

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

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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.

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62 1 Introduction

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

72 Complex dynamics characterize socio-environmental and climate risk: applications may underestimate impacts if they do not
73 take into account the compounding, cascading and amplifying interactions of hazards and their effect on vulnerability and
74 exposure factors. In fact, (i) compounding hazards (co-occurring in the same location and at the same time) can lead to impacts
75 which may be substantially higher than the sum of the single events taken in isolation (Arosio et al., 2020; Zscheischler et al.,
76 2018), (ii) the occurrence of one hazard itself can modify vulnerability or resilience of the system, exposing assets or
77 communities to higher risks, such as in the case of consecutive hazards (de Ruiter & van Loon, 2022), and (iii) impacts and
78 risks can propagate across multiple scales and sectors, extending far beyond the area initially hit and affecting whole systems
79 (Arosio et al., 2021; Pescaroli & Alexander, 2018), such as in the case of high-impact and low-probability events (Linkov et
80 al., 2022). For these reasons, the international community (Intergovernmental Panel on Climate Change (IPCC), 2023;
81 UNDRR, 2020) has recently pledged for a paradigm shift from single hazard towards a more comprehensive representation of
82 multiple and interconnected climatic risks (AghaKouchak et al., 2020; De Angeli et al., 2022; Gallina et al., 2020; Šakić
83 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
84 data-driven methodologies that can analyse and predict the interactions and dependencies between multiple hazards, enabling
85 a more accurate characterisation of their compounding and cascading effects.

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

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

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

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

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

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

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

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

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

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

139 **2 Methodology**

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

148 **2.1 Research questions**

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

- 152 1. Data: How can Machine Learning improve data collection and processing?
 - 153 2. Multi-Hazard: How can Machine Learning and statistical tools be used to analyse extreme events, and model hazard
154 interactions?
 - 155 3. Multi-Risk: How can Machine Learning applications integrate vulnerability and exposure in multi-risk analysis?
 - 156 4. Future: How can Machine Learning and statistical tools be used to predict long-term future multi-hazard and multi-
157 risk?
- 158

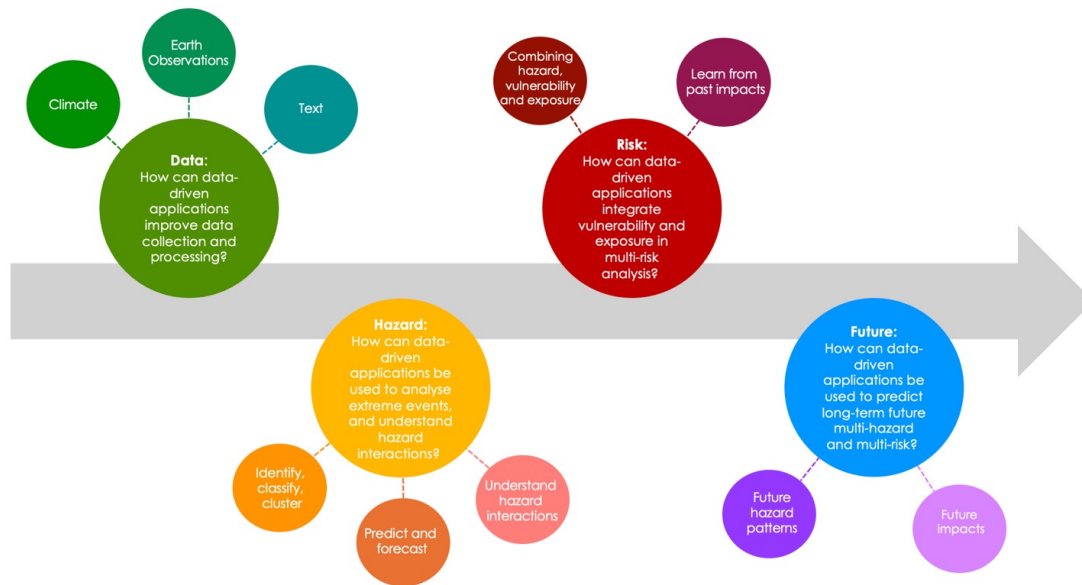


Figure 1: Research questions and sub-themes

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

- 166 I. Climate data (time series of geospatial climate data), which describe the characteristics of climate-related hazards
 167 across space and time. Preparing this data for multi-hazard and multi-risk applications often requires ML methods
 168 (i.e. feature engineering) to increase spatial and temporal resolution, harmonise and extend the time coverage of the
 169 datasets or correct for biases (Schneider et al., 2023).
 170 II. EO, which can be used to characterise exposure and vulnerability layers and extract information on impacts
 171 (Ghaffarian & Emtehani, 2021; Novellino et al., 2024).
 172 III. Textual data, such as newspapers or social media, which in the last years have been leveraged for extracting
 173 information on diverse impacts (Sodge et al., 2023).
 174

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

- 179 I. Analyse which methods can be used to identify, classify and cluster extreme events, producing spatio-temporal
 180 footprints of multi-hazard events (H. Yu et al., 2022).
 181 II. The prediction of (multi-)hazard events, for example through early warning systems or seasonal predictions
 182 (Bhowmik et al., 2023).
 183 III. The analysis of hazard interactions, for example characterising joint distributions through copulas (Bevacqua et al.,
 184 2021) or multi-hazard susceptibility maps (Pourghasemi et al., 2019).

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

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

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

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

203 **2.2 Methodological framework: search methodology, screening, reporting and interpreting**

