Introduction

During the past decades, the frequency and worldwide impacts of natural disasters has increased rapidly (Munich Re, 2014; 2015). A number of major disasters have occurred in Europe, prompting high economic damage and losses, casualties and social disruptions. Examples are the 2010 eruption of the Eyjafjallajökull volcano in Iceland; earthquakes in Italy in 2009 and 2012; droughts and forest fires in Portugal in 2012; and heavy rainfall that caused record floods in Central Europe in 2002 and 2013.

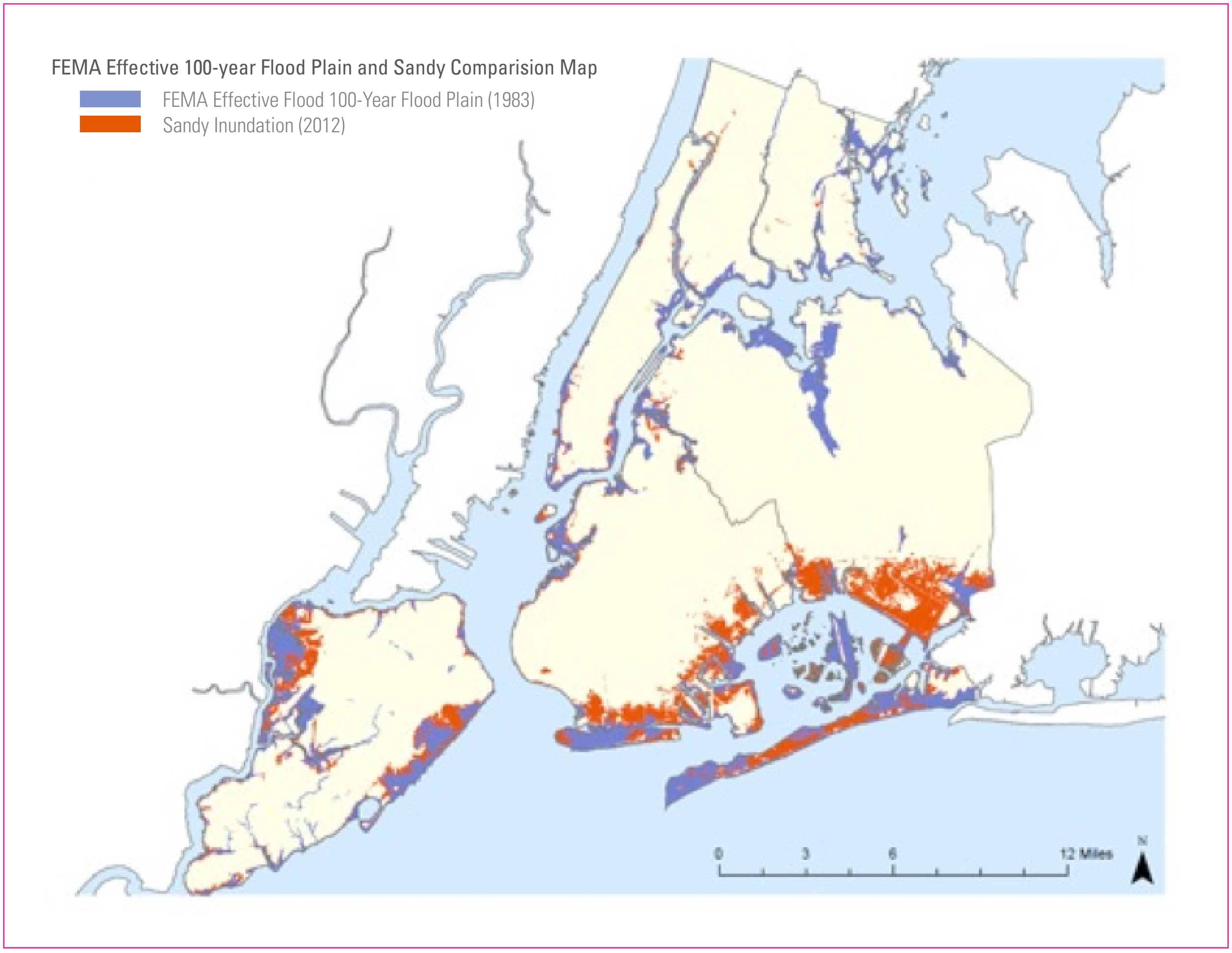
Natural disaster risks are of high policy and citizen concern in Europe. They are expected to rise further as a result of projected demographic development and land use change, with expansion of residential and production activities in hazard-prone areas. Climate change will further exacerbate risk from natural hazards, and it has been demonstrated to have already increased the frequency and severity of certain extreme climate and weather related events, such as droughts, heat waves and heavy precipitation (IPCC, 2012; IPCC, 2014).

