Socio-environmental extremes: rethinking extraordinary events as outcomes of interacting biophysical and social systems

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JB and WT designed and directed the project; VI, AB, MR, and MJ contributed substantially to the writing and editing, managing data inputs, and visualizations; AM, AB, and VI managed the references; AM contributed data and helped design visualizations; BM contributed data; All authors discussed the conceptual framing and contributed to the final manuscript.

Key Points:

- Many extreme events have social and biophysical dimensions that are linked.
- This review provides a definition and framework for understanding these events, termed socio-environmental extremes.
- A proposed research agenda will help scientists better understand and predict the extremes that matter to society.

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Abstract

Extreme droughts, heat waves, fires, hurricanes, floods, and landslides cause the largest losses in the United States, and globally, from natural hazards linked to weather and climate. There is evidence that the frequency of such extremes is increasing, particularly for heat waves, large fires, and intense precipitation, making better understanding of the probability and consequences of these events imperative. Further, these events are not isolated, but rather interact with each other, and with social and ecological vulnerability, to amplify impacts. Less is known about the nature and strength of these interactions. Natural and social science subfields frame extreme events with different definitions and analytical approaches, and most analyses neglect interactions and the subsequent novel extremes that can arise. Here we propose a framework for socio-environmental extremes, defined as extraordinary events that emerge from interactions among biophysical and social phenomena and have some degree of social impact. We review how different fields approach extremes as interacting phenomena and propose a synthetic framework for conceptualizing and defining extremes from both an environmental and social perspective. This approach recognizes multiple drivers and responses that yield extreme events and extreme outcomes, and reconciles the gap between understanding extremes as biophysical processes and their social underpinnings and impacts. We conclude with a future research agenda that adds clarity and direction to understanding the extreme events that matter to society. This agenda will help to identify where, when, and why communities may have high exposure and vulnerability to socio-environmental extremes—informing future mitigation and adaptation strategies.

Plain Language Summary

The frequency and magnitude of some extremes are increasing, e.g., heavy downpours, heat waves, and wildfires, while vulnerabilities in ecosystems and human infrastructure and livelihoods are also changing. This review defines extremes across both their social and environmental dimensions, helping to establish the extremes that matter to society. In 2017, large portions of the western U.S. saw the wettest winter season, the hottest summer temperatures, and one of the driest falls ever recorded—leading to one of the largest and most devastating wildfire seasons in California, which were then followed by deadly mudslides that were partly a response to the burned landscape. This suite of events forces the questions: Are extremes increasing because of changes in natural events or social vulnerability, or both? Are extremes isolated events, or are they acting in concert or emergent from linked biophysical and social drivers? This review establishes a critical set of research questions that need to be addressed to better diagnose, predict, and mitigate extremes—one of the most pressing scientific challenges of our time.

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1. Introduction: Going to extremes

Extreme events disrupt the functioning and well-being of socio-environmental systems, yet less is known about how the interactions among these systems precipitate extremes. Recent disasters have captured societal and scientific attention due to both the extreme attributes and societal costs, including hurricanes Haiyan, Katrina, Sandy, Maria; droughts in Australia and California; floods in Europe and South and Southeast Asia; heat waves in Russia, Europe and India; and wildfires in Australia, Spain, and the U.S. These events not only overwhelm local and national response systems and mitigation resources, but disrupt local ecosystems (e.g., the impact on Puerto Rico habitats and species from Hurricane Maria and previous storms; Boose et al., 2004; Uriarte et al., 2019). Further, these extremes may reduce our ability to maintain species and habitats (Harris et al., 2018) and compromise global sustainable development (United Nations International Strategy for Disaster Reduction (UNISDR, 2015).

These events reveal significant and growing social vulnerabilities. Dramatically increased economic losses due to extremes come from growing wealth and exposed development (Barthel & Neumayer, 2012), but also from global environmental change that alters the atmospheric energy budget, leading to more extreme weather and climate conditions (Herring et al., 2016; A. B. Smith & Katz, 2013). Less is known about trends in ecological implications of extremes (Smith 2011), though land use and cover changes affect the baseline conditions governing ecosystem assemblage (Bagley et al., 2013; Gauthier et al., 2015; Staal et al., 2018; World Wildlife Fund, 2018) and may reduce the buffering capacity of some systems (e.g., deforestation itself contributes to drought (Bagley et al. 2014; Staal et al. 2018). Further, these events can surprise human management systems (e.g., supply chain disruption from the 2011 Thailand floods), and even cause failure of response strategies designed for extremes (e.g., fire-fighting, evacuation plans, and forecast and warning systems under recent California and Canada wildfires and Katrina's storm surge).

Recent events also indicate that most extremes arise from multiple causes, or drivers, such that similar outcomes cans play out via multiple pathways. For example, the Russian heat wave of 2010 emerged from a convergence of atmospheric conditions (Dole et al., 2011), and also set the stage for extreme wildfires and smoke pollution. Outcomes included 55,000 related deaths and the loss of 25% of Russia's wheat crop (Barriopedro et al., 2011). New thinking about environmental extremes goes beyond considering them as rare, isolated events in the tails of their respective distributions to considering them as members of a population of interacting events (Leonard et al., 2014). Socio-environmental models (Liu et al., 2007; B. L. Turner et al., 2003; Billie Lee Turner et al., 2003) may provide the most fruitful analytical approach to understanding such interactions, especially in the Anthropocene during which we may face surprises founded on and amplified by the increasingly tight coupling of earth and social systems, more likely to cross thresholds into novel states (Steffen et al., 2015). However, socio-environmental thinking and theory (Pulver et al., 2018) have yet to be fully applied to understanding extreme events. Further, natural science exploration tends to constrain analysis to the interacting elements on the biophysical side (Gill & Malamud, 2014), and study of social impacts tend to focus on individual events or hazards (Colten, 2009; Klinenberg, 2003; Kreibich et al., 2014; Meyer et al., 2013), neglecting the interacting factors that lead to extreme outcomes.

Extremes, and especially interacting and compound extremes (IPCC, 2012), do pose profound scientific challenges: rarity and novelty, and sometimes extremity itself, can impede the data collection, theory building, simulation, and prediction at the core of the scientific enterprise, while extremes attract public and policy-maker attention, evoking demand for better prediction and prevention (Schoennagel et al., 2017; United Nations International Strategy for Disaster Reduction (UNISDR), 2015b). The low

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probability yet high consequence events (e.g., especially of “fat-tailed” distributions) make public policy decisions difficult, for example, by pushing the limits of traditional decision tools such as cost-benefit analysis (Nordhaus, 2011; Pindyck, 2011; Weitzman, 2011). As such, there is substantial concern over the increasing frequency of extreme events, emergent phenomena, and surprises. However, the relative nature and context dependency of extremes complicates assessment of mechanism or trends. And extremeness in biophysical drivers and societal outcomes are often conflated. For example, Hurricane Lili in 2002, which alternated between category 1 and 2 at landfall, resulted in record-level economic losses ($1.59B+), the largest, most enduring droughts may be either among the most or least costly in the U.S. record, and the Great Smoky Mountains wildfires in 2016, only moderate in size, caused 14 deaths and burned 2400 structures (NOAA, 2019; Fig. 1 A, B and C respectively). We cannot understand the underlying mechanisms if we do not first delineate, in space and time, whether the extreme elements are the drivers, responses, or both.

Several critical research questions must be addressed if we are to understand the nature of recent extremes. When do we need to explore extreme biophysical events, or just the average events that co-occur with extreme societal exposure? When does social exposure and vulnerability precondition average or extreme events to lead to catastrophes? When do interactions among social and environmental drivers and responses lead to impact amplification? In this review, we use socio-environmental frameworks to rethink the events that result from tightly coupled biophysical and social phenomena and have exceptional magnitude or social impact, herein defined as socio-environmental extremes. This framework is informed by multiple disciplines that each offers explicit treatment of interactions and feedbacks that lead to extremes, or has the potential to. We conclude with a future research agenda that adds clarity and direction to understanding the extreme events that matter to society.

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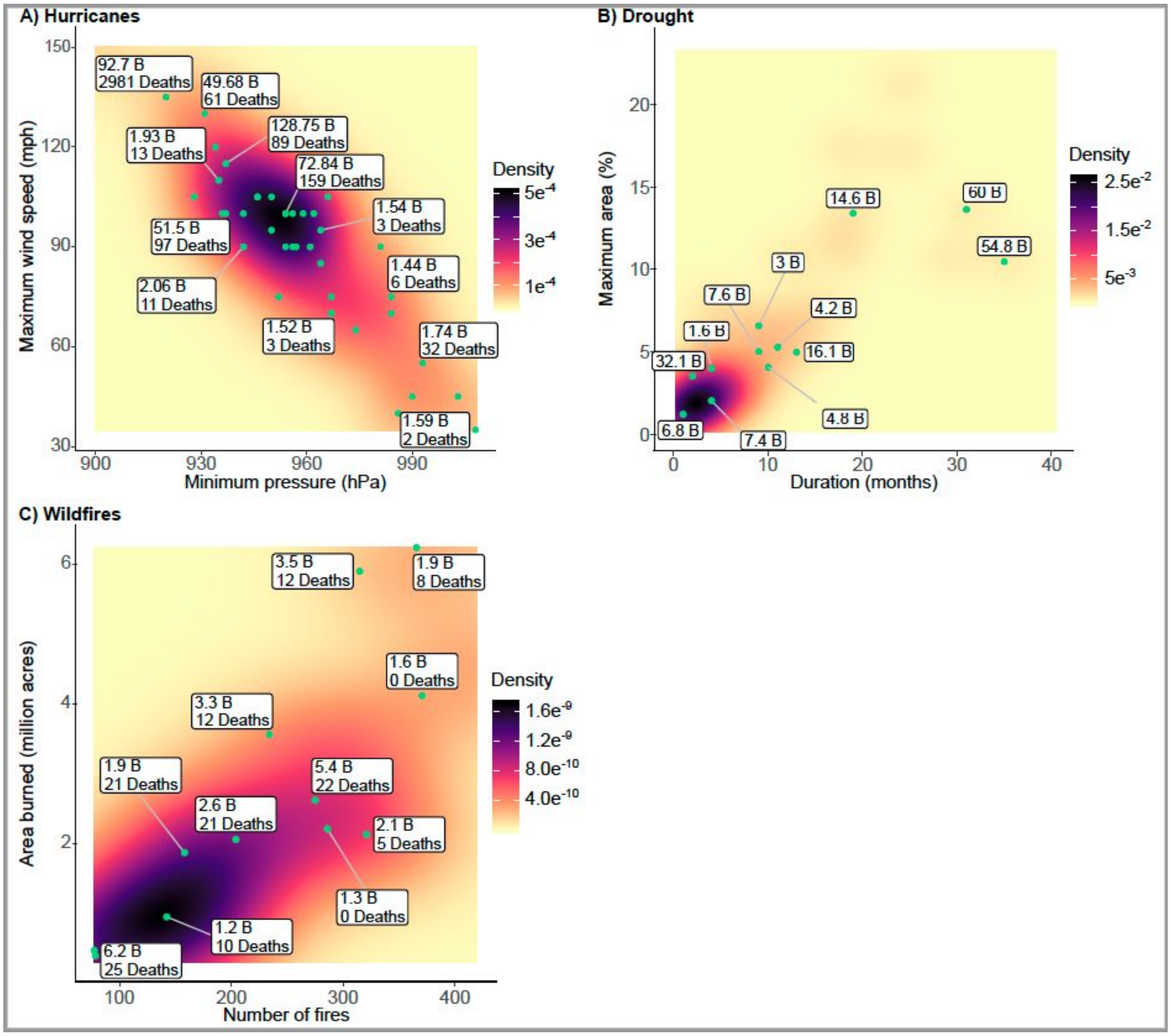

Figure 1: Socio-environmental extremes can be extreme in both the biophysical and social systems or in only one system. Two-dimensional kernel density distribution of: A) hurricane maximum wind speed vs. minimum pressure; B) drought extension vs. duration for the continuous U.S.; and C) annual area burned in the western U.S. vs. number of events >400 ha. In all cases, the green dots depict the events that resulted in damages/costs exceeding one billion dollars (B = billion 2018 USD) included in the National Oceanic and Atmospheric Administration's roster of billion dollar events (NOAA, 2019). Hurricane data from NOAA HURDAT2 (Landsea & Franklin, 2013). Drought events based on the Palmer Drought Severity Index translated into US Drought Monitor category D4, the most severe level (National Drought Mitigation Center, 2019; a drought is defined to start when D4 covers at least 1% of the U.S., and end when D4 drought falls below the 1% area threshold. An online tool for these calculations is available at: https://climate-scatterplot.space. Fire data are from "Monitoring trends in Burn Severity, 1984-2016"; USGS, 2019).

