Assessing the impact of early warning and evacuation on human losses during the 2021 Ahr Valley flood in Germany using agent-based modelling

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Abstract.

Between 12 and 19 July 2021, a quasi-stationary atmospheric low-pressure system named "Bernd" caused intense precipitation on already saturated soil, resulting in severe flooding in Germany, Belgium, and the Netherlands. The Ahr River Valley in Rhineland-Palatinate was particularly affected, with approximately 42,000 residents impacted, around 8,800 buildings damaged, and 134 fatalities recorded. The flood in the Ahr River Valley significantly exceeded the scenarios outlined in official hazard maps, leaving decision-makers and the public unprepared. Substantial issues occurred with the content, issuance, and dissemination of warnings, thereby reducing the effectiveness of emergency response. We evaluate how human losses in the Ahr Valley might have differed under alternative flood early warning and evacuation (FEWE) scenarios, using the agent-based model LifeSim. To run the model for the 2021 Ahr flood, we utilised a reconstructed modelled time series of water depth and flow velocities and estimated the FEWE timeline based on reports and a post-event survey of the affected population. For the reconstructed FEWE timeline, we identified the first flood warning approximately 13 hours before the peak of the flood upstream of the simulated domain. Only 17.5 % of those affected received a warning with evacuation instructions, with most becoming aware of evacuation necessities only after flooding had already reached them. Consequently, only about 34 % of the population evacuated their homes or were rescued. Regarding the life loss estimation, the median of the reconstructed flood overestimates the actual life loss by 28.8 %. Simulations of alternative FEWE scenarios indicate a potential life loss reduction of up to 80 % with timely warning dissemination and increased population evacuation. However, scenarios in which the FEWE prompted the population to evacuate at the moment of the imminent hazard at their buildings result in higher human losses. In these cases, vertical evacuation within buildings is more effective. Using a life loss agent-based model, such as LifeSim, can support decisions on FEWEs and improve emergency response planning.

1 Introduction

Floods represent the most prevalent natural disaster globally (CRED and UNISDR, 2018), and under a climate change scenario, their frequency, particularly of rare events, has increased (Wasko et al., 2021). In Germany, four flood events have been notable in terms of loss of life during the last 40 years. In August 2002, a record-breaking daily rainfall of 314 mm in 24 hours caused flash floods in the Bavarian and Saxon middle hills of Germany. This extreme weather event resulted in the activation of dam spillways, as well as the overtopping and breaching of embankments in many areas, leading to the deaths of 21 people (Kienzler et al., 2015). Between 31 May and 3 June 2013, precipitation of 346 mm fell on already saturated soil, affecting 12 of Germany's 16 federal states. Approximately 1,400 kilometres of river networks experienced 100-year flood discharges and some dike breaches, resulting in 14 fatalities (Thieken et al., 2022). From 26 May to 9 June 2016, a series of flash floods, including peaks of 100 mm in 2 hours in Braunsbach, a small village in Baden-Württemberg, caused significant damage to small and steep catchments, resulting in 11 fatalities (Thieken et al., 2022). In July 2021, the most devastating flood event occurred in terms of fatalities. In total, fewer people died in the 40 years between 1980 and 2020, with 159 victims (Papagiannaki et al., 2022), than in this single 2021 flood event, with 190 victims in Germany (Thieken et al., 2023a, b).

The extraordinary severe event in July 2021 was caused by a quasi-stationary atmospheric low-pressure system named "Bernd". This system brought intense precipitation on already saturated soil, resulting in severe flooding in the western German states, mainly along the Ahr River, located in the Rhineland-Palatinate state. Hydrologically, the 2021 flood was extreme in terms of the rapid-onset of flooding, high flow velocities, and high water depths (Kron et al., 2022). Along the Ahr River, about 42,000 inhabitants were affected by the flood, about 8,800 buildings were damaged (DKKV, 2022), and 134 fatalities had occurred (Szönyi et al., 2022).

The flood extent significantly exceeded what was outlined in official hazard maps, leaving decision-makers and the population unprepared. This lack of preparedness resulted in numerous issues with the warning content and its issuance and dissemination, compromising the efficiency of residents taking protective measures (Szönyi et al., 2022). A survey conducted after the event revealed that 29 % of Ahr Valley residents reported not receiving any warning, and among those who were warned, over 40 % did not know what to do to protect themselves and their houses. Consequently, 84 % of residents were surprised by the magnitude of the flood (Thieken et al., 2023b).

One of the most critical factors contributing to fatalities during floods is the effectiveness of flood early warning and evacuation (FEWE) systems (Petrucci, 2022; Yari et al., 2020). An optimal warning system should be robust, capable of early hazard identification, and equipped with efficient communication channels to promptly inform the population at risk (Kreibich et al., 2021; Kuller et al., 2021). Additionally, an investment in enhancing the population's knowledge of appropriate actions and behaviours in response to flood risks is essential (Aerts et al., 2018; Berghäuser et al., 2023). This comprehensive approach could significantly mitigate the impact of floods and reduce the likelihood of fatalities.

One method to assess the effectiveness of these FEWE systems is through life loss estimation models (Chen et al., 2023; Ge et al., 2022). In estimating fatalities from flood events, some methodologies incorporate behavioural assessments and

macroeconomic indicators to evaluate the impacts (Jongejan et al., 2005). However, assigning a monetary value to the loss of life is complex due to the intangible nature of this type of damage (Merz et al., 2010). Fatalities can also be indirectly related to flooding, occurring outside the inundated areas through incidents such as traffic accidents during evacuations or deaths due to post-flood stress. Despite these indirect impacts, most fatalities result from direct causes (Jonkman and Vrijling, 2008).

65 Since predicting such behaviour is challenging, loss of life is generally classified solely as a direct type of damage. Therefore, the risk assessment addresses this metric directly and quantitatively without assigning a monetary value (Jonkman et al., 2003). Life loss estimation models can be categorised as either empirical or dynamic. The empirical approach integrates some characteristics of the flood event, such as depth, velocity, water rise rate, warning time, and other factors related to the exposure and vulnerability of the population, with a fatality rate. Various empirical models exist for different types of events, including

70 coastal and riverine floods (Boyd et al., 2005; Brazdova and Riha, 2014; Jonkman et al., 2008, 2009; Penning-Rowsell et al., 2005; Yazdani et al., 2023; Zhai et al., 2006), and dam breaks (Brown and Graham, 1988; DeKay and McClelland, 1993; Ge et al., 2021; Graham, 1999; Jiao et al., 2022; Mahmoud et al., 2020; Peng and Zhang, 2012; USBR, 2015). Dynamic models, often called agent-based models (ABMs), use a time-varying quantification of event characteristics correlated with flood exposure criteria and thresholds. These models provide a more detailed simulation of events by modelling individual behaviour

75 and the causes of fatalities (Anshuka et al., 2022; Zhuo and Han, 2020). This detailed simulation is beneficial for evaluating FEWE systems, offering advantages over empirical models (Di Mauro et al., 2012; Shirvani and Kesserwani, 2021).

Numerous agent-based models related to flood risk management have been developed (Anshuka et al., 2022). However, most of these models are designed for specific sites and types of floods and have been applied only in limited research contexts. As a result, only two models have been widely used in flood risk assessment (Lumbroso et al., 2023). The Life Safety Model

80 (LSM) (Johnstone et al., 2005) was utilised to assess the impacts of FEWE in the 1953 Canvey Island flood (Lumbroso and Davison, 2018) and in the 2019 Brumadinho tailing dam break event (Lumbroso et al., 2021). The LifeSim model (Aboelata and Bowles, 2005) was employed to create a generalised life loss estimation model for dam breaks in Switzerland (Kalinina et al., 2021), for traffic management in Morocco (El Bilali et al., 2021), in a proposal for a probabilistic life loss estimation for densely populated areas in Morocco (El Bilali et al., 2022). Additionally, it was used to assess warning and evacuation

85 procedures and their impacts in Brazil for the 2007 São Francisco tailings dam failure (Silva and Eleutério, 2023a) and for a hypothetical case in a high-density area (Silva and Eleutério, 2023b), as well as in order to evaluate the effects of numerous non-structural dam break floods in China (Wang et al., 2024).

The objective of this study is to assess the exceptionally high number of fatalities in the Ahr Valley during the flash flood of 2021. With the help of an ABM, in particular, the effects of FEWE are analysed. Scenarios are used to develop

90 recommendations for improved emergency communication and response. Given the extensive variety of flood types (Needham et al., 2016) and its widespread application in diverse contexts (e.g. flash floods, dike and dam breaches), the agent-based model LifeSim was chosen for this study.

Section 2 outlines the data and methods, providing an overview of the agent-based model LifeSim and detailing its principal inputs and operational considerations. The reconstruction of the human consequences of the 2021 Ahr Valley flood is

95 examined, including flood modelling, exposure analysis, and flood early warning and evacuation procedures. The section concludes with an exploration of alternative warning and evacuation scenarios, as well as general parametrisation and considerations regarding using LifeSim. Section 3 presents and analyses the results of the LifeSim model for human consequence reconstruction and evaluates the impacts of the alternative FEWE scenarios. Section 4 highlights the main limitations of the simulations. Finally, Section 5 summarises the key findings of this study and suggests areas for further

100 research.

2 Data and Methods

The concept for assessing the impact of flood early warning and evacuation (FEWE) on loss of life consists of two main parts (Fig. 1). First, the reconstruction of the 2021 Ahr Valley flood is undertaken to compare the life loss estimation by the agent-based model LifeSim with the actual values. This involves updating an existing hydraulic model, creating a structure inventory

105 with information on buildings and population, and reconstructing the warning and evacuation procedures. Second, the impact of alternative scenarios of FEWE is assessed. Once the life loss model is adjusted to the actual case, two approaches are used to assess the effectiveness of FEWE: one focuses on the efficiency of communication and response using theoretical models of warning dissemination and the mobilisation time taken for the population to begin evacuation, and the other on the timing for issuing the first flood warning considering forecasting capabilities.

