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A typology of compound weather and climate events

Jakob Zscheischler[1,2]✉, Olivia Martius[1,3,4], Seth Westra[5], Emanuele Bevacqua[6], Colin Raymond[7,8], Radley M. Horton[9], Bart van den Hurk[10,11], Amir AghaKouchak[12,13], Aglaé Jézéquel[14,15], Miguel D. Mahecha[16,17], Douglas Maraun[18], Alexandre M. Ramos[19], Nina N. Ridder[20], Wim Thiery[21] and Edoardo Vignotto[22]

Abstract | Compound weather and climate events describe combinations of multiple climate drivers and/or hazards that contribute to societal or environmental risk. Although many climate-related disasters are caused by compound events, the understanding, analysis, quantification and prediction of such events is still in its infancy. In this Review, we propose a typology of compound events and suggest analytical and modelling approaches to aid in their investigation. We organize the highly diverse compound event types according to four themes: preconditioned, where a weather-driven or climate-driven precondition aggravates the impacts of a hazard; multivariate, where multiple drivers and/or hazards lead to an impact; temporally compounding, where a succession of hazards leads to an impact; and spatially compounding, where hazards in multiple connected locations cause an aggregated impact. Through structuring compound events and their respective analysis tools, the typology offers an opportunity for deeper insight into their mechanisms and impacts, benefiting the development of effective adaptation strategies. However, the complex nature of compound events results in some cases inevitably fitting into more than one class, necessitating soft boundaries within the typology. Future work must homogenize the available analytical approaches into a robust toolset for compound-event analysis under present and future climate conditions.

Weather-related and climate-related extreme events (such as droughts, heatwaves and storms) arise from complex interactions between various physical processes across multiple spatial and temporal scales. In many instances, these extreme events (or hazards) can overwhelm the capacity of natural and human systems to cope, in turn creating societal or ecological impacts. When multiple drivers (that is, climatic processes such as weather systems) and/or hazards combine, their impacts are often amplified[1], owing to: multiple hazards occurring at the same time (for example, droughts and heatwaves); previous climate conditions or weather events increasing a system's vulnerability to a successive event (such as heavy rain on saturated soils); or spatially concurrent hazards leading to regionally or globally compounding effects (such as globally synchronized heatwaves affecting global food production[2]).

First introduced by the Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate Extremes (SREX) in 2012 (REF.[3]), research into these so-called compound events (also referred to as correlated or complex[4] extremes) has evolved into an interdisciplinary matter at the interface of climate science, climate-impact research, engineering and statistics. Indeed, compound-event research aims to broadly reveal the physical processes by which weather-related and climate-related hazards combine, in order to improve their predictability, assessment of the societal and environmental impacts and risks, as well as to develop methods for detection and attribution[5–8]. Accordingly, the definition of compound events has also advanced from that of SREX[9] and is now embedded within the IPCC risk framework under the umbrella of: "a combination of multiple drivers and/or hazards that contributes to societal or environmental risk" (REF.[1]).

Despite evolving into a highly diverse and thriving research field, however, a coherent typology (or classification) of compound events is currently lacking. This absence limits the capacity to design suitable modelling approaches and develop robust and effective adaptation strategies, vital, given that many climate-related and weather-related impacts are (and will continue to be) related to compounding drivers. For example, comprehensive design of flood-protection infrastructure like dams must take into account the dependence between multiple flood drivers[5–7,10,11]. Similarly,

✉e-mail: jakob.zscheischler@climate.unibe.ch

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Key points

- Compound events — a combination of multiple drivers and/or hazards that contribute to societal or environmental risk — are responsible for many of the most severe weather-related and climate-related impacts.
- A classification of compound events is proposed, distinguishing events that are preconditioned, multivariate, temporally compounding and spatially compounding.
- The typology aids compound-event analysis by facilitating the selection of appropriate analysis and modelling tools.
- Through altering the distribution of climate variables and their spatial and temporal dependencies, climate change affects the likelihood, nature and impacts of compound events.
- Bottom-up approaches, which link sectoral impacts to physical hazards, can help understand and, ultimately, better prepare for emerging risks posed by compound events.

heat-stress-adaptation strategies in the health, economic productivity and energy sectors would benefit from inclusion of the compound relationship between high temperature and high humidity[12–14], and between high temperature and air pollution[15], not just temperature alone. At the other end of the humidity spectrum, fire-risk-reduction strategies also need to take both fire weather and fuel aridity into account[16]. Without a unifying compound-event perspective, process understanding can remain incomplete and statistical modelling limited in its relevance.

In this Review, we present a typology of compound weather and climate events, with the aim of providing a coherent framework for compound-event analysis. We begin by proposing four key compound-event types based on an assessment of the literature: preconditioned, multivariate, temporally compounding and spatially compounding. We suggest analysis and modelling tools for identifying key elements and quantifying drivers of an event. We further discuss how climate change can affect risks associated with compound events by changing different components of an event, before providing future research priorities. While the interaction between biophysical and societal systems shape local vulnerability and capacity to cope with extremes[17,18], here, we solely focus on the weather and climate aspects of compound events.

Author addresses

[1]Oeschger Centre for Climate Change Research, University of Bern, Bern, Switzerland.
[2]Climate and Environmental Physics, University of Bern, Bern, Switzerland.
[3]Institute of Geography, University of Bern, Bern, Switzerland.
[4]Mobiliar Lab for Natural Risks, University of Bern, Bern, Switzerland.
[5]School of Civil, Environmental & Mining Engineering, University of Adelaide, Adelaide, Australia.
[6]Department of Meteorology, University of Reading, Reading, UK.
[7]Department of Earth and Environmental Sciences, Columbia University, New York, NY, USA.
[8]Jet Propulsion Laboratory/California Institute of Technology, Pasadena, CA, USA.
[9]Lamont-Doherty Earth Observatory, Columbia University, Palisades, NY, USA.
[10]Deltares, Delft, Netherlands.
[11]Institute for Environmental Studies, Vrije Universiteit Amsterdam, Amsterdam, Netherlands.
[12]Department of Civil and Environmental Engineering, University of California, Irvine, Irvine, CA, USA.
[13]Department of Earth System Science, University of California, Irvine, Irvine, CA, USA.
[14]École Nationale des Ponts et Chaussées, Champs sur Marne, France.
[15]LMD/IPSL, École Normale Supérieure, PSL Université Paris, Paris, France.
[16]Max Planck Institute for Biogeochemistry, Jena, Germany.
[17]Remote Sensing Centre for Earth System Research, Leipzig University, Leipzig, Germany.
[18]Wegener Center for Climate and Global Change, University of Graz, Graz, Austria.
[19]Instituto Dom Luiz, Faculdade de Ciências, Universidade de Lisboa, Lisboa, Portugal.
[20]ARC Centre of Excellence for Climate Extremes, University of New South Wales, Sydney, Australia.
[21]Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel, Brussels, Belgium.
[22]Research Center for Statistics, University of Geneva, Geneva, Switzerland.

A typology of compound events

Prior to outlining the typology, we begin by outlining the typical characteristics that constitute a compound event: modulators, drivers, hazards and impacts (FIG. 1). A hazard refers to the climate-related phenomenon before a potential impact (the proximate cause of the impact), and includes events such as droughts, heatwaves, frost, floods, hail, strong winds and wildfire. A hazard does not need to be extreme in a statistical sense, provided that it triggers (or has the potential to trigger) an impact. Hazards themselves are caused by one or several climatic drivers, which could be weather systems such as severe storms, tropical cyclones, cold fronts and stationary high-pressure systems. Drivers, in turn, are affected by modulators — for example, low-frequency modes of climate variability like the El Niño–Southern Oscillation (ENSO) — which could influence the frequency and location of a driver, and, thereby, the frequency and/or intensity of a hazard.