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

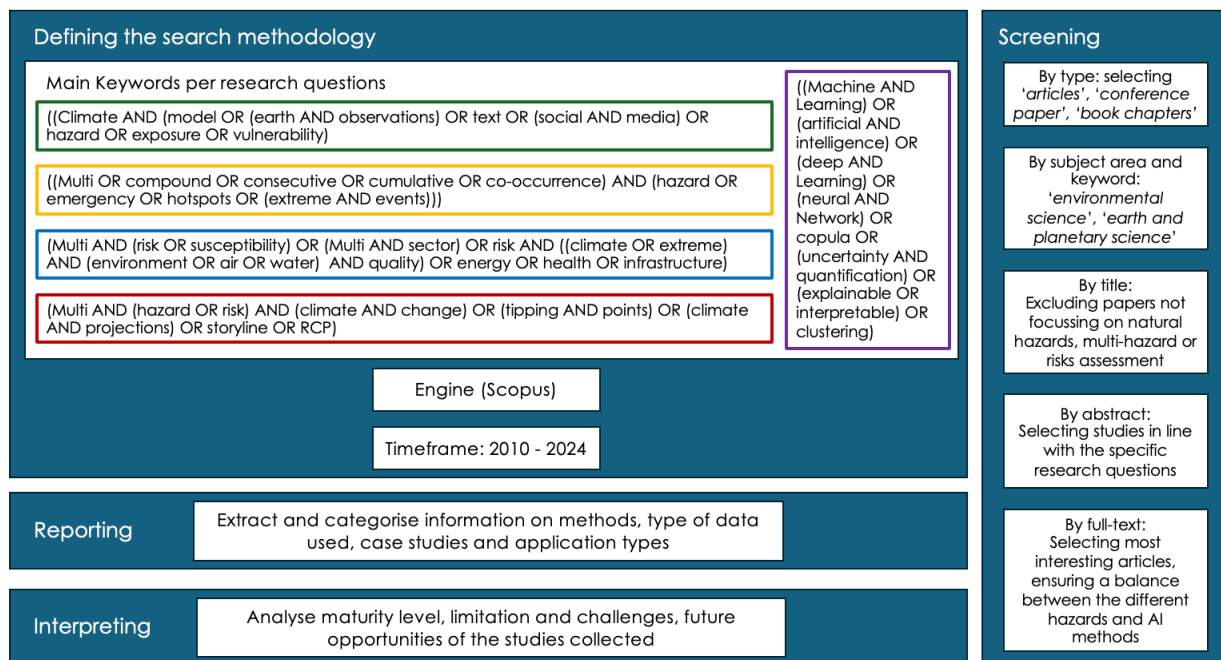


Figure 2: Literature review methodology

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

218 3 Results and discussions

219 3.1 Data

220 3.1.1 Climate datasets

221 The application of ML methods to produce new, complete, or high-resolution hazard datasets (either from meteorological
 222 observations, climate reanalyses or future projection) is quite established, and mainly focuses on data with sparse and irregular
 223 measurements. A typical indicator which is derived with ML methodologies is soil moisture: in-situ measurements are usually
 224 scarce and not uniformly distributed, satellite images (which will be discussed later) often presents temporal gaps and can only
 225 provide information on the first layer and struggles in complex topographies and it presents a complex dynamic that is
 226 influenced by many different drivers (similarly to multi-risk prediction) such as precipitation, temperature, evaporation,

227 topography and land use. For example, Kang et al. (2018) and O. & Orth, (2021) investigate the complex interactions at
228 different soil levels and temporal scales with a Long-Short Term Memory (LSTM) model that takes as inputs the topography,
229 vegetation and atmospheric conditions and predicts each soil moisture layer in succession, using ERA-5 reanalysis as
230 assessment endpoint. LSTM is widely applied to model the behaviour of other hydrological variables, such as snow, run-off
231 and river catchments. Entity-Aware LSTM was used for rainfall-runoff modelling by Kratzert et al., (2018); Kratzert, Klotz,
232 Shalev, et al., (2019), to include both static and dynamic inputs allowing the algorithm to explicitly differentiate the two
233 different types. Ghiggi et al. (2019) applies Random Forest (RF) regression to predict monthly runoff rates in the timeframe
234 1902-2020, based on antecedent precipitation and temperature from an atmospheric reanalysis, validating the results with in-
235 situ streamflow observations. Other research focuses on different variables and in particular investigate the irregular
236 distribution of sensors: Amato et al. (2020) introduces a multi-step methodology to interpolate irregularly distributed spatio-
237 temporal timeseries, first decomposing the signal and then learning stochastic spatial coefficients which can be spatially
238 modelled and mapped on a regular grid with Artificial Neural Networks (ANN), allowing the reconstruction of the complete
239 spatio-temporal signal.

240 ML methods have been applied also to climate reanalyses and models. Early applications, such as He et al. (2016), tested RF
241 regression to statistically downscale spatially precipitation data, using few covariates and demonstrating how this approach is
242 able to catch the non-linear relations between variables, minimising overfitting and collinearity issues between predictors.
243 However, the algorithm struggled with skewed datasets and even the final model, which is the combination of two different
244 RF models, trained respectively on high-precipitation and low-precipitation values, fails to detect the complex spatial and
245 temporal complexity of precipitation data, overestimating the intensity and spatial distribution of low precipitation and
246 underestimating high precipitation. Other applications are focussing on Deep Learning models: CNNs are used to downscale
247 many variables from future climate models (among which, air temperature, precipitation, 10-m wind speed, 2-m relative
248 humidity, downward shortwave radiation) (Lin et al., 2023). Generative models particularly Generative Adversarial Networks
249 (GAN) and diffusion models, are widely used for this task. GANs consist of two neural networks – a generator and a
250 discriminator - that are trained simultaneously in a competitive process. The generator attempts to create realistic fake data
251 that can fool the discriminator, while the discriminator works to distinguish between real and fake data. For example, specific
252 GANs based on Convolutional Neural Networks (CNNs) have been applied to post-process weather forecast outputs. These
253 models can enhance the resolution of precipitation data by a factor of ten, producing more realistic and spatially coherent
254 forecasts compared to the original input data (Harris et al., 2022). Diffusion models, on the other hand, learn to reverse a noise
255 process: first the model adds sequentially noise to input data, then the model learns how to predict the noise at each step, and
256 once trained, it can start with noisy data and work backwards, progressively removing the noise to generate a new, realistic
257 dataset. Diffusion models are related to variational inference, where the forward process defines a probabilistic trajectory from
258 data to noise, and the reverse process defines a generative path from noise back to data. Unlike other generative models like
259 GANs, which learn through a "discriminative" process (trying to fool a discriminator network), diffusion models learn through
260 this smooth diffusion and denoising process (Yeğin & Amasyalı, 2024). For example, diffusion models are applied to

261 downscale multiple climate models, also providing information on the uncertainty downscaling, by generating a large number
262 of ensemble members based on probability distribution sampling (Ling et al., 2024a). DL approaches are often used to
263 downscale low-resolution future models to Convection Permitting (CP) climate models, where the main advantage of these
264 techniques is their reduced computational costs compared to the development of a CP climate models (Bretherton et al., 2022;
265 Clark et al., 2022). The role of Artificial Intelligence (AI) in climate predictions is discussed in Schneider et al. (2023). This
266 study advocates for the development of global models at 10–50 km resolution, harnessing AI and EO for the calibration and
267 development of higher-resolution regional simulations.

