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RESEARCH ARTICLE
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Projecting Future Flood Losses to Company Assets in Europe: The Role of Precautionary Measures

Bhadra Devadas[1,2], Dominik Paprotny[3,4], Heidi Kreibich[1], Max Steinhausen[5], Laurens J. N. Oostwegel[6], Thijs Endendijk[7], Lukas Schoppa[8], Alessio Domeneghetti[9], Attilio Castellarin[9], Francesco Dottori[10], Claudia D'Angelo[11], Lorenzo Mentaschi[12,13], Soumendra Nath Kuiry[2], and Nivedita Sairam[1]

[1]Section 4.4 Hydrology, GFZ Helmholtz Centre for Geosciences, Potsdam, Germany, [2]Department of Civil Engineering, Hydraulic and Water Resources Engineering, Indian Institute of Technology Madras, Chennai, India, [3]Research Department Transformation Pathways, Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Potsdam, Germany, [4]Institute of Marine and Environmental Sciences, University of Szczecin, Szczecin, Poland, [5]Division Hydrology and River Basin Management, Leichtweiß-Institute for Hydraulic Engineering and Water Resources, Technische Universität Braunschweig, Braunschweig, Germany, [6]Seismic Hazard and Risk Dynamics, GFZ German Research Centre for Geosciences, Potsdam, Germany, [7]Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, Amsterdam, The Netherlands, [8]Munich Reinsurance Company, Munich, Germany, [9]Department of Civil, Chemical, Environmental and Materials Engineering, Alma Mater Studiorum Università di Bologna, Bologna, Italy, [10]University School for Advanced Studies (IUSS), Pavia, Italy, [11]European Commission, Joint Research Centre, Ispra, Italy, [12]Department of Physics and Astronomy (DIFA), University of Bologna, Bologna, Italy, [13]CMCC Foundation—Euro-Mediterranean Center on Climate Change, Lecce, Italy

Key Points:

- Loss to company buildings and equipment is quantified using flood hazard maps, object-level exposure data, and a probabilistic loss model
- Future flood losses for European company properties could rise more than sevenfold due to climate change and increasing exposure
- Requiring a minimum level of private precautionary measures through policy can reduce company flood damages by up to 67%

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

N. Sairam and S. N. Kuiry,
nivedita@gfz.de;
snkuiry@civil.iitm.ac.in

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Author Contributions:

Conceptualization: Bhadra Devadas, Dominik Paprotny, Heidi Kreibich, Nivedita Sairam
Data curation: Dominik Paprotny, Max Steinhausen, Laurens J. N. Oostwegel, Thijs Endendijk, Alessio Domeneghetti, Attilio Castellarin, Francesco Dottori, Claudia D'Angelo, Lorenzo Mentaschi
Formal analysis: Bhadra Devadas
Methodology: Bhadra Devadas, Dominik Paprotny, Max Steinhausen, Francesco Dottori, Claudia D'Angelo, Lorenzo Mentaschi, Nivedita Sairam

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Abstract

Flooding has become an escalating threat over the past years, driven by climate, land use and socio-economic changes. In Europe, floods now surpass other natural disasters in severity, causing substantial economic losses, particularly in the companies (commercial and industrial sectors). While river flood impacts on agriculture and residential properties have been extensively studied, research on companies losses remain limited despite their significantly high direct damages. This study enhances fluvial flood risk assessment for company assets by integrating flood hazard scenarios with flexible state-of-the-art Bayesian Network-based flood loss model and object-specific exposure data. It estimates the expected annual damage (EAD) to company properties across Europe under a baseline and potential future scenarios shaped by climate change, exposure dynamics, and their combined effects. Additionally, the study assesses the potential of property-level precautionary measures to mitigate flood risks. Results indicate that, compared to the baseline (year—1995), the EAD values could rise more than 5-fold under RCP4.5 scenario and 7-fold under RCP8.5 scenario by the end of the century. However, a policy scenario in which all companies implement at least one precautionary measure ("measures for all") effectively offsets these projected losses by up to 67%. This underscores the crucial role of individual actions in reducing future flood impacts.

Plain Language Summary

Flooding is a rising problem in Europe, especially for businesses, leading to substantial financial losses. This study analyses how future riverine floods will affect company properties across Europe and predicts damage under different future scenarios. The findings show that, without action such as implementing property-level precautionary measures, flood damage could increase by over 7-fold by the end of the century under RCP8.5 scenario. However, when each company in the business sectors takes simple precautions, the flood risk can significantly be reduced up to 67%. This research provides valuable insights for companies and policymakers, emphasizing the importance of flood preparedness to mitigate financial losses and protect communities.

1. Introduction

Flooding, a rapidly escalating environmental challenge, has become a top priority over the past three decades and is projected to worsen with ongoing global warming (IPCC, 2021). In the last 5 years alone, global flood losses amounted to 304.3 billion euros and are projected to rise annually (Munich Re, 2021). The increasing frequency and severity of floods across Europe underscore the urgency of understanding and managing flood risks more effectively. Recent events highlight the devastating impact of floods on human lives and economies. For example, the October 2024 flood in Valencia, Spain, resulted from torrential rains devastated large areas of the Valencian

Resources: Soumendra Nath Kuiry, Nivedita Sairam
Software: Bhadra Devadas, Lukas Schoppa, Francesco Dottori, Claudia D'Angelo, Lorenzo Mentaschi
Supervision: Nivedita Sairam
Validation: Thijs Endendijk
Visualization: Bhadra Devadas
Writing – original draft: Bhadra Devadas, Dominik Paprotny, Nivedita Sairam
Writing – review & editing: Bhadra Devadas, Dominik Paprotny, Heidi Kreibich, Laurens J. N. Oostwegel, Thijs Endendijk, Lukas Schoppa, Alessio Domeneghetti, Francesco Dottori, Claudia D'Angelo, Lorenzo Mentaschi, Soumendra Nath Kuiry, Nivedita Sairam

Community, Castilla-La Mancha, and Andalusia. This disaster led to 219 fatalities and cost approximately 20.5 billion euros, leading to a 0.2% decline in the GDP of Spain. Of this, 10 billion euros was attributed to infrastructure and businesses. Similarly, the July 2021 floods across western and central Europe due to the low-pressure system caused 189 deaths and 33 billion euros in damages in Germany, while the Netherlands faced 0.9 billion euros in losses to households and businesses (Endendijk et al., 2024; ENW, 2021; Thieken et al., 2023). A recurring pattern across these events is the substantial share of flood-related losses sustained by the companies (commercial and industrial sectors). In Germany, 33% of insurance claims from the July 2021 flood pertained to commercial and industrial properties (Munich Re, 2022) while during the 2016 floods in the Loire and Seine River basins, 28% of claims were associated with company entities (Fédération Française de l'Assurance, 2017). The Netherlands has also experienced high losses to company properties, accounting for over half of the total flood losses, amounting to approximately 0.5 billion euros (Endendijk et al., 2024; ENW, 2021). In Italy, the 2023 Emilia-Romagna flood resulted in an overall loss of 8.8 billion euros, of which 2.2 billion euros was attributed to business-related damages (Arrighi and Domeneghetti, 2023). These statistics highlight the vulnerability of companies to flooding. Flood risk assessment evaluates three interdependent components: flood hazard, exposure, and vulnerability. The hazard component in risk assessment represents the probability and intensity of flood events, characterized by parameters such as flood depth, velocity, and duration, which determine the physical impact of flooding (Merz et al., 2010). The exposure component encompasses people, assets, and infrastructure in flood-prone areas (Olsen et al., 2015). Vulnerability assesses the susceptibility of exposed elements to suffer damage based on their ability to withstand flood impacts, which can vary depending on factors like structural resilience, preparedness, and social factors that influence recovery (Merz et al., 2010).

Rising temperatures, precipitation pattern alterations, and land use changes will likely increase the frequency and intensity of river floods globally, including in Europe (Winsemius et al., 2016). Northern and central European regions are projected to experience heightened flood hazards due to more intense winter rainfall. In contrast, southern Europe may see a reduction in river flood risk due to fewer extreme rainfall events (Mentaschi et al., 2020). Central and Eastern Europe will experience increased extreme flooding events driven by intensified rainfall and seasonal shifts characterized by wetter winters and drier summers (Dankers & Feyen, 2009). Dottori et al. (2018) highlighted that human and economic losses from river flooding will increase with global warming, particularly in economically dense regions. Large-scale flood risk assessments focusing on socio-economic (Alfieri et al., 2016) and macroeconomic impacts (Koks et al., 2019) underscore the need for comprehensive adaptation strategies and resilient infrastructure to mitigate future flood risks.

Despite increased awareness, flood risk assessments for companies remain constrained due to the diversity in building structures, asset types, and operational functions across various economic sectors. Unlike residential properties, company establishments range from small offices to extensive industrial facilities, each presenting distinct exposure and vulnerability profiles. This variability results in significant fluctuations in loss data, complicating the development of standardized modeling approaches (Merz, Kreibich & Dimitrova, 2010; Paprotny et al., 2020; Schoppa et al., 2020). Additionally, reliable, sector-specific post-disaster damage data for businesses is limited, hindering the empirical foundation for effective model development and validation. Estimating asset values is even more challenging due to inconsistencies in available economic, building, and land-use data across different regions (Paprotny et al., 2020). This complexity hinders the development of robust company flood damage models.

Most models for the companies often determine flood damage based on (sectoral) bivariate depth-damage functions that only include inundation depth as a hazard indicator (Huizinga et al., 2017; Porter et al., 2022). These functional relationships in the form of curves generally lack strong calibration, as empirical post-disaster is scarce for the companies, especially when differentiating between impacts on various economic sectors (Paprotny et al., 2020). Additional steps have been taken to develop multivariate models to assess flood damage for companies (e.g., Darnkachatarn & Kajitani, 2025; Paprotny et al., 2020; Seifert et al., 2010). In addition to physical flood damage models, the use of input-output (IO) and Computable General Equilibrium (CGE) models emerged as an approach to understanding the broader economic impacts of floods on commercial and industrial activities (Wouter Botzen et al., 2019). These models simulate how shocks propagate through economic sectors and affect recovery trajectories (Rose & Liao, 2005). However, these models do not yet account for the potential effectiveness of precautionary actions on the building level. To address these limitations, a promising alternative is Bayesian Network models based on empirical data for flood risk assessment of companies. These models account for previous flood experiences, socio-economic characteristics and implementation of precautionary

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measures such as building elevation, waterproofing, and other resilience-enhancing investments, which can significantly reduce flood losses (Sairam et al., 2019; Schoppa et al., 2020). Bayesian Networks offers graphical and probabilistic modeling capabilities that enhance flexibility and adaptability to local data availability.

