Response to Reviewer Report on Manuscript egusphere-2024-3923

"Modeling Regional Production Capacity Loss Rates Considering Response Bias: Insights from a Questionnaire Survey on Zhengzhou Flood"

by Lijiao Yang, Yan Luo, Zilong Li and Xinyu Jiang

We are grateful for your constructive comments and suggestions, which certainly help us to improve the quality of our manuscript. We have seriously taken into account all the comments and addressed the points raised by you as follows. Our responses are divided into three sections: responses to general comments, responses to specific comments and response to minor suggestions. The key parts have been highlighted.

Response to General Comments:

Comment:This paper presents a robust methodological framework for estimating Production Capacity Loss Rate (PCLR) of enterprises affected by floods, while accounting for response bias in post-disaster survey data. The methodology is validated using empirical data from the 2021 Zhengzhou flood and employs probabilistic modeling, damage state classification, and Monte Carlo Simulation to derive loss estimates and uncertainty bounds.
The manuscript is well-structured and offers a clear flow from methodology to results and implications. It contributes meaningfully to the literature on post-disaster economic assessment by bridging micro-level survey data with modeling techniques typically used in structural and hazard analysis. The application to real-world flood data strengthens its practical relevance.

Response: We sincerely appreciate your thoughtful review and kind acknowledgment of our paper's structure, methodological contribution, and practical relevance. Your feedback is invaluable as we strive to enhance the work further.

Response to Strengths:

Comment 1: Novelty and Relevance:Introduces a response-bias-tolerant approach to estimating PCLR, addressing a critical and often underexplored issue in survey-based disaster impact assessments.
Comment 2: Solid Methodological Framework:Combines exceedance probability curves, distribution fitting, and Monte Carlo Simulation to derive robust and

sector-specific loss estimates. Incorporates rate of change analysis, which adds depth to understanding vulnerability dynamics across sectors.

Comment 3: Real-World Application:Empirically applied to the "7.20" Zhengzhou flood using 424 valid enterprise surveys, enhancing both credibility and replicability.

Comment 4: Actionable Sector-Specific Insights:Finds that wholesale and retail trade is more vulnerable at shallow depths, while manufacturing becomes more vulnerable as inundation depth increases. Provides practical implications for targeted flood preparedness and recovery strategies.

Response:

We sincerely appreciate your recognition of the paper's novelty, methodological rigor, and real-world applicability, especially the insights into sector-specific vulnerabilities. Your acknowledgment of these strengths is incredibly motivating and validates our efforts to contribute meaningful, actionable findings to the field.

Response to Specific Comments:

Comment 1:

Handling of Response Bias:

The authors do well to acknowledge and address response bias. The approach of classifying damage states and modeling exceedance probabilities is well-justified. However, a brief comparative note on how this method improves upon traditional regression-based or assumed-PCLR models would help clarify its added value.

Response:

We greatly appreciate your recognition of our efforts to address response bias and the justification of our methodological approach. To clarify the added value, we did compare our damage state classification framework with traditional regression-based models (e.g., Linear Model, Polynomial Model, Linear-log Model, Log-linear Model, Log-log Model, Logistic curve Model, and CDF curve Model) . Fig.1 presents the seven vulnerability curves for all industries; vulnerability curves for other specific industries can be found in Appendix 1. We will examine from two aspects—**model connotations** and **data fitting**—to demonstrate that our method better captures complex bias structures.

In terms of model connotations, vulnerability curve expresses the relationship between hazard intensity and loss ratio, that is, the degree of change in the loss ratio caused by changes in hazard intensity. Both changes can be represented as absolute changes in numerical form and relative changes in percentage form. Within the framework of regression analysis, the former interprets the slope of the model more, and the latter interprets the elasticity of the model more. According to the research focus and the properties of the slopes and elasticities of different models, an appropriate model can be theoretically selected.

Among them, the slope is a key parameter linking the correlation between hazard intensity and loss ratio, and it has predictability. For example, the slope of the Linear model is β_1, a constant, indicating a linear relationship of β_1, units between hazard intensity and loss ratio. While the slope of Polynomial model is $\beta_1 + 2\beta_2 h$, indicating a nonlinear relationship between hazard intensity and loss ratio. That is, when hazard intensity changes by one unit, the magnitude of loss ratio change depends on the slopes β_1、β_2 and the hazard intensity itself.

Compared with the emphasis on predictability by the slope, elasticity is more conducive to linking response policies. Elasticity represents the relative change between hazard intensity and loss ratio: when elasticity is greater than 1, it indicates that loss ratio change is faster than that of hazard intensity. For the objects of such vulnerability curves, more attention should be paid to the loss ratio change; when elasticity is less than 1, it indicates that the loss ratio change is not as fast as that of hazard intensity. Comparing the two, in emergency and risk management, more importance should be attached to the situation where elasticity is greater than 1. The Log-log model is a constant-elasticity model, where the regression coefficient β_1 is the elasticity value, and the sensitivity of the object's loss ratio to hazard intensity can be directly judged according to β_1. For other models, such as the elasticity of the Linear model is $\beta_1 \frac{Y}{X}$, which is related not only to the coefficient but also to the hazard intensity X and the loss ratio Y itself, making the discussion more complex.

<u>**Our methodology is theoretically more appropriate. On the one hand, it restricts the independent variable's range to be greater than 0, which is consistent with the basic properties of flood hazard intensity, such as inundation depth, flow velocity, inundation duration, etc. On the other hand, when defining hazard intensity and loss index, this model adopts the multiplication principle, which is more suitable for considering the interaction of multiple hazard indicators, facilitating the construction of multi-dimensional vulnerability curves (Jiang et al., 2023).**</u>

From the perspective of <u>**data fitting**</u>, each row represents the fitting results of a category of models used for several industries, and the models within each category are comparable, as shown in Fig. 1 and Appendix A. Among the models in the first category, the Polynomial fitting performs the best. However, in some industries, when the inundation depth is over 1 m, PCLR has reached 100% and shows an upward trend, which does not conform to the actual situation. Among the models in the second category, Log-Linear model with better fitting also has this situation. Although PCLR of the models in the third category completely fall within the interval [0,1], theoretically, there are difficulties in interpreting the parameters of such models. In summary, although both the curve models are selectable, yet considering the uncertainty of PCLR data obtained through field surveys, interviews, etc. (for example, during research interviews, enterprises usually provide an estimated range of loss ratios, such as 40%-50%, rather than a precise value), it is more reasonable to use the loss state model. In research, it is difficult to obtain continuous and accurate loss ratio data. Most of the time, only the discrete states of loss can be roughly determined, such as no loss, minor loss, moderate loss, major loss, and complete loss. In such cases, it is difficult to directly fit the relationship between hazard intensity and loss ratio. Therefore, it is necessary to construct a curve model with loss state as the dependent variable. The exceedance probability curve model is a widely applied curve model using damage state.