Knowing the increasing trends in natural disasters and losses, it is imperative to take action on disaster risks to improve resilience of European societies to natural hazards. The main goal, therefore, of the ENHANCE project is to develop and analyse innovative ways to manage natural hazard risks. Key is to develop new multi-sector partnerships (MSPs) that aim at reducing or redistributing risk, and increase resilience of societies. For several reasons, **comprehensive and accurate risk information** is important for MSPs and for policy-making in general. First, a better understanding of natural hazard risk is important **for preventing excessive socio-economic stress** at levels from local to national to international, and in order **to plan for reducing risk from extreme events in the future**. For example, measures that reduce risk (e.g. levees to prevent flooding) require a certain design level or elevation, which can be derived from historical water level data or hydrological simulation models. Second, post-disaster information on the losses from a natural hazard event is important, in order **to prepare (emergency) aid to the region**. In addition, accurate post-event loss information is needed **to estimate whether financial support is needed** in terms of compensation or new investments to recover the area and develop the economy back to its original state.

An example of where inaccurate risk information can lead to is exemplified in **Figure 2.1**. This figure shows a map for NYC, for the actual flooding due to hurricane Sandy in 2012 (red color) and the official 1/100 flood zone (blue colors) provided by the Government before the hurricane occurred. **The figure shows that many of the actual flooded areas are outside the official flood zone. Inaccurate perception of flood risk for an area may lead to the development of urban areas in unprotected areas, or to under-designing levees for protecting people against extreme events**.

Figure 2.1.

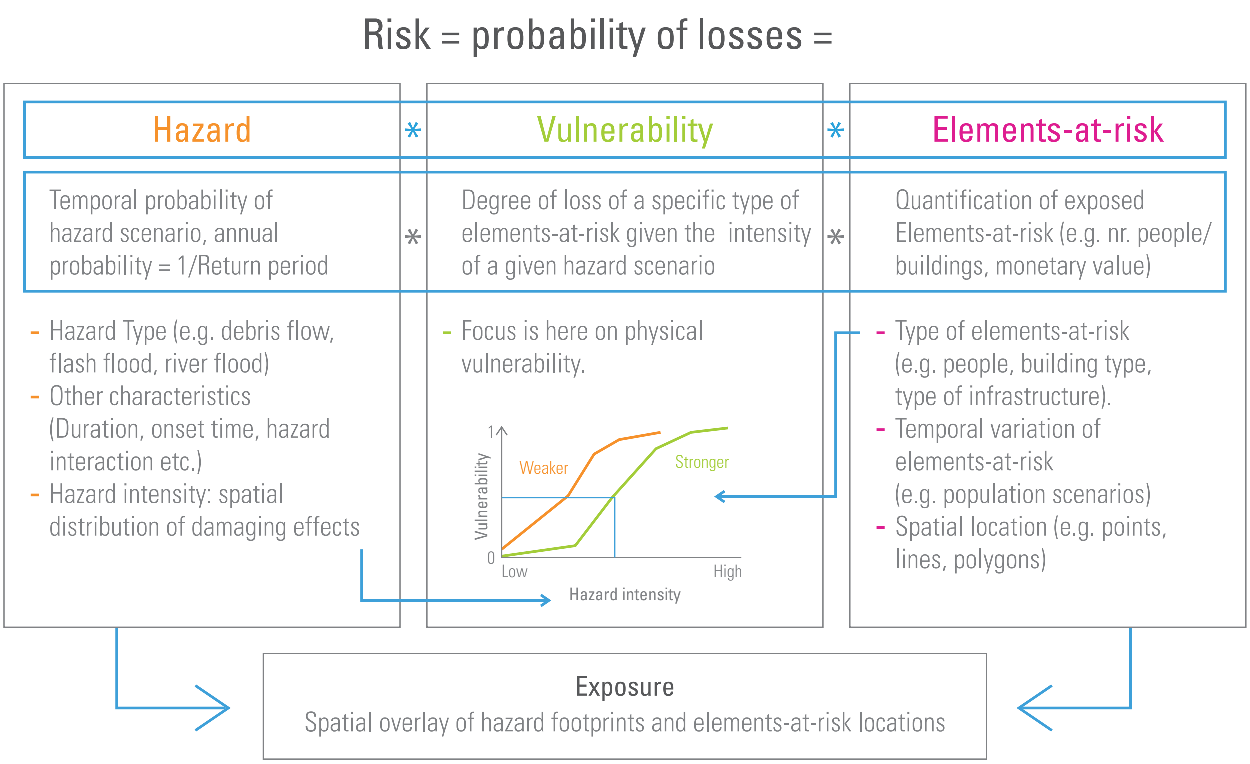
A map for NYC, for the actual flooding due to Hurricane Sandy in 2012 (red color) and the 1/100 flood zone map (blue colors) provided by the Government before the event (Source: NYC, 2013).



A risk-based approach

Within the ENHANCE project, we have followed **a risk-based framework** (see e.g. Kron, 2005) which has several components displayed in **Figure 2.2**: (1) Exposed assets ('Elements at risk'): These are the assets at risk, such as people, buildings and infrastructure. (2) Hazard: the potential magnitude and frequency of hazards that threaten those assets, (3) Vulnerability: the level of protection and preparedness to reduce risk of the exposed assets. Losses can be calculated by combining the hazard information with exposure and vulnerability data. For example, a flood depth and extent map (hazard) can be overlaid with information on exposed buildings with their value (exposure).

