Reviews of Geophysics

REVIEW ARTICLE
10.1029/2020RG000704

Key Points:
- Probabilistic forecasts and rapid estimates of event impacts offer new possibilities for coping with damaging events in the emergency phase
- Developing impact forecasting that includes exposure and vulnerability estimates will tap into synergies across disciplines
- Extending single-hazard to multihazard impact forecasts considering interactions between hazards and vulnerabilities is the next challenge

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Citation:
Merz, B., Kuhlicke, C., Kunz, M., Pittore, M., Babeyko, A., Bresch, D. N., et al. (2020). Impact forecasting to support emergency management of natural hazards. *Reviews of Geophysics*, *58*, e2020RG000704. https://doi.org/10.1029/2020RG000704

Received 10 MAR 2020
Accepted 14 AUG 2020
Accepted article online 24 AUG 2020

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Impact Forecasting to Support Emergency Management of Natural Hazards

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Abstract Forecasting and early warning systems are important investments to protect lives, properties, and livelihood. While early warning systems are frequently used to predict the magnitude, location, and timing of potentially damaging events, these systems rarely provide impact estimates, such as the expected amount and distribution of physical damage, human consequences, disruption of services, or financial loss. Complementing early warning systems with impact forecasts has a twofold advantage: It would provide decision makers with richer information to take informed decisions about emergency measures and focus the attention of different disciplines on a common target. This would allow capitalizing on synergies between different disciplines and boosting the development of multihazard early warning systems. This review discusses the state of the art in impact forecasting for a wide range of natural hazards. We outline the added value of impact-based warnings compared to hazard forecasting for the emergency phase, indicate challenges and pitfalls, and synthesize the review results across hazard types most relevant for Europe.

Plain Language Summary Forecasting and early warning systems are important investments to protect lives, properties and livelihood. While such systems are frequently used to predict the magnitude, location, and timing of potentially damaging events, they rarely provide impact estimates, such as the expected physical damage, human consequences, disruption of services, or financial loss. Extending hazard forecast systems to include impact estimates promises many benefits for the emergency phase, for instance, for organizing evacuations. We review and compare the state of the art of impact forecasting across a wide range of natural hazards and outline opportunities and key challenges for research and development of impact forecasting.

1. Introduction

Over the last decade (2010–2019), relevant natural loss events worldwide caused on average economic losses in excess of USD 187 billion per year (Munich Re, 2019) and displaced an average of 24 million people each year (United Nations Office for Disaster Risk Reduction [UNDRR], 2019). Among the global risks, extreme weather events and geophysical phenomena such as damaging earthquakes and tsunamis are perceived as the top first and third risks in terms of likelihood and as the top third and fifth risks in terms of impact (World Economic Forum, 2019). Urbanization, population growth, increasing interconnectivity, and interdependence of critical infrastructure are expected to further aggravate the risks imposed by natural hazards (Helbing, 2013; Jongman, 2018; Vousdoukas et al., 2018; Winsemius et al., 2016). Climate change is also acting as a major driver and amplifier of the losses related to hydrometeorological events (UNDRR, 2019). Both heat waves and droughts will become more frequent and are expected to persist over longer time periods under climate change (Perkins et al., 2012; Russo et al., 2015; Samaniego et al., 2018). Similarly, climate-driven increases in river, urban, and coastal flooding are a global problem, affecting mainly developing countries and also industrialized regions (Blöschl et al., 2019; Hallegatte et al., 2013; Willner et al., 2018).

Forecasting, early warning and the provision of rapid disaster risk information are cornerstones of disaster risk reduction (UNDRR, 2019). The Sendai Framework for Disaster Risk Reduction, agreed upon at the Third UN World Conference on Disaster Risk Reduction in 2015, calls for a substantial increase in the availability of multihazard early warning systems and rapid disaster risk information by 2030 (United Nations International Strategy for Disaster Reduction [UNISDR], 2015b). Forecast and warning have focused on physical event characteristics, such as magnitude, spatial extent, and duration of the impending event. Recently, the provision of information on the potential event impacts, such as number and location of affected people, damage to buildings and infrastructure, or disruption of services, has gained attention. This requires considering additional information on exposure, that is, people, property, or other elements present in hazard zones (Pittore et al., 2017; UNISDR, 2009), and on vulnerability, defined as the characteristics of the exposed communities, systems, or assets that make them susceptible to the damaging effects of a hazard (UNISDR, 2009). Impact forecasting and warning is an emerging topic in science, for companies developing forecasting technology, and at the level of institutions responsible for natural hazards management (Taylor et al., 2018; Zhang et al., 2019). For instance, the World Meteorological Organization (WMO) has recently launched a program on multihazard impact-based forecast and warning services (WMO, 2015). This program aims to assist WMO members to further develop forecast and warning services tailored to the needs of users to fully perceive and understand the consequences of severe weather events and, as a consequence, to undertake appropriate mitigating actions.

In this paper we review the state of the art in forecasting impacts of hazardous events for a wide range of geophysical and weather-/climate-related natural hazards. We define forecasting as the provision of timely information to improve the management in the emergency phase, that is, shortly before, during and after a hazardous event. Hence, we do not address medium- and long-term risk assessments that are carried out to assist decision makers in risk prevention and mitigation activities. We discuss the added value of impact forecasting (as a basis for impact-based warnings) compared to hazard forecasting (hazard-based warning), indicate challenges and pitfalls, and synthesize the review results across hazard types. Being the first review of impact forecasting of natural hazards, this paper demonstrates that the state of the art in impact forecasting is very different across hazard types and disciplines. As forecasting science and technology are typically advanced within specific disciplinary contexts, this comparative review across hazard types aims at transferring knowledge and harmonizing concepts across discipline borders and bridging gaps between different scientific communities and between science and practice.

1.1. Hazard Forecasting: Provision of Timely Information on the Physical Event Characteristics

The United Nations terminology on disaster risk reduction (UNISDR, 2009) defines an early warning system as "*the set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities and organizations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss*." Monitoring, analysis, and forecasting of hazards are an essential cornerstone of early warning systems. Hazard forecasts provide information on the physical event characteristics, such as the location, timing, and magnitude of a potentially damaging event.

We consider events as natural phenomena with a specific magnitude that unfold with a given space-time footprint and with the potential for adverse consequences. The event footprint may vary significantly across hazards. Examples are short-term, local-scale events, for example, pluvial floods with event duration and extent in the order of 1 hr and 1 km, even shorter-term but large-scale events, such as earthquakes, and creeping events, for example, droughts, with duration and extent in the order of months to years and several hundred to a few thousand kilometers (Figure 1). Accordingly, the possibilities and the challenges for emergency management in response to a forecast vary widely across hazards.

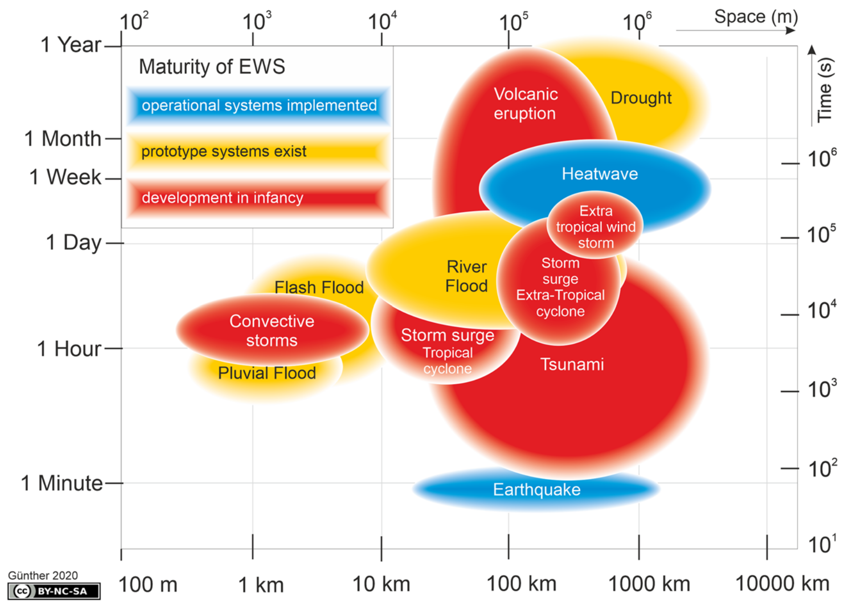

Figure 1. Space-timescales of the hazard types covered. These scales are related to the event's spatial extent (or footprint) and its duration. For earthquakes the spatial scale shown is the range within which severe impacts occur for significant events. Colors code the maturity of impact forecasting systems from "development in infancy" (red) through "prototype systems exist" (yellow) to "operational systems implemented" (blue). The assignment to a certain maturity class is based on our synthesis (section 3.1).

In addition to the large range of event footprints, lead times of operational warning systems and forecast possibilities vary strongly between hazard types (exemplified in Figure 2). In the case of earthquakes, for instance, the prediction of the location, time, and magnitude of an event is not possible prior to its occurrence. However, a rapid estimation of event characteristics may be carried out as soon as the event has been detected. Earthquake early warning (EEW) refers to the prompt detection of a potentially damaging earthquake within a few seconds from its actual onset, possibly triggering immediate risk mitigation measures.

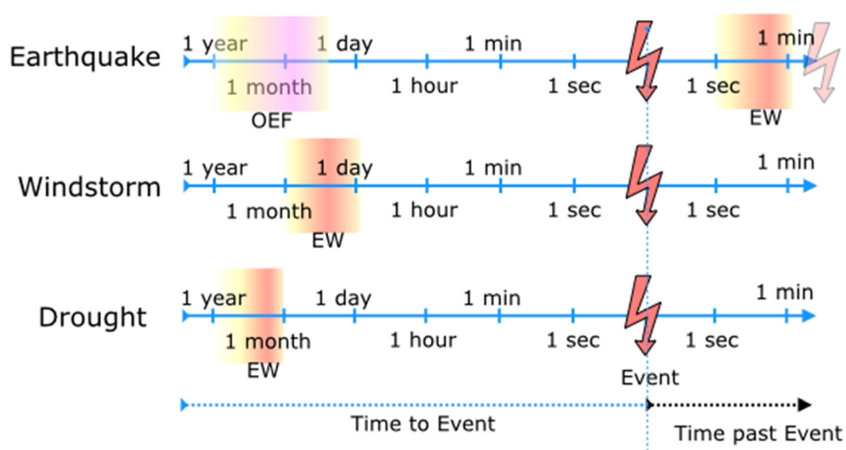

Figure 2. The concept of early warning (EW) and its placement in time with respect to the actual occurrence of the event, exemplified for earthquakes, windstorms, and droughts. In the case of earthquakes, even very short lead times, up to 60 s after the occurrence of the event (dark flash), still allow to automatically trigger real-time mitigation measures, such as emergency braking of high-speed trains, before the most potentially dangerous earthquake waves reach a given location (light flash). For earthquakes also Operational Earthquake Forecasting (OEF) is indicated. Windstorms can be forecasted with lead times from a couple of hours to several days. The lead times of droughts are even longer, in the range of one to several months.

The lead time of EEW systems is thus in the order of several seconds to several tenths of seconds (Minson et al., 2018; Nakamura et al., 2011; Satriano et al., 2011; United Nations Environment Programme [UNEP], 2012). For windstorms, National Hydro-Meteorological Services (NHMSs) issue forecasts and early warnings one to several days in advance, providing estimates of the expected wind gust velocities for the potentially affected locations. Several NHMSs issue weather warnings based on short-term forecasts with lead times of less than 48 hr (e.g., meteoalarm.net from EUMETNET, which currently pools the warnings from 34 European countries; Stepek et al., 2012). Droughts develop much slower compared to earthquakes and windstorms. Here forecasts and early warning can be issued one to several months prior to the event (Pozzi et al., 2013; Sheffield et al., 2014). Consequentially, our understanding of forecasting includes pree-vent predictions, as in the case of windstorms and droughts, to near-real-time assessments once an event has already occurred as in the case of earthquakes.

It is important to consider the uncertainty inherent in a forecast, and it has been argued that probabilistic forecasts have greater value for decision making than single deterministic forecasts (Fundel et al., 2019; Joslyn & LeClerc, 2013; Palmer, 2000; Roulston et al., 2006). Probabilistic forecasts potentially provide more reliable and a greater wealth of forecast information and longer lead time (Boelee et al., 2019; Palmer, 2017) and can increase trust in forecasts (LeClerc & Joslyn, 2015). Nowadays NHMSs frequently use ensemble prediction systems to consider uncertainty inherent in a forecast. Such ensembles are based on tens of weather forecasts with different initial conditions and model physics or by pooling the output of several numerical weather prediction (NWP) models. Ensembles provide not only a general estimate of the uncertainty of forecasts but in particular also the probability of occurrence of extreme events. Different indices to summarize the probability of extreme events are used by weather services for operational warnings. For example, the extreme forecast index (EFI; Lalaurette, 2003) ranks the departure between the statistical distribution of an ensemble forecast and the observational event catalog. It ranges from −1 to +1, with 0 and +1 denoting a standard situation and a record-breaking high value, respectively. Another index is the shift of tails (SOT) index, which indicates whether a fraction of the members forecast an extreme event, even if the rest of the members do not, thus putting even more emphasis on the most extreme events (Zsoter, 2006). In the case of volcanic eruptions, most forecasts are probabilistic and often combine the analysis of monitoring parameters with information about past behavior of a volcano by means of statistical tools, such as Bayesian event trees (Marzocchi et al., 2008; Rouwet et al., 2014; Tonini et al., 2015) or Bayesian Belief Networks (Aspinall & Woo, 2014). For EEW, probabilistic methodologies have been employed, often based on Bayesian statistics, to assimilate noisy or partial instrumental observations (Cua & Heaton, 2007; Meier et al., 2015) or to detect multiple overlapping events (Liu & Yamada, 2014). Probabilistic approaches have been integrated between 2008 and 2016 in the prototyping phase of the EEW system for the West Coast of the United States. Similar to numerical weather models, ensemble forecasting for OEF applications is also increasingly considered (Marzocchi et al., 2014; Shebalin et al., 2014; Van Dinther et al., 2019). Hence, not only event footprints and lead times vary between hazard types but also forecasting concepts, such as providing probabilistic or deterministic forecasts.

1.2. Impact Forecasting: Provision of Timely Information on the Socioeconomic Event Consequences

We use the term *impact forecasting* as illustrated in Figure 3: Impact forecasting considers information on the elements at risk, that is, the exposure and their vulnerability, to extend the traditional forecasting model chain translating the hazard characteristics (intensity, duration, and spatial extent) into impact statements. According to this definition, forecasting the inundation area due to a tsunami, for example, belongs to hazard forecasting. It turns into an impact forecast as soon as the information on inundation areas is combined with exposure and vulnerability information, so that the forecast allows deriving statements about the affected elements and the respective values at risk. Impact forecasts can include direct and indirect effects that can be described by quantitative physical and socioeconomic indicators, such as affected critical infrastructure, number and location of damaged buildings, expected number of fatalities and displaced people, and financial loss resulting from direct damage, business interruption, or disruptions of supply chains.

Particularly for weather hazards, there is a recent development to include general information about expected adverse consequences and general behavioral recommendations (UNISDR, 2015a). For instance,

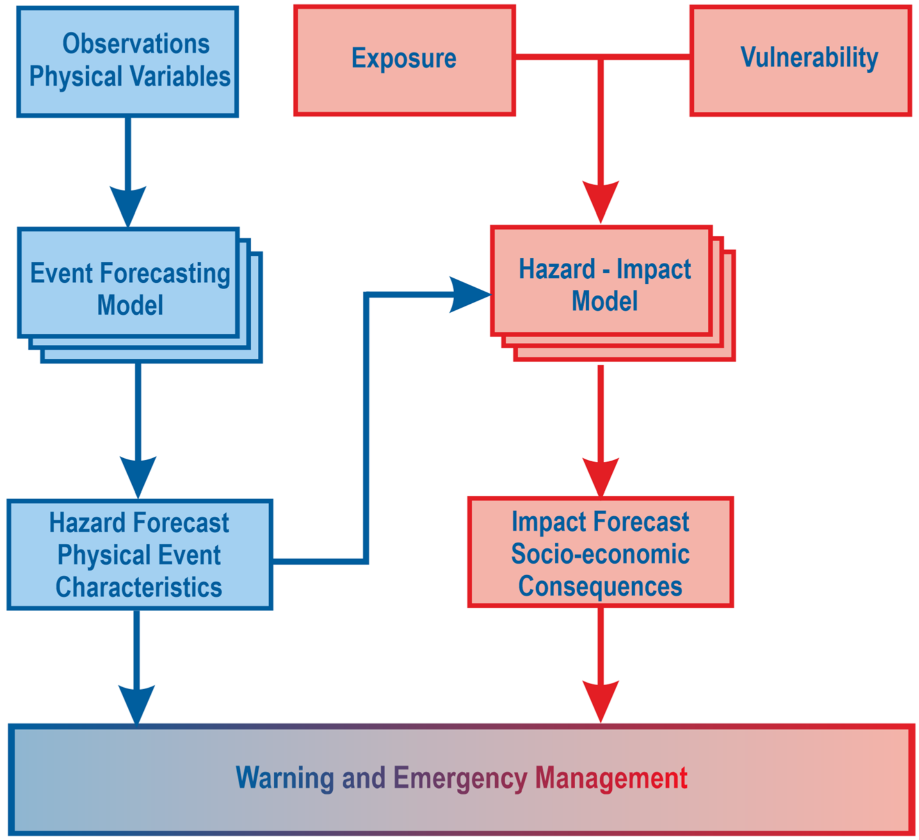

Figure 3. Definition of impact forecasting used in this review: Impact forecasting extends the traditional hazard forecast by including information on exposure and/or vulnerability, translating the physical hazard characteristics into socioeconomic consequences.

severe weather warnings may include statements such as "Mobile homes will be heavily damaged or destroyed," or "Significant damage to roofs, windows and vehicles will occur" (Casteel, 2016). As such warnings do not consider the specific exposure and vulnerability of the affected locations and are not based on a hazard-impact model, we do not include such general impact-oriented forecasts and warnings in our review.

The incorporation of exposure and vulnerability information and the link to the hazard information, for example, through fragility curves, into the forecasting process requires additional efforts, data, and models (Aznar-Siguan & Bresch, 2019), hence adding further uncertainty. To be helpful for decision making, impact forecasting typically depends on detailed knowledge of the local contexts (UNISDR, 2015a). Hence, the perspectives of stakeholders and decision makers earn an even more prominent role when moving from hazard forecasting to impact forecasting. However, impact forecasting is expected to significantly improve the emergency response by providing detailed and comprehensive information about the possible extent of a disaster either prior to or directly after the event (UNISDR, 2015a). This is perceived as more meaningful than mere hazard warnings, since it could provide the basis for more informed decisions pertaining to evacuations and preparedness measures and forward-looking resource allocation in general (WMO, 2015). As has been learned from many past events, an accurate and timely hazard forecast alone does not allow for prevention of major social or economic adverse consequences (WMO, 2015). Impact forecasting is motivated by the observation that exposed people accept warnings more often, when they are provided with specific information about impacts as well as behavioral recommendations on what to do (Weyrich et al., 2018). Hence, more and more NHMS move toward forecasting and warning services that translate hazard information into sector- and location-specific impacts, that is, they move from "what the weather will be" to "what the weather will do" (Campbell et al., 2018).

1.3. Hazard Types Considered and Paper Outline

Our review covers the following hazard types (see also Figure 1): windstorms, severe convective storms (SCSs), droughts and heat waves, floods, coastal storm surges, earthquakes, tsunamis, and volcanic eruptions. This selection covers a wide range of geophysical and climate-related hazards with very different physical characteristics and possibilities for forecasting and emergency management. These hazards are of high relevance for Europe and also for many other regions around the world. Whenever possible, the review of the different hazard types has been based on scientific peer-reviewed articles. For those hazards and sectors, where this constraint would exclude a substantial part of the work done, gray literature has also been considered.

For each hazard type, our review is organized into four sections: (1) hazard forecasting: The state of the art in forecasting hazard characteristics is briefly summarized, including lead times, forecast variables, and indicators. This is supplemented by summary information on the main methodological approaches, on the status in terms of operational forecasting and on the benefit of forecasts. (2) Impact forecasting: This section contains an overview on impact models. It evaluates how hazard forecasts are translated into impact forecasts, including information on the types of impacts that are typically considered and the impact indicators used. (3) Uncertainties and challenges of impact forecasting: A summary on the issues of validation and forecast uncertainty is provided. (4) Maturity and added value of impact forecasting: This section summarizes the state of implementation of impact forecasting and evaluates the evidence on its added benefit compared to hazard forecasts. Section 3 provides a comparative analysis of impact forecasting across the different hazard types. It outlines key challenges in the development of impact forecasting.

2. State of the Art of Impact Forecasting

2.1. Extratropical Windstorms

Extratropical windstorms, also called winter storms or intense midlatitude cyclones, form in association with the strong temperature gradient between cold air in polar regions and warmer subtropical air. Cyclogenesis and intensification typically take place along the polar front, which divides these two air masses. The passage of extratropical storms is associated not only with strong winds and wind gusts (local sudden increases in wind speed, typically a sharp increase of more than 5 m/s and lasting several seconds) but also with intense precipitation and potentially storm surges. Hence, such storms are typically compound events, that is, events for which more than one variable is involved (Zscheischler & Seneviratne, 2017). Western Europe is mostly affected by windstorms in autumn and winter, which travel eastward along the North Atlantic storm track, influenced by large-scale weather patterns and atmospheric currents (Feser et al., 2015; Ulbrich et al., 2009). Extratropical storms generally last for several days and affect areas, which may exceed a thousand kilometers in length and several hundred kilometers in width (Fink et al., 2009). This affected area is generally denominated windstorm footprint. Wind impacts encompass direct damage to humans, infrastructure, agriculture and forestry, transport, and industry due to damaging wind speeds, wind gusts, lightning, hail, and extreme precipitation. Indirect impacts are flooding and storm surges triggered by the storm. We focus here on wind impacts, while rainfall and surges are covered in other sections.

2.1.1. Extratropical Windstorms: Hazard Forecasting

Windstorm forecasts focus on the track and intensity of extratropical cyclones on the synoptic scale and on the associated winds and wind gusts on the mesoscale. They are based on NWP models with grid sizes of tens of kilometers and lead times of 1–2 weeks down to a few kilometers and 1–2 days, which are complemented with real-time observations such as satellite and radar imagery. There are well-established theories on the physical mechanisms leading to the development and intensification of extratropical cyclones, including the formation of surface fronts and associated airflows (see Catto, 2016, for a review), and their tracks and intensity are overall well predicted by NWP models several days in advance (Pantillon et al., 2017). There are also efforts to develop seasonal forecasts for windstorms (Befort et al., 2019; Renggli et al., 2011).

Extreme windstorms can be anticipated using EFI (Lalaurette, 2003; Petroliagis & Pinson, 2014) and SOT (Boisserie et al., 2016) with skill up to 10 days in advance (Pantillon et al., 2017). However, a general issue when using such indices for forecasting extreme events is to identify an adequate tradeoff between a rate of detection and false alarms.

Extratropical storms are operationally forecasted worldwide, for example, using global NWP models from the European Center for Medium-Range Forecasts (ECMWF) in Europe and the National Centers for Environmental Prediction (NCEP) in the United States. In Europe, several National Weather Services (NWS) provide windstorm warnings based on thresholds of wind speed and wind gusts, but those thresholds differ among the weather services, as do the lead times that range between one and several days ahead. This calls for a unified European warning system (Stepek et al., 2012). In the United States, the NWS issues wind warnings for nonconvective storms based on uniform thresholds. As a consequence, the majority of fatal and injury-causing events occurs with winds below the high wind warning threshold (25.9 m/s), while wind warnings are disproportionately issued in areas of complex terrain (Miller et al., 2016). These examples highlight the need for forecasts based on impact rather than on thresholds of hazard variables.

For windstorms with hazardous potential, warnings may encompass official announcements and siren signals, warnings issued via internet, television, and broadcasting and enhanced preparedness for emergency services and disaster control. These early warnings can thus lead to less fatalities, damage reduction, disaster mitigation, and better societal preparedness (Bergen & Murphy, 1978; Potter et al., 2018).

2.1.2. Extratropical Windstorms: Impact Forecasting

Several approaches have been developed to estimate the impacts associated with extratropical windstorms (Klawa & Ulbrich, 2003; Palutikof & Skellern, 1991; Welker et al., 2016). Impact models are typically based on empirical data. They relate the impact to the peak wind or wind gusts during the passage of a storm but may include other meteorological factors such as storm duration. These models are commonly applied to station observations, reanalysis data sets, or climate model data. They are mainly used to quantify the damage to buildings and other infrastructure like roads, railways and bridges. Klawa and Ulbrich (2003) introduced the storm severity index (SSI), a popular insurance socioeconomic loss model. It is based on the cubed wind gusts (V^3) to account for the wind's destructive power and uses only values exceeding the local 98th percentile. This threshold was found to account for the local vulnerability of infrastructure and buildings to wind gusts. The SSI includes population density as a proxy for insured property and is found to highly correlate with actual losses from insurance companies. This simple approach was further developed and successfully applied to reanalyses, global, and regional climate model predictions and projections (Booth et al., 2015; Donat et al., 2011; Leckebusch et al., 2007; Pinto et al., 2012). Other impact models range from simple exponential damage functions to the probabilistic approach proposed by Heneka et al. (2006) to account for the distribution of critical gust speeds among different buildings (Prahl et al., 2015). However, impact models often do not consider a crucial factor, namely, the possible change in population and insured values over time. Impact modeling for extratropical cyclones is a rather recent topic, and limited peer reviewed literature is available.

Although impact models have been widely applied to long data sets for the past and future from reanalysis and climate model projections, they have rarely been combined with NWP models to create impact forecasts. However, a few recent studies have emphasized the potential of this approach. Based on a 20-year homogeneous data set of ensemble forecasts, Pantillon et al. (2017) showed that the SSI of severe European windstorms can be predicted with confidence up to 2–4 days in advance. This lead time may seem short given that first hints of extreme windstorms can be derived from ensemble forecasts up to 10 days ahead, but it is certainly sufficient to issue warnings and take appropriate response. Pardowitz et al. (2016) further demonstrated skill in predicting extratropical windstorm losses over Germany at the district level for lead times beyond 1 week. This was achieved by using a loss model that required training with records of local insurance data. Beyond these published studies, several companies in the insurance sector (e.g., Willis Towers Watson, Aon, Guy Carpenter, AIR, RMS) provide loss estimates of impending or current windstorm events as a service for their clients (see Pinto et al., 2019, for an overview). These models link freely available forecasts from the weather services to in-house company loss models. The results are loss estimates and an uncertainty range, which is useful information for the clients for short-term planning. Unfortunately, little documentation is publicly available on the details of such models. One exception is the recent study of Welker et al. (2020) comparing an insurer's proprietary model with the open-source CLIMADA (CLIMate ADAptation; Aznar-Siguan & Bresch, 2019), which combines hazards, exposure, and vulnerability. This and other open-source initiatives will be key for the further development of impact forecasts.

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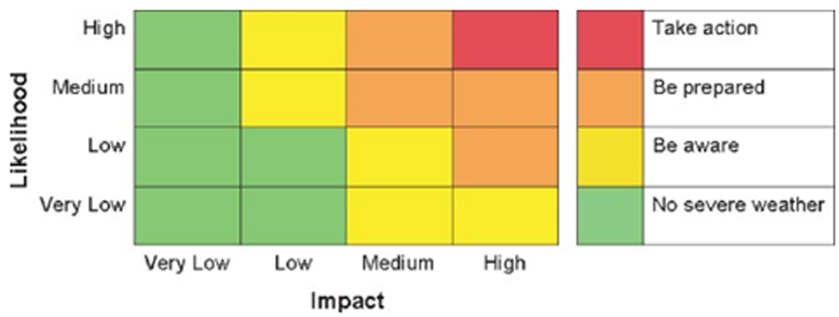

Figure 4. Weather impact matrix and color key for the U.K. National Severe Weather Warning Service (from Neal et al., 2014). Green signifies weather with no significant impact on peoples' day-to-day activities. Yellow signifies "be aware" and stay up to date with the latest forecast, and amber signifies "be prepared" to take action. Red signals "take action" to mitigate impacts.

2.1.3. Extratropical Windstorms: Uncertainties and Pitfalls of Impact Forecasting

Forecasting the impact of extratropical windstorms requires a combination of models for NWP and impact. Uncertainties and pitfalls are thus inherited from both models. Statistical methods are often applied to weather and climate model output to correct model deficiencies. For instance, Roberts et al. (2014) used a statistical model to rescale the intensity of damaging gusts above 20 m/s in windstorm footprints from reanalysis data. This improved the estimated wind impact for the 50 most extreme European windstorms between 1979 and 2012 according to several loss model metrics. Other approaches targeted at a better estimation of wind gusts via postprocessing, providing a closer agreement with observations (Haas & Pinto, 2012; Haas et al., 2014). Intense wind gusts are often related to fine-scale characteristics such as orography, convection, and strong pressure gradients. However, even with a state-of-the-art, kilometer-scale ensemble prediction system, Pantillon et al. (2018) found that specific windstorms show forecast errors less than 1 day ahead, which cannot be corrected with statistical methods.

Concerning the uncertainty in impact models, Prahl et al. (2015) compared four windstorm damage functions. They were applied to meteorological observations from stations over Germany and reanalysis model data and were assessed against insurance loss data from the local to the national level. The authors found that probabilistic models (e.g., Heneka et al., 2006) provide the most accurate estimates of insurance losses, whereas the simpler deterministic SSI of Klawa and Ulbrich (2003) performs well for extreme losses. Similarly, Pardowitz et al. (2016) found best results for forecasting windstorm losses by taking both meteorological and impact model uncertainties into account, the latter arising from the local vulnerability and exposure that are not known exactly. The meteorological model uncertainty was obtained from an ensemble forecast postprocessed with statistical methods, while the damage model uncertainty was based on a logistic regression analysis between gusts and damage records (Pardowitz et al., 2016). Other factors that may play a role include differences in vulnerability, for example, associated with different construction types, and the neglect of temporal changes, for instance, due to adaptation measures. Moreover, multiple consecutive events (cyclone clustering; Pinto et al., 2014) or associated compound events such as flooding and storm surges may lead to enhanced cumulative losses compared to single windstorm events. These results emphasize the need to account for uncertainties in both meteorological and damage models. This will be a crucial requirement for future developments of impact forecasting systems.

2.1.4. Extratropical Windstorms: Maturity and Added Value of Impact Forecasting

Forecasting windstorm impact is still in its infancy and its operational implementation varies between countries, weather services, and private companies. Since 2011 the U.K. National Severe Weather Warning Service delivers an impact matrix for weather forecasts (Figure 4; Neal et al., 2014). The matrix combines the likelihood of a meteorological hazard with its impact, both ranging from very low to high. (The same or similar matrixes are used for SCS and floods, see sections 2.2 and 2.4) The likelihood is given by a dedicated short-term ensemble prediction system combined with statistical postprocessing, while the estimated socioeconomic impact is based on thresholds that vary locally according to the frequency of hazards, the density of population as well as the season. While the highest warning level (red, "take action") requires both high likelihood and high impact, warnings can also result from a combination of low/high likelihood and high/low impact (Figure 4).

Companies in the insurance sector provide similar products for their clients, typically with an early estimate 3 days in advance, followed by updates 48 and 24 hr before the event, and a detailed evaluation in the aftermath (A. Giorgiadis, AON IF, personal communication, 2019). These impact estimates and their uncertainty provide a clear added value to the clients, as they enable them to take measures to minimize potential impacts of an impending storm, for example, to assign staff or to buy short-term additional windstorm damage coverage (Welker et al., 2020). Unfortunately, such information is not widely accessible, which calls for enhanced communication between public and private research (Pinto et al., 2019). To the authors' knowledge, there is no published study on the quantitative benefits of windstorm impact forecasts yet.