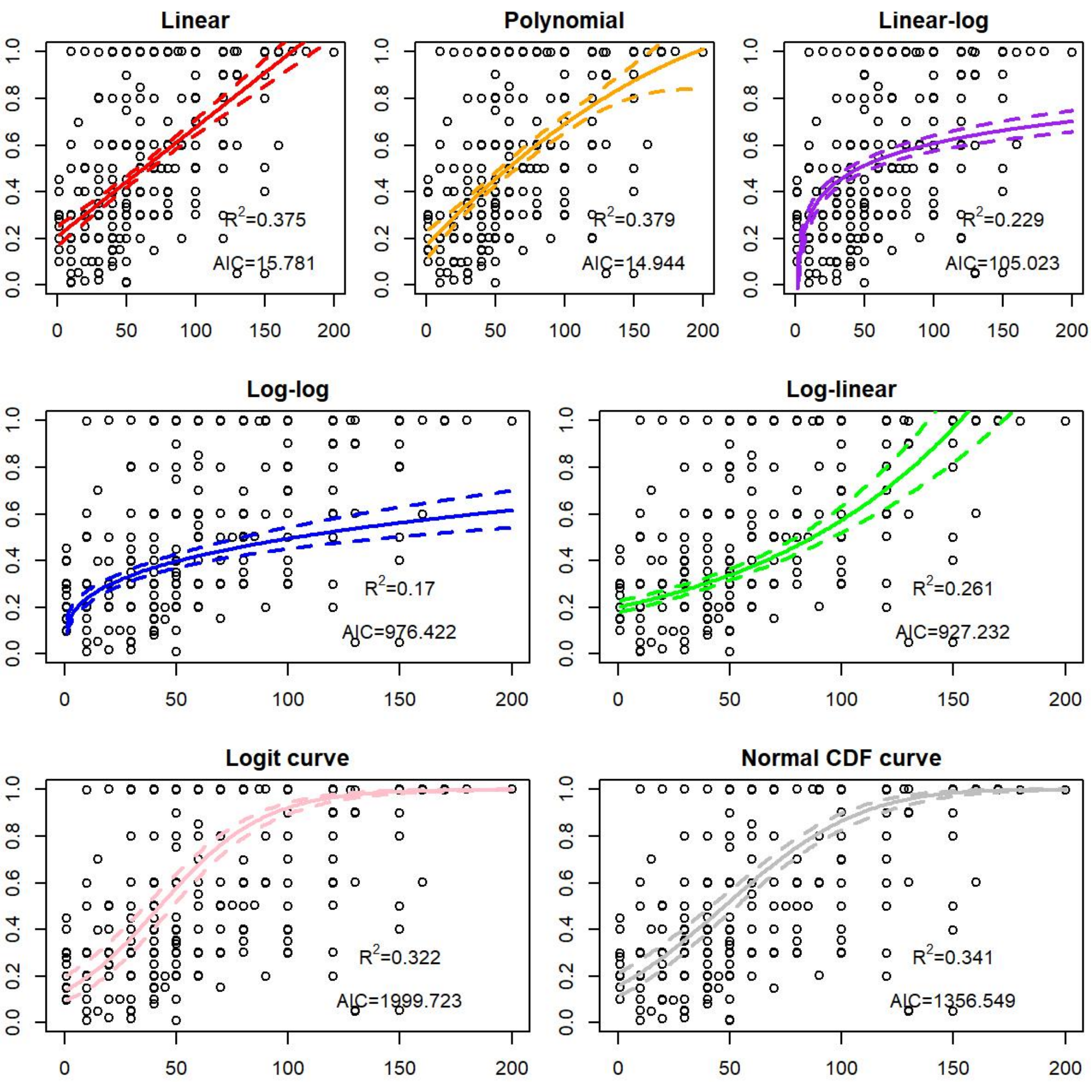

Fig 1.Vulnerability curves of loss rates for seven types across all industries

Comment 2:

Model Generalizability:

The authors acknowledge limitations regarding generalization. Future applicability in diverse geographic and sectoral contexts (e.g., agriculture or public services) could be more explicitly discussed in the conclusion.

Response:

Thank you for your valuable comments. The discussion on model generalization is indeed an important direction that our study needs to further strengthen. Although the possibility of model extension has been preliminarily mentioned in the discussion and conclusion sections, it is necessary to more clearly analyze its applicability to broader fields such as agriculture, public services, and diverse geographic contexts.

<u>We plan to supplement the discussion with the following points on page 16, line</u>

289: "Secondly, incorporating data from diverse regions and sectors is important for enhancing the model's universality. Our framework offers a foundational paradigm for cross-sector risk assessment but requires flexible adaptation for different sectors. For instance, the agricultural sector, significantly influenced by flood inundation depth, crop growth cycles and soil moisture, needs to integrate agricultural monitoring data to refine damage state classification (Yang et al., 2023; Zhong et al., 2018); the public service sector's productivity loss assessment should consider factors such as service network connectivity and backup facility configurations (Li and Yan, 2023), achievable by expanding survey dimensions and infrastructure vulnerability curves. Geographic extensions must account for regional climate characteristics (e.g., differences in flood patterns between monsoon and arid zones) and economic structural variations, with multi-regional data used to calibrate model parameters and enhance generalizability. "

Comment 3:
Classification of Damage States:
Damage state thresholds (e.g., [0, 1/3), [1/3, 2/3)) are sensible, but the paper could briefly discuss the sensitivity of results to these threshold choices or how alternate classifications might impact robustness.

Response:
Thank you for your detailed suggestion regarding damage state classification. I will answer your question from two aspects: first, explaining why we used 1/3 and 2/3 as thresholds; second, providing the results of robustness using different thresholds.
Firstly, previous studies have divided the enterprise production capacity loss rate into several state intervals—[0, 1/3), [1/3, 2/3), [2/3, 1), and 1—to fit PCLR curves (Yang et al., 2016; Liu et al., 2023). In addition, in this study, we adopt damage state intervals of [0, 1/3), [1/3, 2/3), [2/3, 1), and 1, with one core consideration being alignment with standardized classification systems in engineering to ensure methodological reproducibility and interdisciplinary compatibility. Specifically, this classification framework draws on the widely used four-level damage paradigm—minor, moderate, major, and complete failure—commonly applied in earthquake and structural engineering (Shinozuka et al., 2000; Salgado-Gálvez et al., 2023; Shooraki et al., 2024). Such grading methods have long been validated as effective in disaster loss assessment and facilitate data interoperability with infrastructure vulnerability curves (e.g., for bridges and tunnels). The choice of 1/3 and 2/3 as key thresholds essentially quantifies the "functional loss gradient" recognized in engineering fields. For example, minor damage (<1/3)

corresponds to enterprises maintaining basic production capacity, analogous to "repairable minor damage" in structural engineering; moderate damage [1/3-2/3) corresponds to significant capacity reduction without complete interruption, consistent with "functional interruption but short-term recoverable" definitions; major damage (≥2/3) approaches a near shutdown state, similar to a "critical state before structural failure." This standardized classification facilitates direct linkage between enterprise capacity loss and engineering physical damage indicators such as inundation depth and equipment submersion duration, laying a foundation for integrating remote sensing and infrastructure monitoring data in future work.

Secondly, we acknowledge that threshold choices affect result robustness. Therefore, we conducted sensitivity analyses to test how threshold shifts influence the PCLR curves, as shown in Appendix B. In Classification 1, the thresholds are set at 1/3 and 2/3. In Classification 2, the thresholds are 1/4 and 1/2. In Classification 3, the tercile method is used. We found that for most industries under most inundation depth conditions, PCLR curve trends remain consistent across the three classification thresholds, with only slight variations in PCLR values at higher inundation depths. In contrast, the results for wholesale and retail trade industry is nearly identical across the three classification thresholds, as shown in the Figure.

We are considering deleting some content from the Discussion section (lines 293 to 297 on page 17), and then adding the following statement: "(2) Our classification of loss states aligns with the standardized classification system used in the engineering field to ensure interdisciplinary compatibility. Additionally, we have tested different classification thresholds and found that our approach is relatively robust."

Comment 4:

Economic Modeling Link:

The manuscript suggests that PCLR values can serve as inputs for IO and CGE models, which is important. Including a schematic diagram or example of how these values would be plugged into such models would improve clarity for interdisciplinary audiences.

Response:

Thank you for your suggestions. As Hirokazu Tatano pointed out that production capacity loss provides vital data for estimating the economic impacts of disasters. Specifically, a production capacity loss is the input for the supply shock in economic models, such as the Input-Output (I-O) and Computable General

Equilibrium (CGE) models, to calibrate the higher order impacts (Tatano et al., 2022).

For example, based on the PCLR curves constructed in this study, we can determine the production capacity economic loss rates of various industrial sectors in Zhengzhou under the scenario of extremely large-scale flood disasters with a 1m moderate flooding level. On this basis, by combining with the sectoral gross output data from Zhengzhou's multi-regional input-output table, we can estimate the production capacity losses of each industrial sector in this scenario. Subsequently, by inputting the obtained production capacity loss data into the Mixed-MRIO model, we can estimate the ripple losses outside the disaster area caused by inter-regional industrial linkages.

PCLR values can serve as inputs for macroeconomic loss assessment models (such as IO and CGE), and they can be applied in these papers (Tatano and Tsuchiya, 2007; Jiang et al., 2023; Yang et al., 2023).

Comment 5:

Policy Implications:

The policy section is informative, especially the recommendation for sector-specific emergency funds and infrastructure investments. This could be enhanced with a brief discussion on data collection protocols for future disasters to enable rapid PCLR estimation.

