



Invited perspectives: Towards usable compound event research

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5 **Abstract: Supporting stakeholders with science-based decision-making to mitigate and adapt**
to climate change impacts is a central mandate of the climate research community. In
particular, mapping out scenario-dependent climate risk landscapes is one of the most
pressing challenges. Increasingly, communities and regions are experiencing high-impact
 10 **climate and weather extremes that arise from a complex interplay of processes and events**
acting across various spatial and temporal scales. To account for these emerging trends, there
is a growing recognition that both climate impact and early warning research needs to
incorporate risks from compound events to better inform climate adaptation and mitigation
efforts. This demand for more fine-grained and applicable knowledge gives rise to new data
and modeling needs, and can increase uncertainties. Consequently, new methodological
 15 **approaches and effective communication strategies are required for making research usable**
outside scientific communities. In this perspective, we reflect on this usability challenge by
discussing impact data products, early warning and modeling capabilities, and
communication tools, urging climate impact scientists to increasingly incorporate usability
considerations in their research to meet the pressing demand for usable compound event
 20 **research.**

0. Introduction

An increase in more impactful climate and weather extremes is a direct consequence of global
 warming (Intergovernmental Panel On Climate Change (Ipcc) 2023). Unambiguous observational
 25 evidence of more frequent and more intense weather extremes has emerged for various climate
 hazards, from heatwaves (Kornhuber et al. 2024; Perkins-Kirkpatrick and Lewis 2020), to heavy
 rainfall (Robinson et al. 2021; Fischer and Knutti 2016) and floods (Slater et al. 2021), droughts
 (Chen et al. 2025) and wildfire conditions (Jones et al. 2022) – a trend that is consistent with our
 understanding of how the Earth’s climate system responds to increasing greenhouse gas emissions.
 30 These changes contribute to increasing interactions between climate hazards and extremes, through
 physical processes and from mere stochastic reasons driven by rising event frequencies. Thus,
 climate change increasingly leads to situations where the impacts of multiple climate hazards can be
 amplified beyond the sum of single hazard impacts (Messori et al. 2025; Ridder et al. 2022). Under
 these conditions, the assumption that single climate hazards act independently when assessing their
 35 impacts is increasingly inaccurate (Touma et al. 2022; Sarhadi et al. 2018). In particular, climate risk
 assessment frameworks in the private and public sector need to consider the interconnectedness of
 increasingly compounding weather events, which is not a routine exercise to date (Dolk et al. 2023).
 Doing so could avoid the underestimation of some climate risks, and some of the most impactful
 events could be better anticipated. Fully accounting for often complex hazard and impact dynamics,
 40 however, is not a trivial exercise.

Compound event research has emerged as a new perspective in climate and environmental science
 over the past two decades (Field et al. 2012; Brett et al. 2024), recognizing that for a comprehensive
 understanding of the climate risk landscape the full range of spatio-temporal hazard dynamics needs
 45 to be taken into account (Zscheischler et al. 2018; Raymond, Horton, et al. 2020). Compound events
 ‘emerge from the combination of multiple drivers and/or hazards that contribute to societal or
 environmental risks’ (Intergovernmental Panel On Climate Change (Ipcc) 2023; Zscheischler et al.
 2020). A compound event perspective therefore goes beyond former risk-concepts in which climate
 impact drivers are assumed to act independently from each other. Categorized by the three
 50 dimensions over which climate impacts unfold: space, time, and impact drivers, four categories of
 compound events have been defined (Zscheischler et al. 2020; Bevacqua et al. 2021): i. *Multivariate*
events describe co-located, simultaneous drivers or hazards resulting in amplified impacts. ii.
Spatially compounding events describe events where impacts result from multiple spatially separated
 events that co-occur within a restricted time window. iii. *Temporally compounding events* refer to the



55 sequential occurrence of hazards within the same region and within a specific time window. Lastly,
 iv. *preconditioned events* refer to situations in which prior climatic conditions set the stage for a
 hazard to unfold. For example, extensive wildfires that expose hillsides to erosion and scald the
 ground, followed by intense rain, constitute a preconditioned event (Touma et al. 2022). In these
 60 situations, water cannot be absorbed in the hydrophobic soils, increasing the risk of floods and
 mudslides.

Complex risks from compounding factors have been described by other terms in related contexts
 (Simpson et al. 2021). *Multi-hazards*, for instance, consider the full range of hazards, climate impact
 drivers as well as non-climatic hazards (e.g. geological hazards such as earthquakes and landslides
 65 or biological hazards such as epidemics). *Complex risk* on the other hand is an overarching term that
 also considers sectoral dependencies across different societal systems, allowing for the investigation
 of shock cascades (e.g. impacts on the electricity grid and financial-, health- or food systems)
 (Simpson et al. 2021; Kruczkiewicz et al. 2021). Such relationships have also been discussed in the
 contexts of *Systemic Risk* frameworks (*ISC-UNDRR-RISK KAN Briefing Note on Systemic Risk* 2022) and
 70 *Connected Extremes* (Raymond, Horton, et al. 2020), in recognition that human responses to one type
 of hazard can amplify the risk from another (Simpson et al. 2021). In this perspective we focus on
Compound Events from interacting weather, climate and environmental hazards, while
 acknowledging that the other terms and concepts carry value in their respective contexts.

75 Compound events research is strongly motivated by the potential for harmful consequences for
 societal and environmental systems. Due to often complex hazard and impact dynamics, these
 harmful consequences can occur unexpectedly, especially when new hazard combinations emerge
 due to climate change (see e.g. (Ramos et al. 2023). Sectors at risk include infrastructure and urban
 resilience (Hemmati et al. 2022), agriculture (Kornhuber et al. 2023; Lesk et al. 2022), water and
 80 ecosystem management (Lian et al. 2025), and biodiversity conservation, public health (Raymond,
 Matthews, et al. 2020; Rogers et al. 2021), energy systems (Lesk and Kornhuber 2022), and
 particularly globally interconnected networks such as food systems (Kornhuber et al. 2020; Lesk et
 al. 2021), transport, trade and supply chains, and the insurance and financial sectors (Dolk et al.
 2023; Singh et al. 2023). A better understanding of the intricate interconnections of climate hazards,
 85 coupled with a frictionless integration of knowledge into early warning systems (Reichstein et al.
 2025; Kruczkiewicz et al. 2021) and climate adaptation and mitigation processes (Field et al. 2012;
 Raymond, Horton, et al. 2020), carries the potential for a reduction of climate risks and their
 associated societal harm.

90 Bridging science and practice has long been identified as a challenge within climate science (Brett et
 al. 2025). Recently, questions about scientific *usability* were raised to foster introspection about how
 constrained time and budget capacities in academia can be best invested given the reality of an
 unfolding and escalating climate emergency (Coen and Sobel 2022). Sobel & Cohen (Coen and Sobel
 2022) argue that a lack of scientific evidence is often not a limiting factor in ongoing efforts to
 95 mitigate global warming and that scientific efforts should be steered towards adaptation research
 instead of blue-sky fundamental research. In essence, ‘usable climate science is adaptation science’
 (Sobel 2021).

100 While agreeing with the premise of this argument, we propose that *usable* adaptation is reliant on
 accurate climate risk estimates which in turn are only *useful* if based on a *sufficiently* mature
 understanding of the physical processes and statistics of high impact - often compound events - in a
 warming world. Due to the inherent complexity of compound events and their impacts-focussed
 nature, a multitude of disciplines are required to explore, understand, and model risks from
 compound events, including characterizing exposure and vulnerability dimensions. Understanding



physical processes relies on expertise in various components of the weather and climate system, including atmospheric and climate dynamics, meteorology, oceanography, vegetation and land-process science, cryosphere, forestry, and agriculture. Next to physical processes, the rarity and complexity of climate extremes require advanced statistics, as well as reliable data from earth observations and regional and global climate models. Finally, hazards are only one of the determinants of risk: vulnerability and exposure dynamics are challenging to quantify, and require other disciplines including geography, social sciences and disaster risk management perspective (Raymond, Horton, et al. 2020; Simpson et al. 2021; Rusca et al. 2021). Thus, fundamental research in multiple disciplines is needed to effectively map out the dynamical properties of a more complex climate risk landscape associated with compound events.