Anthropogenic climate change has the potential to alter all elements of compound events. For instance, climate change can alter the frequency and intensity of hazards such as heatwaves and droughts by influencing modulators like the ENSO; modify the location and characteristics of climatic drivers such as individual weather systems; and directly affect the physical structure of hazards, such as by raising the temperature baseline for heatwaves or the atmospheric water-holding capacity for heavy precipitation.

The following typology further breaks down this general characterization of compound events into four main categories, the boundaries of which are often blurred and the understanding of which is unequal between classes: those where a hazard causes or leads to an amplified impact because of a precondition (preconditioned); events where multiple co-occurring drivers and/or hazards cause an impact (multivariate); events where sequences of hazards cause an impact (temporally compounding); and events where spatially co-occurring hazards cause an impact (spatially compounding). For each type, we introduce and explain the rationale, review key examples and discuss exemplary atmospheric or climatic processes and their relevant interactions (TABLE 1).

Preconditioned events

In a preconditioned event, one or more hazards can cause an impact, or lead to an amplified impact, only because of a pre-existing, climate-driven condition (FIG. 2a; TABLE 1). This classification is similar to the 'change condition' type in the multi-hazard literature[19], but, in the case of compound weather and climate events, both the precondition and the hazard(s) are caused

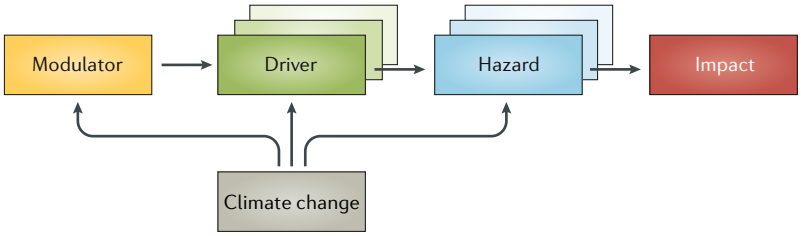

Fig. 1 | **Elements of a compound weather and climate event.** Overview of elements in the climate and weather domain that make up a compound event. Compound events consist of multiple climate drivers and/or multiple hazards (illustrated by the green and blue boxes, respectively) that potentially cause an impact (red box). Modulators (for example, the El Niño–Southern Oscillation) influence the frequency, magnitude and location of the drivers and, thus, possibly change hazard frequency and intensity. Climate change can affect all elements contributing to a compound event, that is, modulators, drivers and hazards. Arrows refer to a direct causal link between the different elements.

by weather or climate drivers. These drivers are not necessarily causally related, but they can be.

For example, preconditioning is a key element in the occurrence of large river floods in Europe[20] and the USA[21]. Here, floods (the hazard) often arise from a combination of saturated soils or extensive snow cover (the precondition) and precipitation and/or snowmelt (the driver), the latter of which is related to cyclones, severe storms and warm conveyor belts[22,23]. In high-latitude[24] and mountainous regions[25,26], rain-on-snow events also represent important flood-generating processes that typify preconditioning. On 10 October 2011, for instance, a rain-on-snow flood in the Bernese Alps, Switzerland caused CHF ~90 million of damage[27] (FIG. 2b). The event was caused by sustained snowfall (the driver of the precondition), leading to extensive snow cover (the precondition). When an atmospheric river (a narrow filament of intense water-vapour transport[28]) subsequently brought warm and moist air towards the Alps, it resulted in intense rainfall and a temperature increase that raised the freezing line from 1,500 m to 3,200 m in 24 h, driving snowmelt. The combination of these two factors (snowmelt and intense rainfall) gave rise to the flood[27] (the hazard).

Initial soil moisture is relevant not only for flooding but also for the incidence of wildfires, wherein dry conditions increase vegetation susceptibility to ignition. For instance, in the larch forests of Siberia, extreme wildfire occurrence (the hazard) can be explained by surface moisture conditions in the previous year[29] (the precondition). Furthermore, in the northern Mediterranean, the exceptional droughts of 2003 and 2016 also contributed to extreme wildfire events in France[30]. Owing to the tight link between soil moisture and precipitation, occurrence of rainfall during the fire season is the strongest control on burned area over the western USA, either directly through its wetting effects or indirectly through feedbacks to vapour-pressure deficit[16].

However, wildfires themselves can also be the drivers of the precondition. Indeed, during precipitation events, earlier fires can increase susceptibility to run-off and, thereby, flash floods (related to soil sealing), as well as mudflows (linked to loss of stabilizing vegetation and rapid ash mobilization)[31]. In 2013, for example, a flash flood in a Ugandan mountain valley killed several people and destroyed infrastructure, triggered by non-extreme precipitation but preconditioned by upstream fires and landslides[32].

Preconditioning is also highly relevant for climate impacts in biological systems[33]. For instance, early spring onset in temperate ecosystems can lead to higher vegetation activity and soil-moisture depletion (the precondition), thereby, potentially exacerbating carbon losses (the impacts) resulting from meteorological drought and heatwaves (the hazard) during summer[34,35]. Similarly, unusual warming events at the end of the winter season in temperate and boreal climates can encourage early vegetation growth (the precondition), causing greater impacts than would occur in the absence of warming when followed by a frost event (the hazard). These so-called 'false-spring' events regularly lead to extensive agricultural losses and damage to native forests[36], though impacts depend on the growth strategies of the affected species[37]. Indeed, a false-spring event in early 2010 in the north-eastern USA caused substantial damage to sugar maple trees[37] (FIG. 2c), while a similar event in Europe during 2017 resulted in EUR 3.3 billion of economic losses from damage to fruit trees and wine crops[38]. Weather conditions can also precondition the risk of livestock mortality, as demonstrated in Mongolia, where mass-mortality events have been linked to an amplifying effect of summer droughts on the mortality response to anomalously cold winters[39].

Multivariate events

Multivariate events refer to the co-occurrence of multiple climate drivers and/or hazards in the same geographical region causing an impact (FIG. 3a; TABLE 1). In such events, multiple drivers can cause one or more hazards (FIG. 3b) or, alternatively, a single driver can cause multiple correlated hazards (FIG. 3c). The notion of multivariate events thus includes concurrent climate extremes in the same location, also referred to as a 'compound hazard' in the multi-hazard literature[19,40]. Moreover, it incorporates extreme multivariate climate anomalies that are not necessarily extreme in the contributing variables, that is, the marginal distributions, but can, nevertheless, cause large impacts[41–43].

A commonly studied multivariate event is compound coastal flooding[5,6,44]. In coastal regions, floods often arise through a combination of multiple drivers, including storm surge, waves, high river discharge and direct surface run-off. These drivers are typically causally related through associated weather patterns (the modulator), for instance, when a storm[7] causes both extreme rainfall and storm surge. In Ravenna, Italy, during February 2015, for example, a low-pressure system produced a storm surge and heavy precipitation in multiple river catchments (the drivers), resulting in compound flooding (the hazard), which caused widespread damage totalling tens of millions of euros[44] (FIG. 3b). Compound flooding risk varies along coastlines and can be estimated indirectly by quantifying the dependence of extreme storm surge with either heavy precipitation[5,45–47] or extreme river discharge (the drivers)[11,48]. Elevated risk has been discovered at the coasts of Australia[45,46], North America[5,11]

and Europe[47], as well as Madagascar, northern Morocco, Vietnam and Taiwan[48].

