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Transboundary Storm Risk and Impact Assessment in Alpine Regions

D4.6 Practical guidelines for storm impact forecasting and risk assessment Towards a cross-border Storm Risk Assessment Framework

eurac research

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1 Introduction

As highlighted in (Merz et al., 2020), the provision of rapid disaster risk information is an important component 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 multi-hazard early warning systems and rapid disaster risk information (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. 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, especially for 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 multi-hazard 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 general, we consider events as natural phenomena that unfold with a given space-time footprint and with the potential for adverse consequences. The event footprint may vary significantly across hazards, even when focusing on hydrometeorological events. Short-term, local-scale events, for example, pluvial floods have event durations and extent in the order of 1 hr and 1 km, while extratropical storms such as the Vaia storm can last for several days and affect areas spanning hundreds of kms (see Figure 1). Accordingly, the possibilities and the challenges for emergency management in response to a forecast vary widely across hazards.

Within this context, 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)

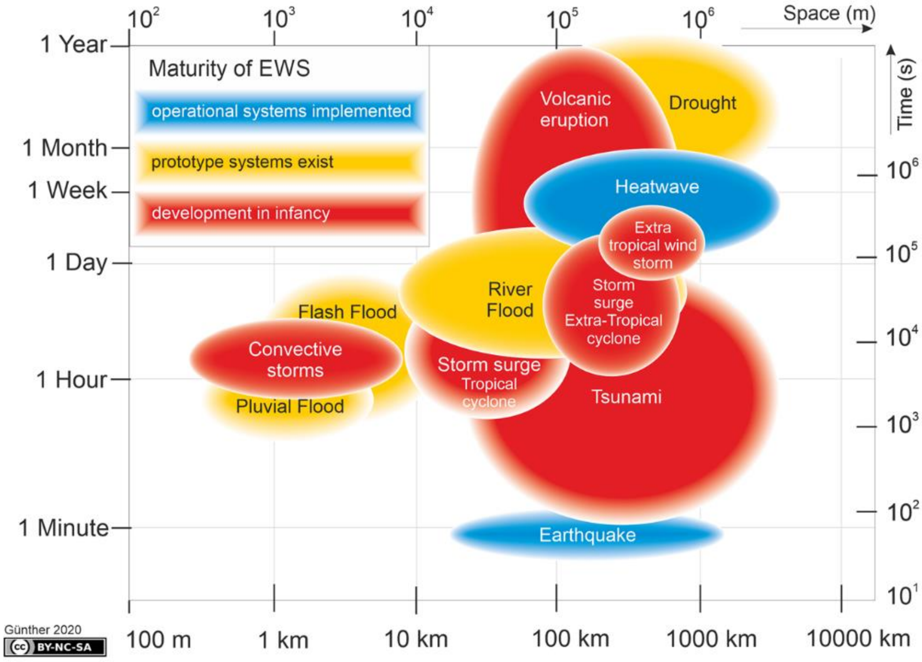

Figure 1 Space-timescales of the hazard types covered. These scales are related to the event's spatial extent (or footprint). Colors code the maturity of impact forecasting systems from "development in infancy" (red) through "prototype systems exist" (yellow) to "operational systems implemented" (blue) taken from Merz et. Al., 2020.

2 (Storm) Impact forecasting

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 flood, 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.

