

# 1 **Review article: Harnessing data driven methods for climate multi-** 2 **hazard and multi-risk assessment**

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16

17 **Abstract.** In recent years, interest in data-driven methods, such as machine learning and multivariate statistics for multi-hazard  
18 and multi-risk assessment has surged, due to their ability to integrate vast amounts of data in modelling complex non-linear  
19 relationships between hazard and risk factors. This review explores data-driven methods in climate multi-hazard and risk  
20 analysis, focusing on four themes: (i) data processing and collection; (ii) hazard identification, prediction and analysis; (iii)  
21 risk analysis; and (iv) future risk scenarios under climate change. Key findings highlight the extensive use of machine learning  
22 to combine Earth observations and climate data for downscaling and land use and land cover characterisation; the application  
23 of deep learning for hazard prediction; the use of ensemble methods for risk analysis; and the growing emphasis on explainable  
24 AI frameworks. Supervised machine learning approaches trained on historical impact data to project future climate risks have  
25 also emerged as a significant research area. Future research in this area should focus on modelling multi-hazard interactions,  
26 particularly triggering and cascading effects, integrate dynamic vulnerability and exposure factors, and address uncertainties  
27 associated with using machine learning for extrapolation. Advancements in Earth observations and textual data integration,  
28 alongside the development of open-access disaster catalogues, will also be crucial for improving multi-risk analyses and  
29 supporting AI-driven early warning systems tailored to regional needs.

## 30 **1 Introduction**

31 The growing interconnectedness between socio-economic and natural systems, coupled with the escalating challenges  
32 presented by climate change, has led to increased complexities in climate risk analysis. At the same time, a wider availability  
33 of data on multiple risk drivers, including weather observations, Earth observations (EO), climate reanalyses and projections,  
34 socio-economic indicators, and social media, coupled with advances in machine learning (ML) and statistical methods, are  
35 increasing the potential of data-driven methodologies, which promise to revolutionise climate risk assessment (Kashinath et  
36 al., 2021a; Reichstein et al., 2019). To unlock the full potential of this data, it is crucial to develop and apply advanced methods  
37 for processing, harmonizing, and integrating heterogeneous datasets. These efforts enable the generation of actionable insights  
38 essential for effective multi-hazard and multi-risk assessments, by leveraging the accessibility of large datasets to be explored  
39 with advanced ML and statistical techniques.

40 Complex dynamics characterize socio-environmental and climate risk: applications may underestimate impacts if they do not  
41 take into account the compounding, cascading and amplifying interactions of hazards and their effect on vulnerability and  
42 exposure factors. In fact, (i) compounding hazards (co-occurring in the same location and at the same time) can lead to impacts  
43 which may be substantially higher than the sum of the single events taken in isolation (Arosio et al., 2020; Zscheischler et al.,  
44 2018), (ii) the occurrence of one hazard itself can modify vulnerability or resilience of the system, exposing assets or  
45 communities to higher risks, such as in the case of consecutive hazards (de Ruiter & van Loon, 2022), and (iii) impacts and  
46 risks can propagate across multiple scales and sectors, extending far beyond the area initially hit and affecting whole systems  
47 (Arosio et al., 2021; Pescaroli & Alexander, 2018), such as in the case of high-impact and low-probability events (Linkov et  
48 al., 2022). For these reasons, the international community (Intergovernmental Panel on Climate Change (IPCC), 2023;  
49 UNDRR, 2020) has recently pledged for a paradigm shift from single hazard towards a more comprehensive representation of  
50 multiple and interconnected climatic risks (AghaKouchak et al., 2020; De Angeli et al., 2022; Gallina et al., 2020; Šakić  
51 Trogrlić et al., 2024; Terzi et al., 2019; Tilloy et al., 2019; Ward et al., 2022). To achieve this shift, it is essential to develop  
52 data-driven methodologies that can analyse and predict the interactions and dependencies between multiple hazards, enabling  
53 a more accurate characterisation of their compounding and cascading effects.

54 To better navigate the many definitions surrounding multi-hazard risk concepts, this paper adopts the terminology used in  
55 Zschau (2017), where *multi-layer single hazards* refers to applications focussing on more than one hazards, without  
56 considering hazard interactions; *multi-hazard* focuses on hazards interaction; *multi-hazard risk* refers to applications  
57 considering risks in a multi-hazard framework, without discussing interactions at vulnerability level, and finally *multi-risk*  
58 refers to the most complex analysis comprising interactions at both hazard and vulnerability level.

59 The complex nature of multi-hazard events presents significant challenges to existing risk assessment methodologies, which  
60 treat hazards and risks singularly and often struggle to handle the non-linear interactions and feedback loops between multiple  
61 risk drivers (Tilloy et al., 2019). ML techniques have recently gained traction in climate science and risk analysis for their  
62 ability to process and integrate large, heterogeneous datasets from sources such as weather observations, Earth observations,

63 climate reanalyses and projections, socio-economic indicators, and even social media. By learning from historical data, they  
64 can uncover non-linear risk patterns and detect correlations across spatial and temporal scales, driving their growing use in  
65 climate risk assessment (Reichstein et al., 2019; Zennaro et al., 2021).

66 Integrating these heterogeneous data sources can help in capturing multi-hazard interactions and characterise their impacts on  
67 social, economic, and natural systems, especially thanks to the introduction of new Deep Learning (DL) architectures and  
68 models, specialized in capturing both spatial and temporal non-linear interactions (S. Park et al., 2023).

69 As ML models have become more complex, attention has shifted toward making these models more interpretable and  
70 explainable (Carvalho et al., 2019). This is especially important for applications focussing on risk, where it is crucial to quantify  
71 the contribution of each input feature to the model's prediction, making it easier to assess how different risk variables impact  
72 the overall risk. In this context, explainability frameworks improve the robustness of risk assessments and enhance trust in the  
73 model's outputs by providing insights into how the model arrives at specific conclusions (S. Jiang et al., 2024; McGovern et  
74 al., 2019), supporting transparency and accountability for stakeholders.

75 In addition to ML methods, this review briefly considers the role of copulas as multivariate statistical tools in multi-risk  
76 assessment. Copulas enable explicit modelling of the dependence structure between variables, making them particularly  
77 valuable for analysing compound events in which multiple hazards occur simultaneously or sequentially (see, for example,  
78 Agrawal, 2022; Hochrainer-Stigler et al., 2019). They have, for instance, been used to characterise the joint occurrence of  
79 droughts and heatwaves, yielding insights into their combined impacts on agriculture and water resources (see e.g. Ribeiro et  
80 al., 2020). Although their application is more specialised than most ML approaches, copulas provide critical information about  
81 inter-hazard dependencies, supporting a deeper understanding of compounding and interacting risks. Their inclusion in this  
82 review therefore highlights their importance in contexts requiring precise statistical modelling of hazard interactions and  
83 underscores how they complement broader ML-based strategies in climate-risk analysis. To advance this field, there is a critical  
84 need for predictive frameworks that can leverage these advanced methods to forecast long-term future multi-hazard and multi-  
85 risk scenarios, addressing uncertainties and guiding adaptive risk management strategies under changing climatic conditions.

86 To support implementation, the development of a wide range of open-source libraries (e.g., *scikit-learn*, *TensorFlow*, *Keras*,  
87 *PyTorch*, *VineCopulas* (Claassen et al., 2024), etc.), allows users to implement, train, validate, and deploy models with  
88 minimal programming expertise, making it possible for non-experts or domain specialists with limited knowledge to efficiently  
89 apply advanced techniques to risk modelling. This democratization of tools reduces the technical barriers for researchers and  
90 practitioners, enabling more interdisciplinary collaborations and accelerating the adoption of data-driven methods in climate  
91 risk management (Rolnick et al., 2019).

92 This paper aims to provide a comprehensive review of data-driven methods, with a specific focus on ML approaches, for multi-  
93 hazard and multi-risk assessment, exploring ongoing applications, current limitations and future perspectives, while also  
94 addressing the use of copulas, a non-ML statistical method, to highlight its role in modelling dependencies in compound hazard  
95 events. Unlike other recent reviews that have focused on ML (particularly DL) for specific hazards or sectors – such as extreme  
96 events (Salcedo-Sanz et al., 2022), hydrology (Tripathy & Mishra, 2024), geophysics (S. Yu & Ma, 2021), wildfires (Jain et

97 al., 2020), and climate risk (Zennaro et al., 2021) – this paper takes a cross-cutting perspective on multi-hazard and multi-risk  
98 assessment. By structuring the discussion around successive stages of risk analysis – data processing, hazard prediction, risk  
99 assessment, and future scenarios – we connect climate risk and data-driven methods while also identifying critical gaps,  
100 particularly in linking hazard interactions with vulnerability.

101

102 The paper is structured as follows: Section 2 Methodology outlines the research questions, and the search methodology  
103 employed for the review. Section 3 Results and discussions summarises the literature review findings and discusses key  
104 insights related to each of the research questions. Section 4 Conclusion provides a summary of the key insights and outlines  
105 the next steps for research in this field. The Appendices provide an abbreviation dictionary (Appendix A: Abbreviations), as  
106 well as the summary tables of main articles collected for each research question (Appendix B: Summary tables of the collected  
107 studies).

## 108 **2 Methodology**

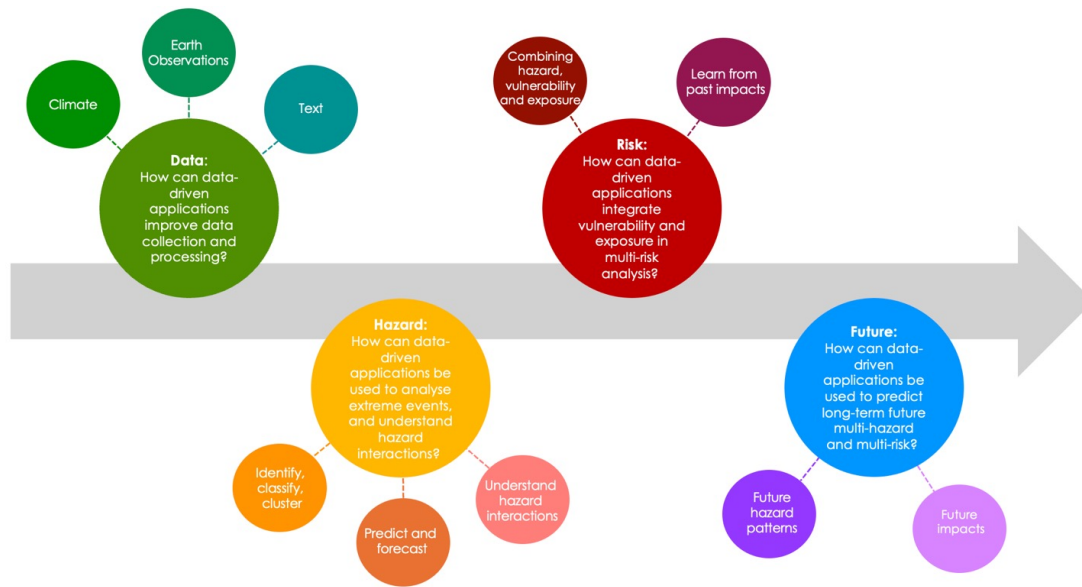
109 This paper follows a systematic review process based on the Preferred Reporting Items for Systematic Reviews and Meta-  
110 Analyses (PRISMA) methodology, which ensures a standardized, systematic, and transparent framework for analysing and  
111 synthesizing existing literature (O’Dea et al., 2021). The method involves several steps, among which the main ones are:  
112 defining of the research questions; developing a protocol detailing the search methodology (including database to search,  
113 keywords, timeframe and selection criteria); collecting and screening relevant literature; synthesizing and interpreting the  
114 findings. Such a stepwise process ensures a thorough search for relevant studies, consistent criteria for the selection of papers,  
115 and clear documentation of the review process, therefore reducing the risk of bias and enhancing the robustness and  
116 replicability of the analysis (Sarkis-Onofre et al., 2021).

### 117 **2.1 Research questions**

118 Each of the four research questions (Figure 1) is focussed on a specific topic and presents several sub-topics, offering a  
119 structured framework to explore current applications, address challenges, and pinpoint future opportunities. These research  
120 questions are:

- 121 1. Data: How can Machine Learning improve data collection and processing?
- 122 2. Multi-Hazard: How can Machine Learning and statistical tools be used to analyse extreme events, and model hazard  
123 interactions?
- 124 3. Multi-Risk: How can Machine Learning applications integrate vulnerability and exposure in multi-risk analysis?
- 125 4. Future: How can Machine Learning and statistical tools be used to predict long-term future multi-hazard and multi-  
126 risk?

127



**Figure 1: Research questions and sub-themes**

128

129

130 The first research question examines how ML can help process diverse types of data, extracting and harmonising the  
 131 information needed to analyse multi-hazard and multi-risk by addressing current gaps such as data sparsity, inconsistency  
 132 across sources, and the lack of harmonised formats. This contributes to improving the quality and comparability of risk  
 133 assessments by enabling integrated use of climate, EO, and textual datasets. In particular, the sub-themes are divided based on  
 134 the type of data analysed:

- 135 I. Climate data (time series of geospatial climate data), which describe the characteristics of climate-related hazards  
 136 across space and time. Preparing this data for multi-hazard and multi-risk applications often requires ML methods  
 137 (i.e. feature engineering) to increase spatial and temporal resolution, harmonise and extend the time coverage of the  
 138 datasets or correct for biases (Schneider et al., 2023).
- 139 II. EO, which can be used to characterise exposure and vulnerability layers and extract information on impacts  
 140 (Ghaffarian & Emtehani, 2021; Novellino et al., 2024).
- 141 III. Textual data, such as newspapers or social media, which in the last years have been leveraged for extracting  
 142 information on diverse impacts (Sodge et al., 2023).

143

144 The second research question investigates how ML and statistical tools improve the identification and modelling of hazard  
 145 dynamics by capturing complex spatio-temporal patterns, compounding effects, and non-linear interactions that traditional  
 146 approaches often overlook. This helps advance multi-hazard and multi-risk analysis by providing more accurate detection,  
 147 classification, and modelling of extreme events. In particular, the key sub-themes are:

- 148 I. Analyse which methods can be used to identify, classify and cluster extreme events, producing spatio-temporal  
 149 footprints of multi-hazard events (H. Yu et al., 2022).
- 150 II. The prediction of (multi-)hazard events, for example through early warning systems or seasonal predictions  
 151 (Bhowmik et al., 2023).
- 152 III. The analysis of hazard interactions, for example characterising joint distributions through copulas (Bevacqua et al.,  
 153 2021) or multi-hazard susceptibility maps (Pourghasemi et al., 2019).

154 The third research question concerns the application of ML for the integration of vulnerability and exposure into multi-risk  
155 analysis addressing the current gap where vulnerability and exposure are often treated as static or secondary layers rather than  
156 dynamic drivers of risk. This integration strengthens the ability of multi-risk assessments to capture how socio-economic  
157 conditions and adaptation measures interact with hazards to shape overall risk In particular, the key themes are:

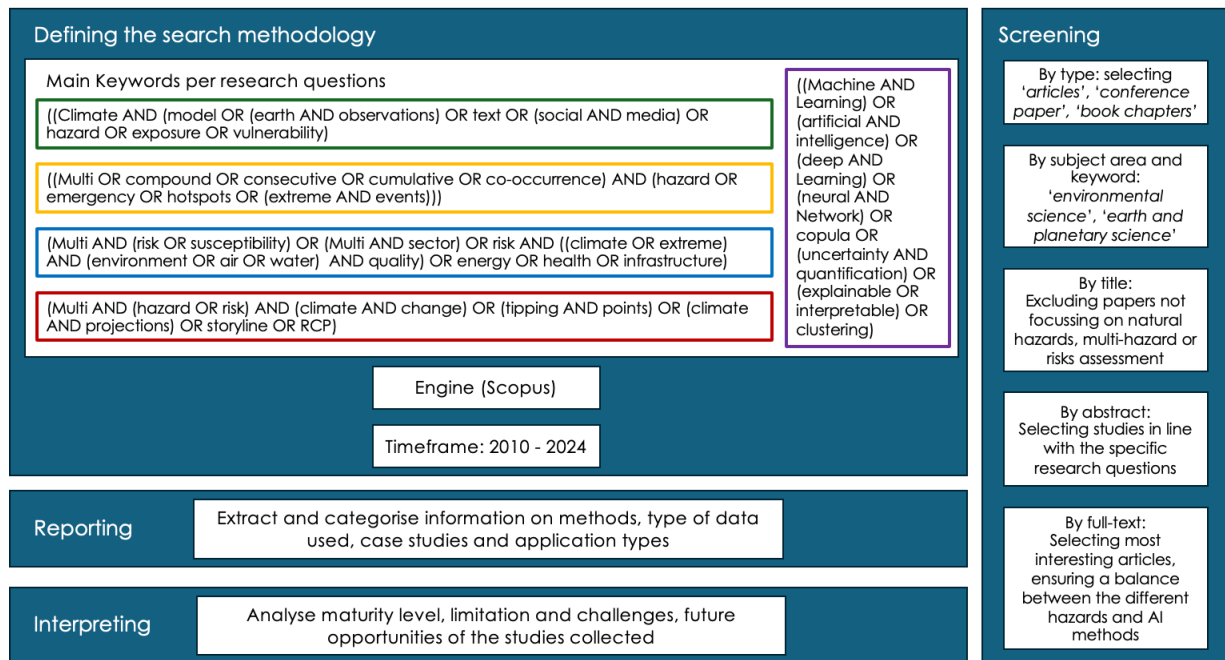
- 158 I. Multi-hazard exposure and vulnerability on assessments, integrating susceptibility mapping with information on  
159 specific exposure layers, such as buildings and population (Rusk et al., 2022).
- 160 II. Modelling risk from past impacts data, often through supervised ML approaches that use hazard, vulnerability and  
161 exposure indicators as predictors (Dal Barco et al., 2024).

162 The fourth research question investigates the possible contribution of ML and statistical tools into the analysis of (long-term)  
163 future multi-hazard and multi-risk, where uncertainty associated with the representation of future extremes in climate  
164 projections further complicates risk modelling, highlighting a critical gap in existing approaches, which often fail to adequately  
165 capture compound and cascading extremes under changing climate conditions This research question clarifies how ML can  
166 enhance scenario building, improve uncertainty quantification, and support more robust long-term multi-risk assessments. In  
167 particular, the key sub-themes are:

- 168 I. Modelling future multi-hazard trends and spatial patterns using statistical methods, in particular for compound and  
169 consecutive events (Zscheischler et al., 2018).
- 170 II. Assessing future impacts based on climate change projections, often using methods trained on historical data and  
171 applied to ensembles of RCP projections (S. J. Park & Lee, 2020).