Co-occurring precipitation and temperature extremes, for instance, concurrent drought and heatwave, provide an additional example of multivariate events, and can occur over various timescales. On shorter timescales, compound hot and dry conditions are attributable to stationary anticyclones, that is, atmospheric blocking[49], and to soil moisture–atmosphere interactions[50]. Such conditions can also promote downwind drought conditions, whereby advection of air masses causes abrupt increases in air temperature and soil desiccation[51]. At longer (seasonal) timescales, compound hot and dry summers (relative to their local climatology) occur particularly frequently in the south-eastern USA, the Amazon region, southern Africa, western Russia, large parts of India and northern Australia[52], probably because of strong land–atmosphere interactions[50].

Table 1 | **Examples of compound events according to the proposed typology**

Event	Modulators[a]	Associated weather systems	Precondition	Climatic drivers	Hazard(s)	Potential impacts
Preconditioned						
Heavy precipitation on saturated soil	–	Tropical and extratropical cyclones, severe storms, warm conveyor belts[22,23]	Saturated soil	Heavy precipitation	Flood, landslide	Infrastructure
Rain on snow	–	Extratropical cyclones[25,27]	Snow-covered land surface	Heavy precipitation, snowmelt	Flood	Infrastructure
False spring	–	Cold front	Early budbreak due to warm temperatures at end of winter	–	Frost	Crops, natural vegetation
Multivariate						
Compound flooding	–	Tropical and extratropical cyclones	–	Precipitation, coastal water levels, river flow, wind speed, wind fetch, duration of high wind speeds	Flood	Infrastructure, human health
Compound drought and heat	Sea-surface temperature patterns[55]	Atmospheric blocks	–	Temperature, precipitation, evapotranspiration, atmospheric humidity	Drought, heatwave	Wildfire, crops, natural vegetation, power plants, fisheries
Humid heatwave	–	Marine-air advection, tropical moisture export[160]	–	Temperature, atmospheric humidity	Heat stress	Human health, energy demand
Compound precipitation and wind extremes	–	Tropical and extratropical cyclones, severe storms[71]	–	–	Heavy precipitation, extreme wind	Infrastructure
Temporally compounding						
Temporal clustering of precipitation events	Large-scale climate modes[76,88]	Recurrent Rossby waves, blocking	–	Precipitation	Flood	Infrastructure, crops
Temporal clustering of storms	Large-scale climate modes[79,89]	Tropical and extratropical cyclones	–	Precipitation, wind speed	Flood, extreme wind	Infrastructure, human health
Sequences of heatwaves	–	Atmospheric blocks	–	Temperature	Heatwave	Human health, energy demand, crops
Spatially compounding						
Spatially concurrent precipitation extremes/floods at regional scale	Large-scale climate modes[99]	Storms, atmospheric blocks	–	Precipitation	Heavy precipitation, flood	Regional trade, (re-)insurance, shipping, emergency response
Spatially co-occurring climate extremes at global scale	Large-scale climate modes[93], circumpolar wave patterns[96]	Dependent on the type of extremes	–	Temperature, precipitation, evapotranspiration, atmospheric humidity	Heavy precipitation, flood, drought, heatwave, frost	Global food system, globally operating (re-) insurance

[a]Modulators are included only if they have been identified explicitly in the literature.

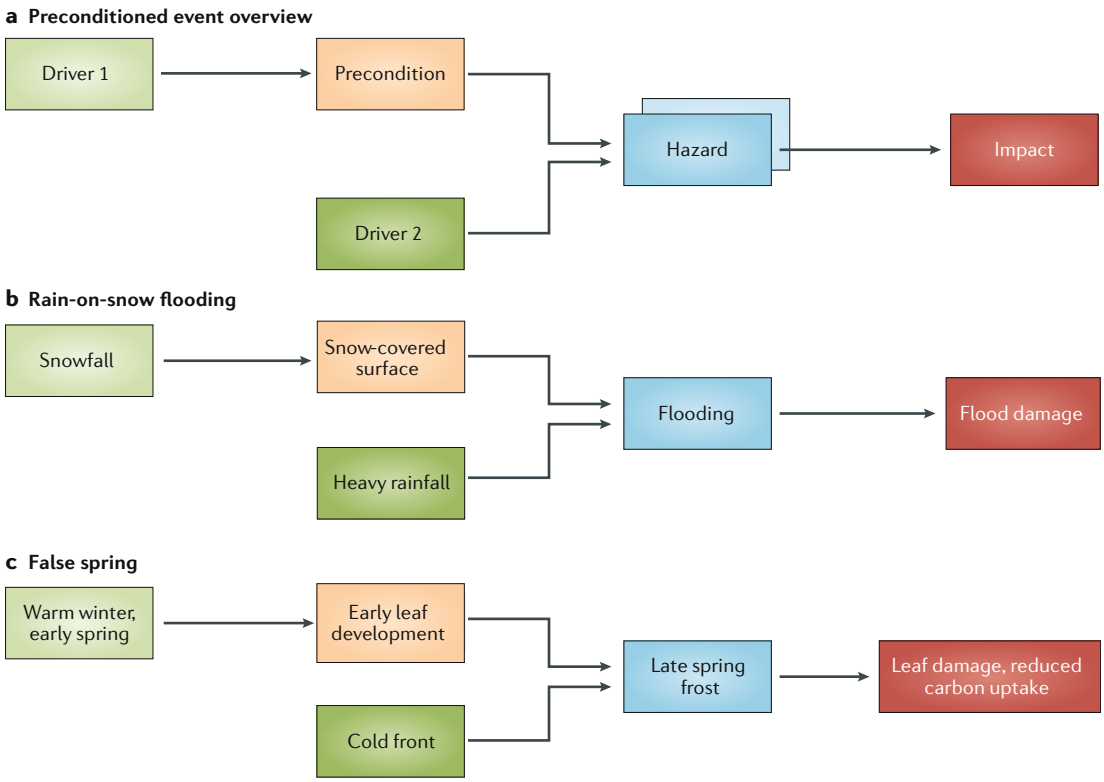

Fig. 2 | **Preconditioned events. a** | Key elements of preconditioned events. **b** | The main features of a rain-on-snow flooding, for instance, in the Lötschen Valley, Switzerland on 10 October 2011 (REF.[27]). **c** | The main features of the false spring event, for instance, in the north-eastern USA during 2010 (REF.[37]). The precondition is a necessary cause for a hazard to cause an impact or strongly amplifies the impact of a hazard.

In many regions, the concurrence of drought and heatwave is closely related to the ENSO, including South Africa[53], South America[54] and the USA. In Texas during 2011, for example, sea-surface temperature patterns that resemble the characteristics of La Niña events[55] (the modulator) promoted stationary Rossby waves (the driver), which, in turn, established compound hot and dry conditions (the hazards) (FIG. 3c). Land–atmosphere feedback further intensified these conditions, which caused record statewide agricultural losses, record-breaking wildfires and massive commercial timber loss[55].

Indeed, compound and extended hot and dry conditions generally lead to tree mortality[56,57], crop failure[58], large reductions in carbon uptake[59–62], wildfires[30,63], thermoelectric power plant failures[64] and are a key climate feature of many weather-related disasters[65]. When precipitation deficits and high temperatures combine with low humidity and strong winds, increased evapotranspiration can quickly deplete soil moisture. Such conditions can cause flash droughts, with often severe impacts on crop yields, livestock forage production and natural ecosystems[66].

Concurrent warm and wet extremes can also lead to severe impacts. In January 2018, for instance, anomalously warm and wet conditions occurred across the Western Alps, triggering widespread landslides at low elevations and massive snowfall higher up, causing critical discharge levels and threatening popular ski resorts owing to a substantially increased avalanche risk[67].

