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DOI
10.1007/s11069-024-07039-5

Publication date
2024

Document Version
Final published version

Published in
Natural Hazards

Natural Hazards
https://doi.org/10.1007/s11069-024-07039-5

ORIGINAL PAPER

Evolution of flood protection levels and flood vulnerability in Europe since 1950 estimated with vine-copula models

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Received: 3 April 2024 / Accepted: 12 November 2024

Abstract

The magnitude of flood impacts is regulated not only by hydrometeorological hazard and exposure, but also flood protection levels (primarily from structural flood defenses) and vulnerability (relative loss at given intensity of hazard). Here, we infer the variation of protection levels and vulnerability from data on historical riverine, coastal, and compound floods and associated impacts obtained from the HANZE database, in 42 European countries over the period 1950–2020. We contrast actual damaging floods, which imply flood protection was locally inadequate, with modelled potential floods, i.e. events that were hydrologically extreme but did not lead to significant impacts, which imply that flood protection was sufficient to prevent losses. Further, we compare the reported magnitude of impacts (fatalities, population affected, and economic losses) with potential impacts computed with depth-damage functions. We finally derive the spatial and temporal drivers of both flood protection and vulnerability through a multivariate statistical analysis. We apply vine-copulas to derive the best predictors out of a set of candidate variables, including hydrological parameters of floods, exposure to floods, socioeconomic development, and governance indicators. Our results show that riverine flood protection levels are much lower than assumed in previous pan-European studies. North-western Europe is shown to have better riverine protection than the south and east, while the divide is not so clear for coastal protection. By contrast, many parts of western Europe have relatively high vulnerability, with lowest value observed in central and northern Europe. Still, a strong decline in flood vulnerability over time is also observed for all three indicators of relative losses, suggesting improved flood adaptation. Flood protection levels have also improved since 1950, particularly for coastal floods.

Keywords Vine copulas · Flood defences · Vulnerability · Risk · Machine learning

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Published online: 29 November 2024

1 Introduction

Floods are a major source of losses in Europe and the threat they pose constantly evolves (Bloeschl et al. 2019; Tarasova et al. 2023). Multiple drivers are responsible for changes in risk (Merz et al. 2021; Kreibich et al. 2022), not all of which are well quantified. Two factors are especially uncertain in flood risk assessments over large geographical areas. One is structural flood protection, particularly in the form of dikes, and the other is vulnerability, i.e. the conditions determined by physical, social, economic and environmental factors which determine the susceptibility of an individual, a community, assets or system to floods (United Nations Office for Disaster Risk Reduction 2016). Many continental or global flood studies have excluded flood defences due to lack of data, but this has implications on estimating both present and future risk from riverine and coastal floods (Ward et al. 2017; Paprotny et al. 2017, 2019). Vousdoukas et al. (2018) has found that assumptions on flood protection levels are the largest individual source of uncertainty in assessing coastal flood risk in Europe, also under climate change conditions. At the same time, vulnerability models are diverse and lead to very different results, as showcased by studies comparing various economic damage functions in the same study area (Carisi et al. 2018; Figueiredo et al. 2018; Paprotny et al. 2020, 2021). Mortality functions are similarly highly uncertain (Jonkman et al. 2008; Brussee et al. 2021). Additionally, evidence shows that vulnerability changes over time, mostly with a downwards trajectory (Jongman et al. 2015; Tanoue et al. 2016; Bouwer and Jonkman 2018; Formetta and Feyen 2019; Sauer et al. 2021). Implications for continental-scale assessments, particularly in Europe, which employs extensive flood adaptation measures (Vousdoukas et al. 2017; Steinhausen et al. 2022; Dottori et al. 2023), are profound. Additionally, impact attribution of past and future losses in context of global change requires even more precise data to quantify the climatic and human drivers of those losses (Kreibich et al. 2019; Mengel et al. 2021; Scussolini et al. 2024).

In practice, pan-European datasets on flood protection and vulnerability are very limited. On the structural defences, a frequently used resource is FLOPROS by Scussolini et al. (2016). It combines information on nominal (design, or policy-defined) flood protection standards with estimates based on the level of economic development. Several European studies have used an alternative literature-based dataset of nominal protection levels from the PESETA IV study (Dottori et al. 2023). However, that study also used empirical flood impact data to improve the estimates of protection levels. A similar approach was employed by Jongman et al. (2014), who differentiated flood protection assumptions by utilizing modelled flood impacts and reported flood losses. More detailed information is available for some countries. The national flood risk assessment for the Netherlands (Vergouwe 2015) indicates that the actual reliability of flood defences can be far below nominal standards prescribed by law. Data on flood protection levels along rivers and coasts of England (Environment Agency 2023) shows far more spatial variation, and usually much lower standards, than assumed in pan-European datasets.

At the same time, dozens of flood vulnerability models are available (Gerl et al. 2016). The major issue is that they are typically based on local data, or even no empirical data at all, and often not transferable across case studies. Even models based on large microscale damage datasets like HOWAS21 for Germany (Kellermann et al. 2020) do not necessarily perform well in other settings (Jongman et al. 2012; Wagenaar et al. 2018; Paprotny et al. 2020). Consequently, pan-European studies either have to rely on vulnerability models developed for a specific environment (Steinhausen et al. 2022) or utilize more generic depth-damage functions such as those developed by Huizinga et al. (2017).

In this study, we present a novel approach to estimate present and past variation in flood protection levels and vulnerability (fatalities, population affected, and economic loss relative to exposed population or assets) in Europe based on constrasting modelled and reported impacts of floods. We build upon recent advances in pan-European riverine and coastal flood modelling (Paprotny et al. 2024b; Tilloy et al. 2024), historical exposure estimation (Paprotny and Mengel 2023), and collection of impact data from documentary sources (Paprotny et al. 2024a). We utilize data spanning from 1950 to 2020 to create a multivariate model that is able to infer the spatial and temporal variation in flood occurrence and their impacts.

We apply vine copulas to model the complex dependency between the predictors (socio-economic drivers, flood risk and experience) and changes in the level of flood protection and flood vulnerability. Vine copulas are graphical models that allow the construction of a complex multivariate probability distribution function through bivariate pieces (bivariate copula functions). Because of their flexibility in representing asymmetries in the joint distribution they have found wide application in different fields. For example, they have been applied in tunnel engineering ('t Hart et al. 2024), reliability analysis of flood defenses (Torres-Alves and Morales-Napoles 2020; Pouliasis et al. 2021), in ocean engineering (Jäger and Morales-Napoles 2017; Mares-Nasarre et al. 2024), hydrology (Tao et al. 2021) among many other fields. Additionally, theoretical developments around vine copulas are still being proposed, as highlighted by Pfeifer and Kovács (2024).

The paper is structured as follows. Section 2 provides details on the input data 2.1 and the procedure of creating vine-copula models 2.2. In section 3, the final vine-copula models 3.1 are validated and compared with other datasets 3.2. This enables generating pan-European maps of flood protection levels and vulnerability from 1950 to 2020 3.3. As historical impact data is very incomplete, we also estimate the magnitude of unreported losses in Europe 3.4. Limitations and uncertainties are discussed in section 4 before concluding in section 5.

2 Materials and methods

2.1 Data

2.1.1 Flood event data

Flood protection levels and flood vulnerability is analysed in this study using historical information on floods and their impacts. The necessary information was obtained from two flood catalogues. The first, HANZE v2.1 (Paprotny et al. 2024a) contains information on date, location and impacts of 2521 riverine, flash, coastal, and compound floods between 1870 and 2020. In this study, we consider a subset of 2037 events that have occurred since 1950. Reported impact data were extracted for three indicators: fatalities (including missing presumed dead), population affected (whose homes were flooded or who have been evacuated), and economic loss (damage or destruction of tangible assets). HANZE also includes information on the area inundated (in km^2), but was not included in the analysis due to much lower availability of data compared to the other indicators.

The other catalogue from Paprotny et al. (2024b) is a model reconstruction of almost 15,000 potential riverine, coastal, and compound floods between 1950 to 2020. Each event of this model catalogue is "potential" as it does not predetermine whether it led to actual impacts to society or economy. However, the potential events were analysed using available historical information to determine which ones caused impacts (linking them to the HANZE database) and which did not. The modelled flood catalogue also estimates potential flood impacts, without flood protection, for the same four indicators as HANZE: area inundated, fatalities, population affected (all population within the flood zone), and economic loss (only considering direct flood damage to tangible assets). Both catalogues cover the majority of the European continent (42 countries, see Fig. 14). In both catalogues, due to large variations in availability of historical records between countries, transnational floods have individual entries for each country affected.

Flood protection level in this study is defined as the return period above which a flood will occur. A flood in this context is an inundation causing significant socioeconomic impacts. The thresholds for considering a flood event "significant" are several and described in detail in Paprotny et al. (2024a), but generally require some level of loss to population and/or assets, rather than mere inundation of land. The analysis is carried out at the resolution of subnational regions (hereafter, "regions"). Regions in this context are administrative or statistical divisions of countries in the study area that are, except for minor exceptions, consistent with the European Union's Nomenclature of Territorial Units for Statistics, level 3, version 2010 (Eurostat 2020). There are 1422 regions defined in the study area, described in detail in Paprotny and Mengel (2023). Both historical and modelled flood impact zones are considered at this resolution, therefore the inferred protection levels indicate the chance of occurrence of a significant flood anywhere within the region, rather than in a particular stretch of the coastline or river. It should be stressed that this approach is very different from the typical characterization of flood protection levels, as the chance of overtopping a dike at a particular location. Our approach is rather similar to the Dutch "dike ring" concept, where the protection level is currently defined as the probability of impacts within a dike ring as a consequence of flood protection failure anywhere around the protected area (Vergouwe 2015). In this approach, the protection level strongly depends on the weakest link, as long as its failure would result in inundation and impacts. Also, we are interested in the actual reliability of flood defences, rather than the nominal, official, or otherwise desired level of protection, which has been the focus of previous datasets such as FLOPROS.

