Egusphere-2025-1715: Deciphering the drivers of direct and indirect damages to companies from an unprecedented flood event: A data-driven, multivariate probabilistic approach

Reviewer #1:

In their revision, the authors have added additional detail and justifications of their methods. It is now clearer to see through the complex chain of methods. The following points remain for me (I'm referring to line numbers in the tracked changes version of the manuscript!):

We sincerely appreciate the feedback and positive evaluation of our revised manuscript. The comments were very helpful in further improving the quality of the manuscript. We provide detailed responses to each comment below, with reviewer comments shown in blue, our responses in black and L refers to the line number in the newly revised manuscript with track changes.

When discussing the objective functions of the various methods, how is the bounded nature of the response variables (0-1 and 0-540, respectively) captured? The duration variable in particular is really a right-censored variable. How is this taken into account? And if not, how do these characteristics of the responses affect the results from the methods chosen?

We thank the reviewer for raising this important point. The objective functions used by Elastic Net, Random Forest, and XGBoost do not inherently enforce the bounded nature of the response variables. In our study, both relative damage (0–1) and business interruption/restriction duration (0–540 days) were modeled directly using the observed empirical values, without imposing explicit constraints to ensure predictions remain within these bounds. Our primary aim is to assess the variable importance rather than to predict losses, and therefore the lack of bounded nature of the response variables has limited practical implications on our conclusions.

This is now explicitly noted as a limitation in the revised manuscript as follows (L569-573):

"*The machine-learning models (EN/RF/XGB) were trained entirely on empirical data, and the bounded nature of the response variables is not explicitly encoded in their objective functions. As our study focuses on the assessment of variable importance rather than on prediction, the lack of bound-preserving objective functions has limited impact on our findings. Nevertheless, future studies should consider incorporating modelling frameworks that explicitly enforce response bounds, particularly when the primary goal is predictive accuracy.*"

The value of the BN is clearer now. I appreciate that the structures inferred (Figure 7) represent conditional dependencies and not (necessarily) causal dependencies (L508). However, the interpretation that follows (L511-534) is rather causal. I advise the authors to check their interpretation once more so that they don't slip into a causal language. What is argued on L520 I don't think can be inferred from those BN structures. It would help further if the authors would discuss the meaning of the DAGs (Figure 7) in terms of conditional independence and what we learn about the drivers of the damages that way.

We have carefully revised to ensure that the descriptions strictly reflect conditional dependencies, consistent with what can be inferred from the DAGs. The revised text now reads as follows (L443-L480):

"Bayesian networks (BN) provide a probabilistic framework for understanding the interdependencies between the top four influencing factors and damage outcomes. We developed data-driven BN models using a score-based structure learning algorithm. The BN structure (Figure 7) provides a probabilistic representation of these relationships, allowing users to estimate both direct and indirect damages along with a quantification of uncertainty. The direction of the arrows represents conditional

dependencies between variables but does not imply causality (Schröter et al., 2014). Some directions may appear unintuitive because the structure is derived from a score-based learning algorithm that optimizes the overall network fit to the data. The results align with previous studies while also offering new insights into key influencing factors.

Consistent with prior research (Kreibich et al., 2010; Nafari et al., 2016; Schoppa et al., 2020, 2022; Seifert et al., 2010; Sieg et al., 2017), our results confirm that water depth (wd) and velocity (v) are strongly associated with direct damages, particularly for building damage (bdam). The direct link between these variables and bdam (Fig. 7a) underscores the predominant role of flood intensity in the network. The BN structure also identifies that contamination (con) is linked to building damage, which is consistent with Sieg et al. (2017). For equipment damage (edam) and goods & stock damage (gsdam), our results show that flow velocity and company characteristics such as size premises (sp) and number of employees (emp) are important nodes in the network (Figures 7b and 7c). This aligns with Schoppa et al. (2020), who emphasized that company-specific characteristics play an important role in explaining non-structural damages. Unlike previous studies that primarily focused on hazard intensity variables (Nafari et al., 2016; Sieg et al., 2017), our results show that company exposure variables also appear as relevant variables in the inferred BN structures, indicating conditional dependencies with damage outcomes.