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

287 Machine learning applications for climate and environmental datasets have greatly improved the reconstruction and
288 downscaling of variables from sparse and irregular observations. However, a critical yet often under-addressed aspect in this
289 field is uncertainty quantification (UQ), which is particularly relevant when these datasets are later used for hazard or risk
290 assessments (Beven, 2018). Uncertainty in ML-based arises from multiple sources: Aleatoric uncertainty stems from the
291 intrinsic variability and noise in the underlying measurements, such as sensor errors, missing satellite observations, or
292 inconsistent temporal coverage; epistemic uncertainty originates from limited or biased training data and model structural
293 choices (Xu et al., 2022). Several probabilistic approaches have been explicitly designed to represent spatial data uncertainty
294 by learning distributions rather than deterministic predictions, mainly involving Bayesian Networks (BN) and Gaussian

295 Processes (GP) (Siddique et al., 2022). For example, Multi-fidelity Gaussian Processes with a $5/2$ Matern kernel in particular,
296 were used to downscale precipitation data from ERA-5 over high mountain terrain. Multi fidelity models combine low-fidelity
297 observations (which are usually more numerous and less expensive to obtain) with high-fidelity ones. This makes the model
298 more suited than other state-of-the-art machine learning methods for smaller datasets and able to quantify and narrow the
299 uncertainty associated with the precipitation estimates, which is especially needed over ungauged areas and can be used to
300 estimate the likelihood of extreme events that lead to floods or droughts (Tazi et al., 2024). Andersson et al., (2023) applies
301 Convolutional Neural Processes (ConvNPs), to suggest informative sensor placements by finding sites that maximally reduce
302 prediction uncertainty, testing it for air temperature anomalies measurements in Antarctica. Convolutional Neural Processes
303 (ConvNPs) extend the probabilistic framework of Gaussian Processes by learning flexible, data-driven covariance structures
304 through neural networks. While traditional GPs provide robust uncertainty estimates but suffer from scalability and stationarity
305 constraints (M. Jiang et al., 2022), ConvNPs maintain a probabilistic foundation while scaling linearly with data size and
306 accommodating irregular spatial inputs (Garnelo et al., 2018). DeepSensor¹, a specific GitHub python package, was developed
307 to facilitate the application of Neural Processes in environmental sciences, especially for downscaling, interpolation, sensor
308 placement and data imputation. Monte Carlo Dropout (MCD) enhances epistemic uncertainty quantification in climate data
309 and was tested on neural networks for probabilistic medium-range weather forecasting (Garg et al., 2022). Deep generative
310 models such as diffusion or GAN frameworks can further approximate uncertainty by generating ensembles of plausible
311 realisations that sample the predictive probability space (Ling et al., 2024b; Saha & Ravela, 2022). Despite these advances,
312 most studies still focus primarily on improving resolution and accuracy, while systematic approaches to quantifying and
313 propagating uncertainty through the modelling chain, from data to hazard and risk estimates, remain limited (Beven, 2018).
314 Addressing this challenge is crucial, as downstream risk assessments rely heavily on the reliability of the climate inputs that
315 feed them.

316 3.1.2 Earth observations

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

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

324 EO provides consistent, near-real time observations of environmental conditions that are critical for early warning and hazard
325 characterisation. For instance, indicators such as vegetation stress (Miyoshi et al., 2020; Schiefer et al., 2020; Veras et al.,

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

326 2022), surface temperature anomalies can enable the early detection of droughts (Barrett et al., 2020), floods (Dasgupta et al.,
327 2022) or wildfires (Jain et al., 2020) especially in remote and data scarce areas. DL and Physics Informed Neural Networks
328 can leverage radar (e.g., Sentinel-1 SAR), to estimate water levels for flood forecasting (Dasgupta et al., 2022; Gierszewska
329 & Berezowski, 2024) or fused into predictive models that refine hazard forecasts for severe weather and anticipate cascading
330 impacts (Flora et al., 2021). Remote sensing plays a crucial role in hazard dataset development by helping mitigate bias that
331 may be inherited by ML-based risk models. These models are often trained on datasets calibrated with data from resource-rich
332 regions, where the majority of weather stations are located. As a result, they may struggle to generalize effectively to
333 underdeveloped areas, which are frequently the most vulnerable to extreme events (McGovern et al., 2019, 2022).

334 EO combined with ML is also used in assessing environmental quality, such as water quality (Sagan et al., 2020; Sit et al.,
335 2020). These applications mainly showcase simpler models, such as short neural networks and SVM (Nazeer et al., 2017),
336 Decision Trees (DT), RF, Cubist Regression and Extreme Gradient Boosting (XGBoost), due to their ease of implementation
337 and relative scarcity of ground measurement data (J. Liu et al., 2023). They focus on optically parameters, such as chlorophyll-
338 a, turbidity and suspended solids, but also others such as of nutrients and other non-optical parameter) can be predicted relying
339 on models integrating meteorological and hydrological variables (S. Chen et al. 2022).

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

347 Moreover, EO enables long-term recovery tracking and vulnerability/exposure monitoring, with applications using proxies
348 such as night-time lights to measure recovery trajectories (Kabiru et al., 2023; Qiang et al., 2020). For examples, studies have
349 used EO and ML to track how rapidly services return to urban slums post disaster, highlighting which population remain
350 exposed and underserved (Ghaffarian & Emtehani, 2021). Similarly, UNET-based CNNs are used to identify deprivation
351 pockets from satellite images and track during their recovery process (J. Wang et al., 2019), or to derive proxy indicators for
352 poverty from satellite night lights (Jean et al., 2016), in combination with transfer learning to overcome scarcity of labelled
353 data (S. J. Pan & Yang, 2010). At longer timescales, techniques like K-Nearest Neighbour (KNN), SVM, ANN and RF are
354 used to classify urban and rural land cover, detect land use changes or informal settlements (Adam et al., 2014; Yuh et al.,
355 2023; Zerrouki et al., 2019).