Figure 2.2.
Schematic figure of risk as a function of hazard, vulnerability and elements-at-risk (Source: Van Westen, 2015).



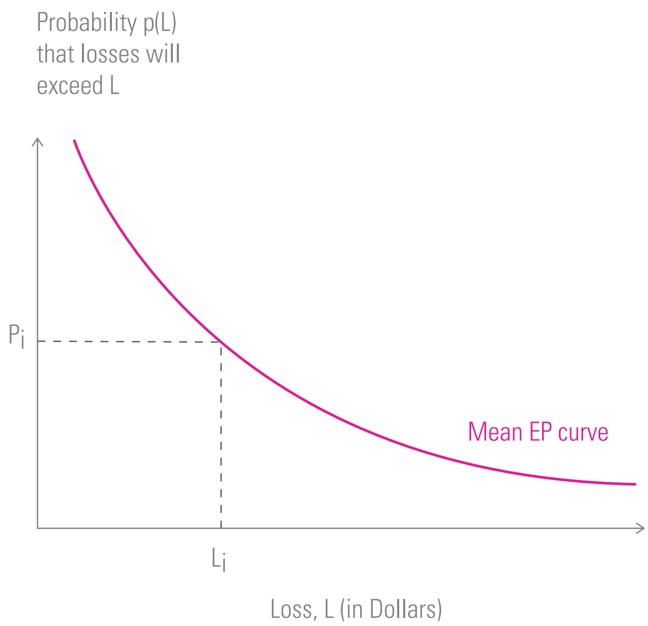
Furthermore, each exposed asset can be further characterised by its vulnerability. For example, for exposed buildings, we can use information on building codes, or use data on empirical losses to buildings from historical records. Losses can be measured in terms of dollars of damage, fatalities, injuries, or some other unit of analysis.

In order to derive risk estimates from calculated losses per event, we also need the probability for each of these events. In this way we can plot the exceedance probability against the potential loss per event, summarised as an **exceedance probability-loss (risk) curve** (EP curve, **Figure 2.3**), where the risk is approximated by the area under the curve (Meyer et al., 2009). The EP curve in Figure 2.3 shows that for the specific loss Li, the likelihood that losses will exceed a certain threshold level of losses Li, is given by Pi. There is some debate on the number of data points needed to construct the curve. For example, Merz and Thieken (2009) used seven return periods to produce risk curves for Cologne, Germany, which is relatively many data points compared to most other studies.

Photo by Donald Bowers/Shutterstock.

Figure 2.3.

Mean Exceedance-Probability curve, showing for a specified event the probability Pi that losses exceeding Li (Source: Grossi and Kunreuther, 2005).



Calculating losses: example Austrian railways and flood risk

The railway transportation system of the Alpine country Austria plays an important role in the European transit of passengers and freights. In total, 11.7 million tons of goods were transported across the Austrian Alps in 2013, which is 28 % of the total volume recorded for the inner Alpine Arc. Also the Baltic-Adriatic Corridor, which is one of the priority axes (No 23) of the Trans-European Transport Network (TEN-T), runs from Gdansk in northern Poland through Austria to northern Italy. It is one of the most important north-south routes in Europe and the easternmost crossing of the European Alps. It connects three other EU member states (Poland, Czech Republic, and Slovakia) with economically important areas in Austria and Northern Italy and also provides a link to other Trans-European Transport Networks – TEN-T priority axes from Eastern to Western Europe, such as the one running from Paris via Vienna to Bratislava (No 17). Moreover, the Austrian railway network is essential for the accessibility of lateral alpine valleys and is thus of crucial importance for their economic and societal welfare. If traffic networks are (temporarily) disrupted, alternative options for transportation are rarely available.

The mountainous environment, in which around 65 % of the national territory of Austria is situated, poses a particular challenge to railway transport planning and management. Relief energy and steep slopes limit the space usable for permanent settlements and infrastructure, e.g. amounting to only 15 to 20 % of the whole Alpine Convention territory. Hence, railway lines often follow floodplains or are located along steep unsteady slopes, which considerably exposes them to flooding and in particular to alpine hazards, e.g. debris flows, rockfalls, avalanches or landslides. As a result, **railway infrastructure and**

operation has been repeatedly impacted by alpine hazards. For example, in June 2013, floods and debris flow events caused substantial damage to the railway infrastructure in Austria. The national railway operator ÖBB reported a total damage of about EUR 75 million to its railway network.

In order to better plan, negotiate, and decide on investments in protection measures, reliable models for estimating potential flood losses to railway infrastructure are needed. Such models are, however, rare and their reliability is seldom investigated. Therefore, the ENHANCE case study 'Building railway transport resilience to alpine hazards' aimed at developing an **empirical modelling approach for estimating direct structural flood damage to railway infrastructure and associated financial losses**. Via a combination of event data, i.e. photo-documented damage on the Northern Railway in Lower Austria caused by the March river flood in 2006, and simulated flood characteristics, i.e. water levels, flow velocities, and combinations thereof, the correlations between physical flood impact parameters and damage occurred to the railway track were investigated and subsequently rendered into a damage model.