Response:

Thank you for your positive feedback on the policy section of our paper. Your suggestion to include a discussion on future disaster data collection protocols to support rapid PCLR estimation is highly constructive. In fact, our research team has conducted multiple field surveys on disasters, including floods and typhoons, and has accumulated considerable experience in variable selection and question design. Additionally, when designing the questionnaire, we took data standardization into account and carried out corresponding standardization processing for production capacity loss data across different industries. For example, for the hotel, we ask enterprises about vacancy rates before and after the disaster. Additionally, we obtain average room rates from online sources to calculate the production capacity loss rate caused by the disaster. For the retail, we inquire about changes in customer flow before and after, and per capita spending, which allows us to calculate the production capacity loss rate of the stores caused by the disaster. We fully agree with your opinion and continue to address and expand on it in the discussion section as follows:

"We propose establishing a disaster emergency data collection template to build a standardized indicator system and design trigger-based questions. Through the government affairs system of emergency management departments, questionnaire templates can be pushed to high-risk enterprises, with automatic pre-filling of business registration information (such as industry type and number of employees). Additionally, a lightweight app could be developed to support voice input (e.g., equipment submerged for 8 hours) and on-site photo recognition (using OCR to extract equipment numbers and damage levels)."

Response to Minor Suggestions:

Comment 1:
Grammar and clarity:
Some long sentences (especially in the introduction and methodology) could be split to improve readability.

Response:
Thank you for your feedback. We have proofread the entire manuscript and optimized the rhythm of the paragraphs by splitting and restructuring complex sentence structures. For example:

- **Original text (On page 1, line 20):** At the macro-economic level, researchers widely utilize Input-Output (I-O) models (Okuyama and Santos, 2014; Koks and Thissen, 2016; Lenzen et al., 2019), Computable General Equilibrium (CGE) models (Kajitani and Tatano, 2018; Gertz et al., 2019), and integrated assessment models (Carrera et al., 2015; Koks et al., 2015) to quantify the economic effects of natural disasters.
- **Revised version:** At the macro-economic level, researchers commonly use several models to quantify the economic effects of natural disasters. These include Input-Output (I-O) models (Okuyama and Santos, 2014; Koks and Thissen, 2016; Lenzen et al., 2019), Computable General Equilibrium (CGE) models (Kajitani and Tatano, 2018; Gertz et al., 2019), and integrated assessment models (Carrera et al., 2015; Koks et al., 2015).

- **Original text (On page 2, line 33):** Recently, production capacity loss rate (PCLR) has been proposed as a competing input for these models, relying on estimated outputs from vulnerability curves (Kajitani and Tatano, 2014; Liu et al., 2022a; Jiang et al., 2015).

- **Revised version:** Recently, production capacity loss rate (PCLR) has been proposed as a competing input for these models. It is based on estimated outputs derived from vulnerability curves (Kajitani and Tatano, 2014; Liu et al., 2022a; Jiang et al., 2015).

- **Original text (On page 2, line 47):** Moreover, PCLR collected is often not continuous loss data that can be estimated using regression methods (Zentner et al., 2017). Consequently, while some researchers either assume loss rate data or simply analyze the relationship between hazard intensity and loss, this approach can overestimate or underestimate the actual loss, thereby amplifying or attenuating the risk.
- **Revised version:** Moreover, PCLR data collected is often discrete rather than continuous, making it unsuitable for regression analysis (Zentner et al., 2017). As a result, some researchers assume loss rate data or analyze only the relationship between hazard intensity and loss. This simplification may lead to overestimation or underestimation of actual loss, which can amplify or attenuate perceived risk.

- **Original text (On page 3, line 60):** Firstly, we conduct a questionnaire survey and classify damage states, and then utilize the exceedance probability curve model to develop exceedance probability curves.
- **Revised version:** First, we conduct a questionnaire survey and classify damage states. Then, we use the exceedance probability curve model to develop corresponding curves.

- **Original text (On page 3, line 64):** Finally, by integrating the expectation of loss rate with their associated probabilities under each damage state, we provide a more adaptable assessment of the mean PCLR for businesses in the post-disaster phase.
- **Revised version:** Finally, we integrate the expectation of loss rate with their associated probabilities for each damage state. This integration allows a more flexible assessment of the mean PCLR for businesses after a disaster.

Comment 2:

Figures:

Figures 3-6 are useful and well-labeled, but some could benefit from annotations or key call-outs to highlight major differences across sectors.

Response:

Thank you for your constructive feedback on the figures. We appreciate your recognition of their utility and labeling. We acknowledge that there were shortcomings in the interpretation of the figures, so we have added textual explanations to some of them. For example (on page 9, line 192):

“Analysis of Table 2 and Fig. 3 reveals differences in the exceedance probabilities of damage states across sectors. Specifically, the exceedance probabilities of major damage (complete damage) are significantly higher in the deep water sectors for accommodation and catering sectors, as shown in Fig.3. In addition, the exceedance probabilities of minor damage (moderate, major, and complete damage) are higher in the shallow water sectors for manufacturing sector. From the perspective of individual industries, wholesale and retail sector as well as other sectors exhibit a relatively even distribution of the four damage states across most inundation depth ranges, as shown in Fig.3(d) and Fig.3(e). This suggests that the loss patterns in these sectors are fairly dispersed and do not show significant concentration under varying flood depths. Such a distribution may reflect the diversity in their business nature and asset structure. As a result, these sectors may possess a certain level of resilience and risk-bearing capacity against flood hazards.”

Comment 3:

Terminology:

The term “response-bias-tolerant framework” is accurate but could be briefly defined when first introduced.

Response:

Thank you for your suggestion to clarify the “response-bias-tolerant framework.” The original text provides a detailed explanation of the sources of response bias. We have further supplemented it with numerous references and additionally defined response bias as follows: It refers to the tendency of survey participants to provide inaccurate responses or answer in a biased manner, resulting in skewed or misleading data (Gove W R and Geerken MR, 1977; Furnham A, 1986; Michalos A C, 2014). Following this, we provide a definition of the “response-bias-tolerant framework”. This term refers to a methodological approach designed to mitigate uncertainties arising from subjective judgments in data collection, particularly when enterprise managers provide potentially biased estimates of production capacity loss rates (PCLR)

during post-disaster surveys. We have defined this term at its first occurrence in the text (On page 3, line 59) and provided additional explanations where necessary throughout the paper.

Thanks for your comments to improve the quality of the paper.
Best Regards!

Lijiao Yang, Yan Luo, Zilong Li and Xinyu Jiang

References

Furnham, A. (1986). Response bias, social desirability and dissimulation. *Personality and Individual Differences*, *7*(3), 385–400. https://doi.org/10.1016/0191-8869(86)90014-0

Gove, W. R., & Geerken, M. R. (1977). Response Bias in Surveys of Mental Health: An Empirical Investigation. *American Journal of Sociology*, *82*(6), 1289–1317. https://doi.org/10.1086/226466

Jiang, X., Lin, Y., & Yang, L. (2023). A simulation-based approach for assessing regional and industrial flood vulnerability using mixed-MRIO model: A case study of Hubei Province, China. *Journal of Environmental Management*, *339*, 117845–117845. https://doi.org/10.1016/j.jenvman.2023.117845

Jiang, X., Ma, X., & Yang, L. (2023). Comprehensive comparative study on the construction method of flood vulnerability and fragility curves under the framework of regression analysis. *Journal of Hydraulic Engineering*. https://doi.org/10.13243/j.cnki.slxb.20220307

Li, Z., & Yan, W. (2023). Service flow changes in multilayer networks: A framework for measuring urban disaster resilience based on availability to critical facilities. Landscape and Urban Planning, 244, 104996–104996. https://doi.org/10.1016/j.landurbplan.2023.104996

Liu, H., Hirokazu Tatano, Yoshio Kajitani, & Yang, Y. (2024). Methodology for Estimating Regional Production Capacity Loss Rate in Industrial Sectors Caused by Disasters: A case study of the 2016 Kumamoto Earthquakes. *International Journal of Disaster Risk Reduction*, *110*, 104631–104631. https://doi.org/10.1016/j.ijdrr.2024.104631

Michalos, A. C. (2014). *Encyclopedia of quality of life and well-being research.* Springer.