2. The nature of interacting extremes

The foundational, probabilistic definition of extremes defines these events as differing from some baseline state or residing in the tails of statistical distributions of some property (Bier et al., 1999), and

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often assumes independence of events and stationarity. This is encapsulated in the IPCC's definition: "The occurrence of a value of the weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable" (IPCC, 2012): 557). This definition, however, neglects critical interactions among drivers and the societal consequences, including how social action can, in turn, amplify the drivers of biophysical disturbances. For example, the late-season 2017 northern California "firestorm" was comprised of up to 250 wildfires, including the Tubbs Fire in Santa Rosa, among the costliest in state history, where the spatial distribution of simultaneous average events overwhelmed the ability to respond, leading to extreme impacts. Such interacting drivers and responses should be explored because they can elucidate the mechanisms resulting in extreme outcomes, show when multiple hazards lead to compound extremes, or demonstrate when societal outcome is itself extreme.

Scientists have argued that extreme climate events be defined based on both the extremeness of climate drivers and the environmental response (M. D. Smith, 2011), focusing on the unidirectional pathway from driver to response. The importance of links among extreme events, extreme impacts, and social responses has also been explicated, but only a fifth of extreme-relevant literature from climatology, earth science, ecology, engineering, hydrology, and social sciences attends to impacts (Mcphillips et al., 2018, p.5). Gill and Malamud (2014) present a framework describing hazard interaction, the effect of one hazard on another, and multihazards, all possible and relevant hazards and their interactions in a given spatial region and/or temporal period. Multiple extremes may happen together in space and/or time (Fig. 2A), such as correlated events at the same time and location (e.g., a tropical cyclone storm surge and winter cold outbreak associated with Hurricane Sandy), sequential events at a location (five hurricanes striking Florida in one season, 2004), or simultaneous events at different locations (e.g., simultaneous droughts in key global grain production regions). These episodes may be causally related or independent, and the difference is worth sorting out. Recent work focuses on interacting events that are causally related, variously referred to as compound or interacting hazards (Leonard et al., 2014; Zscheischler et al., 2018). Understanding compound extremes, particularly climate weather phenomena, is an emergent field, with, for example, studies of interactions among cyclones, fronts, and thunderstorms creating extreme conditions (Dowdy & Catto, 2017). Causal pathways come in at least two flavors (Fig. 2B): multiple events due to a common driver or a cascade of secondary events obligated to the occurrence of the initial event.

But even events that are interpreted as orthodox, statistically-rare outcomes of aleatory uncertainty ('independent extremes' in Fig. 2B), may actually be the result of currently unexamined interactions of interdependent drivers and processes; and they surprise us due to epistemic uncertainty, i.e., "unknown unknowns" (Paté-Cornell, 2012). Zscheischler et al. (2018) make the case that we need to understand the complex causal chains of compound events that lead to exceptional behavior and extreme impacts (p. 470). Compound events have also been defined based on the constituent events being extreme in and of themselves (IPCC, 2012), or the impacts being extreme (Leonard et al., 2014, p. 20), as there is great concern when ordinary events lead to extraordinary outcomes. By studying connected drivers we may be able to shift some surprising extreme events from the realm of unknown unknowns to the realm of known unknowns (Aven & Krohn, 2014).

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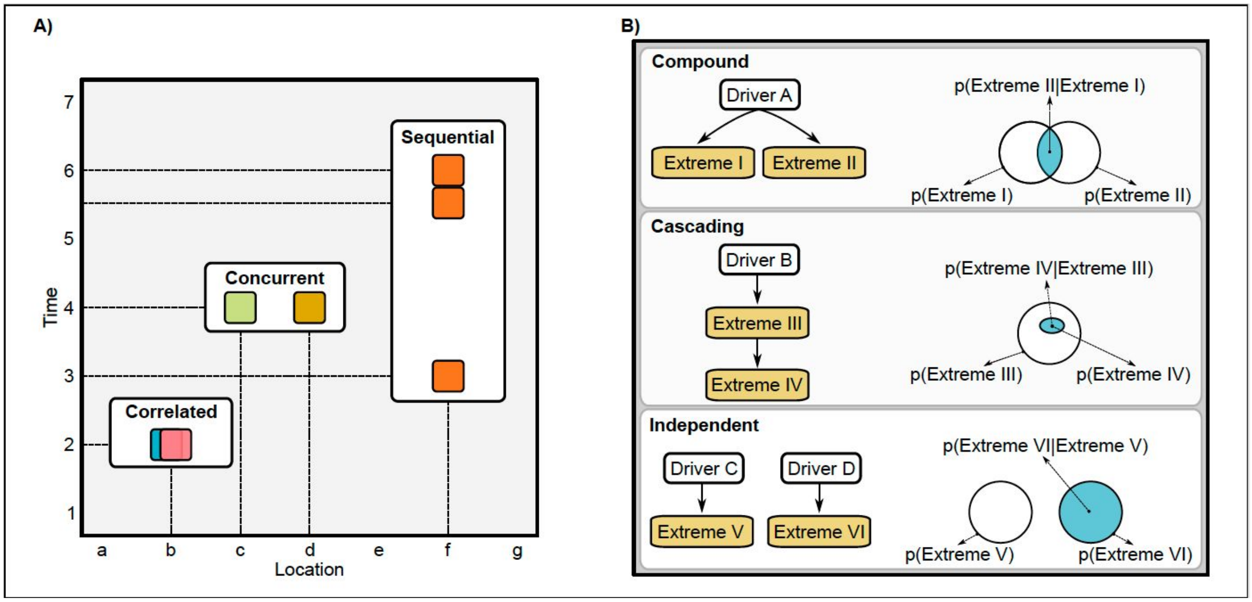

Figure 2: A) Classification of multiple extremes based on the temporal and spatial characteristics of the coupling. B) Classification of multiple extremes based on the causal and probabilistic characteristics of the coupling.

But very few studies explore the extremeness of drivers and responses together, and how they may be interacting in space and time. Even less work quantifies the strength of these interactions, which may vary with time, and how that affects ultimate outcomes. For example, in dry areas or times of drought, groundwater extraction and reservoir impoundment can trigger land subsidence and earthquakes (Davies et al., 2013; Zektser et al., 2005). The seemingly disconnected solution to one extreme, groundwater and water impoundment to mitigate water scarcity, connects two extreme event types, drought and earthquakes, causing unforeseen side effects or consequences and altering the probability of other extreme events. Given the potential for ‘surprises’, where amplification creates greater likelihoods of extreme responses or drivers, it is critical to understand these interactions. This suggests the value of using a socio-environmental framework to focus on: i) evaluating whether drivers and responses, both biophysical and social, are extreme; and ii) exploring whether the interactions among drivers and responses amplify or dampen the likelihood of extreme outcomes.

3. A framework for exploring socio-environmental extremes

We define socio-environmental extremes as rare events, with exceptional properties (e.g., size, intensity, or duration) and at least some degree of social impact, that result from interacting drivers and responses within both environmental and social systems. These events have a specified space and time context and extreme elements that are diagnosed within either the biophysical or social systems. Further, we define “true” socio-environmental extremes as having extreme elements in both systems (Table 1). This definition constrains the focus to major events that are capturing societal and scientific attention because of the extreme biophysical drivers and/or the extreme social outcomes. This definition also allows analytical separation of which elements are extreme by traditional definition, enabling more direct exploration of the driving mechanisms. Such a unified definition is critical as the divergence of the physical, ecological, and societal definitions of extremes creates theoretical and communicative barriers that hinder hazard management and risk assessment.

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Fundamental to this conceptualization (Fig. 3) is that a socio-environmental system framework is needed to account for amplifying (red arrows), dampening (blue arrows), and linear (black arrows) transfer functions between the social and environmental system variables. A network of driver-response relationships in each subsystem makes the overall system more or less predictable. In some cases, our understanding is empirical and internal feedbacks (dashed lines) are embodied in well-codified transfer functions. In other cases, models may implicitly account for the network of causal relationships. This framework helps illuminate the number and nature of vectors, sensitivity of the system, and the emergence of novel phenomena. In general, both social and environmental systems will typically have many driver-response relationships. For example, the case study presented in Text Box 1 shows the network of interactions between social and environmental systems in the Mississippi River Delta system and how adopting the framework shown in Fig. 3 can help identify potential nonlinearities and known sources of uncertainty.

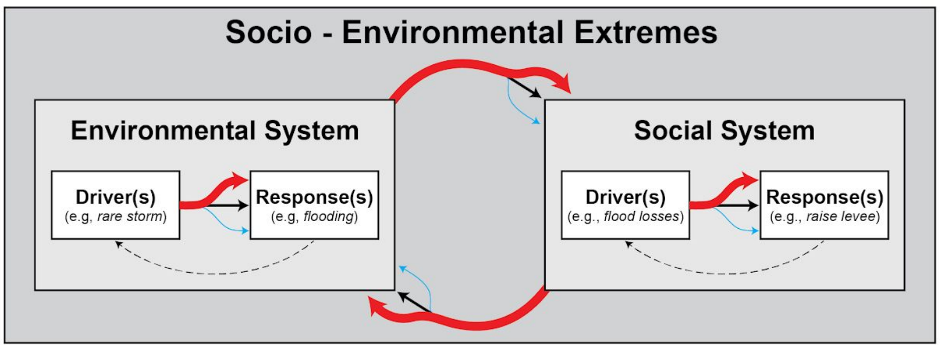

Figure 3: Arrows showing the flow of causality in a coupled socio-environmental system as applied to extreme events. Transfer functions describe the functional relationship beween driver and response variables that can amplify, translate, and dampen responses. Sub-system feedbacks may also exist (dashed lines), but are often unknown due to epistemic uncertainty and / or incomplete system representation. As such, these feedbacks are often implicit to the form of the transfer function themselves.

Social systems interact with and feedback on physical systems in several important ways : 1) Socio-economic drivers can exert force on biophysical drivers; 2) Social responses to an extreme event can feedback on the physical drivers or template of that extreme; 3) Social responses can change the physical drivers of that same extreme; and 4) Social responses from one extreme event can change the physical drivers of another type of extreme event. For example, economic pressure and activity can exert force upon physical drivers of extremes, intentionally or inadvertently. Deforestation and ecosystem change in the Amazon may cause climatic changes across the globe, an unintentional impact of regional economic forces on global physical drivers of extremes (Avissar & Werth, 2005; Hirota et al., 2011). Legacy effects, or the impacts of prior interactions on later conditions (Liu et al., 2007), may flow through systems long after the alteration or modification ceases. For example, historic damming for millponds across the eastern United States during the Industrial Revolution altered watershed and stream channels, the effects of which influence contemporary patterns of flooding and sediment accumulation (Walter & Merritts, 2008).

Environmental systems interact with and feedback on social systems in three main ways: 1) Environmental hazards are directly related to risk, or the likelihood that a hazard causes social harm; 2) Multi-hazard cascades create unanticipated or poorly quantified risk; 3) Changing environmental conditions alter baselines such that design conditions are no longer adequately defined. For example, a dam may be built and managed to mitigate flood hazard such that a population is protected from the 100-year flood. One unintended consequence of these actions is that the channel downstream of the dam will naturally adjust its shape to accommodate the generally lower flows caused by water management. If this reduction in capacity of water conveyance is not associated with commensurate reductions in sediment, then sediment aggrades, channel capacity is reduced, and flood risk can actually

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increase in response to water management decisions (e.g., B. D. Collins et al., 2019). Recent work in the U.S. shows that changes in channel capacity leading to higher flood hazard is more common than increases in hazard due to changes in streamflow (Slater et al., 2015). This relatively simple example of cascading effects (i.e., alteration in streamflow statistics leading to changes in channel capacity leading to changes in flood hazard) shows how unanticipated effects of process interactions can lead to more frequent exceedance of the design flood independent of changes in the environmental forcing. Alternatively, risk assessment is inhibited due to the breakdown of the assumption of stationarity in the hydro-climate. Stationarity asserts that statistical measures of a time-series are invariant. In the case of changing climate or land-cover, this assumption is invalid and can lead to under- or over-estimates of event frequencies.

Text Box 1: Socio-Environmental Extremes Case Study—The Mississippi Delta, Flooding, and Storm Surge

Connecting social with environmental systems is difficult due to nonlinear relationships within and between sub-systems (i.e., Fig. 3). These complex interactions are evident in the Mississippi River Delta (MRD). Deltas are an important nexus between social and environmental systems because a large fraction of Earth's population live on deltas (e.g., >340 million people live on 48 major deltas around the world) and deltaic systems are acutely sensitive to their hydro-geologic setting, water and land management practices, effects of upstream watershed management, and sea level rise (Tessler et al., 2015). River deltas are extensive estuarine systems that provide many ecosystem services, and delta wetlands can attenuate two typical extremes: river flooding and storm surge (Gedan et al., 2011; Van Coppenolle et al., 2018).