After calibrating the loss estimation using recorded repair costs of the Austrian Federal Railways, the loss model was applied to three synthetic flood hazard scenarios with return periods of 1/30, 1/100 and 1/300 years along the March River (see **Figure 2.4**). Next, flood losses were calculated for these three flood hazard scenarios (**Table 2.1**).

Photo by LeksusTuss/Shutterstock.

Figure 2.4.

Estimation of potential structural damage at the Northern Railway for three synthetic flood scenarios: a) a 30-year event, b) a 100-year event, and c) a 300-year event. In damage class 1 the track`s substructure is (partly) impounded, but there is no or only little notable damage. In damage class 2 the track section is fully inundated and significant structural damage has occurred (or must be expected), while in damage class 3 additional damage to substructure, superstructure, catenary and/or signals occurred so that a full restoration of the cross-section is required. The damage classes are estimated for each 100 m-segment (Source: Kellermann et al., 2015).

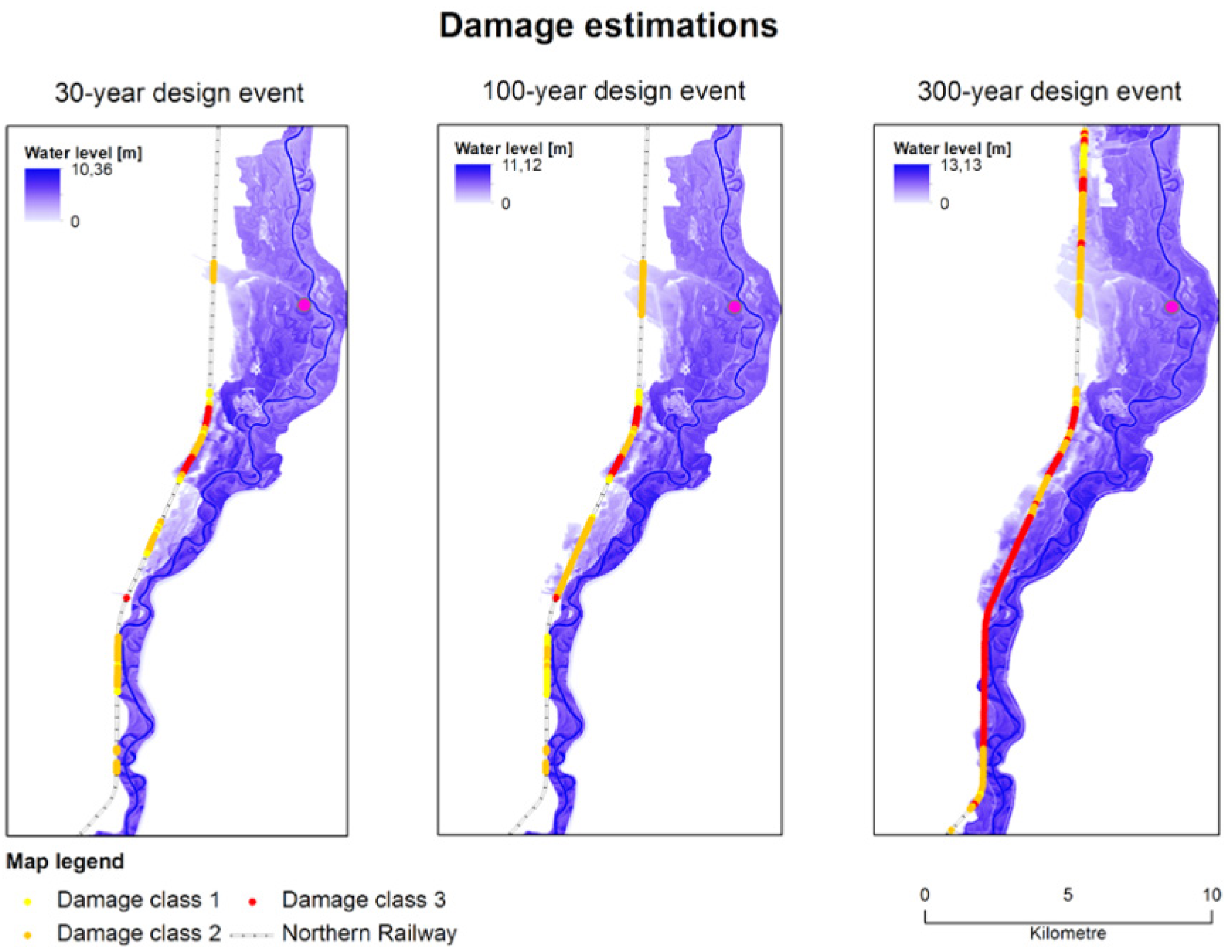


Table 2.1.

Estimated repair costs for different hydraulic scenarios along the March River (Source: Kellermann et al., 2015).

Flood scenario and probability	Repair costs estimated by the RAIL model (euro)
1/30	17.698.600
1/100	21.511.600
1/300	93.168.900

Finally, it was applied to the whole catchment of the river Mur to identify hot spots of flood risk in this part of the railway network (Kellermann et al. 2016).