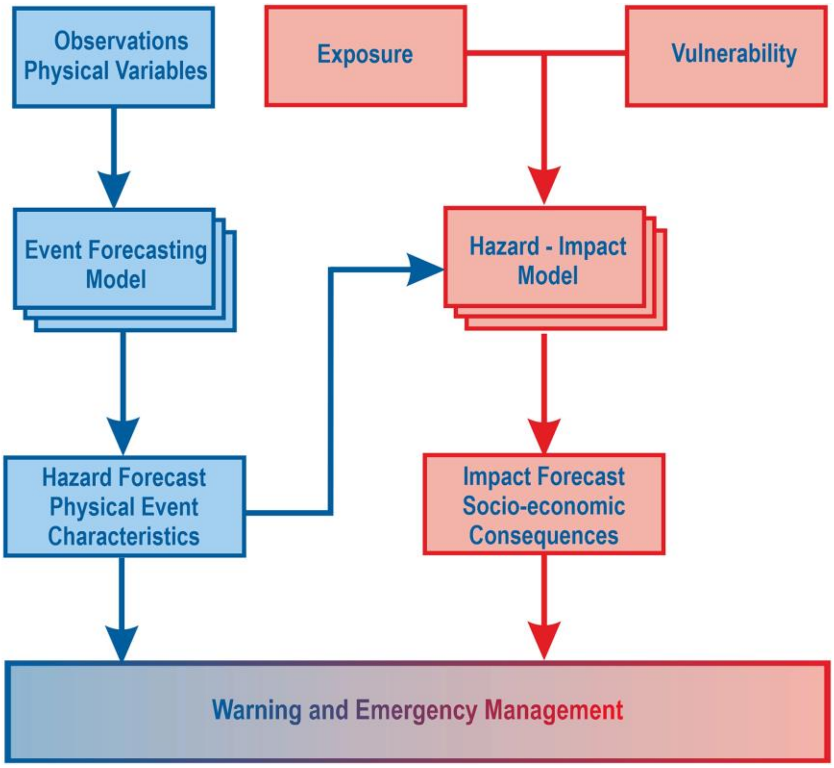

Figure 2 Conceptual definition of impact forecasting (from Merz et al., 2020)

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, 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).

The following section describes the current state of the art of impact forecasting, and is strongly based on the comprehensive review carried out by (Merz et al., 2020). For the convenience of the readers we report the section most relevant to the project TRANS-ALP.

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.

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.

3 Towards a Storm risk assessment framework

The purpose of RA is to provide in depth analysis of the risk resulting from storms (and extreme hydrometeorological events in general) and inform risk practitioners and stakeholder to support prevention and mitigation strategies. As such, it is very important to lay down a basic framework to be implemented at different stages of risk management.

In the following a description of the main components of risk assessment is provided, and for each a specific discussion on the aspects to consider within a transborder storm risk assessment are provided.

Harmonization of DRR with CCA

Many of the actual practices related to risk mitigation refer to the broader framework of Disaster Risk Reduction (UDRR, 2022), which is dating several decades back, and is historically related to the occurrence of abrupt-onset and highly damaging events (also known as *acute* hazards) including, e.g., earthquakes or floods. More recently, in consideration of the increasing and noticeable impact of climate change to most of the natural processes that are also driving natural hazards, the topic of Climate Change Adaptation has soared, leading to some extent to a parallel and slightly different discussion on risk (see, e.g., the IPCC AR4 framework). Many differences are in the wording and understanding of basic concepts such as exposure and vulnerability, that are by their very nature relatively open to different interpretation. There is also an important contribution to the general risk-related discussion coming from the acknowledgement of so called slow-onset events (also known as *chronic* hazards). Starting from IPCC AR5, and more recently with AR6, the most important concepts related to risk have converged towards the DRR framework, as depicted by the well-known “propeller”.

This is streamlining a joint, harmonized management of DRR-related and CCA-related risk management, which is ever more important considering that there is a strong impact of climate change on the frequency and intensity of extreme hydrometeorological events, which blurs the boundaries between slow- and abrupt onset events on the one hand and undermines the basic assumptions of hazard stationarity which is usually implied by DRR.

3.1 Main components and phases of risk assessment

The main components of the risk (and its assessment) are usually hazard, exposure and vulnerability. To these we can also add the notion of impacts, acknowledging the presence of additional (extern) risk drivers to have a more complete picture of all environmental conditions influencing risk (see Figure 2). In the following sections a few specific considerations are provided to better link those factors to the overall topics of interest of TRANS-ALP project, including the transboundary aspects and the consideration of climate change.