Salgado-Gálvez, M. A., Momin, S., Grajales, S., & Carreño, M. L. (2023). Comparison of earthquake risk for masonry and RC buildings in Barcelona using existing sets of vulnerability functions. *Bulletin of Earthquake Engineering*. https://doi.org/10.1007/s10518-023-01800-0

Shinozuka, M., Feng, M. Q., Lee, J., & Naganuma, T. (2000). Statistical Analysis of Fragility Curves. *Journal of Engineering Mechanics*, *126*(12), 1224–1231. https://doi.org/10.1061/(asce)0733-9399(2000)126:12(1224)

Shooraki, M. K., Morteza Bastami, Morteza Abbasnejadfard, & Motamed, H. (2024). Development of Seismic Fragility Curves for Hospital Buildings Using Empirical

Damage Observations. *International Journal of Disaster Risk Reduction*, *108*, 104525–104525. https://doi.org/10.1016/j.ijdrr.2024.104525
Tatano, H., & Kajitani, Y. (2022). *Methodologies for estimating the economic impacts of natural disasters*. Springer.
Tatano, H., & Tsuchiya, S. (2007). A framework for economic loss estimation due to seismic transportation network disruption: a spatial computable general equilibrium approach. *Natural Hazards*, *44*(2), 253–265. https://doi.org/10.1007/s11069-007-9151-0
Yang, H., Feng, X., Wang, H., Yan, H., Zhao, P., Gao, F., Guo, X., & Xie, B. (2023). Long time-series variation of crop yield under drought stress and drought vulnerability curves in Songnen Plain, Northeast China. Ecological Indicators, 154, 110624. https://doi.org/10.1016/j.ecolind.2023.110624
Yang, L., Kajitani, Y., Tatano, H., & Jiang, X. (2016). A methodology for estimating business interruption loss caused by flood disasters: insights from business surveys after Tokai Heavy Rain in Japan. *Natural Hazards*, *84*(S1), 411–430. https://doi.org/10.1007/s11069-016-2534-3
Yang, L., Wang, X., Jiang, X., & Hirokazu Tatano. (2023). Assessing the Regional Economic Ripple Effect of Flood Disasters Based on a Spatial Computable General Equilibrium Model Considering Traffic Disruptions. *International Journal of Disaster Risk Science*, *14*(3), 488–505. https://doi.org/10.1007/s13753-023-00500-2
Zhong, S., Wang, C., Yang, Y., & Huang, Q. (2018). Risk assessment of drought in Yun-Gui-Guang of China jointly using the Standardized Precipitation Index and vulnerability curves. Geomatics, Natural Hazards and Risk, 9(1), 892–918. https://doi.org/10.1080/19475705.2018.1480537

Response to Reviewer Report on Manuscript egusphere-2024-3923

"Modeling Regional Production Capacity Loss Rates Considering Response Bias: Insights from a Questionnaire Survey on Zhengzhou Flood"

by Lijiao Yang, Yan Luo, Zilong Li and Xinyu Jiang

We are grateful for your constructive comments and suggestions, which certainly help us to improve the quality of our manuscript. We have seriously taken into account all the comments and addressed the points raised by you as follows. The key parts have been highlighted.

Response to General Comments:

Comment 1: This study is valuable in the field of natural disaster research. When conducting post-disaster damage assessments, respondents frequently encounter difficulties in providing accurate information. Consequently, addressing response bias effectively becomes paramount for ensuring data reliability and research quality.

Response:

We sincerely appreciate your kind recognition of the study's value in natural disaster research and your emphasis on the critical challenge of response bias in post-disaster damage assessments. Your acknowledgment of the importance of addressing this bias aligns with the core motivation of our methodology — using damage state classification and probabilistic modeling to enhance data reliability despite subjective respondent inputs. This validation reinforces the significance of our approach in bridging empirical survey data with robust analytical frameworks, and we are grateful for your support in highlighting its relevance to research quality.

Response to Specific Comments:

Comment 1:

To what extent can the proposed methodology effectively mitigate respondent biases? Please add more explanations.

Response:

Thank you for your valuable comments. To assess the extent to which our method mitigates response bias, it is generally necessary to have baseline data or true values for comparison. However, since the original production capacity loss rate (PCLR) data cannot be regarded as absolute true values, we face the challenge of lacking a definitive data reference. In this context, we assume that the survey data contains certain biases and therefore use the model-predicted estimated data as the calibrated results for comparative analysis. By doing so, we demonstrate the effectiveness of the model in correcting response bias and provide a reasonable and scientific evaluation framework in the absence of absolute true values. The observed data is obtained by averaging the PCLR of individual firms from survey data at different inundation levels.

As shown in Fig.S1 in the Appendix C, the model explains the observed values better at lower inundation levels, with the prediction intervals effectively encompassing the observations. Prediction intervals are ranges calculated based on the model's uncertainty; when observed values fall within these intervals, it indicates that the model's estimation of uncertainty is reasonable and the prediction results are reliable. However, for locations with deep inundation, due to fewer sample points, the model shows some bias and tends to underestimate the observed values. Nevertheless, the upper bounds of the prediction intervals are still close to the actual observations, indicating that the model can still partially capture the conditions in deeply inundated areas.

Comment 2:

The study should establish clear operational definitions for damage severity categories ("major," "minor," and "moderate"), accompanied by a comprehensive discussion of how these classifications influence outcome variables. This should be supported by relevant empirical evidence from existing literature.

Response:

Thank you very much for your suggestions. We have provided operational definitions for the damage state classifications in Table 1 in the original manuscript. I will further answer your question from two aspects: first, explaining why we used 1/3 and 2/3 as thresholds; second, providing the results of robustness using different thresholds.

Firstly, previous studies have divided the enterprise production capacity loss rate into several state intervals—[0, 1/3), [1/3, 2/3), [2/3, 1), and 1—to fit PCLR curves (Yang et al., 2016; Liu et al., 2024). In addition, in this study, we adopt damage state intervals of [0, 1/3), [1/3, 2/3), [2/3, 1), and 1, **with one core consideration being alignment with standardized classification systems in engineering to ensure methodological reproducibility and interdisciplinary compatibility.** Specifically, this classification framework draws on the widely used four-level damage paradigm — minor, moderate, major, and complete failure — commonly applied in earthquake and structural engineering (Shinozuka et al., 2000; Salgado-Gálvez et al., 2023; Shooraki et al., 2024). Such grading methods have long been validated as effective in disaster loss assessment and facilitate data interoperability with infrastructure vulnerability curves (e.g., for bridges and tunnels).

The choice of 1/3 and 2/3 as key thresholds essentially quantifies the "functional loss gradient" recognized in engineering fields. For example, minor damage (<1/3) corresponds to enterprises maintaining basic production capacity, analogous to "repairable minor damage" in structural engineering; moderate damage [1/3-2/3) corresponds to significant capacity reduction without complete interruption, consistent with "functional interruption but short-term recoverable" definitions; major damage (⩾2/3) approaches a near shutdown state, similar to a "critical state before structural failure." This standardized classification facilitates direct linkage between enterprise capacity loss and engineering physical damage indicators such as inundation depth and equipment submersion duration, laying a foundation for integrating remote sensing and infrastructure monitoring data in future work.

Secondly, we fully acknowledge that threshold choices affect result robustness. Therefore, we conducted sensitivity analyses to test how threshold shifts influence the PCLR curves, as shown in Fig.S1 in the AppendixB. In Classification 1, the thresholds are set at 1/3 and 2/3. In Classification 2, the thresholds are 1/4 and 1/2. In Classification 3, the tercile method is used. We found that for most industries under most inundation depth conditions, PCLR curve trends remain consistent across the three classification thresholds, with only slight variations in PCLR values at higher inundation depths. In contrast, the results for wholesale and retail trade industry is nearly identical across the three classification thresholds, as shown in Fig. S1(d).

We are considering deleting some content from the Discussion section (lines 293 to 297 on page 17), and then adding the following statement: "(2) Our classification of loss states aligns with the standardized classification system used in the engineering field to ensure interdisciplinary compatibility. Additionally, we have tested different classification thresholds and found that our approach is relatively robust."

Comment 3:

The manuscript introduces responder bias as an input condition for ripple loss calculations. This raises important questions: Why does ripple loss estimation require relatively accurate data? Could responder bias compromise input data quality and consequently lead to inaccurate loss estimates? These relationships warrant more detailed examination.

Response:

Thank you for your suggestions. Ripple loss estimation relies on macroeconomic models such as Input-Output (IO) and Computable General Equilibrium (CGE) models. These models require high-quality micro-level industry loss data as input to accurately capture the complex impacts of disasters on supply chains, production networks, and market supply-demand dynamics (Tatano and Kajitani, 2022; Yang et al., 2016). Disaster loss assessment is characterized by “nested layers,” where micro-level errors accumulate within macro models.

Response bias (such as individual perception differences, memory lapse, emotional influence) introduces uncertainty at the data collection source. PCLR relies on subjective assessments from enterprise managers regarding production interruptions (e.g., “approximately 15% loss,” “uncertain”), rather than objective physical indicators (e.g., equipment damage level, inventory loss quantity). Such subjective judgment can cause bias due to differing individual understandings, resulting in high discrepancies of loss data under the same disaster scenario.