In recent years, the availability of building footprints worldwide has dramatically increased due to crowdsourced data from OpenStreetMap and global remote sensing-derived building footprint data sets (Microsoft, 2024; Sirko et al., 2021) further enhanced the potential of Bayesian Network modeling approaches. These developments have led to the potential to use object-specific exposure data sets for risk estimation (Paprotny et al., 2020; Schorlemmer et al., 2024). In contrast to land use-based exposure data sets, we can map assets building-by-building using object-specific exposure to capture finer details such as variations in building size, function, and construction materials. The attributes of the exposure data are based on the building density, form, and heterogeneity in the built environment (mixed land use or even mixed building types within one building). Such details cannot be captured using average exposure values per square meter over large areas, as is common for land use exposure models.

The present study includes the member countries of the European Union, which present a diverse array of climatic zones, hydrological regimes, and topographical conditions. This region, historically susceptible to large-scale flooding, features several significant river basins, including the Danube, Rhine, Elbe, Po, Seine, and Vistula. The topography across the European Union varies considerably, ranging from low-lying coastal and riverine floodplains in nations such as the Netherlands and Belgium to the mountainous regions of the Alps, Carpathians, and Pyrenees, all of which influence runoff patterns and flood peaks. Switzerland is excluded from this study as it is not a member of the European Union, despite being geographically located within Europe.

In this study, we aim to improve the large-scale fluvial flood risk assessment of company assets by integrating flood hazard data of 100 m resolution (Dottori et al., 2022) with the flexible state-of-the-art probabilistic Bayesian Network-based flood loss model (BN-FLEMOcs, Schoppa et al., 2020) and object-specific exposure data (Schorlemmer et al., 2024). Specifically, the study aims to attribute the future expected annual damage of fluvial floods to company assets to the consequences of climate change and exposure changes. A key aspect of this study is evaluating the potential of building-level precautionary measures to reduce future impacts, distinguishing our model by offering a unique approach to risk mitigation. The manuscript is organized in the following sections. The input data sets, including flood hazard, flood protection, exposure data, and the BN-FLEMOcs model, and the scenarios are introduced in Section 2.1. The methodology for calculating loss metrics is detailed in Section 2.2. The results are presented in Section 3, focusing on baseline flood losses, future projections, and the impact of building-level precautionary measures. These findings are analyzed and contextualized in the discussion (Section 4), which addresses key insights, limitations, and uncertainties. Finally, the manuscript summarizes the main findings and recommendations for future research in Section 5.

2. Data and Methodology

2.1. Model Inputs

2.1.1. Hazard

The flood hazard data utilized in this study are from the Joint Research Center (JRC) of the European Commission, as detailed in Dottori et al. (2022). This data set offers 100 m resolution flood extent and depth maps for Europe and the Mediterranean Basin, covering various return periods (10, 20, 50, 100, 200, and 500 years). The return levels were estimated using the non-stationary Extreme Value Analysis (EVA) methodology (Mentaschi et al., 2016), which is able to account for the changes in extremes driven by climate change. The flood scenarios were generated using the LISFLOOD hydrological model to simulate river flow data and the LISFLOOD-FP hydrodynamic model for inundation simulations. These models were driven by climatological data from the European Flood Awareness System (EFAS) of the Copernicus Emergency Management Service. The resulting flood hazard maps encompass river basins exceeding 500 km^2, with each cell value representing water depth in meters. The data set has been extensively applied across multiple domains, including flood risk quantification, policy formulation, and climate adaptation planning. For example, Steinhausen et al. (2022) employed the JRC flood hazard maps to assess the flood risk to European households, highlighting the spatial heterogeneity in exposure resulting in regional disparities. Dottori et al. (2022) utilized flood hazard maps to perform an economic evaluation of adaptive strategies targeted at abating flood risks.

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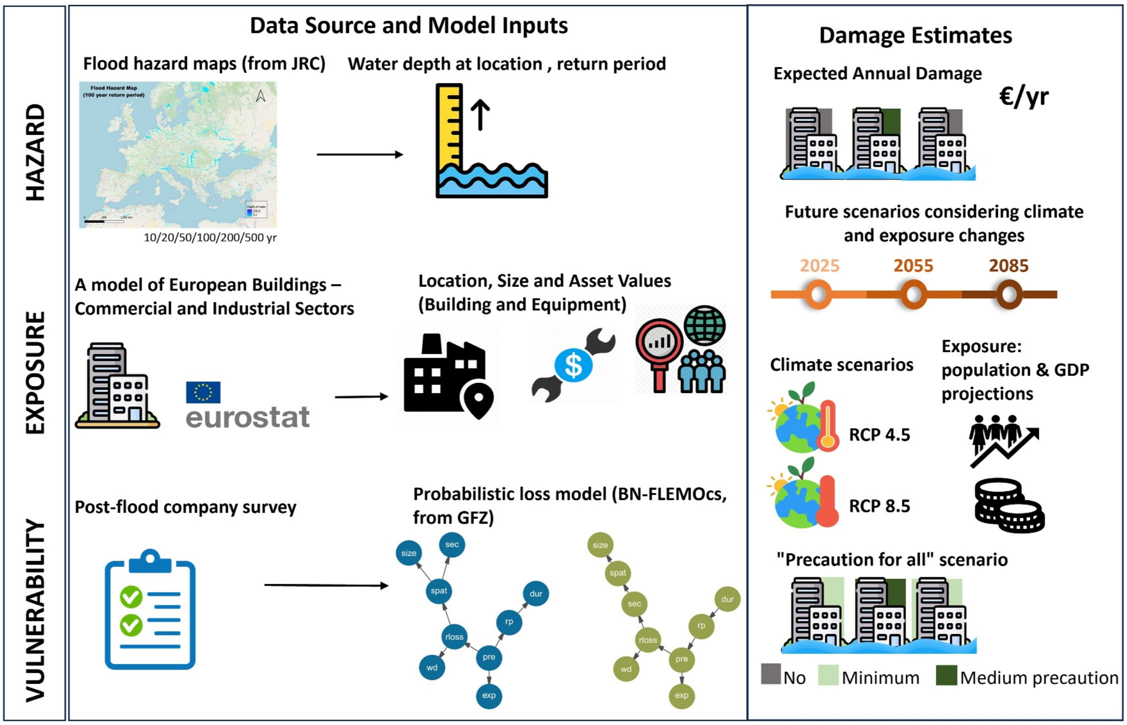

Figure 1. Hazard, exposure and vulnerability components of flood risk assessment—input data, models and scenarios.

The FLOPROS data set (Dottori et al., 2022) defines flood protection levels at river locations based on the design flood's return period. This data set was compiled by integrating diverse sources, including technical reports, scientific literature, and risk modeling frameworks, to determine European countries' most probable protection levels. To maintain consistency with flood hazard data sets in related research, the flood protection data were downscaled to a 100-m grid. The flood protection data set has been widely used to assess flood risk and management strategies. Dolejš et al. (2022) emphasized its role in riverine flood risk management at the national scale, while Tesselaar et al. (2023) with the help of FLOPROS data set tried to project future riverine flood risk at the continental scale.

2.1.2. Exposure

This study uses the location and attributes of exposed company assets sourced from the model of European buildings (Schorlemmer et al., 2024). This is an open data set that combines the ESRM20 aggregated building exposure model (Crowley et al., 2021) with building-by-building exposure data sourced from OpenStreetMap and the Global ML Building Footprint data set. The model is aggregated on a multi-resolution tiled grid between 100 × 100 m and 1 × 1 km and contains a comprehensive overview of building locations, sector types (residential, commercial and industrial), building structural types, monetary value of building structure and population values. Eurostat serves as the source of sector-specific equipment values (Fixed Assets: ICT equipment—AN.1132 and other machinery and equipment—AN.1139) at the NUTS3 level (Nomenclature of Territorial Units for Statistics level 3) based on the 2016 version (European Commission: Eurostat, 2018). The asset and equipment values are in euro (€) in 2015 prices and exchange rates to align with NUTS region definition. The sector-specific equipment values are disaggregated to individual company buildings proportional to the monetary value of building structure. Further information on the disaggregation methodology is provided in Text S1 of Supporting Information S1.

2.1.3. Vulnerability

The vulnerability of companies is modeled in the study using a probabilistic Bayesian Network-based loss model called BN-FLEMOcs (Schoppa et al., 2020). We implement the BN-FLEMOcs models that predict losses to company building structure and equipment at a European scale. Figure 1 presents the hazard, exposure, and vulnerability components of the flood risk assessment conducted in our study, along with the input data sources.