Co-occurring wind and precipitation extremes also exemplify multivariate events. In the mid-latitudes and the subtropics, such events are typically associated with strong extratropical and tropical cyclones, respectively[68], with widespread impacts[69–72]. For example, the strong wind gusts of winter storm Kyrill in 2007 caused substantial damage to buildings and infrastructure that were further exacerbated by heavy rainfall[69]. In several storms, heavy precipitation was caused by thunderstorms located in the unstable air behind the cold front[69,71].

Temporally compounding events

Temporally compounding events refer to a succession of hazards that affect a given geographical region, leading to, or amplifying, an impact when compared with a single hazard (FIG. 4a; TABLE 1). The hazards are promoted by one or more drivers, which, in turn, are caused by a modulator. The succession of hazards can be of the same type (for example, multiple tropical cyclones[73], heatwaves[74,75] or heavy-precipitation events[76]) or consecutive occurrence of different hazards (for example, a flood[77] or tropical cyclone[78], followed by a heatwave). The hazards in temporally compounding events can be correlated through a common driver, directly related as cascading hazards[19] or simply occur by chance. In practice, it is often difficult to distinguish these cases because of limited sample size and an incomplete understanding of the system.

Temporal clustering has been studied extensively for extratropical[79–82] and tropical cyclones[73]. It is widely

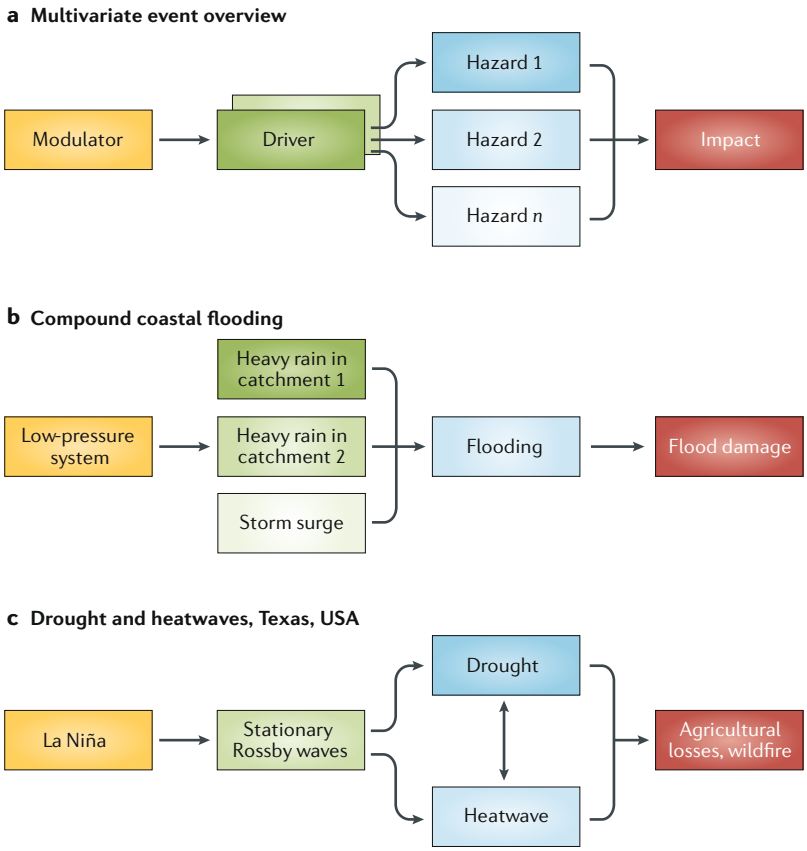

Fig. 3 | **Multivariate events. a** | Key elements of multivariate events. Various boxes of different shading illustrate the possible occurrence of multiple drivers and/or multiple hazards. **b** | The main features of compound coastal flooding, for instance, in Ravenna, Italy during February 2015 (REF.[44]). **c** | The main features of the record-breaking hot and dry summer in Texas, USA during 2011 (REF.[55]). In multivariate events, the impact only occurs (or is more severe) owing to co-occurrence of multiple drivers and/or multiple hazards.

known, for example, that cyclone clusters (multiple cyclone drivers) arise owing to secondary cyclogenesis along trailing fronts and/or persistent and recurrent favourable jet states[79,83,84] (the modulator). The occurrence of cyclone clusters is further related to, and influenced by, modulators such as large-scale teleconnection patterns[85–88], tropical forcing[89] and persistent atmospheric-circulation patterns[76]. For instance, significant temporal clustering of strong cyclones is observed over the eastern Atlantic, the downstream area of the Atlantic storm track and over the central Pacific[79]. The severe storms Lothar and Martin crossing Europe in December 1999 (REF.[81]) and the clustering of storms hitting the UK in January 2014 (REF.[89]) provide high-impact illustrations of temporally compounding extratropical cyclones. Tropical clustering is also apparent in parts of the Caribbean and along the coast of Central America[85].

Temporal clustering of heavy-precipitation events on sub-seasonal timescales is also commonplace, increasing the risk of flooding. In southern Switzerland, for instance, multiple heavy-rainfall events (the drivers) linked to upper-level Rossby-wave breaking resulted in substantial lake flooding (the hazard) and corresponding damage[76] (FIG. 4b). However, as mentioned previously, temporal compounding events can also refer to multiple hazards. In July 2018, for instance, factors influencing the East Asian summer monsoon drove consecutive flooding and heatwaves (the hazards) in southern Japan, resulting in 300 deaths and vast economic losses[77] (FIG. 4c).

Temporally compounding effects relevant for vegetation are dependent on the temporal convolution of several time-continuous drivers. For instance, an increased wildfire frequency in south-eastern Australia can tip a eucalyptus forest to a non-forest state[90]. The extreme 2016 wheat loss in France has further been attributed to a combination of unusually warm temperatures in late autumn and unusually wet conditions in the following spring[91].

Spatially compounding events

Spatially compounding events occur when multiple connected locations are affected by the same or different hazards within a limited time window, thereby causing an impact (FIG. 5a; TABLE 1). The compounding of hazards in different locations is established via a system capable of spatial integration, which accumulates hazard impacts in spatially distant locations. The hazards and hazard drivers are often caused by a modulator[92], which creates a physical link between the different locations.

Impact-integrating systems can operate at the global or regional scale. On the planetary scale, the spatially synchronized occurrence of hazards and associated impacts can be imposed by large-scale modes of climate variability, such as the ENSO[93,94], atmospheric teleconnections[95] or driven by circumpolar-wave patterns[96]. The global food system provides one such illustration, wherein synchronous crop failure due to spatially co-occurring hazards[2] poses a potential threat to food security[94,97], with wide-ranging economic impacts[98]. In 1983, for example, a strong El Niño event (the modulator) fuelled heatwaves and droughts in crop-producing regions (South Africa, North America and Brazil — the hazards), resulting in the largest synchronous wheat failure in modern history[93] (the impact; FIG. 5b). On more regional scales, atmospheric teleconnections[99] and individual weather systems like atmospheric blockings[100] or storms — such as Lothar[101] and Ophelia[102] in Europe — can cause spatially correlated hazards, including heavy precipitation and wind extremes.

In addition to the physical climate hazards, substantial risk also arises in a more societal respect. For instance, an energy system largely based on renewables can be highly vulnerable to weather conditions, which, in certain circumstances, might lead to low energy output from solar panels and wind turbines in multiple regions concurrently[103], increasing the risk of power failures. Road and railway networks are also highly vulnerable to spatially co-occurring climate hazards, especially surface and river flooding, which regularly cause significant damage[104]. Similarly, concurrent storm surges over extended coastline stretches can damage multiple ports, causing interruption in national or international supply chains[105].

