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Trends in geo-hydrological risk to the population of Italy

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Abstract. Geo-hydrological hazards, including floods and landslides, are among the most widespread hazards and a major cause of human loss worldwide. Their impacts are shaped by meteorological forcing and by long-term changes in exposure, vulnerability, and settlement patterns. Yet robust assessments of long-term fatality trends are rare because sufficiently long, accurate, and homogeneous records of damaging events are lacking. A key unresolved question is whether the human toll of geo-hydrological events has changed structurally through time, and which climatic, socio-economic, or policy factors best explain that change. Here we show, using a unique 1950–2024 catalogue of fatal events in Italy, that geo-hydrological risk underwent a marked transition, with fatalities and fatal days declining sharply until about 1970 and then stabilising at much lower levels. This decline was driven mainly by landslides, whereas flood-related losses showed weaker long-term change. The decline was not explained by specific risk policies or management programmes, as most of it preceded their implementation. Instead, precipitation was the main climatic driver of the remaining interannual variability, particularly for floods and days with fatal events. By contrast, population and gross domestic product did not account for the long-term trends once shared temporal changes were considered. Fatal days were less overdispersed and more predictable than fatalities, suggesting that meteorological factors control more directly the occurrence of dangerous conditions than the final death toll. Fatalities, instead, depend strongly on exposure, vulnerability, timing, location, and other event-specific circumstances. Together, these findings indicate that broad socio-economic dynamics can reduce geo-hydrological mortality even as hazardous processes persist, whereas meteo-climatic conditions continue to shape year-to-year risk.

Keywords. geo-hydrological risk, fatalities, time series, trend, Italy

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1 Introduction

Geo-hydrological hazards, including floods and landslides, are among the most widespread and damaging natural hazards worldwide, causing loss of life, damage to property and infrastructure, and environmental disruption. In the first two decades of this century, floods ranked first and landslides fifth among natural disasters by frequency (CRED UNISDR, 2016; CRED UNDRR, 2020). Because precipitation is the primary trigger of both floods and landslides, observed and projected increases in precipitation extremes under climate warming may increase geo-hydrological impacts (Field et al., 2012; Jiménez Cisneros et al., 2014; O'Gorman, 2015; Arnell and Gosling, 2016; Gariano and Guzzetti, 2016; Donat et al., 2016; Dottori et al., 2018; Hu et al., 2018; Haque et al., 2019; Li et al., 2019; Kreibich et al., 2022; Liu et al., 2024; Gariano and Rianna, 2025). At the same time, population growth and expansion into hazardous areas can increase exposure and potential losses (Arnell et al., 2019; Coronese et al., 2019; Haque et al., 2019; Tellman et al., 2021; Kreibich et al., 2022; Intergovernmental Panel on Climate Change, 2023; Ozturk et al., 2022; Rentschler et al., 2023).

Assessing long-term changes in the human impact of geo-hydrological events is difficult because long, accurate, homogeneous, and representative records are rare (Geiger and Stomper, 2020). Fatality catalogues may underrepresent low-impact events, particularly in their earliest sections, and may be affected by changes in reporting practices, data availability, and event classification (Guzzetti, 2000; Haque et al., 2019; Jonkman et al., 2024; Patten and Bhaby, 2025). These limitations can lead to misleading conclusions about whether mortality is increasing, decreasing, or stable. Long national catalogues compiled with consistent criteria therefore provide valuable opportunities to examine how geo-hydrological risk has changed through time.

Italy is a useful case study because it has a long history of damaging geo-hydrological events and a detailed national catalogue of floods and landslide events with human consequences (Salvati et al., 2010, 2018). Using the 1950–2024 portion of this catalogue, we examine whether geo-hydrological risk to the population changed structurally through time, whether floods and landslides followed the same temporal behaviour, and which climatic, socio-economic, or policy-related factors help explain the observed tendencies and changes. We analyse two complementary annual response variables: the number of fatalities, including deaths and missing persons, and the number of days with at least one fatal event. Fatalities measure the severity of the human consequences, whereas fatal days measure the occurrence of conditions that produced fatal outcomes. Comparing the two helps separate the occurrence of dangerous situations from the magnitude of their impacts. We examine the combined geo-hydrological series and its flood and landslide components using exploratory statistics, overdispersion and distributional analyses, trend and change-point tests, and two temporal modelling frameworks: Generalised Additive Models (GAMs; Hastie and Tibshirani, 1986; Wood, 2017, 2025) and Bayesian Dynamic Linear Models (DLMs; West and Harrison, 1997; Petris et al., 2009). We then use time-adjusted GAMs to evaluate the role of precipitation, demographic and economic indicators, and policy timing, and we assess whether fatal days and fatalities differ in their predictability.

The paper is organised as follows. Section 2 provides an appraisal of the literature on flood and landslide fatality series. Section 3 describes the catalogue of fatal geo-hydrological events in Italy used in the study, and Section 4 presents the

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modelling methods used to analyse the time series. The results are reported in Section 5 and discussed in Section 6. Section 7 concludes by summarising the main findings.

2 Temporal trends in geo-hydrological fatalities

Over the last three decades, analyses of flood and landslide fatalities have become central to understanding how geo-hydrological mortality changes through time, how trends differ among regions, and whether observed patterns reflect changes in hazard occurrence, exposure, vulnerability, risk reduction, or data quality. Existing studies differ substantially in scope, data sources, event definitions and geographical coverage.

For floods, much of the literature is global or continental in scope and commonly relies on international disaster databases, including EM-DAT (CRED/UNISDR, 2015; Tanoue et al., 2016; Hamidifar and Nones, 2023; Tin et al., 2024; Jonkman et al., 2024), NatCatSERVICE (Formetta and Feyen, 2019), the Dartmouth Flood Observatory (Hu et al., 2018), and Sendai Framework monitoring (Bubeck et al., 2025), often combined with exposure datasets (Tanoue et al., 2016; Formetta and Feyen, 2019). Regional and national flood-fatality studies have been conducted, for example in the Euro-Mediterranean region using the FFEM-DB catalogue for 1980–2020 (Papagiannaki et al., 2022), in the United States for 1959–2005 (Ashley and Ashley, 2008), in Portugal using the DISASTER database and related hydro-geomorphological mortality records (Zêzere et al., 2014; Pereira et al., 2016, 2017), in Switzerland using national records of flood, debris-flow and landslide fatalities and the Swiss flood and landslide damage database (Hilker et al., 2009; Badoux et al., 2016), in Japan using historical documentary records and disaster statistics (Teramura and Shimatani, 2019), in China using national flood-risk and flood-loss records (Ding et al., 2022), in Australia using the Natural Hazards Research Centre flood-fatality database, compiled from newspapers, historical accounts, and government and scientific reports, for 1788–1996 and 1997–2008 (Coates, 1999; FitzGerald et al., 2010), and in Italy, using the CNR national catalogue of landslides and floods with human consequences, compiled from historical, archival, newspaper, technical, and scientific sources (Guzzetti et al., 2005; Salvati et al., 2010, 2016, 2018). The periods analysed vary broadly, ranging from historical catalogues that extend over several centuries, and in some cases back to BCE (Coates, 1999; Salvati et al., 2010, 2016, 2018), to multi-decadal records covering mainly the second half of the twentieth century and the early twenty-first century (Tanoue et al., 2016; Formetta and Feyen, 2019; Hamidifar and Nones, 2023; Jonkman et al., 2024; Tin et al., 2024; Bubeck et al., 2025; Petrucci et al., 2026).

The landslide literature is more fragmented, but it also includes both global and regional and national analyses. Global studies rely on fatal landslide and multi-source landslide databases, including the Global Fatal Landslide Database (Froude and Petley, 2018) and the Unified Global Landslide Database (Gómez et al., 2023). National and regional studies have been conducted for China (Lin and Wang, 2018; Zhang and Huang, 2018), Bangladesh (Sultana, 2020), British Columbia (Strouth and McDougall, 2021), Japan (Shinohara and Kume, 2022), Portugal (Zêzere et al., 2014), Switzerland (Andres and Badoux, 2019), Nepal (Petley et al., 2007), Colombia and the tropical Andes (Aristizábal and Sánchez, 2020), Turkey (Görüm and

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Fidan, 2021), and Italy (Guzzetti, 2000; Guzzetti et al., 2005; Salvati et al., 2010, 2016, 2018). The temporal coverage of landslide studies is heterogeneous, ranging from long historical catalogues to recent multi-decadal inventories. The Global Fatal Landslide Database covers the period 2004–2016 (Froude and Petley, 2018), and the Unified Global Landslide Database covers 1903–2020 (Gómez et al., 2023). Görüm and Fidan (2021) analysed landslide fatalities in Turkey for 1929–2019, Lin and Wang (2018) used a catalogue for China for 1950–2016, Sultana (2020) analysed a catalogue for Bangladesh for 2000–2018, and Shinohara and Kume (2022) examined landslide fatalities in Japan from 1945 to 2019. The Italian catalogue of landslides and floods with human consequences spans the period 91 BC–2025 (Salvati et al., 2018).

The studies differ in the types of events considered. Flood analyses may include river, flash, urban, coastal or storm-surge floods, depending on the database used and on the scope of the study (CRED/UNISDR, 2015; CRED UNDRR, 2020; Tanoue et al., 2016; Formetta and Feyen, 2019; Hu et al., 2018; Hamidifar and Nones, 2023; Jonkman et al., 2024; Tin et al., 2024; Bubeck et al., 2025). For landslides, the extent to which studies distinguish among landslide types and triggers varies and is not always explicit. Some global catalogues are defined by trigger or origin, such as fatal non-seismic landslides (Froude and Petley, 2018), whereas other global, national or regional studies are described more generally as fatal-landslide or landslide-fatality catalogues (Petley et al., 2007; Zêzere et al., 2014; Lin and Wang, 2018; Zhang and Huang, 2018; Andres and Badoux, 2019; Sultana, 2020; Aristizábal and Sánchez, 2020; Strouth and McDougall, 2021; Shinohara and Kume, 2022; Gómez et al., 2023).

For floods, the overall picture is relatively consistent. Several studies report increasing numbers of recorded flood events and, in some cases, increasing or weakly increasing absolute fatalities (CRED/UNISDR, 2015; CRED UNDRR, 2020; Tanoue et al., 2016; Hu et al., 2018). However, a robust signal is a reduction in flood mortality when impacts are expressed as fatalities per event or as mortality rates relative to the exposed population. The pattern is reported in global and global-to-regional flood analyses. Tanoue et al. (2016) analysed river-flood vulnerability worldwide over 1960–2013; Formetta and Feyen (2019) examined global vulnerability to climate-related hazards, including floods, for 1980–2016; Hamidifar and Nones (2023) analysed flood fatalities globally and by world regions over 1951–2020, with particularly high mortality in Southern, Eastern and South-Eastern Asia; and Jonkman et al. (2024) analysed global flood fatalities from EM-DAT over 1975–2022. These studies show that annual death totals may be stable or without relevant trends, whereas fatalities per event and exposure-normalised mortality decline markedly. At regional and national scales annual death totals are often stable, weakly increasing, or dominated by event-to-event variability, whereas fatalities per event or mortality rates tend to decrease (Hu et al., 2018; Hamidifar and Nones, 2023; Jonkman et al., 2024). In a remarkably long Australian study, Coates (1999) showed that flood death rates declined systematically between 1788 and 1996, despite high annual variability. The decline is commonly interpreted as evidence of reduced vulnerability, associated with improved protection, forecasting, early warning, preparedness and emergency response, despite increasing exposure. Regional differences remain important: flood mortality is concentrated in low-lying, flat and coastal areas; tropical cyclones contribute disproportionately to deaths (Hu et al., 2018); and mortality rates remain stable or increase in low-income countries (Jonkman et al., 2024).