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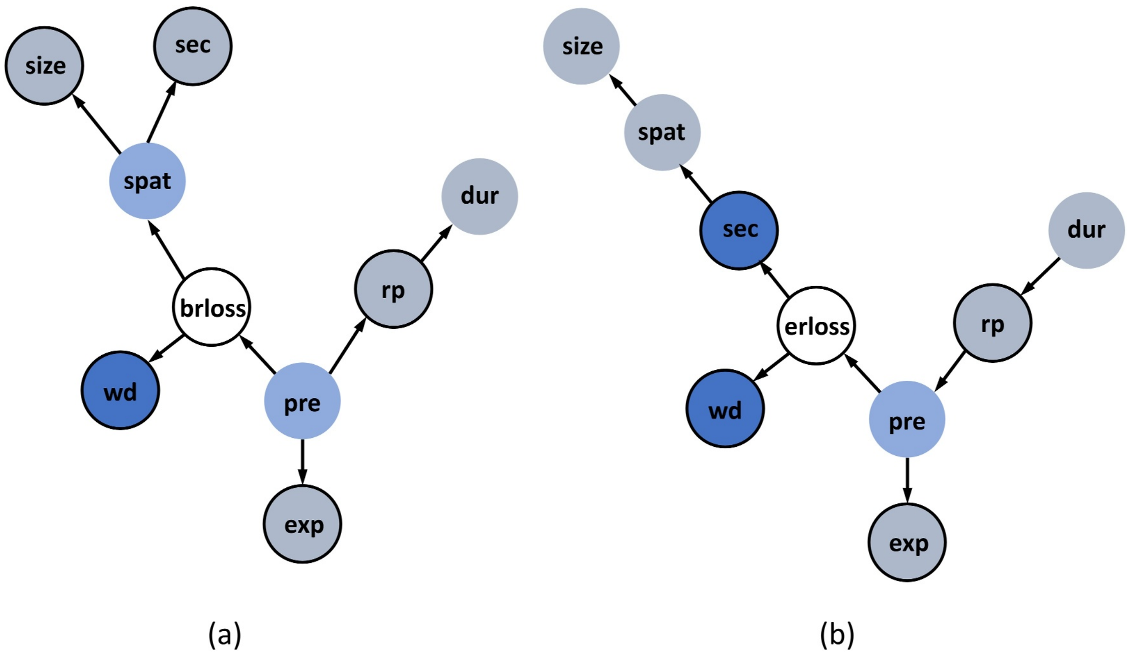

Figure 2. Structure of BN-FLEMOcs (Schoppa et al., 2020)—flood loss model structure for (a) building relative loss (brloss), (b) equipment relative loss (erloss) with the Markov blanket (dark blue nodes) and the missing variables in the Markov blanket at the European scale (light blue nodes). The nodes with a bold outline are the input and target variables used at the European scale. The variables are represented as wd: water depth in centimeters; pre: proportion of precautionary measures implemented; exp: flood experience; rp: return period; dur: duration of inundation; spat: spatial situation of the company; sec: sector; size: company size; brloss: relative loss for building; erloss: relative loss for equipment.

The Bayesian Network approach represents the statistical dependency of several input variables as a directed acyclic graph. The target variable is relative loss which is the absolute loss divided by the total replacement value. In BN-FLEMOcs, the Markov blanket of relative loss includes hazard variable—water depth; company attributes such as sector in the case of equipment losses and spatial situation in the case of building losses and proportion of precautionary measures implemented (see Figure 2). Spatial situation represents the share of the company in the building—whether the company location comprises several buildings, one entire building, one or two floors of a shared building or less than one floor of a shared building. Proportion of precautionary measures is the number of precautionary measures that a specific company implemented divided by the number of relevant measures that this company could have possibly implemented. The relative loss is conditionally independent of all other variables given the variables in the Markov blanket. In case of missing variables in the Markov blanket, their parent nodes are used to estimate the values. That means, while applying the BN-FLEMOcs to Europe, it is not possible to obtain the spatial situation and information on precautionary measures from the exposure data sets. Hence, we estimate these nodes using their parent nodes—the spatial situation is estimated based on company size and company sector; implementation of precautionary measures is estimated based on return period and flood experience. The range of estimates produced by BN-FLEMOcs reflects the modeling uncertainty associated with damage processes and loss valuation.

The BN-FLEMOcs is a discrete Bayesian Network model. That is, the continuous variables in the model are discretized. The discretization levels and structure of the model were learned by a combination of expert and data-driven insights (see Schoppa et al., 2020 for further details). BN-FLEMOcs was calibrated (estimation of conditional probability table values) and validated on empirical loss data (sample size = 1,346) obtained from post-flood company surveys from the Elbe, Danube, Oder and Rhine catchments in Germany (Schoppa et al., 2020). The capability of the BN-FLEMOcs model to generalize to other countries is tested by transferring the model across two other countries in Europe. The model is validated on losses from the Secchia 2014 floods in Italy and the 2021 floods in the Netherlands. Further details on the variables in BN-FLEMOcs, transfer and validation are given in Text S2 of Supporting Information S1.

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2.1.4. Data

The study examines four 30-year time periods, each represented by its midpoint year. The baseline is set in the year 1995, representing the years 1980–2010. For this period, flood hazard data were derived from long-term hydrological simulations using the LISFLOOD model. The hydrological input included synthetic flood hydrographs generated for each section of the European river network, which were used as inputs for the LISFLOOD-FP hydrodynamic model. Flood simulations were conducted for all six return periods (10, 20, 50, 100, 200, and 500 years) to create hazard maps at continental scale representing inundation depth at 100 m resolution (as mentioned in Section 2.1.1). The asset values (building structure and equipment) as of 2015 are adjusted to reflect the retrospective baseline scenario by applying a sector-specific correction factor. The regional estimates (NUTS 3) of the ratio of sector-specific total fixed assets in 2015 to those in the baseline period (Paprotny & Mengel, 2023) are used as the correction factor. In addition to the baseline, losses corresponding to three future time periods centered at 2025, 2055, and 2085 are projected. In the future time steps, combinations of RCP 4.5 and 8.5 climate change scenarios and exposure/asset value projections are simulated (see, Figure 1).

For future periods, flood hazard projections were based on a comprehensive analysis using simulations from the LISFLOOD hydrological model (Mentaschi et al., 2020), which was calibrated to incorporate future climate scenarios. Forcing data were obtained from EURO-CORDEX projections under the RCP 4.5 and RCP 8.5 scenarios. The range of estimates in the climate change simulations results from the variability among the 11 EURO-CORDEX projections used to inform the hydrological and hydraulic models. The assessment of future flood hazards integrated flood frequency changes under the climate scenarios (Steinhausen et al., 2022). Exposure projection is based on the projected change in regional GDP and the projected change in the ratio between industrial and commercial fixed asset stock to GDP. The regional GDP projections combine probabilistic projections of population and GDP per capita changes (Steinhausen et al., 2022). The ratio between industrial and commercial fixed asset stock to GDP from 1950 to 2019 is extrapolated up to 2085. The uncertainty in the exposure projection is quantified by randomly sampling the probabilistic GDP projection and the Standard Error of trend extrapolation (Wooldridge, 2023).

The precaution ratio is calculated as the number of precautionary measures a company implemented prior to a damaging flood event, divided by the total number of relevant measures that could have been implemented by that company (Schoppa et al., 2020). This results in a value between 0 and 1, where higher ratios indicate better preparedness and lower values reflect limited precaution. The measures considered span three categories: adaptation (e.g., adapted use of flood-prone areas, relocation of equipment), mitigation (e.g., improving flood resilience of buildings, installing water barriers), and emergency response (e.g., saving equipment or stock, using water pumps, shutting down machinery, preventing contamination). With the exception of "saving equipment/goods and stock," which is treated as an ordered variable based on the amount saved, all other measures are binary, indicating whether or not they were implemented.

"Status quo" refers to the current level of precautionary measures implemented by companies representing the "Business As Usual" Scenario. "Status quo" is determined based on the historical flood experience and risk awareness within each region, as represented by the BN-FLEMOcs model structure. The potential future flood loss simulations considering combinations of climate scenarios and exposure projections are supplemented by a policy-focused intervention—"measures for all." In this scenario, the lower limit of precaution across companies is increased such that every company has implemented at least one property-level precautionary measure relevant to reducing their potential flood losses. The minimum precaution level is kept consistent across countries and timesteps. This scenario is designed to reflect a conservative assumption about the possible increase in the uptake of precautionary measures in the future and to assess their effectiveness in mitigating flood risk.

2.2. Risk Metric

The Expected Annual Damage (EAD) is calculated as the probability-weighted sum of damages across flood scenarios with different return periods, incorporating the concept of residual risk using Equation 1:

$$\mathrm{EAD} = 1/2 * \Sigma(\Delta P_{\mathrm{RP}_i}\ \Sigma D_{\mathrm{RP}_i}) + R_{\mathrm{res}} \quad (1)$$

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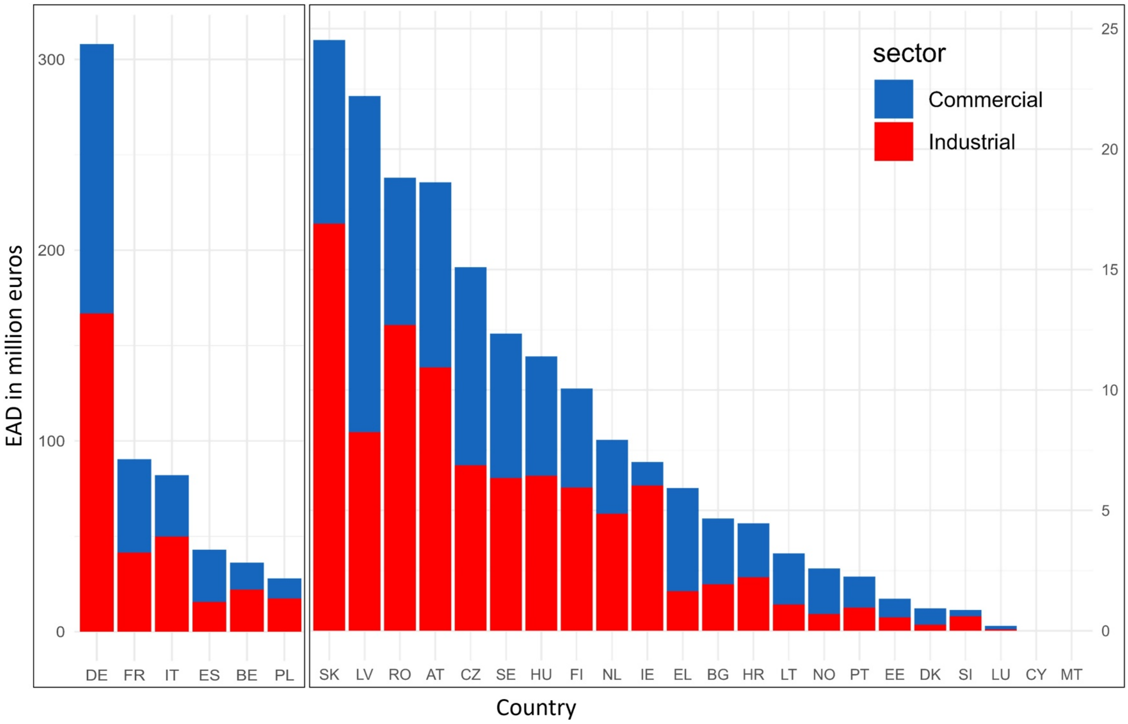

Figure 3. Expected Annual Damage for each country for the baseline period.