This perspective reflects on usability aspects of major pillars of compound event research, impact data, early warning, modelling and uncertainty with a dual purpose: to provide usability guidelines for the research community and a manual for end-users to better understand challenges and limitations. In the first section, we find that *Socioeconomic and environmental impact data* lack a common standard or are not freely available, inhibiting comprehensive compound event databases that would allow for generating usable impact specific damage functions. In the second section on *Prediction and early warning of compound events*, we propose that truly usable early warning systems need to incorporate compound events to avoid blindspots. In section three *Modeling and projecting compound events*, we reflect on compound event specific challenges when modelling extremes at high resolution. In the final section we address *Uncertainty in compound event projections* with a focus on storyline approaches. We close with a synopsis on overarching challenges and a set of recommendations for aligning compound events research with a usability perspective.

1. Socioeconomic and environmental impact data

Effectively mitigating the risks from compound events requires a deep understanding of their potential impact on different socioeconomic and environmental sectors. Impact datasets often stand at the beginning of establishing robust relationships between compound events and impacts as they provide a record of historical event–damage combinations. Damage functions constitute statistical relationships between cause (the event type) and effect (the damage on a specific sector) and are fundamental for projecting and forecasting potential damages from compound events (Hagenlocher et al. 2023; Hobeichi et al. 2022) for the purpose of adaptation and early warning. Impact datasets and damage functions are therefore essential for the usability of compound event science as they help build bridges between academic knowledge and the end-user application. Thus, reliable impact datasets can be equally important as a good understanding of compound event dynamics in providing damage outlooks.

While a wide range of impact datasets exists (e.g. EM-DAT, Desinventar, see Table 1), there are several factors that make it challenging to identify usable connections between compound events and damages. Here we describe three main challenges that go beyond the well known general issues of hazard bias, temporal bias, threshold bias, accounting bias, geographic bias, and systemic bias (Gall et al. 2009), questionable quality of impact data (Moriyama et al. 2018; Panwar and Sen 2020), and data gaps (Jones et al. 2022).

First, events listed in these databases are often not described in their full complexity of events in impact databases, particularly the interactions between different hazards (Gill and Malamud 2014; AghaKouchak et al. 2021; Niggli et al. 2022; De Brito 2021). High impact events are often caused by multiple coincident drivers. For example, tropical cyclones cause damage with high wind speeds as well as flooding from heavy precipitation and storm surges. Impacts, such as casualties and economic



damages, however, are rarely attributed to combinations of multiple impact drivers but rather to a main impact driver. Most existing open impact datasets often cover only specific hazard types, regions, and impact categories (see Table 1 for examples). A well-known exception is the EM-DAT database where events can include multiple hazard types and which has been used for multi-hazard analyses. (Lee et al. 2024) studied the various combinations of natural hazard types in the events and classified them into single-hazard events or one of the four compound event types (multivariate, preconditioning, spatially compounding and temporally compounding). The results show that approximately 19% of the disasters recorded in EM-DAT can be classified as multi-hazard events. However, (Jäger et al. 2025) found that multi-hazard events are also often reported as multiple separate single-hazard events in EM-DAT suggesting a higher percentage of multi-hazard events than reported and pointing to a lack of multi-hazard information in EM-DAT. More detail in impact reporting, especially including information about different contributing hazards, is needed to disentangle the specifics of impact drivers e.g. (Calvella and Pecoraro 2018; Crozier 2017).

Second, impact datasets are often biased towards very high-impact acute events, whereas small-scale “nuisance” events may remain underreported. For example, EM-DAT only reports events above a certain impact threshold (Delforge et al. 2025). Nevertheless, temporally compounding small-scale events can result in a constant stream of local losses without adequate recovery time between events, therefore resulting in substantial losses for the region (De Ruiter et al. 2020; Van Der Wiel et al. 2020; Brennan and Danielak 2022; Moftakhari et al. 2017). In addition, existing databases typically do not account for slow-onset or long-lasting impacts, such as those from drought, which may be felt long after the peak of the physical hazard (Erian et al., 2021) and can precondition and amplify impacts from other hazards (Gill and Malamud 2014).

Third, inconsistent or incomplete information on the temporal and spatial characteristics of the reported events (e.g., (Jäger et al. 2025)) can hinder building robust connections between event types and damages. Spatial information is provided in various forms, for instance, cities, natural features (e.g., the Alps), administrative divisions, whole countries, or geographical areas without clear formal boundaries. Yet, climate events do not follow political boundaries and the impacts of events often extend beyond the region they affect. Similarly, temporal specifications for events in the same hazard category can be assigned a date range in days, months, or years, or only a starting date. These inconsistencies limit the derivation of relationships between impacts and climate anomalies, in particular for compound events where these characteristics are essential for differentiating event types.

To address the challenges described above and develop socioeconomic and environmental impact datasets that are usable for compound events research, efforts must focus on standardization, data assimilation, and integration, along with a more nuanced characterization of events that captures their complexity. A shift in perspective is needed regarding data collection and structuring, including the consideration of amplified impacts generated by compound events. Rather than collecting information about multiple hazards and impacts individually, which can result in the loss of critical interconnections, records need to be linked in a standardized and comprehensive way.

A promising example is the LAND-deFeND database (Napolitano et al. 2018), which allows for storing multiple nature-related, human-related, geospatial-related, and information source-related entries to comprehensively describe geo-hydrological events. Another promising example is the multi-risk database by (Dallons Thanneur et al. 2025), which explicitly documents possible interactions between hazards, their characteristics and detailed impacts for events related to rockfall, landslides, snow avalanches, hydrological and glacial hazards in the French Alps. Lastly, newspaper based databases are also useful even if they are biased towards urban areas. An example of it is the Disaster



Database for Portugal which includes hydro-geomorphologic cases (floods and landslides) that generated human damages in Portugal since 1865 (Pereira et al. 2018).

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In addition, overviews that merge the information from multiple datasets across a wide range of hazards, following the example set by (Lindersson et al. 2020), are useful to understand and address the challenges associated with their use. Some important steps towards standardization have also already been taken by the Centre for Research on the Epidemiology of Disasters (CRED) and other stakeholders to develop a standardised disaster category classification system and the GLoBal IDentifier (GLIDE) number attempts to enable unique identification of events across databases (Nishikawa 2003).

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There is a need for improved impact and hazard datasets, with global coverage and high temporal and spatial resolution, covering multi-hazards and multi-impacts across different sectors to support usable risk assessments. To be *fit for purpose*, we argue that addressing this challenge requires a multi-faceted approach, including three avenues: (1) improved open and collaborative data infrastructure, (2) employing novel data sources, and (3) better leveraging of existing data using statistical methods that have already proven useful for other applications (Fig.1). State institutions, governments, and international organizations should work towards streamlining their data collection and implementing data collection infrastructure to improve global coverage and help close the climate impact data gap (Osuteye et al. 2017). It is, however, important to note that increased access and availability of data from Global South countries should be utilized ethically, with efforts made to meaningfully engage and collaborate with local scientists, facilitate resource investments in local institutions, credit contributions from local researchers and institutions, and support capacity building (Serwadda et al. 2018). In addition, corporate datasets should become openly accessible for scientific research to be truly usable (UNDRR 2024: <https://www.undrr.org/explainer/unaccounted-costs-of-disasters-2023>). In particular those impact data sets that provide information on financial and insurance impacts of natural hazards, are corporate intellectual property and therefore often not freely accessible for climate impact researchers and decision makers (see Table 1 for examples). This lack of access to impact data hinders the public and equitable use of information that could be used to adapt to climate hazards and advance climate science (see comment in New York Times by Justin Mankin: <https://www.nytimes.com/2024/01/20/opinion/climate-risk-disasters-data.html>).