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For landslides, the evidence is less uniform, but several recurrent patterns emerge. At the global scale, Froude and Petley (2018) found no clear linear increase in fatal landslides or fatalities over 2004–2016, with an increase until about 2010 followed by stabilisation or decline. Gómez et al. (2023), using the Unified Global Landslide Database, reported increasing events and fatalities from the mid-twentieth century to around 2010, followed by a marked decline, while recognising that both changes in disaster-risk management and changes in reporting may contribute to the pattern. In China, inventories show increasing fatal landslide occurrence and fatalities, although recent increases are partly attributed to improved data collection and the inclusion of smaller events (Lin and Wang, 2018; Zhang and Huang, 2018). Bangladesh and Nepal also show increasing fatal landslide impacts, with strong monsoon control (Petley et al., 2007; Sultana, 2020). In Colombia and the tropical Andes, long-term records indicate increasing reports and fatalities, but mortality is strongly distorted by a few catastrophic events. By contrast, British Columbia and Japan show clear long-term decreases in landslide mortality, including reductions in population-normalised rates (Strouth and McDougall, 2021; Shinohara and Kume, 2022), while studies for Portugal and Switzerland do not identify significant increasing trends (Zêzere et al., 2014; Andres and Badoux, 2019). Across these regions, rainfall is the dominant trigger for fatal landslides, although earthquakes, volcanic activity and human disturbance can dominate mortality in specific catastrophic events.

A comparison of flood and landslide studies shows that flood-fatality analyses have advanced further in separating event frequency, absolute mortality, exposure and vulnerability. Several flood studies distinguish between total deaths, fatalities per event, exposed population and exposure-normalised mortality, showing that absolute flood deaths may remain stable or vary irregularly while lethality and mortality rates decline (Tanoue et al., 2016; Hu et al., 2018; Formetta and Feyen, 2019; Hamidifar and Nones, 2023; Jonkman et al., 2024). Landslide studies provide more heterogeneous evidence, with fewer comparable normalised metrics and stronger dependence on national or regional inventories. This may partly reflect process differences: floods commonly affect areal or linear domains, and they may cross regional and national boundaries, whereas landslides are usually more localised features. It may also reflect differences in reporting sources, event definitions and catalogue completeness. For both geo-hydrological hazards, temporal trends are complicated by changing reporting practices, incomplete historical records, direct versus indirect deaths, and increasing digital and local information sources (Guzzetti, 2000; Tanoue et al., 2016; Tin et al., 2024; Lin and Wang, 2018; Froude and Petley, 2018; Gómez et al., 2023). Consequently, fatality trends may reflect not only hazard changes, but also exposure, vulnerability, preparedness, mitigation, emergency management and completeness of the catalogues.

Flood and landslide fatality studies have used heterogeneous statistical approaches. For floods, Coates (1999), FitzGerald et al. (2010), Hamidifar and Nones (2023), and Tin et al. (2024) relied mainly on descriptive counts, period comparisons, moving averages, mortality rates, fatalities per event, and regional or demographic summaries. Formal statistical analyses included Mann–Kendall tests, Sen's slope, estimated annual percentage change, chi-square tests, ANOVA, non-parametric regression, and multivariable logistic regression (Jongman et al., 2015; Hu et al., 2018; Jonkman et al., 2024; Liu et al., 2024). Other studies combined fatalities with hydrological or hydraulic models, gridded population and GDP data, exposure estimates, bootstrapping, and sensitivity analyses to derive mortality or vulnerability rates (Jongman et al., 2015; Tanoue et

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al., 2016; Formetta and Feyen, 2019). Other analyses incorporated flood-type classification, mortality fractions, exceedance or threshold analyses, and spatial comparisons involving topography, coastal proximity, income, population density, and tropical cyclones (Hu et al., 2018; Jonkman et al., 2024; Liu et al., 2024). Papagiannaki et al. (2022) focused on database design, coding, duplicate detection, missing-data analysis, and spatial harmonisation.

For landslides, Petley et al. (2007), Petley (2012), Pereira et al. (2017), Zhang and Huang (2018), Sultana (2020), Aristizábal and Sánchez (2020), Strouth and McDougall (2021), and Gómez et al. (2023) relied on descriptive counts, running means, period comparisons, seasonality, and frequency–fatality or frequency–magnitude representations. Badoux et al. (2016), Lin and Wang (2018), Haque et al. (2019), and Shinohara and Kume (2022) used formal statistical tests and analyses, including Mann–Kendall tests, Sen or Theil–Sen slopes, regression, correlation analysis, and non-parametric tests. Additional analyses included 5-day aggregated time series, autocorrelation, rainfall correlations, space–time hotspot analysis, kernel density estimation, Geographical Detector methods, and non-parametric regression with bootstrap confidence bands (Froude and Petley, 2018; Haque et al., 2019; Görüm and Fidan, 2021; Remondo et al., 2026). Across both flood and landslide fatality studies, formal modelling of annual fatality counts remains uncommon, and count models, change-point methods, GAMs, and dynamic time-series models are rarely used.

Overall, our literature analysis shows a gradual shift from descriptive summaries towards formal trend testing, exposure-normalised indicators, and integrated spatial or hazard–exposure–vulnerability analyses, although explicit modelling of annual fatality counts remains uncommon.

Catalogue completeness is recognised as a central limitation in flood and landslide fatality series. For floods, Coates (1999) and FitzGerald et al. (2010) identified incompleteness arising from newspaper and public-report bias, uneven spatial and temporal coverage, remote-area under-reporting, missing demographic or circumstantial information, and the exclusion of indirect or delayed deaths. Global studies based on EM-DAT or NatCatSERVICE emphasised reporting thresholds, changes in data availability and reporting through time, under-representation of low-income countries and earlier decades, inconsistent event classification, country-level aggregation, and incomplete attribution of flood type, location, exposure, or indirect mortality (Tanoue et al., 2016; Hu et al., 2018; Formetta and Feyen, 2019; Hamidifar and Nones, 2023; Tin et al., 2024; Jonkman et al., 2024; Liu et al., 2024). Jongman et al. (2015) also noted under-reporting and uncertainty in impact, exposure, and modelled hazard data. These limitations were partly addressed through temporal restrictions, event reclassification, exclusions, and comparisons among sources. Papagiannaki et al. (2022) provided the most systematic assessment, quantifying missing data, identifying duplicates, and comparing the Flood Fatalities in the Euro-Mediterranean Database (FFEM-DB) with other sources.

For landslides, Petley et al. (2007), Petley (2012), Badoux et al. (2016), Pereira et al. (2017), Froude and Petley (2018), Haque et al. (2019), and Sultana (2020) discussed incompleteness qualitatively or semi-quantitatively, emphasising under-reporting of small or older events, remote locations, delayed deaths, uncertain trigger attribution, language bias, and inconsistent media or institutional coverage. Petley (2012), Pereira et al. (2017), Aristizábal and Sánchez (2020), and Gómez et al. (2023) compared national or global catalogues with broader disaster databases such as EM-DAT, showing that general

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disaster databases often miss low-fatality landslides. Lin and Wang (2018), Shinohara and Kume (2022), and Remondo et al. (2026) addressed completeness indirectly by separating events by event fatality magnitude, comparing overlapping sources, or using fatalities as a proxy for event magnitude to reduce temporal reporting bias. Badoux et al. (2016), Haque et al. (2019), Görüm and Fidan (2021), and Gómez et al. (2023) provided data-quality indicators, including verification rates, coordinate completeness, source overlap or consistency, and estimated under-reporting ranges.

Overall, our literature analysis shows that completeness assessment has progressed from qualitative acknowledgement of missing events towards source comparison, standardised coding, and quantitative data-quality indicators, but formal statistical completeness tests are rare.

3 Data

For our analysis, we use an updated version of the Italian catalogue of geo-hydrological events with human consequences, spanning 91 BC–2025 (Salvati et al., 2018). The complete catalogue lists 8,371 fatal or harmful events that caused 51,298 fatalities, including 3,487 flood events with 36,274 fatalities and 4,884 landslide events with 15,024 fatalities. Floods include river and pluvial floods, whereas debris flows are classified as landslides, that also include shallow and deep-seated failures, earth flows, mud flows, and rock falls. Detailed descriptions and the methods and problems encountered in compiling the catalogue can be found in Guzzetti et al. (2005) and in Salvati et al. (2010, 2016, 2018).

We restrict our investigation to 1950–2024 (**Fig. 1**), a period for which the catalogue is sufficiently homogeneous for quantitative analysis. During these 75 years, the national catalogue records 1,349 fatal geo-hydrological events causing 5,458 fatalities (**Table 1**). By comparison, EM-DAT, the international disaster database curated by the Centre for Research on the Epidemiology of Disasters of the University of Louvain, Belgium, lists only 57 flood and landslide disasters in Italy over the same period, causing 3,594 fatalities. The Italian catalogue therefore captures many small and medium fatal events that are not represented in global disaster-level databases. The two most catastrophic events in the Italian catalogue are the Vajont landslide of 9 October 1963, with 1,917 fatalities, and the Stava mudflow of 19 July 1985, with 268 fatalities. Both were associated with major engineering works – a dam and two tailings dams, respectively – and are not representative of ordinary rainfall-triggered geo-hydrological mortality. We therefore exclude the two events associated to major engineering works from all statistical analyses. After these exclusions, the analysed series contains 3,273 fatalities on 868 fatal days.

We use economic, demographic, and climatic data available from different sources for 1951–2024 as potential driving factors i.e., predictors (**Fig. 2**). We obtain annual gross domestic product (GDP) and population (POP) data from the Osservatorio sui Conti Pubblici Italiani (2025), and national mortality data (MOR) from the Italian National Institute of Statistics. We further obtain climate data, including total annual precipitation (TP) and mean annual temperature (TD), from the nationwide hydrological water-budget dataset BIGBANG 9.0 (Braca et al., 2025). Over 1951–2024, GDP increased 7.8-fold, from €5.25 billion to €1.93 trillion, with broadly steady growth until 2008, followed by decline and partial recovery during 2009–2024. Over the same period, POP increased by 26%, from 46.91 million to 58.97 million, rising steadily until

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1980, more slowly until 2018, and then declining slightly; since 1975, it has remained above the long-term mean. MOR was broadly stable between 9.1 and 10.8 × 10^5 individuals until 2019, after which it increased up to 12.5 × 10^5 in 2020, reflecting the impact of the COVID-19 pandemic. Unlike the socio-economic variables, TP showed no clear long-term trend, whereas TD increased almost continuously from 1978 onward (**Fig. 2**).