Where RP represents return period which can take values 10, 20, 50, 100, 200, and 500 and i represents the index 1–6; D_{RP_i} represents the damage caused by each flood of return period RP_i , determined using Equation 2:

$$\Sigma D_{\mathrm{RP}_i} = D_{\mathrm{RP}_i} + D_{\mathrm{RP}_{i+1}} \tag{2}$$

The exceedance probability interval ΔP_i, defined as the difference between the inverse of two consecutive return periods (RP_i and RP_{i+1}), is calculated using Equation 3:

$$\Delta P_i = 1/\mathrm{RP}_i + 1/\mathrm{RP}_{i+1} \tag{3}$$

Residual risk R_{res} is the risk that persists despite structural flood protection measures. This includes scenarios where flood defenses, such as dikes, are overtopped. Flood protection level (FP) is the return period of the maximum flood the structural flood protection can withstand ranging from 10 to 10,000 years. For areas with FP exceeding the maximum return period considered (500 years), the residual risk is added to the EAD calculation as defined in Equation 4:

$$R_{\mathrm{res}} = \frac{D_{\mathrm{max}}}{\mathrm{FP}} \tag{4}$$

D_{max} denotes the maximum damage caused by a 500-year return period flood, assuming damages do not increase for events exceeding this threshold. This approach ensures that the EAD captures direct damages from events below the protection standard and the residual risk associated with extreme events.

3. Results

3.1. Baseline Period

At the baseline period (centered at 1995), Germany has the highest estimated EAD (308 million euros), with the industrial sector accounting for 54.15% and the commercial sector accounting for 45.85% of the total losses (Figure 3). This is more than three times the damage estimated for the second-highest country, France (90.45

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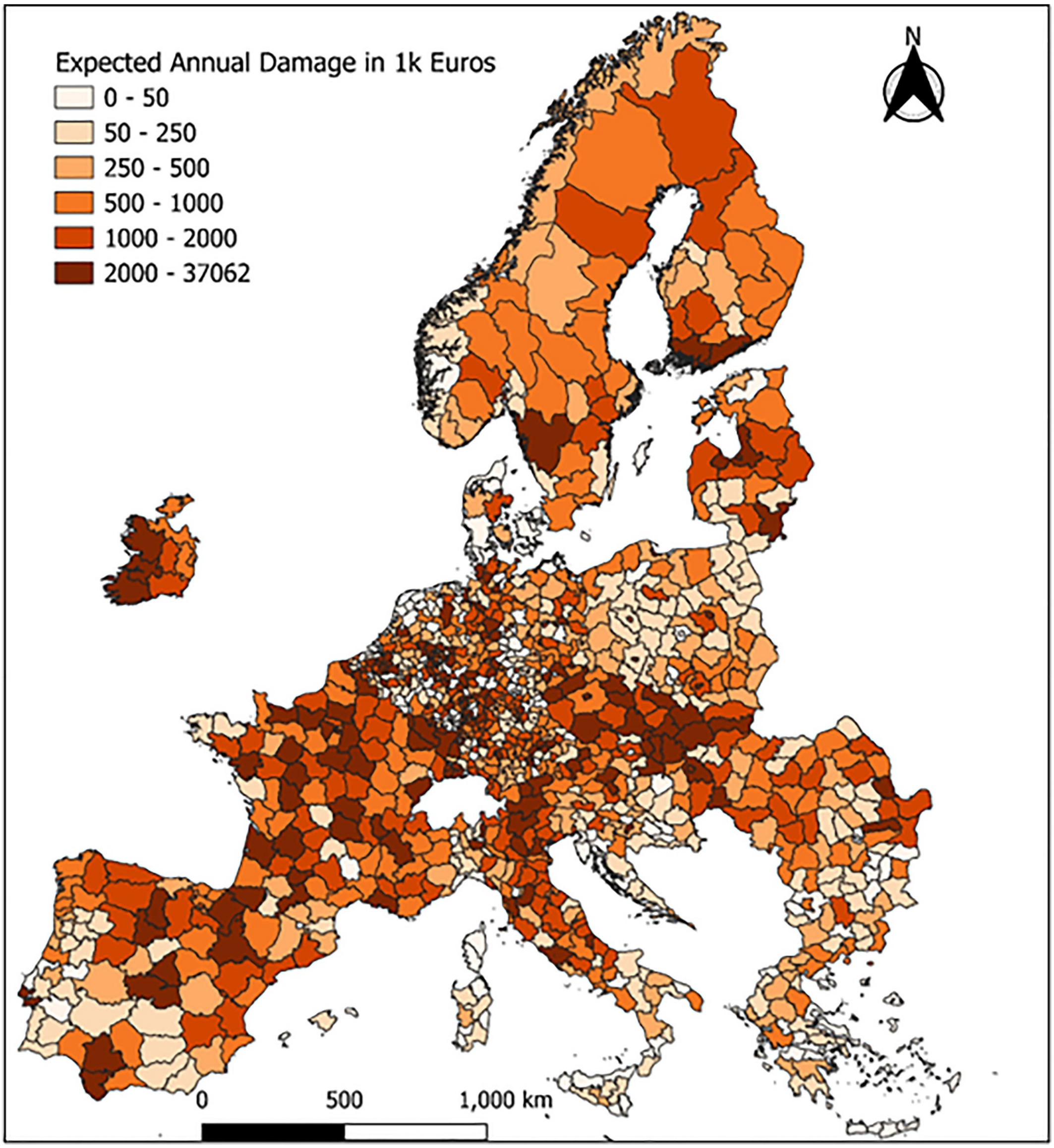

Figure 4. Expected Annual Damage at the NUTS 3 level for the baseline period (1995).

million euros). Italy, Spain, and Belgium follow Germany and France, making them the top five contributors to economic losses from companies. Cyprus and Malta, with no significant rivers, have zero flood loss. The lowest losses are estimated for Lithuania at 0.2 million euros, Slovenia at 0.86 million euros and Denmark at 0.93 million euros. This trend in estimated company losses aligns with findings on EAD to private households (Steinhausen et al., 2022), which show that Germany had the highest EAD—more than 1.5 times that of France, the second-highest.

At the NUTS 3 regional level, the highest aggregate losses in the commercial and industrial sectors are concentrated along major riverbanks (see Figure 4). Mannheim, situated at the confluence of the Rhine and Neckar rivers, records the highest EAD at 37.06 million euros, followed by Riga (34.83 million euros) near the Daugava River, Paris at the confluence of the Seine and Marne, Berlin along the Spree River, and Hamburg at the mouth of the Elbe River. High EAD values in these locations emphasize the significant influence of high-value commercial and industrial assets located on floodplains. Berlin's relatively high EAD, despite lower flood hazard levels, results from the clustering of commercial buildings near the river. Across all these regions, the commercial sector contributes to the share of losses (75.69%). In contrast, regions with low EAD values (<50k€) are generally

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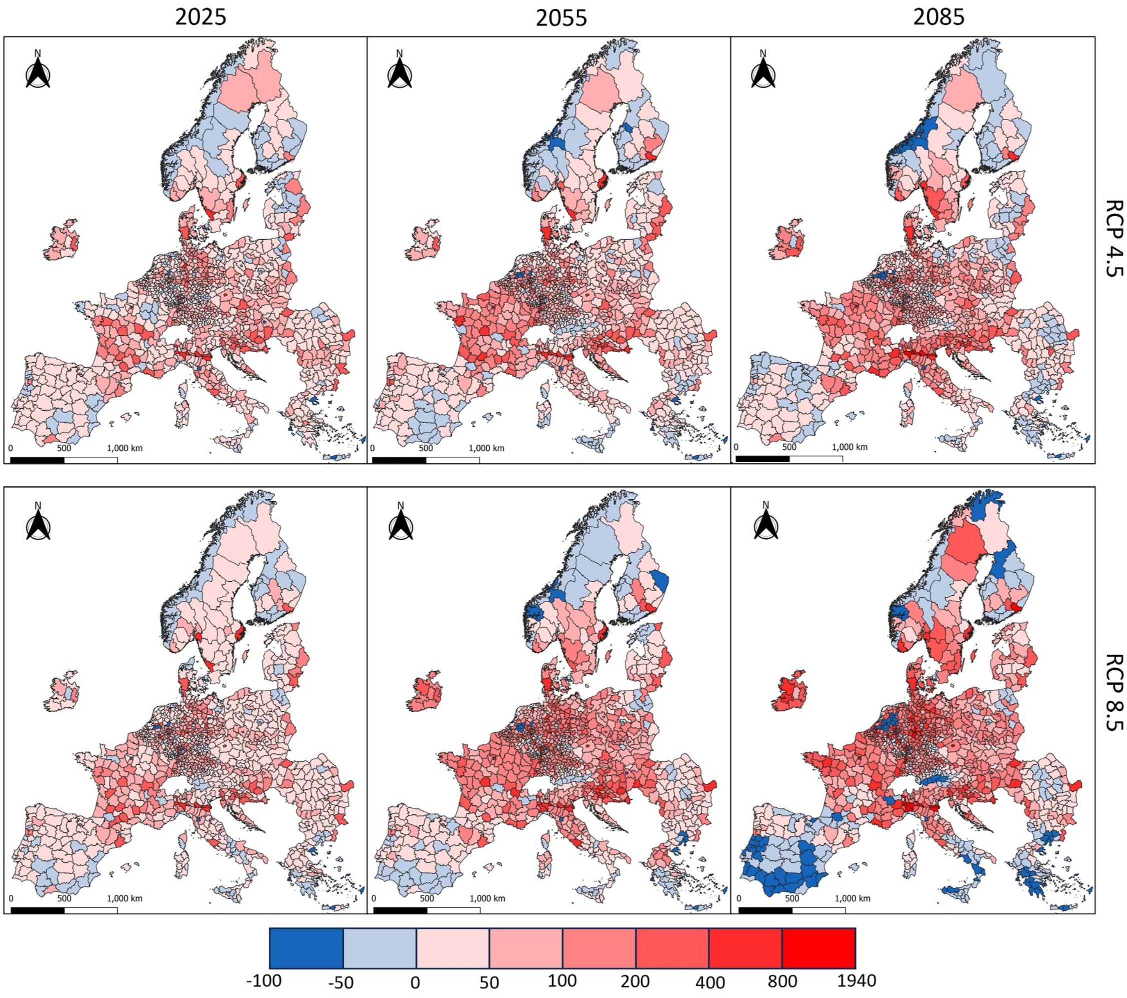

Figure 5. Percentage change in expected annual damage for future climate change scenarios.

distant from rivers, such as Cyprus, Malta, Greece, and Denmark. Parts of the Netherlands also exhibit low EAD due to high flood protection standards.