The modelled flood catalogue of Paprotny et al. (2024b) contains 5067 potential floods for which there is good historical information enabling confidently dividing the events into those that caused significant socioeconomic impacts (1444, or 29 %) and those that did not (3623, or 71 %). However, even impactful floods typically do not affect all regions where they reached hydrologically extreme levels. Non-occurrence of impacts in particular regions during an otherwise impactful event is also of interest. Consequently, our modelling approach includes two levels of impact occurrence: the event level and region level. At first, it is determined whether the flood will have impacts anywhere within the country, and if so, the chance of impacts per potentially-affected region is analysed (Table 1). Out of 45,578 regions within the 5067 potential flood events, 5257 (12 %) were determined to have been actually impacted based on documentary sources. The data include riverine, coastal, and compound events, where the latter denotes events during which both riverine and coastal drivers contributed to flooding. As such compound impact cannot be determined for non-impactful floods, only separate riverine and coastal non-impactful floods were included in the data.

Table 1 Target impact variables modelled in this study

Variable	Description	Number of data points
Flood impact (event level)	Chance of occurrence of significant socioeconomic impacts in the country as a result of a flood event	5067
Flood impact (region level)	Chance of occurrence of significant socioeconomic impacts in a specific region within the flood event's potential impact zone	45,578
Mortality (chance of fatalities)	Chance of occurrence of any fatalities as a result of a flood event	1504
Mortality (magnitude)	Reported fatalities relative to potential modelled fatalities in %, if at least one fatality has occurred	856
Relative population affected	Reported population affected relative to potential modelled population affected in %	773
Relative economic loss	Reported economic loss relative to potential modelled economic loss in %	755

As our target variables of flood protection failures are binary (impact or no impact), they had to be converted into a continuous variable to be used in vine-copulas. Alternative approaches were considered, but ultimately not applied, as explained in more detail in section 4.2. At the event level, potential impact was scaled according to potential impacts relative to maximum loss in the country from any event between 1950 and 2020. The impact was calculated for four indicators and then averaged: area inundated, fatalities, population affected, and economic loss. The index (0–100 %) was converted into 0 to 0.5 range if no impact occurred, and to 0.5 to 1 range if impact did occur. In this way, e.g. 0.4 will represent a hydrologically large flood that had no impacts, but 0.6 will represent a hydrologically small flood that nonetheless caused significant impacts. The impact indicator I for event e is follows:

$$I_e = \frac{1}{4}\left(\frac{D_{A,e}}{\max D_A} + \frac{D_{F,e}}{\max D_F} + \frac{D_{P,e}}{\max D_P} + \frac{D_{E,e}}{\max D_E}\right) \times 0.5 + M_e \tag{1}$$

where D_e is the damage indicator value (A for area inundated, F for fatalities, P for population affected, and E for economic loss) during event e, and M_e has a value of 0.5 if impact occurred during event e, and 0 otherwise.

Impact occurrence at regional level was scaled according to the relative contribution (%) of potential losses in the region to the whole event (average of the four impact indicators). This share of losses was converted into 0–0.5 range if no impact occurred, and to 0.5 to 1 range if impact did occur. The impact indicator I in region r for event e is follows:

$$I_{r,e} = \frac{1}{4}\left(\frac{D_{A,r}}{D_{A,e}} + \frac{D_{F,r}}{D_{F,e}} + \frac{D_{P,r}}{D_{P,e}} + \frac{D_{E,r}}{D_{E,e}}\right) \times 0.5 + M_{r,e} \tag{2}$$

where $M_{r,e}$ has a value of 0.5 if impact occurred in region r for event e, and 0 otherwise.

Flood vulnerability was considered for three variables: fatalities, population affected, and economic loss. Availability of data varies between variables (Table 1). Absolute impact of each was converted into relative impact using the potential modelled loss from the other catalogue. Only historically affected regions were considered when computing potential losses. Modelled loss is based on static depth-damage functions in case of mortality and relative economic loss, while modelled population affected is simply the total exposed population within flooded grid cells. The function for mortality is a S-shaped function shown in Jonkman et al. (2008), and the economic loss functions for five fixed asset types (dwellings, agriculture, industry, services, infrastructure) are from (Huizinga et al. 2017). In total, it was possible to compute potential loss for 1504 (74%) of historical floods in the HANZE database, which represent 81 % of known fatalities in Europe since 1950, and 96 % of both population affected and economic loss. For more information on potential damage modelling, as well as an analysis of the accuracy and completeness of the flood reanalysis we refer to Paprotny et al. (2024b).

Mortality (fatalities relative to exposed population) was considered as two variables, the chance of any fatalities occurring, and then the number of fatalities if more than zero was indicated. This was done because in 43 % of historical floods no deaths were reported, resulting in a highly skewed distribution of mortality. Such a distribution would severely degrade the performance of any statistical model. To compute the chance of fatalities, the same approach as for flood protection was used. The chance of fatalities was scaled according to potential impacts relative to maximum loss in the country from any event between 1950 and 2020. The impact was calculated for four indicators and then averaged: area inundated, fatalities, population affected, and economic loss. The index (0–100 %) was converted into 0 to 0.5 range if no fatalities occurred, and to 0.5 to 1 range if at least one fatality occurred. Equation 1 is applicable here with substituting "impact" for "fatalities".

Finally, relative impact indicators for fatalities, population affected and economic loss were capped at 100 % to avoid a minor share of cases where flood footprint or exposure was strongly underestimated by the modelled flood catalogue.

2.1.2 Predictors

To infer the distribution and changes in flood protection levels and vulnerability, multiple candidate variables were considered (Table 2). Most of them were considered at the level of regions, aggregated to event footprint, actual or potential, where appropriate for a particular target variable. Governance and demographic indicators are at country level, while potential flood impacts and hydrological intensity are based on modelled flood footprints at 100-meter resolution. Each variable refers to socioeconomic situation at the time of the event, unless noted otherwise in Table 2. In addition, several categories of variables ("Economic development" and all further down the table) were additionally considered in a 'lagged' version, i.e. average of conditions in the 30 years preceding the flood event. The data was collected from several sources, which are indicated in Table 2.

2.2 Methods

2.2.1 Vine copulas

Vine copulas are graphical models that allow the specification of a multivariate probability distribution through bivariate pieces. More specifically a *vine* is a sequence of trees (undirected acyclic graphs) $\{T_1, \ldots, T_{d-1}\}$ where T_1 is a tree on d nodes and the edges of each tree become the nodes of next tree for $T_2, \ldots, T_{d-1}$. In particular vine copulas are constructed with *regular vines*. A regular vine is, roughly, a vine where two edges of T_i are joined as nodes in T_{i+1} if they share a common node in T_i for $i \geq 1$. An example of a regular vine on 5 nodes is presented in Fig. 1.

Vine copulas use the graphical structure of a regular vine to construct a multivariate probability distribution. Each node in the first tree of the regular vine is associated with a random variable with an invertible cumulative distribution function, while the probabilistic dependence between variables is approximated through bivariate (conditional) copulas (Nelsen 2006). A bivariate copula C is a bivariate distribution function with uniform [0, 1] margins. If H is the joint distribution of X and Y then $H(x, y) = C(F(x), G(y))$ where F and G are the marginal distributions of X and Y respectively.

In Fig. 1 for example, the pair of numbers in the first tree of the vine indicate the copula joining the corresponding variables. The edges in the lower trees indicate the bivariate copula between the variables to the left of the horizontal line conditional on the variables to the right of the line. For a comprehensive treatment of vine copulas see Czado (2019).

The number of vine copulas that may be fitted to a dataset is extremely large (?). For "lower" dimensional datasets (up to 7 variables), fitting all possible vine copulas may be feasible. However for 8 variables or larger this task becomes computationally challenging. Recently a dataset containing all regular vine structures on up to 8 nodes (more than 660 million) has been presented in Morales-Napoles et al. (2023). For larger dimensions the

Table 2 Candidate predictor variables of flood protection levels and vulnerability

Category	Variables	Description
Flood experience	8	Reported damaging floods in preceding 10, 20, 30, or 50 years, or between 5 and 15, 25, 35, or 55 year ago (specific to the type of flood event analysed) (Paprotny et al. 2024a, 2024b)
Flood risk	6	Average annual (1950-2020) potential modelled impact (fatalities, population affected, economic loss) relative to population or GDP, dynamic (year-of-event) exposure or constant 1990 exposure, in % (specific to the type of flood event analysed) (Paprotny et al. 2024b)
Potential flood impact	3	Potential modelled impact of the event (fatalities, population affected, economic loss) relative to population or GDP, dynamic (year-of-event) exposure, in % (Paprotny et al. 2024b)
Hydrological intensity	3	In the potential flood zone of the event: (1) Average return period of river discharge/coastal water level (1950-2020 detrended); (2) Average water depth; (3) Duration in days (Paprotny et al. 2024b)
Economic development	4	At regional level: GDP per capita (constant 2020 euros), and share of GDP in agriculture, industry and services (Paprotny and Mengel 2023)
Economic structure	6	At regional level: share of tangible fixed assets by six sectors, in % (residential buildings, consumer durables, agriculture, industry, services, infrastructure) (Paprotny and Mengel 2023)
Land use	6	At regional level: share of land use by five classes, in % (urban fabric, other artificial, agriculture, forests, other natural), and average soil sealing (imperviousness) (Paprotny and Mengel 2023)
Population size	2	At regional level: (1) share of urban population, (2) population density per km^2 (Paprotny and Mengel 2023)
Governance	5	At country level: five democracy indices ("Electoral", "Liberal", "Participatory", "Deliberative", "Egalitarian") from Varieties of Democracy (V-Dem) dataset, v13 (Coppedge et al. 2023)
Demography	8	Various demographic indicators at country level: (1) infant mortality rate, (2) life expectancy at birth, (3) median age, (4) net migration rate, (5) population growth rate, (6) population sex ratio, (7) rate of natural change, (8) total fertility rate (United Nations 2022)