The Mississippi River Delta as a complex socio-environmental system

The MRD is a river-dominated deltaic system comprised of five delta complexes reflecting changes in the river's course to the ocean during the Holocene (Coleman et al., 1998). Maintenance of delta land requires that sediment supply and growth of coastal wetlands keep pace with relative sea level rise caused by geologic subsidence and eustatic sea level rise. Though it can be difficult to untangle the relative contributions of social and environmental drivers of land loss and worsened flood hazard, one point of consensus in the MRD is that there has been dramatic losses of wetlands over the historic record (Walker et al., 1987), due to multiple causes (Blum & Roberts, 2014; Nittrouer & Viparelli, 2014). Resource extraction, large-scale watershed management, and social adaptation each have contributed to delta dynamics.

Direct effects from economic systems: Oil and gas extraction

Oil and gas extraction is a major part of the economy in Louisiana, and it has physically altered MRD structure and function (Ko & Day, 2004). One driver is proliferation of oil and gas access canals, most dug since the 1950s (Fig. 4). By altering the hydrologic structure of the wetlands (e.g., due to reduced accretion behind spoil banks and changes in channel density), the canals increased wetland degradation and land loss (R. E. Turner, 1997; Day et al., 2000; Ko & Day, 2004). A second driver of change comes from oil and gas extraction itself, which creates hot spots of subsidence and land loss (Morton et al., 2006) in a delta actually characterized by relatively low overall subsidence rates (Törnqvist et al., 2006).

Indirect effects due to large-scale management: Sediment retention and upstream dams

A large number of dams and flood control structures have been built along the Mississippi River and its tributaries for irrigation and water retention. These reduce both flood frequency and sediment delivery

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to the MRD (Syvitski et al., 2005), with the unintended consequence of limiting delta land growth (Weston, 2014). Dam effects on sediment dynamics are time-lagged with respect to the growth and re-working of coastal sediments (Kirwan et al., 2011), leading to a large degree of uncertainty over their role in modern land loss (Blum & Roberts, 2014; Nittrouer & Viparelli, 2014). Nevertheless, over the long-term, reductions in sediment supply will ultimately limit delta land growth, illustrating how mitigation of one set of extremes, upstream droughts and floods, affects extremes (i.e., river and coastal flooding) that is displaced in both time and space.

Indirect effects due to social adaptation: Local levees and flood control

After extreme flood events, humans often alter the hydrological system to protect against future events and damages. For example, the 1927 Mississippi River flood caused over 240 deaths, the evacuation of 900,000 people, and, afterwards, the construction of 3000 km of artificial levees (Changnon, 1998; Kesel, 2003). Although levees are built with the intention of decreasing flood losses, levees along the Mississippi floodplain buffer settlements from small floods at the expense of large-scale catastrophic flooding (Werner & Mcnamara, 2007). In some cases, levees can lead to more damage, not from the physical levee itself, but from the social and political forces that create a perception of safety behind a levee (Freudenburg et al., 2008; Montz Burrell E. & Tobin Graham A., 2008). Stabilizing river banks has another indirect effect in that such structures actively prevent river avulsions (i.e., abrupt change in river course typically triggered by large floods). While stabilizing river banks is at odds with natural behavior of alluvial rivers in general, delta rivers are unique in that they rely on avulsions to change their course, develop new depo-centers, and maintain their fan-shaped morphology. The Atchafalaya River diversion, an incipient avulsion, would capture most of the Mississippi River flow, if not prevented by humans (e.g., Aslan, Autin, & Blum, 2005). Taken together, these examples show how construction of levees along the lower Mississippi River can lead to unintended consequences in human exposure and vulnerability.

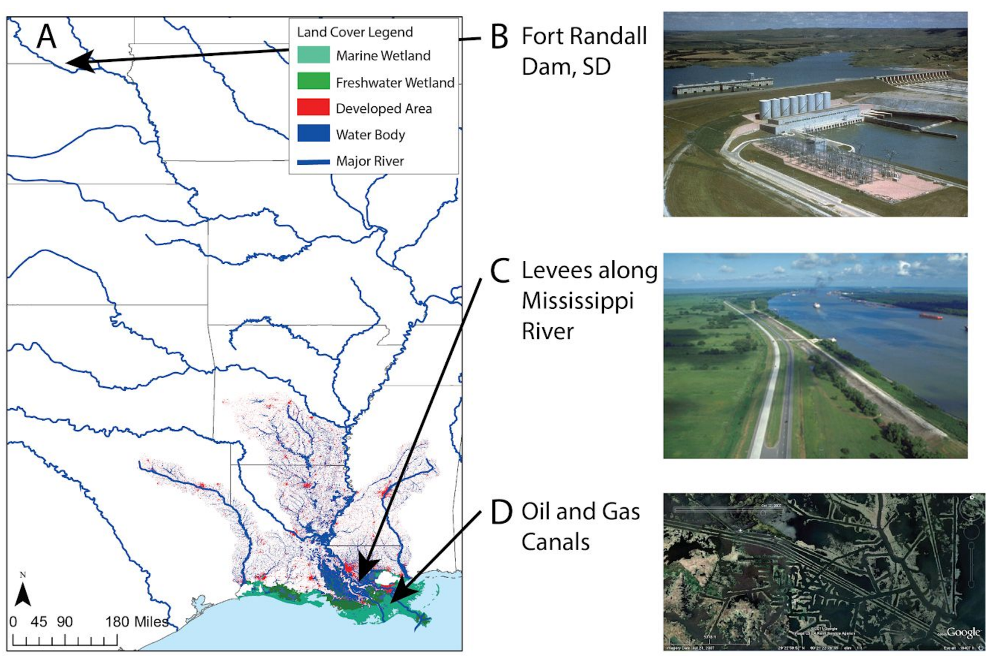

Figure 4: The Mississippi River Delta is an illustration of a complex system that is vulnerable to socio-environmental extremes: a) Louisiana's coast is threatened by many extremes, including riverine flooding and hurricanes (National Wetlands Inventory, National Hydrography Database; National Land Cover Database); b) Interactions across extreme frameworks is depicted through the implementation of

dams for water supply leading to increased risk from storm surge events along the coast (Fort Randall - Meade & Moody, 2010; Picture: USACE); c) Social response to extreme events can change the physical driver, as evidenced by implementation of levees along the Mississippi River to protect human settlements from flood events (Picture: Southeast Louisiana Flood Protection Authority); d) Legacy effects from economic drivers, oil and gas exploration, in the Mississippi Delta have led to degradation of coastal wetlands, leading to greater risk from storm surge events.

3.1 Building on nature-society frameworks to understand socio-environmental extremes

Key ideas from natural hazards theory, coupled human-natural systems, socio-ecological systems, resilience theory, and complex systems theory could be better extended to frame, diagnose, and understand socio-environmental extremes. All of these portray the complex dynamic between nature and society.

Natural hazards research has a strong lineage of thinking about extremes in coupled human-natural or what today are referred to as socio-ecological frameworks. Kates (Kates, 1971) first conceptualized hazards in a "human-ecological" perspective using a systems diagram, and the subsequent hazards model developed by Burton, Kates and White (Burton et al., 1978) defined "hazard" as the interaction of natural extremes with social exposure and vulnerability. They also defined a path-dependency whereby social adaptation to frequent, less extreme events sets up the potential for catastrophic loss from rare extremes. A systems approach also requires defining the forcing from socio-economic drivers to physical drivers across spatial and temporal scales (Billie Lee Turner et al., 2003; Werner & Mcnamara, 2007), including feedbacks to physical systems via social response to previous disasters. Through these drivers and responses, complex interactions and feedback loops develop between human and natural systems (Heffernan et al., 2014; Liu et al., 2007).

Surprisingly, these theories have yet to more fully inform the understanding of driver and response interactions that may lead to extreme behavior and the potential for amplification or dampening of outcomes. For example, coupled human-natural systems thinking has been used to frame ecological drought (Crausbay et al., 2017), but not extreme ecological drought. Wildfires have been considered in a socio-ecological framework (Moritz et al., 2014; Spies et al., 2014), but only recently has the fire science community attempted to define extreme wildfire events as both physical and social phenomena (Buckland, 2019; Tedim et al., 2018). And general socio-ecological systems thinking (Collins et al., 2011) has yet to incorporate explicit treatment of extreme events. Critically we need to answer whether the same set of interactions operates for extremes as for average disturbance events, or whether new interactions emerge, representing fundamentally different drivers and responses.

The advantage of conceptualizing extremes in a socio-environmental framework is explication of the distinct, reciprocal interactions (materials, energy, information) between systems (Alberti et al., 2011). These interactions are typified by the social response to extreme events and the subsequent feedbacks to the physical drivers as society tries to decrease risk. A clear instance of this feedback is the building of flood control structures and stabilization of rivers after the major flood events of the first half of the 20th Century (Changnon, 1998). Human alterations of river channels often lead to unintended consequences, such as increased flooding through alterations to the hydraulic geometry and disconnection of floodplains (Criss & Shock, 2001; Gregory, 2006). These societal feedbacks on physical

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systems illustrate the capacity and desire for humans to buffer the physical system and decrease risk of subsequent disasters.

Resilience theory also offers a perspective on disturbance and system response (e.g., ecological, social, or other), where an interactive and complex set of drivers and outcomes operate near critical thresholds or tipping points (Lenton, 2013; Scheffer & Carpenter, 2003). We argue that surpassing a critical threshold, and the state shift that ensues, represents a *de facto* extreme event. In most cases, resilient systems recover from disturbance through a series of negative, stabilizing feedbacks. However, if the disturbance is unprecedented or it triggers positive feedbacks, the system may shift to a qualitatively different state with important ecological and social ramifications. Importantly, resilience theory posits that average impacts can instigate positive feedbacks that trigger extreme events. Sensitivity to the legacy of past events indicates that spatiotemporally correlated disturbances that are not individually extreme can yield impacts as profound as reorganization or transitions into new states, ecological and social. For example, Florida's multiple hurricanes in 2004 caused an insurance availability crisis and evoked state intervention to stabilize the insurance regime, a re-arrangement still reverberating through insurance and development sectors (Weinkle, 2019a, 2019b). Further, resilience is a time-variant property that emerges from the relationship between the dynamic state of the system, be it natural or social, and disturbance (Carpenter et al., 2012). The ability of a system to recover its function after disruption therefore depends not only on its intrinsic properties and the intensity of the disturbance, but also on the proximity of the system to a tipping point. Conditioning on the properties of the system implies that, if sustainability is a goal, 'extreme events' require an impact-oriented rather than a phenomenological definition (i.e., the concepts of 'large' and 'rare' are site- and time-specific) and highlight the importance of the scale of observation.

In addition, complex systems thinking (Sharma et al., 2013) considers extreme events as an emergent property of many nonlinear systems and that they may arise from the same mechanism that originates small and average events (e.g., self-similarity in the context of self-organized critically; Bak & Paczuski, 1995). Alternatively, they can be the product of an amplification process that is rarely active and triggers the transient organization of the system into a statistically and mechanistically different state (i.e., dragon-kings; (Sornette, 2009)).

3.2 From multi-hazards to compound extremes: biophysical frameworks that offer a key way to look at interactions

A rapidly-growing body of work argues that some, maybe most, extreme outcomes stem from multiple drivers, correlated events, and overlapping phenomena, not simply from an outstanding individual extreme. Two major types of interactions are described in the recent literature: i) the interaction among suites of biophysical drivers; and ii) the interaction between drivers and responses, incorporating important feedbacks that can either amplify or dampen the probability of extreme outcomes.

While there is increasing focus on adoption of a 'multi-hazards' approach at global (Basabe, 2013; United Nations International Strategy for Disaster Reduction (UNISDR), 2015a) and national levels (e.g., FEMA efforts for a national mitigation strategy; FEMA, 2013), this approach, despite its name, often assumes independence of events in space and time. Indeed, multi-hazards is one of many loosely defined terms such as co-occurring or correlated hazards (connected, but not causally related), compound hazards (interacting events), and cascading or secondary hazards (a subset of compound hazards); however, the terminology remains in flux (Cutter, 2018; Gallina et al., 2016; IPCC, 2012; Wahl et al., 2015). We provide a way to distinguish these terms based on the occurrence of events in space

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and time and their causal relationships (Fig. 2). Recent assessments also explicitly try to account for different types of interactions among hazards (Gill & Malamud, 2014; Kappes et al., 2012). Specific case studies that focus on the interactions among biophysical hazards include: secondary hazards induced by volcanic eruptions (Neri et al., 2008), earthquakes (Fan et al., 2019), and concurrent extreme weather events (Forzieri et al., 2016; Vogel et al., n.d.), sequences of droughts, floods and landslides (Nones & Pescaroli, 2016), and wildfires triggering floods, landslides, and debris flows (Bendix and Cowell, 2010; Cannon et al., 2008; Moody et al., 2013; Staley et al., 2005). Gill & Malamud (2017, 2014) provide a framework for natural hazard interactions, some of which yield extreme outcomes, and a review of documented cases, moving beyond the accounting for 'all-hazards-at-a-place' (Hewitt et al., 1971).