2.2. SCSs

Thunderstorms are high-frequent perils that develop in unstable environments with deep-tropospheric wind shear and therefore have been documented on every continent except Antarctica. Those storms that produce hail in excess of 2 cm, damaging winds in excess of 90 km/hr, or a tornado are usually referred to as SCSs; Doswell, 2007, Bluestein, 2013); other phenomena associated with SCS are heavy rainfall, which may lead to flooding and lightning. Even though the associated phenomena usually do not occur at the same time and place, they can be regarded as compound events. Typical time and length scales of these convective phenomena range from seconds to 1 hr and from meters to tens of kilometers, respectively (Markowski & Richardson, 2010). However, SCSs can also travel for hundreds of kilometers during a period of several hours. Of all convective phenomena, hail causes by far the largest damage (Kunz & Geissbuehler, 2017), whereas lightning and flash floods cause the highest number of casualties (EM-DAT, 2020; Holle, 2008; Shabou et al., 2017). Affected assets include buildings (mainly hail and wind to roofs and walls; fire from lightning), vehicles (hail dents, fallen trees, and objects carried by winds), agriculture (hail, wind, and local flooding from rain), and infrastructures (fallen trees, flooded underpasses, and hail accumulation on roads). For cars, exposure varies strongly over the day, whereas crop vulnerability depends on the plant growth state (Bell et al., 2020). Solar panels (photovoltaic or solar thermal), which have been increasingly installed in several European countries in recent years, are particularly susceptible to hail (Gupta et al., 2019).

2.2.1. SCSs: Hazard Forecasting

SCS forecasts and warnings are routinely issued by NWS (Rauhala & Schultz, 2009). The forecasts usually contain the expected convective phenomena including their intensity (e.g., hail size, wind speed, and rain total), the affected area, and a time frame of occurrence. In several countries, a severe thunderstorm warning is issued either when an event is less than 24 hr ahead (e.g., in the United Kingdom or Germany) or when the respective weather event has already been observed (termed as thunderstorm/tornado watch in the United States). Cascading hazards such as flash floods triggered by convective rainfall are usually not forecasted.

The prediction of SCSs and related phenomena is one of the greatest challenges for NWP. Even during convectively unstable situations the predictability of the location, timing, and intensity of SCSs is usually very low (Done et al., 2012). Forecast errors are mainly due to uncertainty in the synoptic-scale setting for convection development (Doswell & Bosart, 2001), initial conditions uncertainty on small scales (Stensrud, 2001), and parameter uncertainty in microphysical schemes (Miltenberger et al., 2018; Wellmann et al., 2018).

The forecast lead time ranges from hours to several days, with uncertainty increasing with lead time. Although NWP models still have low skill in predicting SCSs 1 to 8 days ahead, favorable environments for SCS can be forecasted via various indices, a method referred to as ingredients-based forecasting (such as thermal stability or wind shear; Doswell et al., 1996; Kaltenböck et al., 2009). For lead times of two or more days, mostly probabilistic ensemble forecasts providing a range of possible realizations of future weather are used instead of deterministic models with only one realization (Gensini & Tippett, 2019; Grell & Dévényi, 2002). These forecasts are not intended for individuals to take immediate action but rather to help key stakeholders such as emergency management and broadcasting groups to prepare for subsequent and more accurate predictions. For example, the ECMWF provides the ensemble-based EFI and in particular its SOT products that facilitate forecasting SCS outbreaks especially in the medium range beyond day 2 (Tsonevsky et al., 2018).

More recently, improvements in the forecasting of SCSs have been achieved for short-range prediction (6–36 hr) of storm-scale outputs using high-resolution convection-permitting models with sophisticated assimilation schemes for the inclusion of radar and satellite observations (Clark et al., 2016). In addition, nowcasting tools for very short lead times (0–2 hr), which combine radar and satellite observations with rapid-update cycles of NWP model output and statistical tools, have shown reasonable skill for accurate location, hazard type/intensity, and timing forecasts (James et al., 2018; Nisi et al., 2014).

Substantial difficulties in analyzing convective environments, constraining theory and models, and evaluating model output arise from the lack of consistent, homogeneous, and comprehensive observations of convective phenomena. The number of ground weather stations is too small to reliably detect these events. Hailpad networks, albeit having a very high density, exist only for a few limited regions in Europe and around the globe (Dessens et al., 2016; Ni et al., 2017; Sánchez et al., 2009). To fill this monitoring gap, several databases have been installed that pool eyewitness reports from trained storm spotters or from the public into severe weather archives (e.g., European Severe Weather Database, ESWD; Groenemeijer et al., 2017). Although reporting is selective and biased toward population density, these databases provide valuable information about the frequency and intensity of SCS-related phenomena.

2.2.2. SCSs: Impact Modeling and Forecasting

Because of the large uncertainty inherent in NWP, impacts of SCSs are rarely forecasted. Operational forecasts of impacts are mostly generic, both in the description of potential impacts and in the recommended precautionary measures. Warnings from NWS are usually issued on county level indicated by a color scheme. A red warning is issued when dangerous weather is expected and urgent actions are needed. In this case, it is very likely that there will be a risk to life, substantial disruption of mobility and energy supplies, and widespread damage to property and infrastructure. Similar systems exist from several NWS, such as Meteo France or the German Weather Service (James et al., 2018). The warnings issued by the U.K. Met Office are depicted using the same 4×4 matrix used for windstorms (Figure 4) based on the combination of expected impact severity and the likelihood of those impacts (Neal et al., 2014). In Europe, most of the warnings are summarized by Meteoalarm (www.meteoalarm.eu), an initiative of the European Meteorological Services Network (EUMETNET).

Only a few models are available that explicitly estimate the impact in terms of damage to buildings, vehicles, infrastructures, or crops depending on the event intensity (wind speed, hail size, and precipitation totals). Potential losses have been quantified for single events or scenarios, most of them related to tornadoes in the United States hitting major cities (Simmons & Sutter, 2011; Wurman et al., 2007) or Europe (Antonescu et al., 2018). Hail damage is usually parameterized as a function of the kinetic energy of the hailstones or their expected diameter, which can be roughly estimated from observed radar reflectivity (Hohl et al., 2002; Puskeiler et al., 2016; Schmidberger, 2017). However, the damage increase in case of high horizontal wind speeds, affecting also the walls of a building, is usually not factored in (Schuster et al., 2006). Tornado and straight-line winds are usually parameterized using maximum 3-s gust wind speeds (Holmes, 2015). Local climatic conditions and the time of year are particularly relevant for SCS impacts, as, for example, trees with their leaves are more susceptible to wind damage compared to defoliated trees in winter (Neal et al., 2014).

Sophisticated impact models including vulnerability functions and exposure data are traditionally owned by the insurance industry and are not publicly accessible. The purpose of these models is to assess the damage in the aftermath of an event or to estimate the risk for a particular insurance portfolio (Schmidberger, 2017).

2.2.3. SCSs: Uncertainties and Challenges of Impact Forecasting

Impact forecasting of SCS, based on coupling of NWP and impact models, is hampered by the large uncertainty in the prediction of the convective phenomena on the one hand and by the need for highly accurate vulnerability functions and exposure data to model very localized damage. In order to address the first point, several NWS have made considerable progress in the improvement of SCS predictions mainly by developing convection-resolving NWP models (Giorgetta et al., 2018; Hagelin et al., 2017; James et al., 2018), by developing and implementing sophisticated microphysics schemes, by improving the assimilation of observational data, and by running ensembles also for short lead times between 1 and 12 hr (Rothfusz et al., 2018). For example, within the recently launched project SINFONY (Seamless Integrated Forecasting System; Blahak et al., 2018), the German Weather Service develops a new prediction system for very short range forecasting based on a combination of nowcasting, considering data from remote sensing instruments and the life cycle of SCSs, and high-resolution modeling (kilometer-scale ensembles with rapid update cycles).

The inadequate monitoring of SCS can partially be remedied by additionally considering data from crowdsourcing or civic science contributions. Thanks to the widespread use of digital technologies, such as smartphones or self-regulation techniques implemented in modern automobiles, this additional information has a large potential for a significant contribution to better estimate damage from SCSs. Crowdsourced observations collected and archived through specific platforms such as Weather underground (www.wunderground.com), the European Weather Observer App (Groenemeijer et al., 2017) or the MeteoSwiss App have the potential to overcome the significant underreporting of SCS events (Trefalt et al., 2018). In Switzerland, for example, about 59,000 hail reports have been collected by users between May 2015 and October 2018 (Barras et al., 2019). In addition, crowdsourced observations can also be used for NWP via data assimilation into initial fields (Muller et al., 2015).

Regarding vulnerability functions, institutions like the Insurance Institute for Business & Home Safety (IBHS) or the Swiss association of cantonal building insurers (VKG) foster research on storm impacts to building structures and offer certification for individual components. However, such insights tend to focus on general preventive measures rather than prediction of impacts associated to individual storms. Still, such information can be used to relate meteorological variables to impacts.

2.2.4. SCSs: Maturity and Added Value of Impact Forecasting

Impact forecasts of SCS will only be of significant benefit when the predictions regarding timing, location, and intensity of expected SCSs become more accurate. In that sense, nowcasting tools for lead times of up to 2 hr coupled with impact models have a high potential to reliably predict damage from disruptive and life-threatening convective events. Besides, near-real-time warnings based on observations can be expected to grow in importance as instantaneous communication including crowdsourced observations become more and more available. Also, observations of specific radar signatures associated with heavy rainfall, hail (Nisi et al., 2018; Puskeiler et al., 2016), or tornados in combination with convection-favoring environment conditions from NWP can serve as a basis for near-real-time impact estimates. Such information can help to efficiently guide decisions in emergency management, for example, whether and where an evacuation should be carried out in the event of a severe tornado (Hammer & Schmidlin, 2002; Simmons & Sutter, 2013).

2.3. Droughts and Heat Waves

Droughts are triggered by persistent negative precipitation anomalies, often coinciding with high temperatures leading to high evaporation that can last for several months or years; various other definitions exist for different climates and impacts (UN General Secretariat, 1994). Heat waves are associated with periods of anomalously high temperature, in terms of maximum, minimum, and daily average temperature, or percentiles, ranging from days to months (WMO, 2018). Summer heat waves tend to be colocated with atmospheric blocking (Brunner et al., 2018; Pfahl & Wernli, 2012) and can be amplified by local processes, for example, a lack of soil moisture (Miralles et al., 2014; Seneviratne et al., 2010). Both hazards can reach continental scales of several 1,000 km. Heat and drought can occur as compound events with impacts on agriculture, water and power supply, human, and ecosystem health (Buttlar et al., 2018).

2.3.1. Droughts and Heat Waves: Hazard Forecasting

Forecasting and early warning systems for droughts and heat waves are based on indicators derived from meteorological and hydrological observational data (Haylock et al., 2008) or weather/climate model data (Lavaysse et al., 2018). Common hydrometeorological indicators for droughts are (1) Standardized Precipitation Index (SPI); (2) Palmer Drought Severity Index (PDSI) based on a soil water balance equation and incorporating prior (between 9 and 12 months) precipitation moisture supply, runoff, and evaporation; and (3) Standardized Precipitation Evaporation Index (SPEI) based on precipitation and temperature. The indicators are computed for different accumulation periods (short: 1–6 months; medium: 9–12 months; and long: up to 24 months) quantifying deficit/surplus with respect to the multiyear average, so that negative (positive) values indicate dryer (wetter) than average conditions (Pappenberger et al., 2015). Indicator thresholds are used to define drought severity classes (McKee et al., 1993; Naumann et al., 2015; Vicente-Serrano et al., 2010).

For heat waves, most studies use definitions based on temperatures above given percentile values (Fischer & Schär, 2010) or fixed temperature thresholds. Definitions vary depending on impacts in specific sectors (Meehl & Tebaldi, 2004; Perkins et al., 2012; Russo et al., 2015). For human morbidity and mortality, the studies use apparent temperature (Mitchell et al., 2016), humidity and nighttime temperatures (WMO, 2018). A range of combined heat humidity indices for human morbidity have recently been introduced following projections of more frequent heat-humidity extremes (Buzan & Huber, 2020; Di Napoli et al., 2019; Fischer & Knutti, 2013; Li et al., 2020; Raymond et al., 2020). A global database for comparing different indicators for heat waves has recently become available (Raei et al., 2018). It is based on reanalysis temperature data that allows for the extraction of heat wave data and the computation of heat indices in a toolbox for a range of commonly used heat indices.

There are two main approaches to drought and heat wave forecasting. The first one is based on operational weather forecast models (e.g., ECMWF in Europe, Lavaysse et al., 2015, 2018). These models solve prognostic dynamical and thermodynamic equations for atmospheric variables like temperature and moisture and can be coupled with hydrological models solving for soil water content. Based on the model output, the drought hazard indicators are calculated. The second approach relies on establishing statistical relations between predictors, for example, the North Atlantic Oscillation index time series, which quantify the main mode of atmospheric variability in the Northern Hemisphere and the regional probability for drought occurrence (Bonaccorso et al., 2015).

There exist a multitude of operational drought forecasting and early warning systems. Pulwarty and Sivakumar (2014) identify 21 drought early warning systems established across the globe, including North and South America, Africa, Asia, Australia, and Europe. After the devastating impacts from the 2003 European drought and heat wave, forecasts of both hazards have been implemented in the pan-European operational weather forecast systems of ECMWF (Lavaysse et al., 2015, 2018). Drought forecast is implemented in the European Drought Observatory (EDO) of the Copernicus Emergency Management Service (EMS) (https://emergency.copernicus.eu/). Forecast systems are also becoming available for irrigation management (Ceppi et al., 2014). A particular challenge with forecasting heat waves and droughts is that these are slow-onset hazards with a duration of several days to weeks for heat waves or months to years for droughts. Forecast lead times for droughts can vary widely (1–24 months) depending on the indicator considered. For heat waves, the times for consecutive days of high temperature anomalies are a few days up to 2 weeks (Lass et al., 2013; Lavaysse et al., 2019).

Drought hazard forecasting can be beneficial with respect to early water allocation in periods of water scarcity (Ceppi et al., 2014); it can provide meaningful information for agricultural users and particularly to farmers reducing economic losses due to droughts (Coughlan de Perez et al., 2015; Shafiee-Jood et al., 2014; Steinemann, 2006), and it can also allow international agencies and donors to adjust their support programs early when a strong signals for a likely famine becomes apparent (Pulwarty & Sivakumar, 2014).

2.3.2. Droughts and Heat Waves: Impact Forecasting

Although drought and heat waves exhibit similar meteorological drivers, they are associated with different impacts: while droughts lead to agricultural yield losses, limitations in water supply, water quality and hydropower (Ding et al., 2011; Stahl et al., 2016), wildfires and loss of lives (Turco et al., 2018), heat waves impact human mortality or morbidity (typically cardiovascular or respiratory, Arbuthnott & Hajat, 2017; de' Donato et al., 2015; Ekamper et al., 2010), work productivity (Ciuha et al., 2019), and agriculture (Parker et al., 2020; Souri et al., 2020). Droughts often have secondary impacts whereby outputs from one industry/sector become inputs into other industries/sectors. For example, farmers with crop losses will reduce their supplies to the downstream industries, such as food processors and ethanol plants, and the impacts on water supplies may in turn affect tourism and recreation, public utilities, horticulture, and landscaping services. During the historic drought in the southeast United States in 2007, many businesses were forced to close locations, lay off employees, or even file for bankruptcy (Ding et al., 2011).

A prerequisite for impact forecasting is the availability of sufficient impact data. This is particularly challenging in the case of droughts and heat waves where impact data are scarce due to the extended duration of the events, regionally varying vulnerability as well as the variety of the affected sectors. Droughts impact data are collected by the European Drought Impact Report Inventory (EDII) as text-based reports (Stahl et al., 2016), which state the location and time of occurrence and the type of impact. Heat waves impact data are sourced by national databases for mortality and morbidity indicators (respiratory hospital admissions, GP visits; Arbuthnott & Hajat, 2017). The database for mortality due to heat waves in four large European cities (London, Stockholm, Rome, and Madrid) is hosted by the European Environment Agency. Databases of more general scope are Eurostat and EM-DAT (2020), as well as reinsurance companies, the latter albeit with restricted access.

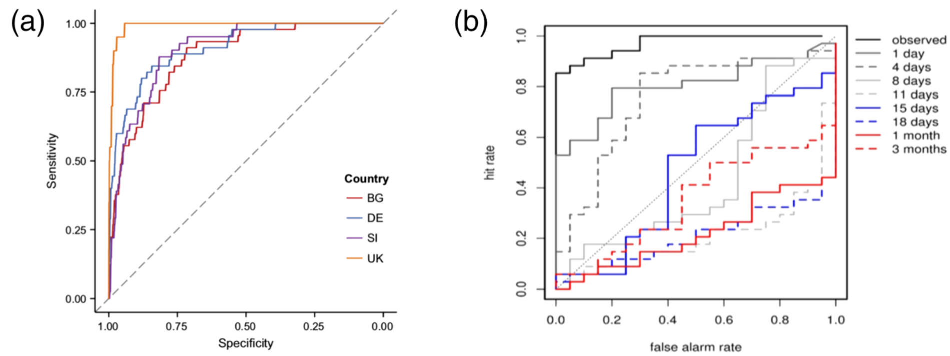

Figure 5. Receiver Operating Characteristics (ROC) curves, quantifying the skill of the impact forecast models. (a) ROC curve for agricultural drought impact models, with countries shown as uniquely colored curves. Sensitivity, or the fraction of correctly predicted impacts, is plotted against the specificity (1 minus the "false-alarm rate", i.e., the fraction of correctly identified nonimpact months; Stagge et al., 2015; Figure 2). (b) Mortality for the 2003 heat wave scenario (Lowe et al., 2016; Figure 4), using a probabilistic mortality model driven by forecast apparent temperature data at lead times ranging from 1 day to 3 months. The ROC curve for the mortality model driven by observed apparent temperature data is shown for reference (black curve). The better skill of the latter shows the importance of reliable heat wave forecasts. For more information, the reader is referred to the source publications.

The development of impact models relies on finding relationships between the predictors (e.g., SPI for droughts and temperature anomalies for heat waves) and the impact occurrence and severity. These relationships are established by either probabilistic methods (e.g., copula functions, Leng & Hall, 2019) or by functional relationships (damage functions). These damage functions are established via logistic and generalized regression or by fitting a power law or exponential dependence; machine learning methods are also emerging (Bachmair et al., 2017; Blauhut et al., 2015; Mitchell et al., 2016; Naumann et al., 2015; Turco et al., 2018). For prognostic models related to human health, the population exposure and vulnerability needs to be included, for instance, in form of the spatial variation of the ratio of fatalities to exposed population (Forzieri et al., 2017).

Three approaches for impact forecasting can be distinguished: (1) When the aim is to develop systems that are able to forecast a specific impact, which is subject to atmospheric variability, droughts and heat waves are typically included in an implicit way. Often indices for large-scale circulation patterns, such as the North Atlantic Oscillation related to temperature and precipitation anomalies over Europe, are used instead of drought and heat wave indicators (Ceglar et al., 2017; Nobre et al., 2019). (2) When the focus is on sector-specific impact forecasts due to a particular hazard (e.g., crop yield loss due to droughts, Leng & Hall, 2019; human mortality due to heat waves, Lowe et al., 2016; Mitchell et al., 2016; wildfires due to low precipitation, Turco et al., 2018), the impact model is often based on output from a climate or weather forecast model and/or hydrological models for soil water (Ceppi et al., 2014). (3) Further, there are approaches where multiple impacts (e.g., crop yield, energy, and water supply loss due to droughts) are grouped and represented by one variable (Bachmair et al., 2016, 2017; Sutanto et al., 2019).

The performance of impact forecasts is assessed through various cross-validation techniques and Receiver Operating Characteristics (ROC) curves (Figure 5). The lead times of skilled impact forecasts are a few days for heat waves and one to several months for droughts and are region and impact dependent.

2.3.3. Droughts and Heat Waves: Uncertainties and Challenges of Impact Forecasting

There is a large variability in the lead time of impact forecasting depending on the region and its vulnerability, for instance, in terms of crop species for droughts and population age distribution for heat waves. For example, agricultural impacts of droughts are best explained by 2- to 12-month anomalies, energy, and industrial impacts (hydropower and energy cooling water) by 6- to 12-month anomalies, while public water supply and freshwater ecosystem impacts are explained by a more complex combination of short (1–3 months) and seasonal (6–12 months) anomalies (Stagge et al., 2015).

A large part of the uncertainty of drought and heat wave impact forecasting have been attributed in the limited skill of prediction models used to forecast the weather conditions responsible for heat waves and droughts (Lowe et al., 2016; Moon et al., 2018), rather than the details of the mathematical formulation of impact models applied (Lowe et al., 2016; see also Figure 5b). This points to the importance of a skilled hazard forecast for a skilled impact forecast. Short-term deterministic weather predictability is limited to 2–3 weeks (Buizza et al., 2015; Domeisen et al., 2018; Zhang et al., 2019), and hence, we cannot currently predict the onset, duration, or strength of a heat wave several weeks ahead (Quandt et al., 2017), while the time needed to prepare for an extreme event is often longer (White et al., 2017). Drought events, on the other hand, tend to be predicted on timescales of about 1 month in advance in more than half of all cases (Lavaysse et al., 2018). The lack of a harmonized definition of these hazards and lack of accurate data on the hazard onset and duration adds another source of uncertainty (Stahl et al., 2016). Further challenges of impact forecasting are regional variations in vulnerability, such as local population health, and in hydrological conditions, and the variety of economic sectors with varying response times (Stagge et al., 2015). Finally, there are several confounding factors; for example, pollution may be responsible for deaths attributed to heat waves (Arbuthnott & Hajat, 2017). Further, human management and adaptation measures are often not included in impact models. For example, the poorer performance of crop models in southwestern versus eastern European countries used to represent impacts of the 2003 European heat wave and drought has been attributed to more widespread irrigation in the former (Schewe et al., 2019).

2.3.4. Droughts and Heat Waves: Maturity and Added Value of Impact Forecasting

The drought impact forecasting and early warning systems in Europe can be regarded as immature. To our knowledge, there is currently no operational system for seasonal drought impact forecasting. There is only one study published for Europe moving from a drought hazard forecasting to an impact forecasting approach, to enable authorities anticipating potential drought impacts 2 to 4 months ahead (Sutanto et al., 2019). The main reason for the lack of more mature systems is the scarcity of impact data in Europe. The situation is different in the African context where droughts can translate into devastating famines and loss of lives. In addition, the reliance on water irrigation systems is much lower in Europe as the crop water use comes quite often from precipitation and irrigation is only applied for specific crops, for example, vegetables, or in specific regions, for example, the Mediterranean region. In Africa, impact-based early warning systems with respect to famines have been installed, for instance, the Famine Early Warning Systems Network (Funk et al., 2019). The further development of drought and heat wave early warning systems is motivated by the predicted increase in the frequency and severity of these hazards, and hence losses, under climate change (Leng & Hall, 2019; Mitchell et al., 2016; Perkins et al., 2012; Russo et al., 2015; Turco et al., 2018).

A range of early warning systems for heat waves and associated mortality impacts have been established for Europe (Lowe et al., 2011; Matthies et al., 2008). An early example is the EuroHEAT project of the World Health Organization (WHO) (2005–2007), providing forecasts of heat wave probabilities with the goal of improving preparedness and response to heat waves. Bissolli et al. (2016) cite 14 advisories, that is, standardized information products about ongoing, pending or foreseen climate anomalies and their potential negative impacts, for heat waves and droughts in Europe since 2012. Heat-health warning systems had been put in place in 12 European countries by 2005 (Kovats & Kristie, 2006; Lowe et al., 2011). By 2009, 28 heat-health warning systems were operational in Europe (Lass et al., 2013), and by 2014, 16 countries had a clearly defined alert system and a health system preparedness component (Bittner et al., 2014; Lowe et al., 2016). Current heat-health warning systems (Lass et al., 2013) commonly contain meteorological forecasts and an impact model linking heat characteristics to health impacts. They are often embedded in heat-health action plans (Matthies et al., 2008) that consider a wide range of stakeholders and comprehensive mitigation and response plans, including education and awareness, guidance on actions and governance, communication, evaluation, health surveillance, and advice on longer-term strategies (Lass et al., 2013).

The added value of impact forecasting is still hypothetical, as there are only limited experiences and studies of the actual benefits. Substantial benefits are expected regarding food and water security by applying so-called forecast-based financing mechanisms (Coughlan de Perez et al., 2015). If predefined thresholds about a severe drought occurrence are passed, funding is disbursed by donors and management procedures are triggered to proactively mitigate the impacts. For the effective application of such financing mechanisms, data on potential impacts and strong stakeholder cooperation are needed to understand where the most severe consequences are to be expected (Bengtson, 2018). First operational methodologies are already available (German Red Cross, 2018; WFP [World Food Programme], 2019).

2.4. Floods

Floods are the outcome of various meteorological conditions and hydrological regimes: short-duration rainfall, high-intensity rainfall, long-duration rainfall, rain on saturated soils, snowmelt, or a combination of snowmelt and rainfall are typical triggers for floods (Merz & Blöschl, 2003). Pluvial floods are directly caused by excessive rainfall usually from local-scale convective storms. Pluvial floods occur when rainfall pours excessive amounts of water, which cannot infiltrate in rural areas or which exceeds the capacity of the drainage system in urban areas and consequently remains on the surface forming shallow layers of water (Blanc et al., 2012). Fluvial floods occur when discharges exceed the conveyance capacity and consequently overtop the river banks. While fluvial floods occur at spatial scales of around 10^2 to 10^5 km^2 and temporal scales from 1 day to several weeks, pluvial floods generally occur at smaller spatial and temporal scales. Flash floods are defined on the basis of the dynamic of the event. Flash floods are characterized by the fast occurrence of floods with water traveling with high speed. In watersheds of less than 500 km^2, flash floods are generally induced by high-intensity short-duration rainstorms, that is, more than 100-mm rainfall in less than 24 hr (Gaume et al., 2009).

2.4.1. Floods: Hazard Forecasting

Warning systems commonly depend on real-time rainfall information, high-resolution numerical weather forecasts, and the operation of hydrological model systems (Collier, 2007). Ensemble approaches, both for rainfall predictions from high-resolution numerical models and for flow forecasts, have proved advantageous together with adaptive approaches using data assimilation (Collier, 2007; Zappa et al., 2010). Flood forecasting differs vastly in respect to flood types and from global (Global Flood Awareness System, GloFAS, Hirpa et al., 2018) to local scales (Acosta-Coll et al., 2018). For instance, pluvial and flash floods are caused by local rainfall peaks, whose extreme features develop on space-time scales below the resolution of most NWPs. Radar-derived now-casting products and radar-NWP blending have increased the accuracy and space-time resolution (i.e., 1–4 km, 5–60 min) at the expense of short forecast horizons of 1–6 hr (Alfieri et al., 2012). Generally, flood early warning is based on forecasts of precipitation amounts. However, some operational early warning systems for pluvial and flash floods forecast simplified indexes based on the concept of extreme conditions. An example is the European Precipitation Index based on Climatology (EPIC), which is continuously calculated on the basis of probabilistic weather forecasts and is aggregating forecasted rainfall on hydrological units over a certain duration (Alfieri et al., 2011, 2012). Warnings for fluvial floods are commonly issued related to certain thresholds in terms of river discharge or water level. Warning lead times, which depend on forecast horizons, differ between below an hour for flash floods up to weeks for downstream areas in large river catchments (Collier, 2007; Kreibich, Müller, et al., 2017). For fluvial floods, thorough model calibration using local data and information as well as skillful forecasters can significantly reduce false alarm rates (Blöschl, 2008).

Official flood warnings have a long history, for example, a first system was established in Germany in 1889 (Deutsch & Pörtge, 2001). Commonly, the meteorological service is responsible for weather monitoring, forecasting, and warning in collaboration with water authorities responsible for flood forecasting and warning as well as with civil protection. Forecasting systems for fluvial floods are operational in many countries, for example, basically in all countries in Europe (Alfieri et al., 2012; Pappenberger et al., 2015; Werner et al., 2009). In contrast, pluvial flood forecasting is restricted to severe weather warnings on district level issued by the weather service including information about the expected maximum rainfall intensities for a maximum lead time of 12 hr in many regions. Pluvial flood early warning systems are implemented, for instance, for suburbs of the city of Copenhagen, Denmark, in the cities of Nîmes and Marseille, France, or in Barcelona, Spain (Deshons, 2002; Henonin et al., 2013). These specific urban systems rely on both thresholds of forecasted rainfall as well as inundation depth and area, for example, based on water level sensors, precalculated scenarios or online 1-D-2-D hydraulic models (Henonin et al., 2013). National alert systems for pluvial floods with a rather coarse spatial resolution exist in the United Kingdom (i.e., warnings issued on county level based on national thresholds), where the extreme rainfall alert service was launched in 2009 (Ochoa-Rodríguez et al., 2018), and in the United States, termed as flash flood guidance system (Villarini et al., 2010).

Flood forecasting and early warning systems primarily aim to protect human life; however, their potential to also reduce economic damage has been recognized since decades (Lustig et al., 1988; Molinari et al., 2013).

Pappenberger et al. (2015) calculated that each Euro invested in the European Flood Awareness System (EFAS) pays off 400 times (with considerable uncertainty). Main aspects determining the effectiveness of early warning systems in reducing losses are the lead time, the flood intensity, dissemination and content of the warning, and the ability of civil protection and affected parties to undertake emergency measures effectively (Kreibich, Müller, et al., 2017; Molinari et al., 2013; Morss et al., 2016). In Europe, the communication of warnings was significantly improved in the 1990s, and recently, significant advances in the extension of warning lead times have been achieved by using ensemble prediction systems and more closely integrating weather and flood forecasts (Parker & Priest, 2012). Flood warning response remains to date as the major challenge for flood warning systems (Parker & Priest, 2012).

2.4.2. Floods: Impact Forecasting

The forecasting of flood impacts is currently an emerging topic on the flood research agenda. It aims to deliver information about the expected consequences of imminent flooding. It uses both qualitative and quantitative indicators. One example for qualitative impact forecasting is the flood guidance statement for emergency response, which is based on a flood risk matrix (Coles et al., 2017). This matrix discerns four categories of flood severity by combining the potential impact severity and flood likelihood (similar to Figure 4). Coughlan de Perez et al. (2015) and Sai et al. (2018) follow a similar approach by defining color codes representing thresholds of flood impacts, which are linked to response actions. Quantitative impact forecasts include estimates of the number of people affected, economic damage, and infrastructure affected. The level of detail varies from the number of buildings affected (Bihan et al., 2017) to economic damage for residential buildings, commerce, agriculture, industry, and transport and infrastructure sectors (Dale et al., 2014; Dottori et al., 2017; Ritter et al., 2020) and economic damage to individual buildings (Dale et al., 2014; Fuchs et al., 2017).

The majority of flood impact models focus on direct economic damage mostly to the residential and commercial sector and also impact models for agriculture and the public sector are available (Gerl et al., 2016). Approaches to estimate, for instance, damage to critical infrastructure or indirect impacts barely exist (Bubeck et al., 2019; Koks, 2018; Merz et al., 2010). Quantitative flood impact models estimate the consequences of flooding usually using information about inundation depth, duration flow velocity, or other metrics of flood intensity and taking the resistance characteristics of affected elements into account (Thieken et al., 2005).

The literature describes impact forecasting approaches for near-real-time applications, that is, providing information at the same time as the event is happening (Kim et al., 2011; Kron et al., 2010) and for short-term forecasts with lead times of a few hours to 1 day. Examples are found in Bihan et al. (2017) and Ritter et al. (2020) for flash floods and in Bhola et al. (2018) and Fuchs et al. (2017) for pluvial floods in urban areas. River flood impact forecasting systems with lead times of several days have been proposed by Dottori et al. (2017), Bachmann et al. (2016), or Brown et al. (2016). The spatial scales of these systems range from urban districts (about 100 km^2; Cole et al., 2016; Coles et al., 2017; Fuchs et al., 2017), small- and medium-sized catchments with areas of several thousand square kilometers (Bachmann et al., 2016; Bihan et al., 2017; Nguyen et al., 2015; Ritter et al., 2020) to national and continental applications (Coughlan de Perez et al., 2015; Dottori et al., 2017).

To forecast inundations and flood impacts, established flood forecasting systems are extended by additional model components, for instance, depth-damage curves or probabilistic multivariable vulnerability models (Dale et al., 2014; Dottori et al., 2017; Fuchs et al., 2017; Kim et al., 2011; Ritter et al., 2020). Some studies aim to include also effects of dike breaches by implementing probabilistic dike failure models (Bachmann et al., 2016; Brown et al., 2016; Kron et al., 2010). A key challenge of this approach is to provide timely and accurate estimations of water levels and inundation areas to determine flood impacts. This is done either by fast hydrodynamic simulation approaches (Bachmann et al., 2016; Brown et al., 2016; Kron et al., 2010; Nguyen et al., 2015) or by using precalculated inundation maps, which are then selected to best represent the forecasted flood situation (Bhola et al., 2018; Dottori et al., 2017; Ritter et al., 2020). An alternative to this simulation-based approach consists in defining impact thresholds. These thresholds represent expected impact severity for given flood intensity levels (e.g., inundation depth) and are combined with warning information and recommended mitigation actions (Cole et al., 2016; Coughlan de Perez et al., 2015; Sai et al., 2018). Alternatively, for thresholds of forecasted precipitation intensity or flood discharge direct relationships to expected impacts are established. For instance, Bihan et al. (2017) derive a relationship between flood discharge and the number of affected houses. Similarly, Dale et al. (2014) propose the use of monetized impacts for defined river peak discharges or water levels as a basis for emergency management.