4 Statistical methods

4.1 Exploratory statistics, trends, and change points

Annual fatalities and fatal days are count variables and may be overdispersed, i.e. the variance of the counts may exceed the mean (Cameron and Trivedi, 1990), especially when occasional high-fatality events occur. To check this, and to provide a simple comparison of changes over time, we first summarise fatalities, fatal days, mortality, and lethality for the entire period 1950–2024, and for three 25-year subperiods: 1950–1974, 1975–1999, and 2000–2024 (**Table 1**). We then assess monotonic trends in the series using Mann–Kendall tests (Mann, 1945). For each series, we calculate the Mann–Kendall statistic, its p-value, and Kendall's τ, adopting α = 0.05 as the significance level. Before testing for trend, we evaluate temporal dependence using the lag-1 autocorrelation coefficient (ACF1) (Box and Jenkins, 1970) and the Ljung–Box test (Ljung and Box, 1978). When autocorrelation is not statistically significant, we apply the standard Mann–Kendall test. When autocorrelation is detected, we use a modified Mann–Kendall test that adjusts the variance of the statistic to account for the effective sample size (Hamed and Rao, 1998; Yue and Wang, 2004). We quantify the trend magnitude with the Sen slope estimator (Sen, 1968) and its confidence interval using standard non-parametric procedures. To assess temporal changes in trend behaviour, we analyse the full series (1950–2024) and the three 25-year sub-periods (1950–1974, 1975–1999, 2000–2024). We further investigate abrupt changes using Pettitt's (1979) test, and we use the Hurst (1951) exponent as an exploratory measure of persistence in the annual series (**Table 2**).

4.2 Distribution analysis

We model the empirical distributions of annual fatalities and fatal days using both a Poisson distribution, as a reference model, and a Negative Binomial (NB) distribution, which includes an additional dispersion parameter and allows the variance to exceed the mean. We compare the fitted distributions using the Akaike and Bayesian information criteria (AIC and BIC) and assess their agreement with the empirical distributions, including the upper tail, through Complementary Cumulative Distribution Functions (CCDFs) (**Fig. 3**). We further inspect the frequency of zero-count years to assess whether zero-inflated formulations are necessary.

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4.3 Time series analysis

To represent the historical evolution of fatalities and fatal-event days, we model the annual counts, Y_t as a function of time, t using Generalised Additive Models (GAMs, Hastie and Tibshirani, 1986; Wood, 2017, 2025). GAMs provide a flexible way to describe the expected annual counts as smooth functions of time, thereby capturing the main long-term structure of the series. Since the count series are overdispersed, we assume a Negative Binomial (NB) distribution, $Y_t \sim \mathcal{NB}(\mu_t, \theta)$, with constant overdispersion parameter θ, and we model the expected value as $\log(\mu_t) = \beta_0 + s(t)$ where $s(t)$ is a smoothing spline for time, with a spline basis dimension constrained to avoid overfitting. We calibrate the models to the 1950–2020 portion of each series, from which we derive the fitted mean trend and the corresponding 95% confidence intervals (CI) for the expected counts i.e., the mean (**Fig. 4**). We also compute prediction intervals (PI) for annual counts, which incorporate the estimated overdispersion parameter (θ) and therefore account for interannual variability. For the evaluation and projection period (2025–2030), we extrapolate the fitted models to obtain out-of-sample predictions of expected values and annual counts, with uncertainty quantified by CI for the mean and PI for individual future observations. Model predictions are evaluated in 2021–2024 and projected to 2030 **(Fig. 4)**.

To complement the overarching long-term trend captured by the GAMs, we implement Bayesian Dynamic Linear Models (DLMs, West and Harrison, 1997; Petris et al., 2009). DLMs provide a state-space alternative in which the log-mean count evolves through a time-varying latent state, allowing the model to adapt to local year-to-year changes in the series of the annual counts, Y_t. Consistent with the GAM formulation, we assume that the annual counts, Y_t follow a Negative Binomial distribution, $Y_t \sim \mathcal{NB}(\mu_t, \theta)$. In this formulation, the log-mean is governed by a time-varying latent state α_t: $\log(\mu_t) = \alpha_t$. To capture the unobserved temporal dynamics, we model the latent state as a first-order random walk, $\alpha_t \sim \mathcal{N}(\alpha_{t-1}, \sigma_\alpha^2)$, where σ_α is the evolution standard deviation, controlling the degree of stochastic variation permitted between consecutive years and estimated via MCMC. We calibrate the model on the 1950–2020 portion of the series to estimate the posterior distributions of the latent states and the variance components. For the projection period 2025–2030, we project the random walk forward in time. We then use the posterior predictive simulations to obtain Bayesian credible intervals (CrI) for the expected means, μ_{T+h} and for the simulated future counts (**Fig. 4**). We use DLMs only for temporal analyses, because their state-space formulation is specifically suited to sequential data and to the representation of unobserved temporal dynamics through time-varying parameters.

4.4 Predictors

To assess the association of annual counts, Y_t with the available economic, demographic, and climatic predictors (**Fig. 2**), we use GAMs.

For each response–predictor pair, we first fit an univariable model $Y_t \sim s(X_t)$. To adjust for temporal trends, we employ a comparative framework comprising three models: a time-only model, a single-predictor model, and a model including both time and the predictor. Specifically, we compare M_A: $\log(\mu_t) = \beta_0 + s(t)$, M_B: $\log(\mu_t) = \beta_0 + s(X_t)$, and M_C: $\log(\mu_t) =$

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$\beta_0 + s(t) + s(X_t)$. A predictor is retained when the smooth term $s(X_t)$ in M_C meets these criteria: $p < 0.05$, and, relative to M_A, $\Delta D_{expl} \geq 0.02$ (change in deviance explained), and $\Delta AIC \leq -2$. We then fit multivariable negative binomial GAMs including combinations of year, TP, TD, log(GDP), log(POP), and MOR. The comparison between the models distinguishes raw associations from associations that remain after shared temporal trends are accounted for.

To examine whether fatalities and fatal days were temporally associated with risk-management policies and programmes (**Fig. 1G**), we define binary indicators around selected policy dates. Specifically, we consider indicators for the policy year, for years within 0–k after policy implementation, and for years within $\pm k$ of policy implementation, with k = 2, 4, 6, and 10 years. These windows allow us to test both post-implementation associations and associations centred on implementation. We then fit NB GAMs with a log link. The baseline model was $M_0\colon \log(\mu_t) = \beta_0 + s(t)$, where $\mu_t = E(Y_t)$ and $s(t)$ is a penalized regression spline representing the smooth effect of calendar year. The augmented model is $M_1\colon \log(\mu_t) = \beta_0 + s(t) + \beta_1 P_t$, where P_t is the binary policy indicator. Model improvement relative to the long-term trend is evaluated using β_1, its p-value, ΔAIC, and the change in deviance explained, ΔD. We further assess significance using 1,000 permutations of the policy years.

4.5 Predictability

To compare the temporal structure of fatalities and fatal days, and to assess whether either series can be anticipated more reliably, we evaluate predictability using two complementary approaches. The first is based on information theory (Shannon, 1948; Song et al., 2010) and assesses intrinsic predictability by quantifying how much information past states provide about future states. The annual series are discretised into empirical-quantile states, and conditional entropy is used to measure how much the uncertainty of the next state is reduced by the knowledge of one or two previous states. This provides measures of stored information and maximum achievable predictability. The approach is suitable for short, skewed and overdispersed count series because it evaluates temporal memory without assuming a specific regression model. The second approach evaluates operational predictability (Tashman, 2000; Gneiting and Raftery, 2007) through rolling one-step-ahead forecasts and examines whether a statistical model can exploit the temporal information in the series to make probabilistic predictions. We fit GAMs using expanding training windows, so that only data available before year *t* are used to predict year *t*. This design mimics an operational forecasting setting and accommodates overdispersed annual counts and non-linear temporal change. Forecast skill is quantified using the mean negative log predictive probability, referred to here as average predictive surprise. Lower values indicate that the model assigned a higher probability to the observed counts and therefore achieved better forecast performance. Together, the two approaches distinguish intrinsic, or potential, predictability from the forecasting skill achieved by a specific statistical model.

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5 Results

5.1 Exploratory statistics, trends, and change points

Over the 75-year period 1950–2024, after excluding the catastrophic Vajont and Stava events associated with major engineering works, geo-hydrological events caused 3,273 fatalities on 868 fatal days, 3.1% of the total number of days in the period, or one fatal day every 32 days. Landslides caused 1,927 fatalities on 547 fatal days (2.1%, one fatal day every 48 days), and floods caused 1,346 fatalities on 381 fatal days (1.4%, one fatal day every 72 days) (**Table 1**). Landslides therefore dominate the human toll in the catalogue, although floods remain an important component of fatal geo-hydrological risk. The temporal structure of the series is strongly non-stationary. Geo-hydrological fatalities and fatal days are much higher during 1950–1974 than during 1975–1999 and 2000–2024, indicating a marked reduction in risk after the early decades of the record (**Table 2**). All annual count series are overdispersed, but the magnitude of overdispersion differs between fatalities and fatal days. Fatality counts are highly variable because a few years contain multi-casualty events (**Table 1**). Fatal days are much less overdispersed, because a high-fatality event generally contributes only one fatal day.

Trend analyses show significant decreases for the combined geo-hydrological series and for landslides alone, whereas flood-related series display weaker or non-significant trends. Mann–Kendall tests identify significant decreasing trends for geo-hydrological fatalities and fatal days over the full period, with Sen's (1968) slopes of about -3.2 fatalities per decade and -1.2 fatal days per decade. Inspection of **Table 2** indicates weak to moderate temporal dependence, with limited short-term autocorrelation and some longer-term persistence. Hurst exponents for the full 1950–2024 series range from 0.569 to 0.723, indicating persistent behaviour in all six series, with the strongest persistence for geo-hydrological and landslide alone fatal days.

The decline is concentrated mainly in the earlier part of the record, with little systematic change thereafter. After 1975, most Hurst exponents are closer to random behaviour, although some persistence remains in the flood-related series. Pettitt's (1979) tests locate significant change points in 1970 for geo-hydrological fatalities and in 1966 for geo-hydrological fatal days, and the significant change points for the landslide series also cluster between 1966 and 1970. By contrast, the change points identified for the flood series are not statistically significant, indicating weaker evidence for a discrete shift in flood fatalities or flood fatal days. These results indicate a transition from an initial higher risk regime to a lower and more stable regime. After this transition, the series are broadly stable, with no comparable long-term decline. Overall, the evidence supports a non-stationary system characterised by an early structural shift followed by relative stability, with stronger and more coherent signals for geo-hydrological events and landslides than for floods.

5.2 Distribution analysis

The distributional analysis provides an order-free summary of the annual counts. It deliberately ignores the temporal sequence of the observations and assumes, for this purpose only, that the counts are drawn from a single stationary distribution, to describe the dispersion and tail behaviour of the series. Under this simplifying assumption, a NB distribution

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provides a better representation than a Poisson distribution for all fatality and fatal-day series, for geo-hydrological events, floods and landslides. This result is consistent with the overdispersion reported in **Table 2**. The improvement is strongest for fatality counts, for which the Poisson distribution greatly underestimates the observed variability. Fatal days are less dispersed but still depart from the Poisson assumption and are better represented by the NB distribution. Zero-count years are absent for the combined geo-hydrological and landslide series and are very limited in the flood series. The CCDFs (**Fig. 3**) further show that fatalities have heavier upper tails than fatal days. Most years have relatively few deaths, but a small number of years account for very large mortality, especially in the geo-hydrological and landslide series. This pattern reflects why annual fatalities are harder to model and project than fatal days: fatalities depend not only on the occurrence of hazardous conditions, but also on event-specific exposure, vulnerability, timing, location and response. Fatal days have a steeper tail decay and a narrower range of values, quantifying the greater regularity and more limited variability of the occurrence of fatal conditions compared with the severity of their consequences.