Another important gap in multi-hazards thinking is the explicit incorporation of social vulnerability, exposure, and feedback. A multi-risk framework, capturing both multiple hazards and multiple vulnerabilities (Gallina et al., 2016), has been proposed. But this framework lacks the possible amplifications of multiple non-extreme events that may lead to extreme impacts or responses, or ultimately may influence the biophysical system properties themselves (e.g., flooding, levees, etc. or probability of wildfire ignitions). The possibility of these interactions leading to extremes has yet to be defined and explored in a socio-environmental framework.

4. Methods to explore interactions that lead to socio-environmental extremes

A key challenge in better diagnosing and predicting socio-environmental extremes is improving our understanding of the interactions among drivers and responses, which can both be subtle and shifting due to global environmental change. Researchers investigating compound extreme natural events recognize this, and are honing both traditional and new analytical methods.

4.1 Statistical approaches

In statistical models, driver-response interactions can be represented by modeling the parameters of the response distribution as functions of the drivers (e.g., Chavez-Demoulin & Davison, 2005). For example, in the bivariate case, interactions among responses can be represented implicitly via copula models to obtain the joint distribution (Durante & Salvadori, 2010). Copula constructions of multivariate extreme value distributions have been applied in myriad applications including , in: hydrology (Renard & Lang, 2007), finance (Di Clemente & Romano, 2004), failure risk in engineering (Ram & Singh, 2009), and the energy sector (Stephen et al., 2010). The foundation for copula constructions of multivariate distributions is provided by Sklar's theorem, which shows that every multivariate distribution can be represented in terms of its marginals and a copula function (Sklar, 1959). In practice, this is convenient because marginal distributions tend to be well-characterized, and the research focus can be placed on formalizing dependence structures between variables, through parametric or non-parametric (Behnen et al., 1985), frequentist or Bayesian approaches (Sadegh et al., 2017). Using copulas to model the dependence between variables allows an assessment of changes in probabilities of compound events accounting for nonstationary climate conditions (Zscheischler & Seneviratne, 2017).

Data sparsity, autocorrelation, covariate shift, and attribution all provide challenges to quantifying driver-response interactions for extreme events. Extremes are rare by definition, and empirical datasets for extremes often consist of relatively few examples. Data sparsity can increase as multiple phenomena come under consideration. Further, many physical and societal extremes exhibit spatiotemporal autocorrelation, which invalidates independence assumptions of simple statistical models (Huser & Davison, 2014). This non-independence can also be an asset, as it allows for information to be shared among spatiotemporal units, e.g., to better predict statistical relationships between climatological

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drivers and wildfires by allowing similar ecoregions to have similar relationships (Fig. 6; Joseph et al., 2019). Still, prediction can be a difficult task when extreme events are caused by conditions that are changing in space and time (Cheng et al., 2014; Salas Jose D. & Obeysekera Jayantha, 2014). For example, minimum relative humidity has a strongly non-linear relationship with the probability of extreme wildfires (Fig. 6), and in some places, climate change is resulting in humidity conditions that are outside of the range of the observed historical record (Ficklin & Novick, 2017). This is a special case of what is referred to in the machine learning literature as covariate shift where explanatory variables that are outside of the distribution of values are used to train a model (Shimodaira, 2000).

4.2 Dynamical modeling approaches

Dynamical models represent these interactions more explicitly, for example by mathematically representing atmosphere-fire coupling to understand how wind speed affects wildfire behavior (Linn and Cunningham, 2005). Operational forecasts can benefit from dynamical models, as made evident by their application in short term streamflow forecasts (Fatichi et al., 2016 and references therein, but see Woolhiser, 1996). One potentially fruitful research approach exists at the interface of dynamical models and the statistical properties of extreme distributions that emerge from such models (Franzke, 2012). Non-linear driver-response interactions embedded in dynamical models have been approximated by statistical models with a wide variety of approaches including Gaussian processes, generalized additive models, neural networks, and finite mixture models (Bracken et al., 2016; Carreau and Vrac, 2011; Padoan and Wand, 2008). Non-linear relationships among extremes have received increased attention recently, particularly in the financial sector following the subprime mortgage crisis (Zimmer, 2012), and can be represented in statistical models using a wide variety of parametric and non-parametric copulas (Joe, 2014; Lopez-Paz et al., 2013; Wahl et al., 2016).

Attribution, or understanding the causes of extremes is challenging for both dynamical and statistical models. In dynamical models, the structure of the model approximates the causal mechanisms that lead to events, but in statistical modeling, the primary conclusions of modeling effort usually are descriptions of associations among variables (Stott et al., 2016).

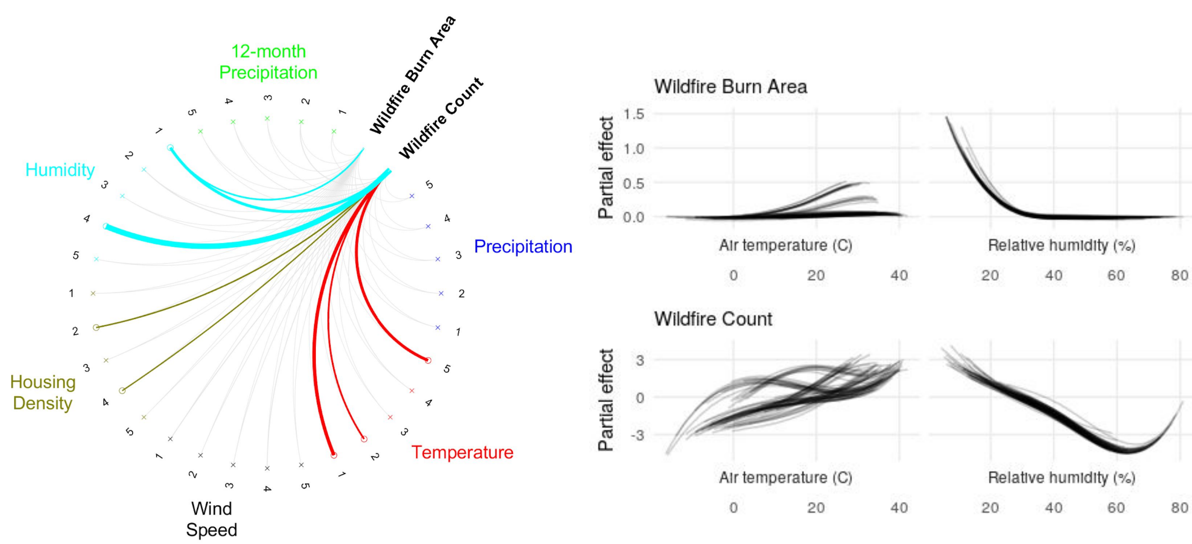

Figure 5: Bayesian approaches can reduce the complexity of interactive drivers. Joseph et al. ((Joseph et al., 2019)) used B-splines to predict wildfire size and count by month. Using 6 predictor variables with

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5 basis vectors each (to account for nonlinear effects), the chord diagram (left panel) shows that only 8 out of the 60 global coefficients were significant at the 95% credible level (colored lines). Line width is scaled by the magnitude of the coefficient, indicating a stronger effect. When spatial interactions were accounted for using nested Level 1-3 EPA ecoregions, the resultant 10,416 coefficients reduced to just 18 at the 95% credible level. As examples, the four panels on the right show partial effects of daily maximum air temperature and minimum relative humidity on wildfire burn area and counts, where each line represents the estimated effects for each EPA level 3 ecoregion (adapted from Joseph et al., 2019).

4.3 Methods from risk assessment of socio-technological extremes

Diagnostic approaches and methods used to understand technological risks, industrial accidents, and even financial crashes can help us better understand socio-environmental extremes, as these frameworks capture interactions that trigger or change the probability of subsequent events. For example, the benchmark study of nuclear power plant safety in the U.S. (U.S. Nuclear Regulatory Commission, 1975) used fault-tree analysis to calculate the probability and consequence of an accident that released radioactive material. The branches of the trees trace direct triggering relationships, with the probability of each triggering event (driver) and subsequent event (response) multiplied down the branch to obtain a final likelihood of that event sequence. A challenge in this approach is accounting for endogenous and exogenous conditions that make events initially judged to be independent, and thus arrayed on different branches, actually connected via a common cause, also known as common-mode failure. The fault trees applied to safety assessments must distinguish between amplifying and dampening pathways as illustrated in Fig. 3. Because of technological innovation, assessors must anticipate, or at least be open to imagining, novel events and outcomes. For example, risk assessments for space shuttles or fleets of autonomous vehicles contend with new and evolving systems that might behave in surprising ways.

Technological risk assessors struggle with the same definitional problem as natural scientists: what is extreme? Risk analysis applies a definition based on combined likelihood and consequence, and extremes are thus low probability/high consequence events (Bier et al., 1999). In many risk analysis subfields, such as toxicology, biomedicine, and safety engineering, extremes are defined by a quantitative threshold for allowable or acceptable conditions of chemical exposure or pollution concentrations. So socio-technical thresholds tend to be based on expected outcomes according to a "dose-response" relationship, an approach that might transfer to socio-environmental extremes.

The systemic approach used in technological risk assessments could add value to the socio-environmental framing of extremes in three major ways. First, most risk assessments and event diagnostics for socio-technical hazards assume that extreme events spring from compounding interactions among multiple drivers and systems; so the field has long grappled with identifying interaction among event drivers. Probabilistic safety assessments for nuclear power plants, for example, include scenarios for multiple triggers and event sequences to estimate the probability of outcomes, ranging from trivial to catastrophic (Lee & McCormick, 2012). Technological risk assessment, reflecting the potential for new and unruly system behavior, also recognizes several species of novel extremes (Paté-Cornell, 2012): (1) Black Swans: Not just unpredictable or rare, but fundamentally unexpected events; (2) Perfect Storms: generally thought of as the most unfortunate combination of events leading to the worst-possible outcome, aka worst case scenario; and (3) Dragon Kings: Novel extreme events interpreted as the combination or interaction of the biggest, but not unheard of, events ("Kings"), like a 30m tsunami on the northeast coast of Japan or the central U.S. droughts of the mid-1930s, transformed

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into events so extreme that they were not thought possible ("Dragons"), what Wheatley et al. (Wheatley et al., 2017) described as "born of unique origins...relative to other events from the same system." (p. 108).

Technological disaster frameworks also often consider the environmental context. The simultaneous loss of three reactors at the Fukushima nuclear power plant (Committee on Lessons Learned from the Fukushima Nuclear Accident for Improving Safety and Security of U.S. Nuclear Plants, 2014), stemmed from an extreme tsunami affecting the site of six nuclear reactors built on the Pacific coast to access the ocean's large heat sink. The historically-extreme impacts of the 1930s droughts in the central U.S. were a combination of climate extremes (still the driest period in the U.S. instrumental record), inappropriate agricultural technology deployed into a semi-arid climate, and a global economic depression (McLeman et al., 2014). Such "beyond-design-basis" events may provide lessons for improving risk assessment of compound and interacting natural hazards, especially in a changing climate. But risk assessments methods do not lend themselves to prediction per se.

5. A research agenda for studying the interactions

Emergent from this review, we identify future research directions that can help develop new ways to identify, quantify, and evaluate interactions among biophysical and social systems that lead to socio-environmental extremes (Table 1). This future research agenda (Text Box 2) identifies what understanding we need to build, how we can leverage data and methods, and how we can apply that knowledge for better prediction and management of socio-environmental extremes. One key knowledge gap is better understanding of what drives amplification across biophysical and social systems, and how that potential is moderated by anthropogenic climate and land use change. Since the 1980s, for example, there has been a substantial increase in the building area across the U.S., which means that more homes are exposed to the combined effects of drought and wildfires (Fig. 6), which are also known to be increasing in the western U.S. (Balch et al., 2018; Westerling, 2016).