The demand for data accuracy in ripple loss estimation fundamentally arises from the economic system’s sensitivity to initial conditions—micro-level input deviations can trigger “butterfly effects” during macroeconomic transmission. Response bias, as a major threat to data quality, can indeed distort loss estimates; however, through structured data processing (e.g., damage state classification, probabilistic modeling) and uncertainty quantification (e.g., MCS prediction intervals), this study provides a feasible framework to mitigate this challenge.

Comment 4:

While future research directions are proposed, the discussion would benefit from greater depth regarding implementation specifics. For instance, suggestions about increasing sample size and incorporating cross-regional, multi-industry data need to address practical considerations: How will data collection be standardized across different contexts? What integration challenges might arise from heterogeneous data sources?

Response:

Thank you very much for your valuable suggestions. In fact, our research team has conducted multiple field surveys on disasters such as floods and typhoons, accumulating rich experience in variable selection and questionnaire design. In addition, during the questionnaire design process, we have fully considered data standardization issues and performed corresponding standardization processing for production capacity loss data across different industries. For example, for the hotel, we ask enterprises about vacancy rates before and after the disaster. Additionally, we obtain average room rates from online sources to calculate the initial production capacity loss rate caused by the disaster. For the retail, we inquire about changes in customer flow before and after, and per capita spending, which allows us to calculate the initial production capacity loss rate of the stores caused by the disaster. We fully agree with your opinion and continue to address and expand on it in the discussion section as follows:

We propose establishing a disaster emergency data collection template to build a standardized indicator system and design trigger-based questions. Through the government affairs system of emergency management departments, questionnaire templates can be pushed to high-risk enterprises, with automatic pre-filling of business registration information (such as industry type and number of employees). Additionally, a lightweight app could be developed to support voice input (e.g., equipment submerged for 8 hours) and on-site photo recognition (using OCR to extract equipment numbers and damage levels).

Comment 5:

A thorough linguistic review is necessary to eliminate grammatical inaccuracies and refine syntactical structures. Particular attention should be paid to ensuring terminological consistency with disciplinary conventions and maintaining an appropriate academic register throughout the manuscript.

Response:

We appreciate your input and have rigorously revised the text for grammatical accuracy, terminological consistency, and academic tone. For example:

- **Original text (On page 5, line 109):** Goodness-of-fit tests, such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), are utilized to evaluate the model's fit. The distribution that fits best is used for further analysis and predictions.
- **Revised version:** To evaluate how well the model fits, we use goodness-of-fit tests such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The distribution that fits the data best will be selected for further analysis and predictions.

- **Original text (On page 6, line 137):** Monte Carlo simulation is employed to solve problems characterized by various uncertainties and has found widespread application across numerous fields (Christensen et al., 2024; Asche et al., 2021; Goda et al., 2020).
- **Revised version:** Monte Carlo simulation (MCS) is used to address problems involving various uncertainties. It has been widely applied across many fields

(Christensen et al., 2024; Asche et al., 2021; Goda et al., 2020).

- **Original text (On page 6, line 139):** The model's iterative estimates generate a dataset of possible outcomes, which, when aggregated, define the range of the true outcome with a specified probability.
- **Revised version:** The model produces iterative estimates that form a dataset of possible outcomes. When these outcomes are aggregated, they define the true outcome's range with a given probability.

- **Original text (On page 17, line 313):** By constructing exceedance probability curves and employing distribution function fitting, we develop a method to estimate mean PCLR considering response bias.
- **Revised version:** We develop a method to estimate mean PCLR while accounting for response bias. This method involves constructing exceedance probability curves and using distribution function fitting.

Comment 6:
The manuscript would benefit from employing more sophisticated transitional devices (e.g., " This methodological approach demonstrates three principal advantages: Primarily, "). Systematic elimination of lexical repetition through careful editing would enhance the text' s professional tone.

Response:
We appreciate your feedback and have enhanced transitional devices while reducing lexical repetition to improve professionalism. For example:

- **Original text (On page 17, line 313):** This study addresses the challenge of estimating mean PCLR after extreme disaster events, a significant issue in disaster research. By constructing exceedance probability curves and employing distribution function fitting, we develop a method to estimate mean PCLR considering response bias. The application of MCS further enhances the reliability of our estimates by providing prediction intervals, which are essential for guiding post-disaster government resource allocation. Additionally, we calculate the rate of change of PCLR to understand the sensitivity of sector-specific PCLR to varying inundation depths. Then, the proposed method is applied to 424 data samples collected after the Zhengzhou rainstorm event in July 2021. The estimated PCLR values can serve as a driving condition in IO and

CGE models, allowing for a more accurate estimation of the ripple effects of flood losses.

- **Revised version:** This study tackles the significant challenge of estimating mean PCLR following extreme disaster events, a crucial topic in disaster research. Our methodological approach demonstrates three principal advantages: first, we develop a method to estimate mean PCLR while accounting for response bias. This method involves constructing exceedance probability curves and using distribution function fitting. Second, the integration of Monte Carlo simulation (MCS) enhances the reliability of these estimates by generating prediction intervals, which are vital for informing government decisions on post-disaster resource allocation. Third, we quantify the rate of change of PCLR to assess the sensitivity of sector-specific PCLR with respect to varying inundation depths. Subsequently, we apply the proposed method to 424 data samples collected after the Zhengzhou rainstorm event in July 2021. Ultimately, the estimated PCLR values serve as critical input parameters in Input-Output (IO) and Computable General Equilibrium (CGE) models, thereby enabling a more precise evaluation of the ripple effects caused by flood losses.

Thanks for your comments to improve the quality of the paper.
Best Regards!

Lijiao Yang, Yan Luo, Zilong Li and Xinyu Jiang

References

Liu, H., Hirokazu Tatano, Yoshio Kajitani, & Yang, Y. (2024). Methodology for Estimating Regional Production Capacity Loss Rate in Industrial Sectors Caused by Disasters: A case study of the 2016 Kumamoto Earthquakes. *International Journal of Disaster Risk Reduction*, *110*, 104631–104631. https://doi.org/10.1016/j.ijdrr.2024.104631

Salgado-Gálvez, M. A., Momin, S., Grajales, S., & Carreño, M. L. (2023). Comparison of earthquake risk for masonry and RC buildings in Barcelona using existing sets of vulnerability functions. *Bulletin of Earthquake Engineering*. https://doi.org/10.1007/s10518-023-01800-0

Shinozuka, M., Feng, M. Q., Lee, J., & Naganuma, T. (2000). Statistical Analysis of Fragility Curves. *Journal of Engineering Mechanics*, *126*(12), 1224–1231. https://doi.org/10.1061/(asce)0733-9399(2000)126:12(1224)

Shooraki, M. K., Morteza Bastami, Morteza Abbasnejadfard, & Motamed, H. (2024). Development of Seismic Fragility Curves for Hospital Buildings Using Empirical Damage Observations. *International Journal of Disaster Risk Reduction*, *108*, 104525–104525. https://doi.org/10.1016/j.ijdrr.2024.104525

Tatano, H., & Kajitani, Y. (2022). *Methodologies for estimating the economic impacts of natural disasters*. Springer.