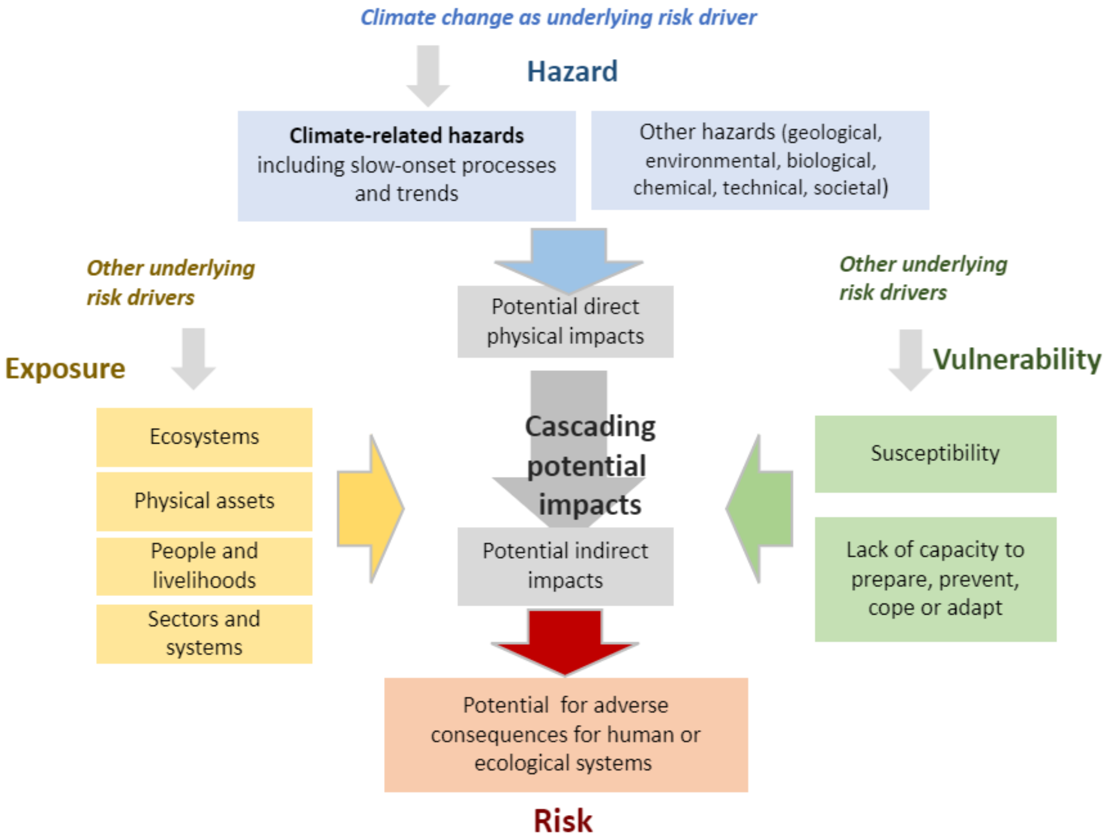

Figure 3 Conceptual representation of the interlink between the different components of risk, based on (UNDRR, 2022). Particular emphasis is given to hazards influenced by climate change.

3.1.1 Hazard

Hazard refers to the set of environmental conditions that can generate damage and loss, either directly or indirectly. In the case of a specific event such as an extratropical storm the hazard component may refer to the individual phenomena that can often be compounded, e.g., the intense precipitation and the wind gusts, each with different, although superimposed spatial and temporal footprint.

This complexity of intense hydrometeorological events has to be accounted for since it potentially increase the susceptibility for and/or trigger further hazard processes (Kaltenböck et al. 2009). Different hazard processes that are connected are called cascading effects. Cascading effects are characterized by, e.g., a mutual amplification of different potentially damaging processes (Pöppl & Sass 2019) as single (single-hazard) or multiple (multi-hazard) processes leading to hazard amplification over several stages or process chains. The European Commission (2011) defines event cascades with coinciding hazard processes as: “Coinciding hazards […, which] are also referred to as follow-on events, knock-on effects, domino effects or cascading events.”

In order to allow for efficient impact forecasting, the hazard components have to be described by quantitative estimates either based on a forecast (within a short timeframe from the expected occurrence of the event) or based on a statistical modelling through calibrated models. In both cases, the hazard estimates will be characterized by a relevant uncertainty which has to be accounted for. This is particularly significant where impacts are depending on the anomalies in the phenomena. Such anomalies are usually difficult to be determined in advance, and as such might be underestimated, potentially leading to insufficient mitigation actions, or overestimated, leading in this case to false alarms that might alter the confidence of local exposed populations in the civil protection authorities.

Of particular importance is the observation that, besides the already existing challenges in forecasting precisely enough the evolution of complex and intense hydrometeorological events, the effect of climate change brings in additional issues. In particular, the assumption of stationarity of the underlying physical processes is being questioned by the empirical observations. This adds on the overall uncertainty, especially as for the most extreme values that could be observed in the next events, that could exceed with higher likelihood the highest observations on record.