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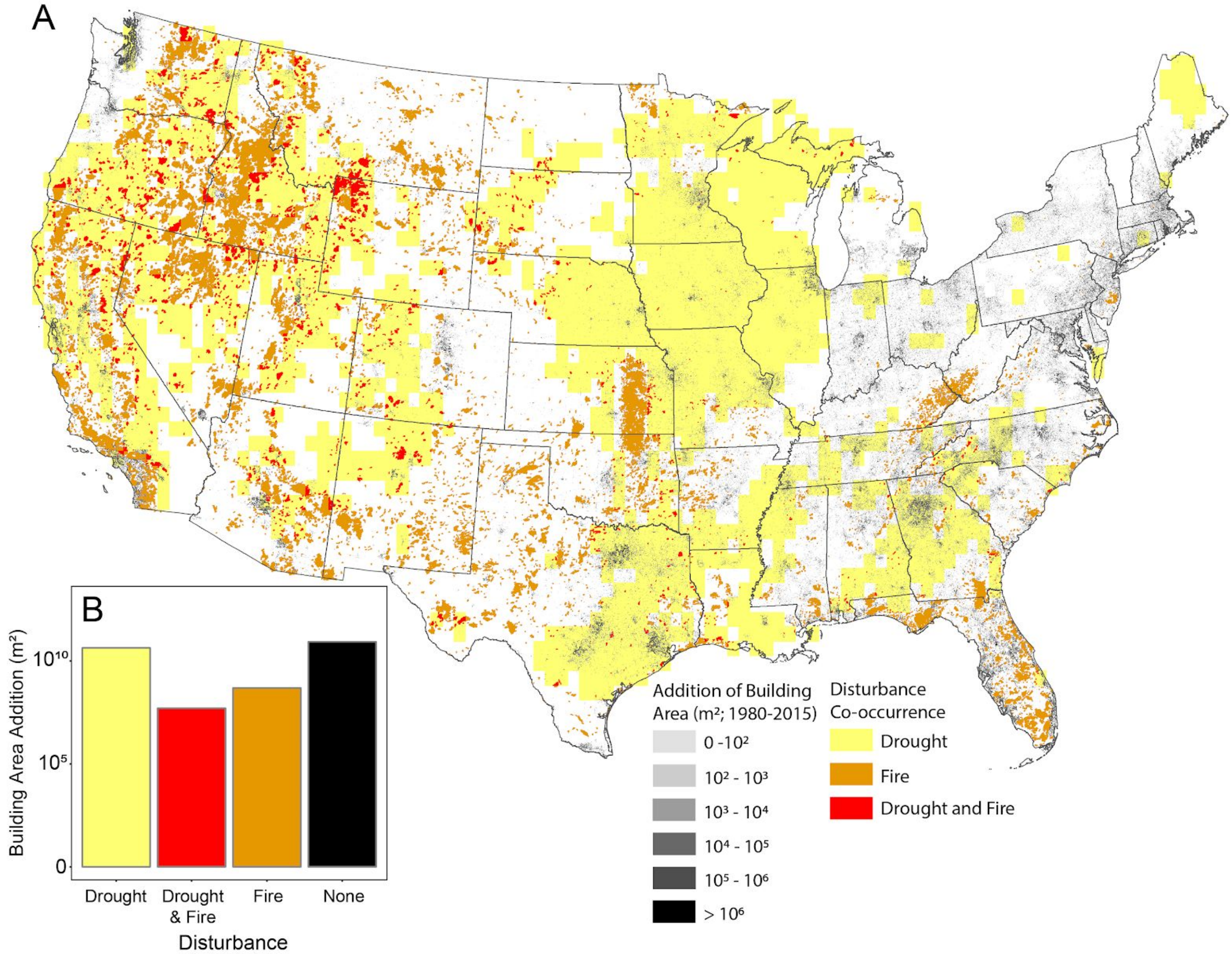

Figure 6: The interactions between social systems and environmental systems may increase as humans move into areas at risk of extreme events. Expanding structure area in locations at risk of disturbance could indicate growing exposure to extremes. Focusing on the intersection between droughts and fires, panel (a) depicts the areas that experienced fires >400 ha (Monitoring trends in Burn Severity, 1984 - 2016; http://mtbs.gov; (United States Geological Survey, 2019)), exceptional drought (category D4, 1984 - 2016; http://metdata.northwesternknowledge.net; (Abatzoglou, 2013) or both combined with structure interior area growth (m2) from Zillow ZTRAX database (1980-2015; https://dataverse.harvard.edu/dataverse/hisdacus; Leyk & Uhl, 2018). (b) Comparison between disturbance types shows that while more building area was constructed in areas not subject to fire or droughts, areas that had experienced drought, fire or both had large increases in structure area, possibly increasing exposure to these extremes.

Furthermore, this amplification may result in subtlety, novelty, or surprise. Subtlety may stem from when extremes come from different systems or sources while masquerading as an extreme member of a well understood family of events (i.e., they are not emergent from an extension of the range of a system's behavior). This may be the source of some surprises, or extremes may result from conditions we have not seen before--both unexpected (black swans) and catastrophic (dragon kings). Research and monitoring should be tuned toward: threshold behavior (e.g., vegetation state shifts; Suding & Hobbs, 2009), time lags (e.g., freshwater flooding with storm surge (Wahl et al., 2015) or delayed heat-related

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deaths (Gasparrini & Armstrong, 2011), or novel drivers (e.g., warmer droughts due to climate change (Marvel et al., 2019)—which may be fundamental to understanding surprises.

Table 1: Examples of "true" socio-environmental extremes, which have extreme elements in both the biophysical and social systems.

Event	Extreme elements of biophysical system	Extreme elements of social system	Interactions
Russian Heat Wave in 2010 (Barriopedro et al., 2011; Shaposhnikov et al., 2014)	Hottest (i.e., temperature) in the past 500 years over an area of 400,000 square-miles.	25% of Russian crops were destroyed via wildfires; 50,000 related deaths.	The heat wave promoted drought that encouraged wildfire spread, resulting in crop loss and smoke pollution.
Florida hurricane season in 2004 (Franklin et al., 2006; Weinkle, 2019b)	Four hurricane landfalls in rapid succession, associated with above normal tropical Atlantic sea surface temperatures, persistent westerly steering currents which delayed recurvature, and below normal wind shear which maintained storm intensity up to landfall.	Increased property exposure in preceding quiet years that exceeded insurance reserves, leading to $45B in property damages and 60 lives lost in the U.S.	A large volume of wind damage claims caused insurance insolvencies, some companies chose to leave the market, and the ensuing crisis in recovery and future development prospects forced a re-arrangement of the insurance market with the state government intervening with subsidies.
Portugal wildfires in 2017 (Comissão Técnica Independente, 2017; Ferreira-Leite et al., 2016; Rego & Silva, 2014; Viegas et al., 2017)	It was the most extreme drought since 1950 (based on the SPEI), which extended the fire season into late fall. More than 540,000 ha burned, representing 60% of the total burned area in the EU that year; this was the highest amount of burned area recorded since 1980.	June & October fires caused 113 deaths, and economic losses of USD1.2B; it was the costliest natural disaster, with $300M in insurance payouts in Portugal.	The [extreme fire conditions] drought resulted, in part, from atypical path of Hurricane Ophelia moving north from off the coast of Africa and causing a strong southerly flow, bringing hot and dry tropical air mass and dust from the Sahara. Agricultural land [abandonment] provided additional fuels, and fire fighting resources had been demobilized with the ned of the "official" fire season. Wildfires were promoted as a function of drought and changing land use is known to increase vulnerability.
Mississippi River increase in flood stage (2-4m) for given discharge along certain reaches over time (Criss & Shock, 2001; Di Baldassarre et al., 2015; NOAA,	Notable historic floods include: the largest flood discharge on record (1844); a large flood in 1903, that had comparable discharge to	Great Flood of 1993 was the most costly non-tropical, inland flood event to affect the United States on record	The 'Levee' effect is prominent in these cases. Lower hazard during more frequent events

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National Centers for Environmental Information, 2019)	1993; the Great Mississippi Flood of 1927; and the Great Flood of 1993.	($37.3B and 48 lives lost).	encourages development in floodplain or even re-classification of floodplain. The Great Mississippi Flood of 1927 was important because it triggered widespread building of levees. Levees then largely protected St. Louis during the Great Flood of 1993.
Hurricane Maria in 2017 (Brindley, 2018; Hu & Smith, 2018; Kishore et al., 2018; Landsea & Franklin, 2013; Pannell et al., 2017; Saker & Rudavsky, 2018; Van Beusekom et al., 2018)	Maria was a Category 5 hurricane, the 10th most intense Atlantic hurricane on record, that denuded the vegetated landscape and further resulted in landslides from excessive rainfall and flooding.	This hurricane was the third costliest tropical cyclone on record (losses over $91B). It killed thousands of people, and damaged 85% of Dominica's houses and destroyed 25%, displacing over 50,000. Communication blackouts and months-long power outages occurred in Dominica.	The effects were compounded with Hurricane Irma. Destruction of the power grid and communications inhibited relief efforts. Production of medical supplies was interrupted, leading to a shortage of IV bags that has been subsequently linked to a more intense flu season.

There is great potential to advance the long-standing goal of predicting extremes utilizing this socio-environmental framework with big and diverse data opportunities, as well as new methods and approaches (e.g., machine learning, Bayesian approaches (Joseph et al., 2019), and data-model integration). First delineating when extremes matter, and when average events matter, will be critical: When do "normal" events create extreme outcomes? And why? There is an opportunity to harness the data revolution, to better quantify the nature and strength of interactions among biophysical and social systems that lead to emergent extremes. New analytical approaches should also allow us to integrate parametric- and process-based models for extreme event attribution and prediction. Prediction may also be aided by real-time analysis of extreme events as they unfold, and harnessing historical datasets for insight on the possible events of the future. Finally, collaborative effort is needed to identify points of interventions that can reduce impacts from socio-environmental extremes. Where are the biggest opportunities for mitigating impacts, exposure, vulnerability? Despite growing understanding and diagnosis of extremes, losses keep increasing (White et al., 2001). We argue that this socio-environmental extremes framework will help to identify leverage points that can reduce future impacts.

Text Box 2: Future research agenda for exploring socio-environmental extremes that highlights what understanding we need to build, how we build that understanding with data & methods, and how we can apply that new knowledge. Key questions to address include:

Building new understanding of socio-environmental extremes

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- What is the nature, dampening or amplification, and strength of interactions among biophysical and social systems that lead to extremes?
- What in particular drives amplification, and how is that potential moderated by and attributed to anthropogenic climate and land use change?
- What are the causes and indicators of surprises, such as threshold behavior (e.g., vegetation state shifts, time lags (e.g., freshwater flooding with storm surge, and novel drivers such as warmer droughts due to climate change)?
- When do extremes stem from a fundamentally different system or source while masquerading as an extreme member of a well-understood distribution of events (i.e., they are not emergent from an extension of the range of a system's behavior)?
- When do extremes matter vs. average or more common events? For example, average biophysical events may have extreme societal response, based on exposure levels (e.g., small wildfires may burn thousands of homes).

Leveraging the data revolution & new methods to understand socio-environmental extremes

- Are there novel data sources, or data integration & synthesis opportunities, that can build national and global datasets on societal impacts (e.g., fine-resolution housing data from Zillow; Leyk & Uhl, 2018))?
- Can we use data opportunities to expand our understanding of baselines in space and time to detect shifts and extreme deviations? & capture temporal lags between long-term drivers and impacts?
- How can parametric- and process-based models for extreme event attribution and prediction be integrated?
- What are the opportunities for real-time indication and analysis of extreme events as they are unfolding to alert early-warning systems?
- Can new approaches for reducing the complexity of interactions be developed specifically for understanding extreme events (e.g., Fig. 5)?
- What new applications of machine learning can be used to better understand extreme events?

Identifying opportunities for prediction and management interventions that can reduce impacts from socio-environmental extremes

- Based on new knowledge, how can we better predict socio-environmental extremes?
- Where are the biggest opportunities for mitigating impacts, exposure, and vulnerability to socio-environmental extremes?

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6. Conclusions

We have highlighted nature-society frameworks that focus on the intersection between social and biophysical events, informing how we can conceptualize socio-environmental extremes. We described the major bodies of work that explore interactions in understanding hazards and extremes, and how the literatures point to an emergence of extremes as a function of driver and response interactions. Key illustrative examples of socio-environmental extremes show the importance of the interactions and point to how we can better leverage analytical tools sourced from a broad range of disciplines. Last, we highlight some key methods that enable exploration of interactions and their role in driving extremes, and suggest a future research agenda to improve our understanding, prediction, and mitigation of socio-environmental extremes.

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This re-conceptualization enables us to better analyze and predict socio-environmental extremes. First, such a framework provides clarity and direction in understanding and studying extremes from a social and biophysical perspective. This reconciles the gap between understanding extremes as biophysical processes only to more fully appreciate the social underpinnings and impacts. Further, this framework enables an interdisciplinary research community to focus on a suite of events that are defined similarly to look for patterns and test specific hypotheses about the driving mechanisms across events. Second, we hypothesize that some of the worst extremes are derivative of the interactions among complex socio-environmental systems, highlighting the importance of this framework. In effect, this effort helps to define what extremes matter to society. Third, this framework comes at an important opportunity to harness the data revolution to better understand and predict extremes, particularly marrying data from remote sensing to social data to capture rare events and their societal drivers and impacts. In conclusion, this research agenda will help to identify where, when, and why communities may have high exposure to socio-environmental extremes—informing future mitigation and adaptation strategies.