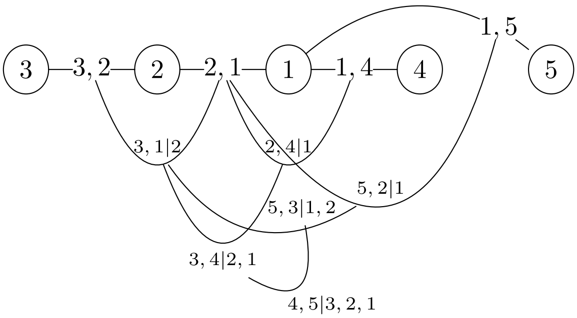


Fig. 1 Example of regular vine on 5 nodes

algorithm proposed in Dißmann et al. (2013) and variations of it are mostly used. In this research because of the large number of possible models under investigation we opted for Dißmann's algorithm.

2.2.2 Creating vine copula-based models

As highlighted in Tables 1 and 2 in section 2.1, there are six target variables analysed in the study and numerous candidate predictors. Obtaining the optimal model configuration was a procedure with several steps. Firstly, six connected vine copula models were defined, representing one target variable each (Fig. 2). Flood protection level is represented by two vines, the first one estimating the impact probability at event level, and the second one at regional level. The event level is used to establish the chances of a significant impact of a potential flood event, while the regional level is used to establish a more precise location of those impacts. Then, the vulnerability models can be applied to the affected area. Relative population affected and economic loss are modelled with one model each, while mortality (fatalities relative to population) is split into two models, one indicating the chance of at least one fatality occurring, and the second estimating the magnitude of fatalities.

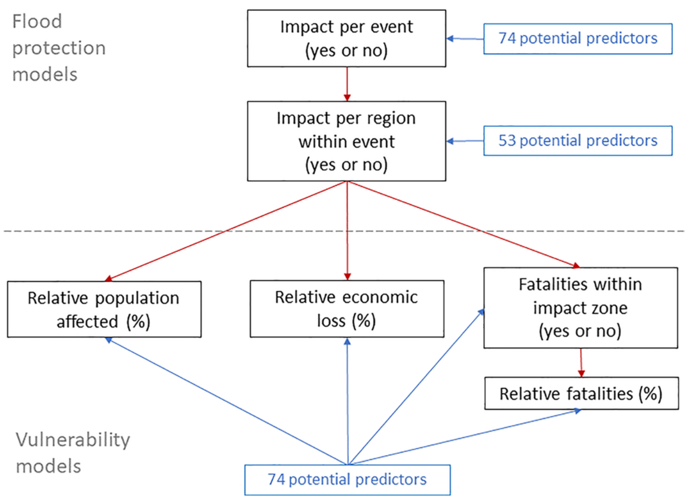


Fig. 2 Structure of the modelling framework. Each target variable is modelled independently with a vine

Each vine model was tested first with 74 potential predictors, except for the impact at regional level, for which not all predictors were appropriate, namely variables aggregated at event (potential flood impact) or country level (governance and demographic indicators). Two aspects of each vine model needed to be optimised: the selection of predictor variables and the dependency structure within the vine. A different approach had to be applied for the two tasks. As the Chimera atlas is capable of working with vines with four to eight nodes, we built each model stepwise starting with four nodes. Within those four nodes, one was the target variable and one was the predictor variable with the highest unconditional rank correlation with the target variable, except for flood impact at event level, which was purposely chosen as return period. This is because this predictor is most relevant to computing the protection level, and was also the highest correlated variable for impact at regional level. The other two variables changed at each iteration, until all possible combinations of remaining predictors were exhausted. Within each iteration, the optimal dependency structure came from the algorithm of Dißmann et al. (2013). Here, the best vine structure, meaning not only the configuration of arcs but also the type of copulas representing each arc, was selected according to the Akaike Information Criterion (AIC). It should be noted that we limited the search of optimal copulas within the vine models only to one- and two-parameter copulas.

Every possible variable combination was then compared according to the validation metric. In case of flood protection models and the chance of fatality occurring, the % success rate in inferring the "yes" or "no" state of the target variable was calculated. For continuous quantities (relative losses), several metrics were analysed, but primarily the coefficient of determination and the Kling-Gupta Efficiency (KGE) score. The latter metric integrates correlation, bias and error and has seen wide use in hydrology (Knoben et al. 2019). The vulnerability models were further applied to the potential losses from the flood catalogue in order to compare the trends in absolute observed and inferred losses. One variable, inclusion of which improved the model's performance the most, was selected as predictor. Then, the test was repeated with five nodes: the target variable, the original predictor from the previous test, the newly selected predictor, and two predictors changing at each iteration. Again, all combinations of the latter two variables were tested. The experiment continued with more nodes added to the vine until it reached eight nodes or addition of further nodes did not improve the model's performance. The same process was done separately for each of the six target variables. After a series of preliminary tests, due to the large computational burden of the algorithm for an adequate amount of samples, the number of candidate predictors was reduced. We excluded predictors that were strongly similar to each other and were almost never better predictors than others: flood experience lagged by 5 years, flood risk in constant exposure, country-level demographic indicators, and 30-year averages of the socioeconomic variables. This has reduced the potential predictors to 35 variables (23 for flood impact per region).

Each run of the vine copula models with a given set of predictor variables was analysed through a 10-fold cross-validation. In case of flood protection models, the training dataset consisted of a random 10% sample of the full dataset, and the remaining 90 % of the data was used for validation. In each of the 10 runs, the training sample had no overlaps with any other run. For vulnerability models, the amount of available data is much smaller, therefore a higher share of data was used for training and therefore could overlap partially with samples in other runs. For modelling the chance of fatalities, 1/3 of data were used for training, while for models inferring the relative loss, 1/2 of the data was used. Average out-of-sample validation results were considered when choosing predictor variables. Once the final selection of predictor was made, the vine copula models for further application were run once more using the algorithm, to define the best dependency structure using the entire sample, except for impact at region level, where due to large sample size, 1/2 of the data was used. Such structured and quantified models were used in section 3, except validation results in Table 4, which are the average in-sample and out-of-sample results.

In section 3.3.1, the implied return period of significant damages from floods is shown. The two vine models of flood protection levels provide the probability of flooding given the predictors, among which is the average return period among affected river sections or coastal segments. This return period was calculated using the peak-over-threshold approach with a Generalized Pareto distribution applied over detrended 1950-2020 6-hourly river discharge and hourly sea level. Therefore, by integrating the hydrological return period with dike failure probability, we could derive the recurrence interval of significant flooding. We approximated the analytical solution to this problem with a numerical method used to compute expected annual damage from flood maps at given return periods based on distribution-free median plotting position (Olsen et al. 2015). This involves generating a series of 1000 random events defined by return period T:

$$T = \frac{n + 0.4}{m - 0.3} \tag{3}$$

where n is the length of the series of events and m is the rank of the event.

3 Results

3.1 Vine copula models

The final vine copula models for inferring flood protection levels and vulnerability have from five to seven nodes, i.e. they have four to six predictors of the target variables (Table 3). In total, 18 different predictors are used at least once among the models. All categories of predictors are present, except country-level demographic indicators. Variables related to economic development occurred most frequently (8 out of 28 cases), with GDP per capita used in four of the models. In each case, it was negatively correlated with flood occurrence or relative losses. Though GDP per capita was not relevant for the number of fatalities, GDP per sector (either share of agriculture or industry in the economy) was important and positively correlated with the chance and magnitude of fatalities. GDP per sector was also presented in the models on flood protection (event level) and population affected.

Hydrological indicators were used six times, always positively correlated with impacts, except for average water depth in the potential impact zone, which was negatively correlated with the magnitude of fatalities. Similarly, flood experience of the past 20 or 30 years was negatively correlated with magnitude of fatalities and economic loss. However, the number of past floods positively correlated with chance of flooding, indicating the persistence of flood protection deficiencies. Relative losses strongly scale to the magnitude of damage potential, as widespread floods tend to have lower individual impacts than smaller flash floods. Similarly, flood occurrence is positively correlated with potential flood risk over 1950-2020, but negatively correlated with relative population affected.

