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Social-Environmental Extremes: Rethinking Extraordinary Events as Outcomes of Interacting Biophysical and Social Systems

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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 social-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 other social and biophysical drivers and conditions, 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, often neglecting interactions and the subsequent novel extremes that can arise. Here we propose a framework for social-environmental extremes, defined as extraordinary events that emerge from interactions among biophysical and social systems. We argue that this definition is critical because it constrains the focus to major events that are capturing societal and scientific attention because of their extreme biophysical drivers and/or the extreme social outcomes. We review how different fields approach extremes as interacting phenomena and propose a synthetic framework that allows analytical separation of the multiple drivers and responses that yield extreme events and extreme effects. We conclude with a future research agenda for 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 social-environmental extremes—informing future mitigation and adaptation strategies.

Plain Language Summary The frequency and magnitude of some extremes are increasing, for example, 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 United States 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.

1. Introduction

If we are to better understand the genesis of recent extremes, we need to understand both their social and environmental underpinnings. Several critical research questions have yet to be addressed: When do we need to explore extreme biophysical events, or just the average events that co-occur with extreme societal

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exposure? When do social exposure and vulnerability precondition average or extreme events to lead to extreme societal outcomes? When do interactions among social and environmental drivers and responses lead to event intensity and impact amplification (e.g., AghaKouchak et al., 2018)? In this review, we extend social-environmental frameworks to rethink the events that result from tightly coupled biophysical and social phenomena and have exceptional magnitude and/or extreme social impact, herein defined as social-environmental extremes. This framework is informed by multiple disciplines that each offers explicit treatment of interactions and feedbacks that lead to extremes, or have the potential to, including natural hazards, coupled human-natural systems, socio-ecological systems (SESs), resilience, and complex systems theory. In this work, we use the term social-environmental to acknowledge a diverse suite of subsystems encompassed by both social and biotic and abiotic environmental systems. “Social” refers to the diverse kinds of social effects and interventions that alter natural system behavior including, for example, differential social vulnerability, human adaptation, policy and governance, and technological interventions and innovations. “Environmental” refers to both biotic and abiotic components including, for example, those that arise from ecological dynamics, biogeochemical evolution, and physical constraints on the natural system. We conclude with a future research agenda that adds clarity and direction to understanding the extreme events that matter to society. Overall, this effort rethinks extraordinary events as outcomes of interacting biophysical and social systems so that we can better understand, predict, and manage the challenges posed by social-environmental extremes.

2. Going to Extremes

Extreme events disrupt the functioning and well-being of human and natural 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, and 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 United States. These extreme events not only overwhelm local and national response systems and mitigation resources but disrupt local ecosystems (Harris et al., 2018); 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, such extremes compromise global sustainable development (United Nations International Strategy for Disaster Reduction [UNISDR], 2015).

These events reveal the ability of interactions between social (including the economy, infrastructure, settlement, and technology) and environmental (including ecological, physical, and chemical components) systems to worsen or lessen extreme events and their impacts. Dramatically increased economic losses come from growing wealth, exposed development, and differential vulnerability (Barthel & Neumayer, 2012; Cutter et al., 2003; Depietri & McPhearson, 2018; Peduzzi et al., 2009), but also from global environmental change that alters the atmospheric energy budget, leading to larger magnitude of weather and climate events (Herring et al., 2018; Smith & Katz, 2013). Less is known about trends in ecological causes and impacts 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 and increase positive feedbacks, as when deforestation contributes to drought (Bagley et al., 2014; Staal et al., 2018).

Recent events also indicate that most extremes arise from multiple drivers with outcomes that propagate via multiple pathways. For example, the Russian heat wave of 2010 emerged from an unusual convergence of atmospheric conditions (Dole et al., 2011) and set the stage for extreme wildfires and smoke pollution. Outcomes included 55,000 related deaths, including among the most vulnerable populations such as the elderly and health-compromised, 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). Coupled natural-human system (CNHS) models, aka SES models (Liu et al., 2007; Pulver et al., 2018; Turner, Kasperson, et al., 2003; Turner, Matson, et al., 2003) or social-ecological-technological systems (SETSs) (Depietri & McPhearson, 2018; Grimm et al., 2017), may provide the most fruitful analytical approaches 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; Verburg et al., 2016). However, social-environmental thinking and theory 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 tends 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, 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 simultaneously attract public and policy-maker attention, evoking demand for better prediction and prevention (Schoennagel et al., 2017; UNISDR, 2015). Low probability yet high consequence events make public policy decisions difficult by pushing the limits of traditional decision tools such as cost-benefit analysis (Nordhaus, 2011; Pindyck, 2011; Weitzman, 2011). The increasing frequency of extreme events, emergent phenomena, and surprises complicate assessment of mechanism or trends and analysis of response options. Extremeness in biophysical drivers and extremeness in societal outcomes are often conflated but are not always directly related (Figure 1). For example, relatively weak landfalling hurricanes in the United States can cause greater damages than stronger storms due to a wide variety of stochastic conditions (Figure 1a), the largest, most enduring droughts may be either among the most or least costly in the U.S. record (Figure 1b), and the Great Smoky Mountains wildfires in 2016, only moderate in size, caused 14 deaths and burned 2,400 structures (Figure 1c). Within communities affected, the most vulnerable populations, including especially low income, people of color, and health compromised, suffer the worse effects and slowest recovery (Adger, 2006; Cutter et al., 2003). 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.