Yang, L., Kajitani, Y., Tatano, H., & Jiang, X. (2016). A methodology for estimating business interruption loss caused by flood disasters: insights from business surveys after Tokai Heavy Rain in Japan. *Natural Hazards*, *84*(S1), 411–430. https://doi.org/10.1007/s11069-016-2534-3

Appendix A

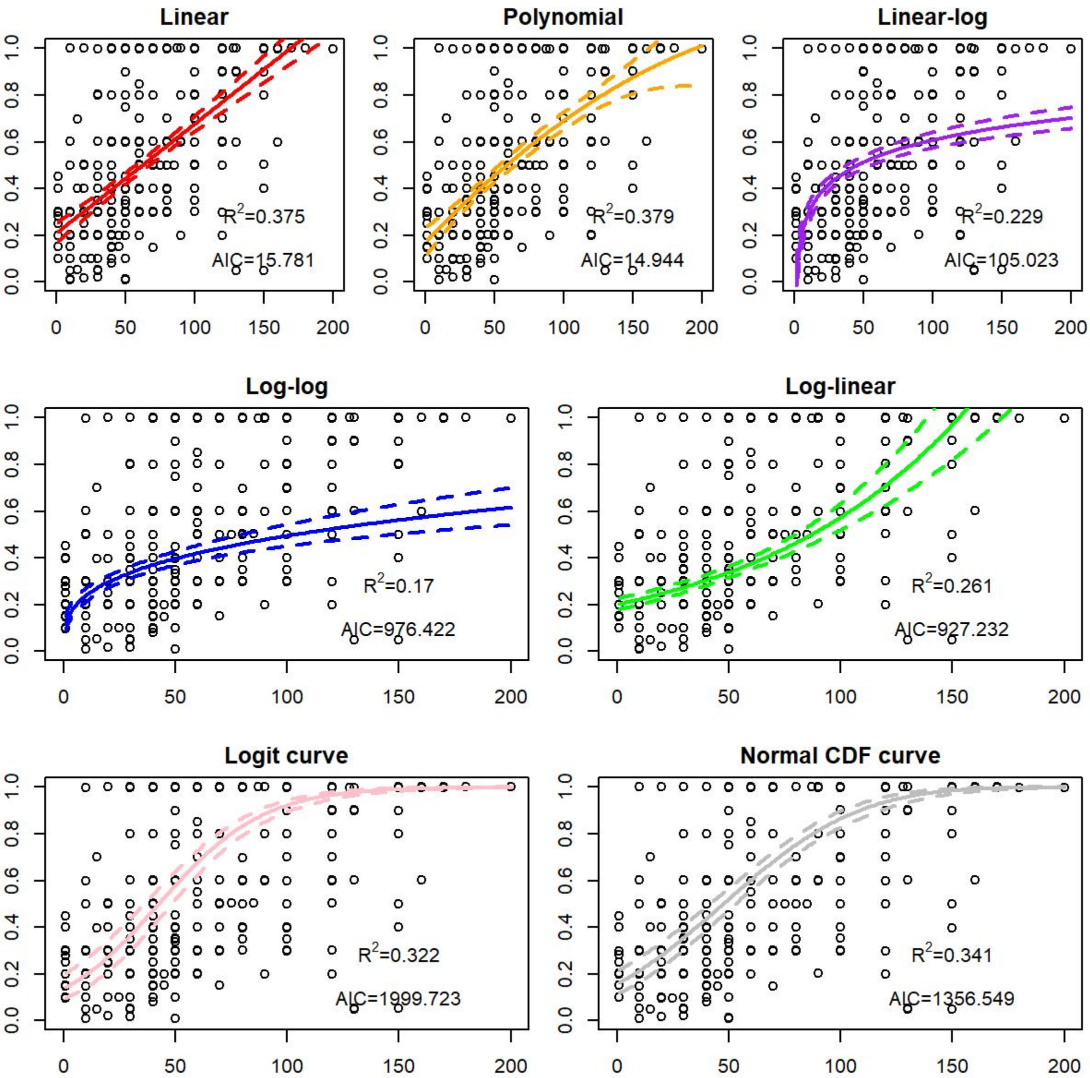

Fig.S1.Vulnerability curves of loss rates for seven types across all sectors

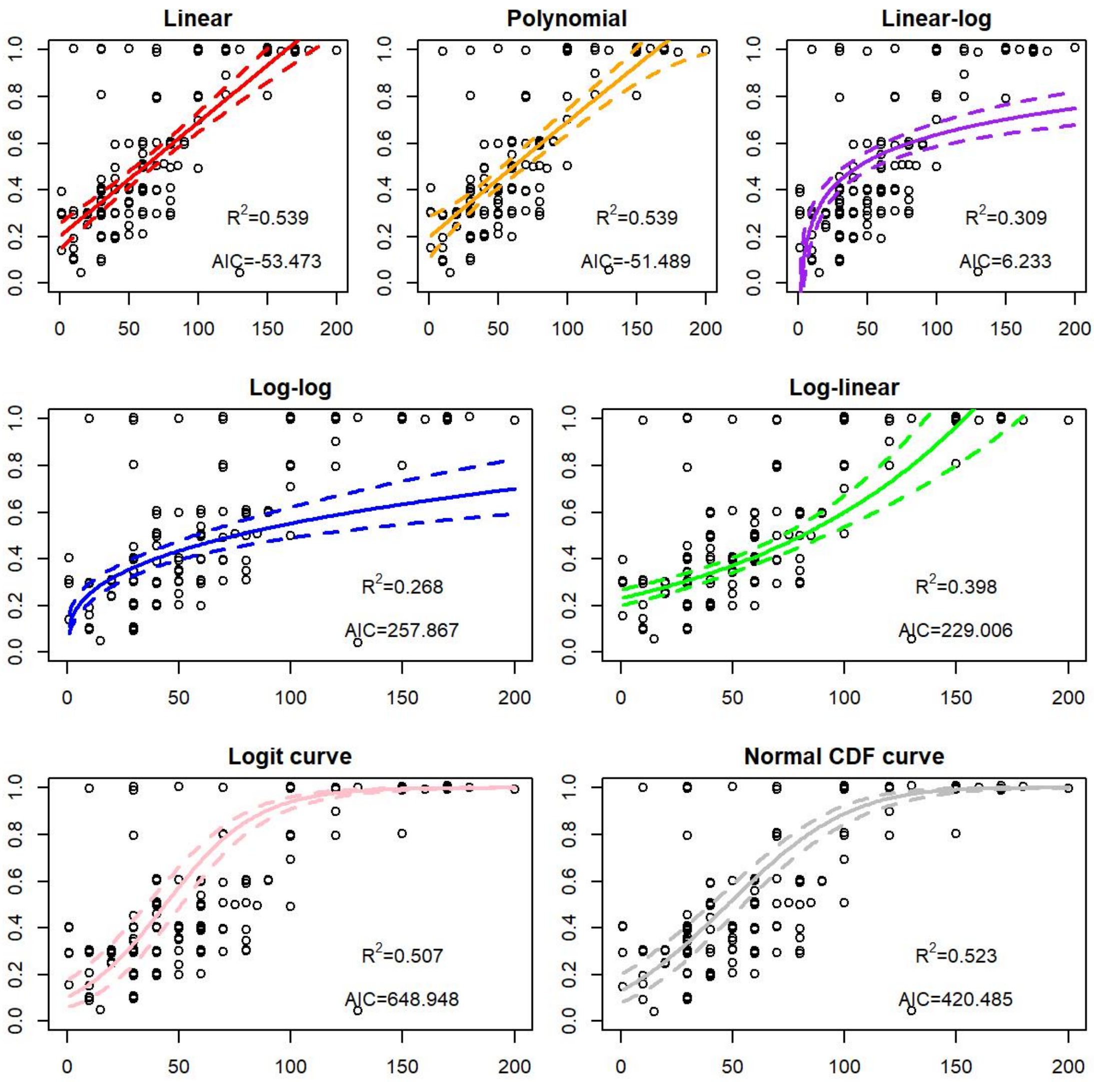

Fig.S2.Vulnerability curves of loss rates for seven types across manufacturing sector