## 172 **2.2 Methodological framework: search methodology, screening, reporting and interpreting**

173 The search was performed on Scopus, focusing on articles published in English. Since the analysis focuses on ML applications  
174 and multi-risk, the timeframe 2010 – 2024 was chosen because both areas of research are recent and other reviews have  
175 addressed earlier periods, highlighting that most applications in ML and climate risk have been published only in the last few  
176 years (Zennaro et al., 2021). For each research question, a dedicated search was performed. Each search string was generated  
177 by the combination of a set of method-related keywords (e.g. those related to ML or statistical methods), common across all  
178 questions, and a set of thematic keywords, specific to each research question (Figure 2).



179  
180 **Figure 2: Literature review methodology**

181 After collecting articles for each research question, the papers were first filtered by following typologies: 'journal articles',  
182 'conference papers', and 'book chapters'. Afterwards, for each research question, the papers were screened by title, then by  
183 abstract, and finally by full text. The final screening selected 153 key papers to be analysed in the literature review. This  
184 information was then summarised into tables, identifying the type of applications, the type of data used, the case study and the  
185 methods used. Finally, for each research questions, the results were discussed to understand the maturity level of the  
186 applications, their limitations and possible future developments.

187 **2.3 Limitations and scope of the review**

188 While this review follows the PRISMA guidelines for search strategy, screening, and reporting, a formal numerical quality  
189 scoring of individual studies was not applied, consistent with standard practice in PRISMA-based reviews of computational  
190 methods in geoscience and climate risk (e.g., Zennaro et al., 2021; Salcedo-Sanz et al., 2022; Ghaffarian et al., 2023). Instead,  
191 quality and relevance were assessed qualitatively during full-text screening based on three criteria: methodological rigour  
192 (evaluated through the presence and type of model validation, e.g., cross-validation, independent test sets, or benchmark  
193 comparisons), relevance to the research questions, and diversity across data sources, geographical coverage, hazard types, and  
194 ML approaches. The latter criterion was applied explicitly to avoid over-representation of any single method or region in the  
195 final corpus, and is documented in Appendix B.

196 Another limitation concerns terminological consistency. Although this review adopts the Zschau (2017) framework to  
197 reclassify papers during full-text screening, the terms multi-hazard, multi-risk, compound, and cascading are used with  
198 considerable inconsistency across the reviewed literature, a well-documented feature of the field (Gill & Malamud, 2014;  
199 Tilloy et al., 2019). Because paper selection was based on keyword matching against author-assigned terminology, the corpus  
200 necessarily reflects this heterogeneity, and the thematic categories used in the synthesis should be understood as analytical  
201 conveniences rather than sharp taxonomic boundaries.

202 Moreover, while this review focuses on ML and copula-based methods as the primary data-driven approaches for multi-hazard  
203 and multi-risk assessment, it is important to acknowledge that several complementary quantitative frameworks exist and have  
204 been the subject of dedicated reviews that fall outside the scope of the present work. Bayesian networks (BNs) provide a  
205 probabilistic framework for multi-hazard causal modelling, capturing conditional dependencies between risk drivers through  
206 directed acyclic graphs and propagating uncertainty in a transparent, interpretable way; they are particularly valuable in data-  
207 sparse contexts where causal structure can be informed by expert knowledge, and their application to climate multi-risk  
208 assessment has been reviewed in depth by Sperotto et al. (2017). Agent-based models (ABMs) simulate the adaptive behaviour  
209 of individuals and institutions under hazard scenarios, making them suited to capturing dynamic vulnerability, evacuation  
210 dynamics, and community resilience processes that purely data-driven models cannot represent; comprehensive reviews of  
211 their application in disaster management are provided by Zhuo & Han (2020) and Anshuka et al. (2022). More broadly, the  
212 full landscape of quantitative methods for modelling hazard interrelationships, including stochastic, empirical, and mechanistic  
213 approaches, is systematically covered by Tilloy et al. (2019), providing a valuable complement to the ML-focused perspective  
214 of the present review.

215 Finally, some considerations need to be taken on the geographical distribution of the 152 papers included in this review, which  
216 reveal a marked concentration in a small number of regions. In terms of lead authorship, Europe (35.5%) and East Asia (27.0%)  
217 together account for nearly two thirds of the corpus, followed by North America (21.1%), while the Global South is  
218 substantially underrepresented: Africa, South America, and Oceania collectively contribute less than 5% of lead authors. A  
219 similar pattern holds for co-authorship, though with a slight broadening of participation: South/SE Asia rises to 6.4% and  
220 Middle East to 7.3%, suggesting that researchers from these regions participate more frequently as collaborators than as lead  
221 investigators. The most pronounced shift occurs in the case study column: Global studies account for 14.9% of the corpus, and  
222 South/SE Asia (10.6%), Middle East (6.8%), and Africa (5.0%) are more represented as study areas than as sources of  
223 authorship, indicating that data-driven methods developed in high-income regions are frequently applied to, rather than  
224 developed within, lower-income contexts. The full breakdown of lead author institution country, co-author countries, and case  
225 study regions, together with a Sankey diagram illustrating the flows between these three dimensions, is provided in Appendix  
226 B. These geographical imbalances should be borne in mind when interpreting the findings of this review, as the methods,  
227 datasets, and risk priorities that dominate the literature inevitably reflect the institutional contexts in which the research was  
228 produced.

229

## 230 **3 Results and discussions**

### 231 **3.1 Data**

#### 232 **3.1.1 Climate datasets**

233 The application of ML methods to produce new, complete, or high-resolution hazard datasets (either from meteorological  
234 observations, climate reanalyses or future projection) is quite established, and mainly focuses on data with sparse and irregular  
235 measurements. A typical indicator which is derived with ML methodologies is soil moisture: in-situ measurements are usually  
236 scarce and not uniformly distributed, satellite images (which will be discussed later) often presents temporal gaps and can only  
237 provide information on the first layer and struggles in complex topographies and it presents a complex dynamic that is  
238 influenced by many different drivers (similarly to multi-risk prediction) such as precipitation, temperature, evaporation,  
239 topography and land use. For example, Kang et al. (2018) and O. & Orth, (2021) investigate the complex interactions at  
240 different soil levels and temporal scales with a Long-Short Term Memory (LSTM) model that takes as inputs the topography,  
241 vegetation and atmospheric conditions and predicts each soil moisture layer in succession, using ERA-5 reanalysis as  
242 assessment endpoint. LSTM is widely applied to model the behaviour of other hydrological variables, such as snow, run-off  
243 and river catchments. Entity-Aware LSTM was used for rainfall-runoff modelling by Kratzert et al., (2018); Kratzert, Klotz,  
244 Shalev, et al., (2019), to include both static and dynamic inputs allowing the algorithm to explicitly differentiate the two  
245 different types. Ghiggi et al. (2019) applies Random Forest (RF) regression to predict monthly runoff rates in the timeframe  
246 1902-2020, based on antecedent precipitation and temperature from an atmospheric reanalysis, validating the results with in-  
247 situ streamflow observations. Other research focuses on different variables and in particular investigate the irregular  
248 distribution of sensors: Amato et al. (2020) introduces a multi-step methodology to interpolate irregularly distributed spatio-  
249 temporal timeseries, first decomposing the signal and then learning stochastic spatial coefficients which can be spatially  
250 modelled and mapped on a regular grid with Artificial Neural Networks (ANN), allowing the reconstruction of the complete  
251 spatio-temporal signal.

252 ML methods have been applied also to climate reanalyses and models. Early applications, such as He et al. (2016), tested RF  
253 regression to statistically downscale spatially precipitation data, using few covariates and demonstrating how this approach is  
254 able to catch the non-linear relations between variables, minimising overfitting and collinearity issues between predictors.  
255 However, the algorithm struggled with skewed datasets and even the final model, which is the combination of two different  
256 RF models, trained respectively on high-precipitation and low-precipitation values, fails to detect the complex spatial and  
257 temporal complexity of precipitation data, overestimating the intensity and spatial distribution of low precipitation and  
258 underestimating high precipitation. Other applications are focussing on Deep Learning models: CNNs are used to downscale  
259 many variables from future climate models (among which, air temperature, precipitation, 10-m wind speed, 2-m relative  
260 humidity, downward shortwave radiation) (Lin et al., 2023). Generative models particularly Generative Adversarial Networks  
261 (GAN) and diffusion models, are widely used for this task. GANs consist of two neural networks – a generator and a  
262 discriminator - that are trained simultaneously in a competitive process. The generator attempts to create realistic fake data

263 that can fool the discriminator, while the discriminator works to distinguish between real and fake data. For example, specific  
264 GANs based on Convolutional Neural Networks (CNNs) have been applied to post-process weather forecast outputs. These  
265 models can enhance the resolution of precipitation data by a factor of ten, producing more realistic and spatially coherent  
266 forecasts compared to the original input data (Harris et al., 2022). Diffusion models, on the other hand, learn to reverse a noise  
267 process: first the model adds sequentially noise to input data, then the model learns how to predict the noise at each step, and  
268 once trained, it can start with noisy data and work backwards, progressively removing the noise to generate a new, realistic  
269 dataset. Diffusion models are related to variational inference, where the forward process defines a probabilistic trajectory from  
270 data to noise, and the reverse process defines a generative path from noise back to data. Unlike other generative models like  
271 GANs, which learn through a "discriminative" process (trying to fool a discriminator network), diffusion models learn through  
272 this smooth diffusion and denoising process (Yeğin & Amasyalı, 2024). For example, diffusion models are applied to  
273 downscale multiple climate models, also providing information on the uncertainty downscaling, by generating a large number  
274 of ensemble members based on probability distribution sampling (Ling et al., 2024a). DL approaches are often used to  
275 downscale low-resolution future models to Convection Permitting (CP) climate models, where the main advantage of these  
276 techniques is their reduced computational costs compared to the development of a CP climate models (Bretherton et al., 2022;  
277 Clark et al., 2022). The role of Artificial Intelligence (AI) in climate predictions is discussed in Schneider et al. (2023). This  
278 study advocates for the development of global models at 10–50 km resolution, harnessing AI and EO for the calibration and  
279 development of higher-resolution regional simulations.

280 In recent years, there has been growing interest in hybrid modelling: approaches that combine data-driven ML methods with  
281 physical or process-based models or constraints, as a way to benefit from both high flexibility and physical realism. Such  
282 hybrid / physics-informed ML methods help address several limitations of pure data-driven models: they can enforce  
283 conservation laws, reduce overfitting to noise, improve generalization especially under conditions outside the training domain,  
284 and provide more interpretable insights into underlying drivers. For instance, He et al., (2023) integrates ML corrections into  
285 a land-surface / atmospheric model using data assimilation, remote sensing LAI and soil moisture to improve climate  
286 simulations. Similarly, Huynh et al., (2025) combines process-based hydrological flux models with neural networks to correct  
287 for scale mismatches and to better capture spatial heterogeneity. Also, (S. Yu et al., 2024) provides benchmarks for ML  
288 emulators that mimic nested high-resolution physical simulations. Despite their promise, hybrid models also face important  
289 limitations. They often require substantial domain and physical knowledge to be formulated appropriately and to ensure  
290 physical consistency (Willard et al., 2022). Moreover, coupling ML architectures with numerical process models can remain  
291 computationally demanding, particularly for high-resolution simulations or large spatio-temporal domains (Reichstein et al.,  
292 2019). Calibration and validation can also be complex, as balancing the contributions of the physical and data-driven  
293 components often involves ad hoc or case-specific tuning (Read et al., 2019). Finally, interpretability may still be reduced  
294 when the ML component acts as a black box, obscuring how physical constraints shape predictions (Kashinath et al., 2021a).  
295 These challenges are also relevant for hazard prediction, where process dynamics such as land–atmosphere feedback play  
296 central roles and require models that are both physically credible and statistically robust. Thus, hybrid models represent an

297 emerging frontier at the interface of ML, process-based modeling, and data assimilation, particularly relevant for both climate  
298 data reconstruction and hazard modelling and deserve explicit consideration in future reviews and benchmarking efforts.  
299 Machine learning applications for climate and environmental datasets have greatly improved the reconstruction and  
300 downscaling of variables from sparse and irregular observations. However, a critical yet often under-addressed aspect in this  
301 field is uncertainty quantification (UQ), which is particularly relevant when these datasets are later used for hazard or risk  
302 assessments (Beven, 2018). Uncertainty in ML-based arises from multiple sources: Aleatoric uncertainty stems from the  
303 intrinsic variability and noise in the underlying measurements, such as sensor errors, missing satellite observations, or  
304 inconsistent temporal coverage; epistemic uncertainty originates from limited or biased training data and model structural  
305 choices (Xu et al., 2022). Several probabilistic approaches have been explicitly designed to represent spatial data uncertainty  
306 by learning distributions rather than deterministic predictions, mainly involving Bayesian Networks (BN) and Gaussian  
307 Processes (GP) (Siddique et al., 2022). For example, Multi-fidelity Gaussian Processes with a 5/2 Matern kernel in particular,  
308 were used to downscale precipitation data from ERA-5 over high mountain terrain. Multi fidelity models combine low-fidelity  
309 observations (which are usually more numerous and less expensive to obtain) with high-fidelity ones. This makes the model  
310 more suited than other state-of-the-art machine learning methods for smaller datasets and able to quantify and narrow the  
311 uncertainty associated with the precipitation estimates, which is especially needed over ungauged areas and can be used to  
312 estimate the likelihood of extreme events that lead to floods or droughts (Tazi et al., 2024). Andersson et al., (2023) applies  
313 Convolutional Neural Processes (ConvNPs), to suggest informative sensor placements by finding sites that maximally reduce  
314 prediction uncertainty, testing it for air temperature anomalies measurements in Antarctica. Convolutional Neural Processes  
315 (ConvNPs) extend the probabilistic framework of Gaussian Processes by learning flexible, data-driven covariance structures  
316 through neural networks. While traditional GPs provide robust uncertainty estimates but suffer from scalability and stationarity  
317 constraints (M. Jiang et al., 2022), ConvNPs maintain a probabilistic foundation while scaling linearly with data size and  
318 accommodating irregular spatial inputs (Garnelo et al., 2018). DeepSensor<sup>1</sup>, a specific GitHub python package, was developed  
319 to facilitate the application of Neural Processes in environmental sciences, especially for downscaling, interpolation, sensor  
320 placement and data imputation. Monte Carlo Dropout (MCD) enhances epistemic uncertainty quantification in climate data  
321 and was tested on neural networks for probabilistic medium-range weather forecasting (Garg et al., 2022). Deep generative  
322 models such as diffusion or GAN frameworks can further approximate uncertainty by generating ensembles of plausible  
323 realisations that sample the predictive probability space (Ling et al., 2024b; Saha & Ravela, 2022). Despite these advances,  
324 most studies still focus primarily on improving resolution and accuracy, while systematic approaches to quantifying and  
325 propagating uncertainty through the modelling chain, from data to hazard and risk estimates, remain limited (Beven, 2018).  
326 Addressing this challenge is crucial, as downstream risk assessments rely heavily on the reliability of the climate inputs that  
327 feed them.

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<sup>1</sup> <https://github.com/alan-turing-institute/deepsensor>

### 328 3.1.2 Earth observations

329 EO data, when combined with ML is increasingly recognised for its critical role in supporting actionable multi-hazard and  
330 multi-risk assessment, as evidenced by new initiatives from ESA and NOAA's Centre for AI, where particular attention is  
331 devoted to the use of EO for discovering impacts in remote areas and developing early warning systems.

332 Remote sensing images are used to improve climate datasets, for example increasing the spatial coverage in areas with sparse  
333 measurements or providing real data to bias-correct/downscale modelled data. Multiple AI methods, such as Support Vector  
334 Machine (SVM) (Ahmad et al., 2010; Jing et al., 2016a), Ridge Regression (Kang et al., 2018), RF (Han et al., 2023; Jing et  
335 al., 2016b) and LSTM (Fang et al., 2017) are applied for developing soil moisture datasets.

336 EO provides consistent, near-real time observations of environmental conditions that are critical for early warning and hazard  
337 characterisation. For instance, indicators such as vegetation stress (Miyoshi et al., 2020; Schiefer et al., 2020; Veras et al.,  
338 2022), surface temperature anomalies can enable the early detection of droughts (Barrett et al., 2020), floods (Dasgupta et al.,  
339 2022) or wildfires (Jain et al., 2020) especially in remote and data scarce areas. DL and Physics Informed Neural Networks  
340 can leverage radar (e.g., Sentinel-1 SAR), to estimate water levels for flood forecasting (Dasgupta et al., 2022; Gierszewska  
341 & Berezowski, 2024) or fused into predictive models that refine hazard forecasts for severe weather and anticipate cascading  
342 impacts (Flora et al., 2021). Remote sensing plays a crucial role in hazard dataset development by helping mitigate bias that  
343 may be inherited by ML-based risk models. These models are often trained on datasets calibrated with data from resource-rich  
344 regions, where the majority of weather stations are located. As a result, they may struggle to generalize effectively to  
345 underdeveloped areas, which are frequently the most vulnerable to extreme events (McGovern et al., 2019, 2022).

346 EO combined with ML is also used in assessing environmental quality, such as water quality (Sagan et al., 2020; Sit et al.,  
347 2020). These applications mainly showcase simpler models, such as short neural networks and SVM (Nazeer et al., 2017),  
348 Decision Trees (DT), RF, Cubist Regression and Extreme Gradient Boosting (XGBoost), due to their ease of implementation  
349 and relative scarcity of ground measurement data (J. Liu et al., 2023). They focus on optically parameters, such as chlorophyll-  
350 a, turbidity and suspended solids, but also others such as of nutrients and other non-optical parameter) can be predicted relying  
351 on models integrating meteorological and hydrological variables (S. Chen et al. 2022).

352 A central application of EO is in supporting impact and damage assessments: change detection techniques that compare pre-  
353 and post- event imagery are used to estimate physical impacts (T. Bai et al., 2023). This includes building damage (Y. Bai et  
354 al. 2018), infrastructure collapse (Sublime & Kalinicheva 2019) due to earthquakes or tsunamis (Ji et al. 2018), but also flood  
355 extent (Munawar et al., 2021), landslides (Lei et al., 2019) and wildfire scars (Bo et al., 2022; Tran et al., 2020). The main  
356 challenges encountered in these applications are due to the return periods of satellites, which may limit their ability to detect  
357 fast changing impacts; to the presence of clouds, which can hamper visibility especially during the occurrence of extreme  
358 events likely to cause damages; and to changes in luminosity or season (Faiza et al., 2012).