5.3 Temporal modelling and short-term projections

Inspection of **Fig. 4** shows that GAMs and DLMs reproduce the same broad evolution identified in the exploratory analyses. For geo-hydrological fatalities and fatal days, both approaches confirm the marked decline from 1950 to about 1970, followed by lower values. The landslide series show a similar pattern, whereas the flood series exhibit weaker temporal structure. GAMs emphasise the long-term smooth transition, whereas DLMs follow short-term fluctuations more closely because the latent state is allowed to evolve from year to year. Model evaluation over 2021–2024 indicates that yearly observations fall within the predictive intervals and that median predictions are generally close to observed values. For 2025–2030, the two approaches agree that annual counts are likely to remain within the comparatively low range observed in recent decades, but they do not always agree on their short-term direction. In particular, the GAM projections for fatalities are broadly stable or weakly decreasing, whereas the corresponding DLM projections increase in response to recent fluctuations. The direction of the projected change in fatalities is model-dependent and should not be interpreted as a robust trend. Projections for fatal days are more consistent between the two approaches. The independent observations for 2025 (red squares in **Fig. 4**, Bianchi and Salvati, 2026), which were not used for model fitting, lie close to the central estimates and within the uncertainty intervals.

Projection uncertainty remains substantial, especially for fatalities (**Fig. 5**). GAM prediction intervals are consistently wider than the corresponding confidence intervals because they include both uncertainty in the estimated mean response and residual year-to-year variability. The widths of the DLM credible intervals are of a similar order of magnitude, but their relationship to the GAM intervals varies among series and projection years. Direct comparisons should be made cautiously because the intervals arise from different model structures and represent uncertainty differently. Overall, uncertainty in realised annual counts remains large, particularly for fatalities, which have more dispersed distributions and longer upper tails than fatal days. The projections should therefore be interpreted as probabilistic envelopes of plausible short-term outcomes, not as deterministic annual forecasts.

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5.4 Climatic, economic, demographic, and policy predictors

Univariable GAMs linking the geo-hydrological, flood and landslide series to individual predictors show that no single predictor explains a large fraction of the variability in fatalities or fatal days. Mean annual temperature (TD) shows no clear association, and the relationships with the economic and demographic variables — GDP, POP and MOR— are largely removed once temporal trends are accounted for. By contrast, total annual precipitation shows a persistent, albeit modest, signal, with the clearest effects for floods, weaker effects for landslides, and intermediate effects for geo-hydrological events. The relationships are stronger for fatal days than for fatalities. Multivariable GAMs confirm the persistent role of precipitation forcing, particularly for flood fatalities and flood fatal days, and provide little or no evidence for independent economic-demographic effects once shared temporal trends are accounted for. In the multiple models, fatalities remain harder to represent than fatal days, consistent with the interpretation that meteo-climatic conditions help determine when dangerous events occur, but do not fully explain the magnitude of the human consequences.

The policy-timing analysis provides little evidence that the main decline is aligned with specific environmental or risk-management policies. Inspection of **Fig. 1G** shows that most of the reduction in fatalities and fatal days occurred before the introduction of modern civil-protection, land-management, flood-risk, and hydrogeological-risk programmes. This is confirmed by the GAM analyses for time windows of $k = 2$, 4, 6, and 10 years. Across 378 policy-window models, 348 cases (92%) show no clear evidence of alignment, whereas 30 cases (8%) show local associations, including 13 with lower counts and 17 with higher counts near policy dates. Only 35 models (9%) have $\Delta\mathrm{AIC} \geq 2$, 14 (4%) have $\Delta\mathrm{AIC} \geq 4$, and 5 (1%) have $\Delta\mathrm{AIC} \geq 6$. The largest improvements are local, with maximum ΔAIC values of about 8 and increases in deviance explained of less than 0.10. Overall, the policy indicators produce occasional model improvements, but do not reproduce the timing of the structural decline as consistently as the long-term temporal component.

5.5 Predictability of fatalities and fatal days

The predictability analyses show clearer operational forecast performance for fatal days than for fatalities, suggesting that fatal days are generally more predictable. State-based metrics indicate only weak intrinsic predictability, with small differences between fatal days and fatalities and bootstrap confidence intervals that commonly include zero. The clearest contrast is obtained from the rolling forecast analysis, where fatal days consistently have lower predictive surprise than fatality counts. Mean predictive surprise is about 1.5–2.0 bits lower for fatal days than for fatalities across the geo-hydrological, landslide, and flood series, with bootstrap confidence intervals above zero for the difference between fatality surprise and fatal-day surprise. Year-by-year differences are mostly positive, confirming that fatalities more often produce larger forecast errors than fatal days.

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6 Discussion

Collectively, our analyses show a clear structural transition in geo-hydrological risk to the population of Italy during 1950–2024. Annual fatalities and fatal days declined markedly from the 1950s to about 1970 and then stabilised at substantially lower levels (**Fig. 1**). This pattern is supported by descriptive statistics (**Table 1**), non-parametric trend and change-point tests (**Table 2**), and two independent modelling frameworks, GAMs and DLMs (**Fig. 4**). The decline is driven mainly by landslides, whereas flood fatalities and flood fatal days show weaker and statistically less robust long-term changes. Because fatal days declined less sharply than fatalities, the transition cannot be interpreted simply as the disappearance of hazardous conditions. Rather, fatal geo-hydrological events became less likely to produce large numbers of deaths and missing persons, suggesting a change in the relation between hazardous processes and human consequences.

The Italian record (**Fig. 1**) shows that geo-hydrological mortality can decline markedly even while floods and landslides persist. The finding is consistent with broader evidence that vulnerability and event lethality can decrease, particularly in high-income or better-prepared settings. For floods, exposure-normalised mortality or fatalities per event have declined in several global analyses, even where total flood occurrence or exposure increased (Tanoue et al., 2016; Hu et al., 2018; Formetta and Feyen, 2019; Hamidifar and Nones, 2023; Jonkman et al., 2024). Similar patterns have been reported for landslides in British Columbia and Japan, where landslide fatalities declined markedly despite population growth or continuing rainfall-triggered landslide occurrence (Strouth and McDougall, 2021; Shinohara and Kume, 2022). These findings caution against attributing fatality trends solely to changes in hazard intensity. For risk management, the results emphasise the importance of maintaining vulnerability reduction, improving preparedness, and recognising that meteorological variability continues to shape year-to-year risk.

The predictor analysis helps explain the structural decline in geo-hydrological risk to the population in Italy. Once the temporal trend is accounted for, most apparent associations weaken sharply, indicating that economic and demographic variables such as GDP, population, and mortality do not exert a systematic independent effect on residual year-to-year variability. Their contribution appears instead to be expressed mainly through the broader historical transition in exposure, vulnerability, preparedness, and risk management. By contrast, mean annual precipitation remains the most consistent driver of residual interannual variability. Its effect is strongest for floods, especially for days with flood fatalities, where the connection between rainfall and dangerous conditions is most direct; weaker and less stable for landslides, whose occurrence also depends on local geomorphological, hydrological, and exposure conditions; and intermediate for the combined geo-hydrological series. This difference indicates that the combined geo-hydrological signal should not be interpreted as a uniform response of all hazardous processes. The stronger association between precipitation and fatal days than between precipitation and fatalities suggests that meteo-climatic forcing mainly controls when potentially dangerous conditions occur. By contrast, the event death toll depends on the intersection between the event and people, infrastructure, behaviour, warnings, emergency response, and other event-specific circumstances. This may also explain why fatal days show lower uncertainty and higher predictability than fatalities.

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The timing of the main decline of geo-hydrological risk is also informative. The main reduction in fatalities and fatal days preceded the establishment of modern policies and programmes for environmental management, civil protection, and natural-risk reduction (**Fig. 1G**). The policy-timing analysis indicates that the decline in geo-hydrological risk to the population cannot be explained simply by specific legislation, technical measures, mitigation programmes, or research programmes. A more plausible explanation is the broader socio-economic transformation of Italy after the Second World War, driven by urbanisation, economic growth, improved housing, better infrastructure and communication systems, changes in occupational structure, and reduced dependence on highly vulnerable rural settings. In this view, socio-economic development acted primarily as a risk mitigation measure by reducing exposure and vulnerability over the long term, whereas precipitation, through meteo-climatic forcing, remained the dominant driver of residual interannual variability. In this respect, Italy fits a broader pattern of high-income countries in which socio-economic development does not eliminate geo-hydrological hazards but progressively reduces their direct human consequences. This interpretation is consistent with the literature showing that, in economically advanced countries, geo-hydrological fatalities have declined even where hazardous processes remain active (Jongman et al., 2015; Formetta and Feyen, 2019; Jonkman et al., 2024).

The distributional and predictability analyses reinforce this distinction between hazardous conditions and human consequences. Data show that fatalities have heavier upper tails than fatal days, because fatality counts combine the occurrence of hazardous conditions with the contingent number of people exposed and killed. Fatal days are less affected by event severity and therefore provide a more stable measure of dangerous conditions through time. Consistently, the predictability analyses indicate that fatal days have lower forecast surprise than fatalities. This suggests that days with fatal events retain more stable temporal structure, whereas the number of people killed on those days depends more strongly on where and when events occur, who is exposed, how vulnerable they are, and how warnings and emergency response unfold.

Our GAMs and DLMs were designed to characterise recent dynamics, support short-term projections, and provide quantitative evidence for risk-management planning, not to produce long-term environmental and climate-change scenarios. Any environmental and climate-related signal present during 1950–2024 is captured implicitly by the time-varying model components and by the precipitation covariate. The short-term projections are consistent with persistence of the recent lower-risk regime through 2030, with no indication of a return to the much higher fatality levels of the 1950s and 1960s. Extrapolating decades ahead under changing climatic, environmental, and socio-economic conditions would require different modelling assumptions and scenario-based inputs. Inspection of **Fig. 5** shows that projection uncertainty remains substantial, especially for fatalities, and rare catastrophic events may still occur even when expected annual risk is low. The projections should therefore be interpreted as conditional extrapolations of the recent lower-risk regime, not as precise annual risk forecasts. They reflect the continuation of the temporal dynamics estimated from the historical data, in the absence of strong predictor effects indicating a different near-term trajectory. In addition, the main model estimates exclude the two catastrophic engineering-related events, namely the Vajont landslide and the Stava mudflow disasters. They should therefore be interpreted as estimates of ordinary geo-hydrological mortality, not as upper bounds on all possible fatal events.

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7 Conclusions

Using an updated version of the long national catalogue of fatal geo-hydrological events in Italy (Salvati et al., 2018), we show that mortality from geo-hydrological events, including floods and landslides, changed markedly during the 75-year period 1950–2024. Fatalities and fatal days both declined strongly from the 1950s to about 1970 and then remained at substantially lower levels, although with year-to-year variability. The transition was driven mainly by landslides, whereas flood fatalities and flood fatal days showed weaker, not statistically significant long-term change. Over the full period, geo-hydrological events caused 3,273 fatalities on 868 fatal days, corresponding to 3.1% of all days between 1950 and 2024. Fatalities and fatal days convey complementary information. Fatal days measure the occurrence of conditions that produce fatal consequences, whereas fatalities measure the severity of the consequences. Fatal days are less overdispersed, have less heavy tails, are more stable, more predictable, and more clearly associated with precipitation, especially for floods. Fatalities have heavier upper tails, are more variable and less predictable because they also depend on where and when events occur, who is exposed, how vulnerable people are, and how warnings, behaviour, infrastructure, and emergency response interact during individual events.