Example of damage and vulnerability calculations: Port of Rotterdam and flood risk

The port of Rotterdam in the Netherlands is the second largest in the world and the Largest Port in Europe. The harbor is situated in the south-western river delta of the Netherlands and is prone to natural hazards (wind storms, flooding) and the impact of climate change on these natural hazards. Potential elements at risk are industries, energy plants, port facilities, railways, tunnels, and container terminals. In addition, a large section of Rotterdam's working population is employed in the port area, and many businesses are highly dependent upon port activities. Severe economic damage can occur from long-term closures of the port and its industry.

Similar to the Austrian case study, **flood inundation maps** with different return periods (probabilities) were used to estimate potential flood losses. This was done by first overlaying the flood maps for the Port with the exposed assets ('buildings') of the area. This database is shown in **Figure 2.5.** Next, we applied so-called **stage-damage curves (SDC)** to represent the vulnerability to flooding for each of the exposed assets classes (**Figure 2.6**). A stage-damage curve for flooding shows how much percentage damage of the total potential damage occurs for a certain flood depth. For example, Figure 2.6 shows that for asset type 'liquid bulk storage', more than 85% of the total damage occurs with a flood depth of 1m.

Figure 2.5.

The six types of exposed assets in the Port of Rotterdam. Photo by Port of Rotterdam Authority, 2012.

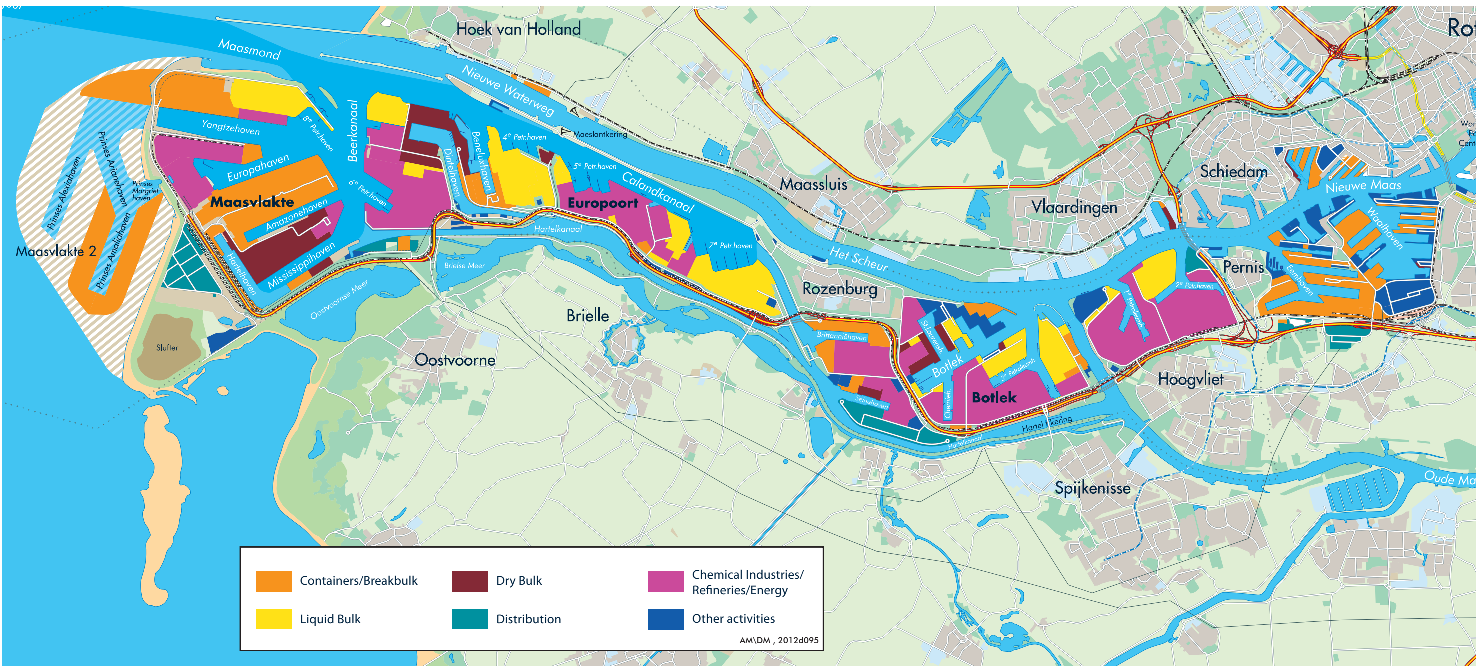
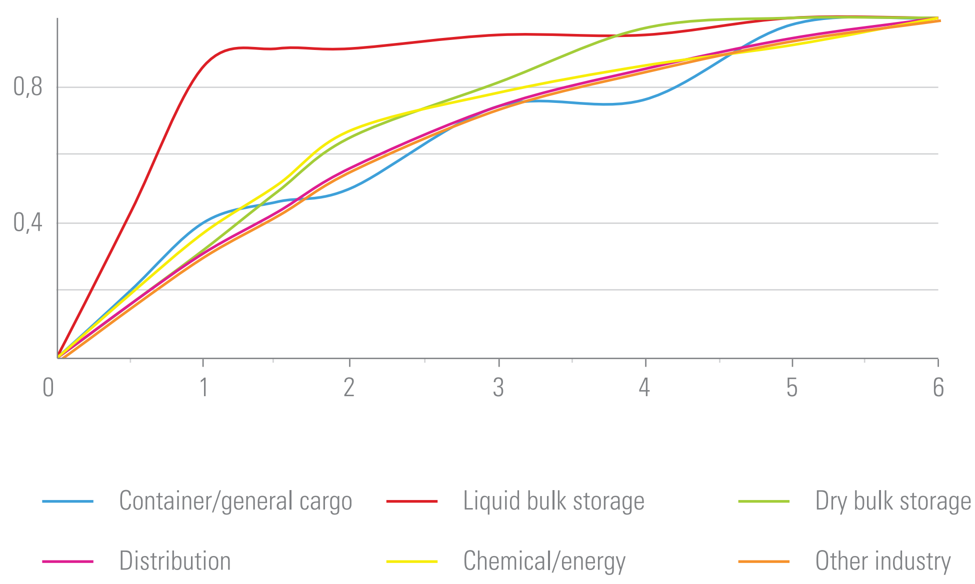