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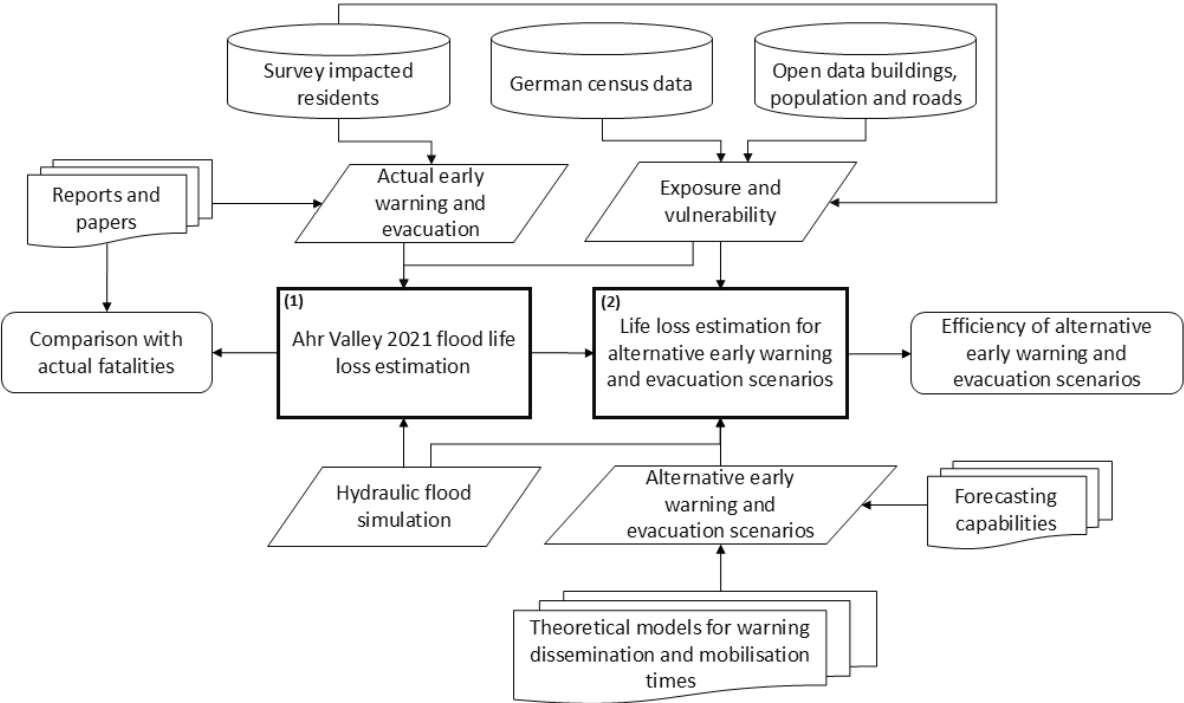
Figure 1: Overview of concept showing methodological components and data relationships for assessing the impacts of early warning and evacuation procedures on life loss estimation in relation to the 2021 Ahr Valley flood.

2.1 LifeSim agent-based model to estimate direct flood fatalities

LifeSim was initially proposed by Aboelata and Bowles (2005) and has since been integrated into a graphical interface by the United States Army Corps of Engineers. This model simulates various outcomes, with focus on direct life loss resulting from exposure to flood hazards, where the magnitude of life loss is influenced by hydrodynamic parameters and the success of the population in locating adequate shelter during flood events. The model is structured with a modular system in which the agent-based approach allows the description and simulation of individual and group behaviours. These modules integrate hydrodynamic spatial and time dependent data and population characteristics data based on geographic information systems layers (USACE, 2020).

The LifeSim model comprises four main modules. The first is the flood routine module, which encompasses a network representation of flood characteristics across the area over time. The shelter loss module, which assesses the exposure of the population that does not evacuate in structures during events, considers submersion and structural damage criteria. The warning and evacuation module that models the distribution and dynamics of the at-risk population following the warning issuance. Finally, the loss of life module which employs probability distributions of fatality rates derived from historical flood event data to estimate potential fatalities (USACE, 2020). A short description of each module related to life loss estimation is shown in the following paragraphs based on the LifeSim version 2.0 (USACE, 2021).

The flood routine module contains hydraulic data about the flood event, encompassing temporal developments of water depth and flow velocities.

The submersion criteria of the shelter loss module are based on thresholds defined by a triangular distribution, determined by the water depth on the highest floor of a building. For the general population, these thresholds correspond to the ceiling level, while for individuals with mobility issues, they also pertain to the floor level. When access to the building's roof is feasible, the threshold is related to the roof floor. If these thresholds are exceeded, the population is designated into the high-hazard zone, where a specific fatality rate is applied according to the life loss module. Mobility in the LifeSim routine is quantified using percentages from the 2017 United States census, indicating the proportion of individuals under 65 years with mobility difficulty and those over 65 years with similar issues. The stability criteria depends on the building's construction type, with most criteria based on the consideration of Clausen and Clark (1990). If this stability threshold is reached, the building is considered to be collapsing, and all individuals inside are allocated to high-hazard zones, as in the submersion consideration.

The process of warning and evacuation involves several milestones separated by time delays, as illustrated in Fig. 2. The timeline begins with the identification of an imminent hazard. The first delay occurs between the identification of the hazard and the decision to issue an evacuation order. Following the issuance of the warning, a second delay represents the time required to disseminate this warning. Once the population receives the warning, a third delay occurs before initiating protective action. These three delays have been identified and substantiated by research, supported by various studies and equations

145 (Sorensen and Mileti, 2015a, b, c). LifeSim incorporates standard curves with an explicit range of uncertainty for these three delays. The uncertainty is inherently present in the delay curves for warning issuance, as probability distribution functions represent them. Cumulative probability functions represent the warning diffusion and mobilisation curves, accounting for the inherent uncertainty. After the evacuation is initiated, the LifeSim routine utilises several criteria and considerations to model the evacuation process and determine whether an agent successfully reaches a safe location.

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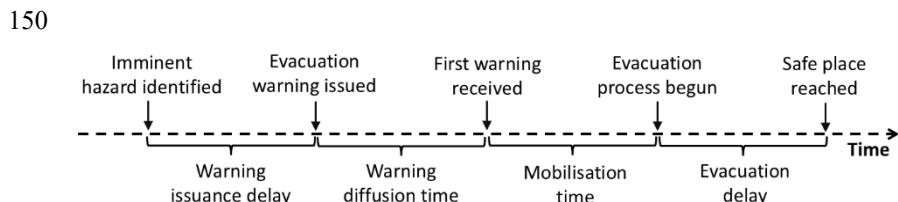
Figure 2: The milestones and respective times between them that represent the warning and evacuation timeline in the LifeSim model.

The simulation of the evacuation dynamics employs the Greenshields traffic flow model (Mahmassani et al., 2009) to represent
155 the effects of traffic density and road capacity on vehicle speed. This model has been adapted to introduce a minimum speed threshold determined by stop-and-go conditions. The Dijkstra optimisation algorithm (1959) defines the fastest path between the building and the pre-defined meeting point for route determination during evacuation. The quantity of vehicles is determined by their occupancy rate, as the user specifies. LifeSim model incorporates certain behavioural decisions of the population, such as the non-evacuation depth, which represents the decision to leave or remain in a structure based on a specific
160 water depth, and the willingness to enter flooded roads, indicating a driver's choice to traverse them. Pedestrian evacuation is also considered, based on a pre-defined fraction of the population evacuating by vehicle and on foot. A constant velocity is used for pedestrian evacuation and does not account for traffic density. If vehicles or individuals are overtaken by flooding during evacuation, stability criteria based on Smith et al. (2017) and Shand et al. (2011) are applied, respectively. If these criteria are exceeded, the affected population is allocated to the high-hazard flood zone; if not, they are allocated to the low-
165 hazard zone.

In the loss of life module, the high-hazard zone refers to situations where the likelihood of dying largely depends on chance, such as being swept downstream, trapped in a collapsing building, or submerged underwater. In contrast, the low-hazard zone denotes areas where risks exist but are minimal. Each zone is characterised by a probabilistic distribution based on historical cases. In each iteration of the probabilistic routine, a fatality rate is sampled for each specific agent from the hazard functions.
170 Then, a random uniform number between 0 and 1 is assigned to each individual. If this uniform number exceeds the sampled fatality rate, the individual survives.

The computation of risk is performed using Monte Carlo simulations, allowing various model parameters to be introduced with uncertainty, examining random and epistemic uncertainties. Consequently, the model's output concerning the quantification of loss of life is probabilistic (USACE, 2020).

175   Despite the challenges in acquiring data to understand event dynamics on an agent-based scale (Needham et al., 2016), validation efforts for Lifesim have successfully modelled several significant events. These include Hurricane Katrina in New Orleans, United States; the Kinugawa levee breach in Japan; the Malpasset Dam failure in France; the Kelly Barnes Dam failure in Georgia, United States; and the Oroville Dam spillway failure in California, United States (USACE, 2020).

The LifeSim routine involves the initial preprocessing of hydraulic data, road networks, and buildings. Hydraulic data is

180   processed to define the flood time series for each structure and road segment. This process uses the Ramer-Douglas-Peuker algorithm to reduce the number of data points in water depth and flow velocity hydrographs, optimising computational time and memory usage. For road networks, the fastest route between each node is pre-defined using Dijkstra algorithm (1959). In the event of traffic jams and flooding on roads, which could necessitate rerouting, the optimal path may change during the simulation. Hydraulic properties are determined at the midpoint of each road segment. Each building is associated with a road

185   segment, and the initial fastest path between the building and an associated safe location is calculated.

The model then simulates each iteration, representing a complete simulation of the warning and evacuation dynamics and their consequences. Iterations are associated with a seed number to ensure reproducibility of the sampling model. For each iteration, LifeSim samples uncertainty parameters such as the warning and evacuation module input times and curves, as well as attributes of people and structures. With the sampling set, the dynamic simulation proceeds, and at the end, the exposure for

190   each agent is determined. Individuals who were not sampled to receive a warning or take proactive action perform independent time vertical evacuations, relocating to the highest floor, attic, or roof of their building, depending on the sampled attributes of the building. Those who evacuate by car or on foot are subject to sampled evacuation parameters, including willingness to enter the flood and stability criteria. Once exposure conditions are defined, the fatality rate association routine is applied to determine the final condition of each individual. This process is repeated for each iteration, resulting in a probabilistic life loss

195   estimation.

2.2 Ahr Valley 2021 flood

Between July 12 and 19, a quasi-stationary atmospheric low-pressure system named "Bernd" brought extreme rainfall to several regions in Europe. The most impacted areas included the federal states of Rhineland-Palatinate (RLP) (Fig. 3a) and North Rhine-Westphalia (NRW) in western Germany as well as adjacent regions in Belgium, Luxembourg, and the

200   Netherlands. In Germany, saturated soil from May and June precipitation, which exceeded the average by 10–40%, coupled with an average of 127 mm of rainfall in 72 hours from 12 to 14 July in some catchments, resulted in up to 33 billion euros in damage and 191 fatalities. Specifically, the Ahr Valley (Fig. 3b) in RLP suffered with about 42,000 affected people and 8,800 damaged buildings, resulting in up to 20 billion euros in economic losses and 134 fatalities. The steep slopes of the Ahr Valley caused torrential flows and elevated water levels, with the flow at the Altenahr gauge, upstream of the most affected area (Fig.

