

Dear Alois,

Thank you for your kind words and the opportunity to address your remaining comments. We are pleased to confirm that the points have been addressed as follows:

1. I think Figure B1 gives a great overlook of the reviewed literature and would deserve to be briefly discussed and integrated at the end or beginning of the result section.

Regarding Figure B1, the figure has been integrated into the main text, specifically at the beginning of Section 3.5 (Limitations and Future Research Directions), where it now serves as a synthetic overview of the methodological landscape before the discussion of limitations. The conclusions have been slightly revised to avoid repetition, and the supplementary section where the figure was previously located has been removed.

2. Putting bullet points inside your summary tables would make them easier to read.

Regarding the summary tables, all tables have been reformatted with a consistent style and bullet point lists to improve readability.

Table 1: Data-related methods, gaps and opportunities.

SECTION	METHODS	GAPS	OPPORTUNITIES
3.1.1 Climate datasets	<ul style="list-style-type: none"> • LSTM for soil moisture & hydrology; • RF for runoff/precipitation; • ConvNPs for sparse sensors; • ANNs for interpolation; • CNNs, GANs, diffusion models for downscaling; • GPs for uncertainty quantification 	<ul style="list-style-type: none"> • Struggles with sparse/irregular data; • Poor scalability (GPs); • Extremes misrepresented; • Limited uncertainty treatment 	<ul style="list-style-type: none"> • Hybrid ML–physics models; • Scalable probabilistic methods; • Better uncertainty quantification; • Generative models for projection ensembles
3.1.2 Earth observations (EO)	<ul style="list-style-type: none"> • SVM, RF, LSTM for soil moisture; • CNNs/autoencoders for land cover, impacts, disaster recovery; • Transfer learning; • ML for water quality (RF, ANN, XGBoost) 	<ul style="list-style-type: none"> • Bias toward data-rich regions for validation/testing; • Revisit gaps/ clouds limit detection; • False positives; • Weak multi-hazard integration 	<ul style="list-style-type: none"> • Robust models for missing/noisy data; • Near-real-time EO pipelines; • Integrate EO with socio-economic data; • Transfer learning for vulnerable regions
3.1.3 Textual data	<ul style="list-style-type: none"> • NLP + ML (Naïve Bayes, RF, SVM, CNN, BERT, LSTM); • Multimodal (text + images); • Rule-based for small datasets 	<ul style="list-style-type: none"> • Few labelled datasets; • Language/ cultural bias; • Imprecise spatial info; • Noisy social media inputs 	<ul style="list-style-type: none"> • Multilingual/ transfer learning; • Improved geolocation extraction; • Integrate with EO/sensor data;

			<ul style="list-style-type: none"> • Robust methods for noisy/misinformation-prone data
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Table 2: Multi-hazard related methods, gaps and opportunities.

SECTION	METHODS	GAPS	OPPORTUNITIES
3.2.1 Identify, classify & cluster	<ul style="list-style-type: none"> • Thresholding (empirical & percentiles) to build multi-hazard catalogues; • Return periods & GEV; • CNNs (semi-/supervised) for extreme-weather object detection in reanalyses; • DBSCAN for spatio-temporal footprints and compound clusters. 	<ul style="list-style-type: none"> • Under-detection of joint (non-univariate) extremes when hazards are merged post-hoc; • Label scarcity & class imbalance for supervised DL; • Skewed datasets; • Sensitivity to spatial/temporal non-stationarity. 	<ul style="list-style-type: none"> • Unified pipelines that detect compound signatures directly (multivariate thresholds + clustering); • Semi-/self-supervised DL to mitigate label scarcity; • Robust cluster tracking of compound hotspots under change.
3.2.2 Hazard forecasting & prediction	<ul style="list-style-type: none"> • LSTM/CNN for hydrology, storm surge, drought-heat; • Transformers for floods; • GNN/GRU for river-network dynamics; • Classical ML (RF/SVM/XGB) for local extremes when data are limited. 	<ul style="list-style-type: none"> • High data demands; • Generalisation beyond observed regimes; • Limited interpretability; • Performance varies with spatial context and input windowing. 	<ul style="list-style-type: none"> • Physics-informed/graph-aware DL for better extrapolation; • Attention/attribution to expose drivers; • Global-to-local transfer learning; • Benchmarking vs. process models for trust.
3.2.3 Modelling hazard interactions	<ul style="list-style-type: none"> • Copulas (pair/vine/Joe) for joint extremes; • Copula-BNs for river-coastal compounding; • XAI on LSTMs/CNNs/Transformers (gradients, attention, sensitivity) to reveal drivers and shifts. 	<ul style="list-style-type: none"> • Copula family selection & tail-dependence in high dimensions; • ML black-box limits causal insight; • Difficulty linking physical drivers to dependence structures. 	<ul style="list-style-type: none"> • Hybrid ML-copula stacks (ML to predict/characterise events, copulas to quantify joint probabilities); • Benchmarking ML-learned dependencies against copula baselines; • Conditional vine copulas for multivariate models.
3.2.3 Susceptibility mapping (multi-hazard)	<ul style="list-style-type: none"> • Supervised ML (LR,GLM, RF, SVM, BRT, CART, ANN, CNN) to build single-hazard susceptibility maps, then combined into multi-hazard maps; • Feature importance to rank drivers. 	<ul style="list-style-type: none"> • Often “<i>multi-layer single-hazard</i>” (weak interaction modelling); • Skewed datasets (few positive samples); • Sampling bias & autocorrelation; 	<ul style="list-style-type: none"> • Spatio-temporal CV (block) to curb leakage; • Dynamic susceptibility that updates with sequences/adaptation; • Explicit hazard interaction terms;