3. 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 the statistical distribution of some property (Bier et al., 1999) and often assumes independence of events and stationarity. This is encapsulated in the Intergovernmental Panel on Climate Change's (IPCC) 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, p. 557). This definition, however, neglects critical interactions among drivers and the societal consequences, including how social action can, in turn, amplify or attenuate the drivers of biophysical disturbances. For example, the late-season 2017 northern California “firestorm” was actually 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 (Smith, 2011), focusing on the 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. Multihazards 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). Further, there is particular interest in the interaction of ordinary events that lead to extraordinary outcomes. Causal pathways come in at least two flavors (Figure 2): multiple events due to a common driver or a cascade of secondary events obligated to the occurrence of the initial event. Multiple extremes may happen together in space and/or time (Figure 2a), such as correlated events at the same time and location (e.g., a tropical cyclone storm surge and winter cold outbreak

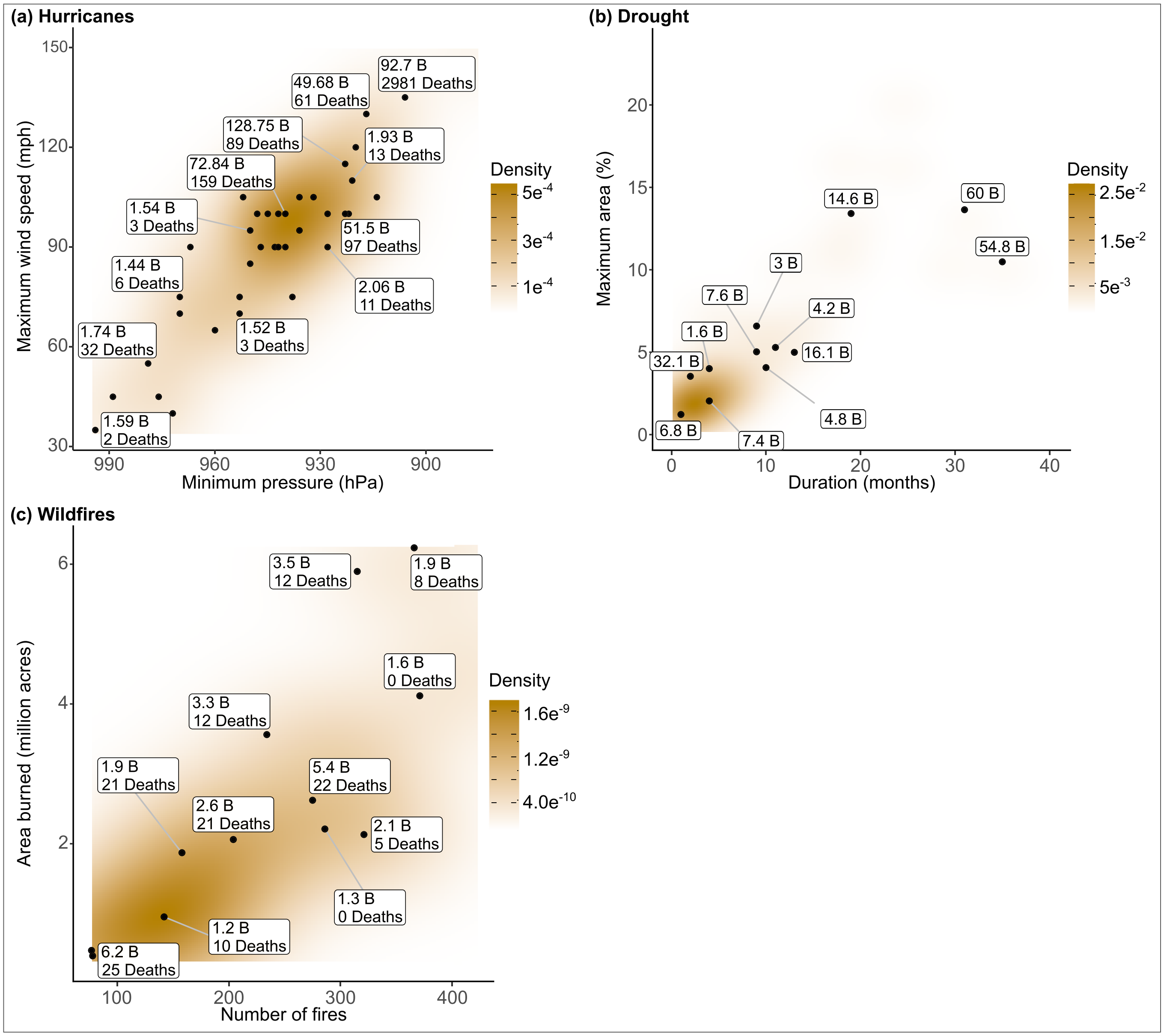

Figure 1. Social-environmental extremes can be extreme in both the biophysical and social systems or in only one system. Two-dimensional kernel density distribution of (a) hurricane maximum wind speed versus minimum pressure; (b) drought extension versus duration for the contiguous United States; and (c) annual area burned in the western United States versus number of events >400 ha. In all cases, the black 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 (Smith, 2020). Hurricane data from NOAA HURDAT2 (Landsea & Franklin, 2013). Drought events based on the Palmer Drought Severity Index translated into U. S. 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 United States 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"; Eidenshink et al., 2007).