205   3c), increasing from less than 10 m^3 s^{-1} up to 700–1200 m^3 s^{-1} within a few hours (DKKV, 2022; Kron et al., 2022; Szönyi et al., 2022). A reconstructed water level hydrograph showed a peak of 10.2 meters, significantly higher than the forecasted 5.74

meters, with the discrepancy attributed mainly to forecast uncertainties but also to the clogging of bridges downstream of the Altenahr gauge (Apel et al., 2022).
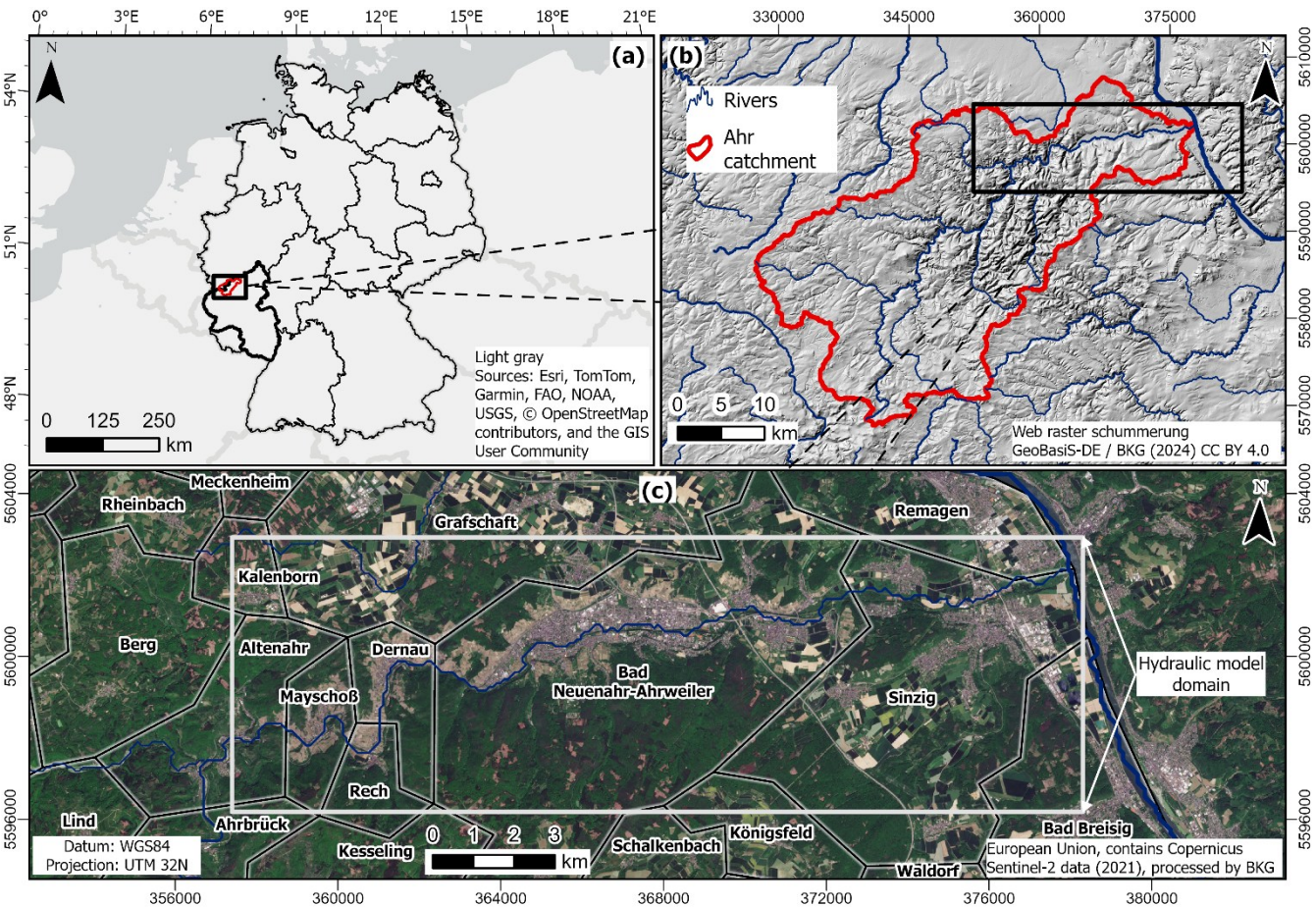
Figure 3: Overview of the Ahr Valley and its most impacted area by 2021 flood. (a) Germany Federal States, highlighting Rhineland-Palatinate and the location of the Ahr Valley catchment. (b) Ahr Valley catchment with drainage system and hillshade base map. (c) Satellite image and local administrative units of the downstream portion and most impacted area of the Ahr Valley, between the cities of Altenahr and Sinzig, at the confluence with the Rhine River. Data sources: Germany Federal states and local administrative units: GeoBasic DE / BKG (2023); Rivers and Ahr catchment: Global dataset of drainage systems (He et al., 2024).

2.2.1 Flood hazard modelling

The 2D raster model RIM2D (Apel et al., 2022; Ghomash et al., 2024; Vorogushyn et al., 2024) was used to simulate the 2021 flood event. This simulation updated the model set by Apel et al. (2022), refining the digital elevation model (DEM) resolution from 10 to 5 meters (Ghomash et al., 2024). This enhancement improves the accuracy of the results, reducing biases related to resolution impacts on flood characteristics and consequences (Brussee et al., 2021; Bryant et al., 2023). Finer resolutions (e.g.,

1 and 2 meters) were also tested but had a negligible impact on flood risk estimation, including the risk of loss of life (Ghomash et al., 2024). Based on these findings, the 5m resolution DEM was selected as the optimal balance between model accuracy and simulation efficiency.

The model domain encompassed the reach between the towns of Altenahr and Sinzig, about 30 kilometres, where the Ahr
225 River flows into the Rhine River (Fig. 3c). Land use classification was sourced from Mundialis 2020 (Riembauer et al., 2021), with Manning's roughness values as follows: sealed surface areas ($\eta = 0.02$, for simulating flow over tarmac or concrete in built-up areas), forest ($\eta = 0.2$), and other classes, including the river channel and floodplains ($\eta = 0.03$). The roughness values were calibrated using the Euclidean Distance objective function, considering flood extent, flood depth in floodplains, and flood dynamics within the river channel. Regions of the DEM overlaid by building footprints from the OpenStreetMap database
230 were excluded from the hydraulic routine to represent urban flow dynamics more accurately (Apel et al., 2022).

The reconstructed water level hydrograph at the Altenahr gauge, showing a maximum water depth of 10.2 meters, was used as the upstream boundary condition. A comparison between the maximum water depth layer (Fig. 4a) and 75 reported water depths revealed a bias of 0.46 meters and a root mean square error of 0.97 meters. To calculate this error metric, a 7.5 meter buffer was applied around the reported markers to gather information from adjacent pixels. The mean depth of inundated pixels
235 within this buffer was then considered. It is important to note that the reported water depths correspond to different vertical datums, including street level, pedestrian walkways, and doorsteps. The simulated flow velocities (Fig. 4b) are consistent with expectations for such a dynamic event, ranging from 2 to 5 m s^{-1} in the river course and 0.1 to 2 m s^{-1} in built-up areas (Apel et al., 2022). The maximum simulated water depth predominantly occurred between 12:00 a.m. and 4:00 a.m. CEST on July 15 (Fig. 4c).

240 LifeSim hydrodynamic module directly accepts input data from simulations conducted using hydraulic models such as HEC-RAS and FLO-2D. For the simulations executed using RIM2D output, the insertion of water depth and flow velocities data was performed through multiple layers, each representing different time intervals and containing parameter values. A 15-minute time series of water depth and flow velocities layers was used as input for the flood routine of the LifeSim model.
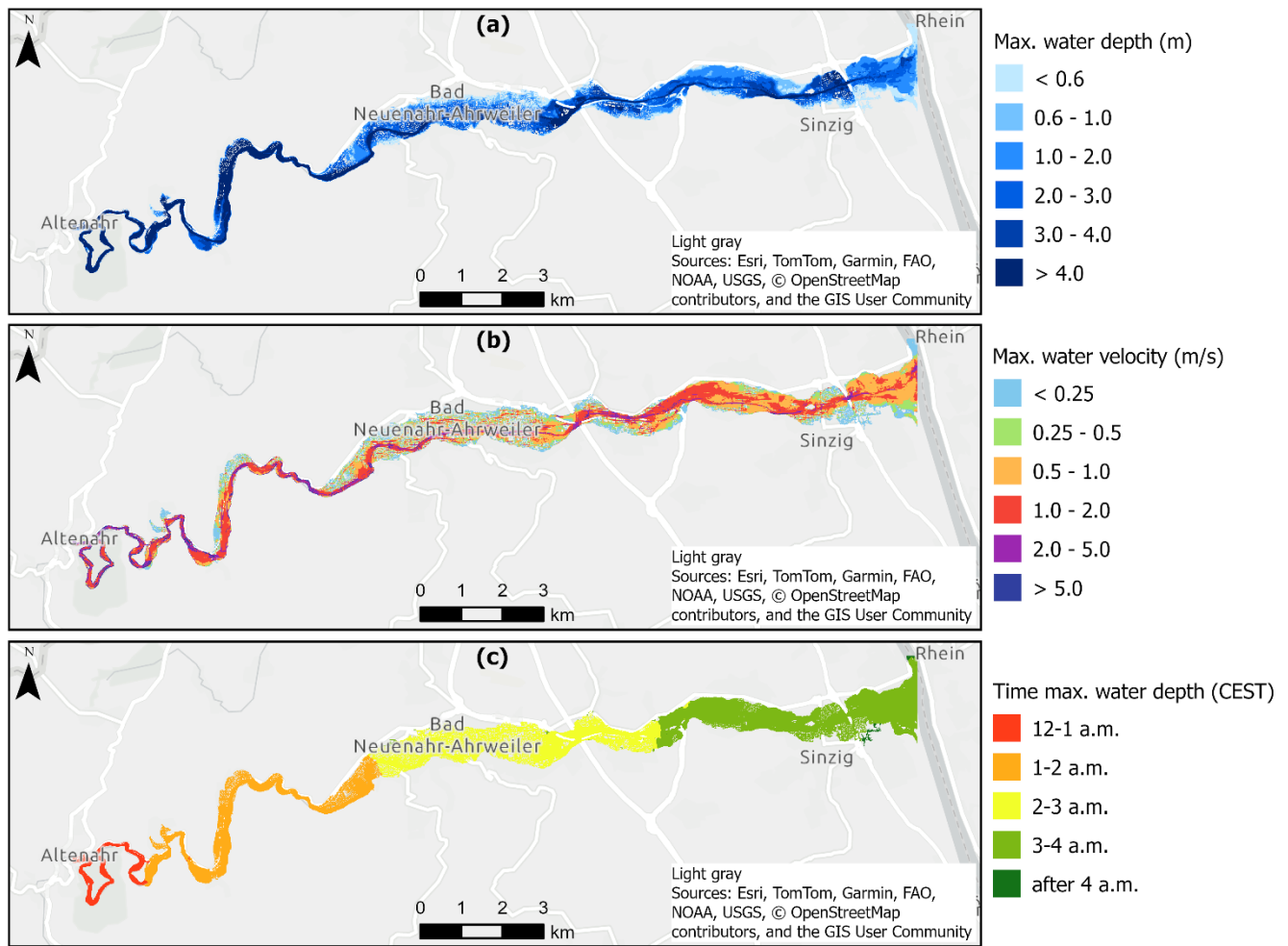
Figure 4: Flood characteristics of the 2021 Ahr Valley flood simulated with RIM2D at a resolution of five meters. (a) Maximum water depth. (b) Maximum flow velocities. (c) Time of maximum water depth on July 15.