2.4.3. Floods: Uncertainties and Challenges of Impact Forecasting

The evaluation and reliability assessment of impact forecasting is complicated due to scarcity of reported impact data at the local scale (Dottori et al., 2017). Particular challenges arise from complex hydraulic situations, such as perched riverbeds, and local effects, such as blockages, which are difficult to incorporate in forecasting systems (Bihan et al., 2017). Kim et al. (2011) report on limitations that involve physical changes in the river network, such as the formation of debris or ice jams on structures or a breach in a levee. Impact forecasting faces further challenges related to the definition of relevant impact information because the forecasted impacts have to be aligned with the contents and details required by the users of this information (Dottori et al., 2017). It requires additional data regarding the exposed elements at risk, for example, population, critical infrastructure, their vulnerability, and emergency measures taken during the event (Bachmann et al., 2016; Brown et al., 2016). This database must be continuously updated as the exposed people may be subject to fluctuations at different timescales. Examples are subdaily variations in terms of commuters or seasonal fluctuations in terms of holiday guests (Doocy et al., 2013). Further, changes in vulnerability, for example, due to the implementation of precautionary measures or improved warning systems (Kreibich, Di Baldassarre, et al., 2017), and changes in flood protection schemes need to be included. Moreover, human behavior and risk awareness are important influences of flood fatalities. A surprisingly high fraction of fatalities is caused by people walking purposely through the flood waters without rescue or evacuation purpose (Ashley & Ashley, 2008), and unnecessary risk-taking behavior contributes significantly to flood deaths (Jonkman & Kelman, 2005). Quantitative impact estimation has to cope with uncertainties in input information from inundation forecasts with weather forecasts in terms of timing, location, and amount of precipitation as the main source of uncertainty for longer lead times. Impact forecasting is subject to additional uncertainty related to incomplete data and simplified methods to estimate consequences. For instance, Brown et al. (2016) describe simplified approaches for loss of life calculations, which do not consider inundation dynamics, location or evacuation of people.

The impact forecasting approach based on EFAS so far computes flood hazard and impact maps using only the median of the ensemble, which ignores less probable but potentially more severe scenarios (Dottori et al., 2017). Ensemble-based impact forecasting is possible and will lead to probabilistic impact predictions that incorporate uncertainties (Brown et al., 2016; Cole et al., 2016; Dale et al., 2014). To achieve minimal computation times, Brown et al. (2016) utilize only a limited number of ensemble members but still preserve statistically sound results. The communication of uncertainty of impact forecasting requires special consideration to ensure that the information is understandable and beneficial (Brown et al., 2016).

2.4.4. Floods: Maturity and Added Value of Impact Forecasting

Impact forecasting of floods is a new field with relatively many recent contributions. The developed approaches range from proof of concepts via prototypes implemented in case study areas to preoperational systems. In research studies, for instance, new methodologies were developed for hydrodynamic-based flood forecasts that work with precalculated scenarios and database queries to select appropriate flood inundation maps in real time (Bhola et al., 2018; Fuchs et al., 2017). Prototype systems have been implemented in several case study areas, for instance, in Germany, France, the Netherlands, or the United States (Bachmann et al., 2016; Bihan et al., 2017; Kim et al., 2011; Kron et al., 2010). Dottori et al. (2017) present a European-wide operational procedure for impact forecasting based on warnings of EFAS.

It might not take much longer until also national and local operational systems will be in place, since the expected benefits of impact forecasts are manifold. They can support the planning of more demanding measures, such as monitoring of flood defenses or deployment of emergency services (Dottori et al., 2017). It is expected that forecasted impact maps, including information about affected population, infrastructures, and cities, would substantially improve emergency response by, for example, prioritizing evacuation planning (Bhola et al., 2018; Coles et al., 2017; Dottori et al., 2017). Coupling inundation modeling with network analysis enables decision makers to identify city districts or single buildings that are most vulnerable to flood impacts or delayed response by emergency services. This information can support the development of contingency plans (Coles et al., 2017). Additional information on expected impacts can effectively support the design and adaptation of emergency measures (e.g., location, time, and type) and may enable cost-benefit analyses of response measures (Bachmann et al., 2016; Dottori et al., 2017). Other benefits may be that decision making can be better informed and improve emergency measures (Dale et al., 2014). Coughlan de Perez et al. (2015) expect that "tailoring of forecast information to the operational contexts of the humanitarian sector can dramatically increase the uptake of existing forecast products." They propose a novel forecast-based financing system to automatically trigger action. This system matches threshold forecast probabilities with appropriate actions, directly disbursing the required funding and proposes standard operating procedures that contain the mandate to act. An important component is a designated preparedness fund that is available for use before a disaster strikes.

2.5. Storm Surges

Storm surges are oscillations of the water level in a coastal or inland water body caused by dynamic wind pressure and associated with extratropical or tropical cyclones. The spatial and timescales of storm surges vary considerably (Gönnert et al., 2001). Tropical cyclones are associated with small and intense surges that have timescales in the order of a few hours and spatial scales in the order of about 50 km. In contrast, extratropical storm surges typically have larger spatial dimensions of up to hundreds of kilometers and longer timescales in the order of up to about 1 day. They may also propagate away from the storm and proceed, in form of long waves, along the coast. In the latter case, they are usually referred to as external surges (Weisse & von Storch, 2010). Because of the higher wind speed in tropical cyclones, tropical surges are usually much higher than their extratropical counterparts. Extratropical cyclones and the surges caused by them preferably occur in fall and winter, while tropical cyclones are tightly coupled to warm water and together with their surges predominantly occur in the late summer season.

2.5.1. Storm Surges: Hazard Forecasting

Forecasting approaches range from empirical approaches to complex numerical models (Kohno et al., 2018; Swail, 2010). Approaches vary by country, region, and lead time of forecasts. A survey conducted by the Expert Team on Wind Waves and Storm Surges (ETWS) of the Joint Technical Commission for Oceanography and Marine Meteorology (JCOMM) in 2010 revealed that approximately 75% of the reported operational or preoperational applications used two-dimensional tide surge models (WMO, 2011). To complement numerical products quickly and cost efficiently, empirical approaches are still widely used. For very long lead times of several days, empirical relations between NWP and expected surge heights may provide first and early indications of the upcoming event. For very short lead times of less than 24 hr, lagged empirical relations between observed wind fields or water levels from surrounding tide gauges may provide quick refinements of the numerical forecasts, in particular in-between subsequent model runs. Such a scheme is implemented, for example, in the operational storm surge warning of the federal state of Lower Saxony, Germany (Kristandt et al., 2014).

Hazard characteristics included in the forecasts vary. Typically, information is provided on intensity, duration, or how fast critical levels are reached. Usually, the height of the surge or total water levels are forecasted. In two-dimensional models, the latter comprises tides and surges and their nonlinear interaction. Wave-related processes such as wave setup may substantially add to extreme coastal water levels but are so far often ignored in operational procedures (Kohno et al., 2018; Melet et al., 2018). Coupling between waves and surges is an area of active research (Staneva et al., 2016), and the results are gradually transferred into operation (Kohno et al., 2018). High surges may coincide with high river discharges or high precipitation and may pose problems for drainage of low-lying coastal areas (Bormann et al., 2018).

The most significant source of uncertainty in storm surge forecasting is related to the uncertainty in the driving wind fields (Flowerdew et al., 2009; Resio et al., 2017; WMO, 2011). In a forecast environment, limited resources and the amount of time available may restrict the production of large ensembles to assess the uncertainty. Attempts are being made to include probabilistic elements into the forecast under such conditions. For tropical surges, an example is described in Davis et al. (2010). Other sources of uncertainties are related to the accuracy of the bathymetry and topography used in the surge models, potential effects related to coupling of waves and surges, or model errors caused by simplified representations of physical processes within the surge models (e.g., Resio et al., 2017).

Monitoring of storm surges is mainly based on tide gauges. When critical levels are exceeded or are expected to be exceeded, warnings or advisories may be issued. The products derived from the operational models are diverse depending on the predictability of the natural system and also with respect to the requirements of the areas to protect. Among others, they comprise warnings for expected exceedances of storm surge or total water level thresholds, expected maximum surge heights and timing of peaks, time-varying forecasts of surges or total water levels for specific locations, or time-dependent maps of surge heights. For extratropical surges, most of the operational applications are issued with lead times between 36 and 72 hr, although a forecast range as long as 120 hr has been reported (WMO, 2011). Forecasts of surges generated by tropical cyclones mostly have shorter lead times, usually in the order of 12 hr to a few days (WMO, 2011). Real-time storm surge products typically become available less than 48 hr before landfall of a tropical cyclone. For longer lead times, forecast errors increase rapidly (Davis et al., 2010).

Studies on benefits or cost-benefit ratios of storm surge forecasts or early warning systems are rare. There are several reasons. In some countries, such as in Germany, to guarantee safety of people and property at risk, the law requires issuing storm surge forecasts as an element of the basic services for the public. Some work exists that analyses cost-benefit ratios of existing or planned coastal protection measures (Davlasheridze et al., 2019; Flemming, 1997). For the case of storm surge barriers or barrages that need to be kept open as much as possible such analyses also include costs of storm surge monitoring and forecasts. An example is given in Flemming (1997) who estimated the costs of minor floods in the London area to be sufficiently high to justify the costs for initial investment, operation and maintenance of the Thames Barrage including costs for the operation of the storm tide monitoring and forecasting system. A case study on Cyclone Evan in Samoa (2012) quantified cost and benefits of early warning services for cyclone hazards and concluded that for every USD invested, there is a return of 6 USD as benefit (Fakhruddin & Schick, 2019). Such studies, however, do not distinguish between costs and benefits from surge or windstorm forecasting.

2.5.2. Storm Surges: Impact Forecasting

Traditionally, coastal flooding and inundation are considered the most obvious impacts of a storm surge event. However, we use a broader perspective where impact considers the exposure and the expected vulnerability of elements at risk (section 1.2). For storm surges, efforts to provide such information are in their infancy. Walker et al. (2018) aimed at developing a fiscally based scale for tropical cyclone storm surges from which an impact forecast can be derived based on information available from existing hazard forecasts. The approach was developed for the U.S. Gulf and East Coasts and basically uses multiple linear regression between loss per capita and surge height and velocity. Similarly, using artificial neural networks, Pilkington and Mahmoud (2017) explored the potential to forecast a range of economic damage resulting from multiple hazards, including storm surges, associated with forecasted tropical cyclone events. When coastlines are massively protected, such as in The Netherlands or Germany, such approaches become problematic, as damages will be closely linked with the extent and specific characteristics of potential failures.

Emergency managers and decision makers increasingly request inundation maps (WMO, 2011), and there are substantial efforts to extent forecast schemes to include information on coastal inundation (Dube et al., 2010). Typically, static inundation maps at different surge or total water levels are produced in advance using steady state models (Dube et al., 2010). During a storm surge event, these precomputed maps are then extracted from libraries depending on forecasted surge or total water level heights. A more dynamic approach is followed by the Copernicus EMS (https://emergency.copernicus.eu/mapping/), where the boundaries of inundated areas are delineated by means of satellite data. The complexity of such maps varies. Typically inundation or flood depth is considered but also information on vulnerability may be included (WMO, 2011). So far, efforts in regions affected by tropical cyclones are most pronounced (Dube et al., 2010). A similar procedure is intended by the EU Floods Directive (EU, 2007), which recommends inundation maps of the surge protected areas based on probabilities of occurrence or at least extreme events, which subsequently may also be used for forecasts. In some areas, consideration of compound or cascading effects of surges, precipitation, and river floods is needed but attempts to do so are still embryonic (https://www.deltares.nl/app/uploads/2018/10/Efficient-Modeling-of-Compound-Flooding.pdf; last accessed 24 April 2019).

For areas where sandy barriers provide some protection from surges, including morphological processes in the forecast is essential. The Emilia-Romagna early warning system, for example, consists of a series of met-ocean and morphological models aiming at forecasting storm surge impacts. In this case, two proxies estimating the impact are forecasted: (i) the so-called *safe corridor width*, which measures the distance from the dune foot to the waterline and represents the fraction of the beach that can be used for safe passages;

and (ii) the so-called *building waterline distance*, that similarly measures the amount of dry beach available between the waterline and beachfront properties (Harley et al., 2016). For areas protected by dikes, a different approach is taken. In addition to the hazard forecast, sensor-based geotextiles aiming at automatic monitoring of the state of the dyke are developed. In combination with the hazard forecast, early warning systems for critical situations may be derived.

Erosion during storm surge events represents another major impact. Impact models such as XBeach (Roelvink et al., 2009) exist but heavily depend on high-resolution local data such as bathymetry or the wavefield during the storm. In the tidal channels and ebb tidal deltas of the Wadden Sea in the southeastern part of the North Sea, major morphological changes result from strongly increased near bottom outflow during storm surge conditions. This is assumed to cause major erosion at groin (Groins are rigid hydraulic structures usually made of wood, concrete, or stone and built from an ocean shore. Their objective in coastal engineering is to interrupt water flow and to limits the movement of sediments.) heads and other coastal protection structures. In a demonstration project, erosion and morphological impacts of storm surges were forecasted (Souza et al., 2014). Time series of wind waves and tide surges from operational forecasts were used to operationally run a two-dimensional model for wave propagation, long waves and mean flow, sediment transport, and morphological changes on beaches, set up for the Sefton coast in Liverpool Bay. The system aimed at forecasting threshold exceedances for storm impacts and the expected extent of dune erosion with the intention to provide a coastal vulnerability early warning system with 48-hr lead time (Souza et al., 2014).

2.5.3. Storm Surges: Uncertainties and Challenges of Impact Forecasting

Key elements of uncertainty are the combined random errors and biases from the NWPs used to drive the storm surge forecasts. In addition, for the numerical tide surge models, high-resolution and up to date bathymetric data are needed to provide reliable coastal forecasts. Seasonal or longer timescale variability of bathymetry may introduce a further level of uncertainty, in particular when impacts such as increased erosion are considered. In the case of sandy barriers, modeling of erosion and assumptions inherent in the modeling add a further level of uncertainty. Inundation forecasting is often based on steady state solutions (Dube et al., 2010), while inundation critically depends on the development of surge heights over time. Moreover, topographic data accuracy and exact forecast of the location of peak water levels will strongly determine inundation and flood depth. In case of coastal protection failure, details of the failure will also significantly affect inundation and impacts.

2.5.4. Storm Surges: Maturity and Added Value of Impact Forecasting

The WMO implemented a coastal inundation forecast demonstration project (CIFDP) aiming at developing integrated systems for inundation forecasts, which can be used in operational environments (WMO, 2013). As of April 2018, there were ongoing or planned national subprojects in Bangladesh, Fiji, the Caribbean, Indonesia, Shanghai, and South Africa.

Early warning systems including both, hydrodynamic hazards and morphological impacts, recently emerged in the United States and in Europe (Harley et al., 2016). In Europe, a series of prototypes at nine sites was developed in the MICORE project (Ciavola et al., 2011).

Impact forecasting in a wider sense as defined in section 1.2 is at its infancy and to our knowledge limited to general considerations (Pilkington & Mahmoud, 2017; Walker et al., 2018).

The added value of the impact forecasting provided by the Emilia-Romagna early warning system was assessed in a hindcast study of the 2012 Halloween storm in northern Italy (Harley et al., 2016). The extent to which the impact forecasts may have helped to reduce the storm impacts was assessed. The analyses showed that due to an underprediction of the extreme water levels, only for two of the eight sites in the early warning system high hazard/impact warnings would have been issued (Harley et al., 2016). Again, this emphasizes the need for accurate met-ocean forecasts.

2.6. Earthquakes

Tectonic earthquakes (hereinafter earthquakes) originate from the sudden release of elastic strain energy in form of a fracture. Part of this energy is released as seismic waves that radiate from the earthquake hypocenter, that is, the point at a given depth under the Earth's surface, where the rupture starts. The ground shaking caused by the seismic waves reaching the surface may be very violent, resulting in widespread damage to buildings and infrastructure and consequent loss of properties and lives. The unfolding of the phenomenon occurs generally on the scale of seconds, with the rupture during the biggest earthquakes lasting up to several minutes and may affect an area ranging from tens to thousands of square kilometers. The different waves generated during the rupture process travel at speeds, typically ranging from 3 to 6 km/s, and are progressively attenuated due to geometrical spreading, energy absorption and scattering. Earthquakes occurring at convergent tectonic plate boundaries release most seismic energy. Strong earthquakes can also occur within tectonic plates (intraplate). Although these events are comparably less frequent (around 5% of the total number of observed events), they can be significantly damaging as they often occur onshore. Strong earthquakes are often the cause of subperils such as tsunamis and landslides and can trigger volcanic unrest.

2.6.1. Earthquakes: Hazard Forecasting

Mainshocks are often preceded by foreshocks (although while a seismic sequence is ongoing such a distinction might not be possible, see, e.g., Gulia & Wiemer, 2019) and often by accelerating seismic activity in the months to days before they occur (Abercrombie & Mori, 1996; Bouchon et al., 2013). Nevertheless, there is no evidence of systematic precursors, and for the sake of all practical and operational applications earthquakes are modeled as random events whose short-term forecasting is characterized by very low probabilities, resulting in limited usefulness for decision making (Geller, 1997; Kagan & Knopoff, 1977). Earthquake forecasting therefore does not aim at the prediction of a given event but rather at the probabilistic characterization of the underlying process. This is usually achieved in a statistical framework, with a strong hypothesis on the substantial stationarity of the process over time windows spanning decades to hundreds of years. On shorter timescales, from days to decades, nonstationary models are considered by so called OEF systems (Jordan et al., 2011) that integrate short-term information, such as the evolving seismicity during an earthquake sequence.

Europe has pioneered the efforts toward the realization of OEF systems (Zechar et al., 2016). For instance, Iceland and Switzerland have started exploring the implementation of OEF systems and in Italy, following the 2009 L'Aquila earthquake, a prototypal system has been developed, providing civil protection authorities with weekly forecasts in terms of probability of exceedance of given magnitudes (for events) or macroseismic intensities at the national scale (Marzocchi et al., 2014). In New Zealand a hybrid OEF system integrating short- and long-term models provides both public and governmental agencies with time-dependent probabilities during earthquake sequences. In the United States several joint earthquake advisories have been issued using ad hoc OEF processes (U.S. Geological Survey Staff, 1990), and in California short-term earthquake probability forecasts have been provided for several years but discontinued in 2010 (Field et al., 2016). More recently, the U.S. Geological Survey (USGS) has developed and tested a national capability for aftershock forecasting after significant earthquakes (Michael et al., 2019).

The assessment and dissemination of authoritative information about time-dependent earthquake probability has multiple benefits. Experimental evidences show that OEF can outperform time-independent Poissonian models on short-term forecasting (Jordan et al., 2014), with a potential for enhancing the earthquake preparedness especially during sequences, where the probability for large earthquakes significantly increases with respect to the seismic background. Although in most cases large events remain unlikely (rarely exceeding 1% probability per day), several protective and mitigation actions are possible, such as conducting disaster-response drills, increasing the readiness of emergency personnel or emphasizing preparedness in media communication (Field et al., 2016).

The term EEW refers to the prompt detection of an earthquake within few seconds after its actual onset and may provide a viable solution for real-time risk mitigation (Wenzel & Zschau, 2014; Wu et al., 2016). A so-called regional EEW approach is based on the early detection of the seismic waves generated by the earthquake's rupture process by means of an extended network of seismic sensors located in proximity of the epicenter. The rapid detection leads to a first estimation of the location and the size of the event. A suitable alert might then be immediately signaled to the target location (i.e., a specific critical structure or an inhabited place that could be adversely impacted) some time before the incoming seismic waves would strike. The lead time is the time interval between issuing the warning and the actual occurrence of the strong shaking at the target location and may range from a few seconds to around 1 min (Minson et al., 2018). Regional EEW systems have been implemented, either operationally or in the testing phase, in Europe (Italy and Romania), the United States, Japan, Mexico, Turkey, and Taiwan (Alcik et al., 2009; Allen et al., 2009; Böse et al., 2007;

Espinosa Aranda et al., 1995; Hoshiba et al., 2008; Hsiao et al., 2009; Satriano et al., 2011; Wu et al., 2013). Recent studies (Parolai et al., 2017; Pittore et al., 2014) have also highlighted the potential for EEW systems in economically developing countries.

An operational EEW system can reduce the impact on the population. It can support their rapid response, taking simple actions that decrease the possibilities to be injured during a seismic event. Automatic actions might help in stopping industrial facility production, medical operations, and so forth, therefore reducing the impact of the event.

2.6.2. Earthquakes: Impact Forecasting

Quantitative estimates can be obtained using engineering approaches, which map the estimated distribution of the ground shaking in terms of macroseismic intensity (MI) or instrumental intensities, such as peak ground acceleration, into an estimated damage distribution employing asset-specific fragility and vulnerability models (Calvi et al., 2006). Physical damage is usually described in terms of a discrete set of damage states that span the full range of consequences (Hill & Rossetto, 2008). Physical damage can be used to estimate the amount of loss, either in terms of replacement cost ratio (e.g., the fraction of replacement cost of a building lost due to the incurred damage to the structure) or affected people (e.g., fatalities, injuries, and displaced persons), with the latter of major importance in the immediate aftermath of the event.

While physical damage indicators refer to single structures, systemic impact indicators describe the expected performance loss of interconnected systems, such as lifelines (transport, power, or communication networks) and critical infrastructure (hospitals and airports), also considering possible cascading effects arising from the functional interdependency among the different components of the networks.

Probabilistic seismic hazard assessment, earthquake operational forecasting, and early warning approaches can all be complemented by suitable loss modeling components. The concept of Operational Earthquake Loss Forecast (OELF) has been first proposed in Italy in 2015 and exemplified with an experimental system, which produces real-time risk maps in terms of building collapses, displaced residents and fatalities (Iervolino et al., 2015). More recently, an OELF system has been implemented for California, based on the UCERF-3 (Uniform California Earthquake Rupture Forecast Version 3), in order to estimate the expected loss in case of scenario earthquakes of different magnitudes, also considering the related sequences of aftershocks (Field et al., 2017). This information is increasingly used to plan medium- and long-term mitigation activities and to raise awareness of the underlying risk for both practitioners and the public.

In the framework of EEW, near-real-time impact estimation can be carried out for an actual (unfolding) earthquake, in order to complement the alarm with first-order estimates of the potential consequences of the incoming ground motion at the target location. This loss estimate can be made available before the actual damaging shaking occurs and used to optimize automatic mitigation. Some of these systems are designed to rapidly estimate the potential shaking arising from an event at a given location, providing decision makers with timely access to information related to the potential losses and its distribution (Bindi et al., 2016; Parolai et al., 2015; Pittore et al., 2014).

Different indicators are used to provide an overview of the expected impact of an earthquake. Physical impact indicators, which refer to direct consequences on built structures, can be assessed employing different, increasingly sophisticated approaches. For instance, the potential for damaging consequences of an earthquake at a given location may be inferred as first order by the estimated MI. Macroseismic scales, such as the EMS-98 scale (Grünthal & European Seismological Commission, 1998), have been derived from empirical observations of past events and refer to observable consequences on people, buildings, and the natural environment. They can be determined using empirical models, once the magnitude and the location of the event is known, estimated from the analysis of real-time ground motion data, or inferred from social media and crowd-sourced observations, for instance, volunteered reports from citizens in the area affected (Atkinson & Wald, 2007; Bossu et al., 2011).

Other empirical impact indicators are based on systematic analysis of past earthquakes and provide semi-quantitative assessments that are suited for large-scale or global applications. Real-time risk scenarios, based on the estimated magnitude and location of the event or simply on the measurement of the ground motion parameters at a few stations, can be calculated considering the availability of exposure and vulnerability models in the target area providing quantitative impact estimates. At the global scale, for instance, the USGS provides rapid postevent impact forecasts in terms of fatalities and economic loss through the PAGER (https://earthquake.usgs.gov/data/pager) service. A threshold on the combination of these two factors is used to rank the alert (Wald et al., 2011).

The Global Disaster Alert and Information System (GDACS, http://www.gdacs.org), a joint effort of the United Nations and the European Commission, provides impact forecasts and alerts based on a combination of damage proxies, for instance, derived from the estimated MI, socioeconomic vulnerability and lack of coping capacity (De Groeve et al., 2006). The latter indicator is based on the Index for Risk Management (INFORM, http://www.inform-index.org/), an interagency collaboration that proposes several hazard-independent analytical products to support international crisis management (Marin-Ferrer et al., 2017). Loss models are available for a large set of assets and infrastructure, but they are currently often not included in operational impact forecasting applications.

2.6.3. Earthquakes: Uncertainties and Challenges of Impact Forecasting

The uncertainty of earthquake impact estimation is mainly driven by (a) uncertainty in the description of the seismic event, (b) time constraints, particularly in EEW applications, (c) quality and reliability of ground motion and site amplification models, and (d) quality and reliability of related exposure and vulnerability models.

The uncertainty in (a) refers to the knowledge of the specific characteristics of the earthquake, including, for example, magnitude, epicenter location, and hypocentral depth. The models mentioned in (c) are used to estimate the ground motion at a given distance from the epicenter considering the attenuation of the seismic waves along the path and their possible amplification due to local soil conditions. Factors mentioned in (a) and (b) are different for each event and for different locations, depending, for example, on the network density and geometry, while factors (c) and (d) depend on the preexisting knowledge about the affected region. The contribution of ground motion models to the impact uncertainty can be significant (Crowley et al., 2008; Weatherill et al., 2015), while the uncertainty of exposure and vulnerability models has been only partially explored (Bal et al., 2010; Crowley et al., 2005). Since damaging earthquakes are infrequent in comparison with other natural hazards, there is a substantial lack of empirical observations for the calibration and testing of vulnerability models and even more of the time dependence of physical vulnerability, which might result from a progressive damage accumulation throughout a seismic sequence. For specific target areas, the availability of cost-effective instruments allows the dense recording of shaking, therefore reducing the necessary spatial interpolation in the estimated scenarios and improving the reliability of the estimates.

According to the specific operational environment, the uncertainty in the event description plays a different role in determining the final uncertainty in the estimates. In EEW applications, for instance, as instrumental data are progressively recorded the main characteristics of the unfolding earthquake are increasingly constrained. In this case the main limitation is the short lead time available to undertake mitigation actions, and a suitable trade-off must be sought between the uncertainty of the estimate and its timeliness (Minson et al., 2019). In the case of rapid response, the time constraint is less tight and there is a higher availability of direct measurements of ground motion intensity and thus the resulting uncertainty on the forecasted impact may be reduced (Stafford, 2012).

Propagating this uncertainty throughout the impact estimation process is burdensome and often results in impact estimation ranges that may even span several orders of magnitude (Wald et al., 2011). Further, the overall impact of an earthquake is strongly affected by the social and environmental conditions in which the event takes place. For instance, the number of casualties may directly depend on the daytime (e.g., day and night), day of the week or season, but also in a more complex way on the weather conditions, and (as we all recently discovered) on pandemic outbreaks limiting the capacities of the first responders (https://www.bbc.com/news/world-latin-america-53160460). It should anyway be considered that in the first aftermath of the event only first-order information is necessary to civil protection authorities for better planning and prioritizing the immediate actions. Nevertheless, the large uncertainty requires effective strategies for communicating the resulting impact estimates to end-users in order to optimize the decision-making process.

2.6.4. Earthquakes: Maturity and Added Value of Impact Forecasting

Earthquake impact forecasting has found increasing attention in research in the last decades, mainly supported by civil engineering applications. However, significant efforts are still needed to meet the requirements of the authorities for practical application. A few operational systems have been implemented complementing OEF models, for instance, in Italy. Impact forecasting is also carried out automatically after large earthquakes by several software platforms, mostly operating at global scale. Local or national systems directly operated by civil protection authorities are also present, but rarely described in the scientific literature.

Systematic impact forecast, also for hypothetic scenarios, for instance, in the case of operational forecasting, would increase the risk awareness of decision makers and the public. This would foster the implementation of short- and longer-term prevention measures and the collection of preevent vulnerability and postevent damage information to reduce the epistemic uncertainty in the impact estimation. Herrmann et al. (2016) have shown that combining OELF-based fatality estimates with cost-benefit analysis can lead to reasonable evacuation strategies during a foreshock-aftershock sequence. Although OEF and OELF may provide actionable information, the related mitigation actions are constrained by the intrinsic uncertainty of the forecasts (Field et al., 2016), since the considered event is always hypothetic, and usually associated with a very small probability over the timeframe of interest. The lack of harmonized short-term seismic catalogs including small-magnitude events, and the computational burden of real-time model updating still hinder large-scale operational implementations (Eberhard, 2014). Furthermore, while OEF methodologies and applications are subjected to test and validation (Marzocchi et al., 2017), to the best of the authors' knowledge, there have not yet been significant efforts on the validation of the impact forecasting component.

2.7. Tsunamis

Depending on the source origin and magnitude, tsunami impact can range from local to transoceanic, encompassing thousands of kilometers of shoreline. Correspondingly, tsunami hazards span timescales from a few minutes to several hours after its origin. While being triggered by various physical phenomena capable to bring the sea level out of its equilibrium state (Grezio et al., 2017), most tsunamis are caused by shallow submarine earthquakes deforming the seafloor and thus disturbing the water column above (Satake, 2002). This fact makes their forecasting similar to that of the earthquake hazard: Whereas it is not possible to predict the exact location and magnitude of a future event, it is possible to quantify source characteristics within a few minutes after the triggering earthquake and use this information to evaluate the tsunami impact before it strikes the coast.

2.7.1. Tsunamis: Hazard Forecasting

There are presently around 20 Tsunami Early Warning Systems (TEWS) worldwide. They aim to forecast the tsunami arrival time as well as its hazard impact, usually given as warning levels. For example, the U.S. National Tsunami Warning Center has adopted the following classification: “tsunami information,” (“no tsunami threat”) “watch,” (“not yet known but stay tuned”) “advisory,” (“strong currents and waves dangerous to those in or very near water”), or “warning” (“dangerous coastal flooding and powerful currents”). In case of physics-based simulation forecasting these levels correspond to wave height thresholds at a coastline. Based on several decades of tsunami early warning practice, Bernard and Titov (2015) proposed as real-time tsunami warning products: (a) tsunami energy, (b) flooding maps, and (c) induced harbor current maps. Lynett (2016) compared numerical forecasts and showed that high-confidence prediction of location-specific currents with a deterministic approach should not be possible in many cases due to the turbulent nature of eddies. He proposed to develop probabilistic approaches for hazard modeling, since tsunami forecasting does currently not include uncertainty estimates.

Devastating tsunamis can affect both local and distant coasts. Depending on the propagation distance, operational TEWS can be classified as near or far field. Near-field or local TEWS (e.g., Japan, Indonesia, Chile, and Mediterranean) operate with hazard lead times as short as 15–20 min. The corresponding time left for forecasting is 5–15 min. Far-field TEWS (e.g., Pacific Tsunami Warning Center, India, Australia) operate with source zones at much greater distances, often transoceanic with lead time of several hours. Such TEWS have much more possibilities to retrieve detailed source parameters and provide a more accurate forecast (see Joseph, 2011, for compilation of modern TEWS).

TEWS provide forecasts limited to earthquake-triggered tsunamis. These types allow source event detection and quantification, which is not, generally, the case for submarine landslides and tsunamigenic mass movement due to volcanic eruptions. A TEWS follows several steps: (a) detect an (earthquake) event, (b) estimate the source parameters, (c) evaluate the tsunamigenic potential, (d) evaluate the expected tsunami physical impact, and (e) disseminate warnings. New observations are used to update the forecast. The minimum parameter set comprises earthquake location and magnitude and can be available within a few minutes. The simplest forecast is based on a decision matrix assigning a warning level to magnitude and source-to-coast distance. Such a matrix is used by, for instance, the Mediterranean TEWS (NEAM-TWS) and as initial warning by the U.S. National TWS. The decision matrix is based on historical experiences. However, due to the infrequent nature of tsunamis and the fact that it is not possible to establish a common attenuation relation by source-to-target distance (tsunami waves can propagate across large distances without significant loss of energy, and their attenuation is controlled by source directivity and individual propagation path), the decision matrix is uncertain.