Other variables are less present in the models: degree of urbanization was important only for the chance of fatalities (positive correlation). Structure of fixed assets in the affected area was included in two models. The share of residential assets was negatively correlated with

Table 3 Variables in the final vine copula models. The numbers before variable names identify variables in the graphs of figures 3 – 8

Model	Target variables	Predictor variables
Fig. 3	1. flood impact (event level)	2. average return period (RPv1), 3. event duration (Duration), 4. average annual potential modelled economic loss relative to regional GDP (Risk_eco), 5. GDP per capita (GDP_pc), 6. floods in previous 20 years (HANZE_events_20yr), 7. share of GDP in agricultural sector (GDP_Agr)
Fig. 4	1. flood impact (region level)	2. average return period (RPv1), 3. GDP per capita (GDP_pc), 4. floods in previous 30 years (HANZE_events_30yr), 5. event duration in the region (Duration)
Fig. 5	1. mortality (chance of fatalities)	2. average return period (RPv1), 3. share of urban population (PopUrban), 4. share of GDP in services sector (GDP_Ser), 5. share of artifical land other than urban fabric (LU_OtherArt)
Fig. 6	1. mortality (magnitude)	2. potential modelled fatalities affected of the event relative to regional population (Pot_rel_loss_fat), 3. share of GDP in the agricultural sector (GDP_Agr), 4. floods in previous 20 years (HANZE_events_20yr), 5. average water depth (WaterDepth)
Fig. 7	1. relative population affected	2. potential modelled population affected of the event relative to regional population (Pot_rel_loss_pop), 3. GDP per capita (GDP_pc), 4. average annual potential modelled economic loss relative to regional GDP (Risk_eco), 5. share of GDP in industry sector (GDP_Ind), 6. share of fixed assets in residential buildings (FA_Res)
Fig. 8	1. relative economic loss	2. potential modelled economic loss of the event relative to regional GDP (Pot_rel_loss_eco), 3. GDP per capita (GDP_pc), 4. floods in previous 30 years (HANZE_events_30yr), 5. share of fixed assets in the agricultural sector (FA_Agr), 6. egalitarian democracy index (EgalDem)

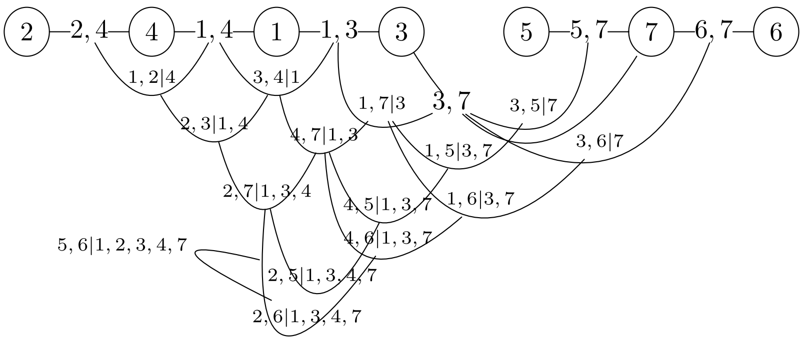


Fig. 3 Vine copula model for flood impact at event level

Fig. 4 Vine copula model for flood impact at region level

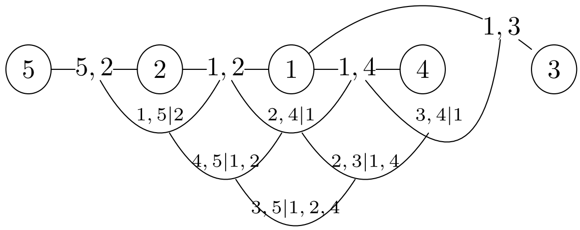


Fig. 5 Vine copula model for mortality (chance of fatalities)

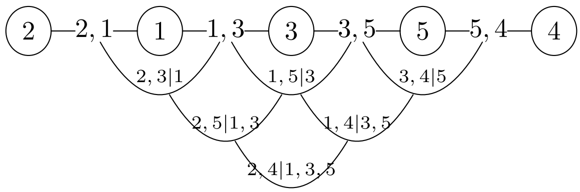
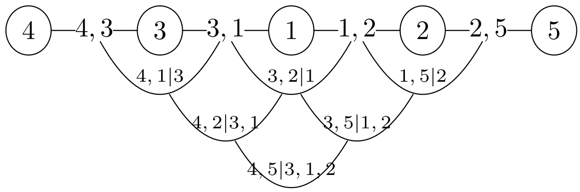


Fig. 6 Vine copula model for mortality (magnitude)



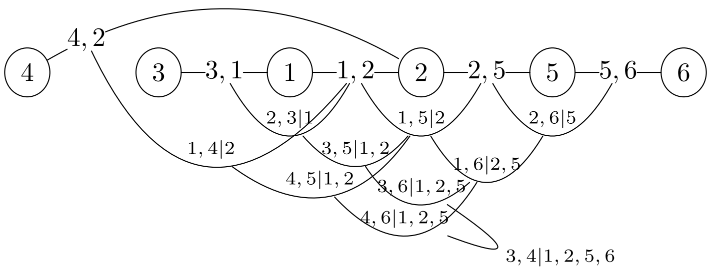


Fig. 7 Vine copula model for relative population affected

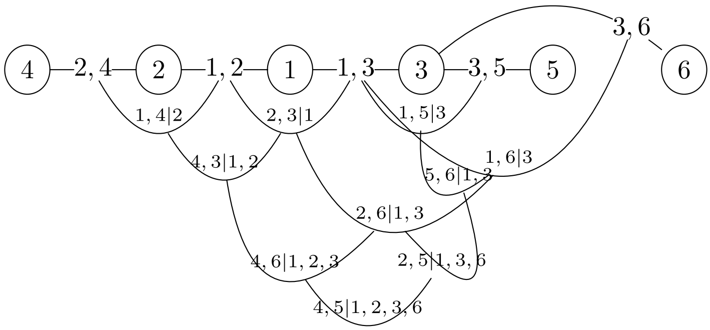


Fig. 8 Vine copula model for relative economic loss

Table 4 Validation results, average for 10-fold cross-validation. Percentages in brackets are the theoretical success rates of a random model. KGE = Kling-Gupta Efficiency (Knoben et al. 2019)

Variable	Metric	In-sample	Out-of-sample
Flood impact (event level)	Impact - % correct	64% [28%*]	63% [29%*]
	No impact - % correct	86% [72%*]	86% [71%*]
Flood impact (region level)	Impact - % correct	31% [11%*]	31% [12%*]
	No impact - % correct	91% [89%*]	91% [88%*]
Mortality (chance of fatalities)	Fatalities - % correct	67% [58%*]	64% [57%*]
	No fatalities - % correct	53% [42%*]	54% [43%*]
Mortality (magnitude)	R^2	0.67	0.67
	KGE	0.58	0.58
Relative population affected	R^2	0.32	0.29
	KGE	0.37	0.37
Relative economic loss	R^2	0.44	0.44
	KGE	0.44	0.45

relative population affected, while the share of agricultural assets was positively correlated with relative economic loss. Land use variables appear only once, with negative correlation between the share of land under artificial surfaces other than urban fabric (mainly industrial/commercial zones and transport-related infrastructure) and the chance of fatalities. Finally, a governance indicator is used only in the vine copula for relative economic loss, with a negative correlation.

More detailed information on the vine copula models is provided in the Supplementary Information: joint distributions of raw, ranked, and sampled data in addition to vine tree sequences (S1), correlation matrices (S2) as well as types and parameters of copulas used (S3).

3.2 Model validation

3.2.1 Sample validation

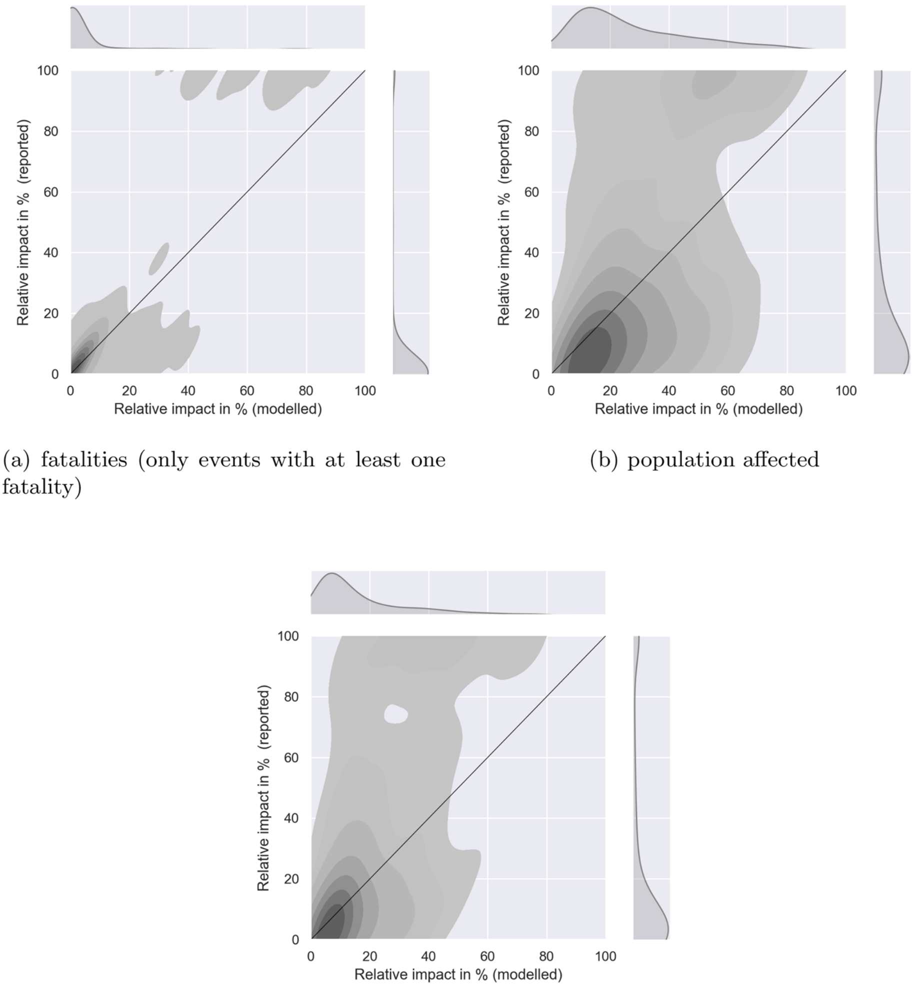
Table 4 presents validation results averaged from 10-fold cross-validation, both in-sample and out-of-sample. Three out of six models were evaluated by the success rate in correctly classifying the events as impactful or non-impactful. In all cases, the models achieved higher performance than a theoretical random model, which would have reproduced the frequency of impacts (or fatalities). Flood protection at event level best considering the ratio of impacts and non-impacts, while the mortality model was the least successful.

