



Supplement of

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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S1 – Fraction of evacuation mode choice

The evacuation mode statistics significantly impact the estimated fatalities across all scenarios and when compared individually ($p < 0.001$). When 100 % of the population evacuates on foot, the median number of fatalities is 229, with an interquartile range of 210–245. In contrast, if the entire population evacuates by vehicles, the median number of fatalities decreases to 133, with an interquartile range of 124-142. These differences affect only fatalities during the evacuation, with extreme median values ranging from 38 to 124 (Fig. S1 and Table S2).

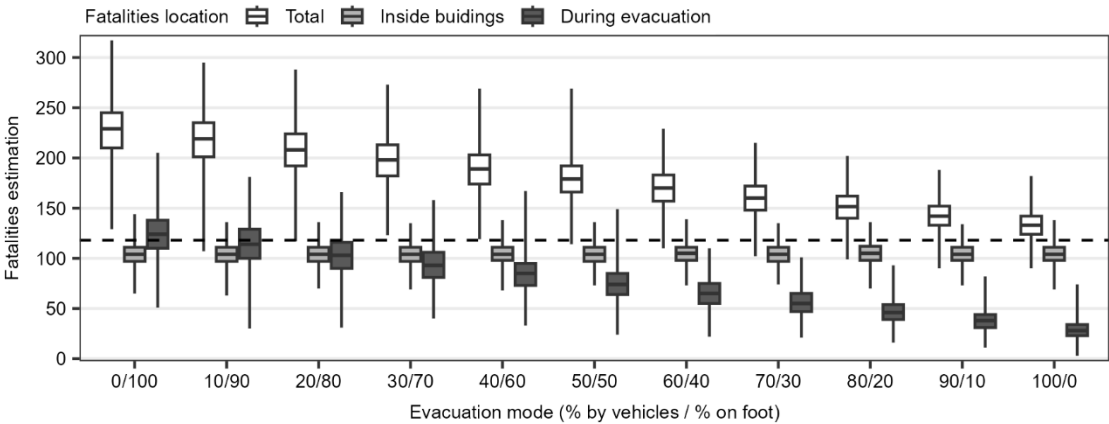


Figure S1: 2021 Ahr Valley flood estimated fatalities and their location for several fractions of evacuation mode.

Table S1: 2021 Ahr Valley flood estimated fatalities statistics for several fractions of evacuation mode.

Evacuation mode (% by vehicles / % on foot)	Fatalities estimation						Fraction of indoor fatalities (%)	
	Median	First quartile	Third quartile	Minimum	Maximum	Median inside structures	Median during evacuation	
0/100	229	210	245	129	317	104	124	45.4
10/90	219	201	235	107	295	104	114	47.5
20/80	208	192	224	117	288	104	103	50.0
30/70	198	182	213	123	273	104	93	52.5
40/60	189	174	203	119	269	104	85	55.0
50/50	179	166	192	114	269	104	74	58.1
60/40	170	157	183	110	229	105	65	61.8
70/30	160	148	172	102	215	104	55	65.0
80/20	151.5	140	162	99	202	105	46	69.3
90/10	142	133	152	90	188	104	38	73.2
100/0	133	124	142	90	182	104	28	78.2

10 Although the evacuation mode of 100 % of the population evacuating by vehicles results in a fatality count closest to the actual number (118), the scenario where 80 % evacuate by vehicles and 20 % on foot most matches the proportion of indoor fatalities. This scenario shows a fraction of indoor fatalities at 69.3 %, compared to 68.5 % in the actual event.

S2 – Alternative warning and evacuation scenarios

15 The principal factors affecting the dissemination of the first warning include the number of channels, their technologies, frequency, and the time of day (Sorensen and Mileti, 2015a). Factors influencing most mobilisation times include, in addition to the warning content and perception of personal impacts, environmental cues and impact intensity (Sorensen and Mileti, 2015b). Theoretical models are proposed to represent each of these processes based on an extensive database of historical cases involving various hazard sources and previous studies.