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

358 3.1.3 Textual data

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

377

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

Section	Methods	Gaps	Opportunities
3.1.1 Climate datasets	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
3.1.2 Earth observations (EO)	SVM, RF, LSTM for soil moisture; CNNs/autoencoders for land cover, impacts, disaster recovery; transfer learning for data-scarce regions; ML	Bias toward data-rich regions; gaps/clouds limit detection; false positives;	Robust models for missing/noisy data; near-real-time EO pipelines; integrate EO with socio-economic data; transfer learning for vulnerable regions

for water quality (RF, ANN, weak multi-hazard
XGBoost) integration

3.1.3 Textual data NLP + ML (Naïve Bayes, RF, SVM, Few labelled datasets; Multilingual/transfer learning; CNN, BERT, LSTM); multimodal language/cultural bias; improved geolocation extraction; (text + images); rule-based for small imprecise spatial info; integrate with EO/sensor data; datasets noisy social media inputs robust methods for noisy/misinformation-prone data

379

380

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

385 **3.2 Multi-hazard**

386 **3.2.1 Identify, classify and cluster**

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

391 The identification of impacts from satellite images to discover hazard footprints, such as for landslides, earthquakes, floods
392 was discussed in the previous section because it is mainly an image processing task, where the goal is to identify differences
393 between two images. This section focuses on the identification of extreme events from climate datasets, which require specific
394 considerations on the typology of hazards and risk considered and is subject to different definitions and multiple interpretations.
395 The most common approach to identify multiple hazards from climate datasets is to use thresholds to identify univariate
396 extreme events and then combine them at a later stage into a multi-hazard database. In order to identify the thresholds, two
397 methods are applied: empirical thresholds (e.g., defining a max temperature over which an event is considered extreme) or
398 statistical thresholds (e.g., calculating a pixel-wise and/or day-wise percentile to identify events that exceeds a threshold that
399 can vary spatially and temporally). Empirical thresholds are usually fine-tuned to link extreme events to impacts on specific
400 sectors or local applications, and many applications focus on temperature extremes and health (Ray et al., 2021; X. Sun et al.,
401 2014). Statistical thresholds are preferred when analysing global trends and merging multi-hazard extremes because they allow
402 a more consistent and probabilistic robust comparison between different hazards. Percentiles can be easily adapted to model
403 spatial and temporal variations in data and are ideal for global application that cover multiple landscapes where a unique

404 empirical threshold cannot be univocally determined. For example, in Ionita et al. (2021), specific percentiles are used to
405 identify heatwaves and drought from temperature and SPI indicators respectively, before applying Empirical Orthogonal
406 Functions to investigate their drivers and their centre of actions over Europe; Similarly, Sutanto et al. (2020) is using
407 percentiles to identify heatwaves, droughts and wildfires from temperature, soil moisture and Fire Weather Index (FWI),
408 analysing spatial overlaps of the daily binary hazard maps to identify simultaneously occurrences of dry hazards and then
409 investigating cascading events by looking at different combinations of hazard sequences. Claassen et al. (2023), proposes a
410 methodology to identify multi-hazard events combining static footprints derived from the processing of satellite images (e.g.
411 for landslides, floods, tsunamis) with dynamic footprints (based on statistical percentiles) of climate hazards (e.g., heatwaves,
412 droughts, extreme precipitation, extreme wind, etc.), proposing a methodology to identify consecutive events using a specific
413 time lag and analysing the global distribution of the various multi-hazard events.

414 Return periods are another statistical technique used to identify extreme events, studying the likelihood of an event of a certain
415 magnitude occurring in a chosen timeframe (Liao et al., 2021). Return periods are most often applied in hydrology, when
416 dealing with flooding and storm surge events (G. Liu et al., 2020, 2023; Mattei et al., 2021; Zanini et al., 2020). These
417 applications fit a probability distribution (typically a Generalised Extreme Value Distribution, calculated over the number
418 exceeding of a threshold or over maxima) which allow for an estimation of the uncertainty of the threshold. Percentile
419 thresholds, returns periods and Generalised Extreme Value (GEV) distributions are also used conjunctly, such as in Orth et al.
420 (2022), where different hydrological hazards (floods, frost, heat waves, droughts, and storms) and their contrasting impacts
421 are analysed against multiple sectoral assessment endpoints (Gross Primary Productivity for vegetation, crop yields, human
422 mortality, damages to properties and public attention).

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

427 Other approaches focus on identifying and classifying extreme events from climate reanalyses using DL, especially in case of
428 cyclones or other hazards that are characterised by the interaction of multiple atmospheric drivers. Y. Liu et al. (2016) was one
429 of the first to apply CNN based on AlexNet to detect and classify tropical cyclones, atmospheric rivers and weather fronts
430 from climate datasets, such as ERA-5, CAM5.1. One of the main challenges in this domain is the scarcity of labelled data for
431 training supervised ML models. This is discussed by Racah et al. (2016), who expanded the previous approach, developing a
432 semi-supervised CNN model to overcome the lack of labelled data and created an extreme weather dataset as benchmark. In
433 general, the skewness of datasets is another common challenge for identifying climate anomalies with supervised approaches:
434 often data on which the ML models are trained on present very few samples of conditions leading to impacts (Dal Barco et al.,
435 2024).

436 Other studies focus on the identification of the spatio-temporal footprints of the climate hazards, in particular with algorithms
437 such as Density Based Spatial Clustering Applications with Noise (DBSCAN, Ester et al., 1996), grouping single point

438 anomalies into clusters in time and space. These approaches are applied in single hazards, such as droughts (Cammalleri &
439 Toreti, 2023), heatwaves (J. Wang & Yan, 2021) or earthquakes (Di Martino et al., 2018a). With regard to multi-hazards
440 applications, DBSCAN is used by Tilloy et al. (2022) to cluster compound precipitation and wind compound extreme events
441 in Great Britain and by (H. Yu et al., 2022) to investigate droughts, heatwaves, cold-waves, extreme wind and extreme
442 precipitation in Eurasian Drylands, studying how the coordinates of the centroid of the clusters are shifting hot and dry events
443 to northern latitudes due to climate change.

444 **3.2.2 Hazard forecasting and prediction**

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

453 Applications that focus on predicting or forecasting hazards are still mainly focussed on single hazard approaches. However,
454 some single hazard approaches were included in this review because their multi-variate approach includes the combination of
455 different static (as land use, topography, socio-economic data) and dynamic (e.g., atmospheric and marine data) parameters
456 and implicitly deal with multi-hazard interactions (e.g., a wildfire may be more probable when dry and hot conditions are
457 present, a drought can be influenced by temperature and soil moisture, etc.). For example, Haggag et al. (2021) propose an
458 ANN prediction model in a multi-hazard perspective, but then test it on past disaster records to predict floods in Ontario using
459 indices for climate extremes inputs. Monte Carlo dropout techniques have been employed to quantify epistemic uncertainty,
460 for example in surge forecasts (Macdonald et al., 2025) and flood modelling (M. Nguyen et al., 2024).