Modern TEWS derive their forecasts from physics-based simulation. These models usually solve the shallow water equations (Satake, 2002) whose parameters are bathymetry and bottom friction (in near-coastal areas). TEWS evaluate the initial conditions for tsunami propagation from earthquake parameters derived from seismic or Global Navigation Satellite System (GNSS) measurements. Tsunami wave propagation and coastal physical impact are then simulated in real time or by retrieving precomputed scenarios. Forecasts are constantly updated with incoming observations additionally constraining the source model. These include land-based (Hoechner et al., 2013; Melgar et al., 2016; Ohta et al., 2018) and sea-based observations like tide gauges and deep ocean bottom pressure units (Titov et al., 2005, and Tang et al., 2009, for DART buoy technology and Tsushima et al., 2009, for cabled systems). In the classical approach, thousands of propagation models were precomputed for all representative sources and stored in scenario databases (e.g., Kamigaichi, 2015, for Japan, Steinmetz et al., 2010, for Indonesia, and Allen & Greenslade, 2016, for Australia). Local solutions may employ very high resolution models providing detailed inundation patterns (Van Veen et al., 2014, for North Sumatra). A hybrid approach developed by National Oceanic and Atmospheric Administration (NOAA) (Titov et al., 2005) linearly combines precomputed propagations from unit sources according to their weights assessed in real time by seismic and deep ocean observations. In the last decade, the increasing availability of processing power has allowed scenario simulations “on the fly” for arbitrary sources (Wang et al., 2012; https://www.gempa.de/products/toast; Musa et al., 2018).

After Japan had installed a dense network of bottom pressure cabled systems (Kanazawa, 2013), a new approach became possible, which avoids source quantification as a prerequisite for propagation simulation. Instead, wave propagation is modeled in real time driven by data assimilation from offshore cabled bottom pressure units able to measure the tsunami wave on its way toward the shore (Maeda et al., 2015; Tanioka & Gusman, 2018; Tsushima et al., 2009).

2.7.2. Tsunamis: Impact Forecasting

In the last two decades significant progress has been made toward tsunami damage assessment. Studies are focused on impact to buildings and, to a lesser extent, to humans. Despite this progress, real-time tsunami impact forecasting is not yet operationally implemented. Most of the studies address the vulnerability component of the impact forecasting scheme (see Figure 3) encompassing both methodology and practical tsunami fragility functions. The latter could be derived from field studies in aftermath of past catastrophic events but also from (numerical) models. For example, Papathoma et al. (2003) and Dall'Osso et al. (2009) proposed the multiparametric Papathoma Tsunami Vulnerability Assessment method to assess the tsunami vulnerability for buildings. An alternative damage assessment methodology was developed in the course of the European FP6 SCHEMA Project (Leone et al., 2010; Valencia et al., 2011; see Pagnoni & Tinti, 2016, for the comparison of the two approaches). Comprehensive reviews of tsunami fragility functions highlighting the current limitations and providing recommendations for model derivation are given by Tarbotton et al. (2015) and Charvet et al. (2017). Studies by Koshimura et al. (2006, 2009), Suppasri et al. (2013, 2018), Goda and Abilova (2016), De Risi et al. (2017), and Aranguiz et al. (2018) illustrate other examples toward fine-scale quantitative estimation of tsunami damages. Very recently, Petrone et al. (2020) employed numerical structural modeling to investigate building response to a coupled earthquake and tsunami loading.

2.7.3. Tsunamis: Uncertainties and Challenges of Impact Forecasting

A main source of uncertainty for modern TEWS is the fast and accurate finite source quantification and in particular the earthquake coseismic slip distribution. Further, reliable impact forecasting requires high-resolution inundation simulations within a few minutes. Until very recently, such simulations were not possible in real time. Precomputed scenarios cannot reach the necessary accuracy in case of near-field tsunamis because the tsunami impact is highly dependent on the actual source parameters (e.g., slip distribution), which are unique for every large earthquake. Another limiting factor is the availability of precise bathymetry and topography necessary for accurate inundation modeling. Griffin et al. (2015) demonstrated that neither SRTM (90-m resolution) nor ASTER (30 m) DEMs possess sufficient accuracy and resolution to be used for tsunami inundation models. Due to the infrequent nature of damaging tsunamis, damage models can be only calibrated in affected regions (Aranguiz et al., 2018; Leone et al., 2010; Suppasri et al., 2013, 2018) and then transferred to other locations (Valencia et al., 2011). This transfer represents another uncertainty source in operational impact forecasting.

2.7.4. Tsunamis: Maturity and Added Value of Impact Forecasting

Operational tsunami impact forecasting has not been established yet. To our knowledge, only the former Decision Support System of the German-Indonesian Tsunami Early Warning System (GITEWS) provided forecasts on the number of people and critical infrastructure affected (Strunz et al., 2011). This information, however, was not based on inundation modeling but reflected the aggregated numbers of people and objects per warning segment, defined typically according to administrative units, under the threat.

The possibility to replicate the damage situation resulting from tsunami inundation has been demonstrated by Arikawa and Tomito (2016) using very detailed simulations. Srivihok et al. (2014) reported about an online tool for tsunami inundation simulation and loss estimation. However, in both cases real-time applications were not possible.

Recently, due to the growth of computing power, the possibility of real-time detailed impact forecasting could be demonstrated. Oishi et al. (2015) were able to compute a tsunami inundation scenario at a 5-m grid in less than 1.5 min (75 times faster than real time) for the Sendai region replicating the Tohoku 2011 event. They also estimated damage probabilities using simulated inundation depth and the fragility curves by Suppasri et al. (2013). Koshimura et al. (2017) and Musa et al. (2018) discussed the "10-10-10 challenge": tsunami source determination in 10 min and tsunami inundation modeling and impact mapping in 10 min with 10-m grid resolution. Given the maximum flow depth distribution, they are able to estimate in real time the affected population using census data and to assess the numbers of damaged structures using tsunami fragility curves. An alternative, two-step approach proposed by Mulia et al. (2018) does not require high-resolution computations to be conducted in real time to provide an instant high-resolution inundation model. Here, a precomputed tsunami database is created comprising pairs of low- and high-resolution images of maximum tsunami elevations and flow depths originating from various hypothetical earthquake scenarios. Then, in real time, a low-resolution propagation simulation for the actual event source parameters is conducted and matched to the database to retrieve the best fitting high-resolution scenario. The obvious disadvantage of this approach is that it is still limited to the variety of the precomputed sources. Although these approaches are promising, there is still a long way of developing and rigorous testing before they become a backbone for operational tsunami impact forecasting.

2.8. Volcanic Eruptions

Volcanoes are spots on the Earth's surface where molten rock (magma) ascending from depth reaches the surface through an existing conduit or a newly formed pathway through the crust. Eruptions may occur from established vents, generally corresponding to the volcano edifice summit, or create a new set of fissures on the volcano's flanks that develop into cone-shaped vents during the course of the eruption. Typically, volcanic eruptions may last from a few hours to several weeks, although some eruptions do last several years or even decades. They are usually preceded by a preparatory phase involving the recharge of one or more magma reservoirs; more rarely magma batches may directly propagate from tens of kilometers depth to the Earth's surface. Some volcanoes erupt continuously (e.g., several explosions per hour at Stromboli volcano, Italy) or very frequently (several times a year), while the dormant phases between eruptions can be very long at other volcanoes, up to about 10,000 years. There is a wide variance in eruption styles, from effusive (gentle flow of lavas down the volcano flanks) to highly explosive (e.g., Plinian eruptions involving explosive columns that may reach the stratosphere); the resulting threats may last only a few minutes and affect the immediate vicinity of the vent or have global impact lasting years to decades.

Volcanoes are inherently multihazard environments: multiple phenomena such as lava flows, pyroclastic flows (avalanches of hot lava fragments and gases due to eruptive column collapse or collapse of lava domes), lahars (volcanic mudflows, due, e.g., to rain storms mobilizing loose eruptive products) or landslides (through the collapse of unstable flanks), tephra (erupted, fragmented lava) fallout, ballistic bombs, emission of poisonous volcanic gases, creation of new eruptive vents, volcanic earthquakes, wildfires, and tsunamis, for example, due to submarine mass movements, can happen simultaneously or in sequences during an eruption and lead to multifaceted damage. Every volcanic area has its own particular mix of hazards and pre-eruptive behavior. The entrapment of water, ice or snow by lava may increase the likelihood and impact of explosive eruptions even at predominantly effusive volcanoes, as demonstrated by the Eyjafjallajökull eruption in Iceland in 2010, which caused significant losses for the aviation industry (Cioni et al., 2014).

2.8.1. Volcanic Eruptions: Hazard Forecasting

Continuous geophysical monitoring represents the fundamental tool for eruption forecasting and early warning (Marzocchi & Bebbington, 2012; Sparks & Aspinall, 2004). Most active volcanoes around the world are now at least sparsely monitored (Loughlin et al., 2015), and technological progress in remote sensing is facilitating a push to global coverage. Volcano observatories work with civil protection authorities and local or national governmental institutions to issue official warnings, with varying degree of overlap in their respective roles depending on the country and culture (Papale, 2017). Most eruptions are preceded by a few weeks or months of volcanic unrest, during which the rate of seismicity, crustal deformation and/or degassing increases. Based on those signals, observatories issue warnings of possible impending eruptions (or, more rarely, the time to eruption) and retrieve information about the moving materials, the plumbing system and stress levels. The size and style of an eruption, however, remain very challenging to forecast (Poland & Anderson, 2020). After the eruption onset, its style, type of product, and mass rate become easier to observe and hazard propagation models become more reliable, although sudden switches in style are sometimes observed. Recent approaches incorporate monitoring anomalies and current environmental conditions, for example, wind or topography changes, into short-term hazard assessments that can be continuously updated throughout an eruption (Selva et al., 2014). Short-term forecasts are ideally based on a combination of information from monitoring signals, eruptive history and structure of the volcano, maps of old deposits, and results of numerical and volcano-specific conceptual models linking magma ascent rates to expected monitoring signals. Numerical models for the propagation of different hazards have become increasingly important in the last decades, since they provide the opportunity to simulate a range of possible scenarios including those never observed at a volcano. Most of the resulting issued forecasts today are probabilistic, often by means of statistical tools such as Bayesian event trees (Marzocchi et al., 2008; Rouwet et al., 2014; Selva et al., 2014; Tonini et al., 2015) or Bayesian belief network analysis (Aspinall & Woo, 2014), which can involve expert judgment (Christophersen et al., 2018). The monitoring of unrest signals is usually performed by volcano observatories. The work of an observatory and associated scientists include a variety of assessments and forecasts, such as the following:

1. Assigning an activity level to the volcano (i.e., state of rest, unrest, impending eruption, erupting), which is publicly declared generally according to color-coded alert levels (Fearnley, 2013; Papale, 2017). These feed into procedures defined by decision makers, and further warnings of societal relevance.
2. In the immediate prerun to an eruption, short-term forecasting of the time of eruption onset and, if possible, refining likely location and size of the eruption. Impending eruptions are generally identified based on an increase in the rate of earthquakes (as already recognized in 1855, e.g., Hoernes, 1893) or swelling of the ground (e.g., Sturkell et al., 2006; Surono et al., 2012).
3. During an eruption, monitoring and forecasting its likely evolution (e.g., defining a series of scenarios) and the propagation of hazards (e.g., lava flow propagation), usually based on a combination of expert judgment and numerical models.

The capabilities of volcano observatories in terms of technical equipment and personnel vary depending on the volcano's destructive history, its activity level, and the available funds. Especially volcanoes that have been dormant for a long time, or are located in countries with limited resources, are not always sufficiently monitored. The systems are, however, usually upgraded once activity levels increase and international scientists often come to help during a crisis (Annen & Wagner, 2003). Many active volcanoes have a dedicated observatory staffed by a multidisciplinary team monitoring the volcano through visual observations and a variety of parameters including seismicity, ground deformation and gas emissions. Such observatories are responsible for the maintenance of the monitoring system and inform authorities and the population about the state of the volcano and likely short-term evolutions. While some automated procedures are in place (e.g., an alarm in the observatory room once a parameter reaches a certain threshold), the interpretation and any decisions are made by humans involving individual expertise and experience.

Lead times for volcanic eruptions are highly variable: Some eruptive phenomena occur essentially without detectable precursors (e.g., the phreatic eruption at Ontake volcano in 2014 (Ogiso et al., 2015) and Wakaari [White Island] in 2019), while geophysical signals associated with magma chamber pressure buildup preceding big eruptions can last for years. In such long unrest phases, it is, however, impossible to predict the exact time of eruption onset. More widespread and dense volcano monitoring networks, progress in hazard assessments, short-term forecasts, hazard communication, and awareness (Leonard et al., 2014; Lindsay et al., 2010; Marzocchi & Bebbington, 2012; Poland & Anderson, 2020; Roberts et al., 2011; Solana et al., 2008; Wadge & Aspinall, 2014) have all immensely reduced the number of fatalities related to volcanic eruptions (e.g., Loughlin et al., 2017). Many lives were saved through evacuations before or during the early phases of eruptions. For example, the population of Plymouth (Montserrat) was successfully evacuated before its complete destruction through the eruption of Soufrière Hills Volcano (Annen & Wagner, 2003). One recent example of successful early warning is the 2018 Kilauea eruption (Hawaii), where numerous eruptive fissures opened on the volcano's flank in inhabited areas. Impacts could be mitigated by various measures, including evacuation of homes and touristic enterprises and closing the Puna Geothermal Venture, quenching and capping geothermal wells and removing inflammable gas stored in the lava pathways.

2.8.2. Volcanic Eruptions: Impact Forecasting

Impact modeling in volcanology is still in its infancy (Wilson et al., 2017). While state-of-the-art hazard propagation models are generally very sophisticated, the progress of impact modeling is very heterogeneous across the various volcanic hazards. Impacts are rarely assessed in a comprehensive manner, and there is large potential for improving vulnerability functions (Douglas, 2007). Thus, impact forecasting is widely omitted. However, the number of studies on volcanic risk and vulnerability has increased significantly in the last decade.

A few studies have developed probabilistic approaches for decision making during a volcanic crisis, which also include different aspects of impact forecasting, such as estimations of fatality outcomes of different eruption scenarios (Baxter al., 2008, for Vesuvius), cost estimations (Sobradelo et al., 2015), or a cost-benefit analysis of an evacuation (Marzocchi & Woo, 2007). A typical approach for impact forecasting is to select a few scenarios deemed likely based on the volcano's eruptive history (in terms of size and expected hazards) and to evaluate the impact considering the infrastructure and population of threatened areas. The evaluation is based on vulnerability functions and numerical models for hazard propagation, whereas each hazard requires its own vulnerability analysis (examples can be found in Jenkins et al., 2014; Martí et al., 2008; Wilson et al., 2017). The investigated impact types range from damage to buildings or the agricultural sector, to health issues and fatalities.

Most studies on volcanic impacts have a risk perspective, while operational methods for event forecasting are rare. Methods vary across different hazardous phenomena. Some studies, however, work toward and stress the need for multihazard models (e.g., Schmidt et al., 2011). Yu et al. (2016) estimate direct and indirect losses due to different eruption scenarios in South Korea, including damage to the industry sector, health damages, and cleaning costs for roads. Spence et al. (2005) develop a multihazard impact model, based on volcanological analyses of the potential hazard combined with engineering analyses of the vulnerability of four European locations threatened by eruptions using population data and building characteristics. Their output includes rates of fatalities, seriously injured casualties, and destroyed buildings for a given scenario. Zuccaro and De Gregorio (2013) present a similar study for Vesuvius, modeling the impact of combined volcanic hazards (pyroclastic flows, earthquakes, and tephra fall) during different eruption scenarios on the built environment in the Naples area, based on stochastic and deterministic modeling, historical reports and expert elicitation. Scaini, Biass, et al. (2014) develop a GIS-based damage tool, based on simulations of different volcanic events, exposure, and vulnerability analysis for the built environment, transportation and urban infrastructures. Long-term, indirect impacts of volcanic eruptions can be significant. McDonald et al. (2017) present one of the first attempts to quantify the long-term economic impact of volcanic eruptions at Mt. Taranaki in New Zealand.

While these studies generally consider multiple types of hazards and/or eruption scenarios, most assessments are limited to individual volcanic hazards. Probably the largest number of vulnerability studies focus on tephra fallout, in particular the impact of ash fall on buildings and infrastructure but also on the agricultural sector and industry, as well as related clean-up costs (Biass et al., 2016; Jenkins et al., 2018; Prata, 2009; Rapicetta & Zanon, 2009; Scaini, Folch, et al., 2014; Wilson et al., 2012). Since the Eyjafjallajökull eruption in Iceland caused immense losses for the aviation industry, the effect of ash on aviation has moved into the research focus especially in Europe (e.g., Alexander, 2013). Studies on the impact of tephra fallout usually perform some form of vulnerability assessment (e.g., of buildings or flight paths), and both probabilistic loss models and empirical data are used to build fragility functions. Several studies have examined the vulnerability of buildings with regard to the impact of a pyroclastic flow or lahar (Alberico et al., 2002; Dagá et al., 2018; Jenkins et al., 2015; Mead et al., 2017; Petrazzuoli & Zuccaro, 2004; Spence et al., 2004; Thouret et al., 2013), mostly based on analysis of damage of past eruptions, although some also include casualty information, physical and/or probabilistic models. Long-term loss assessments are developed in Spence et al. (2004) for pyroclastic flows and Mead et al. (2017) for lahars, based on numerical models, exposure, and vulnerability analyses. Lava flows are easier to address in terms of operational impact forecasting as propagation rates are generally slow (lava flow speeds >4 km/hr are rare) and vulnerability is roughly binary (0 or 1, i.e., complete destruction if a building is inundated by lava), so that hazard maps can be easily convolved with exposure maps into impact forecasts. State-of-the-art lava flow inundation forecasts are performed by combining lava flow models with satellite-based remote sensing data for rapid model validation and calibration of input parameters (Cappello et al., 2019).

2.8.3. Volcanic Eruptions: Uncertainties and Challenges of Impact Forecasting

The complexity of volcanic multihazard scenarios and a poor understanding of the far-reaching societal and economic implications of eruptions limit current impact models and affect decision making and communication during crises. An evaluation of success rates of eruption warnings has been carried out for the Alaska Volcano Observatory, revealing that forecasting of larger eruptions occurring after long repose times at well monitored volcanoes have high success rates, while forecasting small eruptions after short repose times is more difficult (Cameron et al., 2018). Some particular challenges are as follows:

1. Eruption forecasting is complicated by the fact that volcanic unrest is not a definite indicator of an imminent eruption. Many unrest phases, especially those longer than about a year, recede without culminating in an eruption.
2. While forecasting the timing of an impending eruption is often successful, the expected magnitude of an eruption cannot yet be derived from monitoring parameters (Poland & Anderson, 2020) and is usually based merely on long-term magnitude-frequency distributions (Tonini et al., 2015). Since eruption magnitude is naturally a driving factor behind hazard styles, intensity, and propagation, this significantly limits our capability for operational impact forecasting. The development of new continuous, low-cost volcano gravimetry sensors (Middlemiss et al., 2016) may open the possibility to estimate the mass flow rate of ascending magma and thus to forecast eruption size.
3. Once an eruption has started, forecasting its evolution and involved hazards is challenging. Eruptions can change their intensity and style; they interact with weather phenomena and a changing topography and can pause but resume shortly after without warning. Forecasting the end of an eruption is equally difficult. Many of these questions are very challenging to answer as there is still a divide between physics-based models and observations.
4. There are still significant uncertainties related to input parameters for hazard propagation models. Models to forecast the vent or fissure location are purely data driven in spite of being data poor; the available physics-based models are largely untested (Rivalta et al., 2019). Together with the uncertainty associated with expected mass flow rates, this dominates the uncertainty regarding volcanic hazards in many areas (Neri et al., 2015). Moreover, some fundamental parameters, such as the topography of the volcano or the vent diameter, evolve during eruptions in still poorly understood ways.

5. Volcanic hazards have a strong multihazard component and cascading effects are possible. These interactions are still poorly understood at the level of physical mechanisms (e.g., Manga & Brodsky, 2006), let alone with regard to associated impacts.
6. The economic impact of eruptions is still poorly studied. Aside from the comparatively well-studied effect of tephra load on roofs, there is a significant lack of data and impact models for different assets with regard to different volcanic hazards and their mutual interaction.
7. For the same volcanic event at the same volcano, the resulting impact can still be different. For example, only one fatality resulted from the paroxysm of Stromboli volcano (Italy) in July 2019. This was simply due to the timing of the eruption: It occurred in the afternoon, when the crater area is usually deserted. Just a few hours later, the crater area would have been crowded with tourists and fatality numbers would have been much higher. Many other factors such as environmental conditions, for instance, the current wind direction determines the impact of ash fall, the sequence of events, and/or the combination of different types of hazards, influence the impact of an eruption. Thus, eruption impact forecasting is very complex and requires the simultaneous analysis of many—in parts interconnected—drivers in real time.

2.8.4. Volcanic Eruptions: Maturity and Added Value of Impact Forecasting

To our knowledge, no operational impact forecasting systems exist to this date. Risk reduction is mainly achieved by combining operational hazard forecasting with rapid provision of information on how to manage the main hazards. For example, during the 2014–2015 eruption at Bardarbunga-Holuhraun in Iceland, the authorities distributed leaflets containing a color-coded table detailing effects, symptoms and actions to be undertaken to mitigate hazards from SO_2 exposure. They were used to interpret regularly issued probabilistic maps of SO_2 concentration (Barsotti et al., 2020).

Developing methods for operational impact forecasting during an ongoing eruption will be a significant improvement for crisis management. It can support evacuation measures, decision making and a more realistic and faster adaptation to new situations for authorities and inhabitants. For now, the volcanological community appears, however, more focused on progressing toward producing multihazard forecasting and mapping tools (Hayes et al., 2020) rather than toward operational impact forecasting, due to the inherently multihazard nature of volcanic environments.

3. Synthesis Across Hazard Types

3.1. Comparative Analysis

The large number of hazards included in our review allows for the first time comparing how different disciplines have treated the emerging field of impact forecasting. Table 1 summarizes selected aspects of impact forecasting for the different hazards. The range of lead time of hazard and impact forecasts is highly variable between the hazards, from below 1 min in the case of EEW to many months for drought or volcanic eruption forecasts. According to the large variety of the event footprints (Figure 1), there is also a wide variation in the area for which forecasts are provided, from the local scale in case of pluvial floods to the national and regional scale for droughts and heat waves. This wide range of lead times and spatial scales pose different challenges for different forecasting systems.

There is a large range of approaches for impact modeling, not only between different hazard types but also for a given hazard. The impact of an event depends on a range of factors, such as risk awareness, preparedness, or organizational emergency management, which may, in addition, vary substantially in time (Kreibich, Di Baldassarre, et al., 2017). Despite these complexities, impact modeling is often carried out in a simplified way when compared to hazard modeling. This is partially the consequence of the much larger effort that the natural hazards research community has put into understanding and modeling hazards. For instance, windstorms are sufficiently monitored by a large number of ground-based observations in combination with satellite retrievals, and very sophisticated NWP models are operational; damage and vulnerability models, however, are typically derived from sparse data and usually consist of simple relationships between a hazard indicator, for example, wind gust velocity, and a vulnerability estimate, for example, relative building damage. Given this imbalance, more efforts need to be invested in developing and testing impact models.

10.1029/2020RG000704

Table 1
Comparison of Impact Forecasting for the Different Hazards

Hazard	Lead time	Spatial aggregation	Impact models	Main uncertainties	Maturity	Added value
Windstorms	Reliable hazard forecast: 2–4 days. First hints of hazard beyond 1 week based on ensemble forecasts.	Hazard forecasts for entire storm footprint. Warnings issued on district level.	Impact depends on peak wind gusts, but may include other meteorological factors, for example, duration. Relationships between wind characteristics and damage typically derived from observed data.	Related to both hazard (uncertainty in cyclone track and wind intensity) and impact models (e.g., population density used as proxy for assets).	No operational impact forecast system for the public available.	High benefits expected, but quantitative studies lacking.
			Impacts considered: damage to buildings, infrastructure, forest etc.		Insurance: operational forecasts of direct damage for clients provided. NWSs provide impact-oriented forecasts with generic statements about expected impacts and recommended actions.	Clear value to insurance clients, for example, buy short-term additional windstorm damage coverage.
Severe convective storms	NWP hazard forecast: few hours to 7 days.	Hazard forecasts for SCS footprint. Warnings issued on different levels, from municipality to federal states.	Only few impact models available. Damage depends on event intensity, for example, wind speed, hail size.	Related to both hazard (large uncertainty in prediction convective phenomena) and impact models.	Quantitative impacts forecasts not yet available.	Significant benefits only expected when hazard forecasts are more accurate.
	Hazard nowcasting: 0–2 hr.		Impacts considered: damage to buildings, vehicles, crops, infrastructure, etc.		Impact-based forecasts operational in several countries, providing generic descriptions of potential impacts.	Benefit demonstrated in single cases, for example, for evacuation decisions for tornados.
Droughts	1 month to 1 year.	National to regional extent.	Relation between hazard indicators, for example, SPI, and impact modeled by probabilistic methods or damage functions. Impacts considered: loss of life, famine, crop yield, hydropower and energy cooling water; public water supply; irrigation water etc.	Limited skill in hazard forecasting. Lack of impact data. Variety of sectors with varying response, for example, of different crops, to impact occurrence. Confounding factors for impacts.	Operational systems in certain regions, for example, Africa, established. First efforts toward operational systems in Europe.	Substantial benefits, for example, for food and water security, expected, but limited data available.
Heat waves	Few days up to 2 weeks.	National to regional extent.	Relation between hazard indicators, for example, temperature anomaly, and impact modeled by probabilistic methods or damage functions. Impacts considered: health, mortality. Developments to forecast work productivity.	Limited skill in hazard forecasting. Lack of impact data. Variety of sectors with varying response times to impact occurrence. Confounding factors, for example, air pollution may be responsible for deaths attributed to heat waves.	Several systems for mortality established for Europe. Often embedded in heat-health actions plans including mitigation actions.	Substantial benefits expected, but limited data available.
River floods	Few hours to weeks for downstream areas in large river basins.	River basins to national and continental scale.	From relationships linking impact indicators, for example, buildings affected to hazard indicators, for example, river water level, to model chains with sophisticated approaches, for example, hydrodynamic inundation model,	Complex local situations (e.g., blockages, dike breaches). Lack of impact data to develop impact models.	Mainly prototypes and pre-operational systems developed. European-wide operational system for river floods available. First attempts with ensemble-based impact forecasting.	Significant benefits expected, for example, prioritizing evacuation planning, identifying most vulnerable

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Table 1
Continued

Hazard	Lead time	Spatial aggregation	Impact models	Main uncertainties	Maturity	Added value
			dike breach model, multivariate damage model.			objects. May enable cost-benefit analyses of response measures.
Flash floods	1 to few hours	Catchments up to several thousand square kilometers.	Impacts considered: Damage to buildings, infrastructure, direct economic damage, number of people affected etc.	Lack of knowledge on exposure and vulnerability, including its time variation.		
Pluvial floods	Up to 12 hr	Urban areas (up to 100 km^2).				
Storm surges	5 days for extratropical storms. 12 hr for tropical storms.	Coastlines affected.	Impact models in their infancy. Impacts considered: Often limited to inundation, critical situations for defense structures or assets, geomorphological changes. In few cases: economic damage.	Errors from NWP predictions used to drive storm surge model. Local characteristics, for example, bathymetry. Characteristics of defense failures.	Several models for inundation, erosion related to storm surges from extra-tropical storms and TCs are operational. No impact forecast system in operation.	Potential benefits hardly investigated.
Earthquakes	3 s to 1 min early warning time for EEW. Several days to weeks for OELF.	Specific structures and systems for EEW. Regions affected for OELF. Resolution varies from single structure to urban areas.	Empirical or analytical impact models based on forecasted ground motion at target sites. Models for physical damage of objects and for systemic impacts, for example, power networks. Impacts considered: expected damage, loss of functionality for EEW. Expected damage, casualties, injuries, displaced persons, economic loss for OELF.	Uncertainties in hazard forecasting (earthquake source, ground motion, and site amplification effects) including time constraints, and in exposure and vulnerability data and models.	Few local and global EEW systems implemented for specific target objects and automatic mitigation actions. Few operational OELF systems implemented.	Possibility to customize emergency actions and support decision-making (OELF). Increasingly used to plan medium- and long-term mitigation activities, and raise risk awareness for practitioners and public.
Tsunamis	15–20 min for near-field. Several hours for far field.	Coastlines affected.	Impact models in their infancy. Recently more efforts in developing vulnerability models in context of risk assessments. Impacts considered: number of affected people, buildings and infrastructure.	Uncertainties in hazard quantification (source quantification, coseismic slip distribution). Lack of precise data (bathymetry, topography, damage) and impact models.	Operational systems partially include coastal inundation; no impact forecast system in operation.	No studies available.
Volcanic eruptions	Highly variable. From cases without detectable precursors to early alerts up to months.	Areas directly affected.	Impact modeling in its infancy, but recently rapid developments, for example, models for fatalities, health damage, damage to buildings, direct costs. Also models for long-term impacts under development.	Uncertainties in hazard forecasts (eruption forecasting, hazard propagation, variety of cascading effects) and significant lack of impact data and models.	No operation impact forecast system available.	Substantial benefits expected, but no studies available.

Note. (1) Lead times of hazard and impact (if available) forecasts. (2) Spatial aggregation: The area (and spatial resolution) for which impacts are forecasted. (3) Impact models: Main characteristics of impact models used. (4) Main uncertainties: Main sources of uncertainties for impact forecasting, including uncertainty of hazard forecasting. (5) Maturity: Advancement of impact forecasting systems. (6) Added value: Benefit of impact forecasting compared to hazard forecasting.

The important impact types differ between hazards. For instance, crop loss is an important consequence of droughts but not of earthquakes. Despite such differences, we suggest that the joint development of impact models will harness synergies. For some hazards, certain methodological aspects seem to be more advanced from which others could learn. For example, the flood and earthquake research communities have developed rather sophisticated vulnerability and exposure models including uncertainty bounds for the impact estimates.

Further, impact models are mostly limited to direct consequences on objects, areas, and people. Models quantifying systemic impacts, such as the loss of functionality of interconnected networks due to vulnerability interdependency, are rarely addressed—to a large extent due to a lack of empirical data.

The reliability of impact forecasting depends on the quality of the hazard forecast and of the impact modeling. In general, we expect that the uncertainties stemming from the impact modeling are larger than those of the hazard forecasting. We base this expectation on the limited availability of impact data, less experience with impact modeling and the fact that impacts are influenced by a multitude of factors. Some of them can be well constrained, but others are hard or even impossible to quantify, as human behavior or short-term social and economic processes can lead to rapid changes and unpredictable effects. The importance of the different uncertainty sources should be carefully evaluated, and the lead time and the spatial scales at which the forecast takes place may also play a significant role. For instance, a river flood forecasting system, which provides streamflow forecasts, could be complemented by inundation and damage models in order to inform local emergency management. In this case the consideration of local conditions, such as whether a certain defense fails or withstands, would be critical for the successful operational application. When forecasting impacts over large areas to obtain a large-scale overview, such local conditions might instead be neglected.

Although the maturity of impact forecasting varies considerably across hazards (Figure 1), in most cases impact forecasting is still in its infancy. For river, flash and pluvial floods, prototype systems exist and operational systems are expected. Operational impact forecasting systems have been identified for heat waves, droughts (with a focus on famines and loss of life), and earthquakes, that is, for hazards with very distinct forecasting possibilities and lead times. It is interesting to note that impact forecasting, such as potential derailment of high-speed trains, is relatively advanced for earthquakes, although it is not possible to predict the location, time, and magnitude of an event prior to its occurrence. The progress that has been achieved in earthquake impact forecasting should motivate other disciplines to invest in a similar way into this field, as the possibilities for hazard forecasting seem to be brighter compared to earthquakes.

Across the considered hazards, impact forecasting is generally expected to provide significant benefits for emergency management, such as identifying most vulnerable areas, prioritizing emergency measures or organizing evacuation. Unfortunately, we still lack enough robust empirical evidence to validate this assumption. Beyond the difficulties in quantifying benefits, this is likely the result of the early stage of impact forecasts. Postevent evaluations should be systematically performed in order to estimate the additional benefits and lessons learned compared to hazard forecasting. First studies indicate, for example, that warnings based on impact forecasts and containing specific behavioral recommendations are more likely to increase the awareness about a potentially hazardous event and foster positive behavioral changes (Weyrich et al., 2018). However, more systematic and methodologically rigorous research is needed (Zhang et al., 2019)—and last but not least to collect detailed impact data after every event.