Mean annual precipitation was the most coherent driver of residual interannual variability, particularly for flood fatal days. By contrast, the apparent effects of gross domestic product, population, and national mortality weaken once shared temporal trends are accounted for. The main decline in risk preceded most modern environmental, civil-protection, flood-risk, and risk mitigation policies and programmes, and the policy-timing analysis provided little evidence that specific policy and programme dates explain the structural transition. We interpret the historical reduction in geo-hydrological mortality primarily as evidence of broad vulnerability reduction associated with post-war socio-economic transformation. Generalised Additive Models and Bayesian Dynamic Linear Models reproduce the transition and support short-term persistence of the recent lower-risk regime through 2030. However, uncertainty remains substantial, especially for fatalities. Lower recent mortality should therefore not be confused with the disappearance of geo-hydrological hazard, nor with an upper bound on future catastrophic events.

Code and data availability

Economic and demographic series (GDP, POP, MOR) are available from https://osservatoriocpi.unicatt.it/ocpi-servizi-serie-storiche and general national mortality (MOR) from the Istituto Nazionale di Statistica (ISTAT, https://seriestoriche.istat.it/ (1861-2014), https://demo.istat.it/app/?i=ISM (2011-2024). Climate series (TP, TD) are available from https://www.isprambiente.gov.it/pre_meteo/idro/BIGBANG_ISPRA.html. For statistical analyses and modelling we used R programming language (version 4.5.2; R Core Team, 2021), RStudio (version 2026.01.1+403; Posit team, 2025) and Stan (version 2.32.5; Stan Development Team, 2023), implemented in R via RStan (version 2.32). The following R packages were used: AER (1.2.16), Kendall (2.2.2), MASS (7.3.65), mgcv (1.9.4), modifiedmk (1.6), pdp (0.8.3), ppcor (1.1), pracma (2.4.6), trend (1.1.6) and zyp (0.11.1).

Author contributions

ACM, FG and PS conceived the research. PS provided the datasets. FG and PS reviewed the literature. ACM and FG conducted the statistical analyses. AB and AP reviewed the statistical analyses. ACM and FG wrote the text. AB and AP reviewed the text. FG prepared the figures.

Competing interests

The authors declare no competing interests.

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References

Andres, N., Badoux, A.: The Swiss flood and landslide damage database: Normalisation and trends, Journal of Flood Risk Management 12, e12510, https://doi.org/10.1111/jfr3.12510, 2019.

Aristizábal, E., Sánchez, O.: Spatial and temporal patterns and the socioeconomic impacts of landslides in the tropical and mountainous Colombian Andes, Disasters 44, 596–618, https://doi.org/10.1111/disa.12391, 2020.

Arnell, N.W., Gosling, S.N.: The impacts of climate change on river flood risk at the global scale, Climatic Change 134, 387-401, https://doi.org/10.1007/s10584-014-1084-5, 2016.

Arnell, N.W., Lowe, J.A., Bernie, D., Nicholls, R.J., Brown, S., Challinor, A.J., Osborn, T.J.: The global and regional impacts of climate change under representative concentration pathway forcings and shared socioeconomic pathway socioeconomic scenarios, Environmental Research Letters 14, 084046, https://doi.org/10.1088/1748-9326/ab35a6, 2019.

Ashley, S. T., and Ashley, W. S.: Flood fatalities in the United States, Journal of Applied Meteorology and Climatology, 47, 805–818, https://doi.org/10.1175/2007JAMC1611.1, 2008.

Badoux, A., Andres, N., Techel, F.: Natural hazard fatalities in Switzerland from 1946 to 2015, Natural Hazards and Earth System Sciences, 16, 2747–2768, https://doi.org/10.5194/nhess-16-2747-2016, 2016.

Bianchi, C., Salvati, P.: Rapporto Periodico sul Rischio posto alla Popolazione Italiana da Frane e da Inondazioni - Anno 2025, Consiglio Nazionale delle Ricerche, Istituto di Ricerca per la Protezione Idrogeologica, Perugia, https://doi.org/10.30437/REPORT2025, 2026.

https://doi.org/10.5194/egusphere-2026-4342
Preprint. Discussion started: 31 July 2026

Box, G.E.P., Jenkins, G.M.: Time Series Analysis: Forecasting and Control, San Francisco: Holden-Day, 1970.

Braca, G., Bussettini, M., Casaioli, M., Lastoria, B., Mariani, S., Piva, F., Tropeano, R., 2025, Elaborazioni modello BIGBANG versione 9.0, Istituto Superiore per la Protezione e la Ricerca Ambientale - ISPRA, https://groupware.sinanet.isprambiente.it/bigbang-data/library/bigbang_90

Bubeck, P., Ozturk, U., Aristizabal, E., Thieken, A.H., Wagener, T.: Mortality reduction despite changing climate extremes requires better understanding of human behavioral response to warnings, Environ. Res. Lett. 20, 101004, https://doi.org/10.1088/1748-9326/ae034f, 2025.

Cameron, A.C., Trivedi, P.K.: Regression-based tests for overdispersion in the Poisson model, Journal of Econometrics 46, 347–364, https://doi.org/10.1016/0304-4076(90)90014-K, 1990.

Centre for Research on the Epidemiology of Disasters (CRED), United Nations Office for Disaster Risk Reduction (UNDRR) 2020. The human cost of disasters: An overview of the last 20 years (2000-2019). Brussels: CRED; Geneva: UNDRR

Coates, L.: Flood Fatalities in Australia, 1788-1996, Australian Geographer 30, 391–408, https://doi.org/10.1080/00049189993657, 1999.

Coronese, M., Lamperti, F., Keller, K., Chiaromonte, F., Roventini, A.: Evidence for sharp increase in the economic damages of extreme natural disasters, Proceedings National Academies of Sciences U.S.A. 116, 21450-21455, https://doi.org/10.1073/pnas.1907826116, 2019.

CRED UNDRR: Human cost of disasters: An overview of the last 20 years 2000-2019, Brussels, Belgium, 2020.

CRED UNISDR: The human cost of weather-related disasters 1995–2015, 2016.

Ding, W., Wu, J., Tang, R., Chen, X., Xu, Y.: A review of flood risk in China during 1950–2019: Urbanization, socioeconomic impact trends and flood risk management, Water, 14, 3246, https://doi.org/10.3390/w14203246, 2022.

Donat, M.G., Lowry, A.L., Alexander, L.V., O'Gorman, P.A., Maher, N.: More extreme precipitation in the world's dry and wet regions, Nature Climate Change 6, 508-513, https://doi.org/10.1038/nclimate2941, 2016.

Dottori, F., Szewczyk, W., Ciscar, J.-C., Zhao, F., Alfieri, L., Hirabayashi, Y., Bianchi, A., Mongelli, I., Frieler, K., Betts, R.A., Feyen, L.: Increased human and economic losses from river flooding with anthropogenic warming, Nature Climate Change 8, 781-786, https://doi.org/10.1038/s41558-018-0257-z, 2018.

Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (eds.): Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, Summary for Policymakers. Cambridge University Press, Cambridge, UK, 2012.

FitzGerald, G., Du, W., Jamal, A., Clark, M., Hou, X.-Y.: Flood fatalities in contemporary Australia (1997–2008), Emergency Medicine Australasia 22, 180–186, https://doi.org/10.1111/j.1742-6723.2010.01284.x, 2010.

Formetta, G., Feyen, L.: Empirical evidence of declining global vulnerability to climate-related hazards, Global Environmental Change, 57, 101920, https://doi.org/10.1016/j.gloenvcha.2019.05.004, 2019.

Froude, M.J., Petley, D.N.: Global fatal landslide occurrence from 2004 to 2016, Natural Hazards and Earth System Sciences 18, 2161–2181, https://doi.org/10.5194/nhess-18-2161-2018, 2018.

Gariano, S.L., Guzzetti, F.: Landslides in a changing climate, Earth-Science Reviews 162, 227-252, https://doi.org/10.1016/j.earscirev.2016.08.011, 2016.

Gariano, S.L., Rianna, G.: How will the projected climate change influence rainfall-induced landslides in Europe? A review of modelling approaches, Landslides 22, 3011-3027, https://doi.org/10.1007/s10346-025-02550-7, 2025.

Geiger, T., Stomper, A.: Rising economic damages of natural disasters: Trends in event intensity or capital intensity? Proceedings of the National Academy of Sciences U.S.A, 117, 6312-6313, https://doi.org/10.1073/pnas.1922152117, 2020.

Gneiting, T., Raftery, A.E.: Strictly Proper Scoring Rules, Prediction, and Estimation, Journal of the American Statistical Association 102, 359–378, https://doi.org/10.1198/016214506000001437, 2007.

Gómez, D., García, E.F., Aristizábal, E.: Spatial and temporal landslide distributions using global and open landslide databases, Nat Hazards 117, 25–55, https://doi.org/10.1007/s11069-023-05848-8, 2023.

Görüm, T., Fidan, S.: Spatiotemporal variations of fatal landslides in Turkey, Landslides 18, 1691–1705, https://doi.org/10.1007/s10346-020-01580-7, 2021.

Guzzetti, F.: Landslide fatalities and the evaluation of landslide risk in Italy, Engineering Geology 58, 89-107, https://doi.org/10.1016/s0013-7952(00)00047-8, 2000.

Guzzetti, F., Stark, C.P., Salvati, P.: Evaluation of flood and landslide risk to the population of Italy, Environmental Management 36, 15–36, https://doi.org/10.1007/s00267-003-0257-1, 2005.

Hamed, K.H., Rao, A.R.: A modified Mann-Kendall trend test for autocorrelated data, Journal of Hydrology 204, 182-196, https://doi.org/10.1016/S0022-1694(97)00125-X, 1998.

Hamidifar, H., Nones, M.: Spatiotemporal variations of riverine flood fatalities: 70 years global to regional perspective, River 2, 222–238, https://doi.org/10.1002/rvr2.45, 2023.

Haque, U., da Silva, P.F., Devoli, G., Pilz, J., Zhao, B., Khaloua, A., Wilopo, W., Andersen, P., Lu, P., Lee, J., Yamamoto, T., Keellings, D., Wu, J.-H., Glass, G.E.: The human cost of global warming: Deadly landslides and their triggers (1995-2014), Science of the Total Environment 682, 673-684, https://doi.org/10.1016/j.scitotenv.2019.03.415, 2019.

Hastie, T., Tibshirani, R.: Generalised Additive Models, Statistical Science, 1, https://doi.org/10.1214/ss/1177013604, 1986.

Hilker, N., Badoux, A., Hegg, C.: The Swiss flood and landslide damage database 1972–2007, Natural Hazards and Earth System Sciences, 9, 913–925, https://doi.org/10.5194/nhess-9-913-2009, 2009.

Hu, P., Zhang, Q., Shi, P., Chen, B., Fang, J.: Flood-induced mortality across the globe: Spatiotemporal pattern and influencing factors, Science of the Total Environment, 643, 171-182, https://doi.org/10.1016/j.scitotenv.2018.06.197, 2018.

Hurst, H.E.: Long-Term Storage Capacity of Reservoirs, T. Am. Soc. Civ. Eng. 116, 770–799, https://doi.org/10.1061/TACEAT.0006518, 1951.

Intergovernmental Panel on Climate Change: Climate Change 2022, Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 1st ed. Cambridge University Press, https://doi.org/10.1017/9781009325844, 2023.

Jiménez Cisneros, B.E., T. Oki, N.W. Arnell, G. Benito, J.G. Cogley, P. Döll, T. Jiang, S.S. Mwakalila: Freshwater resources, In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, pp. 229-269, 2014.