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A concrete avenue for increasing the quantity of impact data involves exploring novel data sources and developing advanced methods for collecting impact information. For example, natural language processing techniques have predominantly been applied to univariate hazard types, but could be applied to compound events as well: automated data extraction from text has been utilized for estimating the impacts of droughts (Sodoge et al. 2023), floods (Madruga De Brito et al. 2025), as well as for building global, spatiotemporally referenced, multi-hazard impact databases Using LLMs to Build a Database of Climate Extreme Impacts (Li et al. 2024). Another notable area of interest is opportunistic sensing. For example, data from ubiquitous technologies, such as Waze (a navigation app with live traffic information), can be utilized to rapidly identify flooded areas (Lowrie et al. 2022; Yuan et al. 2023), while analyzing credit card transactions can provide insights into spatial patterns of disaster impacts and recovery duration (Yuan et al. 2022), and nighttime light satellite data can be used to assess changes in economic activity and recovery (Qiang et al. 2020; Barton-Henry and Wenz 2022). Social media data can also be used to assess the impacts of individual and compound hazards. For example, (Moore and Obradovich 2020), used social media data to estimate county-level flooding. Such an approach could also be applied to source impact data. Lastly, citizen science, such as people submitting observation reports with descriptions and photos of drought impacts

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(<https://www.drought.gov/data-maps-tools/condition-monitoring-observer-reports-drought-cmor-drought>), has potential a valuable source for impact data (e.g., (Walker et al. 2024)).

255 Finally, as a timely and pragmatic solution, statistical techniques can be applied to currently available
 impact datasets to provide additional information. For example, statistical techniques can be applied
 to fill data gaps. (Jones et al. 2023) provide an overview of studies attempting imputation and
 augmentation techniques to fill data gaps in EM-DAT, however, the authors note that these
 260 approaches “were commonly *ad-hoc* with little statistical basis.” Other studies focus on extending
 impact datasets with additional information. For example, (Tschumi and Zscheischler 2020)
 investigated countrywide climate features associated with disasters in EM-DAT and (Rosvold and
 Buhaug 2021) geo-coded information from EM-DAT into a new GDIS data set to improve usability.
 (Jäger et al. 2025) combined GDIS and EM-DAT and developed an algorithm to identify potential
 265 multi-hazard events and their impacts based on spatio-temporal relationships between individual
 disaster records. Moreover, impacts may be estimated and gaps may be filled using impact domain
 or sector-specific models, for instance, (Wang et al. 2019) applied a mathematical model for road
 networks to estimate large-scale road disruptions due to floods, an approach that could also be
 employed for other types of infrastructure and multiple hazards. Of course, such an approach
 requires substantial knowledge about the hazard(s) in question, which might not always be available.

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Table 1. Selected examples of impact datasets and relevant attributes.

Dataset Name	Dataset Type	Publisher	Open	Link / Reference
Emergency Events Database (EM-DAT)	Multi-hazards disaster impacts database	Centre for Research on the Epidemiology of Disasters (CRED)	Yes	EM-DAT: https://www.emdat.be (Delforge et al. 2025) 11.11.25 11:27:00
International Flood Network (IFNet)	Flood impact database	IFNet	Yes	IFNet: http://www.internationalfloodnetwork.org
Historical Analysis of Natural HaZards in Europe (HANZE)	Flood impact database	-	Yes	(Paprotny et al. 2018; 2024)
Database of Flood Fatalities from the Euro-Mediterranean region (FFEM-DB)	Flood impact database	-	Yes	(Papagiannaki et al. 2022)
Dartmouth Flood Observatory Archive	Flood impact database	Dartmouth College	Yes	Dartmouth Flood Observatory: https://floodobservatory.colorado.edu



U.S. Drought Impact Reporter	Drought impact database	National Drought Mitigation Center	Yes	U.S. Drought Impact Reporter: https://www.drought.gov/data-maps-tools/drought-impact-reporter-dir
European Drought Impact Report Inventory	Drought impact database	European Commission	Yes	European Drought Impact Report Inventory: https://europeandroughtcentre.com/news/european-drought-impact-report-inventory-edii-and-european-drought-reference-edr-database/
NatCatService	Corporate multi-hazard disaster impact database	Munich Re	No	NatCatService: https://www.munichre.com/en/solutions/for-industry-clients/natcatservice.html
Sigma Explorer	Multi-hazards disaster impacts database	Swiss Re	No	Sigma: https://www.swissre.com/institute/research/sigma-research.html
PERILS	Compilation of multi-hazard exposure and loss data from insurance companies	PERILS	No	PERILS: https://www.perils.org

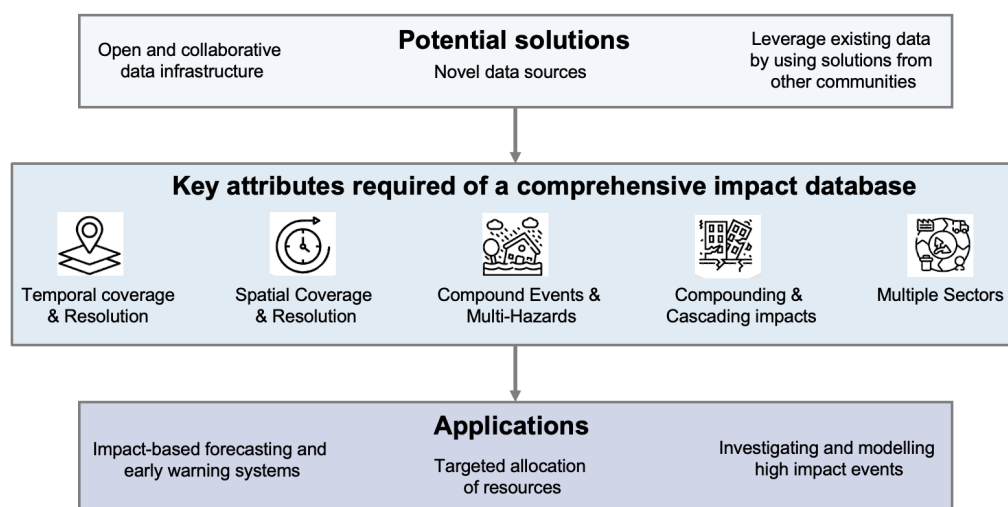


Figure 1. Steps towards usable socioeconomic and environmental impact data for compound events research. From comprehensive datasets to improved process understanding, modeling, projections, and early warning of compounding hazards.

2. Prediction and early warning of compound events

The impacts of extreme weather events can be mitigated through early responses from emergency services, communities, local authorities, and individuals, which are in turn dependent on the availability, quality, and successful communication of local hydrological and weather forecasts, impact forecasts (where available), and early warning systems (Golding 2022; WMO 2023). In 2022, the United Nations launched the Early Warnings for All initiative to build and expand capacity to enable access to early warnings for everyone by 2027 to minimize risks from future climate hazards. Improving early warnings on various predictive timescales can be achieved by considering the complex interconnections between hazards and their drivers, together with knowledge of direct and indirect impacts.

The current ability of early warning systems to provide adequate warnings for extreme weather events, including compound events, strongly depends on the hazard(s) in question (Golding 2022; UNDRR 2022a), the location of the event (Judd 2020), the lead-time required by the user, and the ability to translate hazards into impacts through impact forecasting (Shyrokaya et al. 2024), among other factors. In particular, impact forecasting in a multi-hazard context has been recognized as essential for effective response measures (WMO 2015), yet the field still faces a number of challenges. With many hazards exhibiting increasing trends due to factors including the greater energy and moisture capacity of a warming atmosphere, changing seasonality, and changes in dynamics (e.g., (Rogers et al. 2022)), certain previously rare or unknown hazard combinations have become much more probable (Messori et al. 2025), challenging established univariate warning systems. Further, interactions between certain hazards may not be well understood or considered in existing early warning systems, such as compounding risk from tropical cyclone–extreme heat combinations that have emerged in recent years (Matthews et al. 2019). Challenges and potential solutions for early



305 warning systems for compound events are illustrated in Figure 2 and discussed throughout this section.