The remaining three models reproduced relative losses and were analysed with several metrics (Table 4). The best performance was achieved by the mortality model, though some negative bias was observed (Fig. 9a). Most of the fatality rates are very low - average ratio of reported fatalities to modelled potential fatalities with a static depth-damage function is only 0.5 %. By contrast, the ratio of average reported population affected to potential population exposure is 27 %, and for economic loss – 22 % of potential loss. The latter models have lower performance overall, while relative population (Fig. 9b) tends to be overestimated and relative economic loss underestimated (Fig. 9c). In addition to computing relative loss, the models were analysed in terms of how well they reproduced trends in absolute losses in Europe overall (section 3.2.3)

3.2.2 Comparison with other flood protection level datasets

Probability of impact from the two flood protection models were converted into the implied return period of an significant impactful event in each region (section 2.2.2). In Fig. 10, our results for riverine floods in year 2020 (section 3.3.1) are compared with nominal riverine flood protection standards from FLOPROS (Scussolini et al. 2016) and PESETA IV project (Dottori et al. 2023). In both cases, the nominal standards are far higher than our calculations. Weighted by flood hazard in each region, the average protection level from our data was only 22 years, compared to 186 years in FLOPROS (Fig. 10a) and 209 years in PESETA IV (Fig. 10b). 54 % and 58%, respectively, of regions in the study area have 100-year protection standards in those datasets, compared to only 5 % in our results. However, FLOPROS includes not only direct information on local flood protection policies, but also gap-fills information with a regression with GDP per capita, mostly showing less than 30-year protection for eastern and southern Europe, and 40–60 years for western and northern parts of the continent. PESETA IV, bar one exception, assumes a protection level of at least 50 years across Europe. The spatial comparison between the datasets is shown in Supplement S4.

Despite the large difference between our results and other commonly used datasets, more detailed local data show much better alignment with our results. For instance, the average flood protection standard weighted by dike length for riverine floods in England (Environment Agency 2023) is only 30 years, close to our weighted average of 26 years. Meanwhile, the other pan-European uniformly assume a 100-year protection for all of England, except 1000 years for London. The Environment Agency data indicate such design standards only for 10 % of dikes in England. Weighted average coastal protection in England according to the same source is 159 years, only marginally lower than our average of 167 years. The other datasets do not provide estimates for coastal flood protection levels.



(a) fatalities (only events with at least one fatality)

(b) population affected

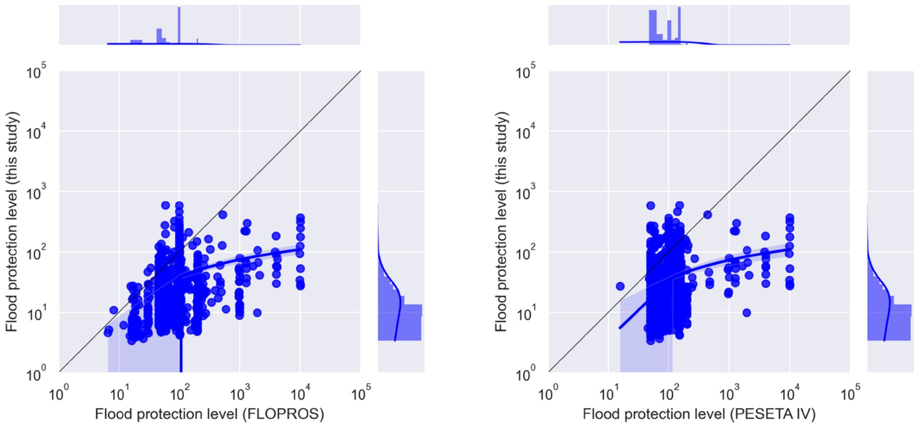
(c) economic loss

Fig. 9 Comparison of modelled (vine copula-based) and reported impact, both relative to potential impact

3.2.3 Absolute impacts and trends

Absolute modelled flood impacts for 1504 historical floods between 1950 and 2020 are compared with reported losses for the same events, where available (as indicated in Table 1). This enables comparing the performance of the model in reproducing historical time series of losses, even though this depends not only on the accuracy of the vulnerability models of this study, but also the hazard and exposure reconstructions of Paprotny and Mengel (2023); Paprotny et al. (2024b).

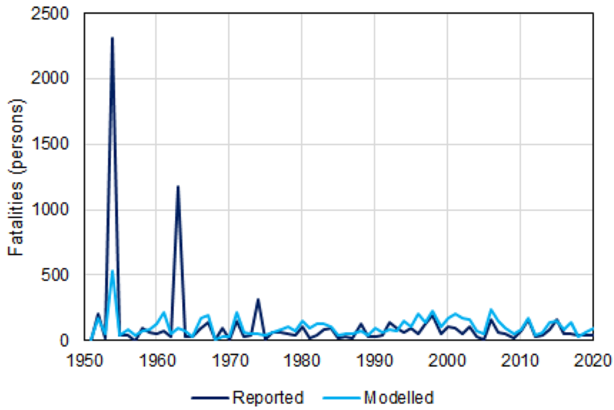
Overall number of fatalities is underestimated by 10 %, primarily for major events (Fig. 11). 43 % of historical fatalities occurred in only five events, all clustered in only three years (1953, 1962 and 1973). In the remaining 851 events, there is a positive bias of 49 %, with both observations and models showing slight upward trends in absolute



(a) FLOPROS (Scussolini et al, 2016)　　(b) PESETA IV (Dottori et al, 2023)

Fig. 10 Comparison between flood protection levels for riverine floods from this study for year 2020 and from two other public datasets, as return period in subnational regions of the study area

Fig. 11 Annual reported fatalities in Europe and model estimate



fatalities (without correcting for population growth or other drivers). The modelled trend is stronger than in reported yearly data.

Population affected and economic loss is less concentrated: the top five events were responsible for about 20 % of reported losses. However, data is only available for about half of the events. Population affected is underestimated by 23 % and economic loss by 22 % (Figs. 12 and 13). Excluding the top 10 events, for which the model strongly under-performs, the bias is 0.2 % and 6 %, respectively, for population affected and economic loss. Whereas upwards trend in the model closely matches the reported one, the trend in economic loss is overestimated. In both cases, the upward trend should not be interpreted standalone, as it was not corrected for exposure growth or other drivers.

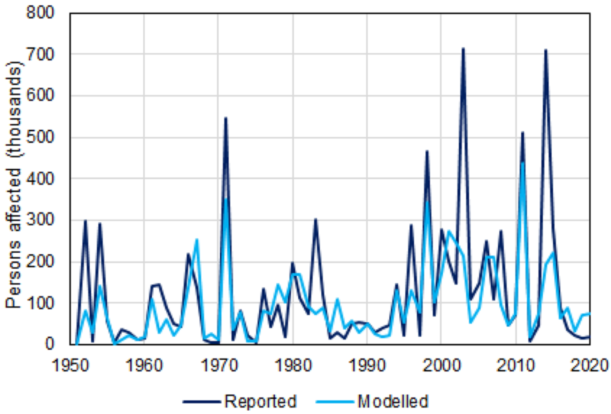


Fig. 12 Annual reported population affected in Europe and model estimate

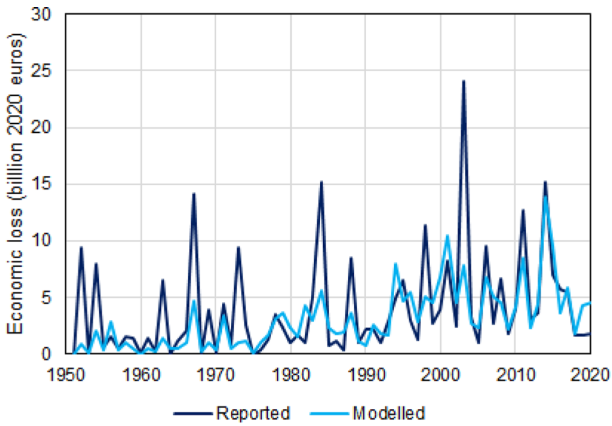


Fig. 13 Annual reported economic loss in Europe and model estimate

3.3 Flood protection levels and vulnerability in Europe, 1950-2020

3.3.1 Flood protection levels

Implied flood protection levels, i.e. the return period of flood with significant impacts, was computed for subnational regions in the study area between 1950 and 2020. We show separate estimates for coastal and riverine events, which cover 405 and 1364 regions, respectively. Separating the two types of floods was possible through three variables: economic risk, duration, and 20-year flood experience, which have different values depending on the type of event. For this analysis, we assume that duration at event or regional level equals duration with the same return period as assumed for discharge or sea level. To estimate the average protection levels across Europe in Fig. 14, we used the synthetic events with different return periods (section 2.2.2) to create a random timeseries of events that would have overwhelmed flood defences in some regions in a given year. The total number of impacts in Europe relative to the number of applicable regions (coastal or riverine) then indicated the average return period of region-level impacts.