461 One of the main algorithms applied to forecast hazards is LSTM: Kratzert, Klotz, Brandstetter, et al. (2019) apply adapted
462 LSTM to disentangle static and dynamic inputs and analyse both high and low extremes in river flows, considering climate
463 susceptibility and integrating static and dynamic inputs. Tiggeloven et al. (2021) propose a LSTM/CNN architecture to predict
464 global storm surge residuals based on atmospheric conditions, investigating how the model's performance varied based on
465 changes of the spatial area input into the convolutional model. With regard to vegetation, long-range temporal dependencies
466 from several climate variables are investigated with a LSTM model (Kraft et al., 2019). Many applications focus on forecasting
467 of air quality hazards, especially in urban areas: compared to other types of environmental impacts, such as water quality, the
468 network of air quality monitoring stations offers hourly data at a high spatial resolution, enabling the training of AI models to
469 dynamically forecast at short lead times. Applications include the short-term prediction of ozone levels in Kuwait (Freeman et

470 al., 2018), the development of a daily air quality index in Beijing and Guilin (Q. Wu & Lin, 2019), or the prediction of
471 concentration of micro particular matter in the air of Seoul (Chang-Hoi et al., 2021).

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

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

491 **3.2.2 Modelling hazard interaction**

492 Recent work has applied interpretable ML frameworks to hazard modelling, aiming not only at prediction but also at identifying
493 key drivers. For instance, S. Jiang, Bevacqua, et al. (2022) and S. Jiang, Zheng, et al. (2022) used LSTMs to study river
494 flooding in Europe, combining feature attribution methods such as Expected Gradients (Erion et al., 2021) and Additive
495 Decomposition (Du et al., 2019) to disentangle the roles of snowmelt and precipitation. By running models across decades,
496 they revealed shifts in dominant flood drivers, with precipitation becoming increasingly important. Other studies have applied
497 gradient-based methods (A. Y. Sun et al., 2021), CNN heatmaps (Patil et al., 2023), attention mechanisms (Castangia et al.,
498 2023), and sensitivity analysis (Bentivoglio et al., 2023; Bonino et al., 2024; Kratzert, Klotz, Shalev, et al., 2019). These
499 advances improve interpretability, yet ML approaches remain limited by high data demands, sensitivity to training biases, and
500 the difficulty of generalising beyond observed conditions (Bentivoglio et al., 2023). Their strength lies in prediction and
501 uncovering nonlinear relationships, but the black-box nature of many models complicates causal modelling (Freeman et al.,
502 2018).

503 While most ML studies focus on univariate hazards, compound events require methods that capture joint extremes. Copulas
504 offer a flexible statistical framework to model dependence structures between variables, such as the co-occurrence of high
505 river discharge, intense rainfall, and coastal surges (Hao & Singh, 2016; Nelsen, 2006). By decoupling marginal distributions
506 from their dependence structure, copulas can assess joint probabilities of rare events with more precision than traditional
507 multivariate models (Tilloy et al., 2019). Applications include pair copulas for compound flooding in Italy (Bevacqua et al.,
508 2017a), Joe copulas for concurrent river–coastal extremes (Sadegh et al., 2017), and copula-based Bayesian networks for
509 flood–drought interactions (Couasnon et al., 2018). However, several challenges remain: selecting appropriate copula families
510 is non-trivial (since different families imply different tail dependencies, yet many common families assume simplistic
511 dependency or exchangeability) (Oh & Patton, 2015); capturing joint tail dependence becomes increasingly difficult in high
512 dimensions (vines, mixtures, or hierarchical copulas may help but bring computational and inference burdens) (Simpson et al.,
513 2020); physical drivers (e.g. precipitation skew, changing climate forcings, watershed characteristics) are often only indirectly
514 represented through marginal or covariate models (Hochrainer-Stigler et al., 2019b). Therefore, while copulas are powerful
515 for probabilistic risk quantification, they are less suited to dynamic forecasting or process-based understanding without
516 additional model structure or ensembles (Tootoonchi et al., 2022).

517 Comparison and complementarities.

518 ML and copula methods approach hazard interactions from distinct perspectives. ML excels at prediction and feature
519 discovery but struggles with transparency and extrapolation, while copulas provide interpretable dependence structures and
520 joint probability estimates but scale poorly with dimensionality and lack causal interpretability. ML can identify critical
521 hazard predictors and generate inputs, while copulas rigorously quantify their joint occurrence. Yet, few studies combine
522 these strengths; most rely on either predictive ML or probabilistic copulas in isolation. For example, an LSTM may forecast
523 river discharge under given precipitation and snowmelt conditions, while a copula model can then quantify the probability
524 that extreme discharge co-occurs with extreme rainfall or sea-level rise. Together, ML and copulas can provide a more
525 complete picture: ML enables forecasting and driver attribution, while copulas ensure rigorous treatment of dependence
526 structures and joint extremes (Sadegh et al., 2017; Tilloy et al., 2019). Combining both approaches offers a promising
527 pathway for advancing compound risk assessments. Some approaches, such as, T. Jiang et al., (2023) used a hybrid ML-
528 copula method to estimate the probability of consecutive drought events (in particular from meteorological to ecological
529 droughts), combining several ML classifiers (KNN, RF, SVM, ...) to estimate the propagation probability of meteorological
530 drought given its characteristics, and C-vine copulas to model conditional probability model of the paired meteorological
531 and ecological drought events. Closing this gap, for instance, by integrating ML-derived drivers into copula frameworks, or
532 benchmarking ML-learned dependencies against copula-based models, represents a promising but underexplored direction
533 for compound risk assessment.

534 **Susceptibility mapping**

535 Susceptibility in the context of natural hazards refers to the predisposition of an area to experience a specific hazard and
536 considers different factors (usually categorised into hazard or vulnerability in risk assessment), such as topography, geology,

537 hydrology, land use and vegetation and highlights “territorial characteristics”, disregarding the more dynamic and time-
538 dependent component of risks (Wubalem, 2022). The methodology for creating multi-hazard susceptibility maps using ML
539 usually consists in three steps: first, for each hazard, the susceptibility factors are identified; then, supervised ML techniques
540 are employed to create single hazards susceptibility maps, considering the different conditioning factors as predictors and the
541 areas impacted by the analysed hazards in the past as assessment endpoints; finally, the single hazard maps are combined to
542 produce the final multi-hazard susceptibility map. Eventually, feature importance techniques are applied as a fourth step to
543 extract the most susceptible factors for each hazard or multi-hazard combination.