Early warning systems for compound events face specific challenges. For example, due to the relatively short lead time of operational forecasts of approximately one week, certain preconditioned or temporally compounding events may not be predictable before the first event has occurred, such as multiple floods in the same location over several months. Knowledge of the second event could impact holistic risk assessments, alter preparations that might otherwise be taken for the first event in isolation, and inform disaster response resources and strategies that might be impacted by successive events. However, an understanding of the historical dependence structures and the temporal relationships between specific hazards, their local and remote physical drivers, and how these relationships may have already changed in a non-stationary climate can provide predictability on subseasonal-to-seasonal scales (Golding 2022). For instance, the knowledge that natural variability modes such as the El Niño-Southern Oscillation can lead to simultaneous droughts in multiple regions (Singh et al. 2021; 2022) can be used to forecast food shortages or food insecurity on seasonal timescales, which can inform the allocation of food aid and humanitarian resources. With such anticipation, coordinated preparation and response plans could be developed. A well-developed multi-hazard warning system could incorporate information about the effects of recent events on physical systems (e.g. preconditioning) or on human systems (e.g. response capacity) to refine risk assessment and communication.

325 Opportunities exist to develop low-cost, but limited, multi-hazard warning systems by combining existing warning products. The harmonization of multiple hazard warning systems is a crucial step when deciding where to deploy limited emergency response resources, or when shaping a single warning message that acknowledges the potentially conflicting responses required of multiple hazards. For example, in March 2021 in the southeastern United States, tornado warnings advised people to seek shelter in basements to provide protection from flying debris, but the advice did not appear to consider simultaneous forecasts for flash flooding, whereby people are typically advised to move to higher ground to avoid the hazard (Henderson et al. 2020; First et al. 2022). Compound event early warning systems should consider the risks associated with such coinciding hazards along with responses that will likely differ for coinciding hazards relative to responses for individual hazards. Substantial expert input would likely be needed for this delicate and context-specific task (Merz et al. 2020).

Forecast uncertainty can come from many factors, including data quality, human judgment, limitations of NWP for certain univariate hazards, and varying prediction skill across compound event components (Rennie et al. 2021; Henderson et al. 2023; Porras et al. 2021). Uncertainty can be quantified through verification methods to support decision making, but this is likely to be difficult to homogenize across compound event types, forecast quality metrics, and prediction type (i.e., deterministic versus probabilistic). By their own nature, distinct event types in different locations require different verification tools, with time aggregations meaningful to users (Domeisen et al. 2022). Appropriate verification methods for compound events are largely unexplored and would require novel skill measures, forecast timescales, and calibration techniques, specifically adapted for forecasts of multivariate extremes, as well as suitable sample sizes to address sampling uncertainties (Coelho et al. 2019). These verification methods need to be designed to build knowledge about the strengths and weaknesses of forecasts, and eventually increase confidence in compound event forecast products and applications (Goddard et al. 2015; White et al. 2022).

Improvements in existing forecasting capabilities can potentially enhance compound event prediction opportunities. The combination of dynamical- and data-driven forecasts, as well as large



ensemble probabilistic forecasts (Maier-Gerber et al. 2021) and subseasonal-to-seasonal forecasts (White et al. 2022), are promising tools to predict extreme events on longer forecasting timescales (Domeisen et al. 2022). Current dynamical models can be additionally improved by resolving processes, whereby spatial resolution is increased to avoid parameterization (Jutd 2020). The propagation of errors is also important (Jutd 2020; Golding 2022), especially with the different temporal and spatial scales involved in compound events. One potential method of error reduction for compound events is via multivariate post-processing of numerical models, to preserve the dependency between variables requiring bias adjustment (see section 3 and (Vrac and Friederichs 2015)). Additional opportunities for forecast improvement arise from recent advances in artificial intelligence (AI) based weather forecasting models, such as ECMWF's Artificial Intelligence Forecasting System (AIFS) (Lang et al. 2024), Pangu-Weather (Bi et al. 2023), and GraphCast (Lam et al. 2023), however, further development is required. After testing four different AI forecasts of a high-impact weather event, (Charlton-Perez et al. 2024) note that while the AI models showed promise compared to traditional NWP models, none of them could replicate the magnitude of the event. Recent analyses suggest that numerical models still outperform AI based approaches when it comes to unprecedented extremes (Zhang et al. 2025).

A lack of knowledge of hazard interactions (in particular in a non-stationary climate) can prevent adequate preparations from being put in place. Knowledge about the complex web of compounding and cascading hazards and impacts is crucial for predicting societal impacts of compound events and for making robust decisions. Given the sheer number of potential interconnections, a pragmatic and location specific focus on the most relevant event combinations is crucial. Probabilistic weather forecasts can be leveraged to evaluate the potential of anticipated low-likelihood, high-impact compound event scenarios, which can also inform planning and response. In addition, AI models can potentially identify hazard relationships and drivers, including causal links, due to the abilities of AI to connect complex chains of compound events (Reichstein et al. 2025; Allen et al. 2025). Developing a comprehensive understanding of historic hazard interactions, how they are changing in a warmer climate, and their consequences requires not only high-quality weather observations, but also readily available socioeconomic and environmental impact data (as discussed in section 1) – all of which should be considered when assessing hazard interactions. A further challenge is posed by the emergence of previously unprecedented events, which can include previously unseen individual hazard intensities due to compounding drivers (Bartusek et al. 2022) or combinations of hazards that do not exist in the observational record (Zscheischler et al. 2018; AghaKouchak et al. 2020; Feng et al. 2022). The complex nature of compound events can lead to overlooking subtleties and potentially underestimating upcoming events or their impacts (Bastos et al. 2023; De Brito et al. 2024).

Useful early warning systems also require an understanding of vulnerability and exposure, both of which are unlikely to be consistent across different hazards (WMO 2023). For example, certain housing types might be well prepared for univariate extreme heat, featuring design elements such as wide verandahs and cross-flow ventilation, but are left vulnerable if the heat co-occurs with high levels of pollution (Ahmed et al. 2021). Certain compound events may have unprecedented impacts, not because the individual hazards are unprecedented, but because exposure and vulnerability are nonstationary and might be modulated by past events (De Ruiter et al. 2020; WMO 2023). That is, if vulnerability and exposure are elevated during the recovery period of an initial hazard, the threshold for compounding impacts from additional hazards will be lower. Thus, the criteria for issuing a warning needs to shift during recovery periods (Manning et al. 2025). For example, a loss of electricity and air conditioning due to a tropical cyclone is likely to lower the threshold for dangerous heat. In this context, subseasonal-to-seasonal forecasts may offer great value (e.g., (White et al. 2022)) allowing for a 'pre-alert' state. Overall, a thorough understanding of historic compound events



that are likely to recur, as well as their impacts, in conjunction with current and projected exposure and vulnerability data can help bridge this gap. Additionally, even more so than univariate extremes, many compound events cause socioeconomically regressive impacts, a factor that should be accounted for if warning systems are to minimize harm.

Communicating warnings that result in efficient action requires effective communication of predictability and uncertainty to the end user, and optimization of the amount of detail in the warning (Krocak et al. 2023), as too much information can lead to confusion and inaction. Given that the success of early warning systems for hazard impact reduction is heavily dependent on products from local weather forecasters and action taken on the ground by first responders (Sengupta et al. 2022), early warning systems should be co-designed with these users to ensure the necessary data, context, and uncertainties are provided. Suggested responses to cope with the risks should also include how the impacts might manifest and options specific to different vulnerable populations, which requires understanding how these communities minimize risk and engaging these populations in the development of early warning messages. The development of useful early warning systems for compound events will not be a simple task and will require bringing together currently discrete communities to instigate a step-change in the way compound event predictions on various time-scales are produced, communicated, and used. As such, this co-design process should also include users and practitioners to ensure the necessary data, context, and uncertainties are provided. It is also crucial that we learn from and share our successes and shortcomings as a global community of researchers and practitioners (UNDRR 2022a). Communication of early warnings should also be adapted to different local languages and provided via multiple communication pathways to reach affected communities, including remote and historically underserved communities.