359 Moreover, EO enables long-term recovery tracking and vulnerability/exposure monitoring, with applications using proxies  
360 such as night-time lights to measure recovery trajectories (Kabiru et al., 2023; Qiang et al., 2020). For examples, studies have

361 used EO and ML to track how rapidly services return to urban slums post disaster, highlighting which population remain  
 362 exposed and underserved (Ghaffarian & Emtehani, 2021). Similarly, UNET-based CNNs are used to identify deprivation  
 363 pockets from satellite images and track during their recovery process (J. Wang et al., 2019), or to derive proxy indicators for  
 364 poverty from satellite night lights (Jean et al., 2016), in combination with transfer learning to overcome scarcity of labelled  
 365 data (S. J. Pan & Yang, 2010). At longer timescales, techniques like K-Nearest Neighbour (KNN), SVM, ANN and RF are  
 366 used to classify urban and rural land cover, detect land use changes or informal settlements (Adam et al., 2014; Yuh et al.,  
 367 2023; Zerrouki et al., 2019).

368 In summary, the integration of EO with ML and statistical techniques offers a powerful toolkit for multi-hazard and multi-risk  
 369 assessment, supporting early warning, targeted preparedness, rapid impact estimation, and recovery monitoring.

### 370 3.1.3 Textual data

371 In addition to remote sensing, textual data from sources such as social media and newspapers offer valuable information for  
 372 impact assessment. Natural Language Processing (NLP) algorithms can harness this textual data, facilitating applications  
 373 across various hazard types, including landslides, volcanoes, drought, earthquakes, floods, and wildfires. In general, the  
 374 procedure typically consists in several steps, in which the textual sources are first screened based on metadata (such as location  
 375 or the presence of disaster-related words in titles); then NLP or semantic algorithms (Angelov, 2020) are used to extract  
 376 keywords from the main text and convert the textual data into tabular/numeric; then a classification algorithm is applied to  
 377 choose between impact/no impact data or link the impacts to a specific sector or hazard. Additional steps may also involve the  
 378 retrieval of spatial information from textual data. Many different algorithms can be employed, with logistic/lasso regression  
 379 (Genkin et al., 2007), Naïve Bayes Classifiers (L. Jiang et al., 2016), KNNs (Shah et al., 2020) and ANNs (Nam et al., 2014),  
 380 being the most common. In the field of disaster mapping, SVM are tested by Asinthara et al. (2022), while Powers et al. (2023)  
 381 compares CNN and specific pre-trained language models; Koshy & Elango (2023) tests a multi-modal method leveraging text  
 382 and images from social media, employing the language models BERT; Mehrotra et al., (2022) test SVM, DT, RF, Adaboost,  
 383 Gradient Boosting, XGBoost, LSTM in combination with language models. Twitter (now X) was the main social media that  
 384 has been used to detect impacts, while newspaper articles have also been used, in particular for slow onset hazards, such as  
 385 droughts. For example, Sodoge et al. (2023) apply several NLP and ML methods to automatize the detection of drought impacts  
 386 from newspaper articles; the procedure classifies impacts into 25 classes, based on the sector (e.g., forestry, livestock, forestry,  
 387 transport etc.) by using different Supervised ML models (Naïve Bayes, Lasso Regression, RF, ANN). In general, rule-based  
 388 methods are preferred to ML models when the number of samples is limited (X. Liu et al., 2018).

389

390 **Table 1. Data-related methods, gaps and opportunities.**

Section	Methods	Gaps	Opportunities
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<b>3.1.1 Climate datasets</b>	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	Struggles with sparse/irregular data; poor scalability (GPs); extremes misrepresented; limited uncertainty treatment	Hybrid ML–physics models; scalable probabilistic methods; better uncertainty quantification; generative models for ensembles
<b>3.1.2 Earth observations (EO)</b>	SVM, RF, LSTM for soil moisture; CNNs/autoencoders for land cover, impacts, disaster recovery; transfer learning for data-scarce regions; ML for water quality (RF, ANN, XGBoost)	Bias toward data-rich regions; gaps/clouds limit detection; false positives; weak multi-hazard integration	Robust models for missing/noisy data; near-real-time EO pipelines; integrate EO with socio-economic data; transfer learning for vulnerable regions
<b>3.1.3 Textual data</b>	NLP + ML (Naïve Bayes, RF, SVM, CNN, BERT, LSTM); multimodal (text + images); rule-based for small datasets	Few labelled datasets; language/cultural bias; imprecise spatial info; noisy social media inputs	Multilingual/transfer learning; improved geolocation extraction; integrate with EO/sensor data; robust methods for noisy/misinformation-prone data

391

392

393 This section contributes to the field of multi-hazard and multi-risk analysis by showing how ML applications to climate  
394 datasets, Earth observations, and textual data can overcome data sparsity and heterogeneity, thereby enabling the generation  
395 of more complete, high-resolution, and multi-source datasets that are essential for capturing hazard interactions and cascading  
396 risks.

### 397 3.2 Multi-hazard

#### 398 3.2.1 Identify, classify and cluster

399 The initial step in conducting a comprehensive multi-risk assessment involves a thorough analysis of hazard factors, which is  
400 critical for effective climate risk evaluation and enhancing disaster preparedness. In this context, identifying various hazards,  
401 classifying them into distinct categories, and extracting their spatio-temporal footprints through clustering techniques are  
402 fundamental processes.

403 The identification of impacts from satellite images to discover hazard footprints, such as for landslides, earthquakes, floods  
404 was discussed in the previous section because it is mainly an image processing task, where the goal is to identify differences  
405 between two images. This section focuses on the identification of extreme events from climate datasets, which require specific

406 considerations on the typology of hazards and risk considered and is subject to different definitions and multiple interpretations.  
407 The most common approach to identify multiple hazards from climate datasets is to use thresholds to identify univariate  
408 extreme events and then combine them at a later stage into a multi-hazard database. In order to identify the thresholds, two  
409 methods are applied: empirical thresholds (e.g., defining a max temperature over which an event is considered extreme) or  
410 statistical thresholds (e.g., calculating a pixel-wise and/or day-wise percentile to identify events that exceeds a threshold that  
411 can vary spatially and temporally). Empirical thresholds are usually fine-tuned to link extreme events to impacts on specific  
412 sectors or local applications, and many applications focus on temperature extremes and health (Ray et al., 2021; X. Sun et al.,  
413 2014). Statistical thresholds are preferred when analysing global trends and merging multi-hazard extremes because they allow  
414 a more consistent and probabilistic robust comparison between different hazards. Percentiles can be easily adapted to model  
415 spatial and temporal variations in data and are ideal for global application that cover multiple landscapes where a unique  
416 empirical threshold cannot be univocally determined. For example, in Ionita et al. (2021), specific percentiles are used to  
417 identify heatwaves and drought from temperature and SPI indicators respectively, before applying Empirical Orthogonal  
418 Functions to investigate their drivers and their centre of actions over Europe; Similarly, Sutanto et al. (2020) is using  
419 percentiles to identify heatwaves, droughts and wildfires from temperature, soil moisture and Fire Weather Index (FWI),  
420 analysing spatial overlaps of the daily binary hazard maps to identify simultaneously occurrences of dry hazards and then  
421 investigating cascading events by looking at different combinations of hazard sequences. Claassen et al. (2023), proposes a  
422 methodology to identify multi-hazard events combining static footprints derived from the processing of satellite images (e.g.  
423 for landslides, floods, tsunamis) with dynamic footprints (based on statistical percentiles) of climate hazards (e.g., heatwaves,  
424 droughts, extreme precipitation, extreme wind, etc.), proposing a methodology to identify consecutive events using a specific  
425 time lag and analysing the global distribution of the various multi-hazard events.

426 Return periods are another statistical technique used to identify extreme events, studying the likelihood of an event of a certain  
427 magnitude occurring in a chosen timeframe (Liao et al., 2021). Return periods are most often applied in hydrology, when  
428 dealing with flooding and storm surge events (G. Liu et al., 2020, 2023; Mattei et al., 2021; Zanini et al., 2020). These  
429 applications fit a probability distribution (typically a Generalised Extreme Value Distribution, calculated over the number  
430 exceeding of a threshold or over maxima) which allow for an estimation of the uncertainty of the threshold. Percentile  
431 thresholds, returns periods and Generalised Extreme Value (GEV) distributions are also used conjunctly, such as in Orth et al.  
432 (2022), where different hydrological hazards (floods, frost, heat waves, droughts, and storms) and their contrasting impacts  
433 are analysed against multiple sectoral assessment endpoints (Gross Primary Productivity for vegetation, crop yields, human  
434 mortality, damages to properties and public attention).

435 It is important to note that these approaches focus initially on univariate extremes, and only at a second stage, the identified  
436 events are merged to produce multi-hazard events, checking for overlapping in time and space. This can lead to the  
437 underestimation of compound joint-extreme events which arise as a combination of multiple indicators not individually  
438 extreme.

439 Other approaches focus on identifying and classifying extreme events from climate reanalyses using DL, especially in case of  
440 cyclones or other hazards that are characterised by the interaction of multiple atmospheric drivers. Y. Liu et al. (2016) was one  
441 of the first to apply CNN based on AlexNet to detect and classify tropical cyclones, atmospheric rivers and weather fronts  
442 from climate datasets, such as ERA-5, CAM5.1. One of the main challenges in this domain is the scarcity of labelled data for  
443 training supervised ML models. This is discussed by Racah et al. (2016), who expanded the previous approach, developing a  
444 semi-supervised CNN model to overcome the lack of labelled data and created an extreme weather dataset as benchmark. In  
445 general, the skewness of datasets is another common challenge for identifying climate anomalies with supervised approaches:  
446 often data on which the ML models are trained on present very few samples of conditions leading to impacts (Dal Barco et al.,  
447 2024).

448 Other studies focus on the identification of the spatio-temporal footprints of the climate hazards, in particular with algorithms  
449 such as Density Based Spatial Clustering Applications with Noise (DBSCAN, Ester et al., 1996), grouping single point  
450 anomalies into clusters in time and space. These approaches are applied in single hazards, such as droughts (Cammalleri &  
451 Toreti, 2023), heatwaves (J. Wang & Yan, 2021) or earthquakes (Di Martino et al., 2018a). With regard to multi-hazards  
452 applications, DBSCAN is used by Tilloy et al. (2022) to cluster compound precipitation and wind compound extreme events  
453 in Great Britain and by (H. Yu et al., 2022) to investigate droughts, heatwaves, cold-waves, extreme wind and extreme  
454 precipitation in Eurasian Drylands, studying how the coordinates of the centroid of the clusters are shifting hot and dry events  
455 to northern latitudes due to climate change.

### 456 **3.2.2 Hazard forecasting and prediction**

457 Before delving into more risk-based applications, it is worth noting that in the last few years, the application of DL models  
458 such as Transformers (Vaswani et al., 2017), Graph Neural Networks (GNN) (Veličković et al., 2017) and Physics Informed  
459 Neural Networks (Kashinath et al., 2021b; Lütjens et al., 2021) has prompted a revolution in weather forecasting. Early  
460 applications of AI models, primarily using RF and SVM, were largely aimed at replacing specific steps within numerical  
461 weather forecasts. More recently, DL tools have gained prominence due to their ability to capture long-range dependencies,  
462 handle complex and irregular data structures and integrate the solutions of equations of physical systems into a unified  
463 framework, enabling DL to be successfully employed for modelling the whole medium range weather forecasting process (Bi  
464 et al., 2022; Chen et al., 2023; Keisler, 2022).

465 Applications that focus on predicting or forecasting hazards are still mainly focussed on single hazard approaches. However,  
466 some single hazard approaches were included in this review because their multi-variate approach includes the combination of  
467 different static (as land use, topography, socio-economic data) and dynamic (e.g., atmospheric and marine data) parameters  
468 and implicitly deal with multi-hazard interactions (e.g., a wildfire may be more probable when dry and hot conditions are  
469 present, a drought can be influenced by temperature and soil moisture, etc.). For example, Haggag et al. (2021) propose an  
470 ANN prediction model in a multi-hazard perspective, but then test it on past disaster records to predict floods in Ontario using

471 indices for climate extremes inputs. Monte Carlo dropout techniques have been employed to quantify epistemic uncertainty,  
472 for example in surge forecasts (Macdonald et al., 2025) and flood modelling (M. Nguyen et al., 2024).

473 One of the main algorithms applied to forecast hazards is LSTM: Kratzert, Klotz, Brandstetter, et al. (2019) apply adapted  
474 LSTM to disentangle static and dynamic inputs and analyse both high and low extremes in river flows, considering climate  
475 susceptibility and integrating static and dynamic inputs. Tiggeloven et al. (2021) propose a LSTM/CNN architecture to predict  
476 global storm surge residuals based on atmospheric conditions, investigating how the model's performance varied based on  
477 changes of the spatial area input into the convolutional model. With regard to vegetation, long-range temporal dependencies  
478 from several climate variables are investigated with a LSTM model (Kraft et al., 2019). Many applications focus on forecasting  
479 of air quality hazards, especially in urban areas: compared to other types of environmental impacts, such as water quality, the  
480 network of air quality monitoring stations offers hourly data at a high spatial resolution, enabling the training of AI models to  
481 dynamically forecast at short lead times. Applications include the short-term prediction of ozone levels in Kuwait (Freeman et  
482 al., 2018), the development of a daily air quality index in Beijing and Guilin (Q. Wu & Lin, 2019), or the prediction of  
483 concentration of micro particular matter in the air of Seoul (Chang-Hoi et al., 2021).

484 Another popular DL architecture is GNN, applied in weather forecasting (Keisler, 2022; Lam et al., 2022) and river  
485 networks/flooding predictions (Bentivoglio et al., 2023; Kazadi et al., 2024; A. Y. Sun et al., 2021). The key advantage of  
486 GNNs over CNNs is their ability to capture complex relationships in non-Euclidean data. While CNNs are limited by fixed  
487 sliding windows and may miss correlations between adjacent pixels or non-adjacent zones, GNNs excel in modelling graph-  
488 structured data, allowing for more accurate representations (Kipf & Welling, 2016). In particular, Kazadi et al. (2024) apply a  
489 combination of GNN and Gated Recurrent Unit (GRU, a type of recurrent neural network), for spatio-temporal flood  
490 prediction, accounting for spatially distributed precipitation data, as well as static features such as bathymetry and topography,  
491 comparing its performances against a LISFLOOD-FP simulation of Hurricane Harvey (2017) in Houston, Texas and showing  
492 improvements in terms of accuracy and faster training (100x) and testing (1000x) times. Similarly, Transformers are applied  
493 for river flood prediction, outperforming other RNNs in terms of computational costs and performances, also increasing the  
494 interpretability of the model (Castangia et al., 2023).

495 CNN, ANN, LSTM are still popular for drought and heat events, which are characterised by longer scale spatio-temporal  
496 dynamics. For example, Bonino et al. (2024) compare the performances of CNN, LSTM and RF for the prediction of marine  
497 heatwaves; Patil et al. (2023) employ CNN to predict drought in East Africa 3 or 4 season ahead, analysing the contribution  
498 of different climate drivers at multiple spatial and temporal scales; ANN are used for forecasting drought risk at near real time  
499 in India, using Artificial Neural Network models (Singh et al., 2021). Other algorithms (SVM, Random Forest, XGBoost,  
500 Extra Trees) are still often applied to analyse low probability extreme events in specific locations, where the lack of data  
501 constrains the training of Deep Neural Networks, such as the storm surge height caused by tropical cyclones in New York  
502 (Ayyad et al., 2022).

### 503 3.2.2 Modelling hazard interaction

504 Recent work has applied interpretable ML frameworks to hazard modelling, aiming not only at prediction but also at identifying  
505 key drivers. For instance, S. Jiang, Bevacqua, et al. (2022) and S. Jiang, Zheng, et al. (2022) used LSTMs to study river  
506 flooding in Europe, combining feature attribution methods such as Expected Gradients (Erion et al., 2021) and Additive  
507 Decomposition (Du et al., 2019) to disentangle the roles of snowmelt and precipitation. By running models across decades,  
508 they revealed shifts in dominant flood drivers, with precipitation becoming increasingly important. Other studies have applied  
509 gradient-based methods (A. Y. Sun et al., 2021), CNN heatmaps (Patil et al., 2023), attention mechanisms (Castangia et al.,  
510 2023), and sensitivity analysis (Bentivoglio et al., 2023; Bonino et al., 2024; Kratzert, Klotz, Shalev, et al., 2019). These  
511 advances improve interpretability, yet ML approaches remain limited by high data demands, sensitivity to training biases, and  
512 the difficulty of generalising beyond observed conditions (Bentivoglio et al., 2023). Their strength lies in prediction and  
513 uncovering nonlinear relationships, but the black-box nature of many models complicates causal modelling (Freeman et al.,  
514 2018).

515 While most ML studies focus on univariate hazards, compound events require methods that capture joint extremes. Copulas  
516 offer a flexible statistical framework to model dependence structures between variables, such as the co-occurrence of high  
517 river discharge, intense rainfall, and coastal surges (Hao & Singh, 2016; Nelsen, 2006). By decoupling marginal distributions  
518 from their dependence structure, copulas can assess joint probabilities of rare events with more precision than traditional  
519 multivariate models (Tilloy et al., 2019) Applications include pair copulas for compound flooding in Italy (Bevacqua et al.,  
520 2017a), Joe copulas for concurrent river–coastal extremes (Sadegh et al., 2017), and copula-based Bayesian networks for  
521 flood–drought interactions (Couasnon et al., 2018). However, several challenges remain: selecting appropriate copula families  
522 is non-trivial (since different families imply different tail dependencies, yet many common families assume simplistic  
523 dependency or exchangeability) (Oh & Patton, 2015); capturing joint tail dependence becomes increasingly difficult in high  
524 dimensions (vines, mixtures, or hierarchical copulas may help but bring computational and inference burdens) (Simpson et al.,  
525 2020); physical drivers (e.g. precipitation skew, changing climate forcings, watershed characteristics) are often only indirectly  
526 represented through marginal or covariate models (Hochrainer-Stigler et al., 2019b). Therefore, while copulas are powerful  
527 for probabilistic risk quantification, they are less suited to dynamic forecasting or process-based understanding without  
528 additional model structure or ensembles (Tootoonchi et al., 2022).