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References:

Alberti, M., Asbjornsen, H., Baker, L. A., Brozovic, N., Drinkwater, L. E., Drzyzga, S. A., et al. (2011). Research on coupled human and natural systems (CHANS): approach, challenges, and strategies. *The Bulletin of the Ecological Society of America*, *92*(2), 218–228. https://doi.org/10.1890/0012-9623-92.2.218

Aslan, A., Autin, W. J., & Blum, M. D. (2005). Causes of River Avulsion: Insights from the Late Holocene Avulsion History of the Mississippi River, U.S.A. *Journal of Sedimentary Research*, *75*(4), 650–664. https://doi.org/10.2110/jsr.2005.053

Aven, T., & Krohn, B. S. (2014). A new perspective on how to understand, assess and manage risk and the unforeseen. *Reliability Engineering and System Safety*, *121*, 1–10. https://doi.org/10.1016/j.ress.2013.07.005

Avissar, R., & Werth, D. (2005). Global hydroclimatological teleconnections resulting from tropical deforestation. *Journal of Hydrometeorology*, *6*(2), 134–145. https://doi.org/10.1175/JHM406.1

Bagley, J. E., Desai, A. R., Harding, K. J., Snyder, P. K., & Foley, J. A. (2013). Drought and Deforestation: Has Land Cover Change Influenced Recent Precipitation Extremes in the Amazon? *Journal of Climate*, *27*(1), 345–361. https://doi.org/10.1175/JCLI-D-12-00369.1

Bak, P., & Paczuski, M. (1995). Complexity, contingency and criticality. *Proceedings of the National Academy of Sciences of the United States of America*, *92*, 6689–6696.

Balch, J. K., Schoennagel, T., Williams, A., Abatzoglou, J., Cattau, M., Mietkiewicz, N., & St. Denis, L. (2018). Switching on the Big Burn of 2017. *Fire*, *1*(1), 17. https://doi.org/10.3390/fire1010017

Barriopedro, D., Fischer, E. M., Luterbacher, J., Trigo, R. M., & García-Herrera, R. (2011). The Hot Summer of 2010: Redrawing the Temperature Record Map of Europe. *Science*, *332*(6026), 220. https://doi.org/10.1126/science.1201224

Barthel, F., & Neumayer, E. (2012). A trend analysis of normalized insured damage from natural disasters. *Climatic Change*, *113*(2), 215–237. https://doi.org/10.1007/s10584-011-0331-2

Basabe, P. (2013). Hyogo Framework for Action 2005–2015. In P. T. Bobrowsky (Ed.), *Encyclopedia of Natural Hazards* (pp. 508–516). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-1-4020-4399-4_180

Behnen, K., Hušková, M., & Neuhaus, G. (1985). Rank estimators of scores for testing independence. *Statistics & Risk Modeling*, *3*(3–4), 239–262. https://doi.org/10.1524/strm.1985.3.34.239

Bendix, J., & Cowell, C. M. (2010). Fire, floods and woody debris: Interactions between biotic and geomorphic processes. *Geomorphology*, *116*(3–4), 297–304. https://doi.org/10.1016/j.geomorph.2009.09.043

Bier, V. M., Haimes, Y. Y., Lambert, J. H., Matalas, N. C., & Zimmerman, R. (1999). A Survey of Approaches for Assessing and Managing the Risk of Extremes. *Risk Anal.*, *19*(1), 83–94. https://doi.org/10.1111/j.1539-6924.1999.tb00391.x

Blum, M. D., & Roberts, H. H. (2014). Is sand in the Mississippi River delta a sustainable resource? *Nature Geoscience*, *7*, 851–852. https://doi.org/10.1038/ngeo2310

Boose, E. R., Serrano, M. I., & Foster, D. R. (2004). LANDSCAPE AND REGIONAL IMPACTS OF HURRICANES IN PUERTO RICO. *Ecological Monographs*, *74*(2), 335–352. https://doi.org/10.1890/02-4057

Bracken, C., Rajagopalan, B., Cheng, L., Kleiber, W., & Gangopadhyay, S. (2016). Spatial Bayesian hierarchical modeling of precipitation extremes over a large domain. *Water Resources Research*, *52*(8), 6643–6655. https://doi.org/10.1002/2016WR018768

Brindley, D. (2018). Months after hurricane Maria, Puerto Rico still struggling. *National Geographic*.

Buckland, M. K. (2019). *What is a megafire? Defining the social and physical dimensions of extreme U.S. wildfires (1988-2014)* (Masters Thesis). University of Colorado Boulder, Boulder, CO.

Burton, I., Kates, R. W., & White, G. F. (1978). Chapter 2: Hazard, response, and choice. In *The*

Environment as Hazard (pp. 19–52). Oxford University Press.

Cannon, S. H., Gartner, J. E., Wilson, R. C., Bowers, J. C., & Laber, J. L. (2008). Storm rainfall conditions for floods and debris flows from recently burned areas in southwestern Colorado and southern California. *Geomorphology*, *96*(3–4), 250–269. https://doi.org/10.1016/j.geomorph.2007.03.019

Carpenter, S. R., Arrow, K. J., Barrett, S., Biggs, R., Brock, W. A., Crépin, A. S., et al. (2012). General resilience to cope with extreme events. *Sustainability*, *4*(12), 3248–3259. https://doi.org/10.3390/su4123248

Carreau, J., & Vrac, M. (2011). Stochastic downscaling of precipitation with neural network conditional mixture models. *Water Resources Research*, *47*(10). https://doi.org/10.1029/2010WR010128

Changnon, S. A. (1998). The historical struggle with floods on the Mississippi River basin: impacts of recent floods and lessons for future flood management and policy. *Water International*, *23*(4), 263–271.

Chavez-Demoulin, V., & Davison, A. C. (2005). Generalized additive modelling of sample extremes. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *54*(1), 207–222. https://doi.org/10.1111/j.1467-9876.2005.00479.x

Coleman, J. M., Roberts, H. H., & Stone, G. W. (1998). Mississippi River Delta: an Overview. *Journal of Coastal Research*, *14*(3). Retrieved from https://journals.flvc.org/jcr/article/view/80663

Collins, B. D., Dickerson-Lange, S. E., Schanz, S., & Harrington, S. (2019). Differentiating the effects of logging, river engineering, and hydropower dams on flooding in the Skokomish River, Washington, USA. *Geomorphology*, *332*, 138–156. https://doi.org/10.1016/j.geomorph.2019.01.021

Collins, S. L., Carpenter, S. R., Swinton, S. M., Orenstein, D. E., Childers, D. L., Gragson, T. L., et al. (2011). An integrated conceptual framework for long-term social–ecological research. *Frontiers in Ecology and the Environment*, *9*(6), 351–357. https://doi.org/10.1890/100068

Colten, C. (2009). *Perilous Place, Powerful Storms: Hurricane Protection in Coastal Louisiana*. University Press of Mississippi. Retrieved from http://www.upress.state.ms.us/books/1696

Comissão Técnica Independente. (2017). Análise E Apuramento de Factos Relativos Aos Incêndios Que Ocorreram Em Pedrogão Grande. *Castanheira de Pera, Ansião, Alvaiázere, Figueiró Dos Vinhos, Arganil, Góis, Penela, Pampilhosa Da Serra, Oleiros E Sertã, Entre*, *17*.

Committee on Lessons Learned from the Fukushima Nuclear Accident for Improving Safety and Security of U.S. Nuclear Plants. (2014). *Lessons learned from the Fukushima nuclear accident for improving safety of U.S. nuclear plants*. Washingotn, DC: National Academies Press.

Crausbay, S. D., Ramirez, A. R., Carter, S. L., Cross, M. S., Hall, K. R., Bathke, D. J., et al. (2017). Defining ecological drought for the twenty-first century. *Bulletin of the American Meteorological Society*, *98*(12), 2543–2550. https://doi.org/10.1175/BAMS-D-16-0292.1

Criss, R. E., & Shock, E. L. (2001). Flood enhancement through flood control. *Geology*, *29*(10), 875–878. https://doi.org/10.1130/0091-7613(2001)?029<0875:FETFC>?2.0.CO

Cutter, S. L. (2018). Compound, Cascading, or Complex Disasters: What's in a Name? *Environment: Science and Policy for Sustainable Development*, *60*(6), 16–25. https://doi.org/10.1080/00139157.2018.1517518

Davies, R., Foulger, G., Bindley, A., & Styles, P. (2013). Induced seismicity and hydraulic fracturing for the recovery of hydrocarbons. *Marine and Petroleum Geology*, *45*, 171–185. https://doi.org/10.1016/j.marpetgeo.2013.03.016

Day, J. W., Britsch, L. D., Hawes, S. R., Shaffer, G. P., Reed, D. J., & Cahoon, D. (2000). Pattern and process of land loss in the Mississippi Delta: A Spatial and temporal analysis of wetland habitat change. *Estuaries*, *23*(4), 425–438. https://doi.org/10.2307/1353136

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Yan, K., Brandimarte, L., & Blöschl, G. (2015). Debates-Perspectives on socio-hydrology: Capturing feedbacks between physical and social

processes. *Water Resources Research*, *51*(6), 4770–4781. https://doi.org/10.1002/2014WR016416
Di Clemente, A., & Romano, C. (2004). A copula-extreme value theory approach for modelling operational risk. In M. Cruz (Ed.), *Operational Risl Modelling and Analysis: Theory and Practice* (pp. 189–208). Risk Books, London.
Dole, R., Hoerling, M., Perlwitz, J., Eischeid, J., Pegion, P., Zhang, T., et al. (2011). Was there a basis for anticipating the 2010 Russian heat wave? *Geophysical Research Letters*, *38*(6), 1–5. https://doi.org/10.1029/2010GL046582
Dowdy, A. J., & Catto, J. L. (2017). Extreme weather caused by concurrent cyclone, front and thunderstorm occurrences. *Scientific Reports*, *7*, 40359. https://doi.org/10.1038/srep40359
Durante, F., & Salvadori, G. (2010). On the construction of multivariate extreme value models via copulas. *Environmetrics*, *21*(2), 143–161. https://doi.org/10.1002/env.988
Fan, X., Scaringi, G., Korup, O., West, A. J., van Westen, C. J., Tanyas, H., et al. (2019). Earthquake-induced chains of geologic hazards: patterns, mechanisms, and impacts. *Reviews of Geophysics*. https://doi.org/10.1029/2018RG000626
Fatichi, S., Vivoni, E. R., Ogden, F. L., Ivanov, V. Y., Mirus, B., Gochis, D., et al. (2016). An overview of current applications, challenges, and future trends in distributed process-based models in hydrology. *Journal of Hydrology*, *537*, 45–60. https://doi.org/10.1016/j.jhydrol.2016.03.026
FEMA. (2013). *National Mitigation Framework* (p. 44). Retrieved from https://www.fema.gov/media-library/assets/documents/32209
Ferreira-Leite, F., Bento-Gonçalves, A., Vieira, A., Nunes, A., & Lourenço, L. (2016). Incidence and recurrence of large forest fires in mainland Portugal. *Natural Hazards*, *84*(2), 1035–1053. https://doi.org/10.1007/s11069-016-2474-y
Forzieri, G., Feyen, L., Russo, S., Vousdoukas, M., Alfieri, L., Outten, S., et al. (2016). Multi-hazard assessment in Europe under climate change. *Climatic Change*, *137*(1–2), 105–119. https://doi.org/10.1007/s10584-016-1661-x
Franklin, J. L., Pasch, R. J., Avila, L. A., Beven, J. L., Lawrence, M. B., Stewart, S. R., & Blake, E. S. (2006). Atlantic Hurricane Season of 2004. *Monthly Weather Review*, *134*(3), 981–1025. https://doi.org/10.1175/MWR3096.1
Franzke, C. (2012). Predictability of extreme events in a nonlinear stochastic-dynamical model. *PHYSICAL REVIEW E*, *85*, 031134. https://doi.org/10.1103/PhysRevE.85.031134
Freudenburg, W. R., Gramling, R., Laska, S., & Erikson, K. T. (2008). Organizing Hazards, Engineering Disasters? Improving the Recognition of Political-Economic Factors in the Creation of Disasters. *Social Forces*, *87*(2), 1015–1038. https://doi.org/10.1353/sof.0.0126
Gallina, V., Torresan, S., Critto, A., Sperotto, A., Glade, T., & Marcomini, A. (2016). A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment. *Journal of Environmental Management*, *168*, 123–132. https://doi.org/10.1016/j.jenvman.2015.11.011
Gasparrini, A., & Armstrong, B. (2011). The impact of heat waves on mortality. *Epidemiology (Cambridge, Mass.)*, *22*(1), 68–73. https://doi.org/10.1097/EDE.0b013e3181fdcd99
Gauthier, S., Bernier, P., Kuuluvainen, T., Shvidenko, A. Z., & Schepaschenko, D. G. (2015). Boreal forest health and global change. *Science*, *349*(6250), 819–822. https://doi.org/10.1126/science.aaa9092
Gedan, K. B., Kirwan, M. L., Wolanski, E., Barbier, E. B., & Silliman, B. R. (2011). The present and future role of coastal wetland vegetation in protecting shorelines: answering recent challenges to the paradigm. *Climatic Change*, *106*(1), 7–29. https://doi.org/10.1007/s10584-010-0003-7
Gill, J. C., & Malamud, B. D. (2014). Reviewing and visualizing the interactions of natural hazards. *Reviews of Geophysics*, *52*, 680–722. https://doi.org/10.1002/2013RG000437.Received

Gill, J. C., & Malamud, B. D. (2017). Anthropogenic processes, natural hazards, and interactions in a multi-hazard framework. *Earth-Science Reviews*, *166*, 246–269. https://doi.org/10.1016/j.earscirev.2017.01.002

Gregory, K. J. (2006). The human role in changing river channels. *Geomorphology*, *79*(3–4), 172–191. https://doi.org/10.1016/j.geomorph.2006.06.018

Harris, R. M. B., Beaumont, L. J., Vance, T. R., Tozer, C. R., Remenyi, T. A., Perkins-Kirkpatrick, S. E., et al. (2018). Biological responses to the press and pulse of climate trends and extreme events. *Nature Climate Change*, *8*(7), 579–587. https://doi.org/10.1038/s41558-018-0187-9

Heffernan, J. B., Soranno, P. A., Angilletta Jr, M. J., Buckley, L. B., Gruner, D. S., Keitt, T. H., et al. (2014). Macrosystems ecology: understanding ecological patterns and processes at continental scales. *Frontiers in Ecology and the Environment*, *12*(1), 5–14. https://doi.org/10.1890/130017

Herring, S. C., Hoerling, M. P., Kossin, J. P., Peterson, T. C., & Stott, P. A. (2016). Explaining Extreme Events of 2014 from a Climate Perspective. *Bulletin of the American Meteorological Society*, *96*(12), S1–S172. https://doi.org/10.1175/bams-explainingextremeevents2014.1

Hewitt, K., Burton, I., & others. (1971). Hazardousness of a place: a regional ecology of damaging events.

