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Title: "FLEMO$_{flash}$ - Flood Loss Estimation MOdels for companies and households affected by flash floods"

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We would like to express our sincere gratitude to the Editor for keeping the discussion open upon request and to the Reviewers for recognizing the significance of our work. We are especially thankful for their constructive comments and valuable suggestions, which we have carefully addressed in the revised version. The comments were found to be very helpful in enhancing the clarity and overall quality of the manuscript.

Reviewer #1:

This paper is in the context of flash floods, loss estimation models, and flood preparedness. The paper introduces the FLEMO*flash* model, using data from past German flash floods; methodologically, it combines machine learning and Bayesian networks to estimate probabilistic losses and their uncertainties. In terms of topics, the paper is relevant for and aligned with NHESS. The paper is well-written and -organised. Comments are mostly minor (even typos).

The authors would like to thank the reviewer for acknowledging significance and for providing us with the valuable feedback. The comments were found to be very helpful in improving the quality of the manuscript and will be acknowledged. We have responded (in black) to each comment (in blue). All references cited in our responses are listed at the end of this letter.

The only major comment is about preparedness. From the paper, I do not understand what is meant by preparedness, and in specific what 'high' and 'low' preparedness mean.

We thank the reviewer for this question. We have added the following text in Section 3.3.1 (P15/L323-330) to address the missing clarification.

"Through feature selection and Bayesian Networks we identified emergency measures success (ms) and knowledge about emergency action (ke) for companies and private households respectively, as the significant variables (see Tables S2 and S3 for details on the questions and responses). Building on this, we conceptualised preparedness using these variables and categorized it into low, medium, and high levels. For companies, high preparedness was defined as having undertaken emergency measures that were perceived to be mostly or completely effective ($ms = 3$) and low preparedness ($ms = 1$) reflected low perceived effectiveness of such measures. For private households, high preparedness was defined as having a clear understanding of emergency actions based on official warnings ($ke \geq 5$), and low preparedness reflected limited to no understanding of what to do ($ke \leq 2$)."

What are the assumptions behind 'preparedness'? e.g. that people with more knowledge of risk will act in a certain way (which way?)? At page 14, it is said: '…doesn't knew what to do'. For high preparedness, what people know about what to do?

Residents with high levels of preparedness are more likely to take effective emergency measures, thereby reducing the severity of flood loss. Despite its importance, the way preparedness is conceptualized in this study has certain limitations. Specifically, the variable does not capture which exact actions respondents undertook. Therefore, it would be misleading to speculate particular actions directly resulted in reduced losses. While the specific actions likely varied across respondents, empirical evidence indicates that having clear knowledge of emergency action generally contributes to better preparedness, consistent with previous findings.

We will mention this limitation in the revised manuscript in P16/L361-367 as follows:

"Residents with high levels of preparedness are more likely to take effective emergency measures, thereby reducing the severity of flood loss (Kreibich et al., 2005; Sairam et al., 2019). Despite its importance, the way preparedness is conceptualized in this study has certain limitations. Specifically, the variable does not capture which exact actions respondents undertook. Therefore, it would be misleading to speculate particular actions directly resulted in reduced losses. While the specific actions likely varied across respondents, empirical evidence indicates that having clear knowledge of emergency action generally contributes to better preparedness, consistent with previous findings (Kreibich et al., 2021)."

The model seems suited to derive the predictive density of losses, however I have doubt about the effect of preparedness. I would be very cautious to include this part in the paper.

Thank you for this helpful feedback. We have revised the manuscript to clarify how predictive densities are summarized. The following text has been added in P15/L330–339:

"While preparedness has been extensively studied in the context of fluvial or riverine floods (Lüdtke et al., 2019; Schoppa et al., 2020; Wagenaar et al., 2018), its role in flash floods has not yet been systematically investigated. To address this gap, we applied the FLEMOflash model to derive predictive densities of $rloss$*. Results were summarized using the median and associated uncertainty (25th and 75th percentiles) for selected combinations of hazard, exposure, and vulnerability conditions, rather than displaying the full predictive densities (Figure 6). For clarity of interpretation, Figure A1 illustrates step by step how predictive densities are derived from the prior and posterior distributions using kernel density estimation based on 1,000 resampled values, while Figure A2 provides an overview of the posterior and predictive densities across varying levels of measure success (preparedness) under same conditions of water depth and number of employees."*