Take-home messages

- Consider the complexity of hazards within intense hydrometeorological events.
- Several hazards should be considered as potentially compounded or cascaded.
- Where possible, quantitative models providing information on the extreme values possibly occurring should be used, considering their uncertainty.
- More complete and dense observations of weather and climatic features should be collected in order to allow for consistent statistical analysis and better detect trends.
- Future events could be unprecedented in terms of intensity with respect to the observed ones.

3.1.2 Exposure

Exposure refers to all systems and assets that are possibly exposed to the hazard components and hence are susceptible to be damaged. Exposure does not only include physical assets (e.g., buildings, roads and bridges) but might also encompass systemic and functional aspects of the systems (e.g., ensuring the provision of power and water, ensuring the transport of people and goods, etc.).

In order to allow for impact forecasting, information on exposure should be available in geospatial format at a consistent spatial resolution and with harmonized format. The use of aggregation areas (e.g., grids and other tessellations) can be instrumental to simplify the exposure description and provide a useful spatial support for subsequent impact assessment. Aggregation also ensures a more robust management of uncertainties in the models.

The exposure model should be harmonized across the available administrative areas, in order to extend and validate impact estimates across borders (see also TRANS-ALP Deliverable XXX).

Take-home messages

- Exposure is a critical element of impact forecasting
- Exposure should consider both physical assets and systemic functions
- Exposed assets and systems might be aggregated onto spatial domains (regular or irregular cells) to simplify estimation and provide more robust results
- Exposure models should be consistently defined and harmonized across borders

3.1.3 Impacts

The concept of impact refers to all direct and indirect influences of hazards which can result in damage and loss, including the loss of lives, the destruction of assets and infrastructure as well as the disruption of systems, functions, and services. Often direct impacts can mix with hazards, given their direct and clear causal link as well as basic uncertainty on the definition. For instance, we refer to landslides as an hazard, but it can be considered as well a direct impact of extreme precipitation. This distinction is relative as soon as we correctly consider the chain (and corresponding order) of impacts. The concept of impact is also very much akin to the one of risk, since the risk can be also seen as the probability of observing (or exceeding) an impact of a given magnitude over a specific time interval.

Impacts, following this definition, are also clearly linking together the other risk components, in the sense that for instance a **hazard** has an **impact** on a given **exposed asset**, and this impact might be influenced (amplified) by a set of **vulnerabilities**.

Impacts, and consequent risks may unfold over different times for extreme and transborder events, following both short-term interactions (e.g., strong rain causing landslides) and long-term ones (e.g., infestation of bark-beetle in the years following extensive windthrows).

Westen et al. (2014) distinguish, depending on the degree of interaction, between coupled events (simultaneous process combinations) and events that change the predisposition, i.e., the basic prerequisite or susceptibility, for further events (process chains) (Pöppl & Sass 2019). Coupled events are triggered simultaneously, e.g., windthrow and falling trees can lead to the detachment of rock blocks that were stabilized by root plates and consequently lead to rockfall. Process chains are also interrelated, but various natural hazard processes occur one after the other, e.g., windthrow → deforestation → changes to the protective effect against snow avalanches → changed predisposition through the establishment of new avalanche release areas after clearing → damaging avalanche events. In this process chain, months to years can lie between the storm and the avalanche event. Windthrow itself does usually not trigger avalanches, but if the damaged vegetation is removed, changes their predisposition, and leads to an increased probability of damaging avalanches in areas that were previously less susceptible.

In the current literature (e.g., Glade et al. 2019), cascading effects are discussed a lot, but rarely in relation to forest cover loss. Some process combinations and historical examples related to severe storm events are of particular relevance for Alpine regions include:

- River channel or lake damming mass movements → displacement of water → tidal wave (e.g., Italy - Vajont / Longarone in 1963)
- Heavy or long-lasting rain fall, rain on snow events or incoming sirocco winds → flooding and frequent occurrence of slope movements (e.g., Austria - Sellraintal in 2015)
- Windthrow → bark beetle infestation → changes to the protective effect of forests against alpine natural hazards (e.g., Austria, Italy – storm Vaia in October 2018)
- Heavy snowfall → frequent occurrence of damaging avalanches (e.g., southern Alps of Italy and Austria – winter storm Xunav / Wenke / Yvonne in December 2020)

Considerations of reliable statistical trends about future developments and systematic overall considerations of cascading effects in hazard and risk management in affected regions are challenging due to the still insufficient knowledge and data about past events as well as the complex interactions involved. Current management strategies and previous scientific publications primarily address single events, which is also a reason for the sparse data availability. Furthermore, due to the unique character of different cascading effects (simultaneous process combinations and process chains), it is challenging to provide concrete recommendations for actions.