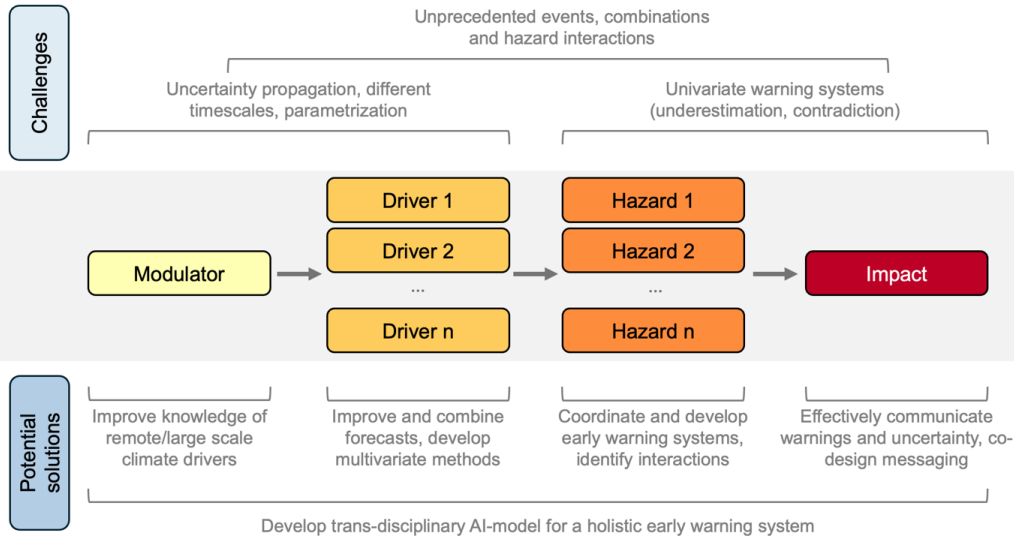


Figure 2 Challenges (top row) and proposed solutions (bottom row) for early warning systems for compound events. The elements of a compound event (middle row) are depicted as described by (Zscheischler et al. 2020).



3. Modeling and projecting compound events

Climate models are essential tools for exploring compound events under different climatic conditions on timescales of decades to centuries. The usability of climate models in the context of compound events research is linked to the degree of certainty with which a specific event probability is provided, the accuracy by which impact-relevant event characteristics are reproduced and the level of temporal and spatial detail provided by the model.

High levels of spatio-temporal detail and uncertainty exploration are limited by computational and storage capacities, while a skillful reproduction of event specifics can also be limited by our process understanding. In particular, for compound events and impacts, a trade-off remains between computational affordability and obtaining localized climate information using high resolution models that can have higher fidelity in representing compounding processes. Furthermore, compound events are often extreme events that contribute to the tails of multivariate distributions. Due to their rare occurrence, large datasets are necessary to narrow down uncertainty ranges and enhance the understanding of the influence of natural variability and physical uncertainty. Different modeling architectures and methods have been proposed to find a balance between high-resolution and extreme event datasets, enabling conclusive sample sizes.

Uncertainty tends to increase substantially with the number of elements included in an analysis (the ‘curse of dimensionality’). The rarity of many compound events and their specific combinations of hazards and drivers requires a large sample size to obtain a representative sample of the joint distribution tails to study these events. Thus, uncertainties in frequencies of compound events over a specific time period are particularly large. For example, the frequency of three consecutive dry years averaged across Central North America varies by a factor of more than 10 across different plausible 31-year datasets (Bevacqua et al. 2023) (see further details on uncertainties discussed in section 4, also).

Large climate model datasets consisting of hundreds to thousands of years of data from large ensemble simulations (e.g. Single Model Initial-condition Large Ensembles (SMILES) (Lehner 2024) and Unprecedented Simulated Extreme Ensembles (UNSEEN), (Thompson et al. 2017) can be used to explore low-likelihood, high-impact scenarios and obtain appropriate uncertainty estimates of very rare, often extreme events in present and future climates. These datasets consist of many simulations done with Earth System Models (ESMs) and General Circulation Models (GCMs), which are highly complex and aim to model all relevant components of the climate system and their interactions. ESMs, particularly those coordinated by CMIP (Eyring et al. 2016), are evolving in accuracy in conjunction with our physical understanding of the earth system and our computational abilities (Intergovernmental Panel On Climate Change (Ipcc) 2023), with some ESMs operating at 50 to 100 kilometer and 3-hourly to daily scales (Olonscheck et al. 2023).

Simple climate models or climate emulators offer rapid and computationally affordable production of climate projections under various emission scenarios, which enables the generation of large datasets to efficiently explore sources of uncertainty surrounding climate projections. In contrast to GCMs and ESMs, emulators are not based on physics but instead rely on statistical approximations of relationships identified from GCM output. Emulators rely on stochastic generative principles that approximate a given variable based on key covariance structures, commonly covariance with global mean temperatures (GMTs) as well as spatio-temporal covariances, which can be informed by process understanding. Thus, emulators can produce realistic estimates of the evolution of global patterns of certain climate variables at given GMT levels. Some emulators manage to leap the climate layer and link GMT levels directly to specific impact drivers such as droughts, wildfires and even



480 impacts themselves (Byers et al. 2025), making emulators a potent tool for high level exploration of climate risks and impacts under different scenarios for climate policy work.

While emulators are able to produce very large and versatile climate datasets, they struggle at accurately modeling the extreme tails of distributions and can fail to capture more complex
 485 interrelationships between different parts of the earth system, both of which are important when considering high-impact, rare compound events. Further, emulations are often univariate, with information provided at low temporal resolution of monthly or annual timescales, making the application to compound events a challenge for which cross-variable covariance structures should be maintained. While most existing emulators model one variable at a time, several approaches have
 490 already been taken for multivariate emulation (e.g., (Nath et al. 2025; Quilcaille et al. 2023)), to jointly generate multiple variables, thus maintaining covariance between variables (e.g. (Claassen et al. 2024). Advances in AI based emulators (e.g. Quickclim (Kitsios et al. 2023)) could provide further avenues for fast, accurate and skillful modeling of compound events, but further research is required.

495 GCMs often operate at coarse spatial resolutions (~100 km). However, climate hazards and impacts can unfold at much finer scales – from sub-kilometer to kilometer scales – scales relevant for, e.g., urban infrastructure and highly localised assets. New generation 1–10 kilometer-scale GCMs offer a better representation of dynamical processes (see e.g., Destination Earth and nextGEMS (Hohenegger et al. 2023; Rackow et al. 2025)), such as ocean and atmospheric eddies, and thermodynamic
 500 mechanisms, including convection and cloud mechanisms. While kilometer-scale models could be particularly valuable for studying compound events due to their ability to resolve relevant meteorological processes, such as strongly improving the representation of convective precipitation, their implementation comes with substantial computational costs and data management challenges, and large ensembles of these higher resolution models are currently not computationally feasible.

505 Downscaling techniques allow for the generation of high resolution climate data based on lower resolution data. The two main downscaling approaches are: statistical downscaling and dynamical downscaling. *Dynamical downscaling* is a physics-based approach that feeds ESM outputs into a nested, high resolution Regional Climate Model (RCM), such as the CORDEX initiative ((Jacob et al.
 510 2014). Dynamical downscaling can produce output at various scales, but at spatial resolutions of 4 km or less, RCMs are assumed to explicitly resolve convection and are therefore called convection-permitting models (CPM; (Prein et al. 2015)). Often, dynamical downscaling experiments are not coupled, thus high-resolution information cannot feed back into the driving global climate. This limits the representation of some compound effects in which two-way interactions with the large-scale
 515 circulation are important. Further, since the spatial extent of RCMs is limited, global interrelationships that extend outside the downscaled region cannot be investigated, such as large-scale co-occurring extreme heat events. Still, RCMs can provide added value compared to the global simulations, both in terms of mean climate and the representation of extremes (Pichelli et al. 2021; Ban et al. 2021; Hundhausen et al. 2024; Poschlo et al. 2024; Klimiuk et al. 2025) and compound
 520 events (Zscheischler et al. 2021). In addition, large multi-model ensembles of high-resolution climate model data over selected areas are available (Coppola et al. 2021; Kendon et al. 2023; Hundhausen et al. 2023). Another approach combines the added value of dynamical downscaling and SMILES, producing RCM SMILES (Aalbers et al. 2018; Leduc et al. 2019), which deliver large sample sizes and high resolution at impact-relevant scales (Ehmele et al. 2022; Santos et al. 2021; Felsche et al. 2024; Van Den Hurk et al. 2015).