Even though our review paper has not focused on the difference in impact modeling among countries and continents, we see that impact forecasting of hydrometeorological extremes in the United States has substantially improved in recent years. This process has reached a higher level of maturity and is better connected with decision makers compared to Europe. The U.S. NWS is well on the way of a transition to providing impact-based decision support services to core partners in public safety and national security as part of its strategic plan for Building a Weather-Ready Nation (NWS, 2018; Uccellini & Ten Hoeve, 2019). For example, Lazo et al. (2020) compare the impacts of two similar winter storms in the New York City area before and after the implementation of impact-based decision support services and suggest that these services reduce socioeconomic impacts, for example, improved recovery time in the ground transportation sector, and reduced duration and number of customers affected by power outages.

3.2. Key Challenges and Opportunities

3.2.1. Research and Development of Impact Forecasting

Our review identifies several knowledge gaps and opportunities for research and development. Across all hazards there is a need for improved impact models including the adequate quantification of exposure and vulnerability. This entails the following:

1. Developing models for all relevant impact types: Impact models are still lacking for important impact types. For example, many impact models have been developed for buildings, but models for impacts on critical infrastructure are hardly available.
2. Developing models for all relevant hazardous events: For instance, impacts of volcanic eruptions are rarely assessed in a comprehensive manner. Many approaches are available for quantifying the impacts of ash fall, which is much less the case for other consequences of volcanic eruptions.
3. Exploring impact models of different complexity and with different data needs: The majority of impact modeling approaches is based on simple relationships between a hazard indicator and vulnerability, while more sophisticated approaches (e.g., high-dimensional complex models) are uncommon. More elaborate models could better match the level of sophistication often available for hazard models. However, the selection of the appropriate approach strongly depends on the forecasting context, and complex impact models require a much higher amount of empirical data to be calibrated.
4. Developing impact models for compound and cascading hazards: The same object can be affected by different hazards during one event. For instance, the vulnerability of buildings to ash fall from volcanic eruptions is different from their vulnerability to a lahar. A comprehensive approach would consider all hazards during such events.
5. Providing comprehensive uncertainty appraisal for impact estimates: Hazard models and forecasts often provide uncertainty estimates, but impact models are often deterministic.

Impact models are usually derived from postevent damage and loss observations. The rarity of such events and the difficulties in transferring impact models across regions often impede their development. These empirical approaches could hence be combined with engineering approaches, such as deriving fragility curves from experiments with wind tunnels or shaking tables or with models elicited from expert knowledge via what-if scenarios.

For impact forecasting systems, human behavior in the emergency phase and the societal context become highly relevant. Considerable advancement has been made in recent years in better understanding the factors shaping individual protective behavior, and the high relevance of behavioral aspects on impacts is increasingly acknowledged (Aerts et al., 2018; Kreibich, Di Baldassarre, et al., 2017). We suggest the following:

1. Scrutinizing human behavior and the vulnerability context more systematically to better understand their effects and to realistically represent them in impact forecasts. This requires dedicated efforts to understand the time variation of vulnerability and to develop impact models that are able to represent temporal changes.
2. Exploring whether knowledge can be transferred between hazards, as it varies considerably with respect to the hazards reviewed. While behavioral aspects have been a focus in social science research on earthquakes (Becker et al., 2012; Paton et al., 2015) and floods (Bubeck et al., 2013), they are less well scrutinized for other hazards.

Developing impact forecasting systems is challenged by data scarcity on exposure, vulnerability and impacts. We recommend the following:

1. Enhancing and harmonizing the efforts to collect and share impact data of real events: Activities are needed like the recently started program GRADE (Global Rapid postdisaster Damage Estimation) of the World Bank (https://www.gfdrr.org/en/publication/methodology-note-global-rapid-post-disaster-damage-estimation-gradeapproach), where the impact of disasters is estimated within a few days. This should always include the systematic collection and provision of detailed event data in open access repositories. Improved data availability would allow to rigorously test impact models—a topic that needs more attention in the future.

2. Exploiting recent developments of new data sources: Examples are crowd-sourced data, for instance, using Twitter data to enhance data collecting during events or exploiting high-resolution, open-access Voluntary Geo-Information (VGI) databases as Open Street Map to integrate authoritative exposure models. This also requires developing sophisticated quality control algorithm (Barras et al., 2019). The integration of open and free, local yet globally consistent data sets would allow the consistent harmonization of exposure and vulnerability models across the globe (Eberenz et al., 2020; Melchiorri et al., 2019).
3. Develop collaborative approaches together with end-users and decision makers: Many data sets are sensitive and not freely accessible but essential for certain categories of impact. For instance, forecasting systemic impacts on lifelines or critical infrastructure requires data about the interconnections between the individual components. Agreements between infrastructure operators and developers and operators of forecasting systems should account for data and information sensitivity.

Hazard forecasting research has typically advanced within different disciplinary boundaries. As exposure and vulnerability aspects have similarities between hazard types, there is a large potential that developing impact forecasting systems allows tapping into synergies. Understanding and quantifying the space-time dynamics of exposure within an area, for instance, could be carried out more efficiently within a common framework for a range of different hazard types. Another example are fragility curves for residential buildings. Although they vary from hazard to hazard, they often rely on similar characteristics, such as object height, age, and material. There are, for example, attempts to develop impact models that work in a consistent way across all hazard types, such as CLIMADA (https://wcr.ethz.ch/research/climada.html). The open source OASIS loss modeling framework (https://www.oasislmf.org) provides a standard in terms of prescribed file formats to link hazard, exposure and vulnerability information for multihazard risk assessment using a state-of-the-art kernel for probabilistic impact computations. We recommend harmonizing taxonomic descriptions of exposure and vulnerability across hazard types (Pittore et al., 2017) and to explore whether synergies can be exploited. Possible examples are to share exposure and vulnerability databases, to share and compare vulnerability models, and to develop common procedures for testing impact models.

3.2.2. Integration of Impact Forecasting Systems Into Decision Making and Emergency Management

Extending hazard forecasting to impact forecasting requires to carefully consider the subsequent operational decision-making context, which is typically very different from the scientific context where the data are collected or produced. Significant differences in terms of roles and responsibilities determine often divergent perspectives and conflicting interests (Marzocchi et al., 2012). For instance, the constraints of practical risk management call for timely, actionable information, easily transferable into operational protocols. On the contrary, the efforts to accommodate uncertainties in the scientific models lead to complex results, difficult to be assimilated without domain-specific scientific knowledge. This may shift the burden of defining thresholds from decision makers to scientists, as observed in volcanology by Papale (2017), thus further generating potential conflictual situations. To deter this tendency, several scholars (e.g., Jordan et al., 2014; Papale, 2017) advocated for a clear separation of roles between the people involved in hazard and risk assessment, which is mostly a scientific and technical task, and the ones tasked with risk analysis and management, which entails decision making and the related responsibilities. Among the duties entailed by risk management there is also the selection of suitable thresholds, upon which to issue official warnings. However, there are neither such thresholds for impacts (i.e., which impact should be associated with which alert level?) nor is there robust empirical knowledge about the benefits of impact forecasts for different users. Moreover, different emergency contexts require different impact forecasts; hence, impact forecasting tends to be more context-specific than hazard forecasting. In some cases, first-order estimates providing order of magnitude statements might suffice to support rescue operations in the very aftermath of the disaster. In other cases, detailed and location-specific information about the expected impacts might be required to trigger specific emergency measures, such as evacuating a hospital. In any case, the roles of scientists in the operational decision-making context needs to be clarified, also considering that different hazard communities have different views on the interface between science and decision making.

An important aspect of impact forecasting is the appropriate level of detail and specificity. During the emergency phase, people and emergency managers are required to make rapid decisions, and the right amount of information will help them to understand the warnings and to make better decisions. Mu et al. (2018) found that increasing the warning information was usually beneficial and increased the trust in the warning system. However, better decisions were not always related to more information. Hence, co-development of impact-based early warning systems are decisive in order to not just understand the needs and requirements of end-users but to also test, validate, and evaluate new developments in an operational setting (Gebhardt et al., 2019).

One example for the required close cooperation between developers and operators of impact forecasts is the use of deterministic or probabilistic forecasts and the communication of uncertainty. Probabilistic forecasts are getting widespread in hazard forecasting. Propagating this uncertainty throughout impact models might result in an overall uncertainty that may even span several orders of magnitude. On the other side, deterministic forecasts might fail capturing the actual range of consequences and hence be misleading in a preparedness context. Pros and cons of these approaches should therefore be thoroughly examined and discussed to determine how such forecasts can be used for decision-making in different operational applications.

4. Conclusions

From our review, covering more than 400 papers, we conclude the following:

1. Impact forecasting is an emerging topic across all hazard types reviewed, which is demonstrated by the recent increase in publications and by specific programs of international organizations such as the WMO project HIWeather. For most hazard types, impact forecasting is in its infancy, while operational impact forecasting systems exist for a few hazard types only, for instance, heat waves and earthquakes.
2. The state of the art in impact forecasting is very different across hazard types. For instance, advanced systems have been developed for earthquakes, for which no event prediction is possible and the forecasting skill is very low compared with other hazards. For some of the perils, impact forecasting seems rather straightforward. For example, several impact models are available for windstorms. They could be combined with hazard forecasts, which have considerable forecast skill for lead times of several days.
3. There is a wide range of impact modeling approaches in terms of process representation and complexity but often very simple approaches are used. Hazard modeling is more advanced compared to impact modeling. Enhanced and more systematic efforts are recommended to move impact modeling to a comparable level.
4. Impact forecasting needs to consider social systems and the structures that support them. Although this environment has been largely created and shaped by human intervention, our knowledge of it is surprisingly weak, therefore resulting in highly uncertain impact models. Developing impact forecasting should therefore be based on the systematic collection and provision of exposure and vulnerability data and models. The collection of spatially explicit, comprehensive postevent impact data should be strongly encouraged, following standard procedures and data formats. We recommend discussions across discipline borders and hazard types on common standards, indicators, and modeling approaches for impact assessments.
5. Exposure and vulnerability can be highly dynamic in space and time. Impact forecasting may require very detailed knowledge about the societal context, such as local risk reduction policies or risk perception of exposed people. A closer collaboration of natural sciences, engineering, and social sciences is required to understand the role of the human factor and its influence on the transformation of a hazard forecast into an impact forecast.
6. Additional complexities arise when transferring traditional hazard forecasts into hazard indicators that are useful for impact forecasting. For example, river flood impact forecasting requires to transfer a streamflow forecast for a given river location to inundation areas including all the complexities of flood defenses or the urban environment. These complexities and those arising from impact modeling can significantly complicate the forecasting task. It seems important to weigh in this additional burden against the expected benefits of impact forecasts.

7. Quantifying the uncertainties of forecasts is important as it provides an honest and fuller picture for informed decision making. The state of the art in uncertainty quantification is very different between hazard and impact modeling. Whereas uncertainties are often provided for hazard modeling, this is hardly the case for impact modeling. We recommend employing probabilistic approaches also for impact modeling.
8. The rapid assessment of impacts immediately after an event and the provision of impact estimates prior to an event have many commonalities but tend to be developed in separate communities. We recommend a more intensive exchange of knowledge between these two forms of impact forecasting and ultimately to blur the boundary between the two by rather advocating for a continuous information flow directed toward decision makers always considering the most up-to-date data and observations available. It is not so much the information flow toward decision makers but rather the close—and transdisciplinary—interaction of actors along the chain of impact to co-design systems fit for purpose.
9. Impact forecasting is expected to offer new possibilities for emergency management and disaster risk reduction, as it provides richer information to manage crisis situations. This is of great importance as extreme events are expected to increase in the future due to climate change and economic and population growth, while simultaneously the complexity of our society, for example, dependence on critical infrastructure, increases. However, the assumption that impact forecasting is more effective than hazard forecasting has hardly been tested across various hazards.
10. Impact forecasting is associated with new challenges for communication and decision making, as (uncertain) impact information may lead to different responses of warned people. Not only are there more studies needed to better understand the effect of impact forecasts, but novel approaches to codevelop and to tailor impact forecasts according to the operational contests.
11. Developing impact forecasting systems for a wide range of hazard types does not only promise societal benefits but could also be used as a leverage to foster interdisciplinary work between different research communities and collaboration between research and end-users.
12. Multihazard impact estimation accounting for compounding and cascading hazards should be increasingly targeted, acknowledging that extreme events rarely can be ascribed to single hazards, and that their consequences have to be considered in such extended framework to be descriptive of the potential impacts. From the impact perspective this also translate in considering nonlinear damage accumulation and cascading effects related to, for instance, interdependence of critical infrastructure.

Glossary and Acronyms

Many terms are not unanimously defined across disciplines. We use the following definitions for important terms in our review.

Term	Definition
Early warning system—EWS	The set of capacities needed to generate and disseminate timely and meaningful warning information to enable individuals, communities, and organizations threatened by a hazard to prepare and to act appropriately and in sufficient time to reduce the possibility of harm or loss (UNISDR, 2009).
Earthquake early warning—EEW	The issuing of warnings and/or the implementation of automatic mitigation actions following the prompt detection and characterization of an earthquake within few seconds after its actual onset, which may provide a viable solution for real-time risk mitigation.
ECMWF	European Center for Medium-Range Forecasts
EFI—extreme forecast index	Index to summarize the probability of extreme events used by weather services for operational warnings based on ensembles. EFI ranks the departure between the statistical distribution of an ensemble forecast and the model history. It ranges from −1 to +1, 0 meaning a standard situation and +1 meaning record-breaking high values (Lalaurette, 2003).
Exposure	People, property, systems, or other elements present in hazard zones that are thereby subject to potential losses (UNISDR, 2009).
Forecasting	Provision of timely information to improve the management in the emergency phase, that is, shortly before, during and after a potentially damaging event.

Term	Definition
Forecast horizon	The forecast horizon is the length of time into the future for which forecasts can be or are to be prepared.
Hazard	A dangerous phenomenon, substance, human activity, or condition that may cause loss of life, injury, or other health impacts, property damage, loss of livelihoods and services, social and economic disruption, or environmental damage (UNISDR, 2009).
Impact	Disaster impacts are consequences of extreme events to human lives, buildings, infrastructure, and natural resources. Direct impacts occur when the element at risk is within the space-time footprint of the event. Indirect impacts are consequences that occur outside the event's geographical footprint or over larger timescales. Examples of indirect impacts are declines in revenue owing to supply chain disruption or longer-term health effects. Tangible impacts can be easily quantified in monetary terms, such as evacuation costs, while intangible impacts include, for example, adverse psychological consequences or ecosystem degradation.
Impact-oriented warning	Warnings include general statements on expected impacts, for example, "Mobile homes will be heavily damaged or destroyed," and general advice.
Impact (or impact-based) forecast	Forecasts include information on affected elements at risk and, if possible, their vulnerability. It extends the traditional forecasting model chain by models translating the hazard characteristics into impact statements.
Lead time	The available time to perform emergency actions, that is, the time interval between the early warning and the actual occurrence of the damaging event or its arrival at a given target site. Warning lead time depends on the forecast horizon.
NCEP	National Centers for Environmental Prediction
Nowcasting	Detailed recording of the current weather situation using data from remote sensing instruments (radar, satellite, and lightning) and interpolation for the next 0 to 2 hr. Modern nowcasting systems include short-term NWP models from the rapid update cycle.
NHMS	National Hydro-Meteorological Service
NWP	Numerical weather prediction
NWS	National Weather Service
Operational Earthquake Forecasting—OEF	Forecasts include spatially explicit information on the probability of occurrence of earthquake events exceeding a given magnitude in a given timeframe, based on the assimilation of recorded short-term seismic activity into medium- and long-term hazard models. Can be used to estimate the likelihood of strong events from observed earthquake swarms, or within a seismic sequence.
Operational Earthquake Loss Forecasting—OELF	Integrates the OEF with impact estimates. Provides spatially explicit, time-varying estimates of the probability of exceeding a specific amount of losses (e.g., fatalities) in a given timeframe.
PSPI	Palmer Standardized Precipitation Index; common drought indicator.
SCS	Severe convective storm
Skill of prediction	The prediction or forecast skill refers to the relative accuracy of a set of forecasts with respect to some set of reference forecasts (e.g., climatological mean fields). The forecast/prediction skill is usually expressed by skill scores, which can be interpreted as percentage improvement over the reference forecasts (Wilks, 2011).
SOT—shift of tails	Index to summarize the probability of extreme events used by weather services for operational warnings based on ensembles. SOT indicates whether a fraction of the ensemble members forecast an extreme event, even if the rest of the members do not (Zsótér, 2006).
SPEI	Standardized Precipitation Evaporation Index; common drought indicator.
SPI	Standardized Precipitation Index; common drought indicator.
TEWS	Tsunami Early Warning System
Vulnerability	The characteristics and circumstances of a community, system, or asset that make it susceptible to the damaging effects of a hazard (UNISDR, 2009).

Conflict of Interest

The authors declare that there is no conflict of interest.

Data Availability Statement

No data were used in producing this manuscript.

Acknowledgments

The idea and concept of this paper were developed within the Cross-Program Activity "Natural Disasters and Warning Systems" of the Helmholtz Association of German Research Centers (HGF). This work is a contribution to the "Helmholtz Climate Initiative REKLIM" (Regional Climate Change), a joint research project of HGF. I. K. and M. P. received funding by the German Federal Ministry of Education and Research (BMBF) for the GROCE (Grant 29599 03F0778B) and RIESGOS (Grant 03G0876) projects. Funding by the Swiss National Science Foundation to D. D. through project PP00P2 170523 is gratefully acknowledged. J. G. P. thanks the AXA Research Fund for support. F. P. acknowledges support from the Transregional Collaborative Research Center SFB/TRR 165 "Waves to Weather" program funded by the German Science Foundation (DFG). C. K. received funding from the European Union's Horizon 2020 research and innovation program (Grant Agreement 700099).

References

Abercrombie, R. E., & Mori, J. (1996). Characteristics of foreshock occurrence to large earthquakes in the western USA. *Nature*, *381*, 303–307. https://doi.org/10.1038/381303a0

Acosta-Coll, M., Ballester-Merelo, F., Martinez-Peiró, M., & de la Hoz-Franco, E. (2018). Real-time early warning system design for pluvial flash floods—A review. *Sensors*, *18*(7), 2255. https://doi.org/10.3390/s18072255

Aerts, J. C. J. H., Botzen, W. J., Clarke, K. C., Cutter, S. L., Hall, J. W., Merz, B., & Kunreuther, H. (2018). Integrating human behaviour dynamics into flood disaster risk assessment/704/242/706/689/2788/706/2805 perspective. *Nature Climate Change*, *8*(3), 193–199. https://doi.org/10.1038/s41558-018-0085-1

Alberico, I., Lirer, L., Petrosino, P., & Scandone, R. (2002). A methodology for the evaluation of long-term volcanic risk from pyroclastic flows in Campi Flegrei (Italy). *Journal of Volcanology and Geothermal Research*, *116*, 63–78. https://doi.org/10.1016/s0377-0273(02)00211-1

Alcik, H., Ozel, O., Apaydin, N., & Erdik, M. (2009). A study on warning algorithms for Istanbul earthquake early warning system. *Geophysical Research Letters*, *36* L00B05 https://doi.org/10.1029/2008GL036659

Alexander, D. (2013). Volcanic ash in the atmosphere and risks for civil aviation: A study in European crisis management. *International Journal of Disaster Risk Science*, *4*(1), 9–19. https://doi.org/10.1007/s13753-013-0003-0

Alfieri, L., Thielen, J., & Pappenberger, F. (2012). Ensemble hydro-meteorological simulation for flash flood early detection in southern Switzerland. *Journal of Hydrology*, *424–425*, 143–153. https://doi.org/10.1016/j.jhydrol.2011.12.038

Alfieri, L., Velasco, D., & Thielen, J. (2011). Flash flood detection through a multi-stage probabilistic warning system for heavy precipitation events. *Advances in Geosciences*, *29*, 69–75. https://doi.org/10.5194/adgeo-29-69-2011

Allen, R., Gasparini, P., Kamigaichi, O., & Böse, M. (2009). The status of earthquake early warning around the world: An introductory overview. *Seismological Research Letters*, *80*(5), 682–693. https://doi.org/10.1785/gssrl.80.5.682

Allen, S., & Greenslade, D. (2016). A pilot tsunami inundation forecast system for Australia. *Pure and Applied Geophysics*, *173*, 3955–3971. https://doi.org/10.1007/s00024-016-1392-y

Annen, C., & Wagner, J.-J. (2003). The impact of volcanic eruptions during the 1990s. *Natural Hazards Review*, *4*, 169–175. https://doi.org/10.1061/(Ouellette)1527-6988(2003)4:4(169)

Antonescu, B., Fairman, J. G. Jr., & Schultz, D. M. (2018). What is the worst that could happen? Reexamining the 24–25 June 1967 tornado outbreak over Western Europe. *Weather, Climate, and Society*, *10*(2), 323–340. https://doi.org/10.1175/WCAS-D-17-0076.1

Aranguiz, R., Urra, L., Okuwaki, R., & Yagi, Y. (2018). Development and application of a tsunami fragility curve of the 2015 tsunami in Coquimbo, Chile. *Natural Hazards and Earth System Sciences*, *18*, 2143–2160. https://doi.org/10.5194/nhess-18-2143-2018

Arbuthnott, K. G., & Hajat, S. (2017). The health effects of hotter summers and heat waves in the population of the United Kingdom: A review of the evidence. Environmental health: A global access science. *Source*, *16*(Suppl 1), 1–13. https://doi.org/10.1186/s12940-017-0322-5

Arikawa, T., & Tomito, T. (2016). Development of high precision tsunami runup calculation method based on a hierarchical simulation. *Journal of Disaster Research*, *11*, 639–646. https://doi.org/10.20965/jdr.2016.p0639

Ashley, S. T., & Ashley, W. S. (2008). Flood fatalities in the United States. *Journal of Applied Meteorology and Climatology*, *47*(3), 805–818. https://doi.org/10.1175/2007jamc1611.1

Aspinall, W. P., & Woo, G. (2014). Santorini unrest 2011–2012: An immediate Bayesian belief network analysis of eruption scenario probabilities for urgent decision support under uncertainty. *Journal of Applied Volcanology*, *3*, 12. https://doi.org/10.1186/s13617-014-0012-8

Atkinson, G., & Wald, D. (2007). "Did you feel it?" Intensity data: A surprisingly good measure of earthquake ground motion. *Seismological Research Letters*, *78*(3), 362–368. https://doi.org/10.1785/gssrl.78.3.362

Aznar-Siguan, G., & Bresch, D. N. (2019). CLIMADA v1: A global weather and climate risk assessment platform. *Geoscientific Model Development*, *12*, 3085–3097. https://doi.org/10.5194/gmd-12-3085-2019

Bachmair, S., Svensson, C., Hannaford, J., Barker, L. J., & Stahl, K. (2016). A quantitative analysis to objectively appraise drought indicators and model drought impacts. *Hydrology and Earth System Sciences*, *20*, 2589–2609. https://doi.org/10.5194/hess-20-2589-2016

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

Bachmann, D., Eilander, D., De Leeuw, A., De Bruijn, K., Diermanse, F., Weerts, A., & Beckers, J. (2016). *Prototypes of risk-based flood forecasting systems in the Netherlands and Italy* (Vol. 7). Paper presented at 3rd European Conference on Flood Risk Management (FLOODrisk 2016), EDP Sciences, Lyon, France. https://doi.org/10.1051/e3sconf/20160718018

Bal, I. E., Bommer, J. J., Stafford, P. J., Crowley, H., & Pinho, R. (2010). The influence of geographical resolution of urban exposure data in an earthquake loss model for Istanbul. *Earthquake Spectra*. https://doi.org/10.1193/1.3459127

Barras, H., Hering, A., Martynov, A., Noti, P.-A., Germann, U., & Martius, O. (2019). Experiences with >50000 crowd-sourced hail reports in Switzerland. *Bulletin of the American Meteorological Society*, *100*, 1429–1440. https://doi.org/10.1175/BAMS-D-18-0090.1

Barsotti, S., Oddsson, B., Gudmundsson, M. T., Pfeffer, M. A., Parks, M. M., Ófeigsson, B. G., et al. (2020). Operational response and hazards assessment during the 2014–2015 volcanic crisis at Bárðarbunga volcano and associated eruption at Holuhraun, Iceland. *Journal of Volcanology and Geothermal Research*, *390*, 106753. https://doi.org/10.1016/j.jvolgeores.2019.106753

Baxter, P. J., Aspinall, W. P., Neri, A., Zuccaro, G., Spence, R. J. S., Cioni, R., & Woo, G. (2008). Emergency planning and mitigation at Vesuvius: A new evidence-based approach. *Journal of Volcanology and Geothermal Research*, *178*, 454–473. https://doi.org/10.1016/j.jvolgeores.2008.08.015

Becker, J. S., Paton, D., Johnston, D. M., & Ronan, K. R. (2012). A model of household preparedness for earthquakes: How individuals make meaning of earthquake information and how this influences preparedness. *Natural Hazards*, *64*(1), 107–137. https://doi.org/10.1007/s11069-012-0238-x

Befort, D. J., Wild, S., Knight, J. R., Lockwood, J. F., Thornton, H. E., Hermanson, L., et al. (2019). Seasonal forecast skill for extratropical cyclones and windstorms. *Quarterly Journal of the Royal Meteorological Society*, *145*, 92–104. https://doi.org/10.1002/qj.3406

Bell, J. R., Gebremichael, E., Molthan, A. L., Schultz, L. A., Meyer, F. J., Hain, C. R., et al. (2020). Complementing optical remote sensing with synthetic aperture radar observations of hail damage swaths to agricultural crops in the Central United States. *Journal of Applied Meteorology and Climatology*, *2020*, 665–685. https://doi.org/10.1175/JAMC-D-19-0124.1

Bengtson, T. J. (2018). *Forecast-based financing: Developing triggers for drought*. Sweden: Lund University. Retrieved from https://lup.lub.lu.se/luur/download?func=downloadFile&recordOId=8947941&fileOId=8947945

Bergen, W. R., & Murphy, A. H. (1978). Potential economic and social value of short-range forecasts of Boulder windstorms. *Bulletin of the American Meteorological Society*, *59*, 29–44. https://doi.org/10.1175/1520-0477(1978)059<0029:PEASVO>2.0.CO;2
Bernard, E., & Titov, V. (2015). Evolution of tsunami warning systems and products. *Philosophical Transactions of the Royal Society A*, *373*, 20140371. https://doi.org/10.1098/rsta.2014.0371
Bhola, P. K., Leandro, J., & Disse, M. (2018). Framework for offline flood inundation forecasts for two-dimensional hydrodynamic models. *Geosciences*, *8*(9), 346. https://doi.org/10.3390/geosciences8090346
Biass, S., Bonadonna, C., di Traglia, F., Pistolesi, M., Rosi, M., & Lestuzzi, P. (2016). Probabilistic evaluation of the physical impact of future tephra fallout events for the Island of Vulcano, Italy. *Bulletin of Volcanology*, *78*, 37. https://doi.org/10.1007/s00445-016-1028-1
Bihan, G. L., Payrastre, O., Gaume, E., Moncoulon, D., & Pons, F. (2017). The challenge of forecasting impacts of flash floods: Test of a simplified hydraulic approach and validation based on insurance claim data. *Hydrology and Earth System Sciences*, *21*(11), 5911–5928. https://doi.org/10.5194/hess-21-5911-2017
Bindi, D., Iervolino, I., & Parolai, S. (2016). On-site structure-specific real-time risk assessment: Perspectives from the REAKT project. *Bulletin of Earthquake Engineering*, *14*, 2471–2493. https://doi.org/10.1007/s10518-016-9889-4
Bissolli, P., Cacic, I., Mächel, H., & Rösner, S. (2016). Climate risk early warning systems in Europe. *WMO Bulletin*, *65*(1). https://public.wmo.int/en/resources/bulletin/climate-risk-early-warning-systems-europe
Bittner, M. I., Matthies, E. F., Dalbokova, D., & Menne, B. (2014). Are European countries prepared for the next big heat-wave. *European Journal of Public Health*, *24*, 615–619. https://doi.org/10.1093/eurpub/ckt121
Blahak, U., Wapler, K., Paulat, M., Potthast, R., Seifert, A., Bach, L., et al. (2018). *Development of a new seamless prediction system for very short range convective-scale forecasting at DWD*. Paper presented at European Geosciences Union General Assembly, EGU European Geosciences Union, Vienna, Austria.
Blanc, J., Hall, J. W., Roche, N., Dawson, R. J., Cesses, Y., Burton, A., & Kilsby, C. G. (2012). Enhanced efficiency of pluvial flood risk estimation in urban areas using spatial-temporal rainfall simulations. *Journal of Flood Risk Management*, *5*(2), 143–152. https://doi.org/10.1111/j.1753-318X.2012.01135.x
Blauhut, V., Gudmundsson, L., & Stahl, K. (2015). Towards pan-European drought risk maps: Quantifying the link between drought indices and reported drought impacts. *Environmental Research Letters*, *10*, 014008. https://doi.org/10.1088/1748-9326/10/1/014008
Blöschl, G. (2008). Flood warning—On the value of local information. *International Journal of River Basin Management*, *6*(1), 41–50. https://doi.org/10.1080/15715124.2008.9635336
Blöschl, G., Hall, J., Viglione, A., Perdigão, R. A. P., Parajka, J., Merz, B., et al. (2019). Changing climate both increases and decreases European river floods. *Nature*, *573*(7772), 108–111. https://doi.org/10.1038/s41586-019-1495-6
Bluestein, H. B. (2013). *Severe convective storms and tornadoes* (Vol. 10). Berlin, Heidelberg: Springer.
Boelee, L., Lumbroso, D. M., Samuels, P. G., & Cloke, H. L. (2019). Estimation of uncertainty in flood forecasts—A comparison of methods. *Journal of Flood Risk Management*, *12*(S1), e12516. https://doi.org/10.1111/jfr3.12516
Boisserie, M., Descamps, L., & Arbogast, P. (2016). Calibrated forecasts of extreme windstorms using the extreme forecast index (EFI) and shift of tails (SOT). *Weather and Forecasting*, *31*, 1573–1589. https://doi.org/10.1175/WAF-D-15-0027.1
Bonaccorso, B., Cancelliere, A., & Rossi, G. (2015). Probabilistic forecasting of drought class transitions in Sicily (Italy) using Standardized Precipitation Index and North Atlantic Oscillation Index. *Journal of Hydrology*, *526*, 136–150. https://doi.org/10.1016/j.jhydrol.2015.01.070
Booth, J. F., Rieder, H. E., Lee, D. E., & Kushnir, Y. (2015). The paths of extratropical cyclones associated with wintertime high-wind events in the northeastern United States. *Journal of Applied Meteorology and Climatology*, *54*, 1871–1885. https://doi.org/10.1175/JAMC-D-14-0320.1
Bormann, H., Kebschull, J., Ahlhorn, F., Spiekermann, J., & Schaal, P. (2018). Modellbasierte Szenarioanalyse zur Anpassung des Entwässerungsmanagements im nordwestdeutschen Küstenraum. *Wasser und Abfall*, *20*(7–8), 60–66. https://doi.org/10.1007/s35152-018-0083-7
Böse, M., Ionescu, C., & Wenzel, F. (2007). Earthquake early warning for Bucharest, Romania: Novel and revised scaling relations. *Geophysical Research Letters*, *34*, L07302. https://doi.org/10.1029/2007GL029396
Bossu, R., Gilles, S., Mazet-Roux, G., Roussel, F., Frobert, L., & Kamb, L. (2011). Flash sourcing, or rapid detection and characterization of earthquake effects through website traffic analysis. *Annals of Geophysics*, *54*(6), 2011. https://doi.org/10.4401/ag-5265
Bouchon, M., Durand, V., Marsan, D., Karabulut, H., & Schmittbuhl, J. (2013). The long precursory phase of most large interplate earthquakes. *Nature Geoscience*, *6*, 299–302. https://doi.org/10.1038/ngeo1770
Brown, E., Bachmann, D., Cranston, M., De Leeuw, A., Boelee, L., Diermanse, F., et al. (2016). *Methods and tools to support real time risk-based flood forecasting—A UK pilot application* (Vol. 7). Paper presented at E3S Web of Conferences, EDP Sciences, Lyon, France. https://doi.org/10.1051/e3sconf/20160718019
Brunner, L., Schaller, N., Anstey, J., Sillmann, J., & Steiner, A. K. (2018). Dependence of present and future European temperature extremes on the location of atmospheric blocking. *Geophysical Research Letters*, *45*, 6311–6320. https://doi.org/10.1029/2018GL077837
Bubeck, P., Botzen, W. J. W., Kreibich, H., & Aerts, J. C. J. H. (2013). Detailed insights into the influence of flood-coping appraisals on mitigating behaviour. *Global Environmental Change*, *23*(5), 1327–1338. https://doi.org/10.1016/j.gloenvcha.2013.05.009
Bubeck, P., Dillenardt, L., Alfieri, L., Feyen, L., Thieken, A. H., & Kellermann, P. (2019). Global warming to increase flood risk on European railways. *Climatic Change*. https://doi.org/10.1007/s10584-019-02434-5
Buizza, R., Leutbecher, M., & Thorpe, A. (2015). Living with the butterfly effect: A seamless view of predictability. *ECMWF Newsletter*, *145*, 18–23. https://doi.org/10.21957/x4h3e8w3
Buttlar, J. V., Zscheischler, J., Rammig, A., Sippel, S., Reichstein, M., Knohl, A., et al. (2018). Impacts of droughts and extreme-temperature events on gross primary production and ecosystem respiration: A systematic assessment across ecosystems and climate zones. *Biogeosciences*, *15*(5), 1293–1318. https://doi.org/10.5194/bg-15-1293-2018
Buzan, J. R., & Huber, M. (2020). Moist heat stress on a hotter Earth. *Annual Review of Earth and Planetary Sciences*, *48*(1), 623–655. https://doi.org/10.1146/annurev-earth-053018-060100
Calvi, G. M., Pinho, R., Magenes, G., Bommer, J. J., Restrepo-Vélez, L. F., & Crowley, H. (2006). Development of seismic vulnerability assessment methodologies over the past 30 years. *ISET Journal of Earthquake Technology*, *43*(3), 75–104.
Cameron, C. E., Prejean, S. G., Coombs, M. L., Wallace, K. L., Power, J. A., & Roman, D. C. (2018). Alaska volcano observatory alert and forecasting timeliness: 1989–2017. *Frontiers in Earth Science*, *6*(86). https://doi.org/10.3389/feart.2018.00086
Campbell, R., Beardsley, D., & Tokar, S. (2018). Impact-based forecasting and warning: Weather ready nations. *WMO Bulletin*, *67*(2), 10–13. https://public.wmo.int/en/resources/bulletin/impact-based-forecasting-and-warning-weather-ready-nations