529 Comparison and complementarities.

530 ML and copula methods approach hazard interactions from distinct perspectives. ML excels at prediction and feature  
531 discovery but struggles with transparency and extrapolation, while copulas provide interpretable dependence structures and  
532 joint probability estimates but scale poorly with dimensionality and lack causal interpretability. ML can identify critical  
533 hazard predictors and generate inputs, while copulas rigorously quantify their joint occurrence. Yet, few studies combine  
534 these strengths; most rely on either predictive ML or probabilistic copulas in isolation. For example, an LSTM may forecast  
535 river discharge under given precipitation and snowmelt conditions, while a copula model can then quantify the probability

536 that extreme discharge co-occurs with extreme rainfall or sea-level rise. Together, ML and copulas can provide a more  
537 complete picture: ML enables forecasting and driver attribution, while copulas ensure rigorous treatment of dependence  
538 structures and joint extremes (Sadegh et al., 2017; Tilloy et al., 2019). Combining both approaches offers a promising  
539 pathway for advancing compound risk assessments. Some approaches, such as, T. Jiang et al., (2023) used a hybrid ML-  
540 copula method to estimate the probability of consecutive drought events (in particular from meteorological to ecological  
541 droughts), combining several ML classifiers (KNN, RF, SVM, ...) to estimate the propagation probability of meteorological  
542 drought given its characteristics, and C-vine copulas to model conditional probability model of the paired meteorological  
543 and ecological drought events. Closing this gap, for instance, by integrating ML-derived drivers into copula frameworks, or  
544 benchmarking ML-learned dependencies against copula-based models, represents a promising but underexplored direction  
545 for compound risk assessment.

#### 546 **Susceptibility mapping**

547 Susceptibility in the context of natural hazards refers to the predisposition of an area to experience a specific hazard and  
548 considers different factors (usually categorised into hazard or vulnerability in risk assessment), such as topography, geology,  
549 hydrology, land use and vegetation and highlights “territorial characteristics”, disregarding the more dynamic and time-  
550 dependent component of risks (Wubalem, 2022). The methodology for creating multi-hazard susceptibility maps using ML  
551 usually consists in three steps: first, for each hazard, the susceptibility factors are identified; then, supervised ML techniques  
552 are employed to create single hazards susceptibility maps, considering the different conditioning factors as predictors and the  
553 areas impacted by the analysed hazards in the past as assessment endpoints; finally, the single hazard maps are combined to  
554 produce the final multi-hazard susceptibility map. Eventually, feature importance techniques are applied as a fourth step to  
555 extract the most susceptible factors for each hazard or multi-hazard combination.

556 ML has been applied extensively to derive multi-hazard susceptibility maps, which can identify areas prone to multiple disaster  
557 and help disaster management planning. However, these applications are typically trained on average, static climatic conditions  
558 and do not consider temporal interactions between risk factors (such as the cumulative impacts of a series of successive extreme  
559 rain events, the duration of a heatwave or changes in vulnerability caused by wildfires). Moreover, the type of multi-hazard  
560 events for which they are applied is often limited to wildfires, landslides, floods, and earthquakes (Abu El-Magd et al., 2021;  
561 Ahmadlou et al., 2021; Cao et al., 2020): in fact, these methods rely on the presence of catalogues of past clearly defined  
562 hazard spatial footprint: for other climate hazards, such as extreme winds, hails, or heatwaves susceptibility is not investigated.  
563 Furthermore, input data for susceptibility mapping are aggregated over long time frames, in order to ensure robustness of the  
564 analysis. However, changes in vulnerability and exposure parameters occurring in the analysed periods, for example due to  
565 newly implemented adaptation measures, are overlooked, potentially leading to overestimation (or underestimation) of areas  
566 at risks.

567 The most common approach for integrating susceptibility parameters into multi-risk assessment is by producing multi-hazard  
568 susceptibility mapping, where susceptibility to multiple hazard (including factors for hazard, such as yearly precipitation, but  
569 also vulnerability parameters, such as slope) can provide a valuable point of reference for decision makers in sustainable land-

570 use planning or infrastructure development. A number of studies are focusing on mountainous regions, using a range of ML  
571 models, including Logistic Regression, ANN, DT, SVM, RF, Boosted Regression Trees (BRT), or Generalised Linear Models  
572 (GLM) (Javidan et al., 2021; Karakas et al., 2023; Kariminejad et al., 2022; H. D. Nguyen et al., 2023; Pourghasemi et al.,  
573 2019, 2020; Pouyan et al., 2021; Yousefi et al., 2020) The multi-hazard combination usually covers floods, landslides,  
574 avalanches and forest fires, which have clear footprints that can be used to train single hazard susceptibility, and integrate other  
575 risks which can be assessed through already available risk maps, such as seismic risk maps at a later stage (Bordbar et al.,  
576 2022). Different hazards are included by Piao et al. (2022), who test BRT, RF and Classification And Regression Trees (CART)  
577 in the Gangwon-do region in South Korea (an area rich in forests and ecological diversity) to establish a multi-hazard  
578 probability map for forest fires and droughts; in this study the multi-hazard interactions are investigated, considering drought  
579 as an amplifying hazard for forest fires. Mandal et al. (2022) focus instead on coastal areas, in particular in West Bengal  
580 (India), considering tropical cyclones, embankment breaching, storm and tidal surge, inundations, extreme rainfall, salinization  
581 and erosion; RF and ANN are applied to produce multi-hazard susceptibility maps. Ullah et al. (2022) test a CNN to produce  
582 flash floods, landslides and debris flow multi-hazard susceptibility mapping, comparing its performances with Logistic  
583 Regression and KNN methods in terms of accuracy, coefficient of determination, Mean Absolute Error and Root Mean Squared  
584 Error. The input data consist of field surveys, topography, hydrology, and environmental data, while the locations of historical  
585 flash flood, debris flow and landslide locations are extracted from Google Earth images. The feature importance scores are  
586 derived using a Random Forest model and are used to enhance the analysis of the multi-hazard maps. It is interesting to note  
587 that in this case, the CNN layer is 1-dimensional and is not used to analyse the spatial context of the pixels, but it runs across  
588 the 14 layers of predicting variables, producing an independent output pixel by pixel.

589 While the literature on this topic is quite established, most of these applications propose a multi-layer single hazard risk, rather  
590 than a full multi-hazard or multi-risk approach: in fact, the single hazard maps are often combined linearly or via a matrix  
591 considering combined risk categories, without elaborating further on the hazard interactions. Another common challenge in  
592 the development of susceptibility maps is the skewness of the training dataset, which are characterized by a predominance of  
593 areas with no damage. These greatly affects the training and testing of the models, and specific sampling procedures are often  
594 applied, rather than relying on balancing weights when training the ML model. Most often, all the positive samples (e.g., where  
595 some impact was recorded) are included; a buffer area is applied to the positive samples and subtracted from the whole dataset  
596 to exclude areas near recorded impacts; a number of points of comparable magnitude to the positive ones is sampled from the  
597 difference dataset to ensure that the final training dataset includes a balanced representation of impacted and non-impacted  
598 areas. This is a key step of the susceptibility mapping and can potentially add biases to the model, if the selected samples are  
599 not representative of the whole dataset or if there is a high autocorrelation. Spatial or temporal autocorrelation needs to be  
600 considered when splitting between training, validation and test data: random splitting methods assume data is independent and  
601 identically distributed. Specific techniques, such as spatio-temporal block cross validation (Zanetti et al., 2022) need to be  
602 considered to account for this. For example, a recent paper by Sweet et al. (2023) shows the impact of different validation

603 techniques in a RF model for the prediction of agricultural yield, and their implications on performances and robustness of the  
 604 interpretation of the model.

605 **Table 2: Multi-hazard related methods, gaps and opportunities.**

Section	Methods	Gaps	Opportunities
<b>3.2.1 Identify, classify &amp; cluster</b>	Thresholding (empirical & percentiles) to build multi-hazard catalogs; return periods & GEV; EOFs; CNNs (semi-/supervised) for extreme-weather object detection in reanalyses; DBSCAN for spatio-temporal footprints and compound clusters.	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.	Unified pipelines that detect <b>compound</b> signatures directly (multivariate thresholds + clustering); semi-/self-supervised DL to mitigate label scarcity; robust cluster tracking of compound hotspots under change.
<b>3.2.2 Hazard forecasting &amp; prediction</b>	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.	High data demands; generalisation beyond observed regimes; limited interpretability; performance varies with spatial context and input windowing.	Physics-informed/graph-aware DL for better extrapolation; attention/attribution to expose drivers; global-to-local transfer learning; benchmarking vs. process models for trust.
<b>3.2.2 Modelling hazard interactions</b>	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.	Copula family selection & tail-dependence in high dimensions; ML black-box limits causal insight; difficulty linking physical drivers to dependence structures.	<b>Hybrid ML-copula</b> stacks (ML to predict/characterise events, copulas to quantify joint probabilities); benchmarking ML-learned dependencies against copula baselines; conditional vines for cascades.
<b>Susceptibility mapping (multi-hazard)</b>	Supervised ML (LR/GLM, RF, SVM, BRT, CART, ANN, CNN) to build single-hazard susceptibility then combine into multi-hazard maps; feature importance to rank drivers.	Often “multi-layer single-hazard” (weak interaction modelling); training skew (few positives); sampling bias & autocorrelation; static inputs ignore evolving exposure/vulnerability.	Spatio-temporal CV (block) to curb leakage; dynamic susceptibility that updates with sequences/adaptation; explicit interaction terms or graph-based fusion; extend beyond the usual

			quartet (fire/landslide/flood/quake).
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606

607 This section contributes to the field of multi-hazard and multi-risk analysis by reviewing methods for identifying, classifying,  
608 and clustering hazard events from diverse datasets, highlighting how threshold-based approaches, clustering algorithms, deep  
609 learning models, and copulas can capture the spatio-temporal footprints and interactions of hazards, thereby advancing the  
610 ability to detect, forecast, and model compound and cascading events.

### 611 3.3 Multi-risk

#### 612 3.3.1 Modelling risk combining susceptibility, exposure and vulnerability

613 Many studies are found to focus on modelling risk by combining hazard maps produced via susceptibility mapping with ML  
614 and vulnerability and exposure layers. Single hazards such as wildfires, floods and landslides are the often considered, and  
615 buildings, population and infrastructures are the Kotaridis & Lazaridou (2022) consider flooding risk in Tuscany and applied  
616 a 2D CNN to produce an urban flooding susceptibility map. Differently from Ullah et al. (2022) the CNN applied here makes  
617 use of the spatial context of each pixel, considering a 5x5 patch centred on a specific pixel (an area of 50 x 50 m<sup>2</sup> since the  
618 pixel size is 10m), creating 20000 different samples from the initial map, each one with a 5x5x9 size, where the last number  
619 corresponds to the different predictors of the susceptibility mapping that are considered as channels in the CNN architecture.  
620 Thus, not only the selection of the initial samples, but also the selection of the size of the patch is a key hyperparameter to be  
621 considered: in this case, a cross validation is used to choose the best patch size. The vulnerability maps are created dividing  
622 the land use into 5 classes, which are then multiplied with the hazard layer to calculate the final risk map. Convolutional Neural  
623 Networks (CNNs) offer significant advantages over traditional algorithms in spatial analysis due to their ability to process  
624 areas as 2D maps. This enables the model to leverage Max Pooling layers to capture and simplify the spatial context of events.  
625 Unlike models that focus on individual point characteristics, CNNs can better model and integrate the broader spatial  
626 relationships. For example, Zhao et al. (2020) test CNN for urban flood susceptibility too but instead of producing separate  
627 maps for hazard and vulnerability, anthropogenic factors were used as predictors for the susceptibility map. The study  
628 compares the performances of different ML models: a simple (with 1 convolutional layer) CNN architecture, LeNet5 (Lecun  
629 et al., 1998), a slightly deeper CNN (with 2 convolutional layers), SVM and RF models. Different input strategies are tested:  
630 a point based strategy that only considers input at a given site; a partial spatial strategy that considers the surrounding pixels,  
631 flattening the 2D image to a 1D vector, thus losing partially the spatial context, but allowing the neighbouring pixels to be  
632 fed to SVM and RF models as additional predictors; a patch strategy, similar to the one described before for the CNN models,  
633 which granted the best performances. This study also discusses the use of Deep CNNs, which is discouraged since the typical  
634 sample size and model is too small to tune the high number of parameters required by Deep CNNs.

635 Rusk et al. (2022) analyse population risk in the Hindu-Kush and Himalaya region, producing a multi-hazard map for  
636 landslides, floods and wildfire with the MaxEnt (Maximum Entropy) algorithm, which is then overlaid with population  
637 distribution. The paper also produces a matrix of multi-hazard interactions, dividing them into three types: when hazards are  
638 directly linked (e.g., flooding causing a landslide), when their linkage is mediated by an environmental condition (e.g., land  
639 use changes caused by wildfires increasing the probability of a landslide), or when their linkage is mediated by infrastructure  
640 or urban processes (e.g., a landslide damaging a dam, triggering a flood). However, a quantitative assessment of these multi-  
641 hazard interactions is not provided and only the records of these events are used to complement the multi-risk map. A similar  
642 approach is used in Austria, (Fuchs et al., 2015) considering river flooding, torrential flooding and snow avalanches as hazards  
643 and buildings as assets. In this case, buildings vulnerability is investigated, categorising them based on location, size, building  
644 category and the construction period. The different urbanisation patterns, very high in mountainous terrain of the Hindu-Kush-  
645 Himalaya (HKH) and quite low for Austria, influenced the final risk score assessment, with the HKH showing more areas at  
646 higher risk (Rusk et al., 2022). Sammonds et al. (2023) analyse hurricane, flood and landslide risk on population, producing  
647 single hazard susceptibility maps with statistical methods and discussing the vulnerability of population, considering gender,  
648 age, and population density; the final multi-hazard hurricane risk is obtained as a product of the single hazard susceptibility  
649 scores, overlaid with weights determined with Analytic Hierarchy Process (AHP), and the vulnerability score. Other  
650 applications focus on Vietnam, where RF is applied to derive risk for buildings and population against multi-hazard  
651 susceptibility maps for floods and wildfires (Luu et al., 2024). RF is applied to calculate single and multi-hazard susceptibility  
652 maps for China for flooding, landslides, and debris flows and the railway infrastructure was overlaid to analyse present and  
653 future risk, considering newly planned railway links (K. Liu et al., 2018). In general, a number of studies are found to apply  
654 non-ML approaches, including multi-criteria decision-making and expert judgements methods to calculate susceptibility and  
655 vulnerability layers, such as in Arvin et al. (2023), that focuses on infrastructure resilience in Iran, considering flooding,  
656 landslides and earthquake as hazards, and 25 indicators at the county level and Khatakho et al. (2021), focussing on population  
657 exposed to flooding, earthquakes and wildfires near Kathmandu (Nepal).

658 A critical limitation of the studies reviewed in this section is the static treatment of vulnerability. Most applications use fixed  
659 proxies – building footprints, land-use classifications, census-derived population density – that do not evolve in response to  
660 hazard occurrence, adaptation measures, or broader socio-economic change (Haer et al., 2019, de Ruiter & van Loon, 2022).  
661 This static framing can substantially underestimate risk in contexts where vulnerability is shaped by governance failures,  
662 structural inequalities, or rapid urban expansion (Ward et al., 2022; Šakić Trogrlić et al., 2024). A particularly underexplored  
663 challenge in multi-hazard risk assessment is that vulnerabilities do not simply add up across hazards: they interact. Synergies  
664 and asynergies between vulnerabilities mean that the combination of hazards can fundamentally alter how exposed elements  
665 are affected. For instance, adaptation measures designed to reduce risk from one hazard may increase vulnerability to another,  
666 and damage caused by a first hazard event can leave a system more vulnerable to a subsequent one (Albulescu & Armaş, 2024;  
667 de Ruiter & van Loon, 2022). Stolte et al. (2024) further demonstrate through a global systematic review of urban vulnerability  
668 that the drivers of vulnerability differ substantially across hazard types, and explicitly call for research into multi-hazard

669 vulnerability dynamics as a necessary step beyond the current dominant paradigm of treating multiple hazards in parallel rather  
670 than in interaction. Despite growing conceptual recognition of this problem, it remains essentially unaddressed in the data-  
671 driven literature reviewed in this study, where vulnerability interactions are neither modelled nor discussed. Social justice  
672 dimensions also remain largely absent from the reviewed multi-risk literature: only few of the papers analysed explicitly  
673 consider vulnerability dimensions such as gender, while the question of how ML-based risk maps might inherit biases from  
674 historically underinvested impact datasets remains largely unaddressed (McGovern et al., 2022).

675 Another aspect to consider is uncertainty and its propagation across the risk modelling chain: attempts to propagate it formally  
676 across the hazard–exposure–vulnerability–risk chain are rare even in single-hazard contexts: Kropf et al., (2022) introduced a  
677 sensitivity and uncertainty analysis framework within the CLIMADA platform that varies hazard, exposure, and vulnerability  
678 inputs simultaneously, and Dawkins et al. (2023) extended this to formally quantify uncertainty contributions from each  
679 component, with an application using GAM for heat-stress risk assessment, but neither study addresses multi-hazard  
680 interactions. However, no study in the reviewed corpus achieves end-to-end UQ in a multi-hazard risk context, propagating  
681 uncertainty from input data through hazard modelling and ML or statistical methods to the final risk estimate.

### 682 **3.3.2 Modelling risk predicting impacts**

683 Another popular approach to model multi-risk with ML is to use impacts as a proxy and training supervised ML models on  
684 past impacts. Examples of possible impacts are excess mortality for health risks, economic damages and monetary losses,  
685 number of emergency signals or specific environmental indicators, such as ecological status. With regard to ML methodology,  
686 approaches are similar to the ones applied for predicting hazard values, considering multiple predictors covering climate,  
687 topography, land use and anthropogenic factors, but the final assessment endpoint, impact data, is very different from typically  
688 hazard data, having a coarser resolution in time and space and resulting in much smaller datasets. Thus, most of the studies  
689 focus on simpler and more interpretable ML methods like ensemble methods, rather than the DL approaches which are popular  
690 for hazard prediction. Moreover, more attention is dedicated to the interpretation of the factors and the explainability of  
691 methods (Ghaffarian et al., 2023), with most applications presenting some form of feature importance analysis, either as a  
692 built-in feature of the model, such as for RF, or as a a-posteriori analysis with SHAP values. In this section, studies are grouped  
693 based on the sectors and type of impact considered, considering health, food security and crops, environmental quality &  
694 biodiversity, physical damages and economic losses.