3.2. Future Periods

We present the role of changing climate, changing exposure and a combination of climate and exposure change on EAD to companies due to flooding over the future 30-year time periods centered at 2025, 2055, and 2085. Throughout this analysis, the reported uncertainty encompasses the accumulated uncertainty from the climate models, exposure projection, and loss model. It is quantified using interquartile ranges (IQR) and percentile spreads (e.g., 25th–75th percentile).

3.2.1. Climate Change Scenarios

Two climate scenarios, RCP4.5 and RCP8.5, are considered for future timeframes. The percentage change in EAD between the baseline and future scenarios exhibits a mix of increasing and decreasing trends (see Figure 5).

At the beginning of the century (centered around 2025), there is minimal difference in overall EAD between the two scenarios, with a median increase of 61% and an interquartile range (IQR) of 16%–132%.

By the mid-century (centered around 2055) and late-century (centered around 2085), the divergence between the two scenarios becomes increasingly evident. EAD shows a steady upward trend under both scenarios, with sharper increases and wider uncertainty under RCP8.5. By 2055, EAD rises to 92% under RCP4.5 and 132%

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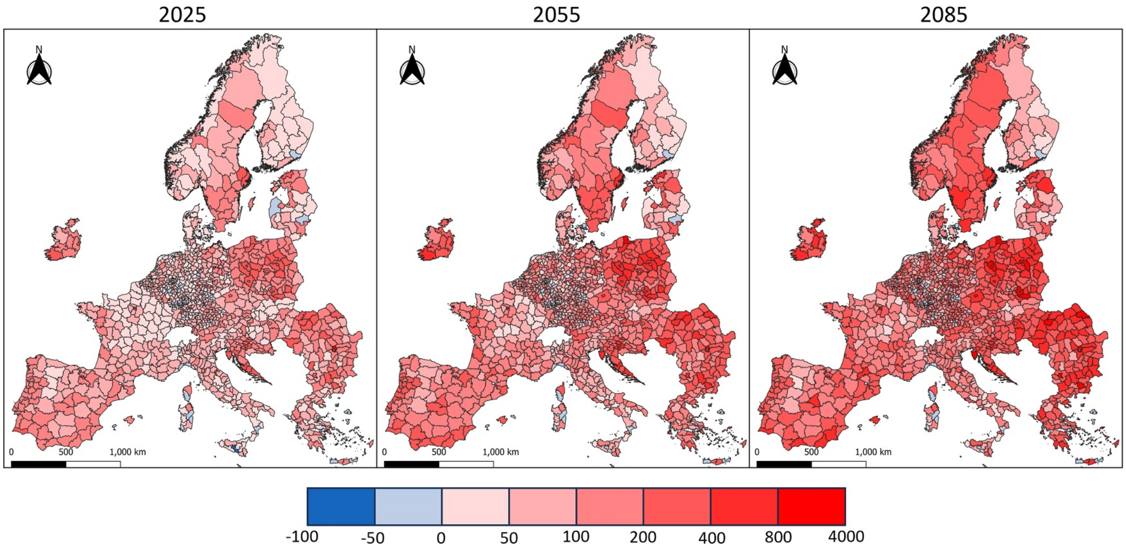

Figure 6. Percentage change in expected annual damage for future exposure change scenarios.

under RCP8.5, reaching 100% and 173%, respectively, by 2085, with RCP8.5 showing a much broader uncertainty range (IQR: 50%–409%). The IQR of the EAD projections corresponding to RCP8.5 highlights the growing uncertainty, with a pronounced skew toward higher rates of change compared to the more optimistic RCP4.5 scenario. The non-monotonic trend in future EAD projections arises from the uncertainty in regional climate simulations, particularly during mid-century when projected changes are comparable in scale to model uncertainties (Coppola et al., 2021).

Countries with the highest increase in flood risk due to climate change are those already experiencing high flood risk in the baseline period, including Germany, France, Italy, and Belgium. In contrast, the least increase in flood risk is observed in Lithuania, Estonia, Denmark, and Portugal. Regions showing a consistent decreasing trend in flood risk across all future climate scenarios include the Mediterranean region, southern Italy, Spain, most of Greece, and parts of Scandinavia, such as Norway, Denmark, and Finland. The projected decline in river flood hazard across the Mediterranean region is attributed primarily to decreasing snowmelt-driven floods (Alfieri et al., 2015).

3.2.2. Exposure Change Scenarios

Considering the exposure changes in the future time periods, most regions show increasing EAD trends. EAD rises consistently across all periods, with sharper increases over time. It is projected to increase by 67.7% in 2025, nearly double to 127% by 2055, and reach 188.2% by 2085 with narrower uncertainty (IQR 130.5%–251%) compared to climate change (see Figure 6).

Regions around cities such as Ilfov in Romania, Gdansk and Warsaw in Poland and Dublin in Ireland show the highest EAD increase due to exposure change. While most regions in Europe experienced an increase in EAD until the end of the century, only a few regions in southern Italy and southern Finland show a decrease in flood risk compared to the baseline period, attributed to a large drop in industrial gross domestic product (GDP) from 1995 to 2025.

3.2.3. Climate and Exposure Change Scenarios

In contrast to the mixed trend observed in the case of projections under climate change scenarios, we see a monotonous increase in the EAD from the baseline to the future time periods in scenarios considering both changing climate and exposure. Compared to the baseline centered in 1995, the EAD values at the beginning of the century (centered at 2025) increased by 170% under changing climate (RCP4.5 and RCP8.5) and exposure. This upward trend continues sharply through the century, with EAD nearly doubling by 2055 and surging further by 2085. By 2055, EAD reaches 328% under RCP4.5 and 415.4% under RCP8.5, escalating to 469.6% and

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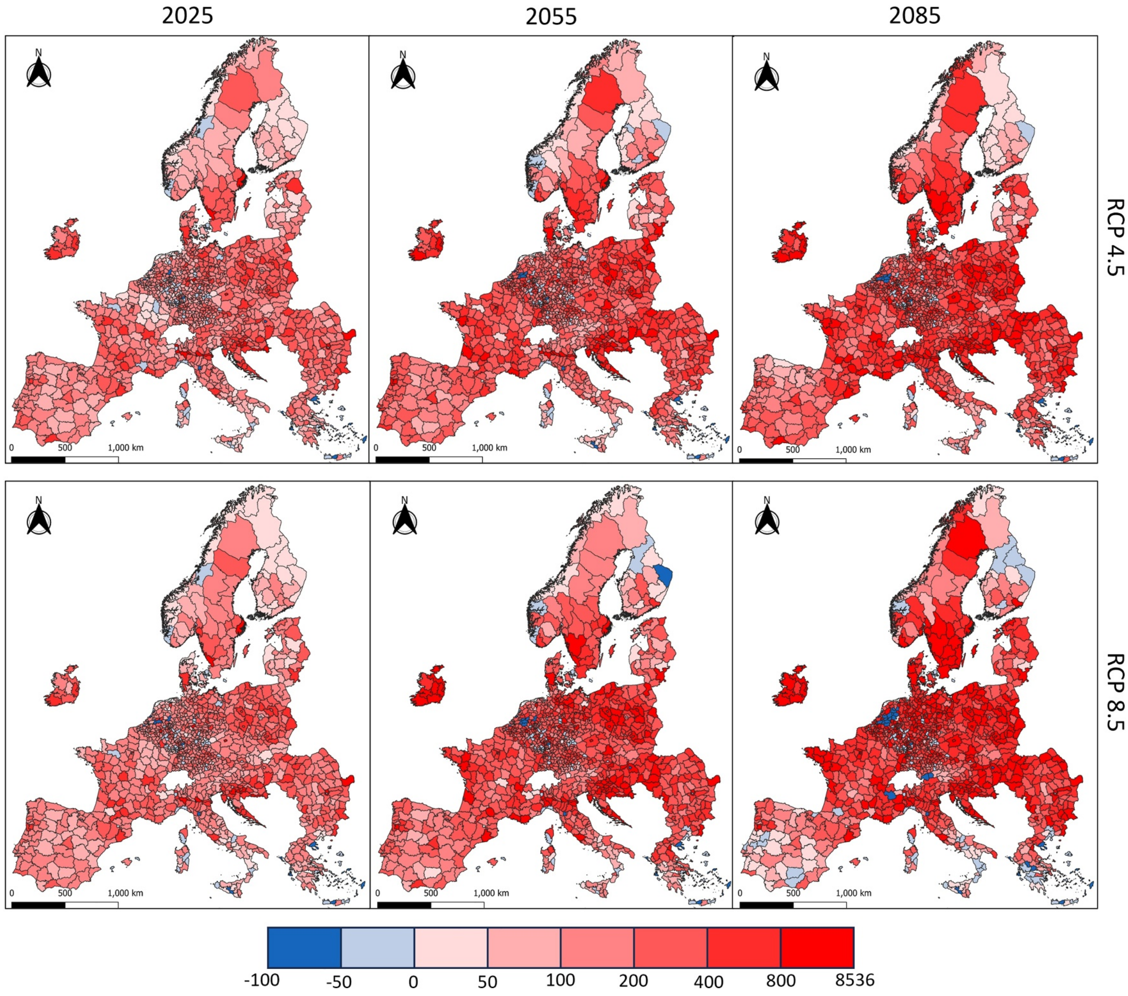

Figure 7. Percentage change in expected annual damage for combined future climate and exposure change scenarios.

660.3%, respectively by 2085. This scenario not only shows the steepest growth but also the greatest variability, underscoring the compounding risk of simultaneous climatic and socioeconomic changes. Under the RCP 8.5 scenario, the influence of climate change takes precedence, reducing flood risk trends in certain regions. Notably, southern Spain, Portugal, and Greece, along with the eastern Netherlands and parts of Finland, show a declining flood risk trend, especially toward the end of the century (see Figure 7).