Emergency-response actions are an additional impact integrator affected by spatially correlated hazards. For instance, the spatial distribution of up to 250 simultaneous wildfires in the late-season 2017

northern California 'firestorm' (the hazards) — linked to low humidity and strong winds[106] (the drivers) — overwhelmed the ability to respond, leading to extreme impacts[18] (FIG. 5c). Spatially co-occurring floods can also affect emergency response. The 2010/2011 wet season in Australia, for example, led to several floods in different regions, affecting many agencies, including state and federal governments, insurers, mining and agriculture industries[9].

Indeed, river systems can be viewed as regional integrators of correlated precipitation extremes. For example, in 2016, a large area of Louisiana, USA, experienced widespread flooding when multiple tributaries of the Mississippi river were simultaneously flooded, the water of which drained downstream, leading to overtopping of floodwalls and levees, causing a human disaster and significant socio-economic impacts[107]. Similarly, correlated extreme river discharges that caused large flood events affecting multiple countries in Europe at the same time put great pressure on transnational risk-reduction and risk-transfer mechanisms[108,109].

Soft boundaries

While the above four categorizations of compound events are comprehensive, the imposed boundaries are subjective. Thus, not all events fit perfectly into the presented categories, and some cannot be easily assigned to a single type, necessitating soft boundaries. For instance, the extremely hot and dry 2011 summer in Texas, USA, is presently placed as a multivariate event, given its connection to a modulator (FIG. 3c). However, dry soils associated with an earlier precipitation deficit also amplified the magnitude of the heatwave and drought via land–atmosphere feedbacks, falling into the precondition category (FIG. 2). In fact, such a combination of a multivariate event (sea-surface temperature patterns or an atmospheric block) and preconditions (dry soils) are a common feature of compound hot and dry events[50,110]. Similar combinations are also commonplace in coastal flooding, wherein deep and extensive low pressure causes a storm surge and heavy precipitation (multivariate), amplified by saturated soils (the precondition), as observed in the Netherlands in January 2012 (REF.[8]).

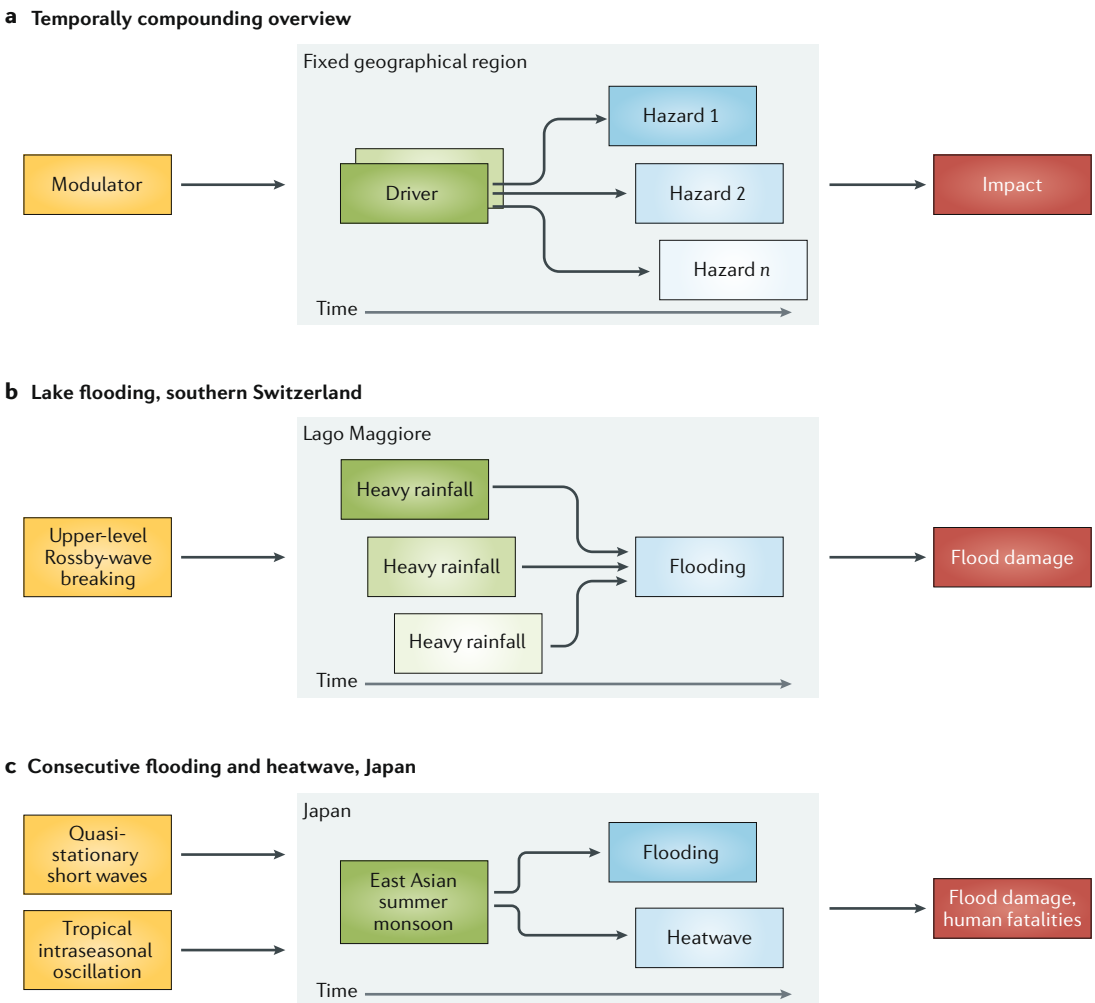

Fig. 4 | **Temporally compounding events. a** | Key elements of temporally compounding events. **b** | The main features of the Lago Maggiore, southern Switzerland, flooding from 19 September to 16 October 2000 (REF.[76]). **c** | The main features of a consecutive flood and heatwave event in Japan during July 2018 (REF.[77]). In temporally compounding events, a modulator causes one or multiple drivers, which, in turn, cause multiple subsequent hazards in the same geographical region, causing (or amplifying) impact.