20 In order to estimate the population warned within a specific minute time step (P_{warned_t}), the Rayleigh distribution can be employed in conjunction with a specific rate of unofficial means of warning (Equation S1). This model is influenced by two key coefficients: B_t and C_t . The coefficient B_t represents the effectiveness of the broadcast channels utilised and serves as the shape parameter of the Rayleigh distribution. Conversely, C_t indicates the efficiency of non-official broadcast means at time step t . Low values of B_t correspond to more efficient broadcast channels, whereas higher values of C_t correlate with an increased rate of the population being warned through informal means. (Sorensen and Mileti, 2015a). For mobilisation, the cumulative probability of being mobilised at minute time t ($P_{mobilised_t}$) is described by Equation S2. This probability depends on the mobilisation speed coefficient (a_m) and the median time for individuals to initiate mobilisation (b_m). As a_m decreases from a value of 2, the response time accelerates. Conversely, when a_m increases, the response time decelerates. Additionally, higher values of b_m indicate a longer duration to complete the initiation of protective action (Sorensen and Mileti, 2015b).

$$30 \quad P_{warned_t} = P_{warned_{t-1}} + \left(\frac{t}{B_t^2} e^{-\frac{t^2}{2B_t^2}} \right) + (1 - P_{warned_{t-1}}) * (P_{warned_{t-1}} * C_t) \quad (S1)$$

$$P_{mobilised_t} = 1 - e^{-(t^2)/a_m b_m^2} \quad (S2)$$

A specific selection of these cases is utilised to define the proposed curves and their uncertainty bounds in LifeSim. There are ten recommended curves (five for each period of the day) for warning diffusion in LifeSim, derived from six historical cases, including chemical spills, hazardous material flow, volcanic eruptions, and flash floods. Additionally, nine mobilisation curves are combined with levels of perception and preparedness, based on evaluations of three cases involving chemical and hazardous material accidents (Sorensen and Mileti, 2015a, b; USACE, 2020). Table S2 presents the utilised curves, their respective coefficients, and mobilisation rates for each scenario.

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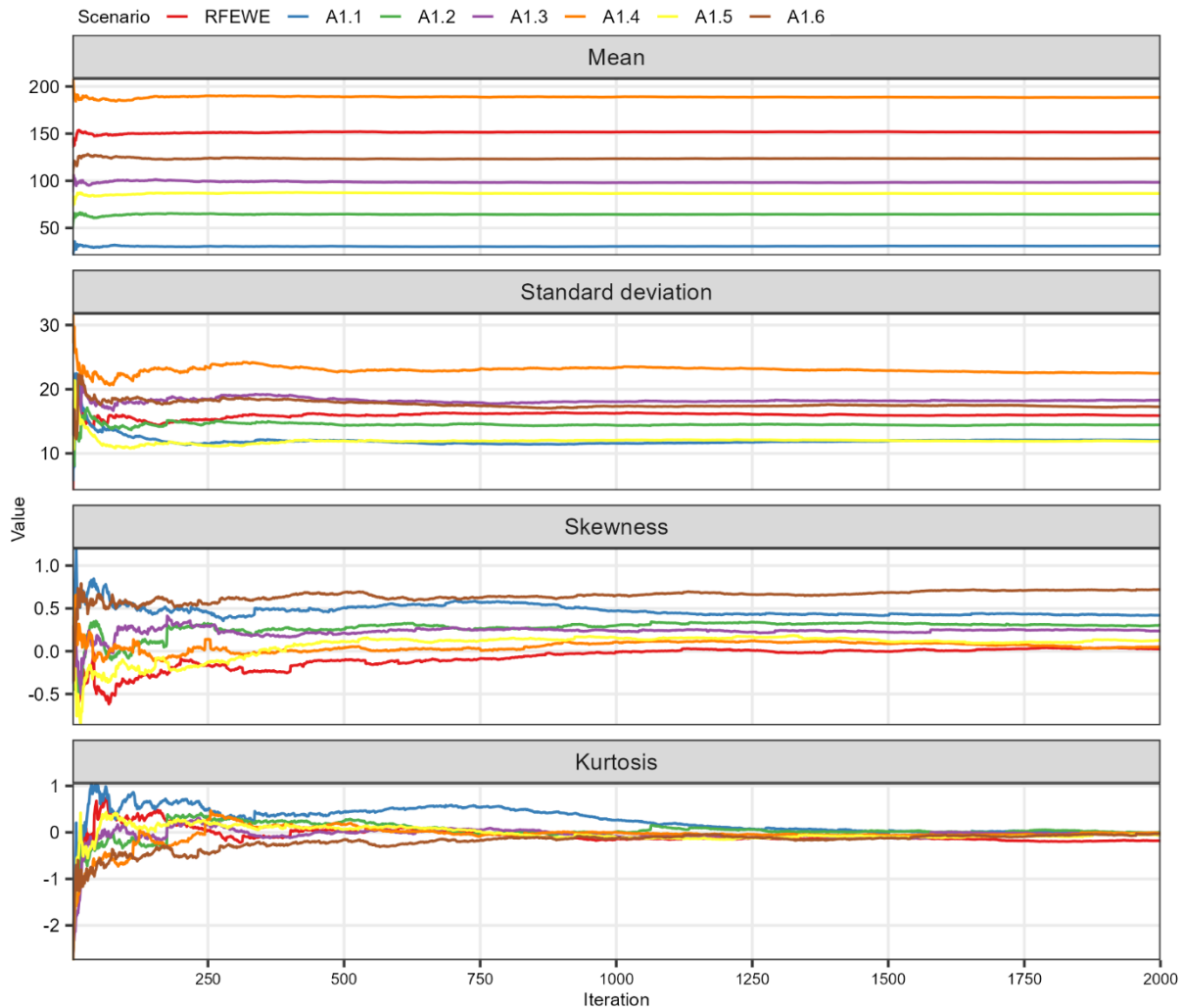
Table S2: First approach of alternative scenarios of early warning and evacuation. Warning diffusion and mobilisation bounds with their coefficients and rates for various scenarios: A1.1 (optimal scenario), A1.2 (intermediate scenario), A1.3 (suboptimal scenario), A1.4 (suboptimal with empirical warning diffusion curve), and A1.5 (suboptimal with empirical mobilisation curve).