#### 695 **Health**

696 Studies focussing on environmental-health risks often analyse the combination of heat and air quality stressors and use excess  
697 mortality as predicant variable. These applications aim at disentangling complex temporal patterns, consisting of a long-term  
698 trend, driven by multiple (and often unknown) factors, and short-term peaks, mainly driven by summer heatwaves; moreover,  
699 time-lags needs to be considered. Thus, statistical methods, such as Distributed Lag non-linear models have been widely  
700 applied (Gasparri, 2014) to model exposure lag-response of mortality to environmental stressors. More recently, RF has been  
701 applied, analysing the role of humidity in urban mortality during heatwaves at the global scale (Guo et al., 2024) or predicting

702 heat-stroke occurrence in China (Y. Wang et al., 2019), while SVM is applied for analysing previous diseases, population  
703 density and urbanisation (X. Wang et al., 2021). One of the most interesting papers, Boudreault et al., (2023) test 9 different  
704 ML, DL and statistical methods (such as Generalised Additive Models – GAMs) in the Metropolitan City of Montreal,  
705 considering weekly all-cause mortality as predictand and air temperature, humidity, wind, Particle Matter (PM) 2.5, Ozone  
706 (O<sub>3</sub>), Nitrogen Dioxide (NO<sub>2</sub>), Sulphur Dioxide (SO<sub>2</sub>), Carbon Monoxide (CO) as predictors. Among the methods tested,  
707 Tree based methods (RF, XGBoost) usually perform better overall, while statistical methods (and GAM in particular) are more  
708 accurate in predicting the mortality peaks; Deep Learning approaches, such as MLP and LSTM have instead the worst  
709 performances. This is partially explained by the limited size of the dataset and the inclusion of non-climate causes in the  
710 predictand, likely to cause overfitting in the DL models. Another study also focussing on Canada proposes an AI-based  
711 framework to extrapolate vulnerability from health-heat relationship: Côté et al. (2024) test this approach considering two  
712 steps: first, a model to predict daily mortality from mean temperature for 3 days, age, income and period of the year as  
713 predictors and then a second model predicting annual mortality over aggregated areas with specific socio-economic and  
714 environmental (air quality, vegetation, ...) characteristics. The model tested are AutoGluon (an automatic ML framework  
715 allowing to train and test ML models without expert knowledge<sup>2</sup>), GP and Deep Gaussian Process (Deep GP). The results  
716 shows that GP are able to model better the daily mortality trends, especially during extreme temperature, while AutoGluon is  
717 slightly better for the annual analysis. GP with non-linear (e.g., 5/2 Matern Kernel (Y. Pan et al., 2021)) are in fact able to  
718 better handle noise and small data samples (J. Wang, 2023), and their limit is their computational costs (M. Jiang et al., 2022);  
719 on the other hand, the more complex Deep GP handed the worst outcomes, highlighting the challenges in tuning more complex  
720 Deep GPs (Tazi et al., 2023). Other studies focus on predicting the influence of water quality parameters, such as turbidity, on  
721 the risk of cholera disease outbreaks in Indian Coastal municipalities using a RF predictor (Campbell et al., 2020).

## 722 **Food security and crops**

723 The second group of reviewed studies focus on the nexus between food production, food security and migrations. For instance,  
724 Busker et al., (2024) apply XGBoost to predict food insecurity in the Horn of Africa. This model, takes as input several factors,  
725 integrating climatological variables, biological hazards, food and fuel prices, macroeconomic indicators, conflicts and  
726 humanitarian assistance, aggregating data on the administrative units for which the assessment endpoint variable (food  
727 security) was available. The model is tested for its ability to predict the onset of crises up to 12 months in advance,  
728 demonstrating superior performance in agro-pastoral areas compared to croplands. SHAP values are employed to analyse the  
729 key risk drivers. The findings of this study highlight its potential application in operational early warning systems, such as  
730 FEWS NET.

731 Tárraga et al. (2024) also investigate the dynamic relationships between droughts, conflicts and food security, focussing on  
732 their impact on population displacement. In this case, ML is not used to predict displacement, but causal discovery methods  
733 are tested to retrieve its drivers within Somalia from 2016 to 2023. In particular, Granger Causality and Peter and Clark

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<sup>2</sup> <https://auto.gluon.ai/stable/index.html>

734 Momentary Conditional Independence (PCMCI) are tested to generate plausible causal graphs of drought displacement,  
735 showing limitations for Granger causality due to the high dimensionality and autocorrelation of the time series, while the  
736 PCMCI method is able to disentangle the intertwined vulnerabilities and different leading times connecting drought impacts,  
737 water and food security systems along with episodes of violent conflict. The reliability of the causal model depends on the  
738 quality of training data and several assumptions are required, such as causal sufficiency (i.e., all possible driving variables of  
739 drought displacement need to be considered in the analysis), no contemporaneous causal effects and causal stationarity. Note  
740 that although causal sufficiency is valid, the associations between the other variables (e.g., SPEI, market prices, fatalities) may  
741 be influenced by confounding factors rather than direct causality.

742 Different types of copulas (Normal, Student's t, Archimedean with different distributions) are tested to model risk by linking  
743 bivariate return periods of temperature and precipitation to crop yields, analysing the impact of dry and hot, dry and cold, wet  
744 and hot, wet and cold conditions (Zscheischler et al., 2017). Nested Archimedean copulas were used to model the tri-variate  
745 dependence between maximum temperature and spring precipitation on crop yields, estimating the impact differences between  
746 single and compound hazards, using combinations of heat and precipitation stress (Ribeiro et al., 2020).

#### 747 **Environmental quality and biodiversity**

748 Numerous studies focus directly on environmental impacts, such as the influence of land use and urban planning on water  
749 quality. For example, R. Wang et al., (2021) apply RF with SHAP values to model stream water quality and specific pollutants  
750 based on four different urban planning scenarios in Texas. The model allows to correlate urban sprawl to water quality  
751 degradation and was used to forecast environmental impacts under different urban development pattern scenarios. In Li et al.  
752 (2022) the ensemble model XGBoost is used to predict water quality in beach locations in lake Eyre, paired with SHAP for  
753 increased explainability. Other studies focus on ecosystem and biodiversity: for example, RF and Logistic regressions are  
754 tested to predict forest loss in Borneo from topographical and anthropogenic variables (distance to urban areas, population,  
755 etc.), highlighting the advantages of RF for modelling multi-scale spatial relationships between risk drivers (Cushman et al.,  
756 2017). Similarly, in Islam et al. (2021), the spatio-temporal dynamics of wetlands in Bangladesh and their negative effects on  
757 biodiversity are analysed using Decision trees, RF and SVM. RF and SVM are the best performing algorithms and in general,  
758 the papers highlighted the role of remote sensing, for mapping wetlands variations in time. Species distributions is also  
759 investigated, with many applications discussing the different spatial approaches for river network modelling. For example,  
760 Schmidt et al. (2020) test the MaxEnt algorithm with two representations of rivers, highlighting how a high-resolution model  
761 based on river reaches is better at discovering individual local habitat features, whereas lower resolution sub-catchment scale  
762 models better account for more general drivers in fish distribution. Teichert et al. (2016) apply a RF model to identify the  
763 dominant stressors for fish presence in estuaries, investigating the interactions among stressors evaluating ecological benefits  
764 expected from reducing pressure. In particular, an RF model is trained to predict ecological status in 90 locations using 17  
765 predictors describing the different stressors (urbanisation, flow changes, water pollution, oxygen depletion, etc.). Then,  
766 simulations are run to analyse the benefit of restorations comparing the difference between the baseline model and a model

767 where the intensity of stressors was varied. The difference between single and multiple restoration action is analysed,  
 768 highlighting the importance of combined restoration schemes and the non-linearity of their effects.

769 **Economic losses and physical damages**

770 This final category focus on studies modelling economic losses or physical impacts: Dal Barco et al. (2024) model the  
 771 occurrence of impacts due to extreme weather events in the Veneto coastal municipalities, with a combination of two ML  
 772 models: first a classifier (RF, SVM, ANN) is trained to predict the probability of daily impacts in coastal municipalities using  
 773 meteorological data as predictors and a Boolean variable based on impact reports from the Regional Authorities as predictand;  
 774 then a Linear Regression is used to predict the yearly occurrences of damages based on the outcome of the first model.  
 775 However, the coarse resolution of the impact data, the biases in human collected impact catalogues, and the skewedness of the  
 776 dataset can pose significant challenges to the training of a ML-model predicting direct physical impacts. Other studies focus  
 777 on modelling tropical cyclones along the East Coast of the US with ANN: Pilkington & Mahmoud (2017) investigate the  
 778 complex connections between all meteorological factors (wind, pressure, storm surge, and precipitation resulting in inland  
 779 flooding) of a tropical cyclone and how those interact with the location of landfalls to produce a certain level of economic  
 780 damage. The vulnerability and resilience of the different coastal locations are investigated essentially using the model to predict  
 781 losses with varying meteorological factors taken from past historical events but switching their landfall location. Other  
 782 approaches, such as Mukherjee et al. (2018) test SVM and RF to analyse impacts on the energy sector in the US caused by  
 783 extreme weather events, leveraging the records of disruptions from outage data of the Department of Energy in the US and  
 784 using as predictors a set of climatic and socio-economic variables aggregated at state level. In this study, two different models  
 785 are trained, in order to account for the differences in the risk drivers between the more frequent energy disruptions and the  
 786 extreme events, which are separated based on their quantile. Finally, other studies focus on the impacts on specific economic  
 787 sectors, such as finance and tourism: Carannante et al. (2024) propose a pricing model for climate change risk, particularly  
 788 physical risk, developing a type of climate risk-insured loan, based on a bioclimatic composite indicator developed with ML.  
 789 In particular, a temporal dynamic RF (considering variables at different lag-times) is used to produce a monthly risk index,  
 790 based on atmospheric variables (wind, precipitation, temperature) obtained mainly from remote sensing datasets, which is used  
 791 to model impacts on beach resorts in Italy and inform the subsequent climate-risk loan mechanism.

792 **Table 3: Multi-risk related methods, gaps and opportunities.**

Section	Methods	Gaps	Opportunities
<b>3.3.1 Risk via susceptibility + exposure + vulnerability</b>	Overlay of single-hazard susceptibility (RF, SVM, ANN, BRT, CART, MaxEnt, CNN with patch context) with exposure (buildings, population,	Often “multi-layer single-hazard” (weak/implicit interaction modelling); vulnerability treated as static; label imbalance and sampling bias; spatial/temporal autocorrelation leakage; limited	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,

	infrastructure) and simple vulnerability layers; AHP/MCDM weighting; feature importance/SHAP to rank drivers.	hazard breadth beyond fire/landslide/flood/quake.	surge; probabilistic risk surfaces with uncertainty bands.
<b>3.3.2 Predicting impacts — Health</b>	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 modeling for driver attribution.	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.	(1) <b>Data &amp; catalogs:</b> build geocoded, event-level, cross-sector impact datasets and standardized labels (health, yields, biodiversity, losses). (2) <b>Causal &amp; lag-aware stacks:</b> combine DLNM / explicit-lag models with ML and causal discovery to capture delayed and causal pathways. (3) <b>Multi-source fusion &amp; transfer:</b> integrate EO, in-situ, socio-economic and market data; use domain-adaptation/transfer learning for cross-region generalization.

793

794 This section contributes to the field of multi-hazard and multi-risk analysis by examining how ML and statistical approaches  
795 combine hazard, exposure, and vulnerability layers or directly predict impacts, highlighting opportunities and challenges in  
796 capturing dynamic vulnerability, addressing data limitations, and improving the interpretability of risk models across health,  
797 food security, environmental, economic, and infrastructure sectors.

## 798 3.4 Future

### 799 3.4.1 Predicting future hazards

800 Several studies focus on data-driven applications to predict long-term future multi-hazard and multi-risk scenarios.  
801 Zscheischler et al. (2018) discuss the importance of compound events for future risk assessment and presents several  
802 approaches and discusses the main challenges related to the use of future climate projections and weather simulations to analyse  
803 future compound events. The role of bias correction and its connection to multi-hazard events and impact models is analysed:  
804 future projections are often bias corrected to align the distribution of the modelled variables to the distribution of the observed  
805 ones, in the reference timeframe. However, some issues can arise: the simplest approaches focus on adjusting the averages of

806 the variables and do not correct the tails of the distributions, thus modifying the behaviour of extreme events. Methods such  
807 as quantile mapping, are needed to align the historical and future datasets before the application of any statistical or ML  
808 methods. Sensitivity analysis can be performed to analyse how the model reacts to changes in inputs and the robustness of  
809 future scenarios (Kim et al., 2023). Moreover, bias corrections are often univariate, and do not consider the effects on joint tail  
810 distributions and consequently impact models based on these inputs are affected; multivariate bias correction models are then  
811 encouraged (Sippel et al., 2016).

812 When dealing with the future of multi-hazard events, statistical methods are most often applied to identify hotspots and test  
813 trends, similarly to the applications focussing on historical data. For example, Ridder et al. (2022) consider hot, dry, wet and  
814 windy compound events by selecting cells which exceed the 99<sup>th</sup> percentile for wind and precipitation in the same day. Then  
815 results are presented in changes in return period and annual event density, where the latter is a measure for how often an event  
816 affects a region and how much of the region is affected, calculated from the number of grid cells affected. Similarly, Zhu et al.  
817 (2023) investigate future compound wind and precipitation extreme at the global scale, analysing 14 CMIP6 models,  
818 identifying compound events through the 95<sup>th</sup> percentile and discussing the sources of uncertainties via the HS09 statistical  
819 method (Hawkins & Sutton, 2009) splitting between internal variability, model uncertainty and scenario uncertainty. Further  
820 analyses discuss the spatial and temporal performances of future projections: Ridder et al., (2021) find good performances in  
821 CMIP6 simulation for precipitation and wind compound extremes over North America, Europe and Asia, but poor  
822 performances over Australia, probably linked to the limits in the modelling of tropical and extratropical cyclones and local  
823 convection systems. Also, copulas are used to analyse spatial complementary patterns of compound events, such as in Ghanbari  
824 et al. (2021), which analyse the joint return period of compound floods along the US coast, incorporating sea level rise and  
825 peak river flows for future climate change risk scenarios with copulas. H. Wu et al., (2023, 2024), employ Vine copulas to  
826 analyse hot & dry and pluvial & hot events in future scenarios, using the Single Model Initial Conditions Large Ensemble  
827 (SMILE) approach.

828 Bevacqua et al., (2023) stress the importance of SMILE for a robust analysis of future compound climate events. In fact, a  
829 SMILE consists of many simulations from a single climate model, each starting from slightly different initial states (differently  
830 from classical model ensembles, like CMIP6, which consists of many different runs from different models). Each realization  
831 differs solely due to internal climate variability and ensures a better quantification of future uncertainties, and at the same time  
832 it provides a much larger dataset to analyse statistically compound events. Multiple SMILEs can then be combined to identify  
833 model differences and distinguish between internal climate variability and structural model differences. Sometimes, especially  
834 when dealing with unprecedented, High-Impact, Low-Probability events, climate projections or even SMILE or statistical  
835 weather generation are not sufficient: in these cases, storyline approaches are often used as alternative to explore future multi-  
836 risk patterns (Moezzi et al., 2017; Shepherd et al., 2018). These approaches fit well within common practices in disaster risk  
837 management, which consider event-based scenarios for emergency preparedness, allowing for interaction with local  
838 stakeholders to evaluate the effectiveness of selected measures (Sillmann et al., 2021) and to explore low-likelihood and high  
839 impact plausibility events (Bevacqua et al., 2021).

### 840 3.4.2 Modelling future impacts

841 A common approach to estimate future risks involves using future climate projections as input data for ML models that have  
842 been trained on historical data of past impacts, similar to applications that focus on assessing current risks by leveraging past  
843 impacts. For example, the study of future cyclone impacts in New York and New Jersey, is feeding four General Circulation  
844 models as input for a SVM / AdaBoost risk model (Ayyad et alPark & Lee (2020)rk & Lee (2020) test the performances of  
845 three algorithms, K-NN, RF and SVM to analyse coastal risks in South Korea, considering rainfall, tides, topography and land  
846 use, training the model on past floodings and then predicting future risks using monthly averages of rainfall and tidal values  
847 from RCP 4.5 and 8.5 ensembles. Future risk scenarios are calculated aggregating the risk model outcomes for each decade  
848 from 2030s to 2080s. In a successive publication, Park et al. (2023) apply a similar ML methodology to investigate adaptation  
849 strategies for coastal flooding: in this case, the ML model is trained on historical data with two different adaptation strategies,  
850 seawalls or green spaces, and then the future adaptation models are implemented, either maintaining current adaptation  
851 infrastructures or increasing one specific strategy. To ensure comparability between the adaptation scenarios, infrastructure  
852 construction costs are standardized, guaranteeing that the two distinct adaptation pathways incurred equal expenses.  
853 In general, it is considered good practice to use ensemble projections and values calculated over multiple years, in order to  
854 increase the robustness of the future scenarios; however, some risk analyses focus on just a few selected years: Lim & Kim  
855 (2022) test RF for future rainfall induced landslides, also analysing different adaptation pathways and considering an increase  
856 in forested or urban areas. Instead of using monthly or daily values for the ML model, yearly values are used in the model, for  
857 specific years (2050, 2092), which are considered significative for representing future scenarios. This approach is valuable for  
858 analysing specific extreme events that may be overlooked when averaging across multiple models or years, and it reduces  
859 computational demands. However, it carries the risk of biasing the analysis, as the selection of specific years may result in  
860 outcomes that are not fully representative of the broader range of future scenarios. Bayesian Networks were tested by Pham et  
861 al., (2023) in a multi-model chain approach combining ocean hydrodynamics models, wind-wave models, and shoreline  
862 extraction models to analyse sea water quality impacts and shoreline erosion under different RCP projections (4.5 and 8.5).  
863 Bayesian Networks are applied due to their ability to integrate heterogeneous data sources, including quantitative and  
864 qualitative inputs and several data fusion steps to harmonise different spatial coverage, temporal resolutions and data formats,  
865 with a final risk assessment conducted at municipality level and yearly/ decadal scale.

866 With regard to the water-food nexus, ML is being progressively employed as an alternative to process or statistical methods  
867 for future crop yield estimation, showing increased performances and higher computational efficiency: Leng & Hall (2020)  
868 test a RF model for annual yield prediction in the US for a 2° C global warming scenario; while Khan et al. (2024) select  
869 Gradient Boosting to model the relationships between daily climate variables, hazard indicators, such as Consecutive dry days  
870 (CDD) and crop production with CMIP6 data. Tabari & Willems (2023) carry out a global risk assessment from hot and dry  
871 events, employing Copulas and integrating data from Shared Socio-economic Pathways (SSP) scenarios, future land use  
872 patterns population and governance. ML methods are used also to predict the risk of increased conflicts due to climate stressors:

873 a RF classifier is applied by Hoch et al., (2021) to predict water-related conflicts in Africa using different SSP future  
 874 projections, integrating socio-economic predictors (population, education, GDP, governance) and climate predictors  
 875 (precipitation, evaporation, flood volume, soil water). The model is trained on historical data up to 2015 and tested with  
 876 projections from 2016 to 2050. Future temperature-related mortality in different European regions is analysed by García-León  
 877 et al., (2024) considering 4 scenarios of global warming (1.5 °C, 2°C, 3°C, 4°C) with an ensemble of CMIP5 models, analysing  
 878 disparities between cold-related deaths and heat-related deaths and analysing the role of age, health infrastructure and climate  
 879 change with a Distributed Lag Non-Linear model. In particular, different scenarios are discussed: present climate and present  
 880 population, present climate with future population from EUROPOP 2019; future climate under different warming level with  
 881 future population exposure.