associated with Hurricane Sandy), sequential events at a location (four hurricanes striking Florida in one season, 2004), or simultaneous events at different locations (e.g., simultaneous droughts in key global grain production regions, a pattern that first drew attention in the 1970s). These episodes may be causally related or independent (Figure 2b), 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 among weather and climate phenomena, is an emergent field, with, for example, studies of interactions among cyclones, fronts, and thunderstorms creating extreme conditions (Dowdy & Catto, 2017).

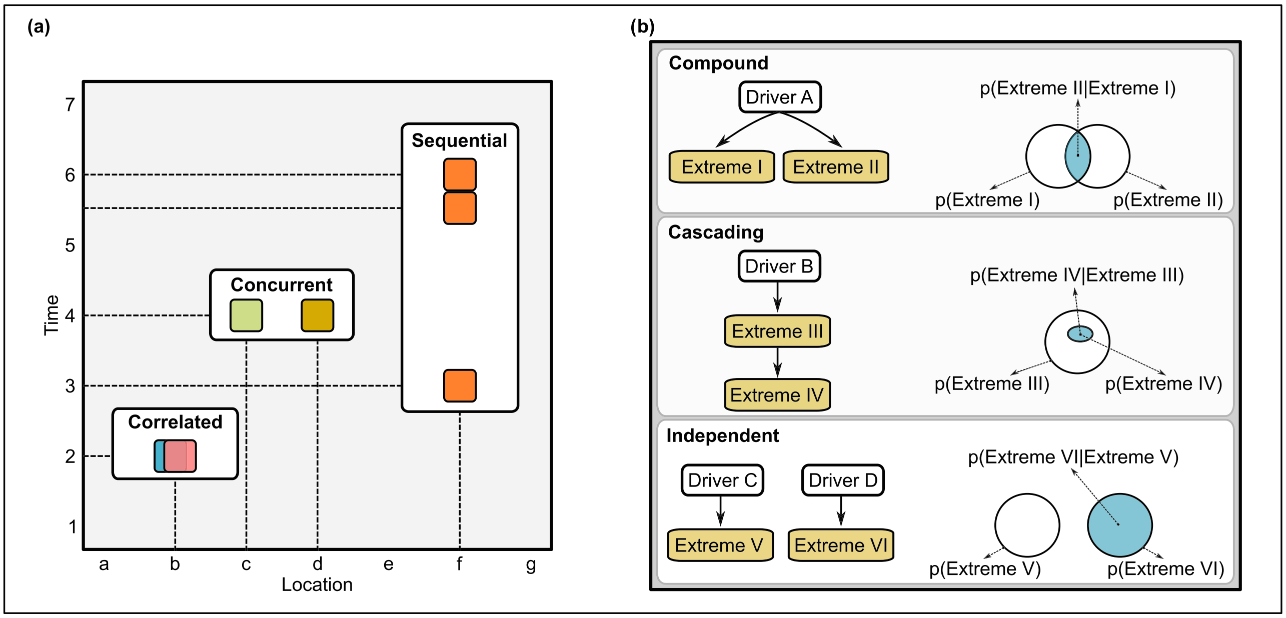

Figure 2. Classification of multiple extremes based on (a) the temporal and spatial characteristics of the coupling and (b) the causal and probabilistic characteristics of the coupling.

Even events that are interpreted as orthodox, statistically rare outcomes may actually be the result of currently unexamined interactions of interdependent drivers and processes. 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). By studying connected drivers, we may be able to shift some surprising extreme events from the realm of unknown unknowns (epistemic uncertainty, i.e., unknown outcome due to lack of quantifiable knowledge about the possibility of a given event) to the realm of known unknowns (statistical uncertainty, i.e., unknown outcome but known probability of a given event; Aven & Krohn, 2014).

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 social-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.