2.2.2 Exposure at buildings scale

In order to apply the life loss model LifeSim, data for each building is required (e.g. number of floors, foundation height, and occupancy type). Similarly, data concerning the number of exposed people and their ages (e.g. more or less than 65 years old) is required. This detailed information was obtained using a combination of available data from OpenStreetMap, HANZE 2.0.3 (Historical Analysis of Natural HaZards in Europe) (Paprotny, 2023), the 2011 German census, and the Singh et al. (2024) survey results database consolidated after the 2021 event.

Population information was sourced from the 100 meter resolution grids of HANZE 2.0.3 for 2020 (Paprotny, 2023). The HANZE 2.0.3 population data at this resolution was derived from a disaggregation technique applied to the 1km resolution population data from the 2011 European GEOSTAT database. This disaggregation considered proportional distribution based

on identified man-made structures, such as buildings, impervious surfaces, roads, and streets. In order to model population growth, a rate of change was used at the Nomenclature of Territorial Units for Statistics (NUTS) 3 level (Paprotny and Mengel, 2023).

Building footprint polygons were obtained from the OpenStreetMap 2021 database, excluding buildings without human occupation potential, such as garages, parking facilities, and toilets. Since we only considered buildings to allocate the population, excluding other man-made structures, we noticed some grids with a 100 meter population resolution in HANZE 2.0.3 lacked buildings overlaying them. In order to address this issue, we first aggregated the 100 meter resolution population data to the 1km resolution. Then, we redistributed the to the 100 meter grid, weighted by the HANZE 2.0.3 population at this resolution, but only considering grids with the selected buildings. This approach ensured that there was no grid population without the selected buildings.

In order to allocate the population within the selected buildings, we performed a weighted distribution of the redistributed population from the 100 meter grid, using building size as the weighting factor. After allocating the population to the buildings, the building centroids were moved to the nearest pixel of the RIM2D simulation, as the hydraulic routing has cut out the building footprints (see section 2.2.1).

Age can significantly relate to flood fatalities mainly due to mobility issues (Vinet et al., 2012). In the LifeSim routine, age influences the probability of mobility issues and the corresponding submergence threshold criteria. In order to incorporate this information, age demographics from the 2011 German census, provided at a 1 km grid resolution, were used to classify the population in the Ahr Valley region. On average, 24.2% of the population within the selected grids is over 65 years old.

Some crucial building characteristics for the LifeSim model (e.g. number of floors, foundation height and possibility of accessing the attic) were unavailable in the HANZE 2.0.3 and the 2011 German census databases. Consequently, data was supplemented by a post-event survey of flood affected residents (Singh et al., 2024). The survey data contains 277 responses from residents of Rhineland-Palatinate state. The number of floors was determined based on the proportion of survey responses, assuming that buildings with higher population densities are more likely to have more floors. For example, 0.4 % of responses indicated that a building had seven floors, the maximum reported. Therefore, the 0.4 % of buildings with the highest population density were assigned seven floors. Foundation height, defined as the elevation difference between the street and the ground floor, was estimated using responses that provided information on floodwater reaching the ground floor. By comparing estimated water levels inside and outside buildings, an average foundation height of 0.57 meters was determined and applied to all buildings. Additionally, it was estimated that 36.5% of buildings have attic access.

Building stability criteria was the defined as 'engineered' according to LifeSim, based on the considerations outlined by Clausen and Clark (1990). For this specific criteria, two curves are considered based on the product of water depth and flow velocity, with a uniform range of uncertainty: the lower curve threshold is set at 7 $m^2\ s^{-1}$, representing traditional and smaller constructions, and the upper curve threshold at 10 $m^2\ s^{-1}$, representing high-quality constructions. In the LifeSim routine, a building collapses if the thresholds of the sampled curve are reached and the flow velocities exceed 2 $m\ s^{-1}$.

Road networks were imported directly from OpenStreetMap, and safe evacuation places were located outside the inundation zones to simulate the dynamics of an actual evacuation event. Figure 5 illustrates the population distribution within buildings at a 100 meter resolution, along with road networks and designated safe places. Buildings within the grids that intersected the 100 meter buffer zone of the inundated boundary were utilised for LifeSim simulations. A total of 10,461 buildings were included, housing 24,076 individuals under 65 years old and 9,467 individuals aged 65 and over.
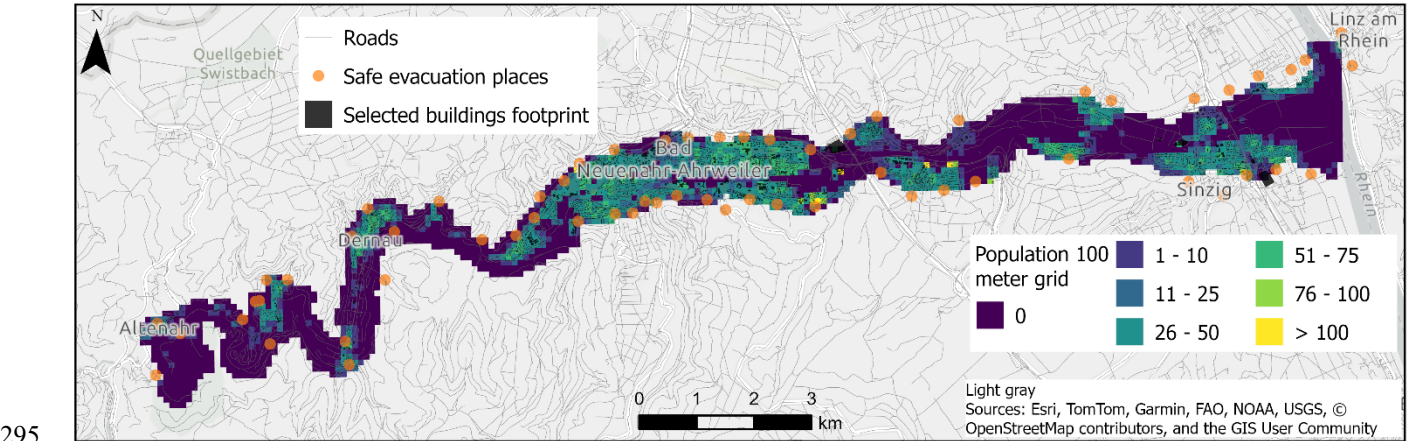
Figure 5: Overview of exposure at building scale. Population counts aggregated at a 100 meter grid resolution, buildings and road network along the Ahr Valley, simulated flood extent, and safe places. Data sources: 100 meter grid: HANZE 2.0.3 (Paprotny, 2023). Roads and buildings: © OpenStreetMap contributors 2021. Distributed under the Open Data Commons Open Database License (ODbL) v1.0.

2.2.3 Early warning and evacuation

In Germany, the National German Weather Service (DWD) is responsible for issuing warnings related to extreme weather events, whereas the federal states legally mandate flood warnings (Kron et al., 2022). Regarding the 2021 flood event, the DWD issued the initial weather warning on July 12 at noon CEST. The first flood warning for the Ahr River and its tributaries was released on July 14, just before noon CEST, reaching approximately 22,000 people. This warning alerted residents to a rapid water level rise and potential flooding within the next 24 hours. Numerous additional weather and flood warnings were disseminated throughout July 14. For instance, at 11 p.m. CEST, a warning was issued to Sinzig, Bad Neuenahr-Ahrweiler and adjacent places residents living within 50 meters of the Ahr River to evacuate their buildings. This significantly underestimated the hazard, as fatalities were later reported in buildings located up to 250 meters from the river. Despite the numerous warnings, the effectiveness of the alert system was severely compromised by miscommunications along the warning chain and a general lack of confidence in the unprecedented severity of the flood (Szönyi et al., 2022).

The information provided by the survey conducted by Singh et al. (2024) about the Ahr Valley's warning and evacuation procedures was used for the description of the timeline in LifeSim (Fig. 2). As the survey had a unit geographic scale of federal

state and the flood occurred at different areas and times between 12 and 19 July 2021 in the states, we applied a filter to use only responses from Rhineland-Palatinate (RLP) state individuals affected during the same time window as the high water

315   levels in the simulated domain. Out of 277 responses from the RLP state, 246 were considered. These respondents reported the occurrence of hazards at their homes between 3 p.m. CEST on July 14 and 9 a.m. CEST on July 15. The first flood warning, adopted for this study, was reported at noon CEST on July 14, representing a notification issued 13 hours before the water level peaked at the Alterahr gauge at 1 a.m. CEST on July 15. As a result, the warning issuance delay in the LifeSim timeline was excluded from the analysis since it occurred before this milestone and would not affect the simulations.

320   To depict the diffusion of this first warning in the context of the LifeSim routine, we considered the reported lead times from individuals who noted that the warning they received was either a call for evacuation or contained information pertinent to evacuation. The reported time of hazard occurrence at the buildings was subtracted by the lead time to establish the first warning time for each individual. In instances where no lead time was reported, or the warning lacked evacuation instructions, individuals were assumed to be warned at the moment of their reported hazard occurrence at their building. Notably, 57.0 %

325   of those affected by the main event reported receiving a warning. However, only 17.5 % received a warning that included explicit evacuation instructions. Some reported no lead time among those who received evacuation instructions, resulting in only 13.8 % of the surveyed people receiving an explicit evacuation warning before the flood reached them.

Figure 6a illustrates the warning diffusion process based on these assumptions and analyses. Given that the hazard occurrence question was framed in hourly ranges, the curves depict these ranges, which were inserted as a uniform distribution in the

330   model. Additionally, the reported lead times were aligned with the first warning issued by the federal state at noon CEST on July 14. Most individuals were warned or became aware from the night of July 14 and the early morning of July 15, correlating with the most frequently surveyed times of hazard occurrence.

Regarding the mobilisation time, we considered the reported time it took individuals to take protective action after receiving the warning or becoming aware of the hazard. In the survey, the protective actions included several mitigation measures and

335   were not solely focused on evacuation. In order to represent the evacuation dynamics of the event, we considered only responses from individuals who left their homes before or during the flood, as well as those who were rescued. Approximately 34 % of the surveyed population left their homes or were rescued, with 6.9 % taking immediate action, 5.3 % reporting a delay in mobilisation, and 22.0 % not specifying when they began protective measures. In order to account for the uncertainty among the 22.0% who did not report a response time, we applied a uniform uncertainty range (Fig. 6b). This range included an upper

340   curve representing the fastest mobilisation, assuming immediate action for this group, and a lower curve representing the slowest mobilisation, considering six hours (the maximum reported delay).

Regarding the evacuation dynamics, the mean family size on the NUTS 3 scale was used to estimate buildings where all residents were warned and mobilised simultaneously. Specifically, buildings housing more than three people were identified, as it was assumed that in such cases, the warning and mobilisation of the population do not occur simultaneously. This criterion

345   was also used to define the size of the evacuating group.