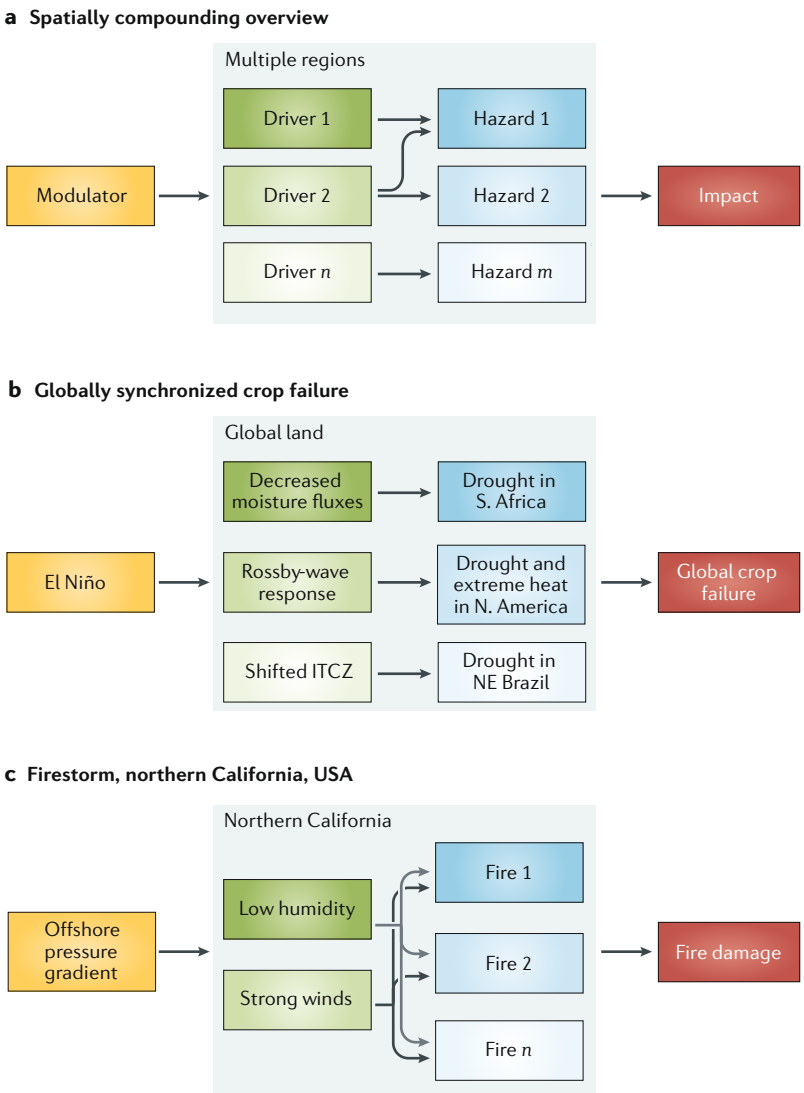

Fig. 5 | **Spatially compounding events. a** | Key elements of spatially compounding events. **b** | The main features of a globally synchronized maize failure event in 1983 (REF.[93]). **c** | The main features of firestorm events in northern California during 8–9 October 2017 (REF.[106]). In spatially compounding events, a modulator causes near-synchronized combinations of drivers and hazards in different regions, impacting the same system. ITCZ, Intertropical Convergence Zone.

In addition, it is often challenging to separate preconditioning and temporally compounding events. For instance, the succession of a warm period at the end of winter and a frost event in spring (a preconditioned 'false spring') can also be interpreted as a temporally compounding event. Conversely, the temporally compounding extreme wheat loss in France during 2016 could alternatively be interpreted as a preconditioned event wherein a mild autumn and winter favoured the build-up of parasites, leading to large-scale disease spread when wet conditions followed in spring[91].

These examples illustrate the diversity and complexity of compound-event processes. In practice, an event will often be a combination of two or three categories. Separating out the different elements will help with further analysis and provide guidance on which approaches to use to study different parts of the event.

Methods for compound-event analysis

Compound-event research aims to increase understanding of key physical processes contributing to an event, improve their prediction, assess associated risks, explore suitable adaptation strategies and quantify projected changes. Thus, an additional goal of the proposed typology is to facilitate and provide guidance for the usage of appropriate analysis and modelling tools, as is now discussed. However, since there is no clear distinction between the proposed classes, the analysis of a given event might require a combination of different approaches. Moreover, owing to the diversity of possible compound events, adaptation of the methods below will likely be required in most cases.

Diagnosing compound-event drivers

The typology provides guidance on the broad classes of causal structure for compound events, which subsequently need to be populated by specific drivers, modulators, preconditions and hazards that collectively lead to the impacts. An initial step for the analysis of compound events is to understand the underlying phenomena (such as which hazards might cause an impact) and identify the hazards' drivers.

In some cases, the causal mechanisms underlying specific events (that is, the connection between modulators, drivers, hazards and impacts) are well documented and congruent with impact models that have a strong physical basis for that class of event. For example, it is known that heat stress in humans and other mammals (such as livestock) is dominated by the combination of temperature and humidity, and, to a lesser extent, by solar radiation and wind[12]. If, however, drivers are unknown, compositing a large number of cases of a given phenomenon can be used both to identify key variables and to understand the physical processes[5,7,46,47,111]. For instance, composite meteorological maps of events causing concurrent storm surge and river-discharge extremes can reveal their atmospheric drivers[7]. Recent advances in dynamical-systems theory for studying joint recurrences[112] have also been successfully applied to reveal the drivers behind spatially and temporally concurrent extremes in wind and precipitation[113]. Here, composites of locations with high joint recurrence rates (that is, a high likelihood of concurrent extremes) are related to atmospheric conditions.

For more complex cases, the key variables (drivers and hazards), and particularly their associated spatial and temporal scales, might not be immediately obvious. For example, the Lake Como reservoir[114] is used to provide hydropower, flood protection and irrigation water supply for downstream districts. Weather and climate influence the system through multiple points of interaction, including: reservoir inflows (affected by the timing and magnitude of rainfall and evaporative processes, combined with snowmelt), water demand, long-term trends in precipitation and evaporation, physical system constraints (how quickly floodwater can be released from the reservoir) and operational policies. Understanding the precise combination of climatic variables (and their associated temporal and spatial scales) that could trigger system failure (and, hence, an impact) might, therefore,

be difficult to assess without a deep understanding of the system, including the human dimension of the problem. Similar issues arise when seeking to understand the key climatic drivers for a range of complex systems that provide water, energy and food security, transport and protection from natural hazards.

For these more complex cases, system-sensitivity analyses (including 'stress tests' or using bottom-up or scenario-neutral assessment methodologies[115]) can identify the most important combinations of weather and climate variables (as well as their spatial and temporal scales) that dominate system performance (that is, exert strong influence on key system variables) and associated societal and/or environmental impacts[116]. The qualification 'bottom-up' refers to the experimental design that starts by defining the system objectives and associated performance boundaries, together with the system boundaries, followed by exploration of the relevant combination of variables that might cause degradation in performance (for example, the capacity of the system to provide flood-mitigation and water-supply functions for the Lake Como system). Bottom-up approaches can also be used to identify multiple climate drivers of extreme impacts[65,117,118]. For a hydrological system, for instance, a scenario-neutral approach could be to systematically vary temperature and precipitation (annual averages, seasonality, extremes, intermittency and interannual variability) within plausible boundaries, providing inputs for models that can determine, for example, the low-flow response. Thus, the non-linear changes or climate drivers that lead to system thresholds being crossed can be identified[115].

Quantifying compound effects

Having identified key variables and scales relevant to specific impacts (the causal structure of the compound event, TABLE 1), it is necessary to identify the strength of relationships between the different causal components (modulators, preconditions, drivers and hazards) in order to assess the likelihood of an event[19,119]. These relationships can exist in time, space and between variables, and can propagate through scales via conditioning relationships[120]. A wide range of modelling tools have been developed to study the strength of the relationship between multiple drivers[121] and to derive multi-hazard scenarios[43]. Here, we provide examples of approaches that have been applied in a compound-event context.

Preconditioning. One approach to disentangle preconditions of high-impact events consists of regression techniques[20,29,35,122] and event compositing[30], requiring a sufficiently long data set. For instance, a multiple linear regression revealed the importance of previous-summer surface moisture for extreme fire occurrence in the Baikal region in Russia[29]. Alternatively, one can conduct controlled factorial experiments in which one (conditioning) factor is altered, while everything else is kept equal. This approach isolates the influence of one factor on a desired target variable, similar to factorial experiments in medicine to test the effectiveness of a drug. Conducting such experiments using observational data alone is often not possible, given the difficulty of controlled interventions in large, complex systems. In this case, process-based models that have been demonstrated to simulate key processes[27,34] can be employed. For example, atmospheric circulation can be kept constant, while sea-surface temperatures are changed in model experiments designed to study the occurrence of atmospheric blocks[123]. Similarly, a vegetation model can disentangle how favourable spring conditions with an elevated photosynthesis rate deplete soil moisture and, thus, exacerbate negative impacts of summer droughts and heatwaves on plant carbon uptake[34].