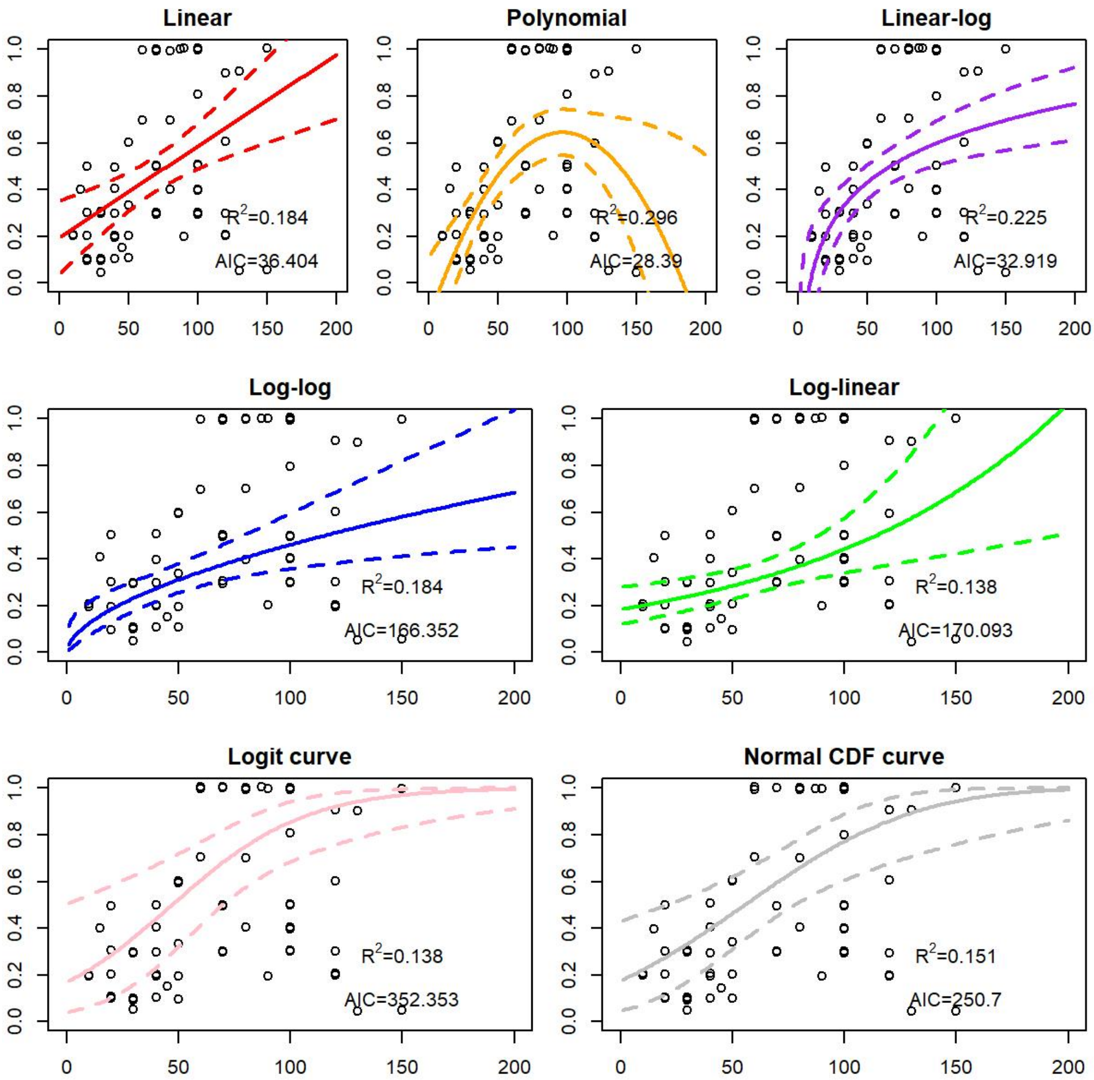

Fig.S3.Vulnerability curves of loss rates for seven types across accommodation and catering sector

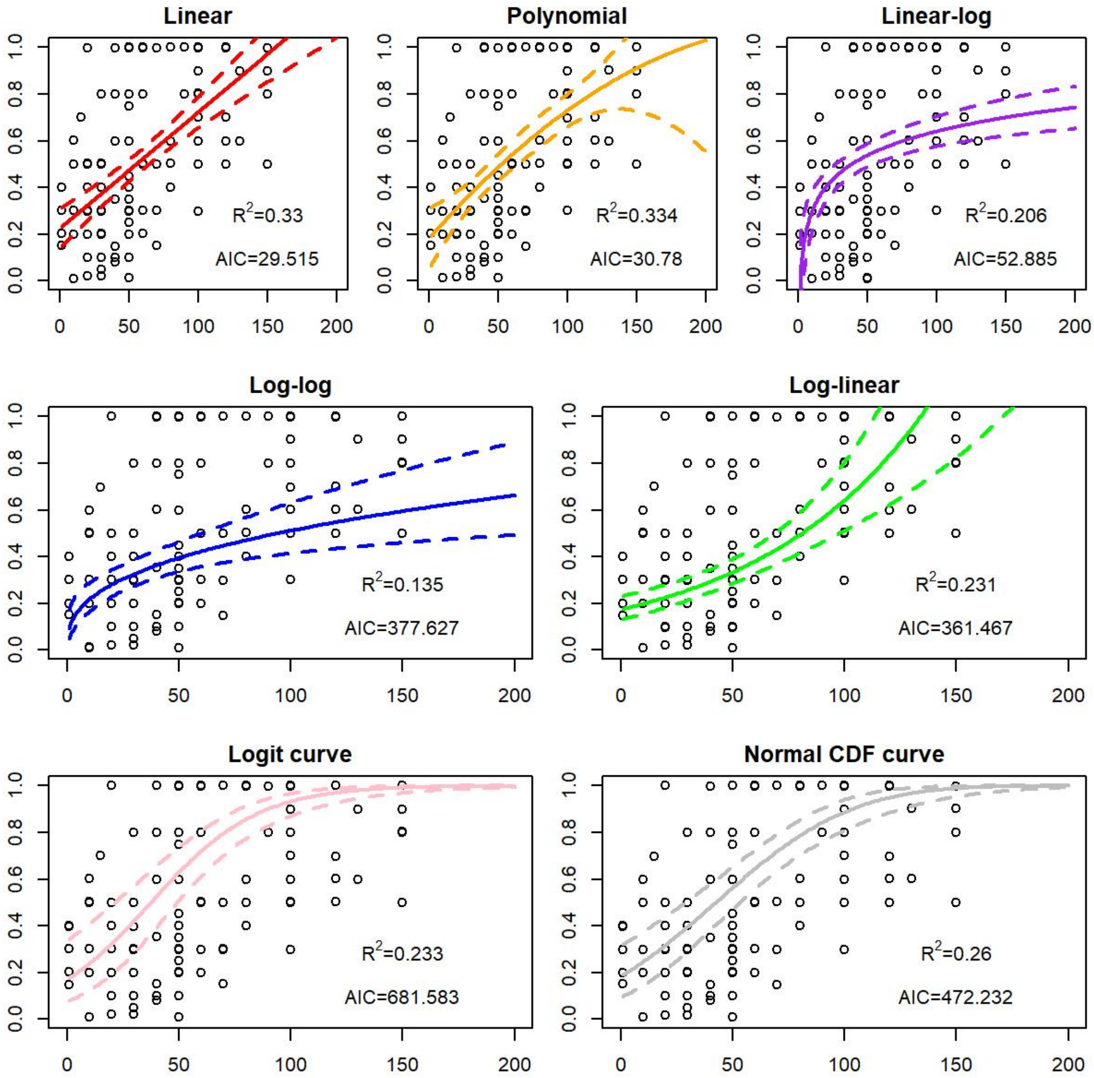

Fig.S4.Vulnerability curves of loss rates for seven types across wholesale and retail trade sector