Overall, there is better protection from coastal floods than riverine, and the former has been improved to a slightly larger degree than the latter (Fig. 14). The average

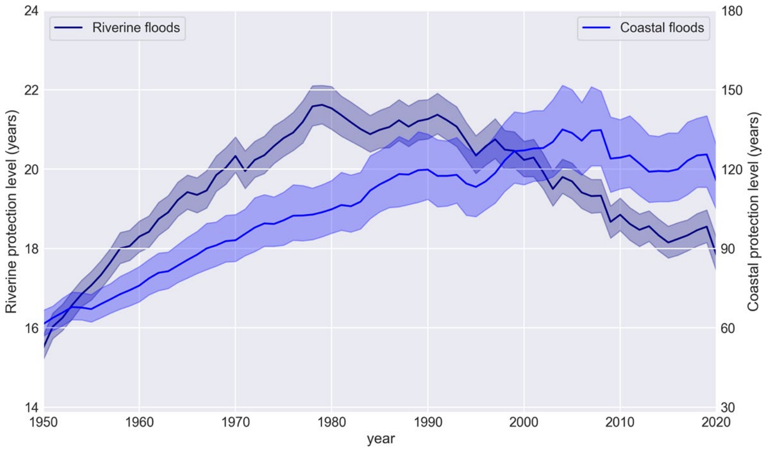
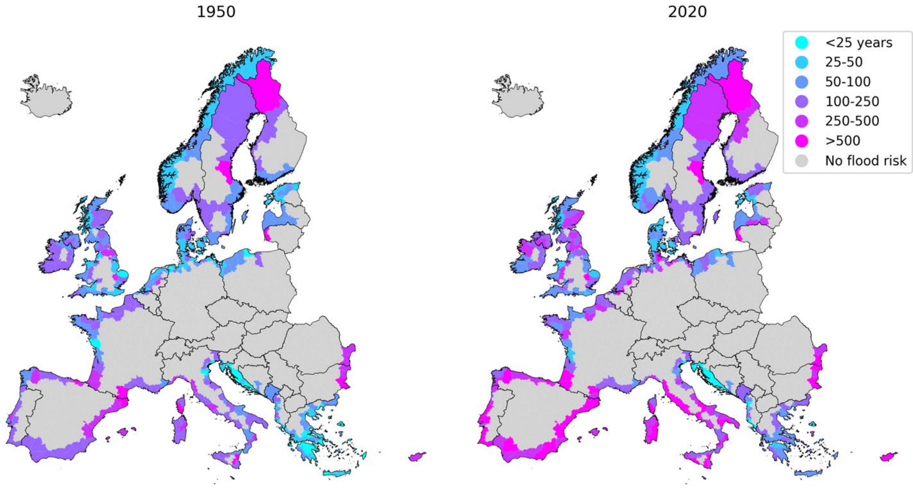


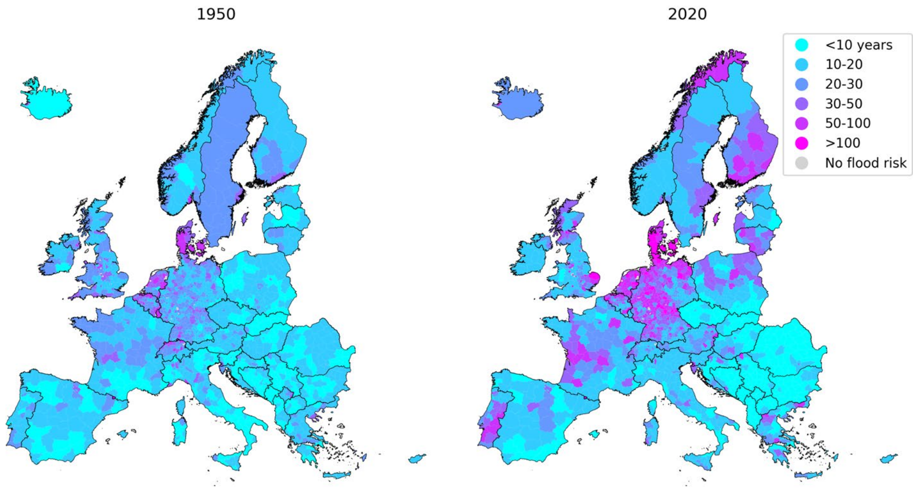
Fig. 14 Changes in protection levels weighted by flood hazard area, by flood type, 1950-2020

European coastal protection level improved from 61 years in 1950 to 135 years in 2004, before declining to 116 years in 2020. By contrast, riverine protection only increased from 15 years in 1950 to 22 years in 1979, when it started declining to only 18 years in 2020. While this is much less than nominal protection standards analysed in section 3.2.2, it is consistent with actual flood occurrence. Riverine flooding, according to data collected in the HANZE dataset (Paprotny et al. 2024a, 2024b), affected an average region in the study area 4.05 times from 1950 to 2020, which implies a return period of 17.5 years. Using a series of random events of different return periods sampled over estimated regional protection, the inferred return period of floods is 19.2 years (95 % confidence interval: 18.7−19.7 years). In case of coastal floods (including compound events), 405 regions where such floods are possible were affected with a return period of 66 years. Average protection from coastal floods over 1950-2020 is estimated here as 99 years (95 % confidence interval: 88-111 years). However, many regions affected by compound events are outside the coastal flood zone; the observed return period for coastal floods only is 120 years. It should be noted that the clear difference between riverine and coastal flood occurrence was captured by the model approach despite all types of floods being assembled together in the input data.

Spatially, riverine flood protection levels (Fig. 15a) follow the somewhat expected pattern of better developed countries exhibiting higher protection levels, but not so much for coastal floods (Fig. 15b). As flood experience is an important predictor of subsequent inundation, and we define flood protection levels in terms of occurrence of significant impacts, locations of major past events are often visible, e.g. North and Adriatic seas for coastal and compound flooding, and mountainous regions for riverine flooding. Many Balkan countries as well as Czechia, Italy, Spain, and Sweden are indicated as having no improvement or deterioration in protection from riverine floods, in contrast to e.g. Germany, the Netherlands, Poland and Portugal, where the opposite was found. The model estimates large improvements in coastal protection everywhere, particularly southern and eastern Europe, with the sole exception of Denmark.



(a) coastal floods



(b) riverine floods

Fig. 15 Flood protection levels (return period in years), by region and type of flood, 1950 and 2020

3.3.2 Flood vulnerability

Similarly to flood protection levels, inferred vulnerability at regional level was computed for all regions. The indicators presented in this section refer to inferred impacts relative to modelled potential impacts of an average event that have (potentially) affected a given region between 1950 and 2020 in constant 2020 exposure level, combined for riverine and coastal floods. The average return period along river sections or coastal segments for computing the chance of fatalities is also an average of region-specific events. Flood experience used in two models was computed based on all types of events.

All three impact indicators - mortality, population affected and economic loss - have shown a considerable decline between 1950 and 2020 (Fig. 16). Relative population affected, weighted by flood hazard area of each region, was estimated at 34 % for the hypothetical average flood event in 1950, but only 17 % in 2020, though higher than around 2010 when it was estimated at 15 %. Economic loss started declining later, in the 1970 s, but still declined substantially from 34 % to 20 %. Relative fatalities had the fastest decline, from 9.0 % in 1950 to 3.8 % in 2015, before increasing narrowly to 4.0 % in 2020.

At regional level, the patterns should be interpreted with the consideration that they are relative to potential damage represented by static depth-damage functions for fatalities and economic losses. Consequently, the distribution of mortality rates (Fig. 17) is not expected to be similar to historical fatality distribution (i.e. strongly skewed towards southern Europe relative to the northern part). Decline in mortality is estimated to be the highest in south-eastern Europe, compared to limited decline or increase in the Alpine region, though it was already relatively low in 1950. By contrast, the model predicts a decline in relative population affected in all countries (Fig. 18), particularly in northern Europe and Germany, and a much smaller decline in the south-eastern part of the continent. On the other hand, the model also predicts that economic vulnerability declined in the southern countries (particularly Portugal and Spain), with less pronounced declines in the northern part of the continent (Fig. 19). For both population affected and economic loss regions impacted by slow-onset, large riverine floods (eastern and south-eastern Europe in particular) have higher vulnerability than those where rapid but spatially limited flash floods are dominant, especially in the Alpine zone.