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

555 The most common approach for integrating susceptibility parameters into multi-risk assessment is by producing multi-hazard
556 susceptibility mapping, where susceptibility to multiple hazard (including factors for hazard, such as yearly precipitation, but
557 also vulnerability parameters, such as slope) can provide a valuable point of reference for decision makers in sustainable land-
558 use planning or infrastructure development. A number of studies are focusing on mountainous regions, using a range of ML
559 models, including Logistic Regression, ANN, DT, SVM, RF, Boosted Regression Trees (BRT), or Generalised Linear Models
560 (GLM) (Javidan et al., 2021; Karakas et al., 2023; Kariminejad et al., 2022; H. D. Nguyen et al., 2023; Pourghasemi et al.,
561 2019, 2020; Pouyan et al., 2021; Yousefi et al., 2020) The multi-hazard combination usually covers floods, landslides,
562 avalanches and forest fires, which have clear footprints that can be used to train single hazard susceptibility, and integrate other
563 risks which can be assessed through already available risk maps, such as seismic risk maps at a later stage (Bordbar et al.,
564 2022). Different hazards are included by Piao et al. (2022), who test BRT, RF and Classification And Regression Trees (CART)
565 in the Gangwon-do region in South Korea (an area rich in forests and ecological diversity) to establish a multi-hazard
566 probability map for forest fires and droughts; in this study the multi-hazard interactions are investigated, considering drought
567 as an amplifying hazard for forest fires. Mandal et al. (2022) focus instead on coastal areas, in particular in West Bengal
568 (India), considering tropical cyclones, embankment breaching, storm and tidal surge, inundations, extreme rainfall, salinization
569 and erosion; RF and ANN are applied to produce multi-hazard susceptibility maps. Ullah et al. (2022) test a CNN to produce
570 flash floods, landslides and debris flow multi-hazard susceptibility mapping, comparing its performances with Logistic

571 Regression and KNN methods in terms of accuracy, coefficient of determination, Mean Absolute Error and Root Mean Squared
572 Error. The input data consist of field surveys, topography, hydrology, and environmental data, while the locations of historical
573 flash flood, debris flow and landslide locations are extracted from Google Earth images. The feature importance scores are
574 derived using a Random Forest model and are used to enhance the analysis of the multi-hazard maps. It is interesting to note
575 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
576 the 14 layers of predicting variables, producing an independent output pixel by pixel.

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

593

Section	Methods	Gaps	Opportunities
3.2.1 Identify, classify & cluster	Thresholding (empirical percentiles) to build multi-hazard catalogs; return periods & GEV; hazards are merged post-hoc; EOFs; CNNs (semi-/supervised) for label extreme-weather object detection in reanalyses; DBSCAN for temporal footprints and clusters.	& Under-detection of joint (non-univariate) extremes when hazards are merged post-hoc; label scarcity & class imbalance for supervised DL; spatio-skewed datasets; sensitivity to spatial/temporal non-stationarity.	Unified pipelines that detect compound signatures directly (multivariate thresholds + clustering); semi-/self-supervised DL to mitigate label scarcity; robust cluster tracking of compound hotspots under change.

Section	Methods	Gaps	Opportunities
3.2.2 Hazard forecasting & prediction	LSTM/CNN for hydrology, storm surge, drought/heat; Transformers for generalisation floods; GNN/GRU for river-network dynamics; classical ML (RF/SVM/XGB) for local extremes when data are limited.	High data demands; limited attention to expose performance drivers; varies with spatial context and input windowing.	Physics-informed/graph-aware DL beyond for better extrapolation; limited attribution to expose global-to-local transfer learning; benchmarking vs. process models for trust.
	3.2.2 Modelling hazard interactions	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.	joint Copula family selection & tail-dependence in high dimensions; ML black-box limits causal insight; difficulty linking physical drivers to dependence structures.
Susceptibility mapping (multi-hazard)	Supervised ML (LR/GLM, RF, SVM, BRT, CART, ANN, CNN) to build single-hazard susceptibility maps; combine into multi-hazard maps; feature importance to rank drivers.	Often “multi-layer single- interaction leakage; dynamic susceptibility that (weak interaction terms or graph-combine into multi-hazard maps; ignore evolving usual exposure/vulnerability.	Hybrid ML–copula stacks (ML to predict/characterise events, copulas to quantify joint probabilities); benchmarking ML-learned dependencies against copula baselines; conditional vines for cascades. Spatio-temporal CV (block) to curb hazard” (weak interaction terms or graph-combine into multi-hazard maps; ignore evolving usual exposure/vulnerability. (fire/landslide/flood/quake).

594

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

599 3.3 Multi-risk

600 3.3.1 Modelling risk combining susceptibility, exposure and vulnerability

601 Many studies are found to focus on modelling risk by combining hazard maps produced via susceptibility mapping with ML
602 and vulnerability and exposure layers. Single hazards such as wildfires, floods and landslides are the often considered, and
603 buildings, population and infrastructures are the moKotaridis & Lazaridou (2022)Kotaridis & Lazaridou (2022) consider
604 flooding risk in Tuscany and applied a 2D CNN to produce an urban flooding susceptibility map. Differently from Ullah et al.

605 (2022) the CNN applied here makes use of the spatial context of each pixel, considering a 5x5 patch centred on a specific pixel
606 (an area of 50 x 50 m² since the pixel size is 10m), creating 20000 different samples from the initial map, each one with a
607 5x5x9 size, where the last number corresponds to the different predictors of the susceptibility mapping that are considered as
608 channels in the CNN architecture. Thus, not only the selection of the initial samples, but also the selection of the size of the
609 patch is a key hyperparameter to be considered: in this case, a cross validation is used to choose the best patch size. The
610 vulnerability maps are created dividing the land use into 5 classes, which are then multiplied with the hazard layer to calculate
611 the final risk map. Convolutional Neural Networks (CNNs) offer significant advantages over traditional algorithms in spatial
612 analysis due to their ability to process areas as 2D maps. This enables the model to leverage Max Pooling layers to capture and
613 simplify the spatial context of events. Unlike models that focus on individual point characteristics, CNNs can better model and
614 integrate the broader spatial relationships. For example, Zhao et al. (2020) test CNN for urban flood susceptibility too but
615 instead of producing separate maps for hazard and vulnerability, anthropogenic factors were used as predictors for the
616 susceptibility map. The study compares the performances of different ML models: a simple (with 1 convolutional layer) CNN
617 architecture, LeNet5 (Lecun et al., 1998), a slightly deeper CNN (with 2 convolutional layers), SVM and RF models. Different
618 input strategies are tested: a point based strategy that only considers input at a given site; a partial spatial strategy that considers
619 the surrounding pixels, flattening the 2D image to a 1D vector, thus losing partially the spatial context, but allowing the
620 neighbouring pixels to be fed to SVM and RF models as additional predictors; a patch strategy, similar to the one described
621 before for the CNN models, which granted the best performances. This study also discusses the use of Deep CNNs, which is
622 discouraged since the typical sample size and model is too small to tune the high number of parameters required by Deep
623 CNNs.