4. A Framework for Exploring Social-Environmental Extremes

We define social-environmental extremes as rare events, with exceptional properties (e.g., size, intensity, duration, or other metric) that result from interacting drivers and responses within both environmental and social systems and that yield at least some degree of social impact. In our usage, an impact can be negative, neutral, or positive when considering societal values. 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" social-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 and

Table 1
Examples of "True" Social-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 by drought and 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, leading to $45B in property damages and 60 fatalities; the coincident losses exceeded insurance reserves.	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 rearrangement 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 and October fires caused 113 deaths and economic losses of USD1.2B; it was the costliest natural disaster, with $300 M in insurance payouts in Portugal.	The extreme fire conditions 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 end 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 (2–4 m) for given discharge along certain reaches over time (Criss & Shock, 2001; Di Baldassarre et al., 2015; Smith, 2020)	Notable historic floods include the largest flood discharge on record (1844); a large flood in 1903, that had comparable discharge to 1993; the Great Mississippi Flood of 1927; and the Great Flood of 1993.	Great Flood of 1993 was the costliest nontropical, inland flood event to affect the United States on record ($37.3B and 48 lives lost).	The "Levee" effect is prominent in these cases. Lower hazard during more frequent events encourages development in floodplain or even reclassification of floodplain. The Great Mississippi Flood of 1927 was important because it triggered widespread building of levees, including those that 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 tenth 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.

allows analytical separation of elements that 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 (Mcphillips et al., 2018).

A social-environmental system framework (Figure 3) 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

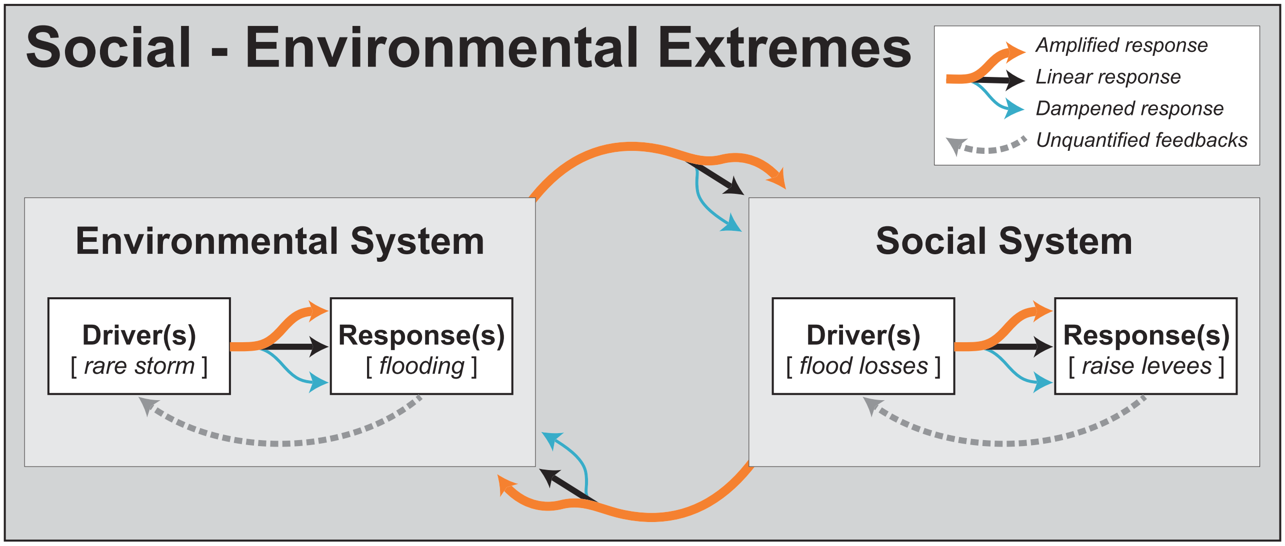

Figure 3. Conceptual framework illustrating the flow of causality in a social-environmental system as applied to extreme events. Transfer functions (solid arrows) describe the relationship between driver and response variables that may be amplified (orange), be linearly translated (black), or dampen (blue) responses. Subsystem feedbacks may also exist (gray 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 functions themselves. This framework is generalizable to all social-environmental system functioning, so we provide an example of extreme events and responses in brackets.

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 Figure 3 can help identify potential nonlinearities and sources of uncertainty.

Social systems interact with and feed back to physical systems in several important ways: (1) Social-economic drivers can exert force on biophysical drivers; (2) social responses to an extreme event can feed back to the physical drivers 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 (Walter & Merritts, 2008).

Environmental systems interact with and feed back to social systems in three main ways: (1) Environmental drivers and responses directly affect risk, or the likelihood that an event causes social harm; (2) multihazard cascades create unanticipated or poorly quantified risk; and (3) changing environmental conditions alter baselines such that design conditions are no longer adequate, thus changing social vulnerability. 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 thus actually increase in response to water management decisions (e.g., Collins et al., 2019). Recent work in the United States 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, accurate risk assessment is inhibited due to the breakdown of the assumption of stationarity in the hydroclimate. Stationarity asserts that statistical measures of a time series are invariant. In the case of changing climate, land cover, or interventions in the hydrograph, this assumption is invalid and can lead to underestimates or overestimates of event frequencies.

Text Box 1: Social-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 subsystems (i.e., Figure 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 hydrogeologic 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 MRD as a complex social-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 (Figure 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 (Day et al., 2000; Ko & Day, 2004; Turner, 1997). 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 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 reworking 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) displaced in both time and space.