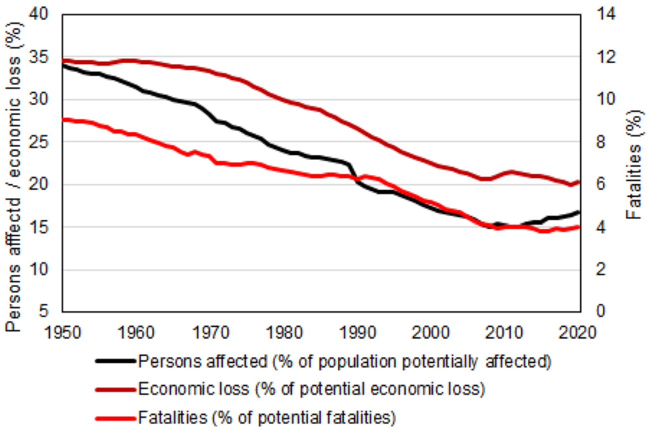


Fig. 16 Inferred impacts of an average flood relative to modelled potential impact, weighted by flood hazard area, by impact type, 1950-2020

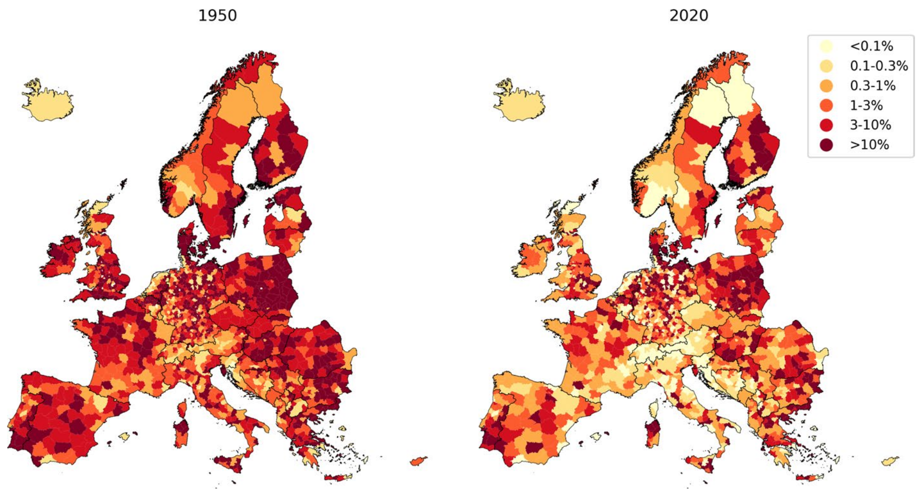


Fig. 17 Inferred fatalities of an average flood relative to modelled potential impact, by region, 1950 and 2020

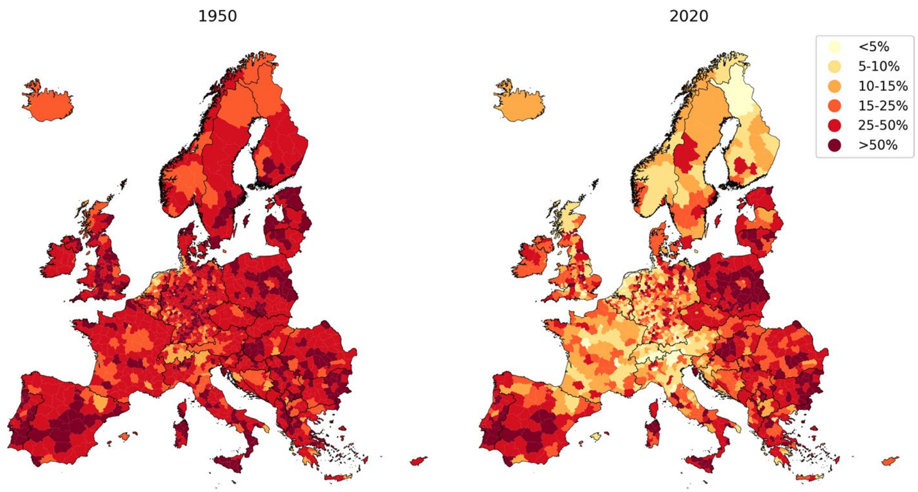


Fig. 18 Inferred population affected by an average flood relative to modelled potential impact, by region, 1950 and 2020

3.4 Estimating unreported flood losses in Europe

Published historical flood impact datasets, such as HANZE (Paprotny et al. 2024a), are not complete. Whereas fatality data was available for 99 % of events in HANZE that have occurred back to 1870, population affected was provided only for 43 % of events, and economic losses for 40 %. Therefore, the full magnitude of flood losses in Europe is unknown, and has implications e.g. for validating pan-European flood risk assessments. Combining the modelled flood catalogue of Paprotny et al. (2024b) with our vulnerability models, it is possible to estimate the missing impact data.

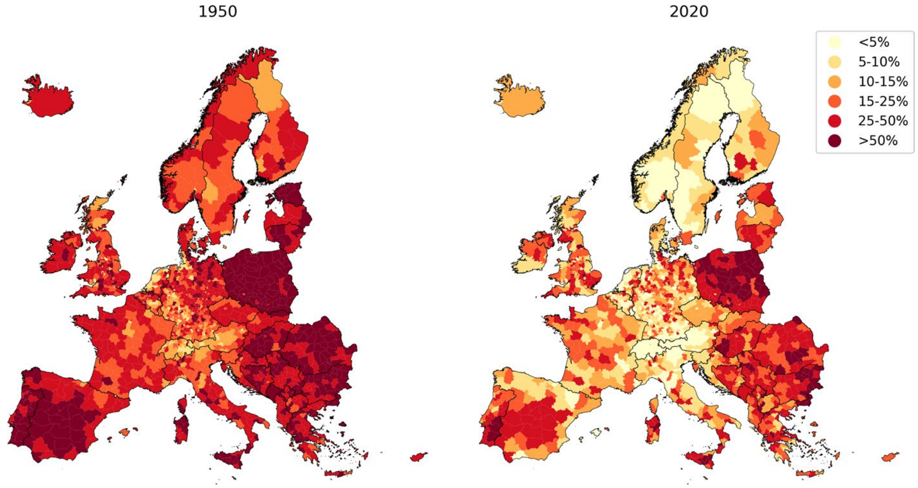


Fig. 19 Inferred economic loss of an average flood relative to modelled potential impact, by region, 1950 and 2020

HANZE contains 2037 events since 1950 where at least one impact statistic (out of four, including inundated area) is known ("A" list). Of these, 1504 events were captured by the model, of which 8 had unknown number of fatalities and almost half were missing the number of population affected and economic loss (Fig. 20). Consequently, the estimated number of unreported fatalities is below 100, adding less than 1 % to the known total. However, missing impacts for the other two categories add 35-38 % to

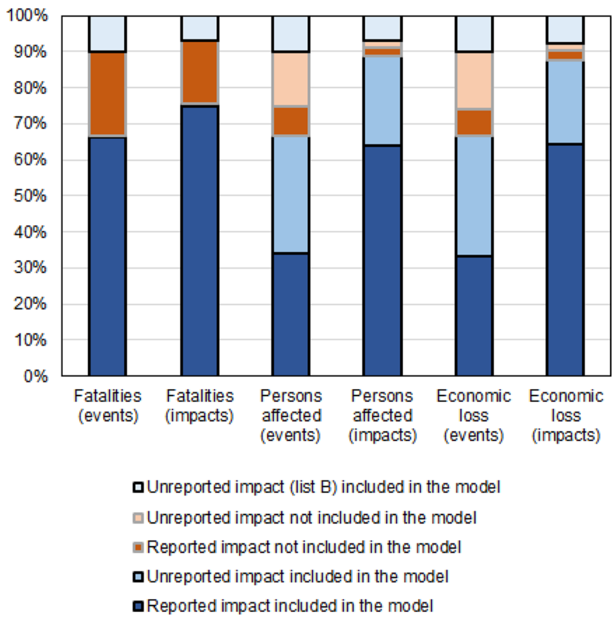


Fig. 20 Estimated impacts of floods in Europe, distinguishing floods with known (dark colors) and unknown (bright colors) impacts, further indicating if they were captured by the model reconstruction in Paprotny et al. (2024b) (dark outline) or not (bright outline)

the total, even if an average event without known impact is estimated to have had 60 % smaller magnitude than an event with recorded impacts.

The remaining 533 events not included in the modelled flood catalogue consist mostly of flash floods. Impact reporting rate for population affected and economic loss is smaller, covering about one-third of events, and where available, they were about six times smaller on average compared to events included in this study. The missing impacts cannot be directly reproduced with our approach, as they are not in the catalogue, but we can extrapolate from the previous categories of events. We assume that the ratio between an average event with unknown impacts and known impacts for the events not included in the model is the same ratio as for those events that were captured in the catalogue. This adds little additional damage to what was reported, namely 0.1 % more fatalities and about 3 % more population affected and economic loss.

Finally, the flood catalogue identified additional 237 floods ("B" list) for which there is no complete impact data, but descriptive sources or partial data indicate that they nonetheless caused significant socioeconomic impacts. Estimated impacts of those events are, on average, similar to those with unknown impacts in the "A" list, and slightly lower than the estimated average for all 2037 events on that list. 12 floods on the "B" lists are related to "A" events such as they represent an earlier or later phase of the "A" event, and their impacts were reported in list "A". The remaining 225 "B" events increase the known impacts by further 7-11 %, depending on the category of impacts. Overall, the 2274 known flood events resulted in an estimated 11,000 fatalities, affected 14 million people and caused 435 billion euro losses between 1950 and 2020 (Table 5). We estimate that the modelled flood catalogue reproduces 83 % of fatalities and 95-96 % of other impacts. On the other hand, the reported impacts cover 92 % of estimated total fatalities, and only 66-67 % of population affected and economic loss. This indicates that while fatality data are reliable enough for use in pan-European flood studies, reported population affected and economic losses should be taken with a degree of caution due to their incompleteness.