For *statistical downscaling*, in turn, statistical relationships are identified between large-scale and local variables from observational data. These relationships are then applied to GCM / ESM output to generate high-resolution simulations (Maraun and Widmann 2018; Maraun et al. 2010). Many



530 implementations of different grades of sophistication exist, for example, statistical downscaling using
 terrain and large-scale atmospheric predictors (e.g. CHELSA (Karger et al. 2023), PRISM (Daly et al.
 2008)), can account for sub-grid climate conditions, thus improving hydrologic simulations (e.g.
 (Michalek et al. 2023)). However, these deterministic methods have limitations – they can break the
 535 physical dependence between variables (Karger et al., 2023) and fail to represent local variability
 and extreme events that occur at scales smaller than the initial resolution. To address these
 shortcomings, stochastic methods have been developed, which are essentially weather generators
 driven by GCM / ESM output. Typical limitations of these models are the representation of local
 feedbacks, interannual variability and spatial dependence (Maraun & Widmann, 2018, Maraun et al.,
 2019; Widmann et al., 2019). Over the last decade, machine learning has emerged as a subclass of
 540 statistical downscaling (Rampal et al. 2024). These approaches outperform earlier statistical
 downscaling approaches (Baño-Medina et al. 2020) and show potential for the fine-scale
 reproduction of extreme events (Rampal et al. 2024; Vosper et al. 2023). However, a key challenge
 remains: preserving interdependencies between climate variables – which is crucial for usable
 compound event research (Quesada-Chacón et al. 2023).

545 Impact relevant event characteristics such as duration, timing, magnitude and frequency must be
 accurately reproduced in models. Bias adjustment, also known as bias correction or calibration, is a
 commonly used approach in impact and hazard modeling to account for known deficiencies of GCMs,
 RCMs and CPMs in the representation of impact relevant variables and their extremes (Suarez-
 550 Gutierrez et al. 2021; Bevacqua et al. 2023). In this process, model output is adjusted by statistical
 postprocessing towards reference observations (Maraun 2016). Being a purely statistical and non-
 physics based approach, bias adjustment needs to be applied carefully, as unwanted artefacts may
 occur (Maraun et al. 2017) and in the worst case may deteriorate the original model simulation.

Bias adjustment is particularly challenging in the context of compound events. For instance,
 555 univariate quantile mapping methods do not necessarily conserve multivariate relationships, as they
 act differently depending on which variable and which part of the distribution they are applied to
 (e.g., (Zscheischler et al. 2019)), without considering physical dependencies (e.g. heat and drought).
 Therefore, bias adjustment methods have been proposed that maintain statistical relationships
 between impact-relevant variables (Vrac and Friederichs 2015; Cannon 2018; Hess et al. 2023).
 560 While some research shows that multivariate methods perform better than univariate methods
 (Vogel et al. 2023), others suggest that univariate methods can maintain inter-variable dependencies
 (Wilcke et al. 2013). All bias correction methods reduce the consistency between the bias corrected
 data and the driving model, however, these inconsistencies can be amplified when using multivariate
 methods (Maraun 2016). Careful consideration should be made as to which aspects of the data can
 565 be adjusted without breaking consistency with the driving processes

The stronger the initial model biases, the stronger the error propagation and final artefacts.
 Therefore, it is often an advantage to use RCM and particularly CPM data as a starting point for bias
 correction, as these models provide a much better representation of the target variables and their
 variability on regional to local scales (Prein et al., 2015, Pichelli et al., 2021). Ideally, hybrid models
 570 can be trained with this very high-resolution model data to provide effective ways for bias correction
 and downscaling of large CMIP ensembles. Another major limitation of bias adjusting climate data is
 a lack of suitable reference datasets in some locations. Bias adjustment without accurate, spatially
 and temporally complete observational data records will be of limited benefit. Since some regions
 have good records for some variables but incomplete records for others (e.g., temperature and
 575 humidity, respectively, over southern Africa, (Rogers et al. 2021)), bias adjustment for derived
 multivariate indices, such as wet-bulb temperature, can pose additional challenges for compound
 events research. Lastly, purely statistical bias adjustment methods might miss changes to



dependence structures and changes in the shape of the distributions induced for example by novel feedback dynamics under different warming levels (Bartusek et al. 2022; Kornhuber et al. 2024).



580 4. Addressing uncertainty in compound event projections

Uncertainty poses a particular challenge to the usability of compound event assessments. Various methods, tools, and frameworks for dealing with compound events under large uncertainty have been developed (Ward et al. 2022). There are three main types of uncertainty in climate models
 585 (Lehner et al. 2020): (1) model uncertainty (see section 3), (2) internal variability, due to the chaotic nature of the climate system, and (3) scenario uncertainty, due to the multiple possible pathways of future greenhouse gas emissions. This section discusses these three types of uncertainty and discusses avenues for addressing them.

590 Model uncertainty arises from our incomplete understanding and representation of the climate system and how impact-relevant variables respond to human-induced climate change on a local scale. Although we are far from a perfect modelling of compound events (Villalobos-Herrera et al. 2021), model uncertainty can be reduced by improving the representation of relevant physical processes in models. Model uncertainty can also be reduced by narrowing the plausible range of
 595 future projections by applying emergent constraints, based on relationships between observable historical variables and future climate responses in models (Wu et al. 2025), and by applying performance constraints, based on the ability of models to reproduce observed processes or metrics (Palmer et al. 2023). Uncertainty related to compound events may be amplified if interactions between components of compound events or cascading hazards are not captured well in models.

600 In contrast to model uncertainty, uncertainty arising from internal climate variability cannot be reduced as it is inherent to the climate system (Hawkins et al. 2016). That is, the chaotic, non-deterministic nature of the climate system, as well as cyclical modes of ocean currents and their atmospheric responses and feedbacks, all contribute to internal variability. This means that a perfect
 605 model, seamlessly initialized with a perfect set of observations from the real world, would not be able to deterministically predict the future climate trajectory beyond the predictability horizon. Beyond this predictability horizon, which ranges from one to two weeks for most atmospheric weather processes such as heatwaves (Lorenz 1969) to a few years for the upper oceans (Branstator and Teng 2010), this idealized perfect model would rather produce a range of plausible climate outcomes
 610 determined by the system's internal variability.

Scenario uncertainty relates to a vast range of possible climate futures that depend mostly on societal decisions in the context of climate policies, such as chosen emissions pathways or land-use change. Although we, as humans, are in control of these decisions, societal actions and their consequences
 615 are very difficult, if not impossible, to predict in a deterministic way (Lehner et al. 2020; Moraga et al. 2022). Uncertainties can be particularly large in the context of compound event projections as each climate variable may contribute its own uncertainties in timing, location and magnitude respectively.

620 In the context of future climate risks from compound events, storylines can be used as a tool to explore the range of plausible future compound climate events (Sillmann et al. 2021; Van Der Wiel et al. 2024) despite potentially large uncertainties. Storylines can be considered stress-testing exercises, in which a plausible high-risk scenario is designed to test the resilience of the system in question, often with the use of climate models. There have also been recent efforts to integrate
 625 societal processes in storylines, to enable linking climate risks to societal impacts (Rusca et al. 2023). In general, storylines describe either physically consistent future climates, hereinafter climate storylines, or individual events, hereinafter weather event-based storylines, under plausible future conditions (Shepherd et al. 2018; Bevacqua et al. 2023; Sillmann et al. 2021; Klimiuk et al. 2025) (Fig.