Jongman, B., Winsemius, H.C., Aerts, J.C.J.H., Coughlan de Perez, E., van Aalst M.K., Kron, W., Ward, P.J.: Declining vulnerability to river floods and the global benefits of adaptation, Proceedings National Academies of Sciences U.S.A. 112, E2271-E2280, https://doi.org/10.1073/pnas.1414439112, 2015.

Jonkman, S.N., Curran, A., Bouwer, L.M.: Floods have become less deadly: an analysis of global flood fatalities 1975-2022, Natural Hazards 120, 6327-6342, https://doi.org/10.21203/rs.3.rs-3571907/v1, 2024.

Kreibich, H., Van Loon, A.F., Schröter, K., Ward, P.J., Mazzoleni, M., Sairam, N., Abeshu, G.W., Agafonova, S., AghaKouchak, A., Aksoy, H., Alvarez-Garreton, C., Aznar, B., Balkhi, L., Barendrecht, M.H., Biancamaria, S., Bos-Burgering, L., Bradley, C., Budiyono, Y., Buytaert, W., Capewell, L., Carlson, H., Cavus, Y., Couasnon, A., Coxon, G., Daliakopoulos, I., de Ruiter, M.C., Delus, C., Erfurt, M., Esposito, G., François, D., Frappart, F., Freer, J., Frolova, N., Gain, A.K., Grillakis, M., Grima, J.O., Guzmán, D.A., Huning, L.S., Ionita, M., Kharlamov, M., Khoi, D.N., Kieboom, N., Kireeva, M., Koutroulis, A., Lavado-Casimiro, W., Li, H.-Y., LLasat, M.C., Macdonald, D., Mård, J., Mathew-Richards, H., McKenzie, A., Mejia, A., Mendiondo, E.M., Mens, M., Mobini, S., Mohor, G.S., Nagavciuc, V., Ngo-Duc, T., Thao Nguyen Huynh, T., Nhi, P.T.T., Petrucci, O., Nguyen, H.Q., Quintana-Seguí, P., Razavi, S., Ridolfi, E., Riegel, J., Sadik, M.S., Savelli, E., Sazonov, A., Sharma, S., Sörensen, J., Arguello Souza, F.A., Stahl, K., Steinhausen, M., Stoelzle, M., Szalińska, W., Tang, Q., Tian, F., Tokarczyk, T., Tovar, C., Tran, T.V.T., Van Huijgevoort, M.H.J., van Vliet, M.T.H., Vorogushyn, S., Wagener, T., Wang, Y., Wendt, D.E., Wickham, E., Yang, L., Zambrano-Bigiarini, M., Blöschl, G., Di Baldassarre, G.: The challenge of unprecedented floods and droughts in risk management, Nature 608, 80-86, https://doi.org/10.1038/s41586-022-04917-5, 2022.

https://doi.org/10.5194/egusphere-2026-4342
Preprint. Discussion started: 31 July 2026

Li, C., Zwiers, F., Zhang, X., Chen, G., Lu, J., Li, G., Norris, J., Tan, Y., Sun, Y., Liu, M.: Larger increases in more extreme local precipitation events as climate warms, Geophysical Research Letters 46, 6885-6891, https://doi.org/10.1029/2019GL082908, 2019.

Lin, Q., Wang, Y.: Spatial and temporal analysis of a fatal landslide inventory in China from 1950 to 2016, Landslides, https://doi.org/10.1007/s10346-018-1037-6, 2018.

Liu, Q., Du, M., Wang, Y., Deng, J., Yan, W., Qin, C., Liu, M., Liu, J.: Global, regional and national trends and impacts of natural floods, 1990-2022, Bulletin of the World Health Organization 102, 410-420, https://doi.org/10.2471/BLT.23.290243, 2024.

Ljung, G.M., Box, G.E.P.: On a measure of lack of fit in time series models, Biometrika, 65(2), 297-303, https://doi.org/10.2307/2335207, 1978.

Mann, H.B.: Nonparametric Tests Against Trend, Econometrica 13, 245, https://doi.org/10.2307/1907187, 1945.

O'Gorman, P.A.: Precipitation Extremes Under Climate Change, Current Climate Change Reports 1, 49-59, https://doi.org/10.1007/s40641-015-0009-3, 2015.

Osservatorio sui Conti Pubblici Italiani – Università Cattolica del Sacro Cuore: Serie storiche di finanza pubblica dal 1861 al 2024, https://osservatoriocpi.unicatt.it/ocpi-servizi-serie-storiche, 2025.

Ozturk, U., Bozzolan, E., Holcombe, E.A., Shukla, R., Pianosi, F., Wagener, T.: How climate change and unplanned urban sprawl bring more landslides, Nature 608, 262-265, https://doi.org/10.1038/d41586-022-02141-9, 2022.

Papagiannaki, K., Petrucci, O., Diakakis, M., Kotroni, V., Aceto, L., Bianchi, C., Brázdil, R., Gelabert, M.G., Inbar, M., Kahraman, A., Kılıç, Ö., Krahn, A., Kreibich, H., Llasat, M.C., Llasat-Botija, M., Macdonald, N., de Brito, M.M., Mercuri, M., Pereira, S., Řehoř, J., Geli, J.R., Salvati, P., Vinet, F., Zêzere, J.L.: Developing a large-scale dataset of flood fatalities for territories in the Euro-Mediterranean region, FFEM-DB, Sci Data 9, 166, https://doi.org/10.1038/s41597-022-01273-x, 2022.

Petris, G., Petrone, S., and Campagnoli, P.: Dynamic linear models with R, Springer, New York, NY, 251 pp., https://doi.org/10.1007/b135794, 2009.

Patten, H.W., Bhaby, Z.: Disasters, Statistics, and the Humanitarian Sector, Annual Review of Statistics and its Application 13, 3.1-3.23, https://doi.org/10.1146/annurev-statistics-042424-061122, 2025.

Pereira, S., Diakakis, M., Deligiannakis, G., Zêzere, J.L.: Comparing flood mortality in Portugal and Greece, International Journal of Disaster Risk Reduction, 22, 147–157, https://doi.org/10.1016/j.ijdrr.2017.03.007, 2017.

Pereira, S., Zêzere, J. L., and Quaresma, I.: Landslide societal risk in Portugal in the period 1865–2015, in: Advancing Culture of Living with Landslides, edited by: Sassa, K., Mikoš, M., and Yin, Y., Springer, Cham, 491–499, https://doi.org/10.1007/978-3-319-59469-9_43, 2017.

Pereira, S., Zêzere, J.L., Quaresma, I.D., Santos, P.P., Santos, M.: Mortality patterns of hydro-geomorphologic disasters, Risk Analysis, 36, 1188–1210, https://doi.org/10.1111/risa.12516, 2016.

Petley, D. N.: Global patterns of loss of life from landslides, Geology, 40, 927–930, https://doi.org/10.1130/G33217.1, 2012.

Petley, D.N., Hearn, G.J., Hart, A., Rosser, N.J., Dunning, S.A., Oven, K., Mitchell, W.A.: Trends in landslide occurrence in Nepal, Natural Hazards 43, 23–44, https://doi.org/10.1007/s11069-006-9100-3, 2007.

Petrucci, O., Papagiannaki, K., Diakakis, M., Badoux, A., Bănescu, A.-I., Brázdil, R., Carvalho, T. M. N., Chromá, K., de Brito, M. M., Ioana-Toroimac, G., Kahraman, A., Kılıç, Ö., Krahn, A., Kreibich, H., Liechti, K., Llasat, M. C., Llasat-Botija, M., Macdonald, N., Moroșanu-Mitoșeriu, G. A., Orieschnig, C., Pereira, S., Řehoř, J., Rossello Geli, J., Sima, M., Thieken, A. H., Vinet, F., Zaharia, L., and Zenker, M.-L.: FFEM-DB 2.0: an updated and extended spatio-temporal dataset of flood fatalities occurred from 1980 to 2024 in the Euro-Mediterranean region, Sci Data, https://doi.org/10.1038/s41597-026-07511-w, 2026.

Pettitt, A.N.: A non-parametric approach to the change-point problem, Journal of the Royal Statistical Society: Series C (Applied Statistics) 28, 126-135, https://doi.org/10.2307/2346729, 1979.

Posit team: RStudio: Integrated Development Environment for R, Posit Software, PBC, Boston, MA, https://www.posit.co/, 2025.

R Core Team: R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria, https://www.R-project.org/, 2021.

Remondo, J., Sánchez-Díaz, M., and Cuesta-Albertos, J. A.: An increasing trend of landslides as a consequence of the global change, Earth Syst. Environ., 10, 1461–1474, https://doi.org/10.1007/s41748-025-00685-0, 2026.

Rentschler, J., Avner, P., Marconcini, M., Su, R., Strano, E., Vousdoukas, M., Hallegatte, S.: Global evidence of rapid urban growth in flood zones since 1985, Nature 622, 87-92, https://doi.org/10.1038/s41586-023-06468-9, 2023.

Salvati, P., Bianchi, C., Rossi, M., Guzzetti, F.: Societal landslide and flood risk in Italy, Natural Hazards and Earth System Sciences 10, 465-483, https://doi.org/10.5194/nhess-10-465-2010, 2010.

Salvati, P., Petrucci, O., Rossi, M., Bianchi, C., Pasqua, A.A., Guzzetti, F.: Gender, age and circumstances analysis of flood and landslide fatalities in Italy, Science of the Total Environment 610-611, 867-879, https://doi.org/10.1016/j.scitotenv.2017.08.064, 2018.

Salvati, P., Rossi, M., Bianchi, C., Guzzetti, F.: Landslide Risk to the Population of Italy and Its Geographical and Temporal Variations, in: Chavez, M., Ghil, M., Urrutia-Fucugauchi, J, (Eds.), Extreme Events: Observations, Modeling, and Economics, Geophysical Monograph Series. John Wiley & Sons, Inc, Hoboken, NJ, pp. 177–194, 2016.

Sen, P.K.: Estimates of the Regression Coefficient Based on Kendall's Tau, Journal of the American Statistical Association 63(324), 1379-1389, https://doi.org/10.1080/01621459.1968.10480934, 1968.

Shannon, C.E.: A Mathematical Theory of Communication, The Bell System Technical Journal 27, 379–423, 623–656, 1948.

Shinohara, Y., Kume, T.: Changes in the factors contributing to the reduction of landslide fatalities between 1945 and 2019 in Japan, Science of The Total Environment 827, 154392, https://doi.org/10.1016/j.scitotenv.2022.154392, 2022.

Song, C., Qu, Z., Blumm, N., Barabási, A.-L.: Limits of Predictability in Human Mobility, Science 327, 1018–1021, https://doi.org/10.1126/science.1177170, 2010.

Stan Development Team: Stan Modeling Language Users Guide and Reference Manual, version 2.32, Stan, https://mc-stan.org/, 2023.

Strouth, A. and McDougall, S.: Historical landslide fatalities in British Columbia, Canada: Trends and implications for risk management, Front. Earth Sci., 9, 606854, https://doi.org/10.3389/feart.2021.606854, 2021.

Strouth, A. and McDougall, S.: Societal risk evaluation for landslides: historical synthesis and proposed tools, Landslides 18, 1071–1085, https://doi.org/10.1007/s10346-020-01547-8, 2021.

Sultana, N.: Analysis of landslide-induced fatalities and injuries in Bangladesh: 2000-2018, Cogent Social Sciences 6, 1737402, https://doi.org/10.1080/23311886.2020.1737402, 2020.