Figure 2.6.

Stage-damage functions for the Port of Rotterdam. The functions show the relation between the exposed assets (6 types), and the % damage of flooding as a function of the flood depth.

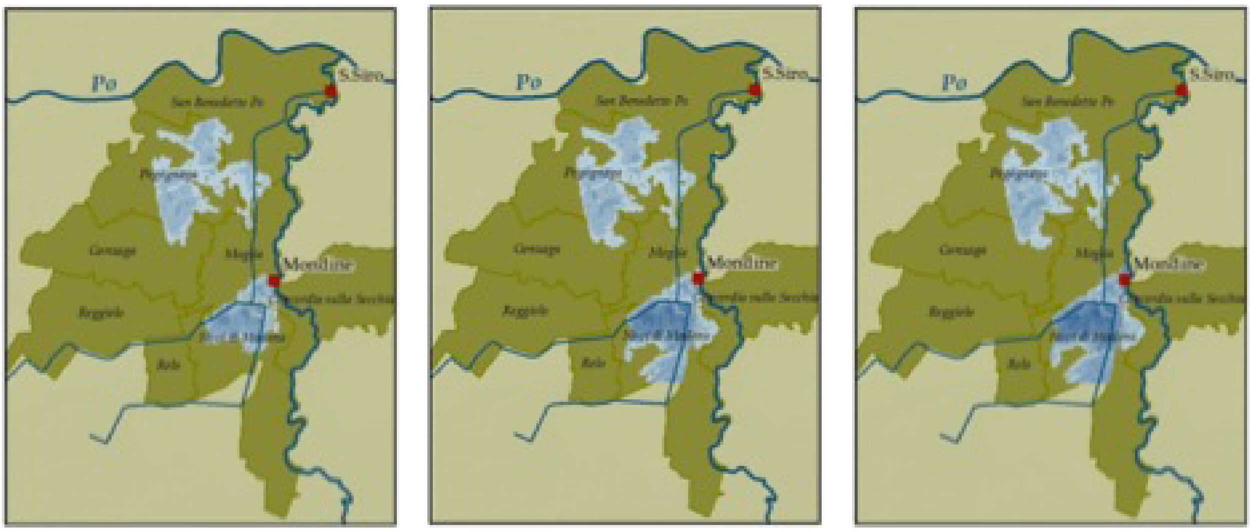


Case study Italy: controlled floods to reduce risk

The flood risk analysis conducted in this case study was compelled as a result of the severe earthquake that hit the Emilia Romagna region (Northern Italy) in 2012, causing a total loss of €16 billion. Among other consequences, the earthquake disrupted the otherwise well-functioning drainage system (DS) protecting the area against flooding. Flood risk increased consistently in urban, industrial, and agricultural areas. To prevent larger impacts, in 2012 a multi-sector partnership was installed between the Civil Protection Agency (CPA), the Land Reclamation and Irrigation Boards (LRIB), and the Regions Lombardy and Emilia Romagna. The partnership, promoted and overseen by the Po River Basin Authority (PRBA), was endorsed as an inter-regional emergency management plan.

The risk assessment delineated the areas exposed to higher flood risk as a result of inoperable DS under different precipitation and disruption scenarios, and estimated economic losses caused by uncontrolled floods in terms of capital stock damage and foregone production losses. First, the simulated volume of drained water and timing of its outflow were analysed using a 2D hydrodynamic model and high-resolution digital elevation model to produce **flooding maps** for each scenario (**Figure 2.7**). Altogether 25 scenarios were analysed, including four network disruption and five rainfall intensity configurations. As in the Port of Rotterdam case, economic losses were estimated using **stage-damage curve model**. The SDC method estimated capital stock damage that ranges between €20 million under normal functioning conditions to around €300 million under catastrophic floods. The analysis also included the effects of climate change and land conversion.