BN structure of business interruption duration (bid) (Fig. 7d) shows dependencies with water depth (wd), velocity (v), and number of employees (emp), which is in agreement with Sultana et al. (2018), who found that company-specific factors (e.g., number of employees (emp)) often outweigh hazard characteristics in estimating business interruption costs. Moreover, our findings complement those of Sakai and Yao (2023), who highlighted that small companies suffer disproportionately higher business interruption relative to turnover. Interestingly, the BN structure of business restriction duration (brd) (Fig. 7e) reveals that precautionary measures (pr) are conditionally linked to the knowledge about flood hazard (kh). This provides a leverage point for risk communication to shape proactive behavior. While previous studies have acknowledged the importance of preparedness (Kreibich et al., 2010; Schoppa et al., 2022), our BN results provides a quantitative depiction of how these variables co-occur within the inferred network. The dependency between precaution measures (pr) and business restriction duration (brd) indicates that proactive measures and restriction duration are closely associated within the network."

On L528, that water depth is a primary factor seems to be in conflict with the variable importance analysis (e.g. Figure 6).

We agree as the paragraph emphasizes on company characteristics, we have removed the sentence in the revised manuscript (L 471).

In the discussion of Figure 8 it should be noted that the predictions for the various scenarios overlap considerably, so the effects of some of the factors should be toned down.

We agree with the reviewer and have rewritten the discussion using a more cautious tone as general tendencies to avoid the impression of definitive outcomes (L489-L544).

"The relative damage to buildings is modeled as a function of water depth and flow velocity (Fig. 8a). As water depth increases, the median damage values generally rise, especially under moderate and torrential flow conditions. At low flow velocities, median damage remains relatively low across all depth levels, however the uncertainty increases with depth, suggesting various possible outcomes. Under moderate flow conditions, damage estimates increase slightly compared to low flow, with overlapping uncertainty bounds. In contrast, torrential flow conditions consistently lead to the highest damage estimates, particularly for water depths exceeding 2 meters, where the 75th percentile

approaches near-total damage. Notably, the uncertainty in damage estimates increases with both rising water depth and flow velocity, indicating heightened variability (or uncertainty) in damage outcomes under extreme flood conditions.

The relative damage to equipment (edam) is assessed as a function of flow velocity and company size premises (Fig. 8b). Flow velocity categories (Low, Moderate, Torrential) are arranged as columns, while the size premises classes (75–500 m², 501–1500 m², >1500 m²) in rows. Under low flow conditions, median damage tends to decrease as size premises increase, especially for the largest category (>1500 m²). Under moderate and torrential flows, companies with size premises < 500 m² show damage values that often reach the maximum. Under torrential flow, high damage values are likely across all size classes. The relative damage to goods & stock is also modeled as a function of flow velocity and size premises (Fig. 8c). Even under low flow conditions, companies with smaller premises (<1500 m²) may experience high damage, whereas companies with premises >1500 m² show median damage estimates of around 50%. Under moderate and torrential flow conditions, the damage values concentrate around 1.0, indicating near-total damage to goods and stock under extreme flood conditions, largely irrespective of size premises. However, the companies with size premises > 1500 m² exhibit greater variability. Overall, the substantial overlap of uncertainty across scenarios indicates a wide range of possible outcomes, suggesting that these patterns should be interpreted as general tendencies rather than definitive outcomes.

The predicted business interruption duration (Fig. 8d) also shows overlapping distributions across company size and flow conditions. Micro-companies (1–9 employees) may experience a median interruption duration of around 22 days under low and moderate flow conditions. While under torrential flow conditions, the interruption duration tends to increase to nearly 60 days. Small companies (10–49 employees) exhibit a similar trend, although their modelled interruption duration under torrential flow may be slightly lower. For medium and large companies (>49 employees), the modelled interruption duration ranges from about 11 to 33 days across all flow conditions. The results indicate that small companies, particularly micro-companies, may have been disproportionately affected during the 2021 flood event. The analysis of business restriction duration (Fig. 8e) emphasizes the role of implementation of precautionary measures. The median restriction duration for companies without precaution is expected to be approximately 210 days for water depth > 2 meters. While for companies with very good precautionary measures, the median restriction durations may be below 150 days. This indicates that very good precautionary measures can help in reducing the restriction periods, however the overlapping distributions says the outcomes may not be uniform across scenarios."