Indirect effects due to social adaptation and vulnerability: 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 3,000 km of artificial levees (Changnon, 1998; Kesel, 2003). Although levees are built with the intention of decreasing flood losses, along the Mississippi floodplain, they 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 & Tobin, 2008). Levee failures in Hurricane Katrina also revealed that vulnerable households experienced larger proportionate loss and recovered more slowly (Sharkey, 2007). Stabilizing riverbanks has another indirect effect of preventing river avulsions (i.e., abrupt change in river course typically triggered by large floods). While stabilizing riverbanks 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 depocenters, 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 et al., 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.

4.1. Building a Social-Environmental Framework to Understand Extremes

Key ideas from natural hazards theory, coupled human-natural systems, social-ecological systems, resilience theory, and complex systems theory could be better extended to frame, diagnose, and understand social-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 natural-human frameworks. Kates (1971) first conceptualized hazards in a "human-ecological" perspective using a systems diagram, and the subsequent model developed by 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 process of "worsening." A systems approach also requires defining the forcing from social-economic drivers to physical drivers across spatial and temporal scales (Turner, Matson, 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 (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. Hazard worsening was recognized but rarely examined analytically until Hurricane Katrina induced failure of the Southern Louisiana protection system (Di Baldassarre et al., 2015; Kates et al., 2006). CNHSs thinking has been used to frame ecological drought (Crausbay et al., 2017), but not extreme ecological drought. Wildfires have been considered in a social-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; Davies et al., 2018; Tedim et al., 2018). Analysts occasionally refer to "mega-droughts" or "mega-fires" but struggle to offer formal definitions. And general social-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 social-environmental framework is explication of the distinct, reciprocal interactions (materials, energy, and 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 reduce 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 twentieth 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).

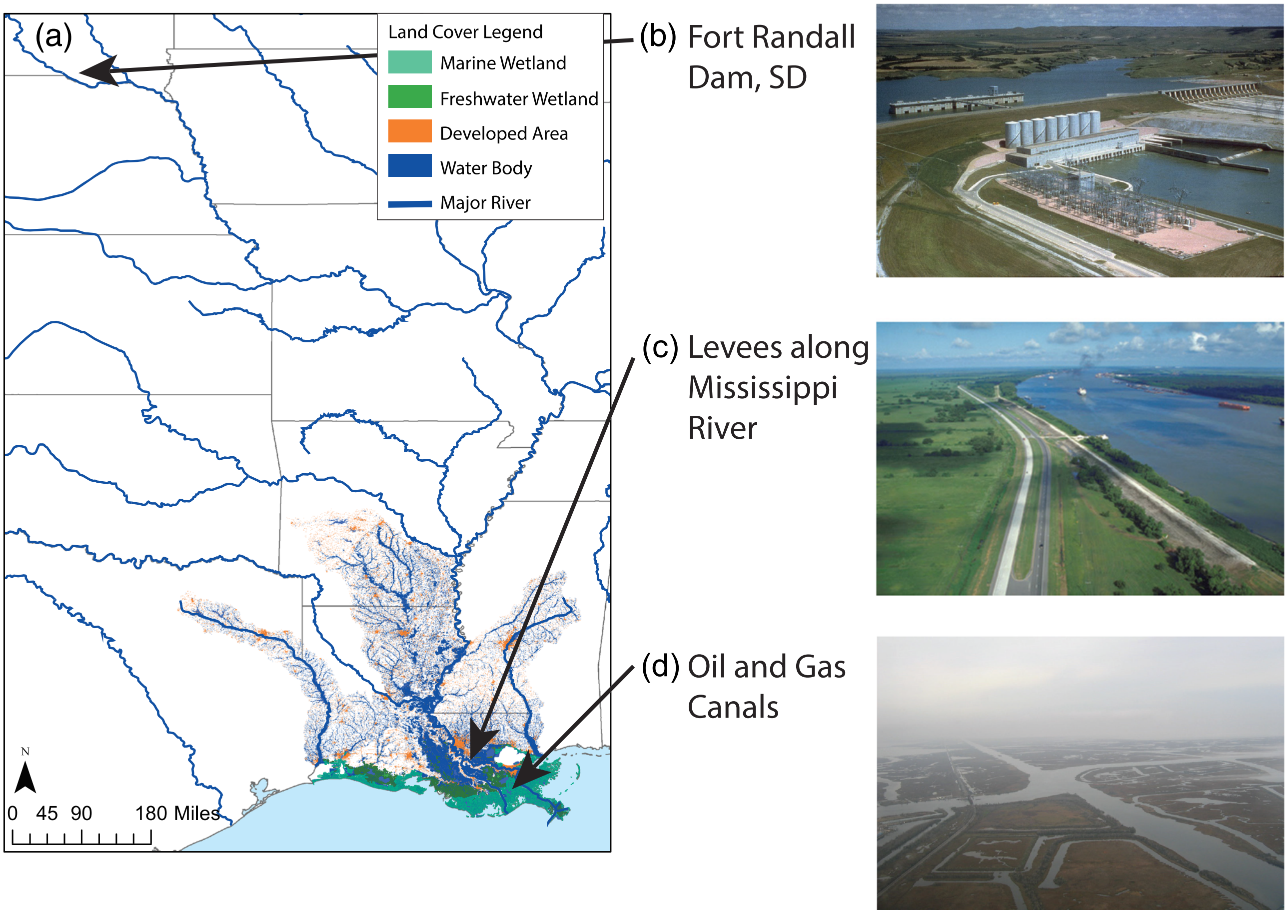

Figure 4. in Text Box 1: The Mississippi River Delta is an illustration of a complex system that is vulnerable to social-environmental extremes: (a) Louisiana's coast is threatened by many extremes, including riverine flooding and hurricanes (National Wetlands Inventory, National Hydrography Database; 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 (Picture: John McQuaid, CC BY-NC 2.0).