For the median projection, climate change and exposure change contribute equally to the rise in losses. However, the combined scenario amplifies their impact, more than doubling the effect of each factor individually. Notably, the uncertainty in loss estimates is far greater when modeling exposure change than in the case of climate change scenarios (see Figure 8).

At the 75th percentile, losses driven by exposure change are three times higher than those driven by climate change. In contrast, at the 25th percentile, exposure change results in only one-third of the losses driven by climate change. Across all percentiles, the combined scenario consistently produces a larger effect, exceeding the sum of individual contributions (see Figure 8).

3.3. Role of Building-Level Precautionary Measures

An intervention scenario, "measures for all" (at least one measure is implemented by all the companies) is applied. The corresponding loss estimates from the BN-FLEMOcs model (see, Section 2.1, Figure 2) results in a reduction of the EAD from 1.50 billion euros to 0.42 billion euros for the baseline time period centered at 1995 (see Figure 8a). Under RCP 4.5 (RCP 8.5), total damages with status quo precaution amount to 2.42 billion euros (2.46

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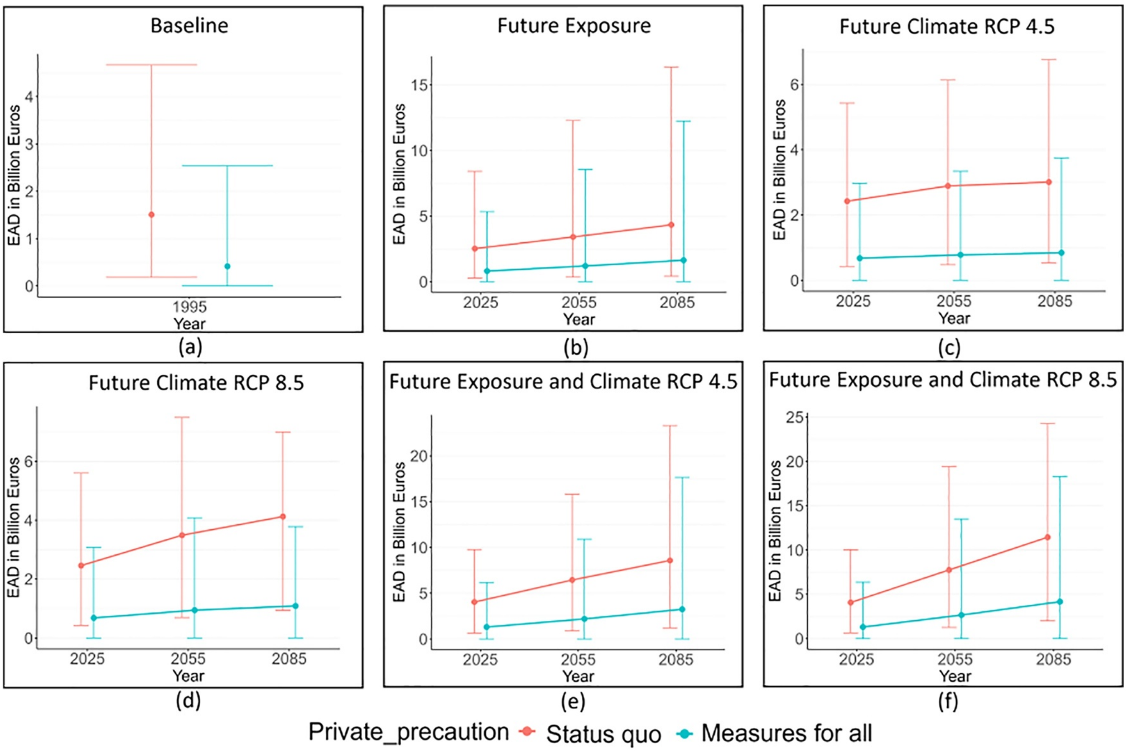

Figure 8. Comparison of total EAD of Europe for status-quo and "measures for all" scenarios.

billion euros), 2.89 billion euros (3.49 billion euros), and 3.01 billion euros (4.12 billion euros) at time periods centered at 2025, 2050 and 2085, respectively. Under the scenario "measures for all," the EAD values drop to 0.68 billion euros (0.68 billion euros), 0.78 billion euros (0.94 billion euros), and 0.85 billion euros (1.09 billion euros), respectively (see Figures 8c and 8d).

Comparable results are observed when considering future scenarios that account for changing exposure (Figure 8b) and combined effects of exposure and climate change (see Figures 8e and 8f). For the combined scenario, a reduction of approximately 67% is observed for the beginning of the century (from 4.04 billion euros to 1.32 billion euros for RCP 4.5 and from 4.08 billion euros to 1.32 billion euros for RCP 8.5), a reduction of approximately 65% for mid-century (from 6.45 billion euros to 2.20 billion euros for RCP 4.5 and from 7.76 billion euros to 2.66 billion euros for RCP 8.5), and a reduction of approximately 62% by the end of the century (from 8.58 billion euros to 3.25 billion euros for RCP 4.5 and from 11.45 billion euros to 4.17 billion euros for RCP 8.5). Notably, the "measures for all" scenario corresponding to the extreme climate and exposure scenarios at the time period centered at 2085 results in a smaller EAD compared to the scenario with status-quo precaution at the baseline time period centered at 1995. This reduction in EAD is comparable with the effect of accommodation measures (up to 50% loss reduction) reported by Dottori et al. (2020). However, it is higher in comparison to the 15% loss-reduction achieved through private precautionary measures in households (Steinhausen et al., 2022). The BN-FLEMOcs model is calibrated based on empirical flood loss data from Germany where companies more likely adopted proactive private precautionary measures rather than relocating to reduce their flood exposure (Schoppa et al., 2020). The widespread adoption of these measures further enhances the potential for substantial reductions in company flood losses. In addition to the high loss-reducing capability, these measures were found to have the best cost-to-benefit ratio—5.2€ saved for each € invested (Dottori et al., 2020).

The intervention "measures for all" reduces the uncertainty of the loss predictions (see Figure 8). By assuming that each company has implemented at least one precautionary measure, the variability between companies is reduced, and the precautionary level is similar everywhere, that is it eliminates the spatial uncertainty as to which company has implemented a precautionary measure.

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4. Discussions

This study offers several advantages over state-of-the-art large-scale flood risk assessments with a focus on the flood losses to companies.

- Unlike traditional flood loss models that rely heavily on sector-specific depth-damage functions using inundation depth as the sole hazard indicator, this research employs a multivariate Bayesian Network-based flood loss model (BN-FLEMOcs). This approach accounts for multiple variables, such as water depth, company size, sector type, and the implementation of precautionary measures, improving the accuracy and adaptability of loss estimations.
- The integration of object-specific exposure data from high-resolution building footprint data sets, such as OpenStreetMap and the Global ML Building Footprint data set, enables property-level risk assessment, which is a significant improvement over land-use-based models that provide only average exposure estimates.
- The study's focus on future scenarios, incorporating both climate change and exposure changes, along with a "measures for all" intervention scenario that evaluates the potential of property-level precautionary measures, provides actionable insights for risk mitigation that are typically overlooked in current large-scale assessments. The spatially explicit loss estimates corresponding to all flood hazard, exposure and intervention scenarios are openly provided with the manuscript.

The use of high-resolution data, advanced modeling techniques, and future-focused projections positions the study as a critical contribution to assessing flood risk to companies in Europe. Despite these advantages, the study is not without limitations. The projections of future flood risk are not deterministic values and are more suitable for inter-country comparisons and for quantifying the effects of global drivers on flood risk dynamics. They possess uncertainties due to limitations from modeling hazard, exposure and flood losses. From the hazard dimension, the spread across the CORDEX models is a major source of heterogeneity for the climate-driven future EAD projections (Knutti et al., 2013). The RCP scenarios considered represent only two specific trajectories of climate change out of many possible futures. RCP4.5 is the 'business as usual' assumption of the continuation of existing socio-economic trends, while RCP8.5 is the high-emission, fossil-fuel-driven future. This study does not account for dike breaches as a failure mechanism; only overtopping of flood protection infrastructure is considered. The uncertainty in flood protection data was not considered, as protection standards vary across Europe, and discrepancies are difficult to quantify (Dottori et al., 2021). Additionally, countries with increasing GDP are likely to implement more efficient flood protection measures with increasing flood hazards (Paprotny et al., 2025), which is considered constant in this study.

Exposure data for both historical and future periods have notable limitations and uncertainties. Errors in the European Buildings model (Schorlemmer et al., 2024) may propagate from their source data sets. OpenStreetMap data, despite being suitable for risk assessments (Simpson et al., 2014), may include misclassifications due to volunteer errors. Global ML Building Footprints, generated by AI, come with inherent uncertainties and are supplemented by a settlement layer in areas with incomplete coverage, which could slightly distort exposure estimates. Disaggregation of fixed assets by sector may also be inaccurate in some areas, though unlikely to significantly affect relative losses or inter-country comparisons. Uncertainty increases in future projections due to variables such as population and GDP changes, intra-country redistribution of exposure, and external factors such as technological progress or global politics (Koch & Leimbach, 2023). We utilize probabilistic projections to quantify this uncertainty (Riahi et al., 2016) and exclude land use changes, which historically have had a smaller impact than raw exposure growth (Paprotny et al., 2018). Finally, we extrapolate the historical trend of fixed asset values relative to GDP. Between 1950 and 2019, commercial assets grew from 120% to 174% of GDP as services expanded from 53% to 80% of gross value added, while industrial assets declined from 79% to 62% of GDP as the industry's share dropped from 32% to 19% (Paprotny & Mengel, 2023). We assume these trends will continue in the coming decades due to the absence of alternative scenarios.

We develop a multi-variable flood loss model (BN-FLEMOcs) capable of assessing flood loss reduction resulting from precautionary measures. Although the BN-FLEMOcs model used for estimating flood losses incorporates precautionary behavior and was calibrated using observed loss data from companies in Germany, it lacks the independent empirical validation of the effectiveness of individual precautionary measures. Future research should aim to disentangle these effects through controlled empirical investigations to improve the accuracy and robustness of intervention-based flood loss modeling. Another limitation is that the model assumes that the uptake of the measures is solely based on past flood experience (see Figure 2) or as a static intervention scenario, such as

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"measures for all." This approach lacks information on protective behavior which is influenced not only by prior flood experience but also by factors like risk perception and self-efficacy. Incorporating the dynamics of adaptive behavior into the flood loss estimation would provide a more realistic representation of the dynamics in flood vulnerability (Schoppa et al., 2024).