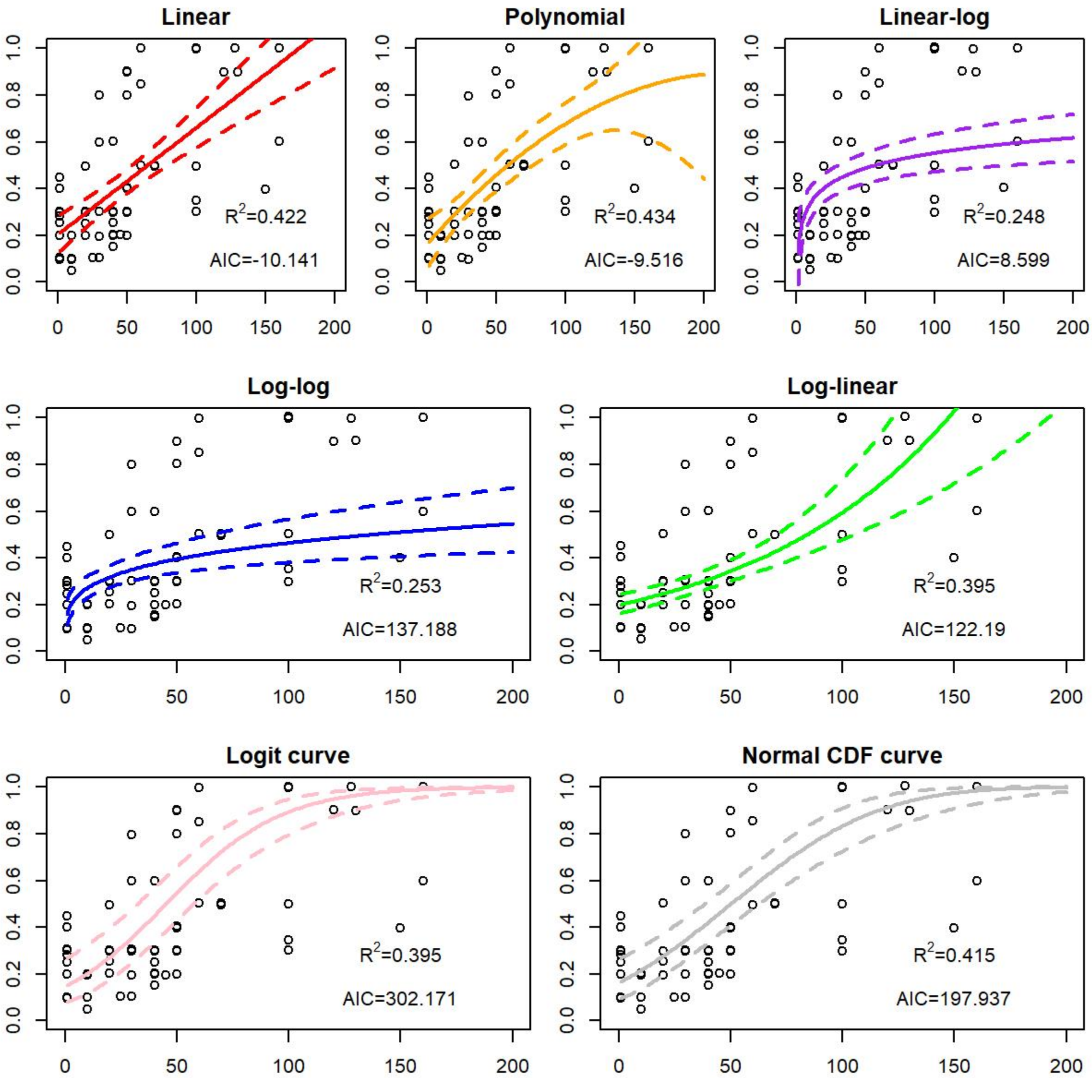

Fig.S5.Vulnerability curves of loss rates for seven types across other sector

Appendix B

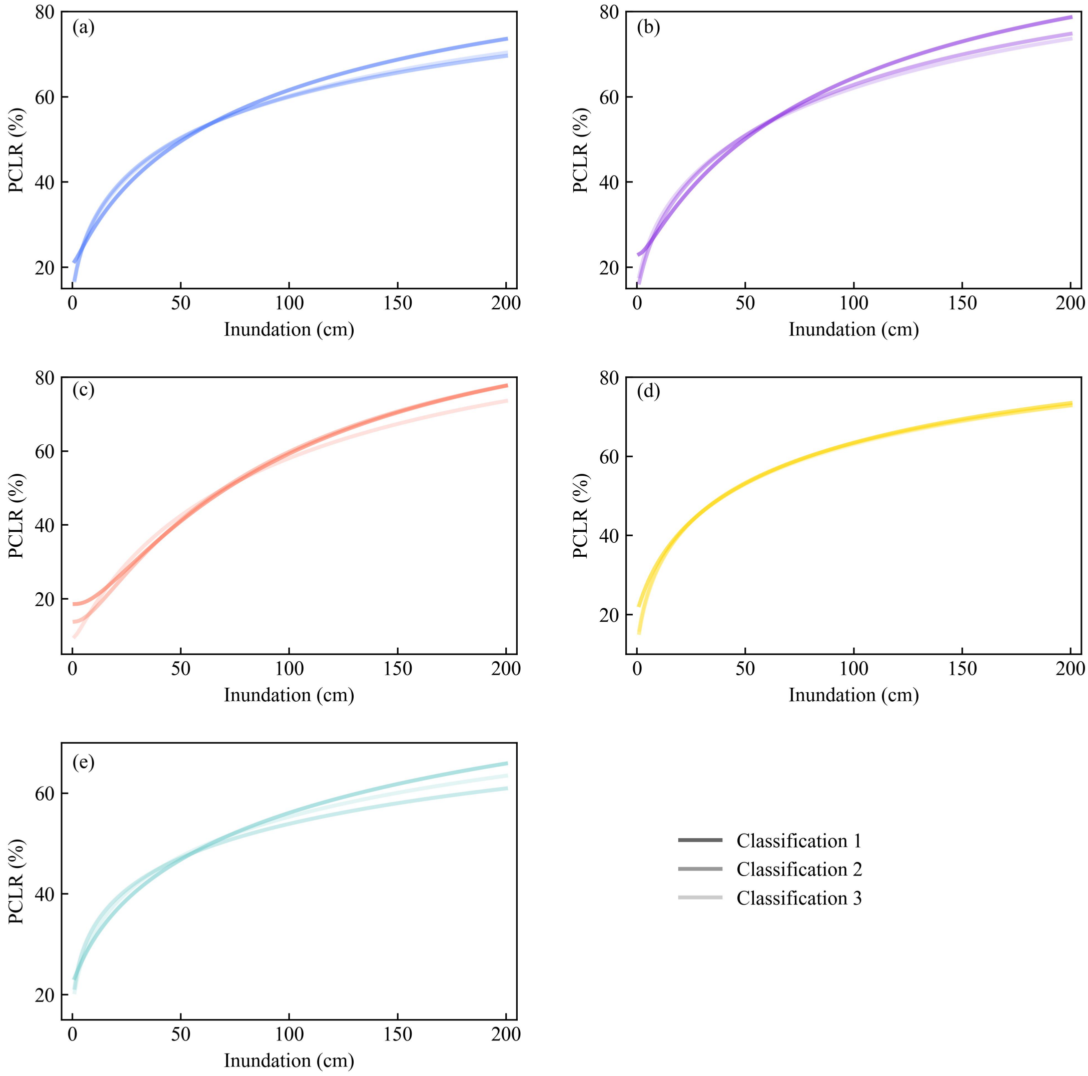

Fig.S1. Comparison under different threshold classifications. (a) All sectors; (b) manufacturing; (c) accommodation and catering; (d) wholesale and retail trade; (e) other sectors.

Appendix C

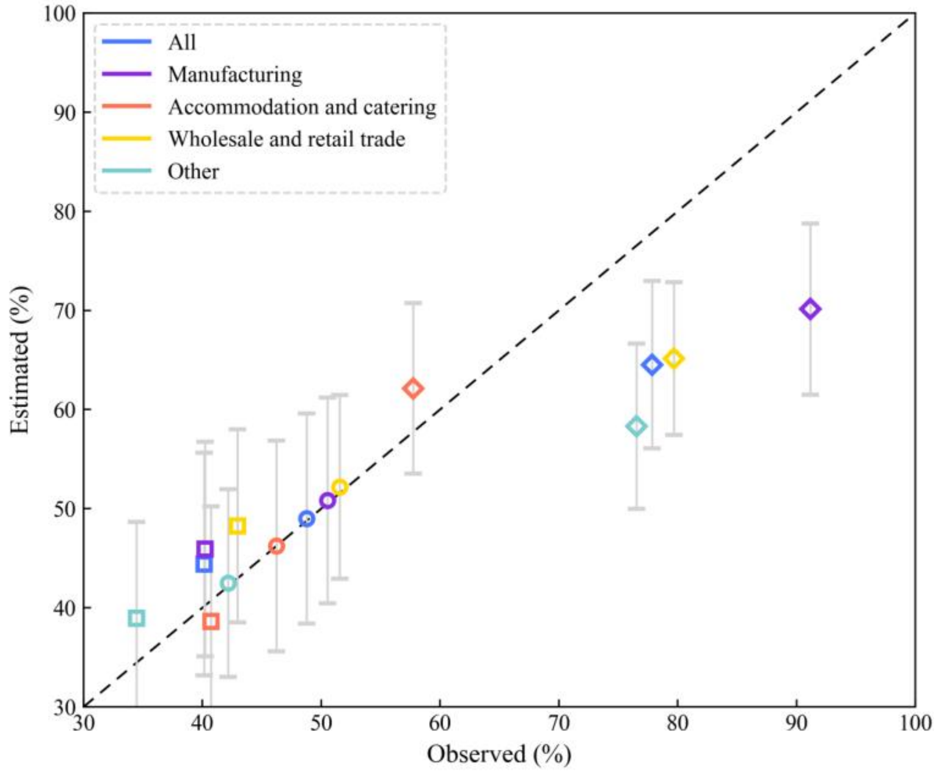

Fig.S1. Comparison results between estimated values and observed values

In addition to the responses to the two reviewers and the corresponding revisions, we have also made some minor modifications to the text, as detailed below:

- Use the preposition "for" uniformly before "different damage state".
- "Estimate" is used to describe probabilities and loss rates, rather than curves.
- The map containing territorial disputes has been removed.