Several authors cited previous studies and stated in Glade et al. (2019) that future research activities should focus more on integrating different processes and their interactions in models to predict their outcome and support decisions (e.g., Wornie et al. 2014, Brierley et al. 2006, Bracken et al. 2013, Pöppl et al. 2017, Rascher et al. 2018).

Take-home messages

- Impacts are the central element of impact forecasting, and may include direct and indirect effects
- Impacts can unfold over different time-frames, ranging from few hours to several years. Impact forecasting should take into account both short- and long-term effects to provide actionable input to disaster risk reduction activities
- Impacts can have multiple interactions, with both compound and cascading type of effects, affecting different exposed systems and being possibly amplified by different

3.1.4 Vulnerability

Vulnerability refers to those elements, intrinsic to the exposure, or extrinsic (related to environmental or institutional characteristics) that might increase the susceptibility of exposed assets or systems to damage and loss, and therefore amplify the resulting risk.

Vulnerability can be addressed from different perspectives, depending on whether it focuses on the physical, functional, or socio-economic properties of exposure. While the former components can be modelled in quantitative ways, socioeconomical vulnerability often entails the use of hybrid, more qualitative approaches. As such, it is very challenging to consider all relevant vulnerabilities in a consistent framework for impact forecasting. On the other side, socio-economic vulnerability might have a significant effect on impacts and risks and should not be underrated.

Quantitative models of physical and functional vulnerability implies a careful calibration phase, which implies the availability of data on both hazard intensity and impact severity collected for past events. Since this data Is currently relatively scarce, most models are used outside their original calibration, which further increases the uncertainty of the estimates. Socioeconomic vulnerability is often elicited from experts and stakeholders, therefore adding a further dimension of uncertainty and highlighting the need for validation.

Take-home messages

- Vulnerability might greatly amplify impacts and increase risks
- Physical and functional vulnerabilities might be addressed by quantitative approaches, but such models require calibration based on observed impacts, damage and loss
- Structured and systematic collection of impact and loss data should be implemented
- Socioeconomic vulnerability often entails more qualitative approaches, and is difficult to be considered, although it may play a relevant role In impact forecasting
- Hybrid impact forecasting approaches able to account for socioeconomic and institutional vulnerabilities should be prioritized.

3.1.5 Risks

Among the different impacts one or more risks can be highlighted and selected for assessment. Impact forecasting can therefore be considered as a type of risk assessment which focuses on specific events and their damaging mechanisms.

Since the event is considered to be fixed (e.g., an intense storm), the resulting risks are mostly related to the potential severity of the impacts to be observed.

Take-home messages

- Impacts and risk are connected, but can be considered separately

- Impacts are more immediately related to the adverse consequences to be observed in the case of an event.
- Impact forecasting focuses on such direct and indirect consequences

3.1.6 External drivers

External drivers are factors that can (even significantly, over shorter time horizons) negatively influence (i.e., amplify) the risk but whose root causes lie outside the typical scope of risk assessment. Also, external factors can refer to macro-scale events that concurrently or in a cascade may have an impact on any (combination of) the basic components of risk mentioned above. Examples of external risk drivers include conflicts (and wars, such as the conflict in Ukraine), macroscale economic crisis (such as the subprime crisis of 2009-2010) or pandemics (such as the COVID-19 2020-2022).

In this context also Climate Change can be considered as an external risk driver, although a more specific consideration of its impact is worth given the extent of its possible influence.

Recovery from already occurred extreme events is also an important element to be considered, given the timeframe over which the recovery might take place and the complex interplay among the different involved processes, as well as the acknowledgment of the different institutions involved in its management.

Take-home messages

- External factors (i.e., outside the control of civil protection authorities) might further amplify impacts and risks
- Climate change in this context can be considered an external factor which strongly affect risks
- Recovery processes from past events should be considered whenever possible, as further external factors

4 Impact and risk Analysis

Impact forecasting should first clearly define which impacts should be addressed, and which specific factors are they depending on. This is particularly important in the case of complex hydrometeorological events (such as a strong storm) where different impacting mechanisms are concurrently affecting a region.

In this situation, a useful tool to conceptualize the impact is the "impact chains" (See TRANS-ALP deliverable D4.2 for a more detailed description of this tool).