On L270, please explain why it was necessary to discretize the variables in the BN. I assume because only a limited set of continuous pdfs is implemented in the software chosen.

Bayesian Networks (BNs) can theoretically handle both continuous and discrete variables. However, in practice, continuous BNs are often limited to normally distributed variables to preserve closed-form probability distributions (Kitson et al., 2023). Because our flood loss data include mixed variable types with some skewed distributions, we adopt discrete BNs for this study.

We have clarified this in the revised manuscript as follows (L237-240):

"BNs can theoretically handle both continuous and discrete variables. However, in practice, continuous BNs are often limited to normally distributed variables to preserve closed-form probability distributions (Kitson et al., 2023). Since our flood loss data include mixed variable types with some skewed distributions, we adopted discrete BNs for this study."

On L275, how was prior knowledge incorporated in this case?

We thank the reviewer for this question. In this study, we employed a uniform prior over the conditional probability tables. This corresponds to setting an equivalent sample size that distributes prior probability mass evenly across all states of each variable. This ensures that all parent–child configurations are treated equally a priori, and that the posterior distributions are driven primarily by the empirical data.

We have clarified this in the revised manuscript as follows (L246-249):

"We employed a uniform prior over the conditional probability tables. This corresponds to setting an equivalent sample size that distributes prior probability mass evenly across all states of each variable. This ensures that all parent–child configurations are treated equally a priori, and that the posterior distributions are driven primarily by the empirical data."

In equation 9, in place of the likelihood the posterior is written again. Please correct.

We apologize for the typo error. We have corrected Eq. 9 (L256).

The notation of conditional probabilities throughout should use "|" instead of "/".

We used "|" throughout in the manuscript and SI.

When turning the discrete output from the BN into a continuous pdf the authors state that the representation is then more precise (L288). However, this is only because the imprecision introduced through fitting the pdf is neglected. This caveat should be mentioned in the text.

We agree with the reviewer and have added the following caveat to the limitations section (L573-577):

"Finally, converting the discretized BN outputs into continuous probability distributions enables a finer representation of predictive uncertainty. However, this step introduces an additional approximation. Specifically, the uncertainty arising from fitting the continuous probability density function replaces the discretization uncertainty inherent in the BN. This additional imprecision should be considered when interpreting the predictive density distribution."

L440-442: Statistical tests could be performed to back up the inference from small, possibly unrepresentative samples to a larger population (with appropriate post-stratification or else to account for unrepresentativeness).

Given that the number of large companies in our dataset is extremely limited (n = 3), formal statistical inference is not feasible. We have explicitly acknowledged this limitation in the manuscript (L385-387, L563), noting that, due to the limited sample size the results cannot be generalized and should be interpreted with caution.

The comparison to the 2022-2016 floods (L595) was not analysed in this paper if I'm not mistaken.

We thank the reviewer for pointing this out. Our earlier wording referred to insights drawn from previous literature covering the 2002–2016 flood events. As our study does not directly compare the July 2021 event with those earlier floods, we have revised the sentences in the conclusion as follows (L590-593)

"*The July 2021 flood in Germany highlighted the significant vulnerability of companies to unprecedented floods, with both direct and indirect damage resulting in substantial financial costs.*

This reaffirms the need for a deeper understanding of how multiple interacting factors shape damage outcomes under extreme conditions."

Editorial comments:

L49: End of sentence from "despite …" is redundant given what was said before.

L47: We have now removed this part from the manuscript.

L205: Optimal values of alpha, gamma … and beta.

The sentence has been revised as follows: (L173-177):

The regression coefficients β were obtained by minimizing the $Obj(\beta)$. The optimal hyperparameters (α, λ) were selected based on the lowest mean absolute error (MAE) obtained from the nested cross validation

Table A1 needs a thorough check. There are some typos, wrong numbering and other small mistakes.

We have carefully proofread the manuscript.