624 Rusk et al. (2022) analyse population risk in the Hindu-Kush and Himalaya region, producing a multi-hazard map for
625 landslides, floods and wildfire with the MaxEnt (Maximum Entropy) algorithm, which is then overlaid with population
626 distribution. The paper also produces a matrix of multi-hazard interactions, dividing them into three types: when hazards are
627 directly linked (e.g., flooding causing a landslide), when their linkage is mediated by an environmental condition (e.g., land
628 use changes caused by wildfires increasing the probability of a landslide), or when their linkage is mediated by infrastructure
629 or urban processes (e.g., a landslide damaging a dam, triggering a flood). However, a quantitative assessment of these multi-
630 hazard interactions is not provided and only the records of these events are used to complement the multi-risk map. A similar
631 approach is used in Austria, (Fuchs et al., 2015) considering river flooding, torrential flooding and snow avalanches as hazards
632 and buildings as assets. In this case, buildings vulnerability is investigated, categorising them based on location, size, building
633 category and the construction period. The different urbanisation patterns, very high in mountainous terrain of the Hindu-Kush-
634 Himalaya (HKH) and quite low for Austria, influenced the final risk score assessment, with the HKH showing more areas at
635 higher risk (Rusk et al., 2022). Sammonds et al. (2023) analyse hurricane, flood and landslide risk on population, producing
636 single hazard susceptibility maps with statistical methods and discussing the vulnerability of population, considering gender,
637 age, and population density; the final multi-hazard hurricane risk is obtained as a product of the single hazard susceptibility
638 scores, overlaid with weights determined with Analytic Hierarchy Process (AHP), and the vulnerability score. Other

639 applications focus on Vietnam, where RF is applied to derive risk for buildings and population against multi-hazard
640 susceptibility maps for floods and wildfires (Luu et al., 2024). RF is applied to calculate single and multi-hazard susceptibility
641 maps for China for flooding, landslides, and debris flows and the railway infrastructure was overlaid to analyse present and
642 future risk, considering newly planned railway links (K. Liu et al., 2018). In general, a number of studies are found to apply
643 non-ML approaches, including multi-criteria decision-making and expert judgements methods to calculate susceptibility and
644 vulnerability layers, such as in Arvin et al. (2023), that focuses on infrastructure resilience in Iran, considering flooding,
645 landslides and earthquake as hazards, and 25 indicators at the county level and Khatakho et al. (2021), focussing on population
646 exposed to flooding, earthquakes and wildfires near Kathmandu (Nepal).
647 Compared to the publications focussing only on the multi-hazard aspect, the applications that also consider exposure and
648 vulnerability do not test multiple ML algorithms, often rely on expert-based judgments or simple frequency analysis.
649 Moreover, while these applications focus on multiple hazards, the analysis of vulnerability factors is often overlooked: in most
650 cases, only exposure layers are used to produce risk maps. Even when vulnerability is explicitly considered, it is calculated
651 only for single hazards and as a static parameter. Recent publications, such as de Ruiter & van Loon, (2022) highlight the
652 importance of considering dynamic vulnerability factors, especially in multi-hazard and multi-risk contexts, where
653 vulnerability can vary because of the changes cause on the system caused by the occurrence of the hazards of extreme events,
654 or because of specific adaptation and responses. Even though the use of EO can help to inform the models of changes in the
655 system (such as land cover changes due to wildfires and landslides, or new urbanisation patterns after reconstructions), these
656 indicators are not yet integrated in multi-risk mappings.

657 **3.3.2 Modelling risk predicting impacts**

658 Another popular approach to model multi-risk with ML is to use impacts as a proxy and training supervised ML models on
659 past impacts. Examples of possible impacts are excess mortality for health risks, economic damages and monetary losses,
660 number of emergency signals or specific environmental indicators, such as ecological status. With regard to ML methodology,
661 approaches are similar to the ones applied for predicting hazard values, considering multiple predictors covering climate,
662 topography, land use and anthropogenic factors, but the final assessment endpoint, impact data, is very different from typically
663 hazard data, having a coarser resolution in time and space and resulting in much smaller datasets. Thus, most of the studies
664 focus on simpler and more interpretable ML methods like ensemble methods, rather than the DL approaches which are popular
665 for hazard prediction. Moreover, more attention is dedicated to the interpretation of the factors and the explainability of
666 methods (Ghaffarian et al., 2023), with most applications presenting some form of feature importance analysis, either as a
667 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
668 based on the sectors and type of impact considered, considering health, food security and crops, environmental quality &
669 biodiversity, physical damages and economic losses.

670 **Health**

671 Studies focussing on environmental-health risks often analyse the combination of heat and air quality stressors and use excess
672 mortality as predicant variable. These applications aim at disentangling complex temporal patterns, consisting of a long-term
673 trend, driven by multiple (and often unknown) factors, and short-term peaks, mainly driven by summer heatwaves; moreover,
674 time-lags needs to be considered. Thus, statistical methods, such as Distributed Lag non-linear models have been widely
675 applied (Gasparrini, 2014) to model exposure lag-response of mortality to environmental stressors. More recently, RF has been
676 applied, analysing the role of humidity in urban mortality during heatwaves at the global scale (Guo et al., 2024) or predicting
677 heat-stroke occurrence in China (Y. Wang et al., 2019), while SVM is applied for analysing previous diseases, population
678 density and urbanisation (X. Wang et al., 2021). One of the most interesting papers, Boudreault et al., (2023) test 9 different
679 ML, DL and statistical methods (such as Generalised Additive Models – GAMs) in the Metropolitan City of Montreal,
680 considering weekly all-cause mortality as predictand and air temperature, humidity, wind, Particle Matter (PM) 2.5, Ozone
681 (O3), Nitrogen Dioxide (NO2), Sulphur Dioxide (SO2), Carbon Monoxide (CO) as predictors. Among the methods tested,
682 Tree based methods (RF, XGBoost) usually perform better overall, while statistical methods (and GAM in particular) are more
683 accurate in predicting the mortality peaks; Deep Learning approaches, such as MLP and LSTM have instead the worst
684 performances. This is partially explained by the limited size of the dataset and the inclusion of non-climate causes in the
685 predictand, likely to cause overfitting in the DL models. Another study also focussing on Canada proposes an AI-based
686 framework to extrapolate vulnerability from health-heat relationship: Côté et al. (2024) test this approach considering two
687 steps: first, a model to predict daily mortality from mean temperature for 3 days, age, income and period of the year as
688 predictors and then a second model predicting annual mortality over aggregated areas with specific socio-economic and
689 environmental (air quality, vegetation, ...) characteristics. The model tested are AutoGluon (an automatic ML framework
690 allowing to train and test ML models without expert knowledge²), GP and Deep Gaussian Process (Deep GP). The results
691 shows that GP are able to model better the daily mortality trends, especially during extreme temperature, while AutoGluon is
692 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
693 better handle noise and small data samples (J. Wang, 2023), and their limit is their computational costs (M. Jiang et al., 2022);
694 on the other hand, the more complex Deep GP handed the worst outcomes, highlighting the challenges in tuning more complex
695 Deep GPs (Tazi et al., 2023). Other studies focus on predicting the influence of water quality parameters, such as turbidity, on
696 the risk of cholera disease outbreaks in Indian Coastal municipalities using a RF predictor (Campbell et al., 2020).