Figure 2.7.
Flood scenarios for the Po River Basin case study, for return periods 1/1, 1/10 and 1/50 years.



Rp1 Rp10 Rp50

Example of EP curve: case study wildfires in Portugal

A key hazard in Portugal is wildfire with many major episodes over the recent past. In 2003, Portugal had the worst ever recorded fire season, with about 450 thousand hectares burned. The central part of the Portuguese mainland was most affected, including the district of Santarém where the ENHANCE case studies, the municipalities of Chamusca and Mação, are located. Chamusca and Mação were especially affected in 2003, and empirical risk data from 2003 were used to study the major drivers that led to the catastrophic fires.

The assessment of wildfire risk was performed in two different complementary components: **spatial** and **temporal**. First, wildfire hazard maps were created showing the extent of the burned areas. Next, each of those hazard maps was translated into losses using a wildfire model. This model integrates the following variables: land cover (CORINE Land Cover data, the exposed assets), slope (Digital Elevation Module 80m) and previously burnt areas (historical data of burnt areas). The model derives fire loss maps by combining the forest fire hazard maps with the economic value of the elements at risk (different types of forests) and their vulnerability. Finally, each fire loss map was assigned a probability that could be statistically derived from a fire database. Using the unit values for losses included in the National Forest Strategy of 2006, an **exceedance-probability loss curve** (**Figure 2.8**) was established indicating loss information for the two most extreme years of 2003 and 2005. It shows that values of estimated losses for the district of Santarém can be higher than €100 million.

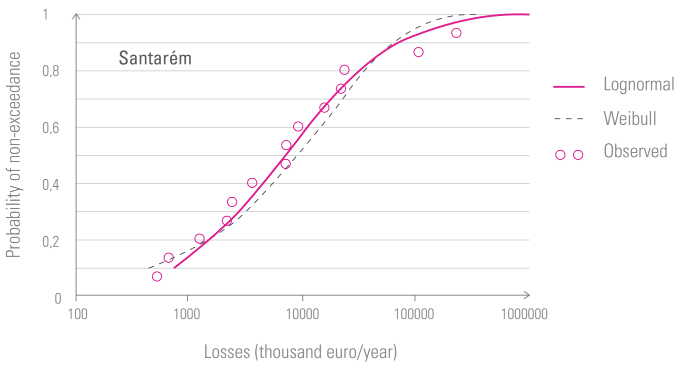


Figure 2.8.
Exceedance probability-loss curve for wildfires in the district of Santarém, showing the relation between forest fire losses and their probability.

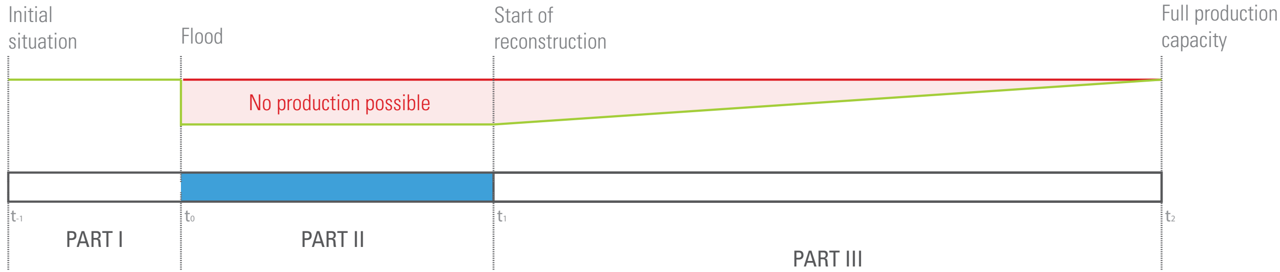
Alternative vulnerability indicators: drought indicators

In the ENHANCE project, we have performed two drought case studies: (1) a **global analysis** on past drought trends and projections of future drought conditions due to climate and socio-economic changes, and (2) a **regional case study in the Júcar Basin** in South Eastern Spain, where we have assessed drought impacts in view of global change and evaluated the effectiveness of drought adaptation.

Drought and water scarcity are two manifestations of water-related risk that are both connected to the deficit of freshwater resources. **Drought** is a natural phenomenon that refers to a deviation from the historical record (Logar & Van den Bergh, 2012; Pereira et al., 2009; Wilhite, 2005). **Water resources scarcity** refers to the overuse of water resources and is often seen as strongly modified by human use. Two hazard indicators often used to assess global and regional scale water scarcity are the **Water Crowding Index (WCI)** and the **Water Scarcity Index (WSI)** (Falkenmark, 1986; Falkenmark et al., 2007). The WCI quantifies water scarcity as the yearly water availability (measured in runoff or discharge) per capita at a country or basin-level. The WSI uses a ratio between withdrawals and resources availability as an indicator for water scarcity conditions.