882 Future risk patterns are also calculated implementing future multi-hazard susceptibility maps: for example, Rahman et al.,  
 883 (2024) analyse future coastal multi-hazard risks in Bangladesh, implementing an LSTM algorithm, in combination with RF  
 884 feature selection and a Genetic Algorithm (GA) optimiser. In particular, GA is used to identify optimal or near-optimal  
 885 solutions, searching the space of LSTM parameters through a process of selection, crossover and mutation. The combination  
 886 of the LSTM's ability to capture sequential patterns and long-term dependencies and GA's efficiency in navigating complex  
 887 search spaces, is proved to achieve better convergence, avoid local minima, and optimise both the architecture and parameters  
 888 of the LSTM model (Zamani et al., 2022). Other future multi-hazard susceptibility approaches include Ya et al., (2023), who  
 889 analysed future risks in the Tibetan plateau considering climate and land use changes. Logistic Regression is used to produce  
 890 susceptibility maps, while future climate scenarios were taken from CMIP6 future projections. In order to create future land  
 891 use, this paper focus on PLUS, a RF-based model analysing the relationship between influencing factors and land use changes  
 892 (Liang et al., 2021). Another approach for future land use is applied by Saha et al., (2021), which focus on modelling cultural  
 893 heritage site future multi-hazard susceptibility in the Sikkim state in India, considering different climate scenarios from CMIP5  
 894 and land use from an empirical model (Dyna-CLUE) incorporating spatial logistic regression (W. Jiang et al., 2015). Bayesian  
 895 Additive Regression Trees and Bayesian Generalised Linear models are applied to produce multi-hazard susceptibility maps,  
 896 considering extreme rainfall, landslides and earthquakes. Another dynamical model, a Cellular Automata- Markov model  
 897 (Clarke et al., 1997) is used to predict future land use changes in Iran to investigate flood risks, testing RF, XGBoost and  
 898 Gradient Boosting as algorithms for producing susceptibility maps (Janizadeh et al., 2021).

899 **Table 4: Future related methods, gaps and opportunities.**

Section	Methods	Gaps	Opportunities
<b>3.4.1 Predicting future hazards</b>	Bias correction for projections (incl. <b>quantile mapping</b> ); hotspot/trend detection via percentile thresholds (e.g., 95th–99th), return periods; uncertainty sources and propagation;	Univariate bias correction can distort extremes/joint tails; regional skill varies; limited direct detection of <b>compound</b>	Adopt <b>multivariate</b> bias correction; combine SMILEs to separate internal variability vs. structural model differences; scale up <b>vine</b> copulas for

	<b>vine copulas</b> for joint tails; <b>SMILE</b> large ensembles; <b>storyline</b> event-based scenarios for HILP analysis.	signals; uncertainty treatment often partial.	compound events; embed <b>storylines</b> for preparedness.
<b>3.4.2 Modelling future impacts</b>	Trained on historical <b>impacts</b> and applied to future ensembles; ensemble ML methods (RF, XGBoost, ...) for coastal risk, conflict risks, crop yield and adaptation scenarios; <b>Bayesian Networks</b> for multi-model chains (hydrodynamics–waves–shoreline); distributed-lag models for future health impacts; future susceptibility integrating land use changes	Impact data often coarse, biased, and sparse; studies often rely on <b>few years</b> → low representativeness; causal discovery hinges on strong assumptions; biases due to scale mismatch in climate–exposure–impact data.	Use <b>multi-model, multi-year ensembles</b> and probabilistic models to quantify and propagate uncertainty.; evaluate <b>adaptation portfolios</b> with standardized costs; integrate dynamic <b>land use + socio-economic</b> pathways (SSPs); uncertainty-aware learning, and open, geocoded impact datasets.

900

901 This section contributes to the field of multi-hazard and multi-risk analysis by reviewing how ML and statistical methods are  
902 applied to predict future hazards and impacts, highlighting the importance of bias correction, ensemble and SMILE approaches,  
903 and storyline methods, as well as the integration of socio-economic and land use projections. It emphasizes how these  
904 approaches can improve the robustness of long-term risk scenarios, support adaptation planning, and guide strategies to address  
905 uncertainties in future multi-risk patterns.

### 906 **3.5 Limitations and future research directions**

907 Beyond the methodological advances documented in the preceding sections, this review also identifies a set of persistent  
908 limitations and structural gaps in the field that are directly relevant to the operational uptake of data-driven approaches in  
909 multi-hazard risk management. A first and fundamental limitation is climate non-stationarity, as highlighted in Section 3.4  
910 Future: ML models trained on historical hazard records implicitly assume that the statistical relationships between predictors  
911 and outcomes will remain stable into the future. As Reichstein et al. (2025) argue in the context of early warning systems,  
912 relying on past norms and training distributions will prove inappropriate under non-stationary risk conditions, where projected  
913 increases in hazard frequency and severity, combined with shifting exposure and vulnerability, create conditions that fall  
914 outside the range of any historical training set. This is particularly acute for compound and cascading events, which are by  
915 definition rare in the historical record yet are precisely the configurations that climate change is projected to intensify.

916 A second limitation is the gap between hazard prediction and impact prediction. Most ML applications reviewed optimise for  
917 hazard or susceptibility metrics, but impact prediction requires integrating physical hazard outputs with dynamic exposure and  
918 vulnerability data at sub-kilometre scales, a challenge that the reviewed papers largely sidestep by using static proxies. This  
919 gap between technical model performance and actionable risk information represents one of the most important unresolved

920 challenges in translating ML-based risk assessment into operational decision-making (Tiggeloven et al., 2025, Reichstein et  
921 al., 2025).

922 A third set of concerns relates to interpretability and trust. The black-box nature of deep learning models creates well-  
923 recognised barriers to adoption in high-stakes regulatory and emergency management contexts, where stakeholders need not  
924 only a prediction but a justification they can interrogate and contest. However, current XAI applications remain predominantly  
925 proof-of-concept and are rarely integrated into operational early warning or risk assessment workflows (Ghaffarian et al.,  
926 2023). Moreover, reproducibility and validation remain a persistent concern. In geoscientific applications, spatial  
927 autocorrelation means that random train-test splits routinely inflate apparent model skill relative to genuinely independent  
928 spatial holdouts (Sweet et al., 2023), and the reviewed literature shows limited adoption of spatially blocked cross-validation  
929 or independent regional test sets. These limitations do not invalidate the contributions reviewed here, but they do underscore  
930 the need for more rigorous validation protocols, realistic appraisal of out-of-sample performance, and explicit discussion of  
931 the conditions under which ML approaches can be expected to generalise beyond their training contexts.

932 Another methodological gap identified by this review is the absence of end-to-end uncertainty quantification frameworks for  
933 multi-hazard risk assessment. Current practice addresses UQ in fragments: aleatory uncertainty in input data is handled at the  
934 start of the chain, epistemic uncertainty in ML models is occasionally addressed through Bayesian or ensemble methods at the  
935 hazard stage, and copula-based approaches characterise joint uncertainty for statistically correlated hazard pairs, but these  
936 efforts are rarely connected, and they do not extend to the full multi-hazard concept, which encompasses cascading and  
937 triggered hazards beyond the reach of shared statistical distributions. A genuinely integrated framework would propagate both  
938 aleatory and epistemic uncertainty continuously from input data through multi-hazard interactions, ML and statistical model  
939 outputs, and exposure and vulnerability components, to the final risk estimate (Beven et al., 2018).

940 A further methodological consideration for future research is the development of data-driven frameworks that move beyond  
941 static representations of vulnerability and exposure. The reviewed literature overwhelmingly treats these components as fixed  
942 spatial layers, with limited engagement with their dynamic, socially differentiated, and governance-mediated dimensions.  
943 Addressing this gap will require closer integration of ML and statistical methods with approaches capable of representing how  
944 vulnerability evolves over time, including agent-based modelling, participatory data collection, and socially-informed  
945 frameworks that explicitly account for adaptive behaviour, equity, and governance processes. Progress in this direction would  
946 not only improve the realism of multi-risk assessments but also strengthen their relevance for policy and decision-making in  
947 contexts where social vulnerability is itself a driver of risk (Cannon 2017; Bankoff and Hilhorst 2022).

948 Finally, the geographical distribution of the reviewed studies, visualised in the Sankey diagram in Appendix B, points to an  
949 imbalance that is worth acknowledging explicitly. Europe, North America and East Asia together account for more than 80%  
950 of lead authorships, while Africa and South America contribute less than 5%. This pattern partly reflects the Scopus, English-  
951 only, 2010–2024 scope of the search strategy, which may systematically underrepresent research published in other languages  
952 or in regional journals not indexed by Scopus. At the same time, the decoupling between authorship geography and case study  
953 geography, with South/SE Asia, the Middle East, and Africa appearing more frequently as study areas than as sources of

954 authorship, suggests that data-driven methods are in several cases developed in data-rich institutional contexts and  
955 subsequently applied to regions with different risk dynamics, data availability, and governance structures (Tiggeloven et al.,  
956 2025). While drawing strong conclusions about data colonialism or algorithmic bias from a bibliometric analysis alone would  
957 go beyond the scope of this review, these patterns do raise questions that the community should engage with: whether training  
958 datasets and validation benchmarks are representative of the contexts in which models are ultimately deployed, and whether  
959 the priorities shaping methodological innovation reflect the needs of the most exposed populations. Future work in this area  
960 should pay closer attention to the transferability of data-driven multi-risk frameworks across different socio-economic and  
961 data environments (Tiggeloven et al., 2025), and collaborative initiatives fostering locally-grounded research in currently  
962 underrepresented regions would strengthen both the scientific robustness and the equity dimensions of the field (Naudé &  
963 Viluesa, 2021).

#### 964 **4 Conclusion**

965 This paper presents a comprehensive review of data-driven applications aimed at modelling and enhancing our understanding  
966 of climate-related multi-hazard and multi-risk events. Based on the selection of over 1,400 studies and an in-depth analysis of  
967 136 key papers, the review addresses four research areas: (i) data processing and collection, (ii) hazard analysis, (iii) risk  
968 analysis, and (iv) future risk scenarios, each divided in several sub-topics. **Error! Reference source not found.** summarises  
969 the main methods used in each research question, illustrating the different approaches for each sub-topic. In particular, the  
970 figure highlights the strong connections between Earth observations processing and ML techniques like CNN; on the other  
971 hand, RF, other ensemble methods and GAM are mostly applied for risk impacts and future risk assessment, while LSTM,  
972 ANN and other DL approaches are most common for hazard prediction, reflecting a growing trend toward leveraging  
973 sophisticated AI architectures for climate and hazards applications, and a focus on simpler, more interpretable models for risk  
974 applications. Despite the current prevalence of single-hazard applications in ML research, there is growing recognition of the  
975 importance of multi-risk strategies. Notable advancements include copula-based compound event analyses and ML-driven  
976 multi-hazard susceptibility maps. Future research should prioritize a more comprehensive understanding of multi-risk  
977 interactions – such as triggering, cascading, or amplifying effects – by considering the interplay between hazard factors,  
978 vulnerability, and exposure dynamics, which are often overlooked or treated independently in current studies. DL methods,  
979 with their capacity to capture complex, non-linear interactions across spatio-temporal dimensions, offer promising avenues for  
980 progress, yet remain underexplored in operational multi-risk contexts. However, these methods require high-resolution impact  
981 data, which remains a significant challenge due to limited availability, inconsistency across regions, and issues of data quality  
982 and standardization. While EO and textual data can aid in generating new multi-risk disaster catalogues, traditional sensor-  
983 based and human-curated disaster catalogues remain essential for validation, representing a major bottleneck that constrains  
984 model validation, transferability, and ultimately the uptake of these methods in practice. By addressing these methodological  
985 and data gaps, the field can move toward more robust, interpretable, and actionable multi-risk assessments, ultimately

986 strengthening the integration of machine learning into climate services that support adaptation, resilience, and disaster risk  
987 reduction.

988 The gap between hazard prediction and impact prediction remains largely unresolved and bridging it will demand closer  
989 integration of data driven model outputs with dynamic representations of exposure and vulnerability, including human  
990 behaviour, adaptive responses, and the social and governance dimensions that determine how risk is distributed across  
991 communities. Explainability is a further priority: XAI methods need to move beyond their current role as exploratory tools and  
992 be embedded into operational early warning and risk assessment workflows, where their ability to illuminate driver interactions  
993 and build stakeholder trust is most consequential. End-to-end uncertainty quantification across the full modelling chain remains  
994 absent and developing integrated frameworks that propagate both aleatory and epistemic uncertainty from inputs through  
995 multi-hazard interactions to the final risk estimate is one of the most important open methodological challenges for the field.  
996 Underlying all of these challenges is the problem of non-stationarity: as climate change intensifies hazard frequency and  
997 severity, shifts exposure and vulnerability, and increases the likelihood of compound and cascading configurations that fall  
998 outside any historical training set, the assumption that past conditions are a reliable guide to future risk becomes increasingly  
999 untenable, with direct consequences for the validity of ML-based projections of multi-risk evolution.

1000 Addressing these gaps, alongside the geographic and equity imbalances documented in this review, will require not only  
1001 methodological innovation but also more inclusive research practices: collaborative frameworks that bring together physical  
1002 scientists, social scientists, and communities in currently underrepresented regions, co-producing knowledge that is robust,  
1003 transferable, and genuinely relevant to those most exposed to the evolving risks of a changing climate.

1004

## 1005 **Appendix A: Abbreviations**

1006 **Table A1: Acronyms of methods (in alphabetical order)**

<b>Acronym</b>	<b>Full Name</b>
AI	Artificial Intelligence
ANN	Artificial Neural Network
BRT	Boosted Regression Trees
CART	Classification and Regression Trees
CNN	Convolutional Neural Network
ConvNP	Convolutional Neural Process
DBSCAN	Density Based Spatial Clustering Application with Noise
DeepGP	Deep Gaussian Process
DL	Deep Learning
DT	Decision Tree

EG	Expected Gradient
GA	Genetic Algorithm
GAM	Generalised Additive Models
GAN	Generative Adversarial Network
GLM	Generalised Linear Models
GNN	Graph Neural Network
GP	Gaussian Process
GRU	Gated Recurrent Unit
IG	Integrated Gradient
KNN	K Nearest Neighbour
LSTM	Long Short Term Memory
MaxEnt	Maximum Entropy
ML	Machine Learning
NLP	Natural Language Processing
PCMCi	Peter and Clark Momentary Conditional Independence
RF	Random Forest
SHAP	Shapley Values
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting

1007

1008 **Table A2: Other acronyms (in alphabetical order)**

Acronym	Full Name
AHP	Analytical Hierarchy Processes
CO	Carbon Monoxide
CDD	Consecutive Dry Days
CMIP	Coupled Model Intercomparison Project
DynaCLUE	Dynamic Conversion of Land Use and its Effect
EO	Earth observations
FWI	Fire Weather Index
GEV	Generalised Extreme Value (distributions)
HKH	Hindu-Kush and Himalaya (Region)
NO2	Nitrogen Dioxide
O3	Ozone
RCP	Representative Concentration Pathways

PLUS	Patch-generating Land Use Simulation
PM	Particle Matter
SO2	Sulphur dioxide
SMILE	Single Model Initial-condition Large Ensemble
SPEI	Standardised Precipitation and Evapotranspiration Index
SPI	Standardised Precipitation Index

1009

## 1010 **Appendix B: Summary tables of the collected studies**

1011 The literature review followed the PRISMA guidelines to ensure transparency and reproducibility in the identification,  
 1012 screening, and selection of studies. The process is summarized in the PRISMA flow diagram and detailed as follows.  
 1013 First, records were retrieved from major scientific databases (Scopus) and filtered by type, retaining only *articles, conference*  
 1014 *papers, and book chapters* and language (English). Next, documents were filtered by subject area and keyword, selecting only  
 1015 those classified under *Environmental Science* and *Earth and Planetary Science* as subjects and considering machine learning,  
 1016 climate change, risk assessments (and their synonyms and variations) as keywords.

1017 In the third step (title screening stage), studies not focusing on *natural hazards, multi-hazard, or risk assessment* were  
 1018 excluded. During the abstract screening stage, each paper was evaluated for its relevance to the review’s research questions,  
 1019 focusing particularly on the use of machine learning (ML) techniques and their application to multi-hazard or multi-risk  
 1020 contexts. Studies were retained if they explicitly applied ML, AI, or statistical learning methods to the modelling,  
 1021 characterization, or assessment of natural hazards, or if they addressed interactions between multiple hazard types (e.g.,  
 1022 cascading or compound events) and their associated risks. Papers focusing solely on single hazards without methodological  
 1023 innovation or on unrelated environmental modelling were excluded. This step ensured that the final selection captured studies  
 1024 advancing methodological understanding of ML-driven hazard analysis, as well as those integrating multiple hazard processes  
 1025 or risk dimensions. Finally, the full-text review identified the most relevant and representative papers, ensuring balanced  
 1026 coverage across different hazard types and AI methodologies. The final selections were based on diversity in data sources,  
 1027 geographical coverage, hazard types and machine learning methods used. This process ensured that the resulting corpus reflects  
 1028 the breadth of current research at the intersection of AI, Earth observation, and multi-hazard risk assessment.

1029 The number of studies retained at each step is summarized in Table B1 (numbers correspond to the four main research  
 1030 questions):

1031 Table B1: summary of the screening step results

<b>Screening step</b>	<b>RQ1</b>	<b>RQ2</b>	<b>RQ3</b>	<b>RQ4</b>
Initial retrieval	24,335	9,542	22,054	1,961
After type filtering	17,676	8,731	3,548	344
After title screening	6,999	801	2,215	104

After abstract screening	376	107	214	67
Full text screening	52	50	29	22

1032

1033

1034 Figures B1, B2 and B3 provide an overview of the methodological and geographic characteristics of the reviewed literature  
1035 and together contextualise some of the limitations discussed in the main text. Figure B1 shows the distribution of ML methods  
1036 across application domains: CNNs dominate EO-processing applications, reflecting their architectural suitability for gridded  
1037 spatial data. Random Forest and other ensemble methods are the predominant choice for risk impact modelling and future risk  
1038 assessment, consistent with their interpretability, robustness to overfitting, and compatibility with tabular socio-environmental  
1039 predictor sets. LSTM and other sequence-to-sequence deep learning architectures concentrate in hazard prediction tasks where  
1040 temporal dynamics and memory effects are critical. Notably, methods specifically designed for multi-hazard interaction  
1041 modelling – such as graph neural networks or multi-output probabilistic models – are conspicuously absent from the reviewed  
1042 literature, confirming that the methodological frontier lies in adapting or designing architectures that natively represent inter-  
1043 hazard dependencies rather than applying single-hazard models independently.