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). In most cases, resilient systems recover from disturbance through a series of stabilizing mechanisms. However, if the disturbance is unprecedented or it triggers self-propagating, destabilizing feedbacks, the system may shift to a qualitatively different state with significant ecological and social ramifications. Support for this hypothesis comes from complex systems thinking (Sharma et al., 2013), which considers extreme events as an emergent property of many nonlinear systems that 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 novel state (i.e., dragon-kings; Sornette, 2009). Slow, gradual changes in environmental drivers can also lead to state shifts. Importantly, resilience and critical system theories posit that average impacts can instigate cascading processes that lead to the reorganization of the system. We argue that, irrespective of the magnitude of the disturbance, surpassing a critical threshold, and the state shift that ensues, represents a de facto extreme event. Further, sensitivity to the legacy of past events indicates that spatiotemporally correlated disturbances that are not individually extreme can yield impacts as profound as 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 rearrangement still reverberating through insurance and development sectors (Weinkle, 2019a, 2019b). Resilience is thus a time-variant property that emerges from the relationship between the dynamic state of the system 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.

4.2. From Multihazards to Compound Extremes: Emphasizing the Role of System 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 "multihazards" approach at global (Basabe, 2013; UNISDR, 2015) and national levels (e.g., Federal Emergency Management Agency [FEMA] efforts for a national mitigation strategy; FEMA, 2013), this approach, despite its name, often assumes independence of events in space and time. Indeed, multihazards 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 and time and their causal relationships (Figure 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) and earthquakes (Fan et al., 2019), 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 & Cowell, 2010; Cannon et al., 2008; Moody et al., 2013; Staley et al., 2005). Gill and 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 early, accounting for "all-hazards-at-a-place" (Hewitt et al., 1971), approach to multihazard risk analysis.

Another important gap in multihazards thinking is the explicit incorporation of social vulnerability, exposure, and feedback (Cutter et al., 2003). A multirisk framework, capturing both multiple hazards and multiple vulnerabilities (Gallina et al., 2016), has been proposed. But this framework lacks the possible amplifications of multiple nonextreme events that may lead to extreme impacts or responses and ultimately may influence the biophysical system properties themselves (e.g., flooding and levees or probability of wildfire ignitions). The possibility of these interactions leading to extremes has yet to be defined and explored in a social-environmental framework.

5. Methods to Explore Interactions that Lead to Social-Environmental Extremes

A key challenge in better diagnosing and predicting social-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.

5.1. 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 hydrology (Renard & Lang, 2007), finance (Di Clemente & Romano, 2004), failure risk in engineering (Ram & Singh, 2009), and the energy sector