Hirota, M., Holmgren, M., Van Nes, E. H., & Scheffer, M. (2011). Global resilience of tropical forest and savanna to critical transitions. *Science*, *334*(6053), 232–235. https://doi.org/10.1126/science.1210657

Hu, T., & Smith, R. B. (2018). The Impact of Hurricane Maria on the Vegetation of Dominica and Puerto Rico Using Multispectral Remote Sensing. *Remote Sensing*, *10*(6), 827. https://doi.org/10.3390/rs10060827

IPCC. (2012). *Special Report of the Intergovernmental Panel on Climate Change*. (C. B. Field, V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, et al., Eds.). Cambridge University Press, Cambridge.

Joe, H. (2014). *Dependence modeling with copulas*. Chapman and Hall/CRC. Retrieved from https://doi.org/10.1201/b17116

Joseph, M. B., Rossi, M. W., Mietkiewicz, N. P., Mahood, A. L., Cattau, M. E., St Denis, L. A., et al. (2019). Spatiotemporal prediction of wildfire size extremes with Bayesian finite sample maxima. *Ecological Applications : A Publication of the Ecological Society of America*, e01898. https://doi.org/10.1002/eap.1898

Kappes, M. S., Keiler, M., von Elverfeldt, K., & Glade, T. (2012). Challenges of analyzing multi-hazard risk: a review. *Natural Hazards*, *64*(2), 1925–1958. https://doi.org/10.1007/s11069-012-0294-2

Kates, R. W. (1971). Natural Hazard in Human Ecological Perspective : Hypotheses and Models. *Economic Geography*, *47*(3), 438–451. https://doi.org/10.2307/142820

Kesel, R. H. (2003). Human modifications to the sediment regime of the Lower Mississippi River flood plain. *Floodplains: Environment and Process*, *56*(3), 325–334. https://doi.org/10.1016/S0169-555X(03)00159-4

Kirwan, M. L., Murray, A. B., Donnelly, J. P., & Corbett, D. R. (2011). Rapid wetland expansion during European settlement and its implication for marsh survival under modern sediment delivery rates. *Geology*, *39*(5), 507–510. https://doi.org/10.1130/G31789.1

Kishore, N., Marqués, D., Mahmud, A., Kiang, M. V., Rodriguez, I., Fuller, A., et al. (2018). Mortality in puerto rico after hurricane maria. *New England Journal of Medicine*, *379*(2), 162–170. https://doi.org/10.1056/NEJMsa1803972

Klinenberg, E. (2003). *Heat Waves: A Social Autopsy of Disaster in Chicago*. University of Chicago Press. Retrieved from https://www.press.uchicago.edu/ucp/books/book/chicago/H/bo20809880.html

Ko, J.-Y., & Day, J. W. (2004). A review of ecological impacts of oil and gas development on coastal ecosystems in the Mississippi Delta. *Integrated Coastal Management in the Gulf of Mexico Large Marine Ecosystem*, *47*(11), 597–623. https://doi.org/10.1016/j.ocecoaman.2004.12.004

Kreibich, H., Van Den Bergh, J. C. J. M., Bouwer, L. M., Bubeck, P., Ciavola, P., Green, C., et al. (2014).

Costing natural hazards. *Nature Climate Change*, *4*(5), 303–306. https://doi.org/10.1038/nclimate2182
Landsea, C. W., & Franklin, J. L. (2013). Atlantic Hurricane Database Uncertainty and Presentation of a New Database Format. *Monthly Weather Review*, *141*(10), 3576–3592. https://doi.org/10.1175/MWR-D-12-00254.1
Lee, J. C., & McCormick, N. J. (2012). *Risk and Safety Analysis of Nuclear Systems*. Newark, NJ: John Wiley & Sons.
Lenton, T. M. (2013). Environmental Tipping Points. *Annual Review of Environment and Resources*, *38*(1), 1–29. https://doi.org/10.1146/annurev-environ-102511-084654
Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., Mcinnes, K., et al. (2014). *A compound event framework for understanding extreme impacts* (Vol. 5). https://doi.org/10.1002/wcc.252
Leyk, S., & Uhl, J. H. (2018). HISDAC-US, historical settlement data compilation for the conterminous United States over 200 years. *Scientific Data*, *5*, 180175. https://doi.org/10.1038/sdata.2018.175
Linn, R. R., & Cunningham, P. (2005). Numerical simulations of grass fires using a coupled atmosphere–fire model: Basic fire behavior and dependence on wind speed. *Journal of Geophysical Research: Atmospheres*, *110*(D13). https://doi.org/10.1029/2004JD005597
Liu, J., Dietz, T., Carpenter, S. R., Folke, C. S., Alberti, M., Charles, L., et al. (2007). Coupled Human and Natural Systems. *Ambio*, *36*(8), 639–649. https://doi.org/10.1579/0044-7447(2007)36
Lopez-Paz, D., Hernández-Lobato, J. M., & Zoubin, G. (2013). Gaussian Process Vine Copulas for Multivariate Dependence. In S. Dasgupta & D. McAllester (Eds.), *Proceedings of the 30th International Conference on Machine Learning* (Vol. 28, pp. 10–18). Atlanta, Georgia, USA: PMLR. Retrieved from http://proceedings.mlr.press/v28/lopez-paz13.html
Marvel, K., Cook, B. I., Bonfils, C. J. W., Durack, P. J., Smerdon, J. E., & Williams, A. P. (2019). Twentieth-century hydroclimate changes consistent with human influence. *Nature*, *569*(7754), 59. https://doi.org/10.1038/s41586-019-1149-8
McLeman, R. A., Dupre, J., Berrang Ford, L., Ford, J., Gajewski, K., & Marchildon, G. (2014). What we learned from the Dust Bowl: lessons in science, policy, and adaptation. *Population and Environment*, *35*(4), 417–440. https://doi.org/10.1007/s11111-013-0190-z
Mcphillips, L. E., Chang, H., Chester, M. V., Depietri, Y., Friedman, E., Grimm, N. B., et al. (2018). Defining Extreme Events : A Cross-Disciplinary Review. *Earth's Future*, *6*, 1–15. https://doi.org/10.1002/eft2.304
Meade, R. H., & Moody, J. A. (2010). Causes for the decline of suspended-sediment discharge in the Mississippi River system, 1940–2007. *Hydrological Processes*, *24*(1), 35–49. https://doi.org/10.1002/hyp.7477
Meyer, V., Becker, N., Markantonis, V., Schwarze, R., Bergh, J. C. J. M. van den, Bouwer, L. M., et al. (2013). Review article: Assessing the costs of natural hazards – state of the art and knowledge gaps. *Natural Hazards and Earth System Sciences*, *13*(5), 1351–1373. https://doi.org/10.5194/nhess-13-1351-2013
Montz Burrell E., & Tobin Graham A. (2008). Livin' Large with Levees: Lessons Learned and Lost. *Natural Hazards Review*, *9*(3), 150–157. https://doi.org/10.1061/(ASCE)1527-6988(2008)9:3(150)
Moody, J. A., Shakesby, R. A., Robichaud, P. R., Cannon, S. H., & Martin, D. A. (2013). Current research issues related to post-wildfire runoff and erosion processes. *Earth-Science Reviews*, *122*, 10–37. https://doi.org/10.1016/j.earscirev.2013.03.004
Moritz, M. A., Batllori, E., Bradstock, R. A., Gill, A. M., Handmer, J., Hessburg, P. F., et al. (2014). Learning to coexist with wildfire. *Nature*, *515*(7525), 58. https://doi.org/10.1038/nature13946
Morton, R. A., Bernier, J. C., & Barras, J. A. (2006). Evidence of regional subsidence and associated interior wetland loss induced by hydrocarbon production, Gulf Coast region, USA. *Environmental*

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27877v1 | CC BY 4.0 Open Access | rec: 30 Jul 2019, publ: 30 Jul 2019

Geology, *50*(2), 261. https://doi.org/10.1007/s00254-006-0207-3
National Drought Mitigation Center. (2019). National Integrated Drought Information System. Retrieved July 2, 2019, from https://www.drought.gov/drought/search/data
Neri, M., Lanzafame, G., & Acocella, V. (2008). Dyke emplacement and related hazard in volcanoes with sector collapse: the 2007 Stromboli (Italy) eruption. *Journal of the Geological Society*, *165*(5), 883–886. https://doi.org/10.1144/0016-76492008-002
Nittrouer, J. A., & Viparelli, E. (2014). Sand as a stable and sustainable resource for nourishing the Mississippi River delta. *Nature Geoscience*, *7*, 350. https://doi.org/10.1038/ngeo2142
NOAA, National Centers for Environmental Information. (2019). U.S. Billion-Dollar Weather and Climate Disasters. Retrieved July 2, 2019, from https://www.ncdc.noaa.gov/billions/
Nones, M., & Pescaroli, G. (2016). Implications of cascading effects for the EU Floods Directive. *International Journal of River Basin Management*, *14*(2), 195–204.
Nordhaus, W. D. (2011). The Economics of Tail Events with an Application to Climate Change. *Review of Environmental Economics and Policy*, *5*(2), 240–257. https://doi.org/10.1093/reep/rer004
Padoan, S. A., & Wand, M. P. (2008). Mixed model-based additive models for sample extremes. *Statistics and Probability Letters*, *78*(17), 2850–2858. https://doi.org/10.1016/j.spl.2008.04.009
Pannell, I., Taguchi, E., & Louszko, A. (2017, October 18). "It's all gone": Hurricane-ravaged Dominica, on the front line of climate change, fighting to survive. *ABC News*.
Paté-Cornell, E. (2012). On "Black Swans" and "Perfect Storms": Risk Analysis and Management When Statistics Are Not Enough. *Risk Analysis*, *32*(11), 1823–1833. https://doi.org/10.1111/j.1539-6924.2011.01787.x
Pindyck, R. S. (2011). Fat Tails, Thin Tails, and Climate Change Policy. *Review of Environmental Economics and Policy*, *5*(2), 258–274. https://doi.org/10.1093/reep/rer005
Pulver, S., Ulibarri, N., Sobocinski, K. L., Alexander, S. M., Johnson, M. L., McCord, P. F., & Dell'Angelo, J. (2018). Frontiers in socio-environmental research: components, connections, scale, and context. *Ecology and Society*, *23*(3). https://doi.org/10.5751/ES-10280-230323
Ram, M., & Singh, S. (2009). Analysis of reliability characteristics of a complex engineering system under copula. *Journal of Reliability and Statistical Studies*, *2*(1), 91–102.
Rego, F. C., & Silva, J. S. (2014). Wildfires and landscape dynamics in Portugal: a regional assessment and global implications. In J. C. Azevedo, A. H. Perera, & M. A. Pinto (Eds.), *Forest Landscapes and Global Change: Challenges for Research and Management* (pp. 51–73). New York, NY: Springer New York. https://doi.org/10.1007/978-1-4939-0953-7_3
Renard, B., & Lang, M. (2007). Use of a Gaussian copula for multivariate extreme value analysis: some case studies in hydrology. *Advances in Water Resources*, *30*(4), 897–912. https://doi.org/10.1016/j.advwatres.2006.08.001
Sadegh, M., Ragno, E., & AghaKouchak, A. (2017). Multivariate Copula Analysis Toolbox (MvCAT): Describing dependence and underlying uncertainty using a Bayesian framework. *Water Resources Research*, *53*(6), 5166–5183. https://doi.org/10.1002/2016WR020242
Saker, A., & Rudavsky, S. (2018, January 14). Hospitals find other ways to deliver medicine amid IV bag shortage. *USA Today*.
Scheffer, M., & Carpenter, S. R. (2003). Catastrophic regime shifts in ecosystems: linking theory to observation. *Trends in Ecology & Evolution*, *18*(12), 648–656. https://doi.org/10.1016/j.tree.2003.09.002
Schoennagel, T., Balch, J. K., Brenkert-Smith, H., Dennison, P. E., Harvey, B. J., Krawchuk, M. A., et al. (2017). Adapt to more wildfire in western North American forests as climate changes. *Proceedings of the National Academy of Sciences*, *114*(18), 4582–4590. https://doi.org/10.1073/pnas.1617464114
Shaposhnikov, D., Revich, B., Bellander, T., Bedada, G. B., Bottai, M., Kharkova, T., et al. (2014). Mortality

Related to Air Pollution with the Moscow Heat Wave and Wildfire of 2010. *Epidemiology (Cambridge, Mass.)*, *25*(3), 359–364. https://doi.org/10.1097/EDE.0000000000000090

Sharma, A. S., Baker, D. N., Bhattacharyya, A., Bunde, A., Dimri, V. P., Gupta, H. K., et al. (2013). Complexity and Extreme Events in Geosciences: An Overview. In *Extreme Events and Natural Hazards: The Complexity Perspective*. A. S. Sharma, A. Bunde, V. P. Dimri and D. N. Baker.