1044 Figure B2 illustrates the geographic distribution of reviewed papers across lead author country, all author countries, and case  
1045 study region, revealing that research output is heavily concentrated in China, the USA, and Western Europe. Figure B3 further  
1046 summarises this regional imbalance: Europe and North America together account for over 55% of lead authorships, while  
1047 regions such as Africa, South/SE Asia, and South America remain substantially underrepresented both as producers and  
1048 subjects of research. This geographic skew has direct methodological implications: the predominance of country-level  
1049 aggregated indicators, and the limited availability of sub-national spatially resolved datasets, partly reflects the data  
1050 infrastructure of the regions where most studies are conducted and may systematically underrepresent the vulnerability  
1051 dynamics of lower-income contexts where disaster impacts are most severe.

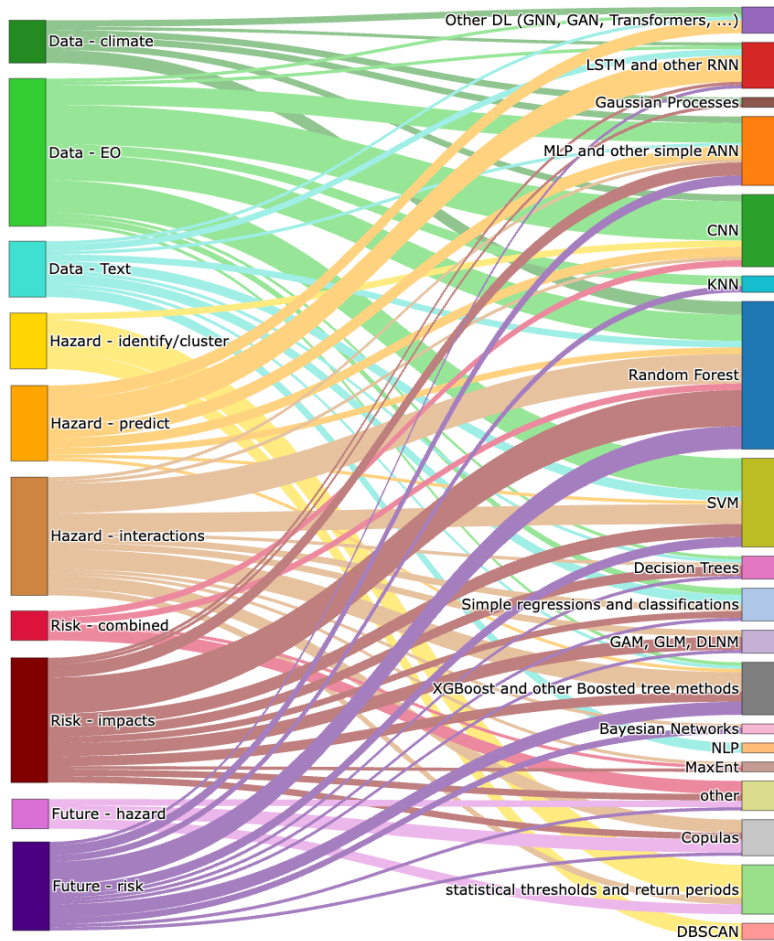
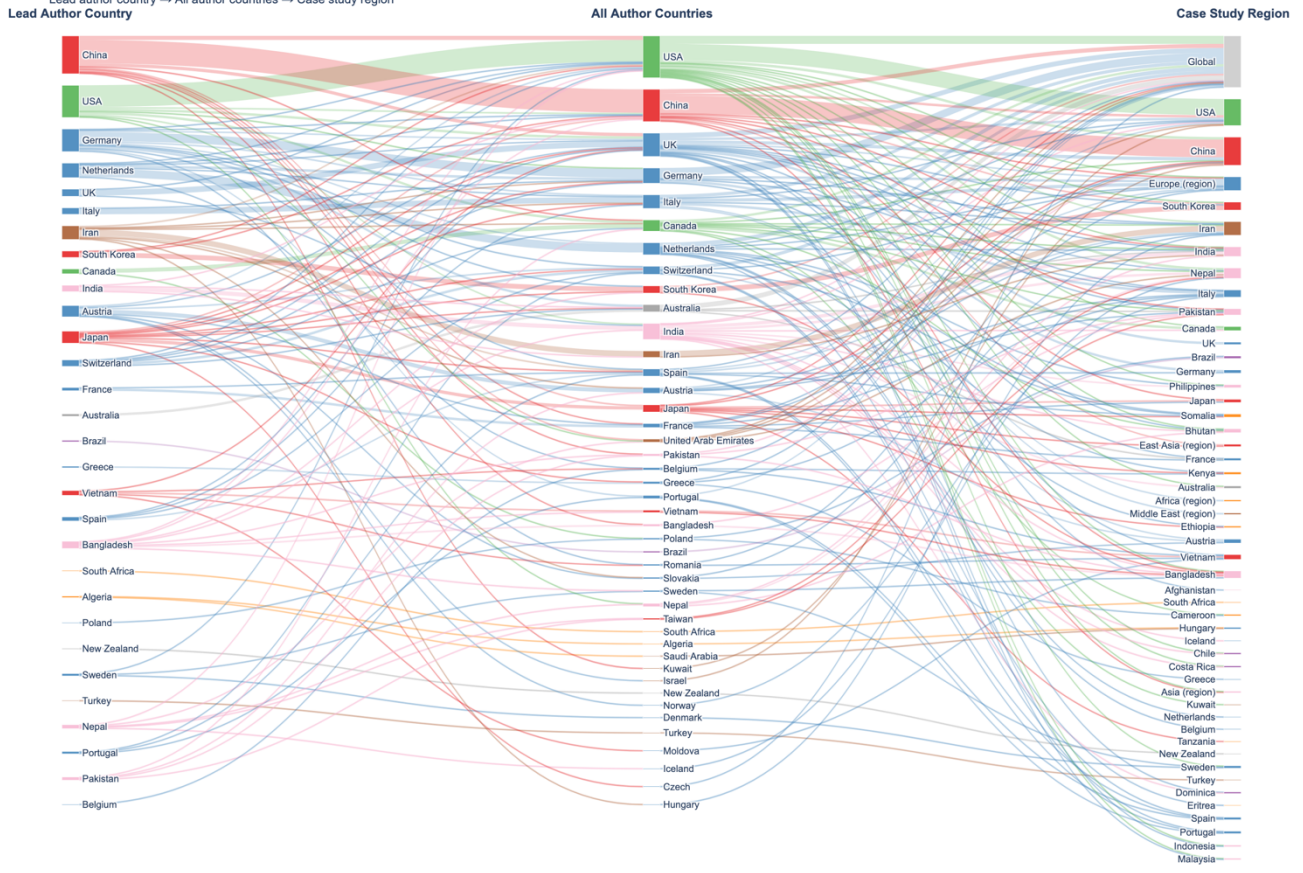


Figure B1: Main methods used for each research topic

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1053

Geographic distribution of reviewed papers

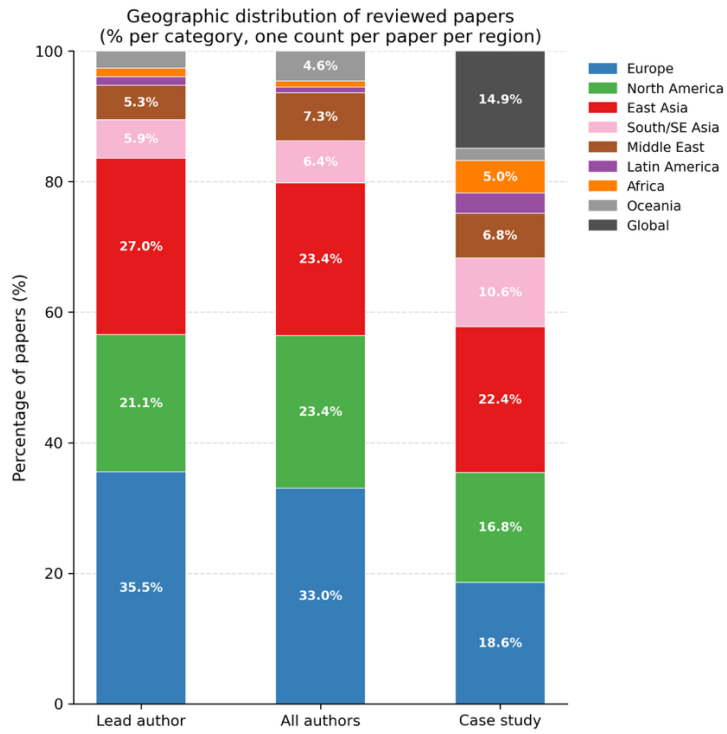
Lead author country → All author countries → Case study region



1054

1055 **Figure B2: Geographic distribution of reviewed papers: Sankey diagrams between main authors countries, co-author countries and**  
1056 **analysed case studies**

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**Figure B3: Summary statistics of geographic distribution of reviewed papers**

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1063 **Table B2: Summary of the research questions and their keywords**

Topic	Research question	Thematic keywords	Method-keywords
Data	How can data-driven applications improve data collection and processing?	Climate, model, observations, reanalysis, remote sensing, earth observations, social media, newspapers, downscaling, bias, impacts	ML (ML), AI (Artificial Intelligence), DL (Deep Learning), NN (neural networks), multivariate statistics, regression, prediction, forecast, classification, anomaly detection, copulas, interpretability, explainability
Hazard	How can data-driven applications be used to identify, classify, and cluster extreme events, and model hazard interactions?	Multi-hazard, drought, flood, heatwave, wildfire, landslide, storm, hurricane, volcanic, earthquake, wind, compound, consecutive, extremes	
Risk	How can data-driven applications integrate vulnerability and exposure in multi-risk analysis?	Multi-risk, climate-risk, multi-sector, environment(al), energy, health, infrastructure, susceptibility, vulnerability, exposure	
Future	How can data-driven applications be used to predict long-term future multi-hazard and multi-risk?	Climate change, tipping points, uncertainty, projections, future risk, RCP, storylines	

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1065

1066 **Table B3: Final selection of studies for RQ1: Data**

Reference	Title	Hazards/ Main variable	ML methods

Topic 1: Data - Climate

(Orth et al., 2022)	Global soil moisture data derived through machine learning trained with in-situ measurements	Soil moisture	LSTM
(Ghiggi et al., 2019)	GRUN: an observation-based global gridded runoff dataset from 1902 to 2014	run-off	RF
(Anderson et al., 2019)	Environmental sensor placement with convolutional Gaussian neural processes	air temperature	CONVNP
(Tazi et al., 2024)	Downscaling precipitation over High-mountain Asia using multi-fidelity Gaussian processes: improved estimates from ERA5	precipitation	GP
(He et al., 2016)	Spatial downscaling of precipitation using adaptable random forests	precipitation	RF
(Lin et al., 2023)	Deep learning downscaled high-resolution daily near surface meteorological datasets over East Asia	Air temperature, humidity, wind, radiation	CNN
(Harris et al., 2022)	A Generative Deep Learning Approach to Stochastic Downscaling of Precipitation Forecasts	precipitation	GAN

(Bretherton et al., 2022)	Correcting Coarse-Grid Weather and Climate Models by Machine Learning From Global Storm-Resolving Simulations	atmospheric variables	RF, ANN
(Clark et al., 2022)	Correcting a 200 km Resolution Climate Model in Multiple Climates by Machine Learning From 25 km Resolution Simulations	atmospheric variables	RF, ANN
(He et al., 2023)	Improving regional climate simulations based on a hybrid data assimilation and machine learning method	Atmospheric, vegetation, soil	Hybrid physics - XGBoost
(Huynh et al., 2025)	A distributed hybrid physics–AI framework for learning corrections of internal hydrological fluxes and enhancing high-resolution regionalized flood modeling	Hydrological	Hybrid physics -ANN
(S. Yu et al., 2024)	ClimSim-Online: A Large Multi-scale Dataset and Framework for Hybrid ML-physics Climate Emulation	Climate/atmospheric	CNN, Encoder/decoder, Heteroskedastic regression, MLP, randomized Prior Network, Conditional Variation Autoencoder
(Willard et al., 2022)	Integrating Scientific Knowledge with Machine Learning for Engineering and Environmental Systems	Literature review	Literature review

(Read et al., 2019)	Process-Guided Deep Learning Predictions of Lake Water Temperature	Water temperature	Hybrid physical / LSTM
(Xu et al., 2022)	Quantifying the uncertainty of precipitation forecasting using probabilistic deep learning	Precipitation	Probabilistic Deep learning
(Siddique et al., 2022)	A Survey of Uncertainty Quantification in Machine Learning for Space Weather Prediction	Space weather, uncertainty quantification	Gaussian Processes, Physics informed Neural Networks
(Ling et al., 2024)	Diffusion model-based probabilistic downscaling for 180-year East Asian climate reconstruction	Climate indices, hot and dry compound events, wind	Diffusion probabilistic downscaling model
(Saha & Ravela, 2022)	Downscaling Extreme Rainfall Using Physical-Statistical Generative Adversarial Learning	Extreme precipitation	Physical/ Generative Adversarial Network
Topic 2: Data - Earth observations			
(Ahmad et al., 2010)	Estimating soil moisture using remote sensing data: A machine learning approach	soil moisture	SVM, ANN, Linear regression

(Kang et al., 2018)	Spatial Upscaling of Sparse Soil Moisture Observations Based on Ridge Regression	soil moisture	Ridge Regression
(Han et al., 2023)	Global long term daily 1 km surface soil moisture dataset with physics informed machine learning	soil moisture	RF
(Jing et al., 2016a)	A Comparison of Different Regression Algorithms for Downscaling Monthly Satellite-Based Precipitation over North China	precipitation	CART, KNN, RF, SVM
(Jing et al., 2016b)	A Spatial Downscaling Algorithm for Satellite-Based Precipitation over the Tibetan Plateau Based on NDVI, DEM, and Land Surface Temperature	precipitation	RF, SVM
(Fang et al., 2017)	Prolongation of SMAP to Spatiotemporally Seamless Coverage of Continental U.S. Using a Deep Learning Neural Network	Soil Moisture	LSTM
(Adam et al., 2014)	Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers	LULC classification (coastal)	RF, SVM
(Yuh et al., 2023)	Application of machine learning approaches for land cover monitoring in northern Cameroon	LULC monitoring	RF, SVM, KNN, ANN

(Zerrouki et al., 2019)	A Machine Learning-Based Approach for Land Cover Change Detection Using Remote Sensing and Radiometric Measurements	LULC change detection	RF, SVM, KNN, ANN
(Miyoshi et al., 2020)	A Novel Deep Learning Method to Identify Single Tree Species in UAV-Based Hyperspectral Images	Tree species mapping	CNN
(Schiefer et al., 2020)	Mapping forest tree species in high resolution UAV-based RGB-imagery by means of convolutional neural networks	Tree species mapping	CNN
(Veras et al., 2022)	Fusing multi-season UAS images with convolutional neural networks to map tree species in Amazonian forests	Tree species mapping	CNN
(J. Wang et al., 2019)	Deprivation pockets through the lens of convolutional neural networks	Identify deprived urban areas	CNN
(Ghaffarian et al., 2021)	Monitoring Urban Deprived Areas with Remote Sensing and Machine Learning in Case of Disaster Recovery	Track disaster recovery in urban deprived areas	SVM
(Nazeer et al., 2017)	Evaluation of Empirical and Machine Learning Algorithms for Estimation of Coastal Water Quality Parameters	Water quality	ANN
(J. Liu et al., 2023)	Monitoring Total Suspended Solids and Chlorophyll-a Concentrations in Turbid Waters: A Case Study of the Pearl River Estuary and Coast Using Machine Learning	Water quality (Turbidity)	ANN, RF, XGBoost, SVM

(S. Chen et al., 2022)	Machine learning-based estimation of riverine nutrient concentrations and associated uncertainties caused by sampling frequencies	Water Quality (River Nutrients)	SVM, RF, ANN
(Sublime & Kalinicheva, 2019)	Automatic Post-Disaster Damage Mapping Using Deep-Learning Techniques for Change Detection: Case Study of the Tohoku Tsunami	Change detection after disaster (earthquake/ tsunami)	CNN based autoencoder
(Ji et al., 2018)	Earthquake/Tsunami Damage Assessment for Urban Areas Using Post-Event PolSAR Data	Change detection after disaster (earthquake/ tsunami)	SVM
(Y. Bai et al., 2018)	Towards Operational Satellite-Based Damage-Mapping Using U-Net Convolutional Network: A Case Study of 2011 Tohoku Earthquake-Tsunami	Change detection after disaster (earthquake/ tsunami)	CNN
(Lei et al., 2019)	End-to-end Change Detection Using a Symmetric Fully Convolutional Network for Landslide Mapping	Change detection (landslide mapping)	CNN
(Bo et al., 2022)	BASNet: Burned Area Segmentation Network for Real-Time Detection of Damage Maps in Remote Sensing Images	Change detection (wildfire mapping)	CNN
(Tran et al., 2020)	Damage-Map Estimation Using UAV Images and Deep Learning Algorithms for Disaster Management System	Change detection (wildfire mapping)	CNN

(Munawar et al., 2021)	UAVs in Disaster Management: Application of Integrated Aerial Imagery and Convolutional Neural Network for Flood Detection	Change detection (flood mapping)	CNN
(Kabiru et al., 2023)	The relationship between multiple hazards and deprivation using open geospatial data and machine learning	Hydrological (floods, landslides), geophysical (earthquake, volcanic), biological, meteorological (temperature), human (transport, industrial, miscellaneous)	Random Forest
(Qiang et al., 2020)	Observing community resilience from space: Using nighttime lights to model economic disturbance and recovery pattern in natural disaster	Hurricane impacts	Univariate/multivariate regression
(Dasgupta et al., 2022)	Towards Daily High-resolution Inundation Observations using Deep Learning and EO	Floods (inundation maps)	Convolutional Neural Network
(Gierszewska & Berezowski, 2024)	A physics-guided neural network for flooding area detection using SAR imagery and local river gauge observations	Floods (inundation maps)	Physics/Neural Network
Topic 3: Data - Texts			
(Asinthara et al., 2022)	Classification of Disaster Tweets using Machine Learning and Deep Learning Techniques	Classifying disaster tweets	SVM, Naïve Bayes