The evacuation mode fraction, whether by vehicle or on foot, is a user-defined input in LifeSim. In order to determine this fraction and represent the evacuation dynamics during the 2021 flood event, we conducted multiple runs, adjusting the evacuation mode by 10 % in each run. The fraction that produced the closest match to the observed ratio of fatalities occurring indoors versus during evacuation was selected. Specifically, 68.5 % of the fatalities occurred indoors or possibly more, given the uncertainty regarding victims discovered outside (Rhein and Kreibich, 2025). We found that an evacuation mode fraction of 80 % by vehicle and 20 % on foot most closely matched the indoor fatality ratio, with 69.3 %. Consequently, this fraction was chosen to represent the reconstruction scenario (see Fig. S1 and Table S1 in the supplementary material section 1).
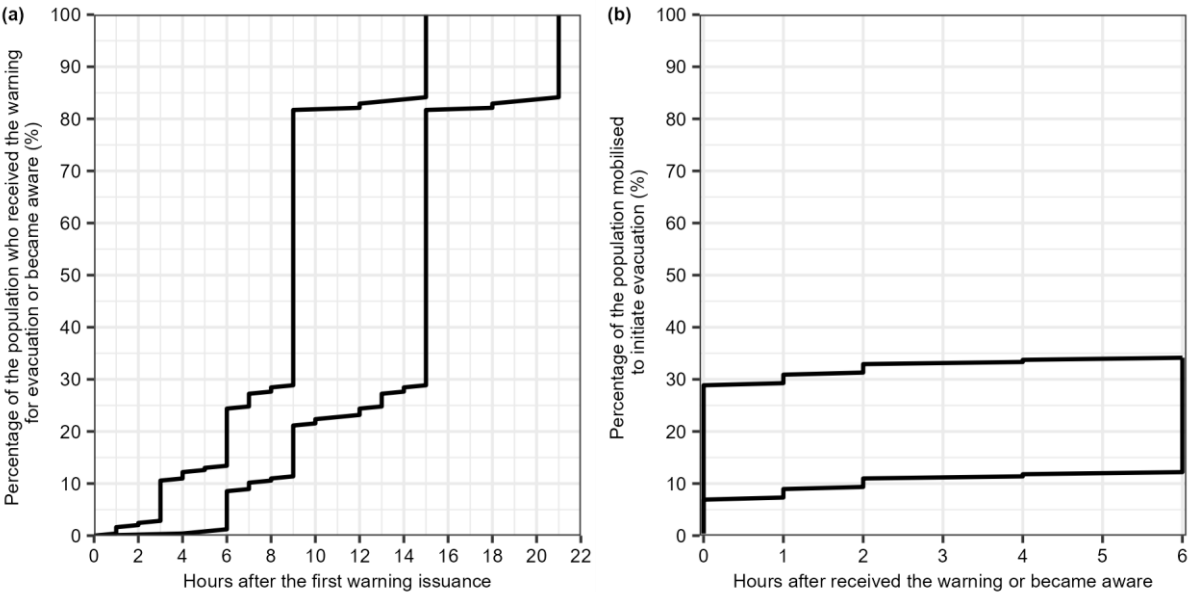
Figure 6: Reconstruction of warning diffusion and mobilisation times in the Ahr Valley 2021 flood based on the post-event survey with flood affected residents. (a) Warning diffusion curves: cumulative proportion of the population who were warned or became aware of the hazard after the first flood warning. (b) Mobilisation curves: cumulative proportion of the population who initiated an outdoor evacuation after receiving or becoming aware of the hazard.

2.2.4 Alternative scenarios of early warning and evacuation

The simulation of alternative warning and evacuation scenarios can illustrate the impact of warning procedures on loss of life (Lumbroso et al., 2021; Lumbroso and Davison, 2018; Silva and Eleutério, 2023a, b; Wang et al., 2024). For the 2021 Ahr Valley flood, we develop and assess alternative scenarios using two approaches. First, we propose scenarios that alter the warning diffusion and mobilisation curves, drawing on historical cases referenced in the LifeSim recommendations. This approach aimed to represent how different strategies of warning dissemination, as well as varying levels of public perception and preparedness, could impact the number of fatalities without changing the time of first warning issuance. Secondly, we

analysed the effect of the timing of the first flooding warning, taking into account the water depth forecasting capabilities for the region.

In order to check the effects of warning diffusion and mobilisation curves, we defined three distinct scenarios, each with its own unique characteristics and implications. The optimal scenario (A1.1) represents a highly effective warning system, employing multiple channels for fast and extensive alert dissemination, with frequent repetition and a well-prepared, trained population. The intermediate scenario (A1.2) features a moderately effective warning system, with a mix of technologies and a population with some awareness of the risks. However, deficiencies in emergency planning affect the likelihood of a high mobilisation rate in a short time. The suboptimal scenario (A1.3) involves a warning system that is less effective, with limited technologies and infrequent warning issuances, hindering fast dissemination. In this scenario, most of the population is unlikely to perceive the threat, and their response is largely improvised. The curves used in these scenarios were proposed by Sorensen and Mileti (2015b, c). The supplementary material (see supplementary material section 2) provides a detailed description of the equations and their coefficients, as proposed by these authors.

The proposed warning diffusion curves, categorised as 'fast', 'moderate', and 'slow' for daytime scenarios, were utilised in this study. These curves incorporate uncertainty modelled through a triangular distribution. The range extends from the upper bound of the "fast" curve, reflecting rapid dissemination similar to the observed in the 1980 eruption-induced mudflow of the Toutle River, Washington, in the USA, to the lower bound of the "slow" curve, which aligns with the behaviour seen in the 1987 Nanticoke chemical accident, Pennsylvania, in the USA (Sorensen and Mileti, 2015b).

Additionally, the proposed mobilisation curves for "preparedness good and perception likely", "preparedness poor and perception likely," and "preparedness poor and perception unlikely" were employed. These curves also utilise a triangular distribution. The uncertainty bounds are derived from the fastest response case of the Confluence (USA) hazardous material flow in 1987, which defined the upper bound for "preparedness good and perception likely," and the slowest case in the database, which corresponded to a similar event in Pittsburgh (USA) in the same year, defining the lower bound for "preparedness poor and perception unlikely". Furthermore, Equation S2 is supplemented by maximum mobilisation rates over different time periods, specifically up to 8, 24, and 74 hours. The two slower response curves have the same coefficients, but different maximum mobilisation rates. These rates represent the maximum population likely to take protective action, with higher mobilisation rates anticipated for longer durations and more optimal scenarios of perception and preparedness (Sorensen and Mileti, 2015c).

Two additional scenarios were evaluated by integrating the theoretically proposed and empirical curves (Fig. 6) for the 2021 flood. These scenarios represent a suboptimal warning system, contextualised within empirical curves for warning diffusion (A1.4) and mobilisation (A1.5). This approach enables the analysis of the impact of each delay in the occurred warning timeline process. The suboptimal curves are employed in these scenarios to reflect the realism of the 2021 event characterised by a deficient warning system. Figure 7 illustrates the combination of the diffusion and mobilisation process curves for each scenario, including the reconstruction scenario designated as reconstructed flood early warning and evacuation (RFEWE). Table S2 presents the utilised curves, their respective coefficients, and mobilisation rates for each scenario.

400 The reconstruction scenario exhibits a more significant delay and lower mobilisation rates in protective action following the first warning issuance than the two worst alternative scenarios, A1.4 and A1.5. Most individuals became aware of the hazard only at the time of its occurrence, despite receiving the first warning 13 hours before the peak of the flood, and the low rate of mobilisation were specific characteristics of this event that were not observed in the other events used in the curves proposed in LifeSim. Hence, an even more extreme alternative scenario (A1.6), theoretically worse than the reconstruction, was assessed

405 by simulating only vertical evacuation, excluding any outside evacuation.
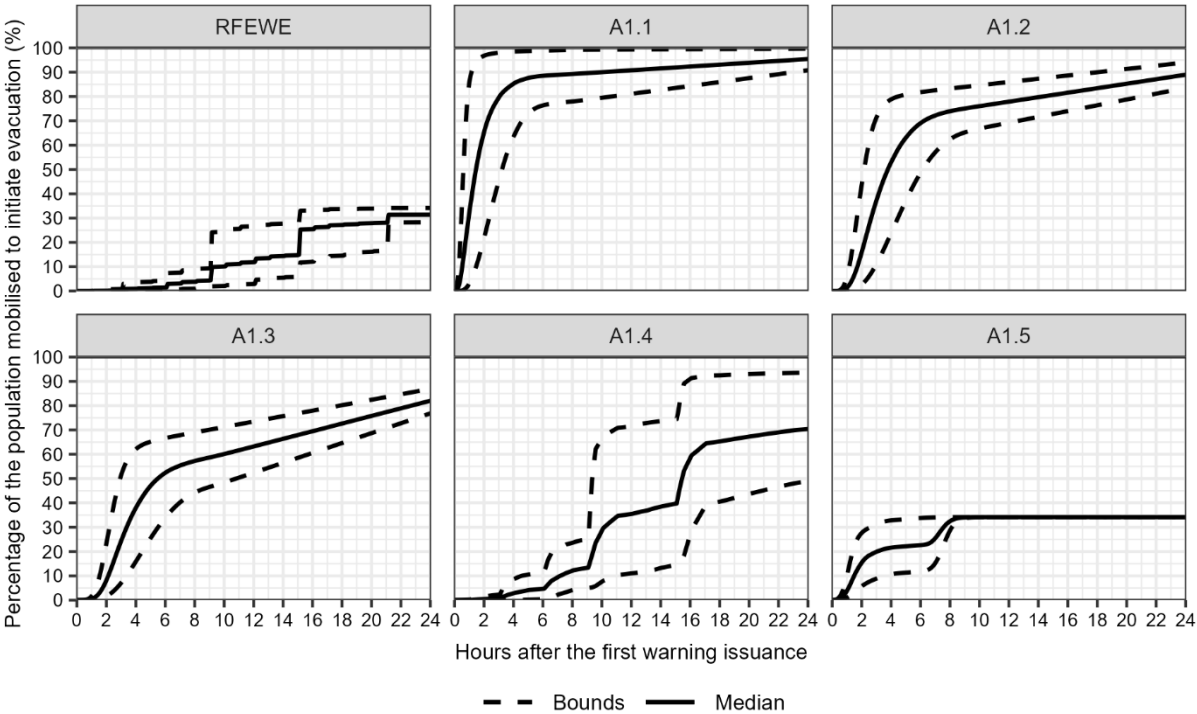
Figure 7: Combination of the warning diffusion and mobilisation curves for each alternative scenario of early warning and evacuation in the first approach. RFEWE (reconstructed scenario of the 2021 flood), A1.1 (optimal scenario), A1.2 (intermediate
410 **scenario), A1.3 (suboptimal scenario), A1.4 (suboptimal with empirical warning diffusion curve), and A1.5 (suboptimal with empirical mobilisation curve).**

In order to assess the timing of the first warning, we employed a uniform distribution to represent the range of possible and reliable times for the first flood warning during the 2021 event. Forecasting techniques indicate that it would be possible to anticipate, with a 75 % probability, that the water level at the Altenahr gauge would exceed the four meter threshold,
415 corresponding to a 100 year event, 17 hours before the peak. This probability would increase to 100% from eight hours before the peak (Najafi et al., 2024). Thus, the potential times for issuing the first warning were considered to fall within a nine hour window, between 8 a.m. and 5 p.m. CEST on July 14. In this second approach, potential desired times for early warnings that

significantly impacted the estimations could be identified (Silva and Eleutério, 2023b). Additionally, the identification of early warnings that could result in traffic jams and, consequently, more people being caught by the flood during evacuation could be comprehensive (El Bilali et al., 2021).