Tanoue, M., Hirabayashi, Y., Ikeuchi, H.: Global-scale river flood vulnerability in the last 50 years, Sci Rep 6, https://doi.org/10.1038/srep36021, 2016.

Tashman, L.J.: Out-of-sample tests of forecasting accuracy: an analysis and review, International Journal of Forecasting, The M3- Competition 16, 437–450, https://doi.org/10.1016/S0169-2070(00)00065-0, 2000.

Tellman, B., Sullivan, J.A., Kuhn, C., Kettner, A.J., Doyle, C.S., Brakenridge, G.R., Erickson, T.A., Slayback, D.A.: Satellite imaging reveals increased proportion of population exposed to floods, Nature 596, 80-86, https://doi.org/10.1038/s41586-021-03695-w, 2021.

Teramura, J., Shimatani, Y.: Quantifying disaster casualties centered on flooding in the Chikugo River middle basin in the past 400 years to determine the historical context of the July 2017 northern Kyushu torrential rainfall, Journal of Disaster Research, 14, 1014–1023, https://doi.org/10.20965/jdr.2019.p1014, 2019.

Tin, D., Cheng, L., Le, D., Hata, R., Ciottone, G.: Natural disasters: a comprehensive study using EMDAT database 1995–2022, Public Health 226, 255–260, https://doi.org/10.1016/j.puhe.2023.11.017, 2024.

West, M., Harrison, J.: Bayesian Forecasting and Dynamic Models, Springer New York, https://doi.org/10.1007/b98971, 1997.

Wood, S.N.: Generalised Additive Models: An Introduction with R, 2nd ed, Chapman and Hall/CRC, https://doi.org/10.1201/9781315370279, 2017.

Wood, S.N.: Generalised additive models, Annual Review of Statistics and its Application 12, 497-526, https://doi.org/10.1146/annurev-statistics-112723-034249, 2025.

Yue, S., Wang, C.: The Mann-Kendall Test Modified by Effective Sample Size to Detect Trend in Serially Correlated Hydrological Series, Water Resources Management 18, 201-218, https://doi.org/10.1023/B:WARM.0000043140.61082.60, 2004.

Zhang, F., Huang, X.: Trend and spatiotemporal distribution of fatal landslides triggered by non-seismic effects in China, Landslides 15, 1663–1674, https://doi.org/10.1007/s10346-018-1007-z, 2018.

Zêzere, J.L., Pereira, S., Tavares, A.O., Bateira, C., Trigo, R.M., Quaresma, I., Santos, P.P., Santos, M., Verde, J.: DISASTER: A GIS database on hydro-geomorphologic disasters in Portugal, Natural Hazards, 72, 503–532, https://doi.org/10.1007/s11069-013-1018-y, 2014.

Figure captions

Figure 1: Time series of the yearly number of fatalities (deaths and missing persons) and fatal days caused by (A, D) geo-hydrological events (floods and landslides); (B, E) landslides, and (C, F) floods in Italy 1950-2024. (G) Main environmental (black) and risk management (violet) policy and programmes. Legend for G: 1, Final report of the "Commissione de Marchi", Interministerial commission for the study of hydraulic engineering and soil protection, 1970; 2, Law n. 183/1989, with regulations for the organisational and functional reorganisation of soil protection, 1989; 3, Law 225/1992, establishment of the National Civil Protection Service, 1992; 4, Law 267/1998, Sarno decree, with mandatory flood and landslide zoning, 1998; 5, Law 365/2000, Soverato decree, establishment of weather radar national network, 2000; 6, DPCM 27/2/2004, operational guidelines for the management of the civil protection national alert system for hydrological, hydraulic, and geomorphological risk, 2004; 7, Directive 2007/60/EC on the assessment and management of flood risks, 2010; 8, Legislative Decree 49/2010, Implementation of Directive 2007/60/EC on the assessment and management of flood risks, 2010; 9, Law 100/2012, Conversion into law, with amendments, of Decree-Law 59/2012, containing urgent provisions for the reorganisation of civil protection, 2012; 10, Prime Ministerial Decree 2/5/2014, establishing the Task Force against hydrogeological instability and for the development of water infrastructure, 2014; 11, Decree Law 133/2014, Urgent measures for the opening of construction sites, the implementation of public works, the digitisation of the country, the simplification of bureaucracy, the hydrogeological instability emergency, and the resumption of productive activities, 2014; 12, Legislative Decree 1/2018, new Civil Protection code, 2018; 13, Prime Ministerial Decree 20/2/2019, National Plan for the mitigation of hydrogeological risk, restoration, and protection of environmental resources, 2019; 14, PNRR, Component 4 (M2C4), Protection of the territory and water resources, 2022.

Figure 2: Climate and economic and demographic drivers in Italy, 1951–2024. Upper panels show (A) annual total precipitation (TP), (B) mean annual temperature (TD), (C) population (POP), (D) general national mortality (MOR), and (E) gross domestic product (GDP). Black lines show 7-year running means. Lower panels (F-J) show the corresponding deviations from the long-term means. Darker shading are values above the mean and lighter shading values are below the mean.

Figure 3: Fitted Negative Binomial (NB) Complementary Cumulative Distribution Functions (CCDFs), and their uncertainty envelopes (shaded areas), for (A) annual fatalities and (B) days with fatalities associated with geo-hydrological hazards (red), floods (blue), and landslides (green) in Italy, 1950–2024, excluding the Vajont (1963) and Stava (1985) events. See text for explanation.

Figure 4: GAM and DLM fits to annual fatalities and fatal days in Italy, 1950-2030. Left panels show GAMs and right panels DLMs for geo-hydrological, landslide, and flood fatalities (A–F) and fatal days (G–L). Thick coloured lines are

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model estimates, and black lines are 7-year running means. Shaded bands are 95% confidence intervals (CI) and prediction intervals (PI) for GAMs, and credible intervals (CrI) for DLMs. Solid vertical lines mark Pettitt change points; dotted and dashed lines mark the start of evaluation (2021) and project (2025), respectively. Red squares indicate observed values for 2025. See text for explanation.

Figure 5: Uncertainty in GAM and DLM estimates during the evaluation (2021–2024) and projection (2025–2030) periods. Rows show geo-hydrological events, G (A, B), landslides, L (C, D), and floods, F (D, E); columns show annual fatalities, f (left) and fatal days, d (right). Plots summarize 2,500 (randomly selected from 10,000) simulated values per series and year sampled from GAM confidence (CI) and prediction (PI) intervals, and from DLM posterior distributions (CrI). Boxes represent interquartile range (25th–75th percentiles) with the median shown by the central line. Whiskers extend to the most extreme values within 1.5 times the interquartile range, excluding outliers. See text for explanation.

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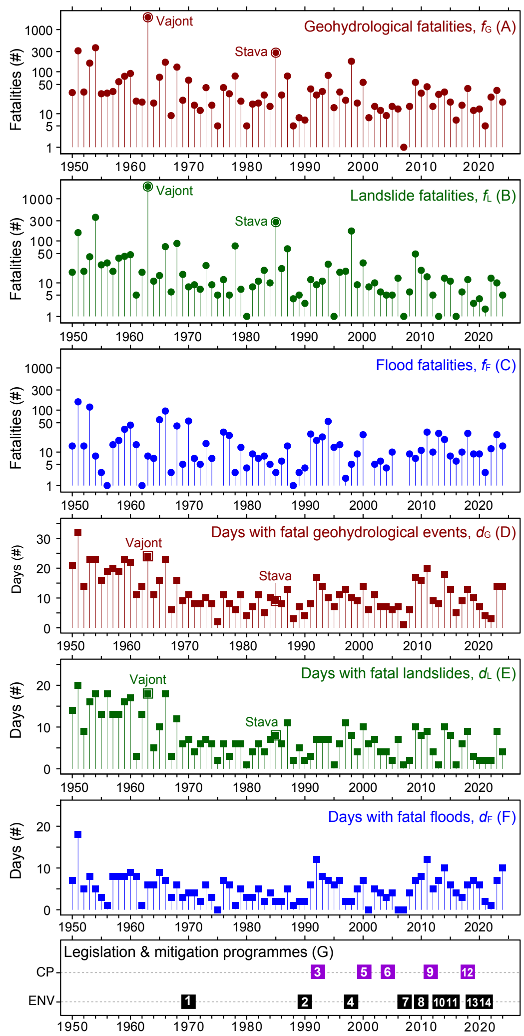

Figure 1

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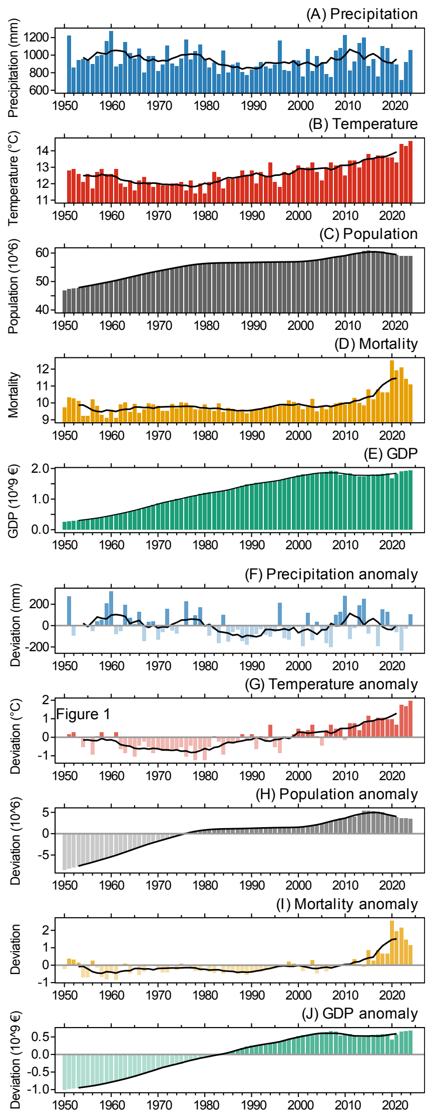

Figure 2

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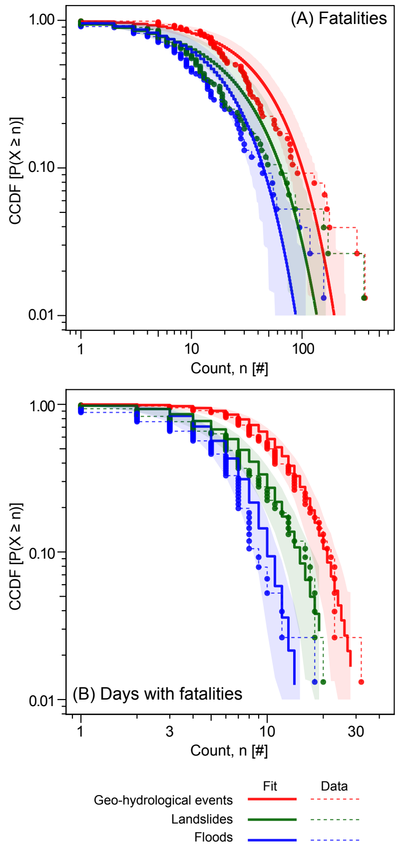