Validation of loss estimates was conducted using microscale data (from post-flood surveys). Though, pan-European validation is challenging due to limited sector-specific data. We compared our results with reported economic losses from the HANZE database (Paprotny et al., 2024), extracting losses from 1981 to 2010 and adjusting price levels from 2020 to 2015 using Paprotny and Mengel (2023). We estimated losses for the industrial and commercial sectors based on their share of total fixed asset value at the time of each event. This approach yielded an EAD of €1.84 billion—14% less than our model estimate of €2.13 billion per year. Given the incomplete loss data for many flood events, this is a close match. Exact comparison is limited by data gaps, uncertainties around sector-specific losses, evolving exposure, and dynamics in flood protection standards. Despite these challenges, the comparison supports the validity of our model's loss estimates for commercial and industrial sectors in Europe.

The "measures for all" approach could be applicable to risk reduction practices in other countries, as well. For instance, the Community Rating System is a voluntary, incentive-based system in the US that encourages community flood risk management practices. While over 1,500 communities participate nationwide, due to the voluntary nature, many communities don't participate, creating gaps in flood risk management practices (FEMA, 2025). This design also leads to unintended consequences in participating communities' floodplains, such as income inequality (Noonan & Sadiq, 2018; Sadiq & Noonan, 2015). However, overall, the effectiveness of the Community Rating System to lower flood damage and costs is widely recognized (Sadiq et al., 2019), and therefore extending it as a mandatory effort, where every community is required to participate, would help to close the protection gap. Further, the system could be extended to focus on individual action alongside community policy, requiring homeowners to adopt household-level flood reduction. Similarly, Japan's "River Basin Disaster Resilience and Sustainability by All" is a national policy that mandates flood risk reduction measures across entire river basins, including watersheds and floodplains. While the policy involves all stakeholders like national and local governments, private enterprises, and residents, the implementation still faces challenges due to conflicting interests, such as concerns over reduced rice yields from paddy field flooding (Bark et al., 2021). This approach requires mandatory actions in three key areas: flood prevention (e.g., levee improvements and predischarge from dams), exposure reduction (e.g., land-use controls and relocation), and disaster resilience (e.g., evacuation systems and building protections) (Koike, 2021). River administrators enforce these measures and update flood control plans based on climate change impacts, like increased rainfall and tide levels (Chen et al., 2025). Making these precautionary actions uniformly required helps close regional protection gaps, and improving awareness through high-resolution data can further support long-term, stakeholder-driven implementation (Kawai et al., 2024). The high-resolution, spatially explicit modeling framework developed in this study can support such initiatives by providing localized, evidence-based insights into flood impacts under future climate scenarios. This granularity enhances stakeholders' understanding of flood risks and the long-term benefits of adaptation, facilitating better-informed decision-making. Moreover, the framework's flexibility allows it to be adapted across diverse geographic and institutional contexts, serving as a valuable tool for countries aiming to design equitable and participatory flood risk management strategies.

5. Conclusions

This study advances large-scale flood risk assessments for the companies by integrating a multivariate Bayesian Network-based flood loss model (BN-FLEMOcs) with object-specific exposure data and future-oriented scenarios. Our results indicate a significant rise in future EAD, driven by both climate change and exposure growth. Projections show a dramatic increase in EAD by 2085, with a 469.6% rise under RCP4.5 and a 660.3% rise under RCP8.5. High-risk countries such as Germany, France, Italy, and Belgium are expected to experience the most severe impacts, while some regions in southern Europe and Scandinavia may see a reduction in flood risks. Despite the advancements in modeling, uncertainties remain due to limitations in hazard modeling, the quality of exposure data, and the disaggregation of asset values. Nevertheless, validation using the observed flood event losses reveals a strong correlation between estimated and reported losses, reinforcing the reliability of the model's outputs.

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In addition to assessing climate and exposure changes, this study evaluates the impact of precautionary measures on mitigating future flood damage. Measures such as flood barriers and improved building design can significantly reduce EAD across all scenarios—by 72% during the baseline period and up to 67% under combined climate and exposure change scenarios. These findings emphasize the crucial role of building-level precautionary measures in flood risk management to enhance resilience in vulnerable areas. By providing spatially explicit loss estimates and demonstrating the effectiveness of precautionary measures, this research offers valuable insights to stakeholders and policymakers involved in flood risk management for the companies throughout different continents.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The data generated from the study are openly provided in the data publication Devadas et al. (2025). The exposure data (Schorlemmer et al., 2024) and river hazard maps (Dottori et al., 2022) are openly accessible.

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References

Alfieri, L., Feyen, L., & Di Baldassarre, G. (2016). Increasing flood risk under climate change: A pan-European assessment of the benefits of four adaptation strategies. *Climatic Change*, *136*(3–4), 507–521. https://doi.org/10.1007/s10584-016-1641-1

Alfieri, L., Feyen, L., Dottori, F., & Bianchi, A. (2015). Ensemble flood risk assessment in Europe under high end climate scenarios. *Global Environmental Change*, *35*, 199–212. https://doi.org/10.1016/j.gloenvcha.2015.09.004

Arrighi, C., & Domeneghetti, A. (2024). Brief communication: On the environmental impacts of the 2023 floods in Emilia-Romagna (Italy). *Natural Hazards and Earth System Sciences*, *24*(2), 673–679. https://doi.org/10.5194/nhess-24-673-2024

Bark, R. H., Martin-Ortega, J., & Waylen, K. A. (2021). Stakeholders' views on natural flood management: Implications for the nature-based solutions paradigm shift? *Environmental Science & Policy*, *115*, 91–98. https://doi.org/10.1016/j.envsci.2020.10.018

Chen, J., Sayama, T., Yamada, M., Tanaka, T., & Sugawara, Y. (2025). Projecting multiscale river flood changes across Japan at +2°C and +4°C climates. *Earth's Future*, *13*(5), e2024EF005884. https://doi.org/10.1029/2024EF005884

Coppola, E., Nogherotto, R., Giorgi, F., Kadygrov, N., Iles, C., Corre, L., et al. (2021). Assessment of the European climate projections as simulated by the large EURO-CORDEX regional and global climate model ensemble. *Journal of Geophysical Research: Atmospheres*, *126*(4), e2019JD032356. https://doi.org/10.1029/2019JD032356

Crowley, H., Despotaki, V., Rodrigues, D., Silva, V., Costa, C., Toma-Danila, D., et al. (2021). European exposure model data repository (v1.0) [Dataset]. *Zenodo*. https://doi.org/10.5281/zenodo.5730071

Dankers, R., & Feyen, L. (2009). Flood hazard in Europe in an ensemble of regional climate scenarios. *Journal of Geophysical Research*, *114*(D16). https://doi.org/10.1029/2008JD011523

Darnkachatarn, S., & Kajitani, Y. (2025). Flood damage assessment model of industrial sectors in a Megacity: Derivation from business survey data in the Bangkok Metropolitan Region. *International Journal of Disaster Risk Reduction*, *118*, 105221. https://doi.org/10.1016/j.ijdrr.2025.105221

Devadas, B., Paprotny, D., Kreibich, H., Steinhausen, M., Oostwegel, L. J. N., Endendijk, T., et al. (2025). Future flood losses to company assets in Europe [Dataset]. *GFZ Data Services*. https://doi.org/10.5880/GFZ.RDOQ.2025.004

Dolejš, M., Raška, P., Kohnová, S., Schinke, R., Warachowska, W., Thaler, T., & Kočický, D. (2022). On the right track of flood planning policy? Land uptake in Central-European floodplains (1990–2018). *Landscape and Urban Planning*, *228*, 104560. https://doi.org/10.1016/j.landurbplan.2022.104560

Dottori, F., Alfieri, L., Bianchi, A., Skoien, J., & Salamon, P. (2022). A new dataset of river flood hazard maps for Europe and the Mediterranean Basin [Dataset]. *Earth System Science Data*, *14*(4), 1549–1569. https://doi.org/10.5194/essd-14-1549-2022

Dottori, F., Mentaschi, L., Bianchi, A., Alfieri, L., & Feyen, L. (2020). *Adapting to rising river flood risk in the EU under climate change*. Joint Research Centre (JRC).

Dottori, F., Mentaschi, L., Bianchi, A., Alfieri, L., & Feyen, L. (2021). *Adaptation is cost effective to offset rising river flood risk in Europe*. National Portal. https://doi.org/10.21203/rs.3.rs-519118/v1

Dottori, F., Szewczyk, W., Ciscar, J., Zhao, F., Alfieri, L., Hirabayashi, Y., et al. (2018). Increased human and economic losses from river flooding with anthropogenic warming. *Nature Climate Change*, *8*(9), 781–786. https://doi.org/10.1038/s41558-018-0257-z

Endendijk, T., Botzen, W. W., de Moel, H., Slager, K., Kok, M., & Aerts, J. C. (2024). Enhancing resilience: Understanding the impact of flood hazard and vulnerability on business interruption and losses. *Water Resources and Economics*, *46*, 100244. https://doi.org/10.1016/j.wre.2024.100244

ENW (Expertise Network Waterveiligheid). (2021). Hoogwater 2021: Feiten en Duiding Task Force Fact Finding Hoogwater 2021. (in Dutch). Retrieved from https://www.enwinfo.nl/publicaties/

European Commission: Eurostat. (2018). *Regions in the European Union—Nomenclature of territorial units for statistics, NUTS 2016/EU-28—Edition 2018*. Publications Office. https://doi.org/10.2785/475524

Fédération Française de l'Assurance. (2017). L'assurance des catastrophes naturelles en 2016. Retrieved from https://www.mrn.asso.fr/wp-content/uploads/2017/01/2017-chiffre-assurance-des-catastrophes_naturelles_2016.pdf

FEMA. (2025). Retrieved from https://www.fema.gov/floodplain-management/community-rating-system

Huizinga, J., de Moel, H., & Szewczyk, W. (2017). Global flood depth-damage functions: Methodology and the database with guidelines (EUR 28552 EN). https://doi.org/10.2760/16510

IPCC. (2021). Summary for policymakers. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, et al. (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate*

Change (pp. 3–32). Cambridge University Press. Cambridge, United Kingdom and New York, NY, USA. https://doi.org/10.1017/9781009157896.001

Kawai, H., Toyoda, R., Tebekari, T., Yoshida, K., & Noda, K. (2024). The gap between farmers and beneficiaries in terms of awareness and expectations regarding the paddy field dam project. *Paddy and Water Environment*, *22*(3), 467–474. https://doi.org/10.1007/s10333-024-00978-6

Knutti, R., Masson, D., & Gettelman, A. (2013). Climate model genealogy: Generation CMIP5 and how we got there. *Geophysical Research Letters*, *40*(6), 1194–1199. https://doi.org/10.1002/grl.50256

Koch, J., & Leimbach, M. (2023). SSP economic growth projections: Major changes of key drivers in integrated assessment modelling. *Ecological Economics*, *206*, 107751. https://doi.org/10.1016/j.ecolecon.2023.107751

Koike, T. (2021). Evolution of Japan's flood control planning and policy in response to climate change risks and social changes. *Water Policy*, *23*(S1), 77–84. https://doi.org/10.2166/wp.2021.287

Koks, E. E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S. A., et al. (2019). A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications*, *10*(1), 1–11. https://doi.org/10.1038/s41467-019-10442-3

Kreibich, H., & Dimitrova, B. (2010). Assessment of damages caused by different flood types. *WIT Transactions on Ecology and the Environment*, *133*, 3–11.