Cappello, A., Ganci, G., Bilotta, G., Herault, A., Zago, V., & Del Negro, C. (2019). Satellite-driven modeling approach for monitoring lava flow hazards during the 2017 Etna eruption. *Annals of Geophysics*, *61*. https://doi.org/10.4401/ag-7792

Casteel, M. A. (2016). Communicating increased risk: An empirical investigation of the National Weather Service's impact-based warnings. *Weather, Climate, and Society*, *8*(3), 219–232. https://doi.org/10.1175/wcas-d-15-0044.1

Catto, J. L. (2016). Extratropical cyclone classification and its use in climate studies. *Reviews of Geophysics*, *54*, 486–520. https://doi.org/10.1002/2016RG000519

Ceglar, A., Turco, M., Toreti, A., & Doblas-Reyes, F. J. (2017). Linking crop yield anomalies to large scale cale atmospheric circulation in Europe. *Agricultural and Forest Meteorology*, *240*, 35–45. https://doi.org/10.1016/j.agrformet.2017.03.019

Ceppi, A., Ravazzani, G., Corbari, C., Salerno, R., Meucci, S., & Mancini, M. (2014). Real-time drought forecasting system for irrigation management. *Hydrology and Earth System Sciences*, *18*(9), 3353–3366. https://doi.org/10.5194/hess-18-3353-2014

Charvet, I., Macabuag, J., & Rossetto, T. (2017). Estimating tsunami-induced building damage through fragility functions: Critical review and research needs. *Frontiers in Built Environment*, *3*, 36. https://doi.org/10.3389/fbuil.2017.00036

Christophersen, A., Deligne, N. I., Hanea, A. M., Chardot, L., Fournier, N., & Aspinall, W. P. (2018). Bayesian network modeling and expert elicitation for probabilistic eruption forecasting: Pilot study for Whakaari/White Island, New Zealand. *Frontiers in Earth Science*, *6*. https://doi.org/10.3389/feart.2018.00211

Ciavola, P., Ferreira, O., Haerens, P., van Koningsveld, M., Armaroli, C., & Lequeux, Q. (2011). Storm impacts along European coastlines. Part 1: The joint effort of the MICORE and ConHaz Projects. *Environmental Science & Policy*, *14*(7), 912–923. https://doi.org/10.1016/j.envsci.2011.05.011

Cioni, R., Pistolesi, M., Bertagnini, A., Bonadonna, C., Hoskuldsson, A., & Scateni, B. (2014). Insights into the dynamics and evolution of the 2010 Eyjafjallajökull summit eruption (Iceland) provided by volcanic ash textures. *Earth and Planetary Science Letters*, *394*, 111–123. https://doi.org/10.1016/j.epsl.2014.02.051

Ciuha, U., Pogačar, T., Bogataj, L. K., Gliha, M., Nybo, L., Flouris, A. D., & Mekjavic, I. B. (2019). Interaction between indoor occupational heat stress and environmental temperature elevations during heat waves. *Weather, Climate, amd Society*, *11*, 755–762. https://doi.org/10.1175/WCAS-D-19-0024.1

Clark, P., Roberts, N., Lean, H., Ballard, S. P., & Charlton-Perez, C. (2016). Convection-permitting models: A step-change in rainfall forecasting. *Meteorological Applications*, *23*(2), 165–181. https://doi.org/10.1002/met.1538

Cole, S. J., Moore, R. J., Wells, S. C., & Mattingley, P. S. (2016). *Real-time forecasts of flood hazard and impact: Some UK experiences* (Vol. 7). Paper presented at 3rd European Conference on Flood Risk Management (FLOODrisk 2016), EDP Sciences, Lyon, France. https://doi.org/10.1051/e3sconf/20160718015

Coles, D., Yu, D., Wilby, R. L., Green, D., & Herring, Z. (2017). Beyond 'flood hotspots': Modelling emergency service accessibility during flooding in York, UK. *Journal of Hydrology*, *546*, 419–436. https://doi.org/10.1016/j.jhydrol.2016.12.013

Collier, C. G. (2007). Flash flood forecasting: What are the limits of predictability. *Quarterly Journal of the Royal Meteorological Society*, *133*(622), 3–23. https://doi.org/10.1002/qj.29

Coughlan de Perez, E., van den Hurk, B., van Aalst, M. K., Jongman, B., Klose, T., & Suarez, P. (2015). Forecast-based financing: An approach for catalyzing humanitarian action based on extreme weather and climate forecasts. *Natural Hazards and Earth System Sciences*, *15*(4), 895–904. https://doi.org/10.5194/nhess-15-895-2015

Crowley, H., Bommer, J. J., Pinho, R., & Bird, J. (2005). The impact of epistemic uncertainty on an earthquake loss model. *Earthquake Engineering & Structural Dynamics*, *34*, 1653–1685. https://doi.org/10.1002/eqe.498

Crowley, H., Bommer, J. J., & Stafford, P. J. (2008). Recent developments in the treatment of ground-motion variability in earthquake loss models. *Journal of Earthquake Engineering*, *12*(S2), 71–80. https://doi.org/10.1080/13632460802013529

Cua, G., & Heaton, T. (2007). The Virtual Seismologist (VS) method: A Bayesian approach to earthquake early warning. In P. Gasparini, G. Manfredi, & J. Zschau (Eds.), *Earthquake early warning systems* (pp. 97–132). Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-540-72241-0_7

Dagá, J., Chamorro, A., Solminihac, H., & Echaveguren, T. (2018). Development of fragility curves for road bridges exposed to volcanic lahars. *Natural Hazards and Earth System Sciences*, *18*, 2111–2125. https://doi.org/10.5194/nhess-18-2111-2018

Dale, M., Wicks, J., Mylne, K., Pappenberger, F., Laeger, S., & Taylor, S. (2014). Probabilistic flood forecasting and decision-making: An innovative risk-based approach. *Natural Hazards*, *70*(1), 159–172. https://doi.org/10.1007/s11069-012-0483-z

Dall'Osso, F., Gonella, M., Gabbianelli, G., Withycombe, G., & Dominey-Howes, D. (2009). A revised (PTVA) model for assessing the vulnerability of buildings to tsunami damage. *Natural Hazards and Earth System Sciences*, *9*, 1557–1565. https://doi.org/10.5194/nhess-9-1557-2009

Davis, J. R., Paramygin, V. A., Forrest, D., & Sheng, Y. P. (2010). Toward the probabilistic simulation of storm surge and inundation in a limited-resource environment. *Monthly Weather Review*, *138*(7), 2953–2974. https://doi.org/10.1175/2010MWR3136.1

Davlasheridze, M., Atoba, K. O., Brody, S., Highfield, W., Merrell, W., Ebersole, B., et al. (2019). Economic impacts of storm surge and the cost-benefit analysis of a coastal spine as the surge mitigation strategy in Houston-Galveston area in the USA. *Mitigation and Adaptation Strategies for Global Change*, *24*(3), 329–354. https://doi.org/10.1007/s11027-018-9814-z

De Groeve, T., Vernaccini, L., & Annunziato, A. (2006). In B. van de Walle & M. Turoff (Eds.), *Modelling disaster impact for the global disaster alert and coordination system* (pp. 409–417). Paper presented at 3rd International ISCRAM Conference, ISCRAM Digital Library, Newark, NJ.

De Risi, R., Goda, K., Yasuda, T., & Mori, N. (2017). Is flow velocity important in tsunami empirical fragility modeling. *Earth-Science Reviews*, *166*, 64–82. https://doi.org/10.1016/j.earscirev.2016.12.015

de' Donato, F. K., Leone, M., Scortichini, M., De Sario, M., Katsouyanni, K., Lanki, T., et al. (2015). Changes in the effect of heat on mortality in the last 20 years in nine European cities. Results from the PHASE project. *International Journal of Environmental Research and Public Health*, *12*(12), 15,567–15,583. https://doi.org/10.3390/ijerph121215006

Deshons, P. (2002). Urban flood forecast and monitoring. Experience of Marseille city. *Houille Blanche*, *2*, 56–59. https://doi.org/10.1051/lhb/2002022

Dessens, J., Sánchez, J., Berthet, C., Hermida, L., & Merino, A. (2016). Hail prevention by ground-based silver iodide generators: Results of historical and modern field projects. *Atmospheric Research*, *170*, 98–111. https://doi.org/10.1016/j.atmosres.2015.11.008

Deutsch, M., & Pörtge, K.-H. (2001). Die Hochwassermeldeordnung von 1889—Ein Beitrag zur Geschichte des Hochwasserwarn und Meldedienstes in Mitteldeutschland. In *Forum Katastrophenvorsorge 2001* (pp. 396–405). Bonn: DKKV.

Di Napoli, C., Pappenberger, F., & Cloke, H. L. (2019). Verification of heat stress thresholds for a health-based heat-wave definition. *Journal of Applied Meteorology and Climatology*, *58*(6), 1177–1194. https://doi.org/10.1175/JAMC-D-18-0246.1

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

Domeisen, D. I. V., Badin, G., & Koszalka, I. M. (2018). How predictable are the Arctic and North Atlantic Oscillations? Exploring the variability and predictability of the Northern Hemisphere. *Journal of Climate*, *31*(3), 997–1014. https://doi.org/10.1175/JCLI-D-17-0226.1

Donat, M. G., Leckebusch, G. C., Wild, S., & Ulbrich, U. (2011). Future changes of European winter storm losses and extreme wind speeds in multi-model GCM and RCM simulations. *Natural Hazards and Earth System Sciences*, *11*, 1351–1370. https://doi.org/10.5194/nhess-11-1351-2011

Done, J. M., Craig, G. C., Gray, S. L., & Clark, P. A. (2012). Case-to-case variability of predictability of deep convection in a mesoscale model. *Quarterly Journal of the Royal Meteorological Society*, *138*(664), 638–648. https://doi.org/10.1002/qj.943

Doocy, S., Daniels, A., Murray, S., & Kirsch, T. D. (2013). The human impact of floods: A historical review of events 1980–2009 and systematic literature review. *PLoS Currents*. https://doi.org/10.1371/currents.dis.f4deb457904936b07c09daa98ee8171a

Doswell, C. A. III (2007). Historical overview of severe convective storms research. *E-Journal of Severe Storms Meteorology*, *2*(1).

Doswell, C. A., III, Brooks, H. E., & Maddox, R. A. (1996). Flash flood forecasting: An ingredients-based methodology. *Weather and Forecasting*, *11*, 560–581. https://doi.org/10.1175/1520-0434(1996)011<0560:FFFAIB>2.0.CO;2

Doswell, C. A. I. I. I., & Bosart, L. F. (2001). Extratropical synoptic-scale processes and severe convection. In C. A. Doswell (Ed.), *Severe convective storms*, *Meteorological Monographs* (pp. 27–69). Boston, MA: American Meteorological Society. https://doi.org/10.1007/978-1-935704-06-5

Dottori, F., Kalas, M., Salamon, P., Bianchi, A., Alfieri, L., & Feyen, L. (2017). An operational procedure for rapid flood risk assessment in Europe. *Natural Hazards and Earth System Sciences*, *17*(7), 1111–1126. https://doi.org/10.5194/nhess-17-1111-2017

Douglas, J. (2007). Physical vulnerability modelling in natural hazard risk assessment. *Natural Hazards and Earth System Sciences*, *7*, 283–288. https://doi.org/10.5194/nhess-7-283-2007

Dube, S. K., Murty, T. S., Feyen, J. C., Cabrera, R., Harper, B. A., Bales, J. D., & Amer, S. (2010). Storm surge modeling and applications in coastal areas, in Global perspectives on tropical cyclones. In J. C. L. Chan & J. D. Kepert (Eds.), *World scientific series on Asia-Pacific weather and climate* (pp. 363–406). Singapore: WORLD SCIENTIFIC.

Eberenz, S., Stocker, D., Röösli, T., & Bresch, D. N. (2020). Exposure data for global physical risk assessment. *Earth System Science Data Discussions*. https://doi.org/10.5194/essd-2019-189

Eberhard, D. A. J. (2014). *Multiscale seismicity analysis and forecasting: Examples from the western Pacific and Iceland* (PhD dissertation) (p. 21897). Zürich, Switzerland: Eidgenössische Technische Hochschule Zürich. Retrieved from www.research-collection.ethz.ch/handle/20.500.11850/101174

Ekamper, P., van Duin, C., Van Poppel, F., & Mandemakers, K. (2010). Summary. *Annales de Demographie Historique*, *120*(2), 55–104. https://doi.org/10.3917/adh.120.0055

EM-DAT (2020). *OFDA/CRED International Disaster Database*. Brussels: Université Catholique de Louvain. http://www.em-dat.net

Espinosa Aranda, J. M., Jiménez, A., Ibarrola, G., Alcantar, F., Aguilar, A., Inostroza, M., & Maldonado, S. (1995). Mexico City seismic alert system. *Seismological Research Letters*, *66*, 42–53. https://doi.org/10.1785/gssrl.66.6.42

EU (2007). *Directive 2007/60/EC of the European Parliament and of the Council of 23 October 2007 on the assessment and management of flood risks (2007/60/EC)*. Brussels, Belgium: European Union. Retrieved from https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32007L0060

Fakhruddin, B. S. H. M., & Schick, L. (2019). Benefits of economic assessment of cyclone early warning systems—A case study on Cyclone Evan in Samoa. *Progress in Disaster Science*, *2*, 100034. https://doi.org/10.1016/j.pdisas.2019.100034

Fearnley, C. J. (2013). Assigning a volcano alert level: Negotiating uncertainty, risk, and complexity in decision-making processes. *Environment and Planning A*, *45*, 1891–1911. https://doi.org/10.1068/a4542

Feser, F., Barcikowska, M., Krueger, O., Schenk, F., Weisse, R., & Xia, L. (2015). Storminess over the North Atlantic and northwestern Europe—A review. *Quarterly Journal of the Royal Meteorological Society*, *141*, 350–382. https://doi.org/10.1002/qj.2364

Field, E. H., Jordan, T. H., Jones, L. M., Michael, A. J., Blanpied, M. L., & Participants, O. W. (2016). The potential uses of operational earthquake forecasting: Table 1. *Seismological Research Letters*, *87*(2A), 313–322. https://doi.org/10.1785/0220150174

Field, E. H., Milner, K. R., Hardebeck, J. L., Page, M. T., Van der Elst, N., Jordan, T. H., et al. (2017). A spatiotemporal clustering model for the Third Uniform California Earthquake Rupture Forecast (UCERF3-ETAS): Toward an operational earthquake forecast. *Bulletin of the Seismological Society of America*, *107*(3), 1049–1081. https://doi.org/10.1785/0120160173

Fink, A. H., Brücher, T., Ermert, V., Krüge,r, A., & Pinto, J. G. (2009). The European storm Kyrill in January 2007: Synoptic evolution, meteorological impacts and some considerations with respect to climate change. *Natural Hazards and Earth System Sciences*, *9*, 405–423. https://doi.org/10.5194/nhess-9-405-2009

Fischer, E. M., & Knutti, R. (2013). Robust projections of combined humidity and temperature extremes. *Nature Climate Change*, *3*(2), 126–130. https://doi.org/10.1038/nclimate1682

Fischer, E. M., & Schär, C. (2010). Consistent geographical patterns of changes in high-impact European heatwaves. *Nature Geoscience*, *3*(6), 398–403. https://doi.org/10.1038/ngeo866

Flemming, N. C. (1997). Estimates of the costs and benefits of operational oceanography at the single industry level. In J. H. Stel, H. W. A. Behrens, J. C. Borst, L. J. Droppert, & J. P. van der Meulen (Eds.), *Operational oceanography—The challenge for European co-operation, Proceedings of the First International Conference on EuroGOOS*, *Elsevier Oceanography Series* (pp. 269–277). Amsterdam: Elsevier.

Flowerdew, J., Horsburgh, K., & Mylne, K. (2009). Ensemble forecasting of storm surges. *Marine Geodesy*, *32*(2), 91–99. https://doi.org/10.1080/01490410902869151

Forzieri, G., Cescatti, A., Batista e Silva, F., & Feyen, L. (2017). Increasing risk over time of weather-related hazards to the European population: A data-driven prognostic study. *The Lancet Planetary Health*, *1*(5), e200–e208. https://doi.org/10.1016/S2542-5196(17)30082-7

Fuchs, L., Graf, T., Haberlandt, U., Kreibich, H., Neuweiler, I., Sester, M., Berkhahn, S., Feng, F., Peche, A., Rözer, V., Sämann, R., Shehu, B., & Wahl, J. (2017). *Real-time prediction of pluvial floods and induced water contamination* (pp. 1–8). Paper presented at 17th International Conference on Urban Drainage, Prague, Czech Republic.

Fundel, V. J., Fleischhut, N., Herzog, S. M., Göber, M., & Hagedorn, R. (2019). Promoting the use of probabilistic weather forecasts through a dialogue between scientists, developers and end-users. *Quarterly Journal of the Royal Meteorological Society*, *145*(S1), 210–231. https://doi.org/10.1002/qj.3482

Funk, C., Shukla, S., Thiaw, W. M., Rowland, J., Hoell, A., McNally, A., et al. (2019). Recognizing the famine early warning systems network: Over 30 years of drought early warning science advances and partnerships promoting global food security. *Bulletin of the American Meteorological Society*, *100*(6), 1011–1027. https://doi.org/10.1175/bams-d-17-0233.1

Gaume, E., Bain, V., Bernardara, P., Newinger, O., Barbuc, M., Bateman, A., et al. (2009). A compilation of data on European flash floods. *Journal of Hydrology*, *367*(1–2), 70–78. https://doi.org/10.1016/j.jhydrol.2008.12.028
Gebhardt, O., Kuhlicke, C., Wolf, L., Vitolo, C., Duo, E., van Lanen, H., et al. (2019). *Results of the co-evaluation of the ANYWHERE tools, products and services at the pilot sites (Deliverable 1.4)*. Leipzig, Germany: UFZ. Retrieved from http://www.anywhere-h2020.eu/wp-content/uploads/docs/D1.4_submitted.pdf (last access 24.02.2020)
Geller, R. J. (1997). Earthquake prediction: A critical review. *Geophysical Journal International*, *131*(3), 425–450. https://doi.org/10.1111/j.1365-246x.1997.tb06588.x
Gensini, V. A., & Tippett, M. K. (2019). Global ensemble forecast system (GEFS) predictions of days 1–15 US tornado and hail frequencies. *Geophysical Research Letters*, *46*, 2922–2930. https://doi.org/10.1029/2018GL081724
Gerl, T., Kreibich, H., Franco, G., Marechal, D., & Schröter, K. (2016). A review of flood loss models as basis for harmonization and benchmarking. *PLoS ONE*, *11*(7), e0159791. https://doi.org/10.1371/journal.pone.0159791
German Red Cross (2018). *A guide to trigger methodology for forecast-based financing*. Berlin, Germany: German Red Cross National Headquarters. Retrieved from http://fbf.drk.de/fileadmin/user_upload/FbF_Manual_-_A_guide_to_trigger_methodology.pdf
Giorgetta, M. A., Brokopf, R., Crueger, T., Esch, M., Fiedler, S., Helmert, J., et al. (2018). ICON-A, the atmosphere component of the ICON Earth System Model. Part I: Model Description. *Journal of Advances in Modeling Earth Systems*, *10*, 1613–1637. https://doi.org/10.1029/2017MS001242
Goda, K., & Abilova, K. (2016). Tsunami hazard warning and risk prediction based on inaccurate earthquake source parameters. *Hazards and Earth System Science*, *16*, 577–593. https://doi.org/10.5194/nhess-16-577-2016
Gönnert, G., Dube, S. K., Murty, T., & Siefert, W. (2001). *Global storm surges. Die Küste* (Vol. 1–623). Retrieved from https://hdl.handle.net/20.500.11970/101448
Grell, G. A., & Dévényi, D. (2002). A generalized approach to parameterizing convection combining ensemble and data assimilation techniques. *Geophysical Research Letters*, *29*, 1693. https://doi.org/10.1029/2002GL015311
Grezio, A., Babeyko, A., Baptista, M. A., Behrens, J., Costa, A., Davies, G., & Thio, H. K. (2017). Probabilistic tsunami hazard analysis: Multiple sources and global applications. *Reviews of Geophysics*, *55*, 1158–1198. https://doi.org/10.1002/2017RG000579
Griffin, J., Latief, H., Kongko, W., & Cummins, P. (2015). An evaluation of onshore digital elevation models for modeling tsunami inundation zones. *Frontiers in Earth Science*, *3*, 32. https://doi.org/10.3389/feart.2015.00032
Groenemeijer, P., Púčik, T., Holzer, A. M., Antonescu, B., Riemann-Campe, K., Schultz, D. M., et al. (2017). Severe convective storms in Europe: Ten years of research and education at the European Severe Storms Laboratory. *Bulletin of the American Meteorological Society*, *98*, 2641–2651. https://doi.org/10.1175/BAMS-D-16-0067.1
Grünthal, G., & European Seismological Commission (1998). *Working group 'Macroseismic scales', European macroseismic scale 1998: EMS-98. Luxembourg: European Seismological Commission*. Luxembourg: Subcommission on Engineering Seismology, Working Group Macroseismic Scales.
Gulia, L., & Wiemer, S. (2019). Real-time discrimination of earthquake foreshocks and aftershocks. *Nature*, *574*, 193–199. https://doi.org/10.1038/s41586-019-1606-4
Gupta, V., Sharma, M., Pachauri, R., & Babu, K. N. D. (2019). Impact of hailstorm on the performance of PV module: A review. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *0*, 1–22. https://doi.org/10.1080/15567036.2019.1648597
Haas, R., & Pinto, J. G. (2012). A combined statistical and dynamical approach for downscaling large-scale footprints of European windstorms. *Geophysical Research Letters*, *39*, L23804. https://doi.org/10.1029/2012GL054014
Haas, R., Pinto, J. G., & Born, K. (2014). Can dynamically downscaled windstorm footprints be improved by observations through a probabilistic approach. *Journal of Geophysical Research: Atmospheres*, *119*, 713–725. https://doi.org/10.1002/2013JD020882
Hagelin, S., Son, J., Swinbank, R., McCabe, A., Roberts, N., & Tennant, W. (2017). The Met Office convective-scale ensemble, MOGREPS-UK. *Quarterly Journal of the Royal Meteorological Society*, *143*, 2846–2861. https://doi.org/10.1002/qj.3135
Hallegatte, S., Green, C., Nicholls, R. J., & Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. *Nature Climate Change*, *3*, 802. https://doi.org/10.1038/nclimate1979
Hammer, B., & Schmidlin, T. W. (2002). Response to warnings during the 3 May 1999 Oklahoma City tornado: Reasons and relative injury rates. *Weather and Forecasting*, *17*, 577–581. https://doi.org/10.1175/1520-0434(2002)017<0577:rtwdtm>2.0.co;2
Harley, M. D., Valentini, A., Armaroli, C., Perini, L., Calabrese, L., & Ciavola, P. (2016). Can an early-warning system help minimize the impacts of coastal storms?: A case study of the 2012 Halloween storm, northern Italy. *Natural Hazards and Earth System Sciences*, *16*(1), 209–222. https://doi.org/10.5194/nhess-16-209-2016
Hayes, J. L., Wilson, T. M., Deligne, N. I., Lindsay, J. M., Leonard, G. S., Tsang, S. W., & Fitzgerald, R. H. (2020). Developing a suite of multi-hazard volcanic eruption scenarios using an interdisciplinary approach. *Journal of Volcanology and Geothermal Research*, 106763. https://doi.org/10.1016/j.jvolgeores.2019.106763
Haylock, M. R., Hofstra, N., Klein Tank, A. M. G., Klok, E. J., Jones, P. D., & New, M. (2008). A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. *Journal of Geophysical Research*, *113*, D20119. https://doi.org/10.1029/2008JD010201
Helbing, D. (2013). Globally networked risks and how to respond. *Nature*, *497*(7447), 51–59. https://doi.org/10.1038/nature12047
Heneka, P., Hofherr, T., Ruck, B., & Kottmeier, C. (2006). Winter storm risk of residential structures—Model development and application to the German state of Baden-Württemberg. *Natural Hazards and Earth System Sciences*, *6*, 721–733. https://doi.org/10.5194/nhess-6-721-2006
Henonin, J., Russo, B., Mark, O., & Gourbesville, P. (2013). Real-time urban flood forecasting and modelling—A state of the art. *Journal of Hydroinformatics*, *15*(3), 717–736. https://doi.org/10.2166/hydro.2013.132
Herrmann, M., Zechar, J. D., & Wiemer, S. (2016). Communicating time-varying seismic risk during an earthquake sequence. *Seismological Research Letters*, *87*(2A), 301–312. https://doi.org/10.1785/0220150168
Hill, M., & Rossetto, T. (2008). Comparison of building damage scales and damage descriptions for use in earthquake loss modelling in Europe. *Bulletin of Earthquake Engineering*, *6*, 335–365. https://doi.org/10.1007/s10518-007-9057-y
Hirpa, F. A., Salamon, P., Beck, H. E., Lorini, V., Alfieri, L., Zsoter, E., & Dadson, S. J. (2018). Calibration of the Global Flood Awareness System (GloFAS) using daily streamflow data. *Journal of Hydrology*, *566*, 595–606. https://doi.org/10.1016/j.jhydrol.2018.09.052
Hoechner, A., Ge, M., Babeyko, A. Y., & Sobolev, S. V. (2013). Instant tsunami early warning based on real time GPS—Tohoku 2011 case study. *Natural Hazards and Earth System Sciences*, *13*, 1285–1292. https://doi.org/10.5194/nhess-13-1285-2013
Hoernes, R. (1893). *Erdbebenkunde*. Leipzig: Verlag Veit.
Hohl, R., Schiesser, H.-H., & Aller, D. (2002). Hailfall: The relationship between radar-derived hail kinetic energy and hail damage to buildings. *Atmospheric Research*, *63*, 177–207. https://doi.org/10.1016/S0169-8095(02)00059-5

Holle, R. L. (2008). *Annual rates of lightning fatalities by country*. Paper presented at 20th International Lightning Detection Conference, Tuscon, AZ.

Holmes, J. D. (2015). *Wind loading of structures* (pp. 1–450). Boca Raton: CRC Press, Taylor & Francis Group.

Hoshiba, M., Kamigaichi, O., Saito, M., Tsukada, S., & Hamada, N. (2008). Earthquake early warning starts nationwide in Japan. *Eos Transactions American Geophyical Union*, *89*(8), 73–74. https://doi.org/10.1029/2008EO080001

Hsiao, N. C., Wu, Y. M., Shin, T. C., Zhao, L., & Teng, T. L. (2009). Development of earthquake early warning system in Taiwan. *Geophysical Research Letters*, *36*, L00B02. https://doi.org/10.1029/2008GL036596

Iervolino, I., Chioccarelli, E., Giorgio, M., Marzocchi, W., Zuccaro, G., Dolce, M., & Mandfredi, G. (2015). Operational (short term) earthquake loss forecasting in Italy. *Bulletin of the Seismological Society of America*, *105*(4), 2286–2298. https://doi.org/10.1785/0120140344

James, P. M., Reichert, B. K., & Heizenreder, D. (2018). NowCastMIX: Automatic integrated warnings for severe convection on nowcasting time scales at the German Weather Service. *Weather and Forecasting*, *33*, 1413–1433. https://doi.org/10.1175/WAF-D-18-0038.1

Jenkins, S. F., Magill, C. R., & Blong, R. J. (2018). Evaluating relative tephra fall hazard and risk in the Asia-Pacific region. *Geosphere*, *14*(2), 492–509. https://doi.org/10.1130/GES01549.1

Jenkins, S. F., Phillips, J. C., Price, R., Feloy, K., Baxter, P. J., Hadmoko, D. S., & de Bélizal, E. (2015). Developing building-damage scales for lahars: Application to Merapi volcano, Indonesia. *Bulletin of Volcanology*, *77*, 75. https://doi.org/10.1007/s00445-015-0961-8

Jenkins, S. F., Spence, R. J. S., Fonseca, J. F. B. D., Solidum, R. U., & Wilson, T. M. (2014). Volcanic risk assessment: Quantifying physical vulnerability in the built environment. *Journal of Volcanology and Geothermal Research*, *276*, 105–120. https://doi.org/10.1016/j.jvolgeores.2014.03.002

Jongman, B. (2018). Effective adaptation to rising flood risk. *Nature Communications*, *9*(1), 1986. https://doi.org/10.1038/s41467-018-04396-1

Jonkman, S. N., & Kelman, I. (2005). An analysis of the causes and circumstances of flood disaster deaths. *Disasters*, *29*(1), 75–97. https://doi.org/10.1111/j.0361-3666.2005.00275.x

Jordan, T. H., Chen, Y. T., Gasparini, P., Mandriaga, R., Main, I., Marzocchi, W., et al. (2011). Operational earthquake forecasting. State of knowledge and guidelines for utilization. *Annals of Geophysics*, *4*. https://doi.org/10.4401/ag-5350

Jordan, T. H., Marzocchi, W., Michael, A. J., & Gerstenberger, M. C. (2014). Operational earthquake forecasting can enhance earthquake preparedness. *Seismological Research Letters*, *85*(5), 955–959. https://doi.org/10.1785/0220140143

Joseph, A. (2011). IOC-UNESCO tsunami early warning systems. In *Tsunamis: Detection, monitoring, and early-warning technologies* (Ch. 14, pp. 171–245). Boston, USA: Elsevier Academic Press. https://doi.org/10.1016/B978-0-12-385053-9.10014-6

Joslyn, S., & LeClerc, J. (2013). Decisions with uncertainty: The glass half full. *Current Directions in Psychological Science*, *22*, 308–315. https://doi.org/10.1177/0963721413481473

Kagan, Y., & Knopoff, L. (1977). Earthquake risk prediction as a stochastic process. *Physics of the Earth and Planetary Interiors*, *14*(2), 97–108. https://doi.org/10.1016/0031-9201(77)90147-9

Kaltenböck, R., Diendorfer, G., & Dotzek, N. (2009). Evaluation of thunderstorm indices from ECMWF analyses, lightning data and severe storm reports. *Atmospheric Research*, *93*, 381–396. https://doi.org/10.1016/j.atmosres.2008.11.005

Kamigaichi, O. (2015). Tsunami forecasting and warning. In R. Meyers (Ed.), *Extreme environmental events*. New York, NY: Springer. https://doi.org/10.1007/978-1-4419-7695-6

Kanazawa, T. (2013). *Japan trench earthquake and tsunami monitoring network of cable-linked 150 ocean bottom observatories, and its impact to earth disaster science*. Paper presented at Proceedings of the International Symposium on Underwater Technology, IEEE, Tokyo, Japan. https://doi.org/10.1109/UT.2013.6519911

Kim, M. H., Morlock, S. E., Arihood, L. D., & Kiesler, J. L. (2011). *Observed and forecast flood-inundation mapping application—A pilot study of an eleven-mile reach of the White River (U.S. Geological Survey Scientific Investigations Report)* (p. 63). Indianapolis, IN: USGS, Indiana Water Science Center.