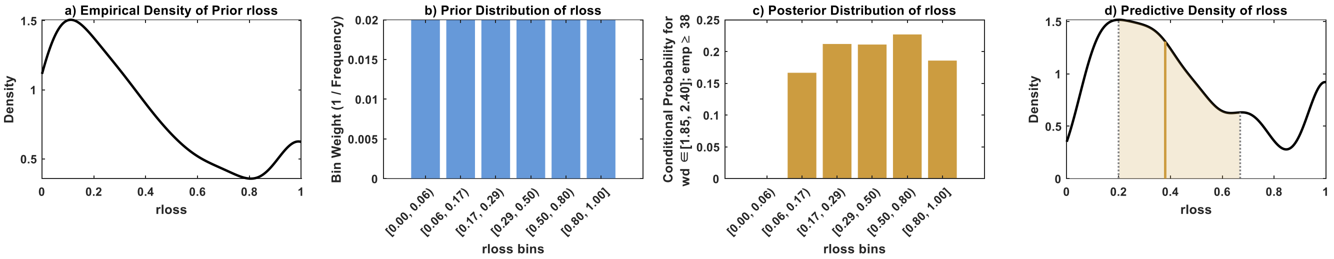

Figure A1: Visualizations of the prior, posterior, and predictive distributions of rloss (a) Empirical kernel density estimate of the prior rloss based on collected data (b) Prior distribution of rloss represented as bin weights (inverse frequency) across discretized intervals (c) Posterior distribution of rloss conditioned on wd ∈ [1.85, 2.40) and emp ≥ 38 (d) Predictive distribution of rloss generated by resampling 1000 values using the prior bin weights and the posterior probabilities. The solid vertical line indicates the median (50th percentile), while the dotted vertical lines represent the 25th and 75th percentiles, representing the predictive uncertainty. Shaded area highlight the interquartile range.

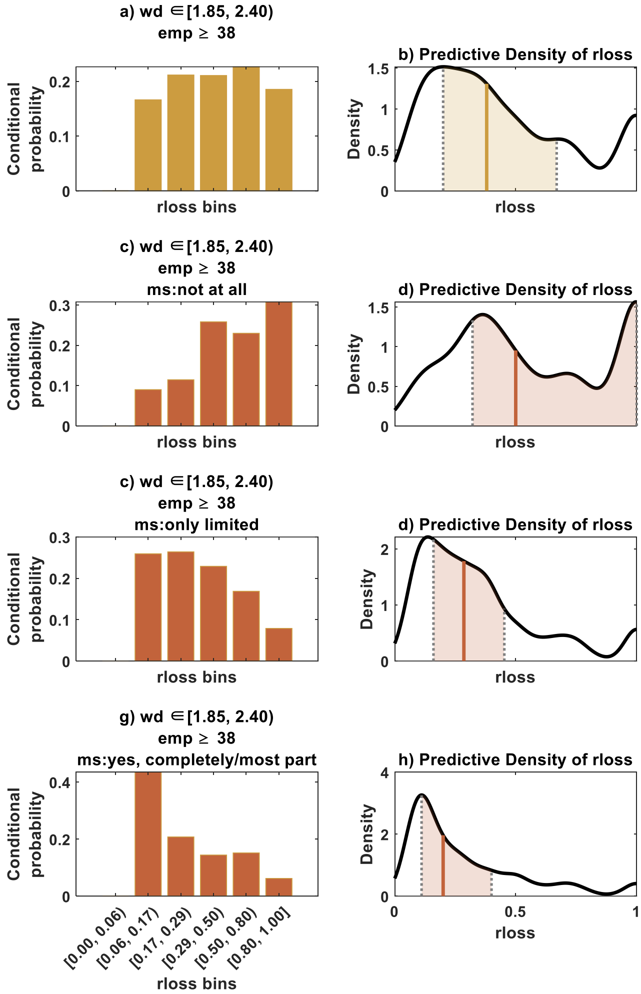

Figure A2: (a) Posterior distribution and (b) predictive density of relative loss (rloss) under condition of water depth (wd) ∈ [1.85, 2.40) and number of employees (emp) ≥ 38. (c–h) Posterior and predictive distributions of rloss for varying levels of measure success (ms): Subplots c, e, g present posterior distributions of rloss under three ms conditions — not at all, only limited, and yes – completely/most part — with wd ∈ [1.85, 2.40) and emp ≥ 38. Subplots d, f, h shows corresponding predictive densities, estimated using kernel density estimation from resampled values (n = 1000). In each density plot, the solid vertical line marks the median (50th percentile), while dotted vertical lines indicate the 25th and 75th percentiles, with shaded regions representing the uncertainty. The sequence from top to bottom illustrates increasing levels of preparedness.