When combined with the second approach of analysing different timings for the first warning issuance, the reconstructed empirical warning dissemination (Fig. 6a) does not represent a realistic scenario. Most surveyed people did not receive an evacuation warning; hence, most of the points on the curve were based on the time of reported hazard occurrence at the surveyed buildings. Using this empirical curve for early warnings issued later than 13 hours before the peak at the Altenahr gauge would suggest that most people would be warned only after the hazard had occurred. Conversely, issuing warnings earlier than 13 hours before the peak does not align with the dissemination dynamics observed in 2021. Therefore, for warning diffusion and mobilisation delays in the second approach of alternative scenarios, we employed the optimal and suboptimal scenario curves proposed in the first part. This allows for examining the influence of varying warning issuance times on estimating loss of life. Additionally, we included a scenario using the slow theoretical warning dissemination and the empirical mobilisation. Table 1 summarises the alternative scenarios and their respective warning and evacuation parameterisation considerations. The scenarios for the second approach are designated as A2.1 for the optimal scenario, A2.2 for the suboptimal scenario, and A2.3 for the suboptimal scenario with the empirical mobilisation curve.

Table 1: Overview of all alternative scenarios for early warning and evacuation, considering the timing of the first flood warning issuance, warning diffusion, and mobilisation curves. A1: First approach, analysing warning diffusion and evacuation curves alongside the actual timing of the first flood warning. A2: Second approach, focusing on the time window for the first warning issuance based on forecasting capabilities. Numbers in brackets indicate the time window for issuing the first flood warning.

Alternative scenario	Time for issuing the first flood warning before peak at Altenahr gauge (h)	Warning diffusion	Mobilisation (preparedness/perception)
A1.1	13	Fast	Good/likely
A1.2	13	Moderate	Poor/likely
A1.3	13	Slow	Poor/unlikely
A1.4	13	Empirical	Poor/unlikely
A1.5	13	Slow	Empirical
A1.6	13	No outside evacuation	
A2.1	$U{\sim}(8,17)$	Fast	Good/likely
A2.2	$U{\sim}(8,17)$	Slow	Poor/unlikely
A2.3	$U{\sim}(8,17)$	Slow	Empirical

2.2.5 Parametrisation and key considerations for using the LifeSim model

The LifeSim version 2.1.3 (USACE, 2023) was employed to assess fatalities resulting from the 2021 Ahr Valley flood. A total
440 of 2,000 iterations was sufficient to achieve convergence of the quantiles, standard deviation, and skewness for the probabilistic
outcomes in scenarios with a deterministic first warning issuance time (see Fig. S2 in the supplementary material section 3).
For scenarios with a variable time range for first warning issuance, 18,000 iterations were conducted, representing
approximately 2,000 iterations for each hourly range. Statistical tests, including those developed by Dunn (1964), Kruskal and
Wallis (1952) and Mann and Whitney (1947), were performed to compare the differences in estimated fatalities across various
445 scenarios. Table 2 provides an overview of the considerations within each LifeSim module used in the analysis.

Table 2: Summary of LifeSim module inputs and parameters for life loss simulations in the 2021 Ahr Valley flood.

Module	Input/parameter	Description
Flood routine	Hydraulic data	RIM2D flood model of Apel et al. (2022) updated to a resolution of 5 meters.
Loss of shelter	Buildings	Selection of 2021 OpenStreetMap buildings footprint and their characteristics from post-event survey (Singh et al., 2024).
	Population	Number of people by HANZE 2.0.3 for 2020 (Paprotny, 2023) and age proportion from the 2011 German Census.
	Building stability	Thresholds for engineered constructions as proposed by USACE (2020) based on Clausen and Clark (1990).
	People submergence	Water depth thresholds for the highest reachable floor of the buildings, considering age to the defined proportion of people with some mobility issue.
Warning and evacuation	First flooding warning	Reconstruction: At noon CEST on July 14 (Szönyi et al., 2022). Alternative scenarios: $U \sim (8,17)$ hours before peak water depth at the Altenahr gauge.
	Warning diffusion delay	Reconstruction: Post-event survey answers on warning information, lead time and hazard occurrence. Defined as the uniform distribution between two curves as the reported hazard occurrence time answers are defined by a range of hours. Alternative scenarios: Theorical scenarios based on Sorensen and Mileti (2015b).
	Mobilisation delay	Reconstruction: Post-event survey answers on evacuation, rescue, and time to start protective measures. Alternative scenarios: Theorical scenarios based on Sorensen and Mileti (2015c).
	Road network	OpenStreetMap.
	Safe evacuation places	Set outside the simulated flood extent along the Ahr River.
	Evacuation route	Optimal path defined by Dijkstra (1959) algorithm.
	Evacuation delay	Vehicle speed defined by OpenStreetMap road classification and modified Greenshields traffic flow model (Mahmassani et al., 2009). Constant speed of 6.44 km h⁻¹ for pedestrians.
	Exposure to caught people	Stability criteria defined by USACE (2020) and based on Smith et al. (2017) for vehicles and Shand et al. (2011) for people.
	Evacuation parameters	80 % evacuation by vehicles and 20 % on foot. People warned and started evacuation simultaneously in buildings with fewer than four people, based on the mean family size from the 2011 German Census.

Loss of life	Fatality rates	Probability distributions for two hazard zones defined by USACE (2020) based on historical cases.

The modelling domain excluded 15 victims from the upstream cities of Ahrbrück, Dümpelfeld, Müsch, and Dorsel. Among the reported fatalities within the domain, one was associated with a pre-impact case where an individual died of a heart attack due to exhaustion, and another was a post-impact case where an individual was caught in a collapsing building and subsequently died in a hospital (Rhein and Kreibich, 2025).

Thus, for the comparative analysis, we excluded the 15 victims from upstream cities and the pre-impact fatalities. The remaining post-impact fatalities, which could be directly attributed to the flood, were included. This adjustment resulted in a comparison value of 118 victims for evaluating life loss estimations. The comparisons between the estimated and reported fatality locations were limited to indoor cases due to uncertainties regarding the actual accident locations of victims found outside buildings.

3 Results and discussion

3.1 Life loss estimation of the Ahr Valley flood in 2021

The LifeSim median estimate for the number of fatalities is 152, which is 28.8 % higher than the actual total of 118. The simulation uncertainties span from 140 to 162 fatalities, corresponding to the first and third quartiles, respectively. The extreme range, defined by the minimum and maximum estimated values, spans from 99 to 202 fatalities, resulting in a range of 103 fatalities. A median of fatalities inside the buildings is 69.3 % of the total estimation, aligning with the reported 68.5 % (Rhein and Kreibich, 2025).

One reason for the variability in estimations is the sampling of the warning diffusion and mobilisation curve. Figure 8 illustrates this influence, showing points near 0.00 meaning iterations where the population is warned or starts the evacuation more slowly (similar to the right curves in Fig. 6), while points nearing 1.00 depict faster responses (similar to the left curves in Fig. 6). In general, the warning diffusion has a similar correlation with the estimated fatalities compared to the mobilisation (R = -0.29 and R = -0.31, respectively) and this can be observed by analysing the central tendency of the fatalities in different regions of the sampling curves. The same estimated fatalities values for warning diffusion and mobilisation levels occur due to the influence of other probabilistic parameters in the model, such as submergence thresholds and stability criteria.

For the warning diffusion, iterations with the sampling curve in the upper quarter (0.75 to 1.00), corresponding to most of the population being warned between 9 hours and 10 hours 30 minutes after the first warning issuance (Fig. 6a), result in a median estimate of 145 fatalities. In contrast, iterations with sampling curves in the lower quarter (0.00 to 0.25), where most of the population becomes aware between 13 hours 30 minutes and 15 hours after the first warning issuance, result in a median estimate of 157 fatalities (Fig. 8a). Regarding mobilisation, the upper quarter, representing immediate action by 23.4 % to 28.9 % of the population (Fig. 6b), has a median of 143 fatalities. Conversely, the lower quarter, representing immediate action by

6.9 % to 12.4 % of the population, yields a median of 158 fatalities (Fig. 8b). Furthermore, a joint analysis of warning diffusion and mobilisation underscores the general influence of these input uncertainties. Iterations with sampling curves exclusively in the upper quarter yield a median of 135 fatalities, indicating an overestimation reduction to 14.4 % of the estimated fatalities compared to the actual value of 118 (Fig. 8c).
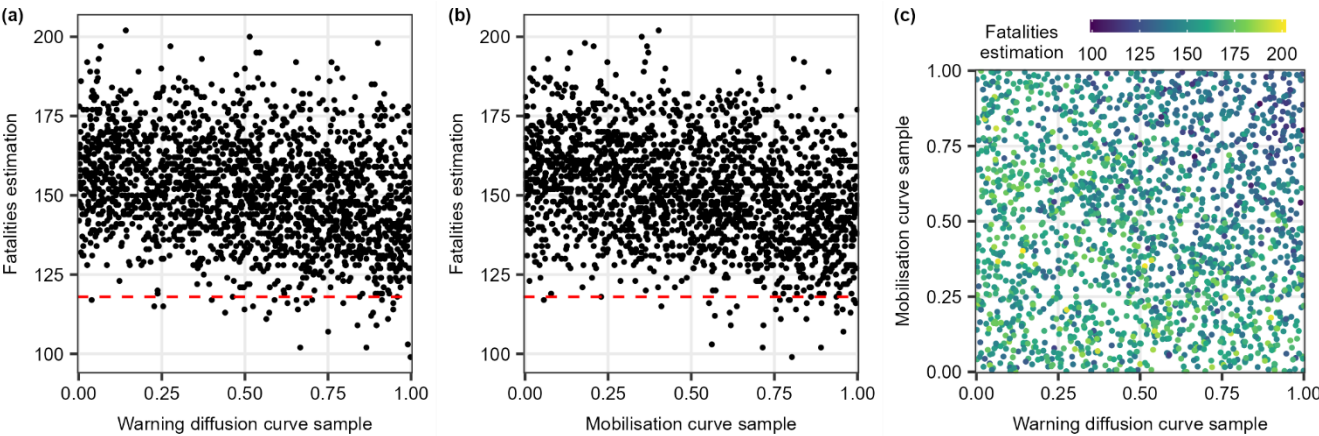
Figure 8: Relation between estimated fatalities and (a) warning diffusion, (b) mobilisation, (c) both processes curve samples for the 2021 Ahr Valley flood. Points near 0.00 indicate slower warning dissemination and initiation of evacuation, while points near 1.00 indicate a faster response.