The Júcar Basin, for example, **uses a combination of indicators for the assessment of current and future drought risk, and for operational use**. Synthetically generated information on streamflow and reservoir storage levels are combined with knowledge on sectoral water needs and costs of potential water shortages to assess the probability of hazardous drought conditions and their associated (economic) impacts. Vulnerability to drought and water scarcity conditions in the Júcar Basin is mainly determined by the portfolio of different water uses being dependent on the same source of water and by the operational management of drought conditions. At this operational level, drought risks are governed by monitoring multiple drought indicators (reservoir volumes, aquifer storage, streamflow, rainfall) and the timely declaration of emergency states if necessary (Monteagudo et al., 2013).

Both global scale indicators and local scale indices for risk assessment and operational use depend heavily on the availability of reliable observations or simulations of meteorological and hydrological conditions (precipitation, evaporation, streamflow, reservoir levels) **and socioeconomic information** (population, water needs, land use, vulnerability). Continuous investments are needed and taking place to assimilate and improve the (open-source) availability and quality of this meteorological, hydrological and socioeconomic information at different spatial scales, for example within the Inter-Sectoral Impact Model Inter-comparison Project (ISI-MIP), the EartH2Observe project (E2O), the Global Runoff Data Centre (GRDC), and the European Drought Observatory (EDO).



Direct and indirect damages

In risk assessment studies, one can distinguish between direct and indirect effects (Koks et al., 2012). **Direct effects** can be defined as the impacts that occur due to direct effects from hazards to properties or people. In the economic literature, direct losses are often referred to as stock losses, which are defined as losses that occur at a given point in time. **Indirect effects**, on the other hand, are often caused by the direct impacts, but are the result of interferences within industrial supply chains (Okuyama and Santos, 2014). Most importantly, indirect effects may also occur outside the hazard area: e.g., companies that are not flooded, but that have economic relations with households and industries that are flooded, cannot supply or demand their goods and services, and therefore, indirectly suffer from the flood.

Numerous studies have developed approaches to estimate flood damage. Many of these studies, often originating from the engineering community, address mainly direct losses of flooding using stage-damage curves, such as illustrated for the cases of Rotterdam and Po (Penning-Rowsell et al., 2010; Kreibich et al., 2010). Estimating indirect losses has mainly been the domain of the economic community, using macroeconomic models such as input-output models or generalised equilibrium models (e.g. Steenge and Bockarjova, 2007; Hallegatte, 2008). A few studies have proposed a more integrative approach for the calculation of both direct and indirect flood damage. For instance, Jonkman et al. (2008) proposed a framework for the combination of direct and indirect losses and FEMA (2009) developed two modules within the HAZUS-FLOOD model to assess direct and indirect losses. However, an integrative model, able to consistently integrate both direct and indirect losses, which gives the total flood risk in terms of expected annual damage, is in our opinion, still missing.

In the ENHANCE project, we have applied an **integrative flood risk model** for the Port of Rotterdam. The framework consists of multiple steps. First, a direct loss assessment (using a direct flood damage model) is conducted in the port region, specifically differentiating the direct damages to various industrial sectors. Second, we simulate indirect losses using an input output model, and calculate how direct losses translate into the loss in economic production per sector (Koks et al. 2014). Next, the input-output model is used to show the time and costs required to reach the pre-disaster state of the economy in the area.

Figure 2.9.

Overview of the different model parts for the indirect risk model: pre-flooding situation; shock to the economy because of a flooding event; post-event situation with the recovery of the economy until initial production is achieved.

Extreme events and statistics

In risk assessment, it is often difficult to attach a probability to a certain hazard event. This pertains especially for low probability events for which there is little or no empirical data. For these situations, **extreme value theory** is needed to model statistical properties of extreme events that lie outside the range of observed data. The usual statistical techniques focus on average events, and have a great bias in estimating extremes. One reason for this is that standard estimation techniques only serve well where there is a large density of observed data. Furthermore, most data is (naturally) concentrated toward the center of the distribution (the average) and so, by definition, extreme data is scarce and therefore estimation is challenging.

Figure 2.10 shows an example of fitting extreme value statistics (A so called 'Gumbel plot') through measured data of river discharges for the river Rhine in the Netherlands (the black dots). Since only ~100-150 years of measurements are available, the rarest event is the maximum discharge in that period: ~12500 m3/s, with a probability of ~1/100. However, for policy reasons, we would like to estimate an extreme discharge that has a probability of 1/1000. Therefore, we need to extrapolate the measured data using extreme value statistics, which gives us a discharge of ~16000 m^3/s.

Figure 2.10.
Fitting an extreme value Gumbel plot through measured discharge data for the Rhine Basin.

A further complication is the dependency between extreme events which is now tackled within the ENHANCE project via a 'Copula approach'. Copulas are useful for modelling dependencies between continuous random variables. Using a copula model allows to separate the selection of the marginal distributions (e.g. the risk in form of loss distributions) from the selection of the copula (e.g. the dependency between risks). In other words, while the marginal distributions contain the information of the separate risks, the copula contains the information about the structure of the dependency. Using flood as an example, the application of a copula approach makes it possible to estimate loss distributions between selected regions and countries, explicitly taking their dependency into account (Jongman et al. 2014).

Flood in York, UK, 2007. Copyright: UNISDR.