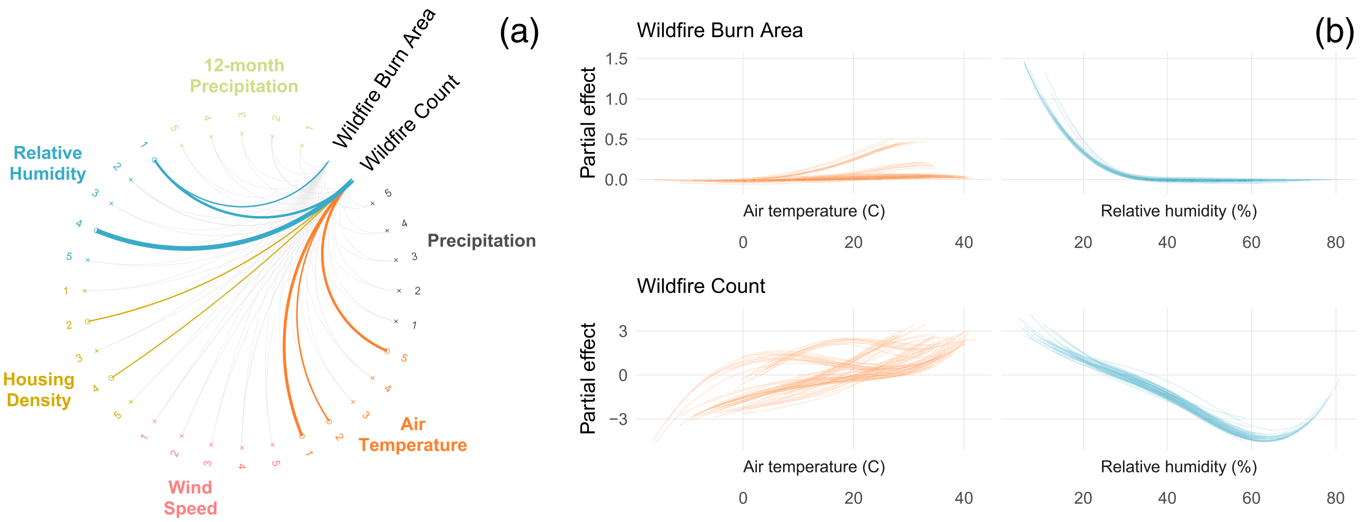

Figure 5. Bayesian approaches can reduce the complexity of interactive drivers. Joseph et al. (2019) used B-splines to predict wildfire burn area and count by month. Using six predictor variables with five basis vectors each (to account for nonlinear effects), the chord diagram (panel a) shows that only eight 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 (panel b) 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).

(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 nonparametric (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 data sets 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 nonindependence can also be an asset, as it allows for information to be shared among spatiotemporal units, for example, to better predict statistical relationships between climatological drivers and wildfires by allowing similar ecoregions to have similar relationships (Figure 5; 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 & Obeysekera, 2014). For example, minimum relative humidity has a strongly nonlinear relationship with the probability of extreme wildfires (Figure 5), 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).

5.2. 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 & 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). Nonlinear 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 & Vrac, 2011; Padoan & Wand, 2008). Nonlinear 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 nonparametric 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).

5.3. Methods From Risk Assessment

Diagnostic approaches and methods used to understand technological risks, industrial accidents, and even financial crashes may also help us better understand social-environmental extremes, as these frameworks focus on interactions that trigger or change the probability of subsequent events. For example, the benchmark study of nuclear power plant safety in the United States (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 or calculated as joint probabilities, actually connected via a common cause, also known as common-mode failure. The fault trees applied to safety assessments must also distinguish between amplifying and dampening pathways as illustrated in Figure 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 social-technical thresholds tend to be based on expected outcomes according to a "dose-response" relationship, an approach that might transfer to social-environmental extremes.

The methods used in technological risk assessments could add value to the social-environmental framing of extremes in three major ways. First, most risk assessments and event diagnostics for 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 30-m tsunami on the northeast coast of Japan or the central U.S. droughts of the mid-1930s, transformed into events so extreme that they were not thought possible ("Dragons"), what 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