Sklar, M. (1959). Fonctions de repartition an dimensions et leurs marges. *Publ. Inst. Statist. Univ. Paris*, *8*, 229–231.

Slater, L. J., Singer, M. B., & Kirchner, J. W. (2015). Hydrologic versus geomorphic drivers of trends in flood hazard. *Geophysical Research Letters*, *42*(2), 370–376. https://doi.org/10.1002/2014GL062482

Smith, A. B., & Katz, R. W. (2013). US billion-dollar weather and climate disasters: Data sources, trends, accuracy and biases. *Natural Hazards*, *67*(2), 387–410. https://doi.org/10.1007/s11069-013-0566-5

Smith, M. D. (2011). An ecological perspective on extreme climatic events: a synthetic definition and framework to guide future research. *Journal of Ecology*, *99*, 656–663. https://doi.org/10.1111/j.1365-2745.2011.01798.x

Sornette, D. (2009). Dragon-Kings, Black Swans and the Prediction of Crises. *International Journal of Terraspace Science and Engineering*, *2*(1), 1–18.

Spies, T. A., Hammer, R., White, E. M., Kline, J. D., Bailey, J., Bolte, J., et al. (2014). Examining fire-prone forest landscapes as coupled human and natural systems. *Ecology and Society*, *19*(3). https://doi.org/10.5751/ES-06584-190309

Staal, A., Tuinenburg, O. A., Bosmans, J. H. C., Holmgren, M., van Nes, E. H., Scheffer, M., et al. (2018). Forest-rainfall cascades buffer against drought across the Amazon. *Nature Climate Change*, *8*(6), 539–543. https://doi.org/10.1038/s41558-018-0177-y

Staley, D. M., Wasklewicz, T. A., & Blaszczynski, J. S. (2005). Surficial patterns of debris flow deposition on alluvial fans in Death Valley, CA using airborne laser swath mapping data. *Geomorphology*, *74*(1–4), 152–163. https://doi.org/10.1016/j.geomorph.2005.07.014

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., et al. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*(6223), 1259855. https://doi.org/10.1126/science.1259855

Stephen, B., Galloway, S. J., McMillan, D., Hill, D. C., & Infield, D. G. (2010). A copula model of wind turbine performance. *IEEE Transactions on Power Systems*, *26*(2), 965–966. https://doi.org/10.1109/TPWRS.2010.2073550

Stott, P. A., Christidis, N., Otto, F. E. L., Sun, Y., Vanderlinden, J.-P., Oldenborgh, G. J. van, et al. (2016). Attribution of extreme weather and climate-related events. *Wiley Interdisciplinary Reviews: Climate Change*, *7*(1), 23–41. https://doi.org/10.1002/wcc.380

Suding, K. N., & Hobbs, R. J. (2009). Threshold models in restoration and conservation: a developing framework. *Trends in Ecology & Evolution*, *24*(5), 271–279. https://doi.org/10.1016/j.tree.2008.11.012

Syvitski, J. P. M., Vörösmarty, C. J., Kettner, A. J., & Green, P. (2005). Impact of Humans on the Flux of Terrestrial Sediment to the Global Coastal Ocean. *Science*, *308*(5720), 376. https://doi.org/10.1126/science.1109454

Tedim, F., Leone, V., Amraoui, M., Bouillon, C., Coughlan, M. R., Delogu, G. M., et al. (2018). Defining Extreme Wildfire Events: Difficulties, Challenges, and Impacts. *Fire*, *1*(9). https://doi.org/10.3390/fire1010009

Tessler, Z. D., Vörösmarty, C. J., Grossberg, M., Gladkova, I., Aizenman, H., Syvitski, J. P. M., & Foufoula-Georgiou, E. (2015). Profiling risk and sustainability in coastal deltas of the world. *Science*, *349*(6248), 638. https://doi.org/10.1126/science.aab3574

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Törnqvist, T. E., Bick, S. J., van der Borg, K., & de Jong, A. F. M. (2006). How stable is the Mississippi Delta? *Geology*, *34*(8), 697–700. https://doi.org/10.1130/G22624.1

Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., et al. (2003). A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences*, *100*(14), 8074–8079. https://doi.org/10.1073/pnas.1231335100

Turner, Billie Lee, Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., et al. (2003). Illustrating the coupled human–environment system for vulnerability analysis: three case studies. *Proceedings of the National Academy of Sciences*, *100*(14), 8080–8085. https://doi.org/10.1073/pnas.1231334100

Turner, R. E. (1997). Wetland loss in the Northern Gulf of Mexico: Multiple working hypotheses. *Estuaries*, *20*(1), 1–13. https://doi.org/10.2307/1352716

United Nations International Strategy for Disaster Reduction (UNISDR). (2015a). *Sendai Framework for Disaster Risk Reduction 2015 - 2030* (No. March) (pp. 1–25).

United Nations International Strategy for Disaster Reduction (UNISDR). (2015b). *Sendai Framework for Disaster Risk Reduction 2015 - 2030* (pp. 1–25).

United States Geological Survey. (2019). Monitoring Trends in Burn Severity. Retrieved July 2, 2019, from https://mtbs.gov/

Uriarte, M., Thompson, J., & Zimmerman, J. K. (2019). Hurricane María tripled stem breaks and doubled tree mortality relative to other major storms. *Nature Communications*, *10*(1), 1362. https://doi.org/10.1038/s41467-019-09319-2

U.S. Nuclear Regulatory Commission. (1975). *Reactor safety study. An assessment of accident risks in U. S. commercial nuclear power plants. Executive Summary. WASH-1400 (NUREG-75/014)* (p. 198). Washington, D.C.: U.S. Nuclear Regulatory Commission. https://doi.org/10.2172/7134131

Van Beusekom, A., Álvarez-Berríos, N., Gould, W., Quiñones, M., & González, G. (2018). Hurricane María in the US Caribbean: Disturbance forces, variation of effects, and implications for future storms. *Remote Sensing*, *10*(9), 1386. https://doi.org/10.3390/rs10091386

Van Coppenolle, R., Schwarz, C., & Temmerman, S. (2018). Contribution of Mangroves and Salt Marshes to Nature-Based Mitigation of Coastal Flood Risks in Major Deltas of the World. *Estuaries and Coasts*, *41*(6), 1699–1711. https://doi.org/10.1007/s12237-018-0394-7

Viegas, D., Almeida, M. F., Ribeiro, L., Raposo, J., Viegas, M., Oliveira, R., et al. (2017). O complexo de incêndios de Pedrógão Grande e concelhos limítrofes, iniciado a 17 de junho de 2017. *Centro de Estudos Sobre Incêndios Florestais, ADAI/LAETA, Departamento de Engenharia Mecânica, Faculdade de Ciências e Tecnologia, Universidade de Coimbra*.

Vogel, M. M., Zscheischler, J., Wartenburger, R., Dee, D., & Seneviratne, S. I. (n.d.). Concurrent 2018 Hot Extremes Across Northern Hemisphere Due to Human-Induced Climate Change. *Earth's Future*, *0*(0). https://doi.org/10.1029/2019EF001189

Wahl, T., Jain, S., Bender, J., Meyers, S. D., & Luther, M. E. (2015). Increasing risk of compound flooding from storm surge and rainfall for major US cities. *Nature Climate Change*, *5*(12), 1093–1097. https://doi.org/10.1038/nclimate2736

Wahl, T., Plant, N. G., & Long, J. W. (2016). Probabilistic assessment of erosion and flooding risk in the northern Gulf of Mexico. *Journal of Geophysical Research: Oceans*, *121*(5), 3029–3043. https://doi.org/10.1002/2015JC011482

Walker, H. J., Coleman, J. M., Roberts, H. H., & Tye, R. S. (1987). Wetland Loss in Louisiana. *Geografiska Annaler: Series A, Physical Geography*, *69*(1), 189–200. https://doi.org/10.1080/04353676.1987.11880207

Walter, R. C., & Merritts, D. J. (2008). Natural streams and the legacy of water-powered mills. *Science*, *319*(5861), 299–304. https://doi.org/10.1126/science.1151716

Weinkle, J. (2019a). Experts, regulatory capture, and the "governor's dilemma": The politics of hurricane

PeerJ Preprints | https://doi.org/10.7287/peerj.preprints.27877v1 | CC BY 4.0 Open Access | rec: 30 Jul 2019, publ: 30 Jul 2019

risk science and insurance. *Regulation & Governance*. https://doi.org/10.1111/rego.12255
Weinkle, J. (2019b). The new political importance of the old hurricane risk: a contextual approach to understanding contemporary struggles with hurricane risk and insurance. *Journal of Risk Research*, *22*(3), 320–333. https://doi.org/10.1080/13669877.2017.1378250
Weitzman, M. L. (2011). Fat-tailed uncertainty in the economics of catastrophic climate change. In *Review of Environmental Economics and Policy* (pp. 275–292). https://doi.org/10.1093/reep/rer006
Werner, B., & Mcnamara, D. E. (2007). Dynamics of coupled human-landscape systems. *Geomorphology*, *91*(3–4), 393–407. https://doi.org/10.1016/j.geomorph.2007.04.020
Westerling, a. L. (2016). Increasing western US forest wildfire activity: sensitivity to changes in the timing of Spring. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *371*(1696). https://doi.org/10.1098/rstb.2015.0178
Weston, N. B. (2014). Declining Sediments and Rising Seas: an Unfortunate Convergence for Tidal Wetlands. *Estuaries and Coasts*, *37*(1), 1–23. https://doi.org/10.1007/s12237-013-9654-8
Wheatley, S., Sovacool, B., & Sornette, D. (2017). Of Disasters and Dragon Kings: A Statistical Analysis of Nuclear Power Incidents and Accidents. *Risk Analysis*, *37*(1), 99–115. https://doi.org/10.1111/risa.12587
White, G. F., Kates, R. W., & Burton, I. (2001). Knowing better and losing even more: The use of knowledge in hazards management. *Environmental Hazards*, *3*(3–4), 81–92. https://doi.org/10.1016/S1464-2867(01)00021-3
Woolhiser David A. (1996). Search for Physically Based Runoff Model—A Hydrologic El Dorado? *Journal of Hydraulic Engineering*, *122*(3), 122–129. https://doi.org/10.1061/(ASCE)0733-9429(1996)122:3(122)
World Wildlife Fund. (2018). *Living Planet Report 2018: Aiming higher*. (M. Grooten & R. E. A. Almond, Eds.). Gland, Switzerland. Retrieved from www.livingplanetindex.org
Zektser, S., Loáiciga, H. A., & Wolf, J. (2005). Environmental impacts of groundwater overdraft: selected case studies in the southwestern United States. *Environmental Geology*, *47*(3), 396–404. https://doi.org/10.1007/s00254-004-1164-3
Zimmer, D. M. (2012). The Role of Copulas in the Housing Crisis. *The Review of Economics and Statistics*, *94*(2), 607–620. https://doi.org/10.1162/REST_a_00172
Zorzetto, E., Botter, G., & Marani, M. (2016). On the emergence of rainfall extremes from ordinary events. *Geophysical Research Letters*, *43*(15), 8076–8082. https://doi.org/10.1002/2016GL069445
Zscheischler, J., & Seneviratne, S. I. (2017). Dependence of drivers affects risks associated with compound events. *Science Advances*, *3*(6), e1700263.
Zscheischler, J., Westra, S., Van Den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., et al. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3

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