Impact chains, as the one depicted in Figure 4, allow a clear conceptualization and an intuitive visualization of significant risk components in a specific class of events, or for a given one.

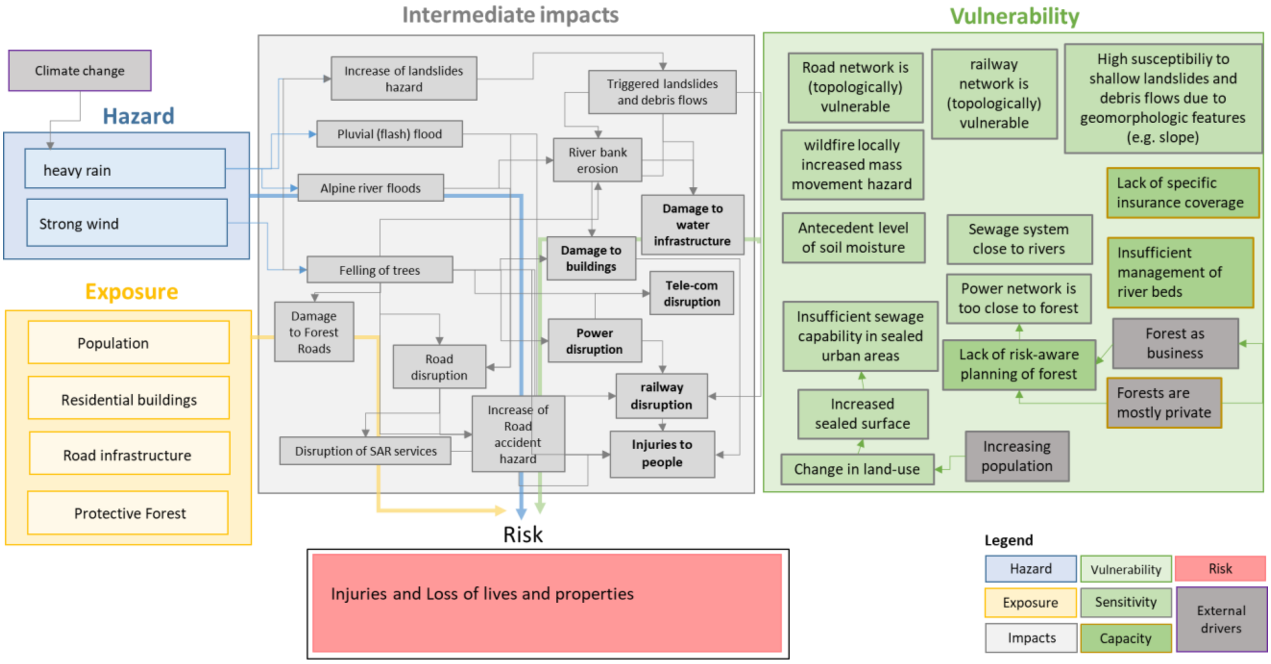

Figure 4 Event Storm "VAIA" - Impact chains related to target risk: "Injuries and loss of lives and properties"

Such representations allow to identify and single-out specific "risk pathways" among a complex set of compounded and cascaded consequences, and to focus the quantification of given impacts without losing the overall picture of the event. An example is provided in Figure 5, which shows a sequence (a chain, indeed) of impacts triggered by the strong winds of the Vaia Storm as the main hazard element. A second example, shown in Figure 6, describes a different chain of impacts, still triggered by the same hazard. We can note that the two types of impact are quite different, and, more importantly, they unfold over very different time frame; few hours for the former (with a few weeks of recovery time), and several years the latter.