We hope that the reviewer is satisfied with the changes proposed. Once again, we thank for the valuable comments that helped us to improve the manuscript.

Reviewer #2:

The manuscript "Deciphering the drivers of direct and indirect damages to companies from an unprecedented flood event: A data-driven, multivariate probabilistic approach" is highly relevant and makes a valuable contribution to the understanding of both direct and indirect flood damages to businesses. The focus on business interruption impacts is particularly important, and this work addresses a notable gap in the literature. I would like to thank the authors for their thorough revision and for their detailed and thoughtful responses to the previous review comments. The manuscript has improved substantially and is now very close to being ready for acceptance. I am satisfied with the revisions overall. However, I would encourage the authors to further elaborate the conclusion. In its current form, it remains somewhat concise and would benefit from clearer linkages to the key results of the study.

In addition, the discussion of limitations and recommendations for future research should be moved to a separate section preceding the conclusion, as such content does not typically belong within the conclusion itself. If the conclusion is expanded to more fully synthesize the findings and the limitations/recommendations are placed in their own section, the manuscript will be suitable for publication.

We sincerely thank the reviewer for the constructive feedback and positive evaluation of our revised manuscript. In the revised manuscript, Limitations and revised conclusions are written in separate sections as follows:

L560-578: ***3.4 Limitations and future scope***

While the study combines a unique dataset with innovative machine learning methods, our approach does have some limitations. First, the sample size for some company categories, particularly large companies, was small, which is due to the fact that the fraction of large companies affected was low. Second, survey participation was voluntary, which may have introduced selection bias. Although 431 responses create a notable sample size given the challenges of post-disaster data collection, future studies should aim for a more diverse, representative sample across different company sizes and sectors. This would further strengthen the generalizability of the findings. Moreover, comparative analyses across multiple extreme flood events in different geographical regions and socio-economic contexts would allow for broader generalization of findings. Future work should also explore sector-specific analysis, given the heterogeneous nature of companies.

The machine-learning models (EN/RF/XGB) were trained entirely on empirical data, and the bounded nature of the response variables was not explicitly encoded in their objective functions. As our study focuses on the assessment of variable importance rather than on prediction, the lack of bound-preserving objective functions has limited impact on our findings. Nevertheless, future studies should consider incorporating a modelling framework that explicitly enforces response bounds, particularly when the primary goal is predictive accuracy. Finally, converting the discretized BN outputs into continuous probability distributions enables a finer representation of predictive uncertainty, however, this step introduces an additional approximation. Specifically, the uncertainty arising from fitting the continuous probability density function replaces the discretization uncertainty inherent in the BN. This additional imprecision should be considered when interpreting the predictive density distribution.

L584-L603: ***4 Conclusions***

The July 2021 flood in Germany highlighted the significant vulnerability of companies to unprecedented floods, with both direct and indirect damage resulting in substantial financial costs. This reaffirms the need for a deeper understanding of how multiple interacting factors shape damage *outcomes under extreme conditions. Our findings indicate that core hazard related variables, including water depth, flow velocity, and contamination, are predictors of damage consistently across the five damage types investigated. Company characteristics such as size of the premises and number of employees also play an important role. These findings strengthen the knowledge gained on basis of earlier flood events while revealing new information in respect to an unprecedented event. What sets the 2021 flood damage processes apart is the elevated importance of emergency preparedness and behavioural responses, particularly in influencing indirect damage such as business restriction duration. A novel insight from this study is the link between knowledge about flood hazard and amount of precaution taken, highlighting its relevance in reducing business restriction duration. Small and micro-companies that implemented very good precautionary measures experienced notably shorter restriction durations. Nonetheless, scenario-based analysis shows considerable overlap and variability across scenarios indicating that the resulting damage outcomes remain highly variable and uncertain. Overall, the results underscore the critical role of preparedness and emergency and risk communication , that support non-structural measures as essential complements to structural protection that may be less effective under unprecedented conditions. This also provide a leverage point for risk communication tailored to business owners.*

We hope that the reviewer is satisfied with the changes proposed. Once again, we thank for the valuable comments that helped us to improve the manuscript.