A secondary comment is that I would add some background about the previous /traditional version of FLEMO (e.g. https://www.gfz.de/en/section/hydrology/ projects/4-flood-loss-model-flemo-for-residential-and-commercial-sectors); there is none at the moment I think.

Thank you for the helpful suggestion. In the revised manuscript (P2-3/L54-75), we have incorporated additional background.

"Traditionally, flood loss estimation relied on univariate stage-damage functions (SDF) (Middelmann-Fernandes, 2010). To improve the description of complex damage processes, the Flood Loss Estimation MOdel (FLEMOps) for the private sector, was developed as rule-based, multivariate, deterministic model (Thieken et al., 2008). Merz et al. (2013) and Sieg et al. (2017) introduced decision tree-based damage models that explicitly quantify uncertainty associated with both data variability and model structure uncertainty through bootstrap aggregation. Subsequently, Bayesian Networks were used (BN-FLEMO), enabling the modelling of complex flood loss processes through conditional probability relationships (Lüdtke et al., 2019; Schoppa et al., 2020; Schröter et al., 2014; Vogel et al., 2018).

In parallel, various machine learning approaches have also been developed for flood loss estimation, including neural networks (Salas et al., 2023), random forests (Ghaedi et al., 2022), Bayesian regression (Mohor et al., 2021). Among these, Bayesian networks are particularly advantageous due to their probabilistic representation of conditional dependencies among multiple variables, handle missing data, and model transferability (Schröter et al., 2014). Bayesian models enhance the understanding of flood loss dynamics by quantifying uncertainty and offering probabilistic estimates. For instance, Wagenaar et al. (2018) developed a regional and temporal transferable BN-FLEMO for microscale residential applications, which was later upscaled to mesoscale by Lüdtke *et al. (2019). In addition to the FLEMO typology, various synthetic, multivariate, rule-based flood loss models have been proposed for fluvial flood contexts (Amadio et al., 2019; Dottori et al., 2016; Nofal et al., 2020; Sairam et al., 2020).*

However, all these loss models were developed to simulate damage processes during fluvial floods. In this study, we present the first probabilistic flash flood loss model – Flood Loss Estimation Model affected by flash floods (FLEMO$_{flash}$) using a BN-based approach and gain new knowledge about flash flood damage processes based on the conditional probabilities among multiple influencing variables. The study identifies the important variables and underlying processes that govern the flash flood losses. Additionally, we examine the predictive performance of FLEMO$_{flash}$ model and compare it with conventional SDF models. Finally, we illustrate the effect of preparedness in controlling the extent of loss reduction"

Specific comments (P for page, L for line):

Valid for all direct citations: coma is not needed before the year, e.g. Smith et al. (2000) - and not Smith et al., (2000)

Thank you for pointing this out. We have corrected it.

Valid for the whole paper: equation factors, such as rloss, need to be in italic in the main text of the manuscript

Corrected.

Valid for the whole paper: do not use contracted forms like 'doesn't'. L223: The direction of the arrow represents an association between two variables but doesn't necessarily represent causality.

We have corrected it in the revised manuscript.

P2L42: double parenthesis in the citation

Corrected.

P2L50: double space before 'significant'

Corrected.

P4L101: double space before 'The percentage'?

Corrected.

P7L146, P11L236: 'This' what? Add a noun, specify

Thank you for pointing out this lack of clarity. The revised text now reads as follows:

P7/L154-156: *"Within the predicted bins of the discrete BN (rloss bins), we fit a continuous distribution by applying weighted sampling to the empirical loss data, resulting in a smoothed representation of the loss distribution (Schoppa et al., 2020). For further details on the BN structure learning we refer to Text S1 and Figure A1."*

P11/L241-243: *"Examining the performance with optimal predictors while modifying the number of bins, revealed significant differences for companies but not for households, which could be attributed to the fact that the number of data points for companies is relatively limited and more heterogenous (Schoppa et al., 2020) compared to households."*

P9L190: remove the dot before the parenthesis of Fig. 1d-e

Corrected. We will carefully proofread the revised manuscript.

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