Mentaschi, L., Alfieri, L., Dottori, F., Cammalleri, C., Bisselink, B., Roo, A. D., & Feyen, L. (2020). Independence of future changes of river runoff in Europe from the pathway to global warming. *Climate*, *8*(2), 22. https://doi.org/10.3390/cli8020022

Mentaschi, L., Vousdoukas, M., Voukouvalas, E., Sartini, L., Feyen, L., Besio, G., & Alfieri, L. (2016). The transformed-stationary approach: A generic and simplified methodology for non-stationary extreme value analysis. *Hydrology and Earth System Sciences*, *20*(9), 3527–3547. https://doi.org/10.5194/hess-20-3527-2016

Merz, B., Kreibich, H., Schwarze, R., & Thieken, A. (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

Microsoft/GlobalMLBuildingFootprints. (2024). [Python]. Microsoft. (Original work published 2022). Retrieved from https://github.com/microsoft/GlobalMLBuildingFootprints

Munich Re. (2021). NatCat SERVICE Database Munich RE, Munich.

Munich Re. (2022). NatCat SERVICE Database Munich RE, Munich.

Noonan, D. S., & Sadiq, A. A. (2018). Flood risk management: Exploring the impacts of the community rating system program on poverty and income inequality. *Risk Analysis*, *38*(3), 489–503. Epub 2017 Jun 27. PMID: 28656653. https://doi.org/10.1111/risa.12853

Olsen, A. S., Zhou, Q., Linde, J. J., & Arnbjerg-Nielsen, K. (2015). Comparing methods of calculating expected annual damage in urban pluvial flood risk assessments. *Water*, *7*(1), 255–270. https://doi.org/10.3390/w7010255

Paprotny, D., Kreibich, H., Morales-Nápoles, O., Castellarin, A., Carisi, F., & Schröter, K. (2020). Exposure and vulnerability estimation for modelling flood losses to commercial assets in Europe. *Science of the Total Environment*, *737*, 140011. https://doi.org/10.1016/j.scitotenv.2020.140011

Paprotny, D., & Mengel, M. (2023). Population, land use and economic exposure estimates for Europe at 100 m resolution from 1870 to 2020. *Scientific Data*, *10*(1), 1–25. https://doi.org/10.1038/s41597-023-02282-0

Paprotny, D., Sebastian, A., & Jonkman, S. N. (2018). Trends in flood losses in Europe over the past 150 years. *Nature Communications*, *9*(1), 1–12. https://doi.org/10.1038/s41467-018-04253-1

Paprotny, D., Terefenko, P., & Śledziowski, J. (2024). HANZE v2.1: An improved database of flood impacts in Europe from 1870 to 2020. *Earth System Science Data*, *16*(11), 5145–5170. https://doi.org/10.5194/essd-16-5145-2024

Paprotny, D., 't Hart, C. M. P., & Morales-Nápoles, O. (2025). Evolution of flood protection levels and flood vulnerability in Europe since 1950 estimated with vine-copula models. *Natural Hazards*, *121*(5), 6155–6184. https://doi.org/10.1007/s11069-024-07039-5

Porter, J. R., Shu, E. G., Amodeo, M. F., Freeman, N., Bauer, M., Almufti, I., et al. (2022). Commercial real-estate at risk: An examination of commercial building and economic impacts in the United States using a high-precision flood risk assessment tool. *Frontiers in Water*, *4*, 875995. https://doi.org/10.3389/frwa.2022.875995

Riahi, K., Van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., et al. (2016). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rose, A., & Liao, S. Y. (2005). Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions. *Journal of Regional Science*, *45*(1), 75–112. https://doi.org/10.1111/j.0022-4146.2005.00365.x

Sadiq, A.-A., Tyler, J., & Noonan, D. S. (2019). A review of community flood risk management studies in the United States. *International Journal of Disaster Risk Reduction*, *41*, 101327. https://doi.org/10.1016/j.ijdrr.2019.101327

Sadiq, A. A., & Noonan, D. S. (2015). Flood disaster management policy: An analysis of the United States Community Ratings System. *Journal of Natural Resources Policy Research*, *7*(1), 5–22. https://doi.org/10.1080/19390459.2014.963373

Sairam, N., Schröter, K., Lüdtke, S., Merz, B., & Kreibich, H. (2019). Quantifying flood vulnerability reduction via private precaution. *Earth's Future*, *7*(3), 235–249. https://doi.org/10.1029/2018EF000994

Schoppa, L., Barendrecht, M. H., Paprotny, D., Sairam, N., Sieg, T., & Kreibich, H. (2024). Projecting flood risk dynamics for effective long-term adaptation. *Earth's Future*, *12*(3), e2022EF003258. https://doi.org/10.1029/2022EF003258

Schoppa, L., Sieg, T., Vogel, K., Zöller, G., & Kreibich, H. (2020). Probabilistic flood loss models for companies. *Water Resources Research*, *56*(9), e2020WR027649. https://doi.org/10.1029/2020WR027649

Schorlemmer, D., Oostwegel, L. J. N., Lingner, L., & Evaz Zadeh, T. (2024). A model of European buildings. V. 23/07 [Dataset]. *GFZ Data Services*. https://doi.org/10.5880/GFZ.2.6.2023.011

Seifert, I., Kreibich, H., Merz, B., & Thieken, A. H. (2010). Application and validation of FLEMOcs—A flood-loss estimation model for the commercial sector. *Hydrological Sciences Journal*, *55*(8), 1315–1324. https://doi.org/10.1080/02626667.2010.536440

Simpson, A., Murnane, R., Saito, K., Phillips, E., Reid, R., & Himmelfarb, A. (2014). *Understanding risk in an evolving world: Emerging best practices in natural disaster risk assessment*. Global Facility for Disaster Reduction and Recovery, The World Bank, UN International Strategy for Disaster Reduction. Retrieved from https://www.gfdrr.org/sites/default/files/publication/Understanding_Risk-Web_Version-rev_1.8.0.pdf

Sirko, W., Kashubin, S., Ritter, M., Annkah, A., Bouchareb, Y. S. E., Dauphin, Y., et al. (2021). Continental-scale building detection from high resolution satellite imagery (Version 2). *arXiv*. https://doi.org/10.48550/ARXIV.2107.12283

Steinhausen, M., Paprotny, D., Dottori, F., Sairam, N., Mentaschi, L., Alfieri, L., et al. (2022). Drivers of future fluvial flood risk change for residential buildings in Europe. *Global Environmental Change*, *76*, 102559. https://doi.org/10.1016/j.gloenvcha.2022.102559

Tesselaar, M., Botzen, W. J., Tiggeloven, T., & Aerts, J. C. (2023). Flood insurance is a driver of population growth in European floodplains. *Nature Communications*, *14*(1), 1–14. https://doi.org/10.1038/s41467-023-43229-8

23284277, 2025, 11, Downloaded from https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2025EF006285 by Helmholtz-Zentrum Potsdam GFZ, Wiley Online Library on [04/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Thieken, A. H., Bubeck, P., Heidenreich, A., Von Keyserlingk, J., Dillenardt, L., & Otto, A. (2023). Performance of the flood warning system in Germany in July 2021–insights from affected residents. *Natural Hazards and Earth System Sciences*, *23*(2), 973–990. https://doi.org/10.5194/nhess-23-973-2023

Winsemius, H. C., Aerts, J. C., Van Beek, L. P., Bierkens, M. F., Bouwman, A., Jongman, B., et al. (2016). Global drivers of future river flood risk. *Nature Climate Change*, *6*(4), 381–385. https://doi.org/10.1038/nclimate2893

Wooldridge, J. M. (2023). What is a standard error? (And how should we compute it?). *Journal of Econometrics*, *237*(2), 2A. https://doi.org/10.1016/j.jeconom.2023.105517

Wouter Botzen, W. J., Deschenes, O., & Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, *13*(2), 167–188. https://doi.org/10.1093/reep/rez004

References From the Supporting Information

Kok, M., Slager, K., & Hans (2023). Rapid damage assessment caused by the flooding event 2021 in Limburg, Netherlands. *Journal of Coastal and Riverine Flood Risk*, *2*. https://doi.org/10.59490/jcrfr.2023.0010

Orlandini, S., Moretti, G., & Albertson, J. D. (2015). Evidence of an emerging levee failure mechanism causing disastrous floods in Italy. *Water Resources Research*, *51*(10), 7995–8011. https://doi.org/10.1002/2015WR017426

Wagenaar, D., Lüdtke, S., Schröter, K., Bouwer, L. M., & Kreibich, H. (2018). Regional and temporal transferability of multivariable flood damage models. *Water Resources Research*, *54*(5), 3688–3703. https://doi.org/10.1029/2017WR022233

23284277, 2025, 11, Downloaded from https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2025EF006285 by Helmholtz-Zentrum Potsdam GFZ, Wiley Online Library on [04/11/2025]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License