3a). For both storyline types, emphasis is placed on the physical plausibility of the storyline rather than on its probability given the difficulty associated with attaching probability accurately (Shepherd, Boyd, Calel, Chapman, Dessai, Dima-West, Fowler, James, Maraun, Martius, Senior, Sobel, Stainforth, Tett, Trenberth, van den Hurk, et al. 2018). To illustrate how climate storylines can help address model uncertainty, we explore the example of hot-dry summers in southern Africa, which are climatic impact-drivers threatening agriculture and food security, in a world that is 3 °C warmer than pre-industrial conditions (Fig. 3b, c). Potential high-impact and low-impact storylines are compared, which are represented by a model with a high frequency of future hot-dry events (GFDL-ESM2M) and one with a lower frequency (CanESM2). Note that both of these outcomes are physically plausible outcomes from climate models, which are a priori equally likely. Scenario uncertainty can be addressed in a similar way, e.g. by anchoring storylines to different emission pathways and associated warming levels. In contrast, where internal climate variability controls uncertainty, divergent climate conditions can be identified using different ensemble members from the same SMILE (Deser 2020).

To better understand specific compound event types in the future, weather event-based storylines can be used to identify historic high-impact events or near misses (Woo 2021) and explore how they may unfold in the future. For example, using a severe landslide event that occurred in Austria in 2009 due to compounding effects of rainfall and soil moisture, Maraun et al. (2022) (Maraun et al. 2022) provided stakeholders with information on probabilities of future landslide and options for adaptation by revealing how the event may unfold under multiple plausible future climates and land-use changes. As another example, (Goulart et al. 2024) generated storylines of Hurricane Sandy, including the effects of both climate change and natural variability, with a compound flood modeling framework to explore and quantify alternative flood impacts of Sandy on critical infrastructure in New York City.

A standard approach for event-based storylines are pseudo global warming simulations, in which the meteorological conditions associated with an observed event are reproduced in a regional climate model with boundary conditions from historic and future conditions (Takayabu et al. 2015; Ludwig et al. 2023). Given that large-scale atmospheric circulation is fixed in these simulations, internal variability is considerably reduced for weather event-based storylines, which improves the signal-to-noise ratio, enabling better quantification of the actual event-specific thermodynamic and local responses to climate change. These simulations can show what certain historic events would have looked like under different global warming levels. Another approach is downward counterfactuals (Ciullo et al. 2021). This approach builds plausible events for storylines by modifying one or more impact relevant components of an observed event to simulate alternative, more severe outcomes (Woo 2021). This approach can be used for stress-testing exercises, or to account for both grey swan events (rare but foreseeable high-impact events) and black swan events (extreme outliers with severe consequences that have no historical analogue). For example, a study evaluating the impacts of tropical cyclones on the European Union Solidarity Fund found that some counterfactuals of tropical cyclones increased impacts by 90% (Ciullo et al. 2021).

The inability to model potential unprecedented event types or interactions between multiple climate drivers under future warming is a limitation for weather event-based storylines that are built solely on past high-impact events. Examples include the recent emergence of tropical cyclone–deadly heat events (Matthews et al. 2019) and the unprecedented intensity of the 2021 heatwave in northwestern North America (Bartusek et al. 2022). To anticipate emerging compound events driven by new combinations of climate drivers at a specific location, insights can be drawn from historic events at other locations. For instance, to help anticipate occurrences of megafloods in a given



catchment in Europe, observations of megafloods in hydrologically similar catchments in other climate zones can be used (Bertola et al. 2023).

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Despite their limitations, event-based storylines provide a useful modeling framework to link climate and impact simulations. To translate climate storylines into associated impacts, impact models—such as renewable energy, hydrological, or crop models—can be forced with the most extreme storylines (Goulart et al. 2021; Lucia Martin et al. 2025). Such storylines can be identified via an impact indicator, which should be co-designed by climate scientists, impact modelers, and stakeholders, carefully considering that extreme impacts often result from unexpected combinations of hazards (van der Wiel et al., 2020; Lehner et al. 2024). For example, for the renewable energy sector, an impact indicator could use climate model simulations to identify future extreme, widespread heatwaves and wintertime cold spells (Singh et al. 2024; Mattu et al. 2025), (which increase electricity demand), that co-occur with very low wind conditions (which decrease energy production) (Meng et al. 2025). In general, estimating impacts from specific compound event types requires a clear understanding of weather–impact relationships. A systematic assessment of these relationships relies on well maintained and comprehensive impact datasets (see section 1) as well as high-quality weather observations.

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One of the major challenges associated with communicating future climate change impacts and risk is the accurate yet concise communication of uncertainty and the implications it has for how to interpret climate projections. This challenge is complicated when considering the multiple hazards and/or drivers comprising compound events. Further, too much information can result in inaction as deciding on a course of action is too difficult, but too little information can result in overconfidence in an action, followed by dissatisfaction, for example, when an adaptation falls short of an actual hazard impact. Lessons can be learned from related disciplines that have developed effective methods and strategies for effective communication of complex risks, e.g., the frameworks for systemic multi-hazard and multi-risk assessment and management developed in (Hochrainer-Stigler et al. 2023). This six-step framework provides a generic approach for analysing risk across a spectrum ranging from single to multi-risk and systemic risk, providing a user with simple ‘guidance protocols’ for each step, i.e., guiding questions to help them carry out the steps. Another popular approach is the use of impact chains (e.g. (Schneiderbauer et al. 2013; Zebisch et al. 2021). These are conceptual models using cause-effect chains that include all major factors and processes leading to specific risks in a given context. These, and other approaches such as narrative descriptions, hazard wheels, hazard matrices, network diagrams, and hazard/risk indices, (Kappes et al. 2012; Tilloy et al. 2019; Gill and Malamud 2014) could be integrated into the research on compound climate events, which would assist in further aligning these fields. This is also important in the context of the global agendas (e.g. Sendai Framework for Disaster Risk Reduction, Paris Agreement on Climate Change, Sustainable Development Goals), which are increasingly focusing on common targets and goals, further alignment, and more closely synergising the closely-related fields of climate adaptation and disaster risk management (UNDRR 2022b).

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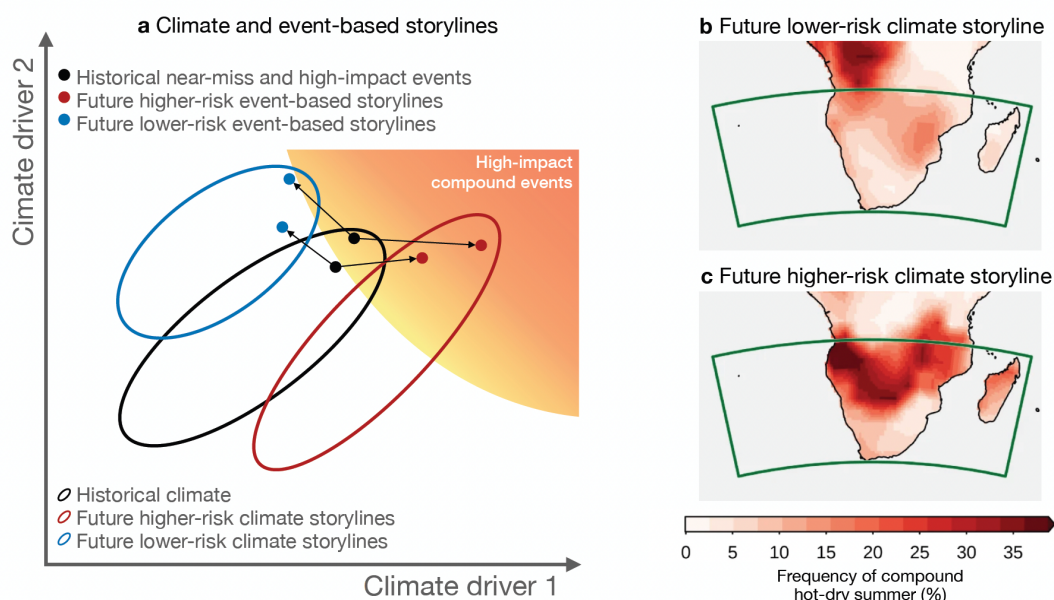


Figure 3 Climate and event-based storylines. **a** Climate and event-based storylines to explore uncertainties in future climatic conditions for a representative compound event type defined by two climate drivers. Impacts increase with higher values of both drivers (top-right corner). The historical climate (black ellipse) may shift in multiple ways – via changes in mean and variance of the climate drivers, as well as their correlations – as represented by a higher-risk (red) and lower-risk (red) climate storylines. Event-based storylines are shown as dots, with two historical events (in black, a near miss without impacts and a historical impactful event), which can evolve differently into higher-risk (red) to lower-risk (blue) future event-based storylines. **b**, **c** Future climate storylines characterized by high and low frequency of compound hot-dry summers in Southern Africa in a 3 °C warmer world than pre-industrial conditions. The storylines are obtained by ranking seven climate models (selected based on their large sample size so as to ensure a robust frequency of compound events) in terms of the future frequency of compound hot-dry summers averaged over the Southern Africa region (green box). Adapted from (Bevacqua et al. 2023).