Klawa, M., & Ulbrich, U. (2003). A model for the estimation of storm losses and the identification of severe winter storms in Germany. *Natural Hazards and Earth System Sciences*, *3*, 725–732. https://doi.org/10.5194/nhess-3-725-2003

Kohno, N., Dube, S. K., Entel, M., Fakhruddin, S. H. M., Greenslade, D., Leroux, M.-D., et al. (2018). Recent progress in storm surge forecasting. *Tropical Cyclone Research and Review*, *7*(2), 106–127. https://doi.org/10.6057/2018TCRR02.04

Koks, E. (2018). Moving flood risk modelling forwards. *Nature Climate Change*, *8*(7), 561–562. https://doi.org/10.1038/s41558-018-0185-y

Koshimura, S., Hino, R., Ohta, Y., Kobayashi, H., Murashima, Y., & Musa, A. (2017). Advances of tsunami inundation forecasting and its future perspectives. In *OCEANS 2017—Aberdeen* (pp. 1–4). Aberdeen, UK: IEEE. https://doi.org/10.1109/OCEANSE.2017.8084753

Koshimura, S., Katada, T., Mofjeld, H., & Kawata, Y. (2006). A method for estimating casualties due to the tsunami inundation flow. *Natural Hazards*, *39*, 265–274. https://doi.org/10.1007/s11069-006-0027-5

Koshimura, S., Namegaya, Y., & Yanagisawa, Y. (2009). Tsunami fragility: A new measure to identify tsunami damage. *Journal of Disaster Research*, *4*(6), 479–488. https://doi.org/10.20965/JDR.2009.P0479

Kovats, R. S., & Kristie, L. E. (2006). Heatwaves and public health in Europe. *European Journal of Public Health*, *16*(6), 592–599. https://doi.org/10.1093/eurpub/ckl049

Kreibich, H., Di Baldassarre, G., Vorogushyn, S., Aerts, J. C. J. H., Apel, H., Aronica, G. T., et al. (2017). Adaptation to flood risk: Results of international paired flood event studies. *Earth's Future*, *5*, 953–965. https://doi.org/10.1002/2017ef000606

Kreibich, H., Müller, M., Schröter, K., & Thieken, A. H. (2017). New insights into flood warning reception and emergency response by affected parties. *Natural Hazards and Earth System Sciences*, *17*(12), 2075–2092. https://doi.org/10.5194/nhess-17-2075-2017

Kristandt, J., Brecht, B., Frank, H., & Knaack, H. (2014). Optimization of empirical storm surge forecast—Modelling of high resolution wind fields, Die Küste, *81*, 301–318.

Kron, A., Nestmann, F., Schlüter, I., Schädler, G., Kottmeier, C., Helms, M., et al. (2010). Operational flood management under large-scale extreme conditions, using the example of the Middle Elbe. *Natural Hazards and Earth System Sciences*, *10*(6), 1171–1181. https://doi.org/10.5194/nhess-10-1171-2010

Kunz, M., & Geissbuehler, P. K. (2017). Natural catastrophe risk management and modelling. A practitioner's guide. In M. Mitchell-Wallace, J. H. Jones, & M. Foote (Eds.), *Chapter 3.4 Severe convective storms* (pp. 209–217). Chichester, U.K: Wiley Blackwell.

Lalaurette, F. (2003). Early detection of abnormal weather conditions using a probabilistic extreme forecast index. *Quarterly Journal of the Royal Meteorological Society*, *129*, 3037–3057. https://doi.org/10.1256/qj.02.152

Lass, W., Haas, A., Hinkel, J., & Jaeger, C. (2013). Avoiding the avoidable: Towards a European heat waves risk governance. In *Integrated Risk Governance* (pp. 119–144). Berlin, Heidelberg: Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-31641-8_8

Lavaysse, C., Naumann, G., Alfieri, L., Salamon, P., & Vogt, J. (2019). Predictability of the European heat and cold waves. *Climate Dynamics*, *52*(3–4), 2481–2495. https://doi.org/10.1007/s00382-018-4273-5

Lavaysse, C., Vogt, J., & Pappenberger, F. (2015). Early warning of drought in Europe using the monthly ensemble system from ECMWF. *Hydrology and Earth System Sciences*, *19*, 3273–3286. https://doi.org/10.5194/hess-19-3273-2015

Lavaysse, C., Vogt, J., Toreti, A., Carrera, M. L., & Pappenberger, F. (2018). On the use of weather regimes to forecast meteorological drought over Europe. *Natural Hazards and Earth System Sciences*, *18*(12), 3297–3309. https://doi.org/10.5194/nhess-18-3297-2018

Lazo, J. K., Hosterman, H. R., Sprague-Hilderbrand, J. M., & Adkins, J. E. (2020). Impact-based decision support services and the socioeconomic impacts of winter storms. *Bulletin of the American Meteorological Society*, *101*, E626–E639. https://doi.org/10.1175/bams-d-18-0153.1

Leckebusch, G. C., Ulbrich, U., Fröhlich, L., & Pinto, J. G. (2007). Property loss potentials for European midlatitude storms in a changing climate. *Geophysical Research Letters*, *34*, L05703. https://doi.org/10.1029/2006GL027663

LeClerc, J., & Joslyn, S. (2015). The cry wolf effect and weather-related decision making. *Risk Analysis*, *35*, 385–395. https://doi.org/10.1111/risa.12336

Leng, G., & Hall, J. (2019). Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. *Science of the Total Environment*, *654*(2019), 811–821. https://doi.org/10.1016/j.scitotenv.2018.10.434

Leonard, G. S., Stewart, C., Wilson, T. M., Procter, J. N., Scott, B. J., Keys, H. J., et al. (2014). Integrating multidisciplinary science, modelling and impact data into evolving, syn-event volcanic hazard mapping and communication: A case study from the 2012 Tongariro eruption crisis, New Zealand. *Journal of Volcanology and Geothermal Research*, *286*, 208–232. https://doi.org/10.1016/j.jvolgeores.2014.08.018

Leone, F., Lavigne, F., Paris, R., Denain, J. C., & Vinet, F. (2010). A spatial analysis of the December 26th, 2004 tsunami-induced damages: Lessons learned for a better risk assessment integrating buildings vulnerability. *Applied Geography*, *31*, 363–375. https://doi.org/10.1016/j.apgeog.2010.07.009

Li, D., Yuan, J., & Kopp, R. E. (2020). Escalating global exposure to compound heat-humidity extremes with warming. *Environmental Research Letters*, *15*(6), 064003. https://doi.org/10.1088/1748-9326/ab7d04

Lindsay, J., Marzocchi, W., Jolly, G., Constantinescu, R., Selva, J., & Sandri, L. (2010). Towards real-time eruption forecasting in the Auckland Volcanic Field: Application of BET_EF during the New Zealand National Disaster Exercise 'Ruaumoko'. *Bulletin of Volcanology*, *72*(2), 185–204. https://doi.org/10.1007/s00445-009-0311-9

Liu, A., & Yamada, M. (2014). Bayesian approach for identification of multiple events in an early warning system. *Bulletin of the Seismological Society of America*, *104*(3), 1111–1121. https://doi.org/10.1785/0120130208

Loughlin, S., Barsotti, S., Bonadonna, C., & Calder, E. (2017). Geophysical risk: Volcanic activity. In *Science for Disaster Risk Management 2017: Knowing better and losing less* (pp. 3–2). France: Université de Genève, Faculté des Sciences/Section des Sciences de la Terre et de l'Environnement/Département des Sciences de la Terre.

Loughlin, S. C., Sparks, R. S. J., Sparks, S., Brown, S. K., Jenkins, S. F., & Vye-Brown, C. (2015). *Global volcanic hazards and risk*. Cambridge, UK: Cambridge University Press.

Lowe, D., Ebi, K. L., & Forsberg, B. (2011). Heatwave early warning systems and adaptation advice to reduce human health consequences of heatwaves. *International Journal of Environmental Research and Public Health*, *8*(12), 4623–4648. https://doi.org/10.3390/ijerph8124623

Lowe, R., García-Díez, M., Ballester, J., Creswick, J., Robine, J.-M., Herrmann, F. R., & Rodó, X. (2016). Evaluation of an early-warning system for heat wave-related mortality in Europe: Implications for sub-seasonal to seasonal forecasting and climate services. *International Journal of Environmental Research and Public Health*, *13*(2), 206. https://doi.org/10.3390/ijerph13020206

Lustig, T. L., Handmer, J. W., & Smith, D. I. (1988). The Sydney floods of 1986: Warnings, damages, policy and the future. In *Hydrology and water resources symposium* (pp. 206–210). Canberra, Australia: Institution of Engineers.

Lynett, P. (2016). Precise prediction of coastal and overland flow dynamics: A grand challenge or a fool's errand. *Journal of Disaster Research*, *11*(4), 615–623. https://doi.org/10.20965/jdr.2016.p0615

Maeda, T., Obara, K., Shinohara, M., Kanazawa, T., & Uehira, T. (2015). Successive estimation of a tsunami wavefield without earthquake source data: A data assimilation approach toward real-time tsunami forecasting. *Geophysical Research Letters*, *42*, 7923–7932. https://doi.org/10.1002/2015GL065588

Manga, M., & Brodsky, E. (2006). Seismic triggering of eruptions in the far field: Volcanoes and geysers. *Annual Review of Earth and Planetary Sciences*, *34*, 263–291. https://doi.org/10.1146/annurev.earth.34.031405.125125

Marin-Ferrer, M., Vernaccini, L., & Poljansek, K. (2017). *Index for risk management INFORM concept and methodology Report—Version 2017, EUR 28655 EN, 2017*. Luxembourg: Publications Office of the European Union. https://doi.org/10.2760/094023

Markowski, P., & Richardson, Y. (2010). *Mesoscale meteorology in midlatitudes* (pp. 1–407). USA: Wiley Blackwell.

Martí, J., Aspinall, W. P., Sobradelo, R., Felpeto, A., Geyer, A., Ortiz, R., & Lopez, C. (2008). A long-term volcanic hazard event tree for Teide-Pico Viejo stratovolcanoes (Tenerife, Canary Islands). *Journal of Volcanology and Geothermal Research*, *178*(3), 543–552. https://doi.org/10.1016/j.jvolgeores.2008.09.023

Marzocchi, W., & Bebbington, M. S. (2012). Probabilistic eruption forecasting at short and long time scales. *Bulletin of Volcanology*, *74*(8), 1777–1805. https://doi.org/10.1007/s00445-012-0633-x

Marzocchi, W., Garcia-Aristizabal, A., Gasparini, P., Mastellone, M. L., & Di Ruocco, A. (2012). Basic principles of multi-risk assessment: A case study in Italy. *Natural Hazards*, *62*(2), 551–573. https://doi.org/10.1007/s11069-012-0092-x

Marzocchi, W., Lombardi, A. M., & Casarotti, E. (2014). The establishment of an operational earthquake forecasting system in Italy. *Seismological Research Letters*, *85*(5), 961–969. https://doi.org/10.1785/0220130219

Marzocchi, W., Sandri, L., & Selva, J. (2008). BET_EF: A probabilistic tool for long- and short-term eruption forecasting. *Bulletin of Volcanology*, *70*, 623–632. https://doi.org/10.1007/s00445-007-0157-y

Marzocchi, W., Taroni, M., & Falcone, G. (2017). Earthquake forecasting during the complex Amatrice-Norcia seismic sequence. *Science Advances*, *3*(9), e1701239. https://doi.org/10.1126/sciadv.1701239

Marzocchi, W., & Woo, G. (2007). Probabilistic eruption forecasting and the call for an evacuation. *Geophysical Research Letters*, *34*, L22310. https://doi.org/10.1029/2007GL031922

Matthies, F., Bickler, G., Marin, N., & Hales, S. (2008). In F. Matthies, G. Bickler, N. Marin, & S. Hales (Eds.), *WHO Europe, Heat-health action plans*. Copenhagen, Denmark: WHO Regional Office for Europe.

McDonald, G. W., Cronin, S. J., Kim, J.-H., Smith, N. J., Murray, C. A., & Procter, J. N. (2017). Computable general equilibrium modelling of economic impacts from volcanic event scenarios at regional and national scale, Mt. Taranaki. *New Zealand Bulletin Volcanology*, *79*, 87. https://doi.org/10.1007/s00445-017-1171-3

McKee, T. B., Doesken, N. J., & Kleist, J. (1993). *The relationship of drought frequency and duration to time scales* (pp. 179–184). Paper presented at 8th Conference on Applied Climatology, American Meteorological Society, Anaheim, CA.
Mead, S. R., Magill, C., Lemiale, V., Thouret, J.-C., & Prakash, M. (2017). Examining the impact of lahars on buildings using numerical modelling. *Natural Hazards and Earth System Sciences*, *17*, 703–719. https://doi.org/10.5194/nhess-17-703-2017
Meehl, G. A., & Tebaldi, C. (2004). More intense, more frequent, and longer lasting heat waves in the 21st century. *Science*, *305*(5686), 994–997. https://doi.org/10.1126/science.1098704
Meier, M.-A., Heaton, T., & Clinton, J. (2015). The Gutenberg algorithm: Evolutionary Bayesian magnitude estimates for earthquake early warning with a filter bank. *Bulletin of the Seismological Society of America*, *105*(5), 2774–2786. https://doi.org/10.1785/0120150098
Melchiorri, M., Pesaresi, M., Florczyk, A. J., Corbane, C., & Kemper, T. (2019). Principles and applications of the global human settlement layer as baseline for the land use efficiency indicator-SDG 11.3. 1. ISPRS. *International Journal of Geo-Information*, *8*(2), 96. https://doi.org/10.3390/ijgi8020096
Melet, A., Meyssignac, B., Almar, R., & Le Cozannet, G. (2018). Under-estimated wave contribution to coastal sea-level rise. *Nature Climate Change*, *8*(3), 234–239. https://doi.org/10.1038/s41558-018-0088-y
Melgar, D., Allen, R. M., Riquelme, S., et al. (2016). Local tsunami warnings: Perspectives from recent large events. *Geophysical Research Letters*, *43*, 1109–1117. https://doi.org/10.1002/2015GL067100
Merz, B., Kreibich, H., Schwarze, R., & Thieken, A. H. (2010). Review article "Assessment of economic flood damage". *Natural Hazards and Earth System Sciences*, *10*(8), 1697–1724. https://doi.org/10.5194/nhess-10-1697-2010
Merz, R., & Blöschl, G. (2003). A process typology of regional floods. *Water Resources Research*, *39*, 1340. https://doi.org/10.1029/2002WR001952
Michael, A. J., McBride, S. K., Hardebeck, J. L., Barall, M., Martinez, E., Page, M. T., et al. (2019). Statistical seismology and communication of the USGS operational aftershock forecasts for the 30 November 2018 *Mw* 7.1 Anchorage, Alaska, Earthquake. *Seismological Research Letters*, *91*, 153–173. https://doi.org/10.1785/0220190196
Middlemiss, R. P., Samarelli, A., Paul, D. J., Hough, J., Rowan, S., & Hammond, G. D. (2016). Measurement of the Earth tides with a MEMS gravimeter. *Nature*, *531*(7596), 614–617. https://doi.org/10.1038/nature17397
Miller, P. W., Black, A. W., Williams, C. A., & Knox, J. A. (2016). Maximum wind gusts associated with human-reported non convective wind events and a comparison to current warning issuance criteria. *Weather and Forecasting*, *31*, 451–465. https://doi.org/10.1175/WAF-D-15-0112.1
Miltenberger, A., Field, P., Hill, A., Shipway, B., & Wilkinson, J. (2018). Aerosol–cloud interactions in mixed-phase convective clouds—Part 2: Meteorological ensemble. *Atmospheric Chemistry and Physics*, *18*(14), 10593–10613. https://doi.org/10.5194/acp-18-10593-2018
Minson, S. E., Meier, M.-A., Baltay, A. S., Hanks, T. C., & Cochran, E. S. (2018). The limits of earthquake early warning: Timeliness of ground motion estimates. *Science Advances*, *4*(3). https://doi.org/10.1126/sciadv.aaq0504
Minson, S., Baltay, A., Cochran, E., Hanks, T., Page, M., McBride, S., et al. (2019). The limits of earthquake early warning accuracy and best alerting strategy. *Scientific Reports*, *9*. https://doi.org/10.1038/s41598-019-39384-y
Miralles, D. G., Teuling, A. J., van Heerwaarden, C. C., & Vilà-Guerau de Arellano, J. (2014). Mega-heatwave temperatures due to combinded soil desiccation and atmospheric heat accumulation. *Nature Geoscience*, *7*, 345–349. https://doi.org/10.1038/NGEO2141
Mitchell, D., Heaviside, C., Vardoulakis, S., Huntingford, C., Masato, G., Guillod, P., & Allen, M. (2016). Attributing human mortality during extreme heat waves to anthropogenic climate change. *Environmental Research Letters*, *11*(7), 074006. https://doi.org/10.1088/1748-9326/11/7/074006
Molinari, D., Ballio, F., & Menoni, S. (2013). Modelling the benefits of flood emergency management measures in reducing damages: A case study on Sondrio, Italy. *Natural Hazards and Earth System Sciences*, *13*(8), 1913–1927. https://doi.org/10.5194/nhess-13-1913-2013
Moon, H., Gudmundsson, L., & Seneviratne, S. I. (2018). Drought persistence errors in global climate models. *Journal of Geophysical Research: Atmospheres*, *123*, 3483–3496. https://doi.org/10.1002/2017JD027577
Morss, R. E., Mulder, K. J., Lazo, J. K., & Demuth, J. L. (2016). How do people perceive, understand, and anticipate responding to flash flood risks and warnings? Results from a public survey in Boulder, Colorado, USA. *Journal of Hydrology*, *541*, 649–664. https://doi.org/10.1016/j.jhydrol.2015.11.047
Mu, D., Kaplan, T. R., & Dankers, R. (2018). Decision making with risk-based weather warnings. *International Journal of Disaster Risk Reduction*, *30*, 59–73. https://doi.org/10.1016/j.ijdrr.2018.03.030
Mulia, I. E., Gusman, A. R., & Satake, K. (2018). Alternative to non-linear model for simulating tsunami inundation in real-time. *Geophysical Journal International*, *214*, 202–213. https://doi.org/10.1093/gji/ggy238
Muller, C., Chapman, L., Johnston, S., Kidd, C., Illingworth, S., Foody, G., et al. (2015). Crowdsourcing for climate and atmospheric sciences: Current status and future potential. *International Journal of Climatology*, *35*(11), 3185–3203. https://doi.org/10.1002/joc.4210
Musa, A., Abe, T., Inoue, T., & Kobayashi, H. (2018). A real-time tsunami inundation forecast system using vector supercomputer SX-ACE. *Journal of Disaster Research*, *13*(2), 234–244. https://doi.org/10.20965/jdr.2018.p0234
Nakamura, Y., Saita, J., & Sato, T. (2011). On an earthquake early warning system (EEW) and its applications. *Soil Dynamics and Earthquake Engineering*, *31*(2), 127–136. https://doi.org/10.1016/j.soildyn.2010.04.012
Naumann, G., Spinoni, J., Vogt, J. V., & Barbosa, P. (2015). Assessment of drought damages and their uncertainties in Europe. *Environmental Research Letters*, *10*, 124013. https://doi.org/10.1088/1748-9326/10/12/124013
Neal, R. A., Boyle, P., Grahame, N., Mylne, K., & Sharpe, M. (2014). Ensemble based first guess support towards a risk-based severe weather warning service. *Meteorological Applications*, *21*, 563–577. https://doi.org/10.1002/met.1377
Neri, A., Bevilacqua, A., Esposti Ongaro, T., Isaia, R., Aspinall, W. P., Bisson, M., & Orsucci, S. (2015). Quantifying volcanic hazard at Campi Flegrei caldera (Italy) with uncertainty assessment: 2. Pyroclastic density current invasion maps. *Journal of Geophysical Research: Solid Earth*, *120*, 2330–2349. https://doi.org/10.1002/2014JB011776
Nguyen, P., Thorstensen, A., Sorooshian, S., Hsu, K., & AghaKouchak, A. (2015). Flood forecasting and inundation mapping using HiResFlood-UCI and near-real-time satellite precipitation data: The 2008 Iowa flood. *Journal of Hydrometeorology*, *16*(3), 1171–1183. https://doi.org/10.1175/JHM-D-14-0212.1
Ni, X., Liu, C., Cecil, D. J., & Zhang, Q. (2017). On the detection of hail using satellite passive microwave radiometers and precipitation radar. *Journal of Applied Meteorology and Climatology*, *56*, 2693–2709. https://doi.org/10.1175/JAMC-D-17-0065.1
Nisi, L., Ambrosetti, P., & Clementi, L. (2014). Nowcasting severe convection in the Alpine region: The COALITION approach. *Quarterly Journal of the Royal Meteorological Society*, *140*, 1684–1699. https://doi.org/10.1002/qj.2249
Nisi, L., Hering, A., Germann, U., & Martius, O. (2018). A 15-year hail streak climatology for the Alpine region. *Quarterly Journal of the Royal Meteorological Society*, *144*(714), 1429–1449. https://doi.org/10.1002/qj.3286

Nobre, G., Hunink, J. E., Baruth, B., Aerts, J. C. J. H., & Ward, P. J. (2019). Translating large-scale climate variability into crop production forecast in Europe. *Scientific Reports*, *9*, 1277. https://doi.org/10.1038/s41598-018-38091-4

NWS (2018). Service description document—Impact-based decision support services for NWS core partners. In *National Weather Service Report* (pp. 1–24). Silver Spring, USA: National Oceanic and Atmospheric Administration National Weather Service. Retrieved from www.nws.noaa.gov/im/IDSS_SDD_V1_0.pdf

Ochoa-Rodríguez, S., Wang, L.-P., Thraves, L., Johnston, A., & Onof, C. (2018). Surface water flood warnings in England: overview, assessment and recommendations based on survey responses and workshops. *Journal of Flood Risk Management*, *11*(S1), S211–S221. https://doi.org/10.1111/jfr3.12195

Ogiso, M., Matsubayashi, H., & Yamamoto, T. (2015). Descent of tremor source locations before the 2014 phreatic eruption of Ontake volcano, Japan. *Earth, Planets and Space*, *67*, 206. https://doi.org/10.1186/s40623-015-0376-y

Ohta, Y., Inoue, T., Koshimura, S., Kawamoto, S., & Hino, R. (2018). Role of real-time GNSS in near-field tsunami forecasting. *Journal of Disaster Research*, *13*(3), 453–459. https://doi.org/10.20965/jdr.2018.p0453

Oishi, Y., Imamura, F., & Sugawara, D. (2015). Near-field tsunami inundation forecast using the parallel TUNAMI-N2 model: Application to the 2011 Tohoku-Oki earthquake combined with source inversions. *Geophysical Research Letters*, *42*, 1083–1091. https://doi.org/10.1002/2014GL062577

Pagnoni, L., & Tinti, S. (2016). Application and comparison of tsunami vulnerability and damage models for the town of Siracusa, Sicily, Italy. *Pure and Applied Geophysics*, *173*, 3795–3822. https://doi.org/10.1007/s00024-016-1261-8

Palmer, T. (2017). The primacy of doubt: Evolution of numerical weather prediction from determinism to probability. *Journal of Advances in Modeling Earth Systems*, *9*, 730–734. https://doi.org/10.1002/2017ms000999

Palmer, T. N. (2000). Predicting uncertainty in forecasts of weather and climate. *Reports on Progress in Physics*, *63*, 71–116. https://doi.org/10.1088/0034-4885/63/2/201

Palutikof, J. P., & Skellern, A. R. (1991). *Storm severity over Britain: A report to Commercial Union General Insurance*. Norwich, UK: Climatic Research Unit, *School of Environmental Science*, University of East Anglia.

Pantillon, F., Lerch, S., Knippertz, P., & Corsmeier, U. (2017). Revisiting the synoptic-scale predictability of severe European winter storms using ECMWF ensemble reforecasts. *Natural Hazards and Earth System Sciences*, *17*, 1795–1810. https://doi.org/10.5194/nhess-17-1795-2017

Pantillon, F., Lerch, S., Knippertz, P., & Corsmeier, U. (2018). Forecasting wind gusts in winter storms using a calibrated convection-permitting ensemble. *Quarterly Journal of the Royal Meteorological Society*, *144*, 1864–1881. https://doi.org/10.1002/qj.3380

Papale, P. (2017). Rational volcanic hazard forecasts and the use of volcanic alert levels. *Journal of Applied Volcanology*, *6*, 13. https://doi.org/10.1186/s13617-017-0064-7

Papathoma, M., Dominey-Howes, D., Zong, Y., & Smith, D. (2003). Assessing tsunami vulnerability, an example from Herakleio, Crete. *Natural Hazards and Earth System Sciences*, *3*, 377–389. https://doi.org/10.5194/nhess-3-377-2003

Pappenberger, F., Cloke, H. L., Parker, D. J., Wetterhall, F., Richardson, D. S., & Thielen, J. (2015). The monetary benefit of early flood warnings in Europe. *Environmental Science & Policy*, *51*, 278–291. https://doi.org/10.1016/j.envsci.2015.04.016

Pardowitz, T., Osinski, O., Kruschke, T., & Ulbrich, U. (2016). An analysis of uncertainties and skill in forecasts of winter storm losses. *Natural Hazards and Earth System Sciences*, *16*, 2391–2402. https://doi.org/10.5194/nhess-16-2391-2016

Parker, D. J., & Priest, S. J. (2012). The fallibility of flood warning chains: Can Europe's flood warnings be effective. *Water Resources Management*, *26*(10), 2927–2950. https://doi.org/10.1007/s11269-012-0057-6

Parker, L. E., Ostoja, S. M., McElrone, A. J., & Forrestel, E. J. (2020). Extreme heat effects on perennial crops and strategies for sustaining future production. *Plant Science*, *295*, 110397. https://doi.org/10.1016/j.plantsci.2019.110397

Parolai, S., Bindi, D., Boxberger, T., Milkereit, C., Fleming, K., & Pittore, M. (2015). On site early warning and rapid damage forecasting using single stations: Outcomes from the REAKT project. *Seismological Research Letters*, *86*(5), 1393–1404. https://doi.org/10.1785/0220140205

Parolai, S., Boxberger, T., Pilz, M., Fleming, K., Haas, M., Pittore, M., et al. (2017). Assessing earthquake early warning using sparse networks in developing countries: Case study of the Kyrgyz Republic. *Frontiers in Earth Science*, *5*, 74. https://doi.org/10.3389/feart.2017.00074

Paton, D., Anderson, E., Becker, J., & Petersen, J. (2015). Developing a comprehensive model of hazard preparedness: Lessons from the Christchurch earthquake. *International Journal of Disaster Risk Reduction*, *14*, 37–45. https://doi.org/10.1016/j.ijdrr.2014.11.011

Perkins, S. E., Alexander, L. V., & Nairn, J. R. (2012). Increasing frequency, intensity and duration of observed global heatwaves and warm spells. *Geophysical Research Letters*, *39*, L20714. https://doi.org/10.1029/2012GL053361

Petrazzuoli, S. M., & Zuccaro, G. (2004). Structural resistance of reinforced concrete buildings under pyroclastic flows: A study of the Vesuvian area. *Journal of Volcanology and Geothermal Research*, *133*, 353–367. https://doi.org/10.1016/S0377-0273(03)00407-4

Petroliagis, T. I., & Pinson, P. (2014). Early warnings of extreme winds using the ECMWF extreme forecast index. *Meteorological Application*, *21*, 171–185. https://doi.org/10.1002/met.1339

Petrone, C., Rossetto, T., Baiguera, M., De La Barra, C., & Ioannou, I. (2020). Fragility functions for a reinforced concrete structure subjected to earthquake and tsunami in sequence. *Engineering Structures*, *205*(2), 110120. https://doi.org/10.1016/j.engstruct.2019.110120

Pfahl, S., & Wernli, H. (2012). Quantifying the relevance of atmospheric blocking for co-located temperature extremes in the Northern Hemisphere on (sub)daily time scales. *Geophydical Research Letters*, *39*, L12807. https://doi.org/10.1029/2012GL052261

Pilkington, S. F., & Mahmoud, H. N. (2017). Real-time application of the multihazard hurricane impact level model for the Atlantic Basin. *Frontiers in Built Environment*, *3*, 1135. https://doi.org/10.3389/fbuil.2017.00067

Pinto, J. G., Gómara, I., Masato, G., Dacre, H. F., Woollings, T., & Caballero, R. (2014). Large-scale dynamics associated with clustering of extratropical cyclones affecting western Europe. *Journal of Geophysical Research: Atmospheres*, *119*, 13,704–13,719. https://doi.org/10.1002/2014JD022305

Pinto, J. G., Karremann, M. K., Born, K., Della-Marta, P. M., & Klawa, M. (2012). Loss potentials associated with European windstorms under future climate conditions. *Climate Research*, *54*, 1–20. https://doi.org/10.3354/cr01111

Pinto, J. G., Pantillon, F., Ludwig, P., Déroche, M. S., Leoncini, G., Raible, C. C., et al. (2019). From atmospheric dynamics to insurance losses—An interdisciplinary workshop on European windstorms. *Bulletin of the American Meteorological Society*, *100*, ES175–ES178. https://doi.org/10.1175/BAMS-D-19-0026.1

Pittore, M., Bindi, D., Stankiewicz, J., Oth, A., Wieland, M., Boxberger, T., & Parolai, S. (2014). Toward a loss-driven earthquake early warning and rapid response system for Kyrgyzstan (Central Asia). *Seismological Research Letters*, *85*, 1328–1340. https://doi.org/10.1785/0220140106

Pittore, M., Wieland, M., & Fleming, K. (2017). Perspectives on global dynamic exposure modelling for geo-risk assessment. *Natural Hazards*, *86*(Supplement 1), 7–30. https://doi.org/10.1007/s11069-016-2437-3

Poland, M. P., & Anderson, K. R. (2020). Partly cloudy with a chance of lava flows: Forecasting volcanic eruptions in the twenty-first century. *Journal of Geophysical Research: Solid Earth*, *125*, e2018jb016974. https://doi.org/10.1029/2018JB016974

Potter, S. H., Kreft, P. V., Milojev, P., Noble, C., Montz, B., Dhellemmes, A., et al. (2018). The influence of impact-based severe weather warnings on risk perceptions and intended protective actions. *International Journal of Disaster Risk Reduction*, *30*, 34–43. https://doi.org/10.1016/j.ijdrr.2018.03.031

Pozzi, W., Sheffield, J., Stefanski, R., Cripe, D., Pulwarty, R., Vogt, J. V., et al. (2013). Toward global drought early warning capability: Expanding international cooperation for the development of a framework for monitoring and forecasting. *Bulletin of the American Meteorological Society*, *94*, 776–785. https://doi.org/10.1175/BAMS-D-11-00176.1

Prahl, B. F., Rybski, D., Burghoff, O., & Kropp, J. P. (2015). Comparison of storm damage functions and their performance. *Natural Hazards and Earth System Sciences*, *15*, 769–788. https://doi.org/10.5194/nhess-15-769-2015

Prata, A. J. (2009). Satellite detection of hazardous volcanic clouds and the risk to global air traffic. *Natural Hazards*, *51*, 303–324. https://doi.org/10.1007/s11069-008-9273-z

Pulwarty, R. S., & Sivakumar, M. V. K. (2014). Information systems in a changing climate: Early warnings and drought risk management. *Weather and Climate Extremes*, *3*, 14–21. https://doi.org/10.1016/j.wace.2014.03.005

Puskeiler, M., Kunz, M., & Schmidberger, M. (2016). Hail statistics for Germany derived from single-polarization radar data. *Atmospheric Research*, *178–179*, 459–470. https://doi.org/10.1016/j.atmosres.2016.04.014

Quandt, L.-A., Keller, J. H., Martius, O., & Jones, S. C. (2017). Forecast variability of the blocking system over Russia in summer 2010 and its impact on surface conditions. *Weather and Forecasting*, *32*(1), 61–82. https://doi.org/10.1175/waf-d-16-0065.1

Raei, E., Nikoo, M. R., AghaKouchak, A., Mazdiyasni, O., & Sadegh, M. (2018). Data descriptor: GHWR, a multi-method global heatwave and warm-spell record and toolbox. *Scientific Data*, *5*. https://doi.org/10.1038/sdata.2018.206

Rapicetta, S., & Zanon, V. (2009). GIS-based method for the environmental vulnerability assessment to volcanic ashfall at Etna Volcano. *GeoInformatica*, *13*, 267–276. https://doi.org/10.1007/s10707-008-0061-4

Rauhala, J., & Schultz, D. M. (2009). Severe thunderstorm and tornado warnings in Europe. *Atmospheric Research*, *93*, 369–380. https://doi.org/10.1016/j.atmosres.2008.09.026

Raymond, C., Matthews, T., & Horton, R. M. (2020). The emergence of heat and humidity too severe for human tolerance. *Science Advances*, *6*(19), eaaw1838. https://doi.org/10.1126/sciadv.aaw1838

Munich Re. (2019). *Natural disasters of 2019 in figures*. Munich, Germany: Münchener Rückversicherungs-Gesellschaft. Retrieved from https://www.munichre.com/topics-online/en/climate-change-and-natural-disasters/natural-disasters/natural-disasters-of-2019-in-figures-tropical-cyclones-cause-highest-losses.html

Renggli, D., Leckebusch, G. C., Ulbrich, U., Gleixner, S. N., & Faust, E. (2011). The skill of seasonal ensemble prediction systems to forecast wintertime windstorm frequency over the North Atlantic and Europe. *Monthly Weather Review*, *139*, 3052–3068. https://doi.org/10.1175/2011MWR3518.1

Resio, D. T., Powell, N. J., Cialone, M. A., Das, H. S., & Westerink, J. J. (2017). Quantifying impacts of forecast uncertainties on predicted storm surges. *Natural Hazards*, *88*(3), 1423–1449. https://doi.org/10.1007/s11069-017-2924-1

Ritter, J., Berenguer, M., Corral, C., Park, S., & Sempere-Torres, D. (2020). ReAFFIRM: Real-time assessment of flash flood impacts—A regional high-resolution method. *Environment International*, *136*, 105375. https://doi.org/10.1016/j.envint.2019.105375

Rivalta, E., Corbi, F., Passarelli, L., Acocella, V., Davis, T., & Di Vito, M. A. (2019). Stress inversions to forecast magma pathways and eruptive vent location. *Science Advances*, *5*(7), eaau9784. https://doi.org/10.1126/sciadv.aau9784

Roberts, J. F., Champion, A. J., Dawkins, L. C., Hodges, K. I., Shaffrey, L. C., Stephenson, D. B., et al. (2014). The XWS open access catalogue of extreme European windstorms from 1979 to 2012. *Natural Hazards and Earth System Sciences*, *14*, 2487–2501. https://doi.org/10.5194/nhess-14-2487-2014

Roberts, M. R., Linde, A. T., Vogfjord, K. S., & Sacks, S. (2011). *Forecasting eruptions of Hekla Volcano, Iceland, using borehole strain observations* (Vol. 13). Paper presented at 2011 EGU General Assembly, Vienna, Austria.