Figure 3

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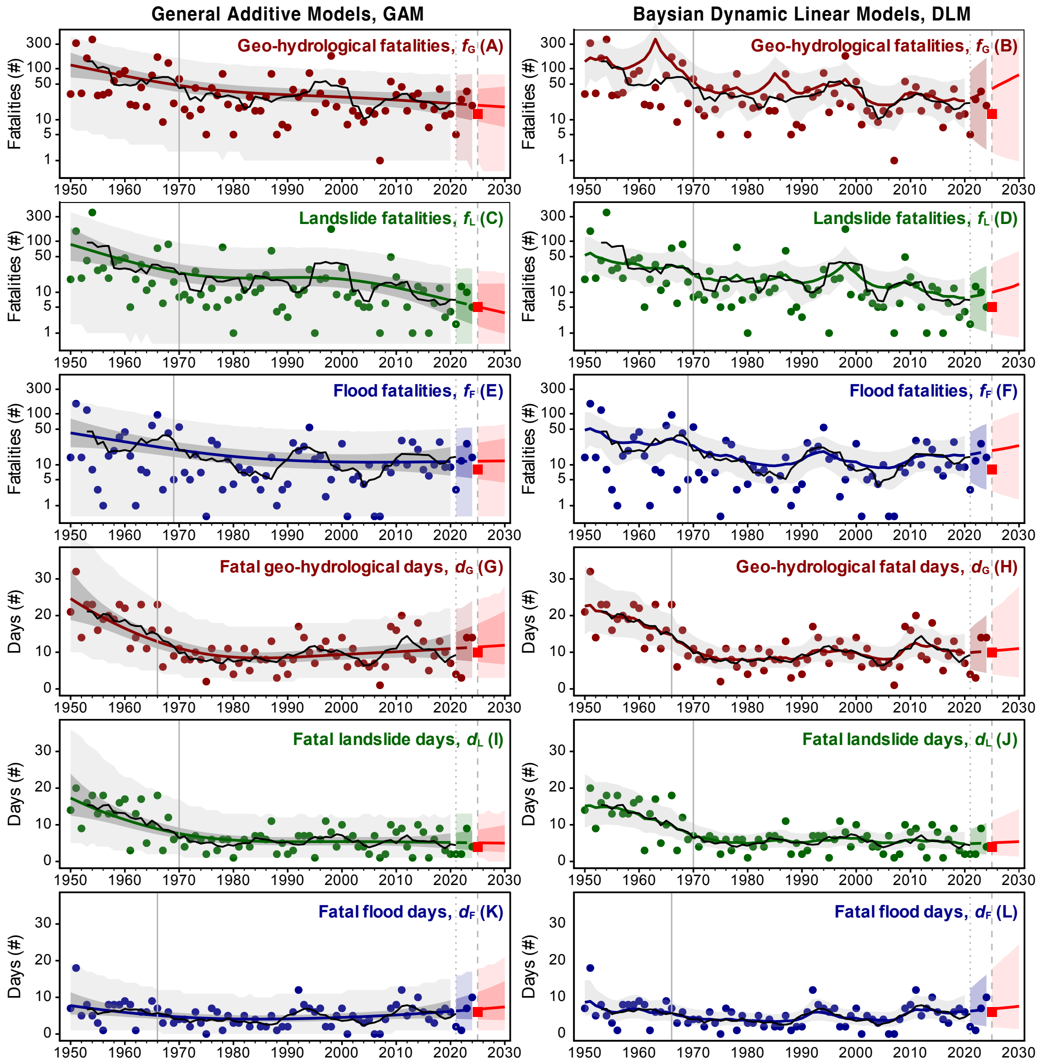

Figure 4

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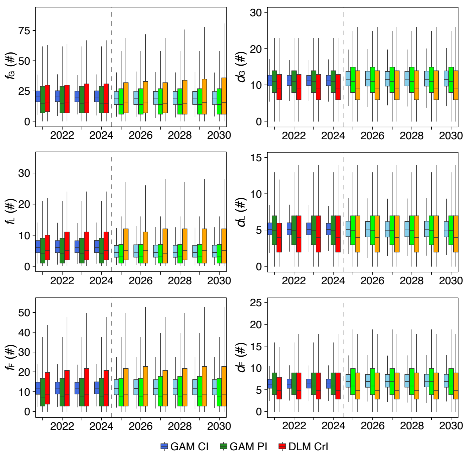

Figure 5

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Tables

Table 1: Summary statistics of fatalities (f) and fatal-event days (d) for geo-hydrological (G), flood (F) and landslide (L) events for 1950–2024 and for the subperiods 1950–1974, 1975–1999 and 2000–2024. Mortality, average hazard mortality (# fatalities/10^5 people, per year); Lethality, average hazard lethality (average of # fatalities/# fatal days, per year). The Vajont landslide (9 October 1963; 1,917 fatalities) and the Stava mudflow (19 July 1985; 268 fatalities) are not included.

Type	Period	Years	Fatalities (*f*)						Fatal-event days (*d*)						Mortality		Lethality	
			#	μ	median	σ	min	max	#	μ	median	σ	min	max	μ	σ	μ	σ
G	1950-2024	75	3,273	43.6	25	61.7	1	371	868	11.6	10	6.1	1	32	0.08	0.13	3.36	3.21
	1950-1974	25	1,882	75.3	34	92.0	9	371	406	16.2	16	6.6	6	32	0.15	0.19	3.94	3.48
	1975-1999	25	847	33.9	21	37.2	5	177	217	8.7	8	3.6	2	17	0.06	0.07	3.88	3.94
	2000-2024	25	544	21.8	15	15.1	1	56	245	9.8	9	5.0	1	20	0.04	0.03	2.26	1.50
F	1950-2024	75	1,346	17.9	9	25.8	0	157	381	5.1	5	3.2	0	18	0.03	0.05	3.16	3.02
	1950-1974	25	753	30.1	14	39.9	1	157	148	5.9	6	3.5	1	18	0.06	0.08	4.14	4.24
	1975-1999	25	302	12.1	8	12.2	0	54	105	4.2	4	2.8	0	12	0.02	0.02	2.63	1.51
	2000-2024	25	291	11.6	9	9.3	0	30	128	5.1	5	3.2	0	12	0.02	0.02	2.61	2.35
L	1950-2024	75	1,927	25.7	11	49.5	1	363	547	7.3	6	4.9	1	20	0.05	0.10	2.89	3.53
	1950-1974	25	1,129	45.2	19	74.0	5	363	284	11.4	13	5.4	3	20	0.09	0.15	3.29	3.89
	1975-1999	25	545	21.8	11	36.1	1	172	132	5.3	6	2.7	1	11	0.04	0.06	3.50	4.47
	2000-2024	25	253	10.1	6	10.4	1	49	131	5.2	4	3.2	1	10	0.02	0.02	1.88	1.32

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Table 2: Results of autocorrelation diagnostics, trend analysis, and Hurst persistence analysis for annual series of fatalities (*f*) and fatal-event days (*d*) for geo-hydrological (G), landslide (L), and flood (F) events in Italy, for 1950–2024 and for the subperiods 1950–1974, 1975–1999 and 2000–2024. The Vajont (9 October 1963) and Stava (19 July 1985) associated with major engineering works were excluded.

			ACF1	Ljung & Box	Man-Kendall			Sen			Hurst		Change point
Series	Period	Years		p-value	Method	T	p-value	slope	slope per decade	CI	H		Pettitt
f_G	1950-2024	75	0.116	0.014	M	-0.219	0.006	-0.320	-3.200	-0.62, -0.11	0.620	P	1970
	1950-1974	25	-0.026	0.469	S	-0.277	0.055	-1.220	-12.200	-4.13, 0.12	0.572	P	
	1975-1999	25	-0.138	0.712	S	0.118	0.426	0.360	3.600	-0.67, 1.62	0.504	R	
	2000-2024	25	0.082	0.860	S	0.088	0.558	0.220	2.200	-0.62, 0.92	0.545	R	
	1975-2024	50	-0.054	0.383	S	-0.040	0.694	-0.050	-0.500	-0.38, 0.23	0.524	R	
f_L	1950-2024	75	0.033	0.205	S	-0.322	0.000	-0.240	-2.400	-0.38, -0.12	0.569	P	1969
	1950-1974	25	-0.066	0.565	S	-0.305	0.035	-1.000	-10.000	-2.38, -0.1	0.527	R	
	1975-1999	25	-0.084	0.856	S	0.159	0.281	0.380	3.800	-0.2, 1.0	0.509	R	
	2000-2024	25	0.133	0.809	S	-0.178	0.231	-0.180	-1.800	-0.67, 0.17	0.504	R	
	1975-2024	50	-0.014	0.811	S	-0.116	0.247	-0.080	-0.800	-0.24, 0.04	0.494	R	
f_F	1950-2024	75	0.039	0.037	M	-0.057	0.478	-0.050	-0.500	-0.17, 0.06	0.601	P	-
	1950-1974	25	-0.135	0.205	S	-0.098	0.512	-0.270	-2.700	-1.36, 0.5	0.501	R	
	1975-1999	25	0.237	0.542	S	0.071	0.640	0.110	1.100	-0.43, 0.71	0.580	P	
	2000-2024	25	0.129	0.913	S	0.272	0.064	0.330	3.300	0.00, 0.80	0.611	P	
	1975-2024	50	0.192	0.491	S	0.121	0.224	0.090	0.900	-0.07, 0.21	0.512	R	
d_G	1950-2024	75	0.461	0.000	M	-0.268	0.001	-0.120	-1.200	-0.18, -0.05	0.723	P	1966
	1950-1974	25	0.250	0.006	M	-0.580	0.000	-0.630	-6.300	-0.92, -0.30	0.668	P	
	1975-1999	25	0.021	0.992	S	0.228	0.126	0.170	1.700	0.00, 0.38	0.562	P	
	2000-2024	25	0.301	0.356	S	0.034	0.833	0.000	0.000	-0.22, 0.33	0.566	P	
	1975-2024	50	0.207	0.447	S	0.112	0.267	0.050	0.500	-0.03, 0.15	0.543	R	
d_L	1950-2024	75	0.393	0.000	M	-0.314	0.000	-0.110	-1.100	-0.16, -0.06	0.721	P	1970
	1950-1974	25	0.116	0.008	M	-0.507	0.001	-0.460	-4.600	-0.67, -0.14	0.646	P	
	1975-1999	25	-0.001	0.853	S	0.219	0.148	0.080	0.800	0.00, 0.25	0.419	AP	
	2000-2024	25	0.006	0.490	S	-0.119	0.436	-0.060	-0.600	-0.29, 0.12	0.435	AP	
	1975-2024	50	-0.011	0.531	S	0.021	0.846	0.000	0.000	-0.06, 0.07	0.475	R	
d_F	1950-2024	75	0.280	0.083	S	-0.058	0.481	0.000	0.000	-0.04, 0.02	0.644	P	-
	1950-1974	25	0.108	0.811	S	-0.276	0.066	-0.150	-1.500	-0.33, 0.00	0.500	R	
	1975-1999	25	0.287	0.384	S	0.145	0.342	0.060	0.600	-0.06, 0.25	0.626	P	
	2000-2024	25	0.344	0.340	S	0.171	0.258	0.120	1.200	-0.07, 0.29	0.593	P	
	1975-2024	50	0.326	0.113	S	0.177	0.082	0.050	0.500	0.00, 0.11	0.557	P	

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Legend: f_G, geo-hydrological fatalities; f_L, landslide fatalities; f_F, flood fatalities; d_G, days with geo-hydrological fatalities; d_L, days with landslide fatalities; d_F, days with flood fatalities; Y, number of years; CI, 5% and 95% confidence intervals; H, Hurst exponent. Mann–Kendall test: S, standard; M, modified. Hurst classification: P, persistence; AP, anti-persistence; R, random behaviour.