(Powers et al., 2023)	Using artificial intelligence to identify emergency messages on social media during a natural disaster: A deep learning approach	Classifying disaster tweets	BERT, XLNet, SVM
(Koshy & Elango, 2023)	Multimodal tweet classification in disaster response systems using transformer-based bidirectional attention model	Classifying disaster tweets and images	BERT, Transformers, LSTM
(Mehrotra et al., 2022)	A Multi-stage Classification Framework for Disaster-Specific Tweets	Classifying disaster tweets	SVM, DT, RF, ADABOOST, GBM, XGB, LSTM, BERT, XLNET
(Sodoge et al., 2023)	Automatized spatio-temporal detection of drought impacts from newspaper articles using natural language processing and machine learning	Classifying drought impacts from newspapers	Naïve Bayes, Lasso Regression, RF, ANN

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1069 **Table B4: Final selection of studies for RQ2: Hazard**

Reference	Title	Hazards/ Main variable	ML methods
Topic 1: Hazard – identify, classify, cluster			
(Ionita et al., 2021)	Compound Hot and Dry Events in Europe: Variability and Large-Scale Drivers	Hot and Dry compound events	Percentile based thresholds, Empirical Orthogonal Functions

(Sutanto et al., 2020)	Heatwaves, droughts, and fires: Exploring compound and cascading dry hazards at the pan-European scale	Heatwave, drought, wildfire	Percentile based thresholds
(Claassen et al., 2023)	A new method to compile global multi-hazard event sets	Heatwave, coldwave, drought, wildfire, floods, earthquakes, wind, tsunami, tropical cyclone, volcano, landslide	Percentile based thresholds
(Liao et al., 2021)	Growing Threats From Unprecedented Sequential Flood-Hot Extremes Across China	consecutive flood - heatwave	Return periods
(Sfetsos et al., 2023)	Multi-Hazard Extreme Scenario Quantification Using Intensity, Duration, and Return Period Characteristics	Heatwave, coldwave, precipitation, snowfall, wind extremes	Return periods
(Orth et al., 2022)	Contrasting biophysical and societal impacts of hydro-meteorological extremes	Heatwave, Drought, Floods, Wildfire	Return periods, percentiles
(Y. Liu et al., 2016)	Application of Deep Convolutional Neural Networks for Detecting Extreme Weather in Climate Datasets	Extreme weather (Tropical cyclones, atmospheric rivers, weather fronts)	CNN
(Racah et al., 2016)	ExtremeWeather: A large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events	Extreme weather (Tropical cyclones, atmospheric rivers, weather fronts)	CNN (semi-supervised)
(Cammalleri & Toreti, 2023)	A Generalized Density-Based Algorithm for the Spatiotemporal Tracking of Drought Events	Drought	DBSCAN, Percentile based thresholds

(J. Wang & Yan, 2021)	Rapid rises in the magnitude and risk of extreme regional heat wave events in China	heatwaves	DBSCAN, Percentile based thresholds
(Di Martino et al., 2018b)	Spatiotemporal extended fuzzy C-means clustering algorithm for hotspots detection and prediction	earthquakes	DBSCAN
(Tilloy et al., 2022)	A methodology for the spatiotemporal identification of compound hazards: wind and precipitation extremes in Great Britain (1979–2019)	Wind and precipitation	DBSCAN, Percentile based thresholds
(H. Yu et al., 2022)	Hotspots, co-occurrence, and shifts of compound and cascading extreme climate events in Eurasian drylands	Drought, heatwave, coldwave, precipitation, wind	DBSCAN, Percentile based thresholds
Topic 2: Hazard - Predict			
(Haggag et al., 2021)	A deep learning model for predicting climate-induced disasters	Multi-Hazard (flood tested)	ANN
(Kratzert, Klotz, Shalev, et al., 2019)	Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets	Floods	LSTM
(Kratzert, Klotz, Brandstetter, et al., 2019)	Using LSTMs for climate change assessment studies on droughts and floods	Floods, droughts	LSTM
(Tiggeloven et al., 2021)	Exploring deep learning capabilities for surge predictions in coastal areas	Storm Surge	LSTM, CNN, ANN

(S. Jiang, Bevacqua, et al., 2022)	River flooding mechanisms and their changes in Europe revealed by explainable machine learning	River floods, pluvial floods, snowmelt floods	LSTM
(Kraft et al., 2019)	Identifying Dynamic Memory Effects on Vegetation State Using Recurrent Neural Networks	Hot and dry events (impacts on vegetation)	LSTM
(Freeman et al., 2018)	Forecasting air quality time series using deep learning	LSTM	
(Q. Wu & Lin, 2019)	A novel optimal-hybrid model for daily air quality index prediction considering air pollutant factors	Air quality (various pollutants)	LSTM
(Chang-Hoi et al., 2021)	Development of a PM2.5 prediction model using a recurrent neural network algorithm for the Seoul metropolitan area, Republic of Korea	Air quality (PM 2.5)	RNN
(Bentivoglio et al., 2023)	Rapid spatio-temporal flood modelling via hydraulics-based graph neural networks	Floods	GNN
(Kazadi et al., 2024)	FloodGNN-GRU: a spatio-temporal graph neural network for flood prediction	Floods	GNN-GRU
(A. Y. Sun et al., 2021)	Explore Spatio-Temporal Learning of Large Sample Hydrology Using Graph Neural Networks	Floods	GNN
(Castangia et al., 2023)	Transformer neural networks for interpretable flood forecasting	Floods	Transformers

(Bonino et al., 2024)	Machine learning methods to predict sea surface temperature and marine heatwave occurrence: a case study of the Mediterranean Sea	marine heatwaves	CNN, LSTM, RF
(Patil et al., 2023)	Predicting extreme floods and droughts in East Africa using a deep learning approach	drought	CNN
(Singh et al., 2021)	Drought risk assessment and prediction using artificial intelligence over the southern Maharashtra state of India	drought	ANN
(Ayyad et al., 2022)	Machine learning-based assessment of storm surge in the New York metropolitan area	storm surge	RF, XGBoost, Extra Trees, SVM
(Macdonald et al., 2025)	Robust storm surge forecasts for early warning system: a machine learning approach using Monte Carlo Bayesian model selection algorithm	Storm surge	Monte Carlo dropout + Bayesian NN
(M. Nguyen et al., 2024)	Estimating uncertainty in flood model outputs using machine learning informed by Monte Carlo analysis	Flooding	Monte Carlo dropout + Bayesian NN
Topic 3: Hazard - Interactions			
(Couasnon et al., 2018)	A Copula-Based Bayesian Network for Modeling Compound Flood Hazard from Riverine and Coastal Interactions at the Catchment Scale: An Application to the Houston Ship Channel, Texas	Compound river and coastal flood	Copulas, Bayesian Networks

(Sadegh et al., 2017)	Multivariate Copula Analysis Toolbox (MvCAT): Describing dependence and underlying uncertainty using a Bayesian framework	droughts, floods	Copulas
(Bevacqua et al., 2017b)	Multivariate statistical modelling of compound events via pair-copula constructions: analysis of floods in Ravenna (Italy)	River floods, precipitation, coastal floods	Copulas
(Bevacqua et al., 2021)	Guidelines for Studying Diverse Types of Compound Weather and Climate Events	compound flooding, precipitation/landslide	Copulas, regressions, percentile thresholds, clustering
(Hochrainer et al., 2019)	Large scale extreme risk assessment using copulas: an application to drought events under climate change for Austria	drought	copulas
(Tootoonchi et al., 2022)	Copulas for hydroclimatic analysis: A practice-oriented overview	Temperature, precipitation	copulas
(Jiang et al., 2023)	Estimating propagation probability from meteorological to ecological droughts using a hybrid machine learning copula method	Droughts	Copulas, 3D clustering, 11 ML methods (KNN, SVM, GP, DT, MLP, AdaBoost, Naive Bayes, quadratic discriminant analysis, Gradient Boosting, XGBoost, Random Forest)
(Cao et al., 2020)	Multi-geohazards susceptibility mapping based on machine learning—a case study in Jiuzhaigou, China	rockfall, landslide, debris flow	RF, SVM, XGBoost
(Javidan et al., 2021)	Evaluation of multi-hazard map produced using MaxEnt machine learning technique	flood, landslide, gully erosion	MaxEnt

(Karakas et al., 2023)	A Hybrid Multi-Hazard Susceptibility Assessment Model for a Basin in Elazig Province, Türkiye	Landslide, Flood, Earthquake	RF
(Kariminejad et al., 2022)	Analytical techniques for mapping multi-hazard with geo-environmental modeling approaches and UAV images	collapsed pipe, gully erosion, landslide	BRT, Flexible discriminant analysis, Multivariate adaptive regression spline, Mixture discriminant analysis, RF, GLM and SVM
(H. D. Nguyen et al., 2023)	Multi-hazard assessment using machine learning and remote sensing in the North Central region of Vietnam	Flood, landslide	SVM, RF, AdaBoost
(Pourghasemi et al., 2020)	Assessing and mapping multi-hazard risk susceptibility using a machine learning technique	Flood, landslide, wildfire	RF
(Pouyan et al., 2021)	A multi-hazard map-based flooding, gully erosion, forest fires, and earthquakes in Iran	gully erosion, wildfire, earthquake	RF, SVM, BRT
(Yousefi et al., 2020)	A machine learning framework for multi-hazards modeling and mapping in a mountainous area	avalanche, landslide, wldfire, subsidence, flood	SVM, BRT, GLM, FDA
(Piao et al., 2022)	Multi-hazard mapping of droughts and forest fires using a multi-layer hazards approach with machine learning algorithms	drought, wildfire	CART, RF, BRT
(Ullah et al., 2022)	Multi-hazard susceptibility mapping based on Convolutional Neural Networks	flash flood, debris flow, landslide	CNN, RF

(Mandal et al., 2022)	Mapping the multi-hazards risk index for coastal block of Sundarban, India using AHP and machine learning algorithms	cyclones, storm surge, coastal erosion	ANN, RF
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1072 **Table B5: Final selection of studies for RQ3: Risk**

Reference	Title	Hazards/ Main variable	ML methods
Topic 1: Risk - Combining hazard, exposure and vulnerability			
(Kotaridis & Lazaridou, 2022)	Integration of convolutional neural networks for flood risk mapping in Tuscany, Italy	flood	CNN
(Zhao et al., 2020)	Urban flood susceptibility assessment based on convolutional neural networks	flood	CNN
(Rusk et al., 2022)	Multi-hazard susceptibility and exposure assessment of the Hindu Kush Himalaya	flood, landslide, wildfire	MaxEnt
(Fuchs et al., 2015)	A spatiotemporal multi-hazard exposure assessment based on property data	river flood, snow avalanche, torrential flood	Frequency ratio
(Sammonds et al., 2023)	Hurricane risk assessment in a multi-hazard context for Dominica in the Caribbean	hurricane, landslides, floods	Frequency ratio, analytical hierarchy process
(Luu et al., 2024)	Integrating multi-hazard susceptibility and building exposure: A case study for Quang Nam province, Vietnam	flood, wildfire	RF, CART

(K. Liu et al., 2018)	Susceptibility of existing and planned Chinese railway system subjected to rainfall-induced multi-hazards	flood, landslide, debris flow	RF
(Arvin et al., 2023)	Assessment of infrastructure resilience in multi-hazard regions: A case study of Khuzestan Province	flood, landslide, earthquake	analytical hierarchy process
(Khatakho et al., 2021)	Multi-Hazard Risk Assessment of Kathmandu Valley, Nepal	flood, earthquake, wildfire	analytical hierarchy process
Topic 2: Risk – Predicting impacts			
(Gasparrini, 2014)	Modeling exposure–lag–response associations with distributed lag non-linear models	heatwave, air pollution	Distributed Lag Non-Linear Models
(Guo et al., 2024)	Regional variation in the role of humidity on city-level heat-related mortality	heatwave, humidity	RF
(Y. Wang et al., 2019)	A random forest model to predict heatstroke occurrence for heatwave in China	heatwave, humidity	RF
(X. Wang et al., 2021)	Quantitative Impact Analysis of Climate Change on Residents' Health Conditions with Improving Eco-Efficiency in China: A Machine Learning Perspective	heatwave, humidity, previous diseases	SVM
(Boudreault et al., 2023)	Machine and deep learning for modelling heat-health relationships	heatwave, air pollution	DT, RF, GBM, SLP, MLP, LSTM, GLM, GAM, DLNM
(Côté et al., 2024)	Vulnerability assessment of heat waves within a risk framework using artificial intelligence	heatwave, air pollution	Auto-Gluon, GP, Deep GP

(Busker et al., 2024)	Predicting Food-Security Crises in the Horn of Africa Using Machine Learning	Heatwaves, droughts, precipitation, conflict	XGB
(Tárraga et al., 2024)	Causal discovery reveals complex patterns of drought-induced displacement	drought, precipitation, conflict	Granger Causality, PCMCI
(Zscheischler et al., 2017)	Bivariate return periods of temperature and precipitation explain a large fraction of European crop yields	drought, heatwave, precipitation	Copulas
(Ribeiro et al., 2020)	Risk of crop failure due to compound dry and hot extremes estimated with nested copulas	drought, heatwave	Copulas
(R. Wang et al., 2021)	Predicting stream water quality under different urban development pattern scenarios with an interpretable machine learning approach	water quality, land use planning	RF
(Li et al., 2022)	Interpretable tree-based ensemble model for predicting beach water quality	water quality	DT, RF, CatBoost, GBM, XGBoost
(Cushman et al., 2017)	Multiple-scale prediction of forest loss risk across Borneo	forest loss	RF, logistic regression
(Islam et al., 2021)	Machine learning algorithm-based risk assessment of riparian wetlands in Padma River Basin of Northwest Bangladesh	drought, topography, environmental and antropogenic stressors	RF, SVM, DT, ANN

(Schmidt et al., 2020)	The role of spatial units in modelling freshwater fish distributions: Comparing a subcatchment and river network approach using MaxEnt	topography, environmental and antropogenic stressors	MaxEnt
(Teichert et al., 2016)	Restoring fish ecological quality in estuaries: Implication of interactive and cumulative effects among anthropogenic stressors	topography, environmental and antropogenic stressors	RF
(Dal Barco et al., 2024)	A machine learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy)	precipitation, wind, sea level rise, storm surges	AN(Pilkington & Mahmoud, 2017)n
(Pilkington & Mahmoud, 2017)	Spatial and temporal variations in resilience to tropical cyclones along the United States coastline as determined by the multi-hazard hurricane impact level model	wind, storm surge, precipitation, flooding	ANN
(Mukherjee et al., 2018)	A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S.	heatwave, wildfire, hurricane, coldwave, wind, precipitation	SVM, RF
(Carannante et al., 2024)	Machine learning-based climate risk sharing for an insured loan in the tourism industry	wind, precipitation, heatwave	RF

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1076 **Table B6: Final selection of studies for RQ4: future**

Reference	Title	Hazards/ variable	Main	ML methods
Topic 1: Future: hazard				
(Zscheischler et al., 2018)	Future climate risk from compound events	compound events		copulas, storylines
(Ridder et al., 2022)	Increased occurrence of high impact compound events under climate change	drought, heatwaves, precipitation, wind		percentile threshold, return period
(Zhu et al., 2023)	Compound wind and precipitation extremes at a global scale based on CMIP6 models: Evaluation, projection and uncertainty	wind, precipitation		percentile threshold, return period
(Ridder et al., 2021)	Do CMIP6 Climate Models Simulate Global or Regional Compound Events Skillfully?	wind, precipitation		percentile threshold, return period
(Ghanbari et al., 2021)	Climate Change and Changes in Compound Coastal-Riverine Flooding Hazard Along the U.S. Coasts	coastal flood, river flood, sea level rise		copulas
(H. Wu et al., 2023)	Increasing Risks of Future Compound Climate Extremes with Warming Over Global Land Masses	drought, heatwave, precipitation		copulas
(H. Wu et al., 2024)	Predicting compound agricultural drought and hot events using a Cascade Modeling framework combining Bayesian Model Averaging ensemble with Vine Copula (CaMBMAViC)	drought, heatwave		copulas

(Bevacqua et al., 2021)	Guidelines for Studying Diverse Types of Compound Weather and Climate Events	High-Impact Low-Probability Events	storylines
Topic 2: Future – Risk			
(Ayyad et al., 2023)	Climate change impact on hurricane storm surge hazards in New York/New Jersey Coastlines using machine-learning	hurricane, storm surge	SVM, AdaBoost
(S. J. Park & Lee, 2020)	Prediction of coastal flooding risk under climate change impacts in South Korea using machine learning algorithms	precipitation, storm surge, sea level rise	KNN, RF, SVM
(S. Park et al., 2023)	Adaptation strategies for future coastal flooding: Performance evaluation of green and grey infrastructure in South Korea	precipitation, storm surge, sea level rise	KNN, RF, SVM
(Lim & Kim, 2022)	Can Forest-Related Adaptive Capacity Reduce Landslide Risk Attributable to Climate Change? -Case of Republic of Korea	precipitation, landslide	RF
(Pham et al., 2023)	Multi-model chain for climate change scenario analysis to support coastal erosion and water quality risk management for the Metropolitan city of Venice	coastal erosion, water quality, storm surge	Bayesian Network
(García-León et al., 2024)	Temperature-related mortality burden and projected change in 1368 European regions: a modelling study	heatwave, future population, economic factors	weighted averages

(Rahman et al., 2024)	Multi-hazard could exacerbate in coastal Bangladesh in the context of climate change	flash floods, river floods, coastal floods, landslide	LSTM
(Ya et al., 2023)	Increased flood susceptibility in the Tibetan Plateau with climate and land use changes	flood	logistic regression
(Liang et al., 2021)	Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China	Future land use	RF
(Saha et al., 2021)	Modelling multi-hazard threats to cultural heritage sites and environmental sustainability: The present and future scenarios	earthquake, landslide, precipitation	BRT, BART, BGLM
(Janizadeh et al., 2021)	Mapping the spatial and temporal variability of flood hazard affected by climate and land-use changes	Floods	GBM, XGB
(Leng & Hall, 2020)	Predicting spatial and temporal variability in crop yields: an inter-comparison of machine learning, regression and process-based models	precipitation, drought, heatwave	RF
(Khan et al., 2024)	Association of precipitation extremes and crops production and projecting future extremes using machine learning approaches with CMIP6 data	Precipitation	XGB

(Tabari & Willems, 2023)	Global risk assessment of compound hot-dry events in the context of future climate change and socioeconomic factors	drought, heatwaves	Copulas
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1090 **Author contribution**

1091 DMF: Conceptualisation, Methodology, Formal analysis, Investigation, Data curation, Visualisation, Writing – original draft.  
1092 MS: Conceptualisation, Methodology, Validation, Writing – review and editing.  
1093 MM: Conceptualisation, Data curation, Writing – review and editing.  
1094 AC: Funding acquisition, Supervision, Conceptualisation, Writing – review and editing.  
1095 ST: Funding acquisition, Supervision, Conceptualisation, Project administration.

1096 **Competing interest**

1097 The authors declare that they have no conflict of interest.

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