Alternative scenario	Bounds	Warning diffusion			Mobilisation					
		Curve	B_t	C_t	Curve	a_m	b_m	Maximum mobilisation rate		
								8 hours	24 hours	72 hours
A1.1	Upper	Fast	5.0	0.100	Preparedness good perception likely	1.00	25.0	100.0	100.0	100.0
	Most likely		9.5	0.098		1.37	64.0	88.8	95.7	98.6
	Lower		51.5	0.081		1.80	114.0	77.1	91.1	97.2
A1.2	Upper	Moderate	58.0	0.080	Preparedness poor perception likely	1.35	61.8	81.5	95.0	98.5
	Most likely		100.0	0.060		1.79	111.8	74.3	90.0	95.0
	Lower		142.0	0.043		2.20	161.9	67.1	85.0	92.0
A1.3	Upper	Slow	103.0	0.060	Preparedness poor perception unlikely	1.35	61.8	65.9	88.7	92.8
	Most likely		145.0	0.042		1.79	111.8	57.0	84.2	90.0
	Lower		150.0	0.040		2.20	161.9	48.0	79.8	87.2
A1.4	Upper	Empirical			Preparedness poor perception unlikely	1.35	61.8	65.9	88.7	92.8
	Most likely					1.79	111.8	57.0	84.2	90.0
	Lower					2.20	161.9	48.0	79.8	87.2
A1.5	Upper	Slow	103.0	0.060			Empirical			
	Most likely		145.0	0.042						
	Lower		150.0	0.040						

S3 – Life loss model convergence

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Figure S2 illustrates the estimated fatalities mean, standard deviation, skewness, and kurtosis over model iterations for the reconstruction scenario and the first approach of alternative scenarios. The results indicate that 2,000 iterations are sufficient for the convergence of these statistics.



50 **Figure S2: Estimated fatalities Mean, standard deviation, skewness, and kurtosis trace for reconstructed scenario of the 2021 flood and for the alternative early warning and evacuation scenarios, which 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), and A1.5 (suboptimal with empirical mobilisation curve).**

References

- 55 Sorensen, J. H. and Mileti, D. S.: First Alert or Warning Diffusion Time Estimation for Dam Breaches, Controlled Dam Releases and Levee Breaches or Overtopping, Lakewood, Colorado, 2015a.
- Sorensen, J. H. and Mileti, D. S.: Protective Action Initiation Time Estimation for Dam Breaches, Controlled Dam Releases, and Levee Breaches or Overtopping, Lakewood, Colorado, 1–51 pp., 2015b.

