnas.1607542113
Walz, Y., Janzen, S., Narvaez, L., Ortiz-Vargas, A., Woelki, J., Doswald, N., & Sebesvari, Z. (2021). Disaster-related losses of ecosystems and their services. Why and how do losses matter for disaster risk reduction? *International Journal of Disaster Risk Reduction*, *63*, 102425. https://doi.org/10.1016/j.ijdrr.2021.102425
Ward, P. J., Daniell, J., Duncan, M., Dunne, A., Hananel, C., Hochrainer-Stigler, S., et al. (2022). Invited perspectives: A research agenda towards disaster risk management pathways in multi-(hazard-)risk assessment. *Natural Hazards and Earth System Sciences*, *22*(4), 1487–1497. https://doi.org/10.5194/nhess-22-1487-2022
Ward, P. J., de Ruiter, M. C., Mård, J., Schröter, K., Van Loon, A., Veldkamp, T., et al. (2020). The need to integrate flood and drought disaster risk reduction strategies. *Water Security*, *11*, 100070. https://doi.org/10.1016/j.wasec.2020.100070
West, H., Quinn, N., & Horswell, M. (2019). Remote sensing for drought monitoring & impact assessment: Progress, past challenges and future opportunities. *Remote Sensing of Environment*, *232*, 111291. https://doi.org/10.1016/j.rse.2019.111291
White, C. T., Mitasova, H., BenDor, T. K., Foy, K., Pala, O., Vukomanovic, J., & Meentemeyer, R. K. (2021). Spatially explicit fuzzy cognitive mapping for participatory modeling of stormwater management. *Land*, *10*(11), 1114. https://doi.org/10.3390/land10111114
Wiebe, K., Zurek, M., Lord, S., Brzezina, N., Gabrielyan, G., Libertini, J., et al. (2018). Scenario development and foresight analysis: Exploring options to inform choices. *Annual Review of Environment and Resources*, *43*(1), 545–570. https://doi.org/10.1146/annurev-environ-102017-030109
Wijermans, N., Schill, C., Lindahl, T., & Schlüter, M. (2022). Combining approaches: Looking behind the scenes of integrating multiple types of evidence from controlled behavioural experiments through agent-based modelling. *International Journal of Social Research Methodology*, *25*(4), 569–581. https://doi.org/10.1080/13645579.2022.2050120
Wouters, L., Couasnon, A., de Ruiter, M. C., van den Homberg, M. J. C., Teklesadik, A., & de Moel, H. (2021). Improving flood damage assessments in data-scarce areas by retrieval of building characteristics through UAV image segmentation and machine learning – A case study of the 2019 floods in southern Malawi. *Natural Hazards and Earth System Sciences*, *21*(10), 3199–3218. https://doi.org/10.5194/nhess-21-3199-2021
Yoon, J., Klassert, C., Selby, P., Lachaut, T., Knox, S., Avisse, N., et al. (2021). A coupled human–natural system analysis of freshwater security under climate and population change. *Proceedings of the National Academy of Sciences*, *118*(14), e2020431118. https://doi.org/10.1073/pnas.2020431118
Yoon, J., Romero-Lankao, P., Yang, Y. C. E., Klassert, C., Urban, N., Kaiser, K., et al. (2022). A Typology for characterizing human action in multisector dynamics models. *Earth's Future*, *10*(8), e2021EF002641. https://doi.org/10.1029/2021EF002641
Yuan, F., Fan, C., Farahmand, H., Coleman, N., Esmalian, A., Lee, C.-C., et al. (2022). Smart flood resilience: Harnessing community-scale big data for predictive flood risk monitoring, rapid impact assessment, and situational awareness. *Environmental Research: Infrastructure and Sustainability*, *2*(2), 025006. https://doi.org/10.1088/2634-4505/ac7251
Yuan, F., Yang, Y., Li, Q., & Mostafavi, A. (2022). Unraveling the temporal importance of 1350 community-scale human activity features for rapid assessment of flood impacts. *IEEE Access*, *10*, 1138–1150. https://doi.org/10.1109/ACCESS.2021.3137651
Zebisch, M., Terzi, S., Pittore, M., Renner, K., & Schneiderbauer, S. (2022). Climate impact chains—A conceptual modelling approach for climate risk assessment in the context of adaptation planning (pp. 217–224). https://doi.org/10.1007/978-3-030-86211-4_25
Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., et al. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3
Zwarteveen, M., Kemerink-Seyoum, J. S., Kooy, M., Evers, J., Guerrero, T. A., Batubara, B., et al. (2017). Engaging with the politics of water governance. *WIREs Water*, *4*(6), e1245. https://doi.org/10.1002/wat2.1245