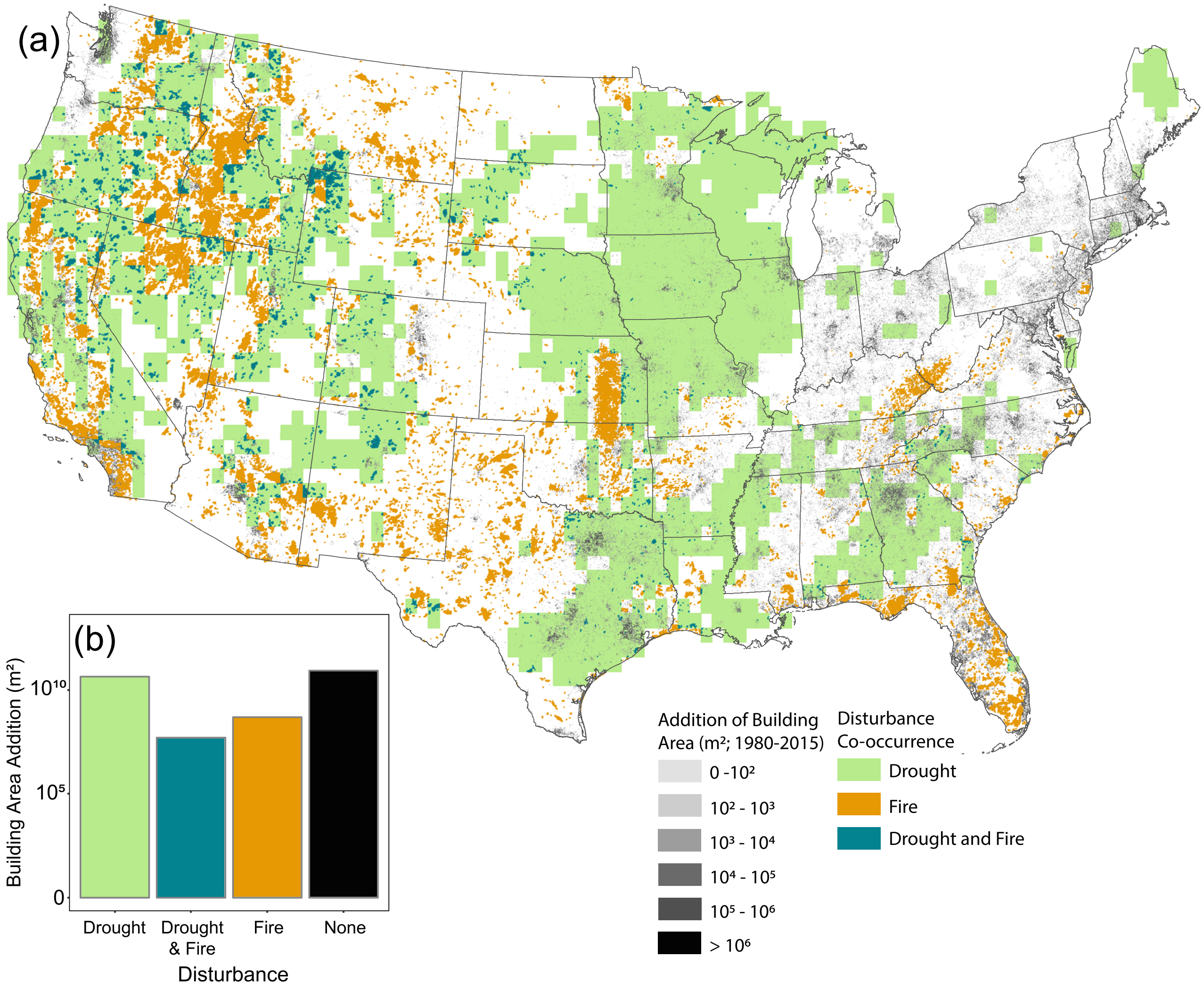

Figure 6. The interactions between social systems and environmental systems may increase ashumans move into areas at risk of extreme events. Expanding structure area in locations at risk of disturbance could indicate growing exposure to extremes. Focusing on the intersection between droughts and fires, panel (a) depicts the areas that experienced fires >400 ha (Monitoring trends in Burn Severity, 1984–2016; http://mtbs.gov; Eidenshink et al., 2007), exceptional drought (category D4, 1984–2016; http://metdata.northwesternknowledge.net; Abatzoglou, 2013), or both combined with structure interior area growth (m^2) 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.

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 United States 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 that made some populations especially vulnerable to extreme loss (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.

6. A Future Research Agenda for Studying Social-Environmental Extremes

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 social-environmental extremes. 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 social-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 United States, which means that more homes are exposed to the combined effects of drought and wildfires (Figure 6), which are also known to be increasing in the western United States (Balch et al., 2018; Westerling, 2016).

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 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.

There is great potential to advance the long-standing goal of predicting extremes utilizing this social-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, it is critical to delineate when extremes matter and when average events matter: When do "normal" events create "abnormally" extreme outcomes? And why? An opportunity exists 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 data-driven and process-based models for extreme event attribution and prediction (Joseph, 2020). Applying theories from other disciplines, such as flickering and critical slowing down from resilience theory (Scheffer et al., 2009), can lead to improved understanding and forecasting of extreme events. Prediction can be aided by real-time analysis of extreme events as they unfold. Historical data sets can offer for insight on the possible events of the future. Finally, collaborative effort is needed to identify points of interventions that can reduce impacts from social-environmental extremes. Where are the biggest opportunities for mitigating impacts, exposure, and vulnerability? Despite growing understanding and diagnosis of extremes, losses keep increasing. We argue that this social-environmental extremes framework will help to identify leverage points that can reduce future impacts.

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

New understanding of social-environmental extremes

- Identify the strength and style of interactions within social-environmental systems that lead to extreme events.
- Quantify amplifying and dampening feedbacks within social-environmental systems, specifically those triggered by anthropogenic climate and land use change.
- Predict and account for thresholds in social-environmental systems that may lead to novel system behavior and surprising phenomena.
- Determine which events arise from well-understood probability distributions versus those that derive from new generative processes (e.g., dragon-kings).

Leveraging the data revolution and new methods to understand social-environmental extremes

- Identify novel data sources or data integration and synthesis opportunities to build national and global data sets on societal impacts and damages.
- Increase the ability to detect shifts, deviations, and lags by using higher temporal and spatial resolution data.
- Integrate data-driven and process-based models for better attribution and prediction of extreme events, including hybrid science-based deep learning approaches.

- Identify and develop approaches for reducing complexity of interactions for understanding extreme events (e.g., Figure 5).
- Implement techniques from resilience theory, such as flickering and slowing down, to detect and understand future extreme events.

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

- Assess the relative consequences of extremes versus average or more common events in social systems. For example, average biophysical events may have extreme societal response, based on exposure levels (e.g., small wildfires may burn thousands of homes).
- As better prediction of social-environmental extremes emerges, invest in ways to ensure that the information is useful to decision makers.
- Develop real-time indicators of extreme events to inform early-warning systems.
- Identify points in social-technical systems with the biggest potential pay-offs in terms of reduced exposure and vulnerability to social-environmental extremes.

7. Conclusions

We have highlighted nature-society frameworks that focus on the intersection between social and biophysical events, informing how we can conceptualize social-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 across systems. Key illustrative examples of social-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 social-environmental extremes.

This reconceptualization enables us to better analyze and predict social-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 social-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 drivers and impacts. In conclusion, this research agenda will help to identify where, when, and why communities may have high exposure to social-environmental extremes—informing future mitigation and adaptation strategies.

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