Dependence between variables. The joint dependence between multiple drivers or hazards can be represented statistically using multivariate probability distribution functions, which represent both the marginal and joint features of multiple random variables. The most common depiction of dependence is the correlation coefficient, which is directly related to the covariance of a bivariate normal distribution, a concept that is easily extended to higher dimensions. Copula-based approaches[119,121,124] significantly expand the number of multivariate models and can represent asymmetric dependencies. Copulas are used to represent the dependence within complete multivariate distributions, and non-stationary approaches based on dynamic copulas have been proposed to incorporate changing climatic conditions[125–127]. Copulas can also be used in a Bayesian network framework, where a set of variables and their conditional dependencies are modelled with a graphical representation. This approach has been applied to model compound flooding, including riverine and coastal interactions at the Houston Ship Channel in Texas[128]. Multivariate extreme-value modelling[129] focuses only on the tails of the joint distribution, including the behaviour of extremal dependence in the tails. Choosing the appropriate temporal and spatial scales for an event of interest is challenging and becomes even more difficult in higher dimensions. Process-based model experiments can also be designed to understand the potential impacts of compound events through testing a wide range of hazard scenarios[8].

Temporal dependence. Clusters or sequences of events are commonly studied with point processes, for instance, Poisson processes[129]. The strength of clustering can be assessed by testing the homogeneity of the process[76,88]. The influence of modulators on the clustering can be analysed by regressing the frequency of events against teleconnection indices[73,79,86]. For instance, the clustering of extratropical cyclones in the North Atlantic region and western Europe is related to the North Atlantic oscillation and the East Atlantic pattern[79]. In a similar way, non-homogeneous Markov models provide a means of representing temporal dependence of weather variables, as well as their dependence on large-scale weather and climate drivers[130].

Spatial dependence. Spatial extremes can be modelled with various dependence measures, including the extremal coefficient and the semivariogram[131]. For instance, applying the indicator semivariogram, spatial

scales of observed precipitation extremes have been investigated in the USA[132]. The application of a spatial extreme-value model, more specifically, a max-stable process, revealed that daily rainfall extremes tend to co-occur along the crest line of the Massif Central in the French Mediterranean region[133]. With a similar approach, the dependence between extreme rainfall in a catchment near Sydney, Australia, was modelled, while additionally accounting for the varying hydrological response times of subcatchments, which is highly relevant for assessing the risk of critical infrastructure such as road networks[134]. If an integrating system such as a river network is involved, methodological adaptations to this approach are needed[109]. At larger spatial scales, dependencies between extremes can be revealed through composite analysis[135] or networks of event synchronization[95].

Mapping drivers on impacts

Once key dependencies between drivers and hazards are understood and modelled, they need to be mapped to potential impacts. This mapping is often done using predefined 'hazard scenarios', which represent combinations of events that are of interest. Choosing the most appropriate hazard scenario in a specific setting is usually a somewhat subjective decision that depends on the event context, objective, expert judgement and available data. For example, in a bivariate space, the so-called 'and' hazard scenario corresponds to concurrent exceedance of two variables above a predefined threshold[136]. Using the 'and' scenario can be appropriate for analysing compound hot and dry conditions[52], which lead to particularly large impacts on ecosystems when they co-occur[60]. The 'or' hazard scenario, by contrast, refers to exceedances of either variable above their respective predefined threshold, which might be an appropriate choice to investigate coastal flooding that can occur by either high ocean-water levels or high fluvial flows[6]. If the impact function is known or can be estimated[137], there is no need to use predefined hazard scenarios, as the impact for different combinations of drivers can be directly calculated[136] and the effect of driver dependencies on the impact can be investigated[44]. Estimating the likelihood of an impact via hazard scenarios has mostly been applied for bivariate events[136] but should, in principle, be applicable to all types of compound event.

Typically, compound events are found in a small corner of a multidimensional probability space, making it difficult to assess their occurrence probability. Robust analyses, therefore, require many samples, which can be achieved either by very long time series or large-ensemble model simulations[138]. All process-based model simulations are characterized by model biases, which vary across the multivariate distribution of key variables, requiring extra care when such simulations are bias-adjusted to model compound-event impacts[139]. Validating model simulations with a compound-event focus is methodologically challenging and might reveal previously undetected limitations in commonly used observational data sets. For instance, evaluating the interannual correlation between summer temperature and precipitation — a relevant metric for the probability of concurrent drought and heatwaves — revealed that commonly used observation-based data sets do not offer a sufficient constraint in large parts of the Southern Hemisphere; specifically, it is unclear whether the differences between models and observation-based data sets stem from model errors or the way limited station observations are processed to generate a gridded data product[52]. For very complex or rare events, storyline approaches[140] might be more appropriate than standard probabilistic approaches based on simulations.

In principle, a wide variety of statistical-modelling approaches are available to deal with many aspects of compound events, as discussed above. Over recent years, several crucial innovations have been put forward to deal with multivariate extreme events in particular. Compound-event analyses relevant for risk assessment are rare because the sampling of the relevant tail region by observations is sparse by definition. Thus, estimates of dependence in the tails of a distribution are often very uncertain, a limitation that is even more relevant in a climate-change context. Indeed, for a good estimation of risks associated with compound events in a changing climate, a correct representation of the causal relationships between drivers and hazards in statistical or process-based models is essential.

Climate change and compound events

As anthropogenic climate change is anticipated to alter the distributions of virtually all climate variables[141] and some of their dependencies[52], it can be expected that trends in the likelihood of compound events will be observed over decadal to multi-decadal timescales. The proposed typology aids in disentangling the effects of climate change on the different elements of a compound event (FIG. 1), including the preconditioning drivers, hazards and modulators (and, thus, the multivariate characteristics of drivers and hazards), as well as the spatial and temporal scales of events and their spatio-temporal dependencies. However, rigorous attribution of changes in compound events due to human-induced climate change is challenging owing to the small sample size and low signal-to-noise ratio.

Nevertheless, several studies have examined potential climate-change effects on the occurrence and intensity of some compound events. Indeed, interactions between rising sea levels, storm surges[142] and fluvial flooding[6] are likely to produce more frequent and more intense compound coastal-flooding events (multivariate events). For example, compound precipitation–storm-surge flood risk is projected to more than double along large parts of the northern European coasts, mostly driven by increases in heavy precipitation[47]. Moreover, an increase in the dependence between storm surge and heavy precipitation has been observed at many stations along the coasts of the USA[5], resulting in increased compound-flooding risk.

In general, an increase in temperature is also anticipated to increase the frequency of compound dry and hot conditions (multivariate events; FIG. 6a), even in regions where precipitation trends are negligible[126] or even positive[58], posing threats to forests[56] and crops[58,126]. In fact, in recent decades, the frequency of compound

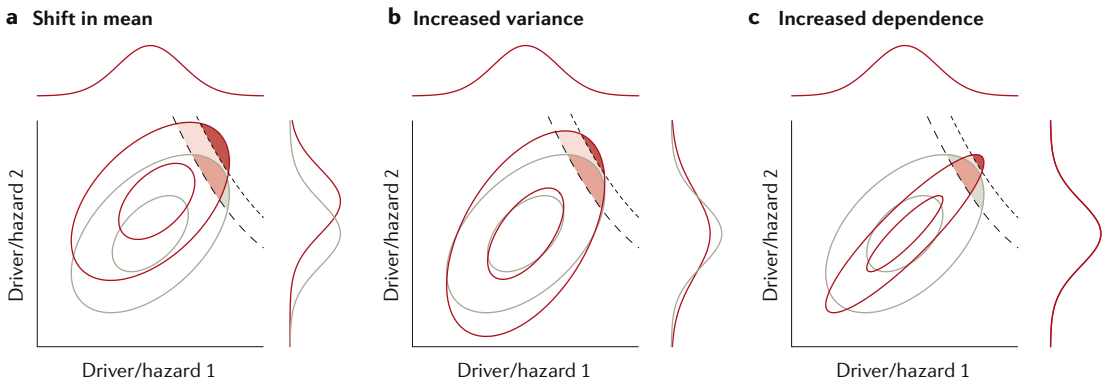

Fig. 6 | **Climate-change effects on compound events.** Hypothetical responses in the probability of compound events (shift of the bivariate distribution from grey to red) arising from a shift in the mean of driver or hazard 2 (panel **a**), an increase in the variability of driver or hazard 2 while holding correlation between the variables constant (panel **b**) and an increase in the strength of the dependence between driver or hazards 1 and 2 (panel **c**). The illustrated patterns can occur in combination and have an impact on both the frequency and the magnitude of compound events. The dashed line indicates a threshold with moderate impact, assumed fixed for present and future climate conditions. The dotted line denotes a threshold that is only exceeded under changed climate conditions, illustrating the emergence of new compound events, potentially causing impacts with unprecedented magnitude. Consequently, the coloured areas highlight events with a moderate (light shading) and a large (darker shading) impact, respectively.