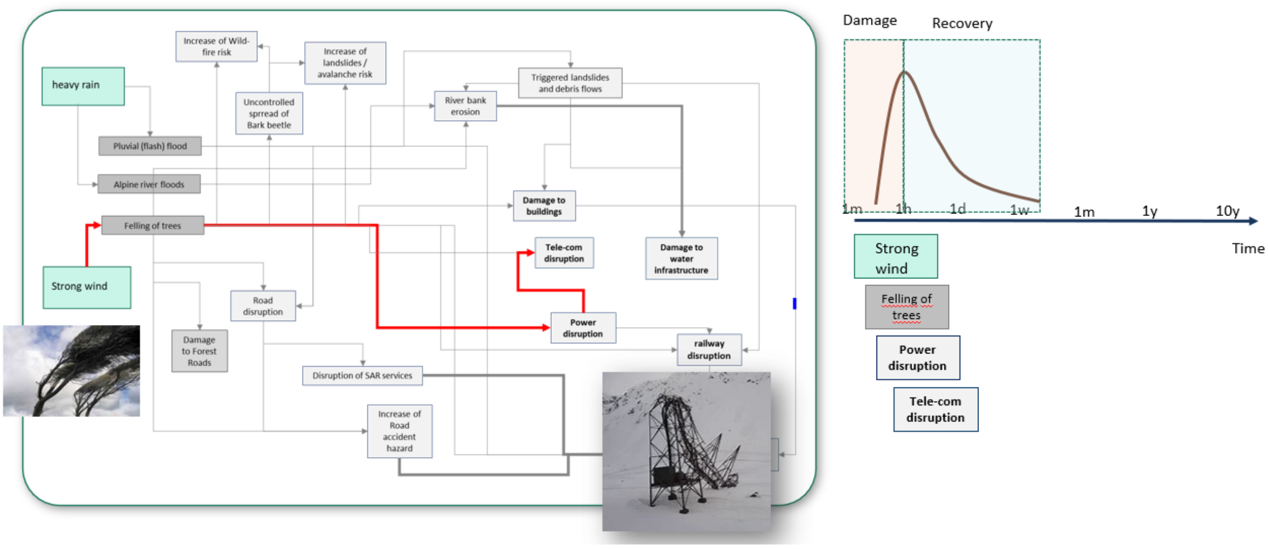

Figure 5 first- and second-level impacts for the impact chain represented above. The time-based unfolding of damage and recovery is shown on the right side.

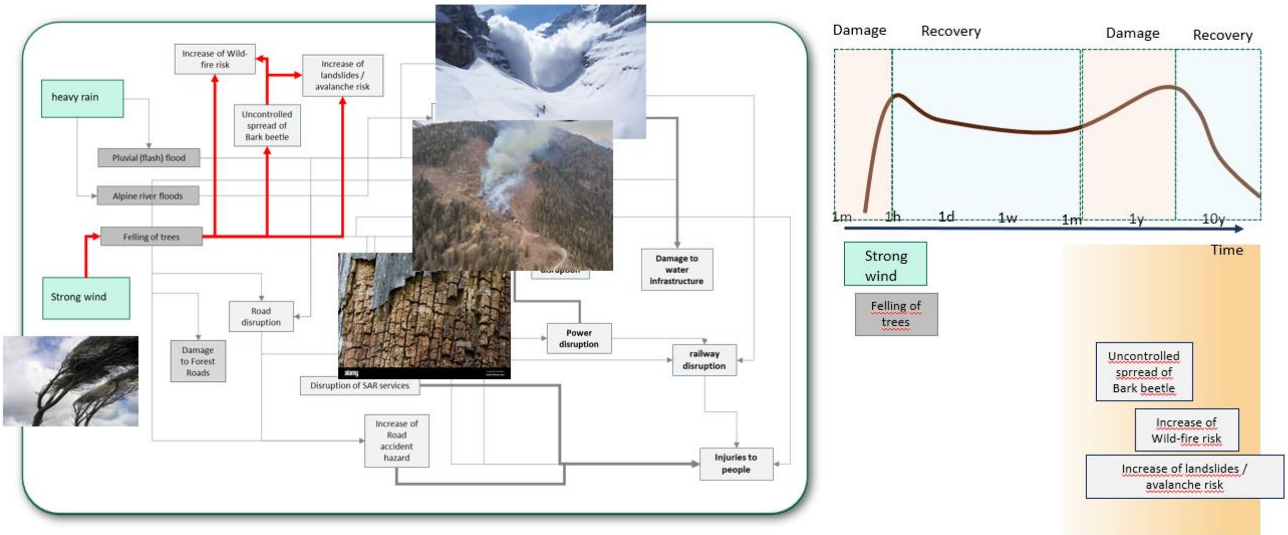

Figure 6 A different type of indirect impacts related to the same event is shown here, unfolding over a very different time frame with respect to those shown in the previous figure.