		<ul style="list-style-type: none"> Limited hazard breadth beyond fire/ landslide/ flood/ earthquake. 	<ul style="list-style-type: none"> Extend beyond the typical geohazards
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Table 3: Multi-risk related methods, gaps and opportunities.

SECTION	METHODS	GAPS	OPPORTUNITIES
3.3.1 Risk via susceptibility + exposure + vulnerability	<ul style="list-style-type: none"> Overlay of single-hazard susceptibility (RF, SVM, ANN, BRT, CART, MaxEnt, CNN with patch context) with exposure (buildings, population, infrastructure) and simple vulnerability layers; AHP/MCDM weighting; feature importance/ SHAP to rank drivers. 	<ul style="list-style-type: none"> Vulnerability and exposure treated as static layers; modelling only direct impacts and risks; Ignores cascading and indirect effects and their propagation across multiple spatial scales 	<ul style="list-style-type: none"> Dynamic vulnerability/exposure updates using EO and time-sequenced hazards; spatio-temporal block cross-validation; interaction-aware fusion (graphs, learned weights); extend to wind, hail, heat, storm surge; probabilistic risk maps with uncertainty bands.
3.3.2 Predicting impacts – Health	<ul style="list-style-type: none"> Ensemble and hybrid ML approaches (RF, XGBoost, SVM, DL, copulas, causal ML) applied to health, food, environmental, and economic impacts; explainable AI (SHAP) and probabilistic modelling for driver attribution. 	<ul style="list-style-type: none"> Impact labels are sparse, coarse, biased, and confounded; scale mismatches and aggregation blur signals; extremes and tails poorly represented; DL tends to overfit and transfer poorly across cities/regions/climates; uncertainty quantification and causal attribution often limited. 	<ul style="list-style-type: none"> Data & catalogues: build geocoded, event-level, cross-sector impact datasets and standardized labels (health, yields, biodiversity, losses); Causal & lag-aware stacks: combine DLNM / explicit-lag models with ML and causal discovery to capture delayed and causal pathways; Multi-source fusion & transfer: integrate EO, in-situ, socio-economic and market data; use domain-adaptation/ transfer learning for cross-region generalization.

Table 4: Future related methods, gaps and opportunities.

SECTION	METHODS	GAPS	OPPORTUNITIES
3.4.1 Predicting future hazards	<ul style="list-style-type: none"> Bias correction for projections (incl. quantile mapping); 	<ul style="list-style-type: none"> Univariate bias correction can distort extremes/ joint tails; Regional skill varies; 	<ul style="list-style-type: none"> Adopt multivariate bias correction; Combine SMILEs to separate internal

	<ul style="list-style-type: none"> • Hotspot/ trend detection via percentile thresholds (e.g., 95th–99th), return periods; • Uncertainty sources and propagation; • Vine copulas for joint tails; • SMILE large ensembles; • Storyline event-based scenarios analysis. 	<ul style="list-style-type: none"> • Limited direct detection of compound signals; • Uncertainty treatment often partial. 	<p>variability vs. structural model differences;</p> <ul style="list-style-type: none"> • Scale up vine copulas for compound events; • Embed storylines for preparedness.
3.4.2 Modelling future impacts	<ul style="list-style-type: none"> • Trained on historical impacts and applied to future ensembles; ensemble ML methods (RF, XGBoost, ...) for coastal risk, conflict risks, crop yield and adaptation scenarios; • Bayesian Networks for multi-model chains (hydrodynamics–waves–shoreline); • Distributed-lag models for future health impacts; • Future susceptibility integrating land use changes 	<ul style="list-style-type: none"> • Impact data often coarse, biased, and sparse; • Studies often rely on few years → low representativeness; • Causal discovery hinges on strong assumptions; • Biases due to scale mismatch in climate–exposure–impact data. 	<ul style="list-style-type: none"> • Use multi-model, multi-year ensembles and probabilistic models to quantify and propagate uncertainty; • Evaluate adaptation portfolios with standardized costs; • Integrate dynamic land use + socio-economic pathways (SSPs); • Uncertainty-aware learning, and open, geocoded impact datasets.

3. Line 529 of revised manuscript: Comparison and complementarities. Should be in bold?

Yes, now it has been corrected.

4. Line 968 of revised manuscript: Error! Reference source not found.

This referred to the old Figure B1, which has now been moved to the main text and renumbered as Figure 3.

We hope the manuscript is now ready for final acceptance and thank you again for your careful handling of the paper.

Kind regards