4 Discussion

4.1 Uncertainties in input data

The study is based on extensive data collection and modelling effort carried out primarily in several preceding studies (Paprotny and Mengel 2023; Paprotny et al. 2024a, 2024b; Tilloy et al. 2024). Inevitably, there are numerous sources of uncertainty involved in the

Table 5 Estimated impacts of floods in Europe by impact category. Numbers in brackets are the 95 % confidence interval

Category	Estimated total	% of estimated total captured by model	Known impacts as % of estimated total
Events	2262	76.4	x
Fatalities (thousands)	11.2 [10.8–11.9]	82.7 [82.1–83.6]	91.6 [85.6–94.9]
Population affected (millions)	13.8 [13.0–14.7]	95.8 [95.8–95.8]	66.2 [62.1–70.5]
Economic loss (billions, 2020 euros)	435 [403-472]	95.3 [95.2–95.3]	67.0 [61.7–72.3]

input data. This relates to both the reported impacts and their reconstruction in the modelled potential flood catalogue. Observed impacts were compiled from many sources with a varying level of reliability and completeness. The availability of information also strongly varies between countries, or even within countries, with a noticeable temporal bias, analysed in detail in Paprotny et al. (2018). For example, there are extensive flood databases and catalogues available for France, Italy, Norway, Portugal, Spain, Switzerland, and certain Balkan countries, but large scattering of information makes it difficult to collect data for other countries, such as Austria, Germany, and the United Kingdom. There are also large gaps in data resulting from Communist-era suppression of public flood impact reporting, even if they were clandestinely recorded in minute detail and sometimes made available in more modern times. Apart from missing data, major errors in flood impact databases occur. They were corrected in HANZE only to the extent that alternative sources of information allowed. In addition, the data on non-impacts is incomplete and not even across the domain, due to limitations in sources and difficulty of ruling out the possibility of impacts for many events. For more detailed discussion we refer to Paprotny et al. (2024a, 2024b).

The modelled flood catalogue (section 2.1.1), which enabled converting absolute losses into relative losses, also has limitations. Spatial and temporal resolution of the hydrological model, despite being the highest ever applied to model European riverine floods, is still not enough to capture many smaller flash floods. Also, the flood footprint was reconstructed using flood hazard maps made for rivers with a minimum catchment area of 100 km^2. Consequently, only 55 % of flash floods in HANZE were included in the model catalogue, and only 84 % of affected regions within that subset were included in the footprint. For slow-onset riverine floods, the statistics are better, as the model captured 91 % of both events and their footprints. This nonetheless can lead to underestimation of exposure during the event, overestimating relative losses, and underestimate the gap-filled losses (section 3.4). Coastal floods, though modelled using a storm surge model of Paprotny et al. (2016) that is not as precise as some newer studies like Muis et al. (2020), are most complete, with 90% of events reproduced in the model together with 98 % of their region-level footprints. It should be noted that the models performed well throughout the time period in question, with only some degraded performance in the 1950 s. For a more detailed analysis of the accuracy of the modelled data we refer to Paprotny et al. (2024b); Tilloy et al. (2024).

4.2 Uncertainties in the analysis and results

Limitations in the data notwithstanding, there are many choices possible to analyse it statistically. Here, we opted for the vine-copula method, which required converting some of the target variables to continuous by combining it with another variable (section 2.2.2). We tested a different approach to discrete variables (impact or fatality occurrence), such as discrete Bayesian Networks and Random Forests, but they did not lead to better results than the method used herein. We also tested whether adding flood event type in a Random Forest would improve results, but it was indicated as one of the least useful predictors. As for the vine-copulas, we tested the optimal model structures within a given set of variables using the algorithmic approach of Dißmann et al. (2013). A brute force approach (testing all possible vine configurations) would not be computationally feasible when testing concurrently all possible variable combinations, though is an option with a fixed variable list. Applying the brute force approach to the final variable composition would have slightly improved the AIC score of the final models. The validation metrics would improve only slightly for all models, by less than 1 percentage point for flood protection and chance of mortality (section 3.2.1). Virtually no difference for magnitude of fatalities and economic loss was recorded, only for population affected the brute force model would improve both R^2 and KGE by up to 0.02. Due to the small impact on validation and to keep the approach consistent, we utilized the algorithm throughout.

Estimating flood vulnerability from a large set of very diverse flood events spanning over 70 years was shown as feasible in this study, even if results are far from a perfect match with observations (section 3.2.1). Low correlations between potential predictors and relative losses are a persistent problem even in microscale, using building-level data (Merz et al. 2013; Wagenaar et al. 2018; Paprotny et al. 2020). At European scale, validation of modelled absolute losses has rarely been published. Recent studies still show a large difference between modelled and reported economic losses. In Steinhausen et al. (2022) modelled residential riverine flood losses for 1981-2010 were 39 % below total estimated on HANZE in its previous, much less complete iteration of (Paprotny et al. 2018). For the same period, Dottori et al. (2023) estimated total riverine economic losses in the same period as 75 % above those reported by the reinsurer Munich Re, and even more above EM-DAT or the 2018 version of HANZE. Our inference for 1981-2010 for all types of floods is 5 % below reported. In general, lower overall bias in estimating absolute losses was achievable, but at the detriment of reproducing the historical temporal trend. However, both total losses and trends in the past 70 years are heavily influenced by a very small number of high-magnitude events, particularly in case of fatalities (section 3.2.3). Excluding less than 1 % of the top events gives greater alignment in the trends and lower bias, except for bias in fatalities. Graphs of absolute losses excluding 10 largest events are shown in Supplement S5.

Flood protection levels follow a specific definition, not comparable to nominal protection levels used in other studies (section 3.2.2). The most comparable data to our approach is available for the Netherlands, where probability of flooding is evaluated holistically for entire systems of primary flood defences ("dike rings") protecting a large area. The VNK project data (Vergouwe 2015) indicate that dike rings have been mostly below nominal protection levels. Almost a quarter of Dutch population within dike rings lives in those with an actual protection level below 100 years. This includes the North Holland dike ring (population 1 million), which is routinely indicated as having 1 in 10,000 years protection. However, due to degraded reliability of some hydraulic structures in the area, actual protection level was shown to be below 100 years. Similarly low protection levels were found in many areas at risk of riverine floods, though no precise value was given. Our weighted average protection for the Netherlands is 59 (riverine) or 144 years (coastal), though with large variations between regions.

Still, they are consistent with empirical flood occurrences in Europe. This approach has drawbacks, however, for vulnerability estimation. We calculate relative losses as the actual impact divided by potential impact, the latter of which assumes no defences in affected regions. In reality, flood protection will not fail everywhere, even in the scale of a subnational region. Further, we assume a static depth-damage relation for mortality and economic loss, only using total exposure for the population affected. The relative loss magnitudes need to be interpreted in this particular model setting. On the other hand, this is comparable with the approach of previous pan-European studies, where either there is no flooding or whole regions or countries are flooded everywhere (Jongman et al. 2014; Dottori et al. 2023). Our method introduces more spatial variation in protection levels and vulnerability, and reduces bias in estimating impacts of floods. Still, it has to be highlighted that the return period was computed as geometric averages for affected river segments or coastal sections. The actual, impactful flooding could have occurred in locations where the return period was particularly high. Using the return period of the peak would be an alternative, but increase the uncertainty and likely overestimate the protection level, which would be rather lower than the peak. Again, as pan-European flood hazard maps are created for a uniform return period throughout the domain, the hydrological intensity over a broader area should be considered.

The input return periods were computed with a specific method and temporal resolution of the data (section 2.2.2). The protection levels from this study could mismatch water levels computed with a different approach to extreme value analysis. However, the same is true for any published flood protection levels dataset, and ultimately, our results were shown to be consistent with the empirical recurrence interval of floods in European regions for both coastal and riverine floods (section 3.3.1). Further, the maps of flood protection levels and vulnerability (section 3.3) were computed using assumptions for the values of certain variables, representing a more "average" flood event. By contrast, unreported flood losses (section 5) were calculated using information for specific, historical events. The models can be applied in different settings depending on the purpose, and trends shown in this study (Figs. 14 and 16) could be different in such cases.

5 Conclusions

In this study, we constructed the first pan-European maps of flood protection levels and flood vulnerability at subnational level covering a period of 70 years using advanced probabilistic models such as vine-copulas. Informed by reported flood impacts combined with model reconstruction of past floods, our models and data have the potential to redefine how those aspects are parameterized in pan-European flood risk assessments. This work does not aim to be a substitute for local knowledge, such as microscale damage models trained on case studies, or detailed flood protection data, from high-resolution elevation models or dike reliability assessments (such as the VNK study for the Netherlands). Rather, it enables applying a consistent approach to continental-scale studies and fills gaps where more detailed data or methods are not available.

An important application of the study would be impact attribution. Counterfactual flood protection levels and flood vulnerability would enable testing the sensitivity of impacts from different historical floods to changes in flood management and adaptation in Europe. It could enable detecting, for instance, events and regions in the potential flood impact catalogue that would have caused losses without improved protection. Conversely, it could identify floods that would not have happened without an increased return period of flooding induced by climate change or human alterations in the catchment-level water cycle. Economic analysis of adaptation options (structural protection versus reducing vulnerability) could also be improved with our results. Finally, it could help create more realistic baseline projections of future protection levels and vulnerability under changing (and uncertain) socioeconomic conditions.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11069-024-07039-5.

Acknowledgements The authors would like to thank Patricia Mares-Nasarre for technical discussions.

Author Contributions Conceptualization, data collection and funding acquisition: DP. Method development and writing the original draft: DP and OMN. Implementation of the methods: DP and CMPH. Visualization, reviewing and editing: all authors.

Funding This research has been supported by the German Research Foundation (DFG) through project "Decomposition of flood losses by environmental and economic drivers" (FloodDrivers), grant no. 449175973.

Data Availability The input flood catalogue is available on Zenodo (https://doi.org/10.5281/zenodo.10629443). The output flood vulnerability and protection estimates for Europe are also available on Zenodo (https://doi.org/10.5281/zenodo.10911302). The data can also be viewed online on https://naturalhazards.eu/.

Code Availability All code used to generate the results of this study are available on Zenodo (https://doi.org/10.5281/zenodo.10911786). Running the code requires input data also available on Zenodo (https://doi.org/10.5281/zenodo.10911515).

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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