These two examples highlight the challenge in considering such variety and complexity of impacts, which has to be taken into account. We further note that when impacts are occurring on such long-term scale, they can be affected (and possibly amplified) by other slow-onset events which result compounded. In the case of Vaia, for instance, the spread of bark beetle infestation on the windthrows of October 2018 has been negatively affected by the anomalies in temperature and precipitation of the same year 2018 and the subsequent years. This feedback effect might to lead to further increase of landslides and avalanche risk over a time-frame of more than 10 years after the original event, and has been superimposing with other extreme events affecting the same regions in 2019 and 2020.

Once one or more risk pathways are selected, Impact / Risk analysis can be carried out with different quantitative or hybrid approaches.

Indicator-based approaches for instance are based on the combination of geospatial information which is describing the different elements to be considered, e.g., hazards, exposure and vulnerability. Each layer is a single raster array (2d matrix of numerical values) which can be weighted and combined with the other layers in a multiplicative scheme (see equation in Figure 7).

$$\text{Risk} = \frac{(\text{Hazard} * w_H) + (\text{Vulnerability} * w_V) + (\text{Exposure} * w_E)}{w_H + w_V + w_E}$$

Figure 7 indicator-based estimation of risk based on three weighted layers

Alternatively, if more specific information is provided on the impacting mechanism, a less simplified approach can be followed using so called impact functions to analytically describe the impacting mechanism, as shown in Figure 8,

$$x_{ij} = \mathrm{val}_j \, f_{\mathrm{imp}}(h_{ij}|\gamma_j),$$

Figure 8 Analytic description of impact in terms of the individual components and a generic impact function (Aznar-siguan and Bresch, 2019)

Where "x" represents an impact based on a function of hazard, exposure and vulnerability. From the specific impacts, and assuming information on the frequency of events are also known to some extent, further statistical metrics of risk can be obtained, as for instance the expected annual impact for an exposure asset j, as shown in Figure 9,

$$\begin{aligned}\mathrm{EAI}_j = \; & \sum_{\bar{i}=1}^{N_{\mathrm{hist}}} E[X|E_{\bar{i},j}]F(E_{\bar{i}}) \\ & = \sum_{\bar{i}=1}^{N_{\mathrm{hist}}} \sum_{\hat{i}} x_{\hat{i}j} F(E_{\hat{i}}) = \sum_{i=1}^{N_{\mathrm{ev}}} x_{ij} F\left(E_i\right),\end{aligned}$$

Figure 9 Analytic description of Expected Annual Impact in terms of the individual impacts and the expected frequency of damaging events (Aznar-Siguan and Bresch, 2019)

Where E stands for expectation, E_i is an event and F is the frequency of the event. The latter approach can provide much more flexibility in the forecasting of impacts but requires a more careful and custom modelling of the different processes at play, hence requiring a substantial amount of data and knowledge to ensure enough confidence in the model. The former, indicator-based approach, on the other side, is relatively more straightforward but, in many cases, it also provides a very crude simplification of the impacting processes.

In the two examples described above, as well in the case of other approaches to impact estimation, specific information has to be collected and prepared to describe hazard, exposure and vulnerability. Hazard information might be provided by empirical observation (e.g., measurement of temperature or precipitation) or can be provided by numerical models providing a realistic simulation of a specific event or a category of relevant events. The capacity of simulating events and producing scenarios is particularly useful to assess risks, stress-test emergency protocols and improve mitigation and adaptation measures (see also TRANS-ALP Deliverable D2.3).

Take-home messages

- Use impact chains to conceptualize complex impacting mechanisms within intense multi-hazard events, also highlighting as much as possible the vulnerability factors contributing to the individual impacts and eventually to the overall risk
- Impacts can unfold over different time-frame and generate adverse consequences even decades after the occurrence of the trigger event
- Define the risk pathways to be considered for impact forecasting, and evaluate the availability of data for the relevant factors contributing to the impacts
- According to knowledge and information about the impacting mechanism, a suitable approach can be chosen (e.g., indicator-based or custom-modelling)

5 CONCLUSIONS

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. Impact forecasting is expected to provide significant benefits for emergency management, such as identifying most vulnerable areas, prioritizing emergency measures or organizing evacuation

The reliability of impact forecasting depends on the quality of the hazard forecast and of the impact modeling. In general the uncertainties stemming from the impact modeling are larger than those of the hazard forecasting, due to the limited availability of impact data 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 time and 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.

Further, currently 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.

Post-event evaluations should in fact 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 the systematic collection of detailed impact data after every event is paramount.

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