Roelvink, D., Reniers, A., van Dongeren, A., van Thiel de Vries, J., McCall, R., & Lescinski, J. (2009). Modelling storm impacts on beaches, dunes and barrier islands. *Coastal Engineering*, *56*(11–12), 1133–1152. https://doi.org/10.1016/j.coastaleng.2009.08.006

Rothfusz, L. P., Schneider, R., Novak, D., Klockow, K., Gerard, A. E., Karstens, C., et al. (2018). FACETs: A proposed next-generation paradigm for high-impact weather forecasting. *Bulletin of the American Meteorological Society*, *99*(10), 2025–2043. https://doi.org/10.1175/BAMS-D-16-0100.1

Roulston, M. S., Bolton, G. E., & Kleit, A. N. (2006). A laboratory study of the benefits of including uncertainty information in weather forecasts. *Weather and Forecasting*, *21*, 116–122. https://doi.org/10.1175/waf887.1

Rouwet, D., Sandri, D., Marzocchi, W., Gottsmann, J., Selva, J., Tonini, R., & Papale, P. (2014). Recognizing and tracking volcanic hazards related to non-magmatic unrest: A review. *Journal of Applied Volcanology*, *3*, 17. https://doi.org/10.1186/s13617-014-0017-3

Russo, S., Sillmann, J., & Fischer, E. M. (2015). Top ten European heatwaves since 1950 and their occurrence in the coming decades. *Environmental Research Letters*, *10*(12), 124003. https://doi.org/10.1088/1748-9326/10/12/124003

Sai, F., Cumiskey, L., Weerts, A., Bhattacharya, B., & Haque Khan, R. (2018). Towards impact-based flood forecasting and warning in Bangladesh: A case study at the local level in Sirajganj district. *Natural Hazards and Earth System Sciences Discussions*, 1–20. https://doi.org/10.5194/nhess-2018-26

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

Sánchez, J., Gil-Robles, B., Dessens, J., Martin, E., Lopez, L., Marcos, J., et al. (2009). Characterization of hailstone size spectra in hailpad networks in France, Spain, and Argentina. *Atmospheric Research*, *93*, 641–654. https://doi.org/10.1016/j.atmosres.2008.09.033

Satake, K. (2002). Tsunamis. In W. Lee et al. (Eds.), *International handbook of earthquake and engineering seismology, Part A* (Vol. 81A, pp. 437–451). Amsterdam, The Netherlands: Academic Press.

Satriano, C., Wu, Y.-M., Zollo, A., & Kanamori, H. (2011). Earthquake early warning: Concepts, methods and physical grounds. *Soil Dynamics and Earthquake Engineering*, *31*(2), 106–118. https://doi.org/10.1016/j.soildyn.2010.07.007

Scaini, C., Biass, S., Galderisi, A., Bonadonna, C., Folch, A., Smith, K., & Höskuldsson, A. (2014). A multi-scale risk assessment for tephra fallout and airborne concentration from multiple Icelandic volcanoes—Part 2: Vulnerability and impact. *Natural Hazards and Earth System Sciences*, *14*, 2289–2312. https://doi.org/10.5194/nhess-14-2289-2014

Scaini, C., Folch, A., Bolić, T., & Castelli, L. (2014). A GIS-based tool to support air traffic management during explosive volcanic eruptions. Transportation research part C: Emerging technologies. *Transportation Research Part C: Emerging Technologies*, *49*, 19–31. https://doi.org/10.1016/j.trc.2014.09.020

Schewe, J., Gosling, S. N., Reyer, C., Zhao, F., Ciais, P., Elliott, J., et al. (2019). State-of-the-art global models underestimate impacts from climate extremes. *Nature Communications*, *1005*(2019), 10. https://doi.org/10.1038/s41467-019-08745-6

Schmidberger, M. (2017). *Hagelgefährdung in Deutschland basierend aufeiner Kombination von Radardaten und Versicherungsdaten. Ph.D. thesis*. Germany: Karlsruhe Institute of Technology (KIT).

Schmidt, J., Matcham, I., Reese, S., King, A., Bell, R., Henderson, R., & Heron, D. (2011). Quantitative multi-risk analysis for natural hazards: A framework for multi-risk modelling. *Natural Hazards*, *58*, 1169–1192. https://doi.org/10.1007/s11069-011-9721-z

Schuster, S. S., Blong, R. J., & McAneney, K. J. (2006). Relationship between radar-derived hail kinetic energy and damage to insured buildings for severe hailstorms in Eastern Australia. *Atmospheric Research*, *81*, 215–235. https://doi.org/10.1016/j.atmosres.2005.12.003

Selva, J., Costa, A., Sandri, L., Macedonio, G., & Marzocchi, W. (2014). Probabilistic short-term volcanic hazard in phases of unrest: A case study for tephra fallout. *Journal of Geophysical Research: Solid Earth*, *119*, 8805–8826. https://doi.org/10.1002/2014JB011252

Seneviratne, I. S., Corti, T., Davin, I. E., Hirschi, M., Jaeger, B. E., Lehner, I., et al. (2010). Investigating soil moisture-climate interactions in a changing climate: A review. *Earth-Science Reviews*, *99*, 125–161. https://doi.org/10.1016/j.earscirev.2010.02.004

Shabou, S., Ruin, I., Lutoff, C., Debionne, S., Anquetin, S., Creutin, J.-D., & Beaufils, X. (2017). MobRISK: A model for assessing the exposure of road users to flash flood events. *Natural Hazards and Earth System Sciences*, *17*, 1631–1651. https://doi.org/10.5194/nhess-17-1631-2017

Shafiee-Jood, M., Cai, X., Chen, L., Liang, X. Z., & Kumar, P. (2014). Assessing the value of seasonal climate forecast information through an end-to-end forecasting framework: Application to U.S. 2012 drought in Central Illinois. *Water Resources Research*, *50*, 6592–6609. https://doi.org/10.1002/2014WR015822

Shebalin, P. N., Narteau, C., Zechar, J. D., & Holschneider, M. (2014). Combining earthquake forecasts using differential probability gains. *Earth, Planets and Space*, *66*, 37. https://doi.org/10.1186/1880-5981-66-37

Sheffield, J., Wood, E. F., Chaney, N., Guan, K., Sadri, S., Yuan, X., et al. (2014). A drought monitoring and forecasting system for sub-Sahara African water resources and food security. *Bulletin of the American Meteorological Society*, *95*, 861–882. https://doi.org/10.1175/BAMS-D-12-00124.1

Simmons, K., & Sutter, D. (2013). *Economic and societal impacts of tornadoes* (pp. 1–282). Heidelberg, Germany: Springer Science & Business Media.

Simmons, K. M., & Sutter, D. (2011). Tornado climatology and society's tornado risk. In *Economic and societal impacts of tornadoes* (pp. 9–44). Boston, MA: American Meteorological Society. https://doi.org/10.1007/978-1-935704-02-7_2

Sobradelo, R., Martí, J., Kilburn, C., & López, C. (2015). Probabilistic approach to decision-making under uncertainty during volcanic crises: Retrospective application to the El Hierro (Spain) 2011 volcanic crisis. *Natural Hazards*, *76*, 979–998. https://doi.org/10.1007/s11069-014-1530-8

Solana, M. C., Kilburn, C. R., & Rolandi, G. (2008). Communicating eruption and hazard forecasts on Vesuvius, Southern Italy. *Journal of Volcanology and Geothermal Research*, *172*(3–4), 308. https://doi.org/10.1016/j.jvolgeores.2007.12.027

Souri, A. H., Wang, H., González Abad, G., Liu, X., & Chance, K. (2020). Quantifying the impact of excess moisture from transpiration from crops on an extreme heat wave event in the midwestern U.S.: A top-down constraint from Moderate Resolution Imaging Spectroradiometer water vapor retrieval. *Journal of Geophysical Research: Atmospheres*, *125*, e2019JD031941. https://doi.org/10.1029/2019JD031941

Souza, A. J., Brown, J. M., Williams, J. J., & Lymbery, G. (2014). Application of an operational storm coastal impact forecasting system. *Journal of Operational Oceanography*, *6*(1), 23–26. https://doi.org/10.1080/1755876X.2013.11020142

Sparks, R. S. J., & Aspinall, W. P. (2004). Volcanic activity: Frontiers and challenges in forecasting, prediction and risk assessment. In *The state of the planet: Frontiers and challenges in geophysics* (Vol. 150, pp. 359–371). International Union of Geodesy and Geophysics and the American Geophysical Union.

Spence, R. J. S., Baxter, P. J., & Zuccaro, G. (2004). Building vulnerability and human casualty estimation for a pyroclastic flow: A model and its application to Vesuvius. *Journal of Volcanology and Geothermal Research*, *133*, 321–343. https://doi.org/10.1016/S0377-0273(03)00405-0

Spence, R. J. S., Kelman, I., Calogero, E., Toyos, G., Baxter, P. J., & Komorowski, J.-C. (2005). Modelling expected physical impacts and human casualties from explosive volcanic eruptions. *Natural Hazards and Earth System Sciences*, *5*, 1003–1015. https://doi.org/10.5194/nhess-5-1003-2005

Srivihok, P., Honda, K., Ruangrassamee, A., Muangsin, V., Naparat, P., Foytong, P., et al. (2014). Development of an online tool for tsunami inundation simulation and tsunami loss estimation. *Continental Shelf Research*, *79*, 3–15. https://doi.org/10.1016/j.csr.2012.08.021

Stafford, P. J. (2012). Evaluation of structural performance in the immediate aftermath of an earthquake: A case study of the 2011 Christchurch earthquake. *International Journal of Forensic Engineering*, *1*(1), 58–77. https://doi.org/10.1504/IJFE.2012.047447

Stagge, J. H., Kohn, I., Tallaksen, L. M., & Stahl, K. (2015). Modeling drought impact occurrence based on climatological drought indices for Europe. *Journal of Hydrology*, *530*, 17–50. https://doi.org/10.1016/j.jhydrol.2015.09.039

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

Staneva, J., Wahle, K., Koch, W., Behrens, A., Fenoglio-Marc, L., & Stanev, E. V. (2016). Coastal flooding: Impact of waves on storm surge during extremes—A case study for the German Bight. *Natural Hazards and Earth System Sciences*, *16*(11), 2373–2389. https://doi.org/10.5194/nhess-16-2373-2016

Steinemann, A. C. (2006). Using climate forecasts for drought management. *Journal of Applied Meteorology and Climatology*, *45*(10), 1353–1361. https://doi.org/10.1175/jam2401.1

Steinmetz, T., Raape, U., Tessmann, S., Strobl, C., Friedemann, M., Kukofka, T., et al. (2010). Tsunami early warning and decision support. *Natural Hazards and Earth System Sciences*, *10*, 1839–1850. https://doi.org/10.5194/nhess-10-1839-2010

Stensrud, D. J. (2001). Using short-range ensemble forecasts for predicting severe weather events. *Atmospheric Research*, *56*, 3–17. https://doi.org/10.1016/S0169-8095(00)00079-X

Stepek, A., Wijnant, I. L., van der Schrier, G., van den Besselaar, E. J. M., & Klein Tank, A. M. G. (2012). Severe wind gust thresholds for Meteoalarm derived from uniform return periods in ECA&D. *Natural Hazards and Earth System Sciences*, *12*(6), 1969–1981. https://doi.org/10.5194/nhess-12-1969-2012

Strunz, G., Post, J., Zosseder, K., & Muhari, A. (2011). Tsunami risk assessment in Indonesia. *Natural Hazards and Earth System Sciences*, *11*, 67–82. https://doi.org/10.5194/nhess-10-1839-2010

Sturkell, E., Einarsson, P., Sigmundsson, F., Geirsson, H., Ólafsson, H., Pedersen, R., et al. (2006). Volcano geodesy and magma dynamics in Iceland. *Journal of Volcanology and Geothermal Research*, *150*(1–3), 14–34. https://doi.org/10.1016/j.jvolgeores.2005.07.010

Suppasri, A., Mas, E., Charvet, I., Gunasekera, R., Imai, K., Fukutani, Y., et al. (2013). Building damage characteristics based on surveyed data and fragility curves of the 2011 Great East Japan tsunami. *Natural Hazards*, *66*, 319–341. https://doi.org/10.1007/s11069-012-0487-8

Suppasri, A., Muhari, A., Syamsidik, Yunus, R., Pakoksung, K., Imamura, F., et al. (2018). Vulnerability characteristics of tsunamis in Indonesia: Analysis of the Global Centre for Disaster Statistics database. *Journal of Disaster Research*, *13*(6), 1039–1048. https://doi.org/10.20965/jdr.2018.p1039

Surono, J. P., Pallister, J., Boichu, M., Buongiorno, M. F., Budisantoso, A., Costa, F., et al. (2012). The 2010 explosive eruption of Java's Merapi volcano—A '100-year' event. *Journal of Volcanology and Geothermal Research*, *241*, 121–135. https://doi.org/10.1016/j.jvolgeores.2012.06.018

Sutanto, S. J., van der Weert, M., Wanders, N., Blauhut, V., & Van Lanen, H. A. J. (2019). Moving from drought hazard to impact forecasts. *Nature Communications*, *10*(1), 4945. https://doi.org/10.1038/s41467-019-12840-z

Swail, V. (2010). Storm Surge. In *Proceedings of OceanObs'09: Sustained ocean observations and information for society* (pp. 949–960). Venice, Italy: European Space Agency.

Tang, L., Titov, V., & Chamberlin, C. (2009). Development, testing, and applications of site-specific tsunami inundation models for real-time forecasting. *Journal of Geophysical Research*, *114*, C12025. https://doi.org/10.1029/2009JC005476

Tanioka, Y., & Gusman, A. R. (2018). Near-field tsunami inundation forecast method assimilating ocean bottom pressure data: A synthetic test for the 2011 Tohoku-oki tsunami. *Physics of the Earth and Planetary Interiors*, *283*, 82–91. https://doi.org/10.1016/j.pepi.2018.08.006

Tarbotton, C., Dall'Osso, F., Dominey-Howes, D., & Goff, J. (2015). The use of empirical vulnerability functions to assess the response of buildings to tsunami impact: Comparative review and summary of best practice. *Earth-Science Reviews*, *142*, 120–134. https://doi.org/10.1016/j.earscirev.2015.01.002

Taylor, A. L., Kox, T., & Johnston, D. (2018). Communicating high impact weather: Improving warnings and decision making processes. *International Journal of Disaster Risk Reduction*, *30*, 1–4. https://doi.org/10.1016/j.ijdrr.2018.04.002

Thieken, A. H., Müller, M., Kreibich, H., & Merz, B. (2005). Flood damage and influencing factors: New insights from the August 2002 flood in Germany. *Water Resources Research*, *41*, W12430. https://doi.org/10.1029/2005WR004177

Thouret, J.-C., Enjolras, G., Martelli, K., Santoni, O., Luque, J. A., Nagata, M., et al. (2013). Combining criteria for delineating lahar- and flash-flood-prone hazard and risk zones for the city of Arequipa, Peru. *Natural Hazards and Earth System Sciences*, *13*, 339–360. https://doi.org/10.5194/nhess-13-339-2013

Titov, V., Gonzalez, F., Bernard, E., Eble, M., Mofjeld, H., Newman, J., & Venturato, A. (2005). Real-time tsunami forecasting: Challenges and solutions. *Natural Hazards*, *35*, 41–58. https://doi.org/10.1007/1-4020-3607-8_3

Tonini, R., Sandri, L., & Thompson, M. (2015). PyBetVH: A Python tool for probabilistic volcanic hazard assessment and for generation of Bayesian hazard curves and maps. *Computational Geosciences*, *79*, 38–46. https://doi.org/10.1016/j.cageo.2015.02.017

Trefalt, S., Martynov, A., Barras, H., Besic, N., Hering, A. M., Lenggenhager, S., et al. (2018). A severe hail storm in complex topography in Switzerland—Observations and processes. *Atmospheric Research*, *209*, 76–94. https://doi.org/10.1016/j.atmosres.2018.03.007

Tsonevsky, I., Doswell, C. A. III, & Brooks, H. E. (2018). Early warnings of severe convection using the ECMWF extreme forecast index. *Weather and Forecasting*, *33*, 857–871. https://doi.org/10.1175/WAF-D-18-0030.1

Tsushima, H., Hino, R., Fujimoto, H., Tanioka, Y., & Imamura, F. (2009). Near-field tsunami forecasting from cabled ocean bottom pressure data. *Journal of Geophysical Research*, *114*, B06309. https://doi.org/10.1029/2008JB005988

Turco, M., Jerez, S., Doblas-Reyes, F. J., AghaKouchak, A., Llasat, M. C., & Provenzale, A. (2018). Skilful forecasting of global fire activity using seasonal climate predictions. *Nature Communications*, *9*, 2718. https://doi.org/10.1038/s41467-018-05250-0

U.S. Geological Survey Staff (1990). The Loma Prieta, California, earthquake: An anticipated event. *Science*, *247*, 286–293. https://doi.org/10.1126/science.247.4940.286

Uccellini, L. W., & Ten Hoeve, J. E. (2019). Evolving the National Weather Service to build a weather-ready nation: Connecting observations, forecasts, and warnings to decision-makers through impact-based decision support services. *Bulletin of the American Meteorological Society*, *100*, 1923–1942. https://doi.org/10.1175/bams-d-18-0159.1

Ulbrich, U., Leckebusch, G. C., & Pinto, J. G. (2009). Extra-tropical cyclones in the present and future climate: A review. *Theoretical and Applied Climatology*, *96*, 117–131. https://doi.org/10.1007/s00704-008-0083-8

UN General Secretariat (1994). *United Nations convention to combat drought and desertification in countries experiencing serious droughts and/or desertification, Particularly in Africa, Paris*. Paris, France: United Nations Treaty Collection.

United Nations Office for Disaster Risk Reduction (UNDRR) (2019). *Global assessment report on disaster risk reduction*. Geneva, Switzerland: United Nations Office for Disaster Risk Reduction. https://gar.unisdr.org

United Nations Environment Programme (UNEP) (2012). *Early warning systems: A state of the art analysis and future directions*. UNEP, Nairobi, Kenya: United Nation Environment Program. (https://europa.eu/capacity4dev/unep/documents/early-warning-systems-state-art-analysis-and-future-directions).

United Nations International Strategy for Disaster Reduction (UNISDR) (2009). *UNISDR terminology on disaster risk reduction*. Geneva, Switzerland: United Nations International Strategy for Disaster Reduction.

UNISDR (2015a). *GAR2015—Global Assessment Report on Disaster Risk Reduction*. Geneva, Switzerland: United Nations Office for Disaster Risk Reduction.

UNISDR (2015b). *Sendai framework for disaster risk reduction 2015–2030*. Geneva, Switzerland: United Nations Office for Disaster Risk Reduction.

Valencia, N., Gardi, A., Gauraz, A., Leone, F., & Guillande, R. (2011). New tsunami damage functions developed in the framework of SCHEMA project: Application to European-Mediterranean coasts. *Hazards and Earth System Science*, *11*, 2835–2846. https://doi.org/10.5194/nhess-11-2835-2011

van Dinther, Y., Künsch, H. R., & Fichtner, A. (2019). Ensemble data assimilation for earthquake sequences: Probabilistic estimation and forecasting of fault stresses. *Geophysical Journal International*, *217*(3), 1453–1478. https://doi.org/10.1093/gji/ggz063

Van Veen, B. A. D., Vatvani, D., & Ziji, F. (2014). Tsunami flood modelling for Aceh & west Sumatra and its application for an early warning system. *Continental Shelf Research*, *79*, 46–53. https://doi.org/10.1016/j.csr.2012.08.020

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate*, *23*, 1696–1718. https://doi.org/10.1175/2009jcli2909.1

Villarini, G., Krajewski, W. F., Ntelekos, A. A., Georgakakos, K. P., & Smith, J. A. (2010). Towards probabilistic forecasting of flash floods: The combined effects of uncertainty in radar-rainfall and flash flood guidance. *Journal of Hydrology*, *394*(1), 275–284. https://doi.org/10.1016/j.jhydrol.2010.02.014

Vousdoukas, M. I., Mentaschi, L., Voukouvalas, E., Bianchi, A., Dottori, F., & Feyen, L. (2018). Climatic and socioeconomic controls of future coastal flood risk in Europe. *Nature Climate Change*, *8*(9), 776–780. https://doi.org/10.1038/s41558-018-0260-4

Wadge, G., & Aspinall, W. P. (2014). A review of volcanic hazard and risk-assessment praxis at the Soufrière Hills Volcano, Montserrat from 1997 to 2011. *Geological Society, London, Memoirs*, *39*(1), 439–456. https://doi.org/10.1144/m39.24

Wald, D., Jaiswal, K., Marano, K., Earle, P., & Allen, T. (2011). Advancements in casualty modelling facilitated by the USGS Prompt Assessment of Global Earthquakes for Response (PAGER) System. In R. Spence, E. So, & C. Scawthorn (Eds.), *Human casualties in earthquakes*, *Advances in Natural and Technological Hazards Research* (Vol. 29, pp. 221–230). Dordrecht: Springer.

Walker, A. M., Titley, D. W., Mann, M. E., Najjar, R. G., & Miller, S. K. (2018). A fiscally based scale for tropical cyclone storm surge. *Weather and Forecasting*, *33*(6), 1709–1723. https://doi.org/10.1175/WAF-D-17-0174.1

Wang, D., Becker, N. C., Walsh, D., Fryer, G. J., Weinstein, S. A., McCreery, C. S., et al. (2012). Real-time forecasting of the April 11, 2012 Sumatra tsunami. *Geophysical Research Letters*, *39*, L19601. https://doi.org/10.1029/2012GL053081

Weatherill, G. A., Silva, V., Crowley, H., & Bazzurro, P. (2015). Exploring the impact of spatial correlations and uncertainties for portfolio analysis in probabilistic seismic loss estimation. *Bulletin of Earthquake Engineering*, *957–981*(2015), 13. https://doi.org/10.1007/s10518-015-9730-5

Weisse, R., & von Storch, H. (2010). Marine weather phenomena. In R. Weisse, & H. von Storch (Eds.), *Marine climate and climate change* (pp. 27–76). Berlin, Heidelberg: Springer Berlin Heidelberg.

Welker, C., Martius, O., Stucki, P., Bresch, D. N., Dierer, S., & Brönnimann, S. (2016). Modelling economic losses of historic and present-day high-impact winter storms in Switzerland. *Tellus A*, *68*, 29546. https://doi.org/10.3402/tellusa.v68.29546

Welker, C., Röösli, T., & Bresch, D. N. (2020). Comparing an insurer's perspective on building damages with modelled damages from pan-European winter windstorm event sets: A case study from Zurich, Switzerland. *Natural Hazards and Earth System Sciences Discussion*. https://doi.org/10.5194/nhess-2020-115

Wellmann, C., Barrett, A., Johnson, J., Kunz, M., Vogel, B., Carslaw, K., & Hoose, C. (2018). Using emulators to understand the sensitivity of deep convective clouds and hail to environmental conditions. *Journal of Advances in Modeling Earth Systems*, *10*, 3103–3122. https://doi.org/10.1029/2018MS001465

Wenzel, F., & Zschau, J. (Eds) (2014). *Early warning for geological disasters: Scientific methods and current practice*, *Advanced Technologies in Earth Sciences.* Berlin (u.a.): Springer. https://doi.org/10.1007/978-3-642-12233-0

Werner, M., Cranston, M., Harrison, T., Whitfield, D., & Schellekens, J. (2009). Recent developments in operational flood forecasting in England, Wales and Scotland. *Meteorological Applications*, *16*(1), 13–22. https://doi.org/10.1002/met.124

Weyrich, P., Scolobig, A., Bresch, D. N., & Patt, A. (2018). Effects of impact-based warnings and behavioral recommendations for extreme weather events. *Weather, Climate, and Society*, *10*(4), 781–796. https://doi.org/10.1175/wcas-d-18-0038.1

WFP (World Food Programme) (2019). *Forecast-based financing (FbF): Anticipatory actions for food security*. Rome, Italy: United Nations World Food Programme. Retrieved from https://docs.wfp.org/api/documents/WFP-0000104963/download/

White, C. J., Carlsen, H., Robertson, A. W., Klein, R. J. T., Lazo, J. K., Kumar, A., et al. (2017). Potential applications of subseasonal-to-seasonal (S2S) predictions. *Meteorological Applications*, *24*(3), 315–325. https://doi.org/10.1002/met.1654

Wilks, D. (2011). *Statistical methods in the atmospheric sciences* (Vol. 100, pp. 1–704). Academic Press.

Willner, S. N., Levermann, A., Zhao, F., & Frieler, K. (2018). Adaptation required to preserve future high-end river flood risk at present levels. *Science Advances*, *4*(1). https://doi.org/10.1126/sciadv.aao1914

Wilson, G., Wilson, T. M., Deligne, N. I., Blake, D. M., & Cole, J. W. (2017). Framework for developing volcanic fragility and vulnerability functions for critical infrastructure. *Journal of Applied Volcanology*, *6*(14). https://doi.org/10.1186/s13617-017-0065-6

Wilson, T. M., Stewart, C., Sword-Daniels, V., Leonard, G. S., Johnston, D. M., Cole, J. W., et al. (2012). Volcanic ash impacts on critical infrastructure. *Physics and Chemistry of the Earth*, *45–46*(5–23). https://doi.org/10.1016/j.pce.2011.06.006

Winsemius, H. C., Aerts, J. C. J. H., Van Beek, L. P. H., Bierkens, M. F. P., Bouwman, A., Jongman, B., et al. (2016). Global drivers of future river flood risk. *Nature Climate Change*, *6*, 381–385. https://doi.org/10.1038/NCLIMATE2893

WMO (2015). *WMO guidelines on multi-hazard impact-based forecast and warning services. WMO-No.1150. XWMO (2018). Multi-hazard early warning systems: A checklist*. Geneva, Switzerland: World Meteorological Organization.

WMO (2018). www.wmo.int/pages/prog/wcp/ccl/documents/GUIDELINESONTHEDEFINTIONANDMONITORINGOFEXTREMEWEATHERANDCLIMATEEVENTS_09032018.pdf

World Economic Forum (2019). *The global risks report 2019*. Geneva, Switzerland: World Economic Forum. Retrieved from http://wef.ch/risks2019

World Meteorological Organization (WMO) (2011). *Guide to storm surge forecasting*, *WMO Report 1076*. Geneva, Switzerland: World Meteorological Organization. Retrieved from https://library.wmo.int/pmb_ged/wmo_1076_en.pdf

World Meteorological Organization (2013). *Coastal inundation forecasting demonstration project*. Geneva, Switzerland: World Meteorological Organization. Retrieved from www.jcomm.info/CIFDP

Wu, Y., Chen, D., Lin, T.-L., Hsieh, C.-Y., Chin, T.-L., Chang, W.-Y., et al. (2013). A high-density seismic network for earthquake early warning in Taiwan based on low cost sensors. *Seismological Research Letters*, *84*, 1048–1054. https://doi.org/10.1785/0220130085

Wu, Y., Liang, W.-T., Mittal, H., Chao, W.-A., Lin, C.-H., Huang, B.-S., & Lin, C.-M. (2016). Performance of a low-cost earthquake early warning system (P -Alert) during the 2016 *ML* 6.4 Meinong (Taiwan) earthquake. *Seismological Research Letters*, *87*, 1050–1059. https://doi.org/10.1785/0220160058

Wurman, J., Alexander, C., Robinson, P., & Richardson, Y. (2007). Low-level winds in tornadoes and potential catastrophic tornado impacts in urban areas. *Bulletin of the American Meteorological Society*, *88*(1), 31–46. https://doi.org/10.1175/BAMS-88-1-31

Yu, S., Yoon, S. M., Choi, E. K., Kim, S. D., Lee, Y. J., Lee, Y., & Choi, K. H. (2016). Quantitative assessment of national resilience: A case study of Mount Paektu eruption scenarios on South Korea. *International Journal of Disaster Risk Reduction*, *19*, 118–132. https://doi.org/10.1016/j.ijdrr.2016.09.002

Zappa, M., Beven, K. J., Bruen, M., Cofiño, A. S., Kok, K., Martin, E., et al. (2010). Propagation of uncertainty from observing systems and NWP into hydrological models: COST-731 Working Group 2. *Atmospheric Science Letters*, *11*(2), 83–91. https://doi.org/10.1002/asl.248

Zechar, J. D., Marzocchi, W., & Wiemer, S. (2016). Operational earthquake forecasting in Europe: Progress, despite challenges. *Bulletin of Earthquake Engineering*, *14*(9), 2459–2469. https://doi.org/10.1007/s10518-016-9930-7

Zhang, Q., Li, L., Ebert, B., Golding, B., Johnston, D., Mills, B., et al. (2019). Increasing the value of weather-related warnings. *Science Bulletin*, *64*(10), 647–649. https://doi.org/10.1016/j.scib.2019.04.003

Zscheischler, J., & Seneviratne, S. I. (2017). Dependence of drivers affects risks associated with compound events. *Science Advances*, *3*(6). https://doi.org/10.1126/sciadv.1700263

Zsótér, E. (2006). Recent developments in extreme weather forecasting. *ECMWF Newsletter*, *107*, 8–17.
Zuccaro, G., & De Gregorio, D. (2013). Time and space dependency in impact damage evaluation of a sub-Plinian eruption at Mount Vesuvius. *Natural Hazards*, *68*(3), 1399–1423. https://doi.org/10.1007/s11069-013-0571-8