The reported indoor fatalities were 48 (59 %), 15 (19 %), 10 (12 %), 6 (7 %), and 2 (3 %) for the Local Administrative Units (LAUs) of Bad Neuenahr-Ahrweiler, Sinzig, Dernau, Altenahr and Mayschoss, respectively (Rhein and Kreibich, 2025). The mean of the simulations is 59 (57 %), 0 (0 %), 16 (15 %), 11 (11 %), and 15 (14 %) for the same places, with 3 (3 %) more fatalities in Rech. For Bad Neuenahr-Ahrweiler, the model represents the proportion of fatalities. However, it overestimates fatalities for upstream LAUs and underestimates them for Sinzig. This discrepancy may be attributed to the generalisation of the warning and evacuation procedures across the entire modelling domain. During the simulation, the cumulative sampling of the population warned and mobilised is randomly distributed among the buildings within this domain. This likely results in some people being warned later than in the actual event in upstream regions and earlier than in the actual event in downstream regions, thus failing to represent the actual spatial and temporal distribution of the population that began evacuation. Figure 9 depicts the spatial distribution of the mean estimated fatalities, aggregated at a 500 meter grid resolution.
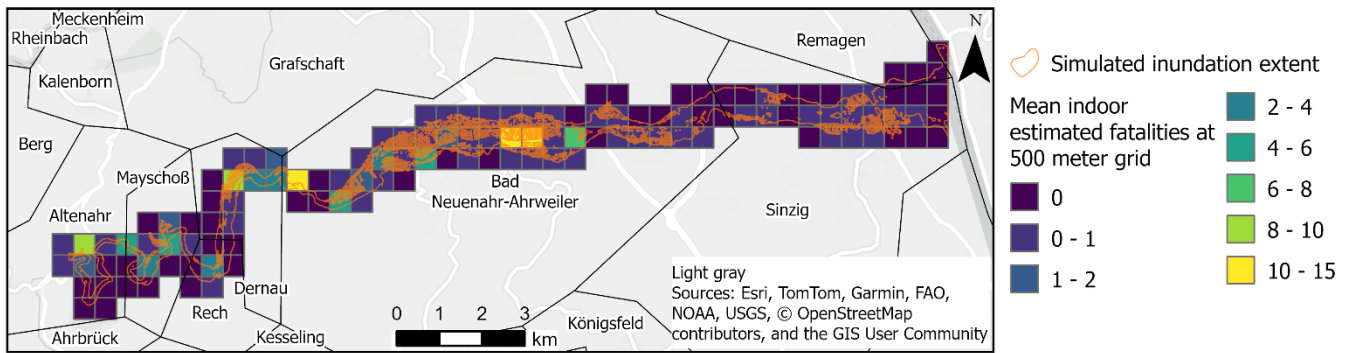
Figure 9: Mean of indoor estimated fatalities for the 2021 Ahr Valley flood at a 500 meter grid resolution. Data source: Germany local administrative units: GeoBasic DE / BKG (2023); 500 meter grid resolution: GeoGitter GeoBasis-DE / BKG (2020).

3.2 Life loss estimation of alternative scenarios with improved early warning and evacuation

The reconstructed warning and mobilisation curves indicate a greater delay compared to the alternative scenarios (Fig. 7). Despite the rapid-onset nature of the flood, the reconstructed warning diffusion curve exhibits a trend similar to that of a slow-onset event. Approximately 80 % of the population is warned between 9 and 15 hours after the first alert (Fig. 6a), mirroring patterns observed in slow-onset hazard events such as Hurricanes Katrina (2005) and Rita (2005), and the Boston water contamination (2010) (Lindell et al., 2021). In contrast, in the recommendations curves in LifeSim, which are based on historical cases, the warning diffusion times range from 15 minutes for the fastest to 3 hours for slower ones for the same rate (USACE, 2020). For the mobilisation time, the only comparable event in the LifeSim database is the 1987 Pittsburgh (USA) hazardous material flow, the worst case of protective action times, where about 40 % of the population took protective action approximately 5 hours after becoming aware of the hazard (USACE, 2020).

Figure 10 illustrates outcomes from the Lifesim model concerning the initial approach to evaluating alternative scenarios, specifically examining the impacts of warning diffusion and mobilisation curves. The optimal (A1.2), intermediate (A1.2), and suboptimal (A1.3) scenarios show significantly lower reductions in life loss (p < 0.001), indicating that the actual scenario (RFEWE) fares worse than theoretical scenarios. Simulation uncertainties range from 22 to 39, 54 to 74, and 85 to 111 fatalities, representing the interquartile range across these scenarios. Among these scenarios, the A1.3, with a median of 98 fatalities, is the closest to approximate compared to RFEWE. However, the distribution of fatalities within buildings and during evacuation does not mirror the actual event, where 68.5 % of fatalities occurred indoors.

The most critical scenario in terms of estimated fatalities, A1.4, incorporates empirical warning dissemination and a poor preparedness/unlikely perception mobilisation curve. While fatalities within buildings are comparable to RFEWE (86–103 versus 98–112 for the interquartile range), fatalities during evacuation are significantly higher, ranging from 83 to 105, more than double the values of 39 to 54 for RFEWE. Since most individuals became aware shortly before the hazard occurred with empirical warning diffusion, an optimal mobilisation strategy could potentially worsen the situation by increasing the number of people outside buildings when the flood reaches them.

Scenario A1.5 employs a slower theoretical warning diffusion curve in conjunction with empirical mobilisation, highlighting

525   the deficiencies in warning dissemination observed during the 2021 flood. The worst theoretical dissemination curve reduces the interquartile estimated fatality range of 78 to 95. This reduction is primarily due to a higher rate of the population initiating evacuation promptly after the first warning compared to scenarios RFEWE and A1.4. As shown in Fig. 7, approximately 34 % of the population mobilises within 8 hours when considering all possible samplings in the warning and evacuation simulation.

530   Scenario A1.6 examines a strategy where the population moves to the highest building floors instead of evacuating outside. This approach has an interquartile estimated fatalities range of 111 to 133 for the first and third quartiles, exclusively indoors. The findings suggest that for individuals who receive a warning or become aware of the hazard shortly before its occurrence, seeking safety within their buildings is more advantageous than attempting an outside evacuation.

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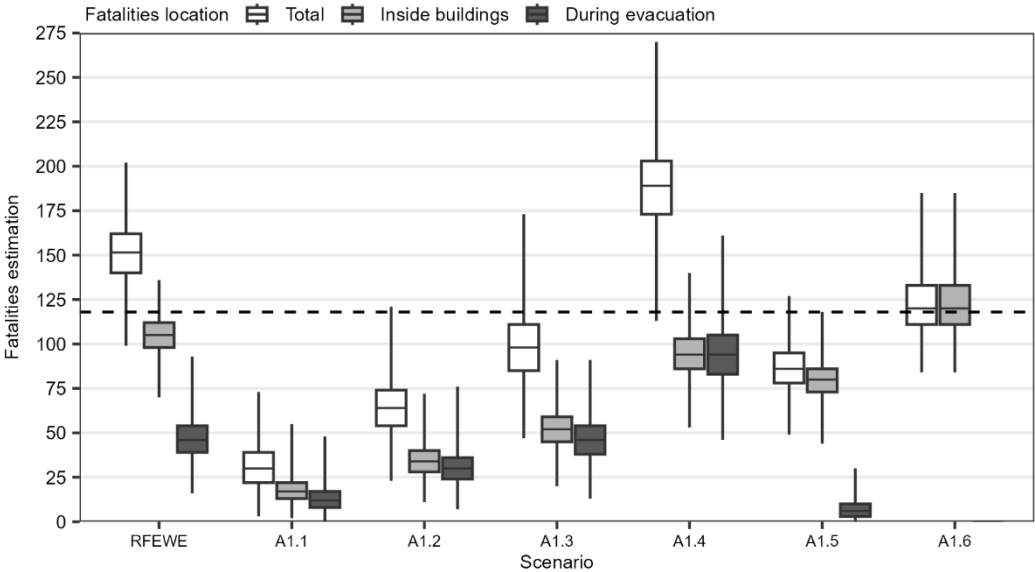


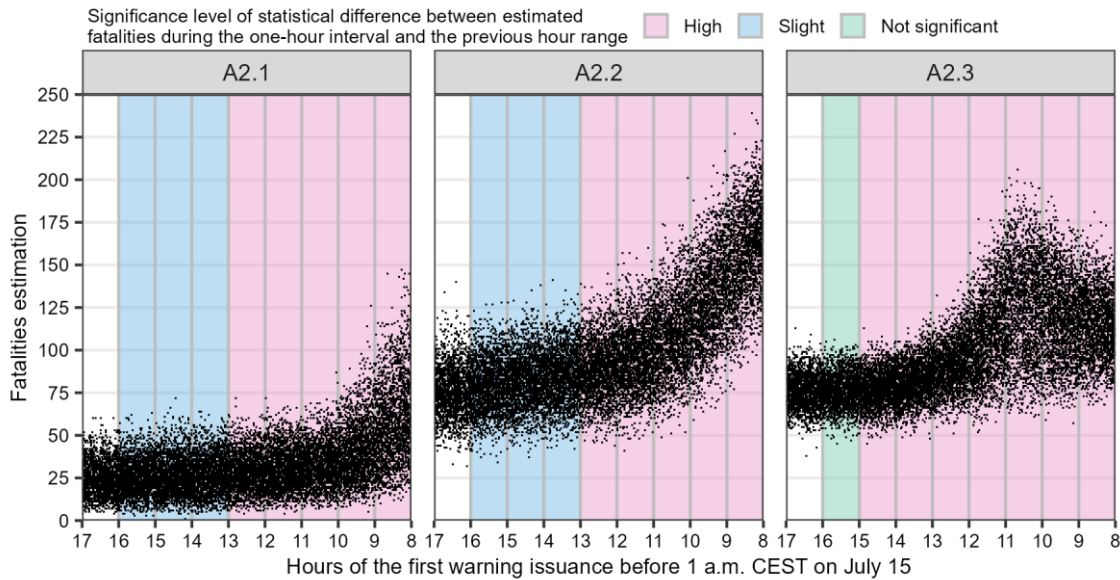
Figure 10: Estimated fatalities for the alternative early warning and evacuation scenarios focus on evaluating the warning diffusion and mobilisation curves. RFEWE (reconstructed scenario of the 2021 flood), A1.1 (optimal scenario), A1.2 (intermediate scenario), A1.3 (suboptimal scenario), A1.4 (suboptimal with empirical warning diffusion curve), A1.5 (suboptimal with empirical mobilisation curve), and A1.6 (without outside evacuation).

540   Figure 11 presents estimations of potential loss of life relative to the time preceding the water level peak at the Alteranhr gauge, which occurred at 1 a.m. CEST on July 15, marking the issuance of the first flood warning based on forecasting capabilities. The colours indicate the statistical significance level of differences in estimated fatalities, aggregated by hour, between hourly intervals and their anticipated hour range. Concurrently, at the same warning issuance time, uncertainties within the LifeSim

approach, such as the warning diffusion and mobilisation curves, probabilistic fatality rates and structural stability criteria for buildings, vehicles, and individuals, may contribute to variations in the estimated fatalities range.