5. Overarching challenges and the way forward

While compound events have occurred throughout the historical record, new compound event combinations, as well as the rapidly increasing frequency and intensity of many types of events, pose emerging risks to societies in a changing climate (Messori et al. 2025). While univariate climate risk assessments are on the way to being operationalized as ready to use frameworks by non-academic, private sector entities, compound events remain a scientific frontier where out-of-the-box approaches are not yet readily available. Similarly, an improved understanding of amplified impacts from compound events can be used to produce more informative and usable impact data and warnings. Setting standards for usable compound event research could help provide publicly accessible climate risk knowledge. We therefore propose four guiding principles, detailed below.



Accessibility and interpretability: Climate risk information should be provided free of charge and presented in an intuitive way.

Impact datasets constitute the foundation of compound event research as they allow us to establish robust event–impact relationships and inform the search for highly-impactful event combinations. Often impact datasets are not publicly accessible, are incomplete, or are structured in ways that hinder the investigation of compound events (see section 1). We call for impact data from a variety of sectors, such as health, agriculture, energy, and insurance, to be made readily. This shared data will facilitate the advancement of our understanding of the impacts of individual and compound climate events. There are substantial data gaps over certain regions, particularly South America, Africa, and parts of Asia, that limit the characterization of compounding climate risks in those regions. Alongside efforts to increase data availability from these regions, (Serwadda et al. 2018) underscore the need for researchers to employ best practices for ethical use of the data, engage in local collaborations that are meaningful and equitable, and support the development of local capacity and resources to support climate resilience. In contrast, much progress has been made regarding accessible hazard data, where numerous ready to use datasets can be found online (e.g., (Kong and Huber 2025)). Online tools for downloading time series and geospatial analyses, such as the Climate Impact Explorer (<https://climate-impact-explorer.climateanalytics.org>) could be extended to include a wide range of standardized compound event types, such as those provided in the framework of (Yin et al. 2025).

Interpretability can be fostered by working towards a common goal. Different scientific fields, such as climatology, hydrology, disaster risk science, and social sciences, often use the same terms to describe slightly to completely different concepts (Gill et al. 2022). For example, an impact can refer either to a hazardous event caused by climatic drivers (from a compound perspective) or the physical or economic loss resulting from a combination of hazard, exposure, and vulnerability from a (multi-hazard) disaster science or IPCC perspective. Furthermore, terms like "impact" and "risk" are subjective and context-dependent. Setting standards and agreement on common definitions (e.g. through glossaries) can help to reduce confusion across scientific communities (Zscheischler et al. 2021, Simpson et al 2021). Positive examples include the DAMOCLES Cost Action on Compound Events, which included research from a multitude of scientific backgrounds, and the Risk Knowledge Action Network (Risk KAN) on Emergent Risks and Extreme Events, a joint initiative from Future Earth and WCRP consisting of a set of working groups that bring together practitioners and researchers from different disciplines. [ANTICIPATE](#), a newly funded European COST Action, will focus on the prediction of compound events on different timescales and will tackle challenges discussed in section 2 of this perspective.

Fitness for purpose: Sufficient detail in time and space at certainty levels that match the application.

To ensure fitness for purpose, compound event scientists, stakeholders, decision makers, and hazard responders must come together in the co-development process from the outset, to ensure that the development of models, metrics, and other tools are truly usable on the necessary temporal and spatial scales. Transdisciplinary approaches with non-academic stakeholders for co-developing the research design and generating knowledge can help (Norström et al. 2020). Integrating researchers, agencies, and other stakeholders helps to dissolve barriers between different sectors and align the expectations of the different stakeholders by focusing on shared outcomes and creating a common understanding, bridging the science-policy-practice gap (Gall et al. 2015; Brett et al. 2025). Expectation management is a key part of such processes as uncertainties are an inherent part of climate risk projection and early warnings. This holds in particular for highly resolved spatial and temporal risk estimates, which can go beyond the capacities of what the state-of-science can deliver.



Communicating the full range of uncertainties is also important to enable users to determine the level of risk that they want to incorporate in their applications of this information, whether it be for design, planning, or preparedness.

800 *Timeliness and pragmatism: The best available knowledge should be provided, as early as possible.*

Unmitigated climate change leads to situations in which the emergence of compound hazards and the need for actionable information outpaces scientific progress. As compound climate events affect societies now, imperfect and available information might at times be the preferred option, compared to a perfect solution potentially available beyond undefined time-horizons (e.g., accurate and near deterministic risk estimates at sub kilometer-scales). In this context, the communication of underlying assumptions and limitations of chosen approaches are of high importance. Considerations around timeliness and pragmatism should therefore be tailored towards the specific target audience. While technical professionals in public agencies need detailed data on climate models and risk assessments for effective risk management, policymakers require concise, comprehensible evidence to quickly inform policies and emergency preparedness without being overwhelmed by technicalities. On the other hand, the private sector, including agriculture and insurance, requires detailed risk assessments and forecasts to plan for business continuity and to manage risks.

815 *Transparency and accountability: Assumptions, limitations and methods need to be clearly stated and underlying data needs to be publicly available.*

In a landscape of imperfect solutions, transparency of underlying assumptions and limitations of chosen approaches can prevent misinterpretation and inappropriate application of compound event knowledge. While strict code and data availability requirements are becoming standard in academic research, no such scrutiny exists in the private sector. Transparency of methodologies is also imperative to ensure that analyses are repeatable and reproducible. This transparency also allows researchers and other users to better understand analyses and potentially identify unforeseen limitations, again reducing the misinterpretation of results and allowing methods to be improved in the future. Profit interests in a competitive market can disincentivize transparent communication of methods and limitations of the offered products and services, with risks of maladaptation leading to increased exposure and vulnerability to hazards. New accountability standards for hazard and climate risk estimates from the private sector could help in securing the reliability and trust in such products. Further, an open, intellectual environment, with best practices shared across disciplines, geographies, and hazards, encourages the needed dynamism for meaningful, usable climate-impact advances.

As extreme events are already occurring at a rate that increasingly outpaces climate scientists' capacity to thoroughly investigate them, a slowdown and reversal of global warming to meet the Paris Agreement targets by mitigating greenhouse gas emissions is imperative. Notwithstanding this objective an improved knowledge of the complex interactions of hazards and their climate impact drivers in a non-stationary climate is certainly needed. More comprehensive and standardized climate impact datasets and modeling efforts are a key element in moving towards producing more usable climate information and reducing uncertainties. While these efforts will not be able to eliminate limits to adaptation, which are set by local adaptive capacity, human liveability and survivability thresholds, and global tipping points that might cause rapid irreversible changes in the climate system, an improved, more holistic understanding of hazards and their impacts can help us understand when, where, and which aspects of weather extremes merit the greatest devotion of research and operational resources. While there is always the potential to extent our knowledge,



more systematic usability reflections facilitated by the presented guidelines could help maximize the application potential of the insights and methodologies already at hand right now.

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