drought and heatwave events has already increased by >25% in large parts of the USA[143], Europe[144] and India[145]. In addition, the dependence between temperature and precipitation is projected to increase in many land areas, particularly in the Northern Hemisphere, leading to a doubling in probability of extremely hot and dry summers on top of long-term climate trends[52]. These changes in compound heat and drought are not only linked to shifts in precipitation patterns and temperature but also by long-term trends in atmospheric CO_2 concentrations and corresponding shifts in water-use efficiency, which amplifies heat extremes due to reduced evaporative cooling[146,147]. Conversely, the reduced evapotranspiration can reduce the duration and intensity of droughts[148], although increases in the total amount of vegetation in a higher-CO_2 world would be an offsetting factor[149,150]. The effects of increasing temperatures can also be counter-intuitive. For instance, a 2 °C warmer world might increase frost-damage risk for apple fruit trees in Germany up to 10% relative to the present day[38]. This increased damage occurs because warmer winters lead to earlier blossom of fruit trees, increasing their exposure to frost days after apple blossom, which counteracts the effect of a general decline in the number of frost days (false spring, preconditioned event).

Climate change can also alter second-order statistics such as interannual variability, serial clustering and the dependence between compound-event drivers, thereby, affecting the risk associated with all types of compound events. An increase in variability in one hazard or driver can substantially increase the risk of compound events in a multivariate setting (FIG. 6b). For instance, a 25% to 100% increase in extreme dry-to-wet precipitation events has been identified for California for the twenty-first century[151] (temporally compounding), posing serious challenges to California's water infrastructure and wildfire risk[152]. Similarly, a projected increase in variability of maize yields due to climate change increases the probability of simultaneous large production losses in any given year from virtually zero today to 7% and 86% under 2 °C and 4 °C warming, respectively[153] (spatially compounding). Global crop risk failure might also emerge from increases in the spatial coherence in temperature variability[154], leading to more frequent spatially concurrent heatwaves (spatially compounding). Such increases have already led to a significantly increased risk of simultaneous crop failure in the major breadbasket regions across the globe for wheat, maize and soybean between the time periods 1967–1990 and 1991–2012 (REF.[155]). Similarly, an increase in the spatial scales of synchronous river flooding in Europe over the past 50 years[156] requires reconsideration of cross-national risk-reduction measures (spatially compounding). An intensification of the dependence between drivers or hazards increases the risk of compound events (FIG. 6c) and has been identified for compound flooding[5] and drought-heat events[52] (multivariate events).

As well as changing the frequency and intensity of existing compound events, anthropogenic warming will also facilitate the emergence of new types of compound events. For instance, weather conditions might change in a way such that tropical cyclones can occur in regions that typically do not experience them, such as Western Europe[157], potentially leading to compound heavy precipitation, storm surge and wind extremes higher than previous thresholds (multivariate events). Furthermore, a successive deadly heatwave can compound the impacts of a tropical cyclone (temporally compounding) and pose a serious threat to humans, given the strong reliance on air conditioning in tropical regions and the fact that tropical cyclones often lead to mega-blackouts. Increases in global mean temperature could increase the number of people that experience at least one such event in a 30-year period from currently 0.4 million to 2 million at 2 °C and 11.8 million at 4 °C global warming[78].

By affecting the characteristics of modulators, the location and intensity of drivers, and the probability distribution of drivers, hazards and their spatio-temporal

dependence structure, climate change has already shifted and will continue to shift the likelihood of compound events of all types. Even changes in a single variable can affect overall risk (FIG. 6a,b). Climate-change effects can manifest as changes in preconditioning variables (preconditioned events), changes in dependence between variables (multivariate events), changes in temporal structure (temporally compounding) and changes in dependence between different locations (spatially compounding).

Summary and future perspectives

Compound weather and climate events are an integral part of almost all climate-related risks and pose significant challenges to many risk-reduction measures. Therefore, better understanding and modelling of compound events is crucial for better risk assessment, improving understanding of the key processes. However, current approaches for compound-event analysis and modelling are extremely diverse and depend on several subjective choices, such as identifying the relevant compounding mechanisms and variables, a reasonable hazard scenario, a representative dependence model and appropriate temporal and spatial scales. In this Review, we, therefore, proposed a typology that identifies four distinct categories of compound events: preconditioned, multivariate, temporally compounding and spatially compounding. Although, in many cases, an event cannot be fully described by a single type, the classification aids in structuring the vast variety of events (TABLE 1) and provides a starting point for selecting the appropriate modelling tools for analysis.

The four types provide a basis for a unified language to discuss compound effects across different scientific disciplines and sectors. Similar modelling approaches can be used for events with similar causal structure, even if the events themselves apply to very different impact domains, such as biological systems and human infrastructure. In this way, the typology paves the way to a unified set of compound-event-analysis tools for a wide array of applications.

This typology is critical not only in today's climate to improve adaptation but also in the future climate, where traditional univariate approaches tailored to historical conditions might be highly inadequate. Moreover, given that anthropogenic warming has already affected various characteristics of compound events, and could lead to new types of events in the future, there is a clear need for a systematic approach to compound-event classification this typology offers.

Clear guidelines such as recommendations and analysis protocols on how to select key compounding mechanisms and their temporal and spatial scales are needed, which will depend on the research question. Furthermore, approaches that assess the suitability of process-based models to simulate compound events need to be developed. These could be new evaluation metrics that are sensitive to compound events in appropriately region-specific and/or sector-specific ways. A common compound-event-analysis framework based on the typology presented here would provide guidance on identifying the most relevant elements of a compound event, given data limitations; offer analysis tools for a spectrum of research questions and compound-event types; and, ultimately, aid in anticipating impacts on all affected sectors. Complementarily, there is a need for increasing the completeness and consistency of impacts data, to identify the most important weather and climate drivers. Compound-event analysis often demands larger sample sizes than quantitative historical records can provide, a limitation that can be overcome partly by incorporating operational-forecast data[158] and large climate-model ensembles[159], and partly by using methodologies that can make the most of incomplete data sets. Climate models also enable hypotheses about complex climate-change responses to be rigorously tested. Finally, the interdisciplinary collaboration between climate and impacts modellers, engineers, statisticians and risk experts[17] — which has been so successful to date — must be continued to ensure progress in compound-event research.

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Author contributions

J.Z., O.M. and A.M.R. drafted the first ideas of the classification. J.Z. and O.M. conceived the main structure, created Figs 1–5 and wrote the first draft of the manuscript. J.Z. created Fig. 6. J.Z. and S.W. wrote the 'Methods for compound-event analysis' section, with substantial input from E.B., A.J., D.M. and E.V. All authors made substantial contributions to the discussion of content.

Competing interests

The authors declare no competing interests.

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