In scenario A2.1, characterised by optimal warning diffusion and mobilisation, the interquartile range of fatalities decreases from 40–74 to 18–32 during the 8–9 hour and 16–17 hour intervals before 1 a.m. CEST on 15 July. The analysis identifies a slight statistically significant difference ($0.01 < p < 0.05$) between the 13–14 hour and 14–15 hour intervals, with the interquartile range of 19–35 fatalities. This is followed by two other slightly significant differences between the earlier intervals. These findings suggest that issuing a warning at least 13 hours in advance is likely optimal for reducing fatalities. However, issuing warnings as early as possible appears crucial for effectiveness, as a non-significant level of statistical difference ($p > 0.05$) is not observed in the comparisons between the hour ranges.

In scenario A2.2, characterised by suboptimal warning diffusion and mobilisation, fatalities decrease from an interquartile range of 138–174 to 66–85 across the extreme hour ranges. This scenario exhibits a similar pattern to scenario A2.1, with a further reduction in the interquartile range to 74–95 during the 13–14 hour interval. These results underscore the critical importance of issuing warnings as early as possible to mitigate the potential loss of life in this scenario effectively.

In the suboptimal scenario with the empirical mobilisation curve (A2.3), estimated fatalities decrease from an interquartile range of 102–128 to 39–82 across extreme hour ranges. Fatalities increase from the first extreme hour range to the 10–11 hour interval, with an interquartile range of 103–147, indicating that warnings issued within this interval result in more people being caught during evacuation. This outcome can be attributed to the combined effect of warning diffusion and mobilisation, the same as scenario A1.5 in Fig. 7, where the higher rise in the number of people on the streets occurs approximately three hours after the warning is issued, coinciding with the peak of the flood. Following this interval, significant reductions in fatalities ($p < 0.001$) are observed until stabilisation begins approximately 15 hours before the flood peak, suggesting that this is an optimal time for issuing the first flood warning. This scenario underscores the inadequacy of warning dissemination during the 2021 event and its impact on the estimated consequences. Even for later warning issuance times and the same mobilisation behaviour, this scenario can result in lower estimated fatalities, with a median estimate of 115 fatalities, 24.3 % lower than the RFEWE scenario, when the warning is issued between 8–9 hours before the peak.

570 **Figure 11: Estimated fatalities for the alternative early warning and evacuation scenarios focus on evaluating the time of the first flood warning, highlighting the significance level of the statistical difference between estimated fatalities during the one-hour interval and the previous hour range. A2.1 (optimal warning diffusion and mobilisation), A2.2 (suboptimal warning diffusion and mobilisation), and A2.3 (optimal warning diffusion and empirical mobilisation).**

3.3 Discussion of limitations

575 The LifeSim approach utilises Monte Carlo simulation to address epistemic and aleatory uncertainties. However, when interpreting scenarios, analysing and considering other limitations and uncertainties related to specific inputs and model assumptions is essential.

Although the flood hazard simulation provided a reasonable representation of water depths, flow velocities, and maximum arrival times, even slight variations in the hydrodynamic model could lead to high sensitivity in LifeSim outcomes, depending
580 on the case study. For instance, a test simulation adjusting the water depth time series by subtracting the bias value of 0.46 meters from all pixels across all layers in the hydraulic simulation resulted in a reduced fatality estimate, with the median value decreasing to 126, i.e. 17% lower than the reconstructed scenario. It is important to note that the reported water depths used to calculate the bias correspond to different vertical datums, including street level, pedestrian walkways, and doorsteps. Moreover, this test represents an extreme generalisation of the bias across the entire domain, preliminary assessing the life loss
585 model's sensitivity concerning the hydrodynamic simulation for this case study.

Furthermore, other uncertainties and factors could significantly influence life loss estimation. The hydraulic model does not account for bridges within the simulated domain, potentially altering flood characteristics due to possible clogging, particularly affecting nearby buildings, as observed during the actual flood event. Additionally, building footprints were excluded from the digital elevation model, turning it into a digital surface model to enhance urban flow simulation. For the loss of life estimation,

the highest hazard of the adjacent pixels was chosen. This may introduce a bias towards higher fatalities. However, if this is the case has to be tested by an analysis using the lowest or mean hazard around the buildings.

The detailed information required for buildings elements in LifeSim results in numerous hypotheses, as obtaining such detailed data is often challenging. Upscaling 100 meter resolution population data to buildings, weighted by building footprint size, can inaccurately associate more population with large areas that actually have a lower population capacity than smaller ones due to verticalisation. Moreover, specific occupancy patterns and individual characteristics are complex to represent using open data. For example, 12 of 15 fatalities in Sinzig were related to people in an inpatient residence, who were not able to leave the building by themselves. Additionally, some building footprints may pertain to commercial or other non-residential sectors, introducing further uncertainty since the population data used only accounts for residential individuals. The impact of this consideration is less significant during nighttime hazards compared to daytime scenarios when population distribution varies based on the sectoral distribution of buildings. Furthermore, attributes such as the number of building floors are determined by the post-event survey, potentially lacking accurate representation due to non-representative sampling.

The lack of representative survey sampling can also impact the reconstruction of warning and evacuation processes. Additionally, the reconstruction of these curves for the 2021 Ahr Valley flood aimed to represent the time spent between the warning issuance and the initiation of proactive evacuation actions. Several filters were applied to the survey data to isolate responses related explicitly to evacuation, as the survey initially encompassed a broader context of mitigation measures. Notably, 83 % of respondents recognise the need for self-protection only at the moment of the hazard occurrence, which can impact comparative analysis with historical cases, given that the warning diffusion curve is not based on an official warning channel. The content of the warning and the perception of personal impacts significantly influence the mobilisation times (Lindell et al., 2020). The lack of detailed evacuation information, received by only 17.5 % of respondents, combined with 84 % being surprised by the flood, likely contributes to the low mobilisation rate. This rate might improve if the population received timely warnings and clear instructions, as 76 % of respondents stated they clearly understood what actions to take.

Even when applying a filter to the survey to account for people directly impacted by the main event in the simulated domain, generalising the warning and evacuation process in this domain can lead to overestimating fatalities in upstream regions. The generalisation is necessary due to the lack of precise building location data for survey respondents. The overestimation arises because there is a 2 to 3 hour difference between the arrival time of the flood in upstream cities compared to downstream areas, and most people were warned only when the flood reached them. As a result, individuals in upstream regions may have taken earlier action than the model sampling.

Furthermore, alternative scenarios were developed to incorporate realistic elements into theoretical models and their parameterisation proposed by Sorensen and Mileti (2015b, c). However, most of the cases used to propose the parameterisation of these theoretical models are based on older events primarily focused on the context of the United States. Incorporating recent flood events from diverse locations could enhance the representation of realistic scenarios.

Concerning evacuation dynamics, summarising flood values using the mid-point could distort actual parameter values along roads, especially over extended road length. Additionally, LifeSim does not consider prior vehicle conditions on road networks, which could significantly impact the representation of traffic jams, particularly in high-density areas.

4 Conclusions

The agent-based model (ABM) LifeSim is used to evaluate the impact of warning system procedures on life loss estimates during the 2021 Ahr Valley flood. After defining the reconstruction scenario, we evaluated the impact of alternative scenarios for flood early warning and evacuation. The median of the probabilistic LifeSim model results overestimates actual fatalities by 28.8 % within the same simulated domain. Nonetheless, the output maintains a consistent proportion of indoor to outdoor fatalities. The distribution of fatalities along the Ahr Valley is overestimated in upstream regions and underestimated in downstream regions. This discrepancy is attributed mainly to generalising the early warning and evacuation processes within the simulated domain, which may lead to variations in evacuation start times across different regions compared to the actual event, particularly in these extreme domain areas.

The 2021 Ahr Valley flood warning diffusion had a significant delay and lower mobilisation rates in protective actions following the first flood warning issuance compared to the worst theoretical alternative scenarios. The median of estimated fatalities could be reduced by 80 % in an optimal theoretical scenario of warning diffusion and mobilisation (scenario A1.1 in Fig. 10). However, under the actual conditions of warning dissemination, where most of the population was either just warned or became aware when the flood reached them, higher mobilisation rates could result in increased fatalities. In such situations, seeking safe places on the upper floors of buildings is a more effective protective action, as in scenarios without outside evacuation, the median of estimated fatalities is lower than in the reconstructed scenario.

The early flood warning reported 13 hours before the water level peak in the upstream domain appears to be the critical window to effectively reduce fatalities in scenarios with theoretical warning dissemination and evacuation. Thus the existing flood warning system provides information in due time. The problem is rather the information content (spatially distributed water depth forecasts are missing), warning dissemination, and the reaction of the population to the warnings. The presented simulation of early flood warning times underscores the significant impact of the actual poor dissemination during the 2021 event. Even with later warning issuance times, if accompanied by better warning diffusion and the same mobilisation behaviour as observed in the actual event, fatalities could be reduced by 24.3 % (scenario A2.3 in Fig. 11).

Using life loss ABMs in flood risk assessments can enhance the evaluation of flood hazards and the effectiveness of warning systems. Dynamic simulations over time and space offer valuable insights into optimal intervention timings and critical regions for implementing mitigation measures. The LifeSim model can incorporate both epistemic and random uncertainties, resulting in probabilistic rather than deterministic outcomes. However, several critical aspects of uncertainty must be acknowledged. Efforts are recommended to better represent the variations in warning diffusion and evacuation responses in the specific case study, with benefits incorporating the different responses across various impacted zones. Additionally, ABMs require high-

resolution data, which can be challenging to obtain accurately. Comparing these models with empirical ones could enhance the understanding of their differences, as empirical models can be deployed more swiftly, offering faster outcomes in forecasting and nowcasting scenarios.

Code availability

LifeSim model is available on the Risk Management Center website of the Institute for Water Resources, which is part of the United States Army Corps of Engineers (https://www.rmc.usace.army.mil/Software/LifeSim/). RIM2D is available for non-commercial use at https://git.gfz-potsdam.de/hydro/rfm/rim2d under the European Union Public Licence v. 1.2. Permission to the repository is granted upon request to heiko.apel@gfz-potsdam.de.

Data availability

RIM2D data, including time series of water depth and flow velocities, are available upon reasonable request to the author. The Mundialis 2020 Land cover dataset can be accessed at https://www.mundialis.de/en/germany-2020-land-cover-based-on-sentinel-2-data/. The OpenStreetMap road network and buildings data are available from © OpenStreetMap contributors 2021, distributed under the Open Data Commons Open Database License (ODbL) v1.0. HANZE 2.0.3 data can be accessed at https://doi.org/10.5281/zenodo.7885990. Results from the 2011 German Census at a 1 kilometer grid level are available at https://www.zensus2022.de/EN/What-is-the-census/grid_cells_results_2011.html, and detailed tables can be found at https://ergebnisse.zensus2022.de/datenbank/online/statistic/1000X/details. Survey data is available upon reasonable request to the Geography and Disaster Risk Research Lab, University of Potsdam.

Author contribution

AFRS established the Ahr Valley LifeSim model, conducted the analysis, and drafted the manuscript. JCE and HK supervised the research, contributed to writing, and revised the manuscript. HA established the Ahr Valley RIM2D model, conducted the hydraulic simulations, contributed to writing, and revised the manuscript.

Competing interests

HK is a member of the editorial board of Natural Hazards and Earth System Sciences.

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