697 **Food security and crops**

698 The second group of reviewed studies focus on the nexus between food production, food security and migrations. For instance,
699 Busker et al., (2024) apply XGBoost to predict food insecurity in the Horn of Africa. This model, takes as input several factors,
700 integrating climatological variables, biological hazards, food and fuel prices, macroeconomic indicators, conflicts and
701 humanitarian assistance, aggregating data on the administrative units for which the assessment endpoint variable (food
702 security) was available. The model is tested for its ability to predict the onset of crises up to 12 months in advance,

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

703 demonstrating superior performance in agro-pastoral areas compared to croplands. SHAP values are employed to analyse the
704 key risk drivers. The findings of this study highlight its potential application in operational early warning systems, such as
705 FEWS NET.

706 Tárraga et al. (2024) also investigate the dynamic relationships between droughts, conflicts and food security, focussing on
707 their impact on population displacement. In this case, ML is not used to predict displacement, but causal discovery methods
708 are tested to retrieve its drivers within Somalia from 2016 to 2023. In particular, Granger Causality and Peter and Clark
709 Momentary Conditional Independence (PCMCI) are tested to generate plausible causal graphs of drought displacement,
710 showing limitations for Granger causality due to the high dimensionality and autocorrelation of the time series, while the
711 PCMCI method is able to disentangle the intertwined vulnerabilities and different leading times connecting drought impacts,
712 water and food security systems along with episodes of violent conflict. The reliability of the causal model depends on the
713 quality of training data and several assumptions are required, such as causal sufficiency (i.e., all possible driving variables of
714 drought displacement need to be considered in the analysis), no contemporaneous causal effects and causal stationarity. Note
715 that although causal sufficiency is valid, the associations between the other variables (e.g., SPEI, market prices, fatalities) may
716 be influenced by confounding factors rather than direct causality.

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

722 **Environmental quality and biodiversity**

723 Numerous studies focus directly on environmental impacts, such as the influence of land use and urban planning on water
724 quality. For example, R. Wang et al., (2021) apply RF with SHAP values to model stream water quality and specific pollutants
725 based on four different urban planning scenarios in Texas. The model allows to correlate urban sprawl to water quality
726 degradation and was used to forecast environmental impacts under different urban development pattern scenarios. In Li et al.
727 (2022) the ensemble model XGBoost is used to predict water quality in beach locations in lake Eyre, paired with SHAP for
728 increased explainability. Other studies focus on ecosystem and biodiversity: for example, RF and Logistic regressions are
729 tested to predict forest loss in Borneo from topographical and anthropogenic variables (distance to urban areas, population,
730 etc.), highlighting the advantages of RF for modelling multi-scale spatial relationships between risk drivers (Cushman et al.,
731 2017). Similarly, in Islam et al. (2021), the spatio-temporal dynamics of wetlands in Bangladesh and their negative effects on
732 biodiversity are analysed using Decision trees, RF and SVM. RF and SVM are the best performing algorithms and in general,
733 the papers highlighted the role of remote sensing, for mapping wetlands variations in time. Species distributions is also
734 investigated, with many applications discussing the different spatial approaches for river network modelling. For example,
735 Schmidt et al. (2020) test the MaxEnt algorithm with two representations of rivers, highlighting how a high-resolution model
736 based on river reaches is better at discovering individual local habitat features, whereas lower resolution sub-catchment scale

737 models better account for more general drivers in fish distribution. Teichert et al. (2016) apply a RF model to identify the
738 dominant stressors for fish presence in estuaries, investigating the interactions among stressors evaluating ecological benefits
739 expected from reducing pressure. In particular, an RF model is trained to predict ecological status in 90 locations using 17
740 predictors describing the different stressors (urbanisation, flow changes, water pollution, oxygen depletion, etc.). Then,
741 simulations are run to analyse the benefit of restorations comparing the difference between the baseline model and a model
742 where the intensity of stressors was varied. The difference between single and multiple restoration action is analysed,
743 highlighting the importance of combined restoration schemes and the non-linearity of their effects.

744 **Economic losses and physical damages**

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

767

Section	Methods	Gaps	Opportunities
3.3.1 Risk via susceptibility + exposure + vulnerability	Overlay of single-hazard susceptibility (RF, SVM, ANN, BRT, CART, MaxEnt, Often “multi-layer single-hazard” CNN with patch context) (weak/implicit interaction updates using EO and time-sequenced with exposure (buildings, modelling); vulnerability treated as hazards; spatio-temporal block cross-population, infrastructure) static; label imbalance and sampling validation; interaction-aware fusion and simple vulnerability bias; spatial/temporal autocorrelation (graphs, learned weights); extend to layers; AHP/MCDM leakage; limited hazard breadth wind, hail, heat, surge; probabilistic weighting; feature beyond fire/landslide/flood/quake. risk surfaces with uncertainty bands.		
			(1) Data & catalogs: build geocoded, event-level, cross-sector impact Ensemble and hybrid ML Impact labels are sparse, coarse, datasets and standardized labels approaches (RF, XGBoost, biased, and confounded; scale (health, yields, biodiversity, losses). (2) SVM, DL, copulas, causal mismatches and aggregation blur Causal & lag-aware stacks: combine ML) applied to health, food, signals; extremes and tails poorly DLNM / explicit-lag models with ML environmental, and represented; DL tends to overfit and and causal discovery to capture delayed economic impacts; transfer poorly across and causal pathways. (3) Multi-source explainable AI (SHAP) and cities/regions/climates; uncertainty fusion & transfer: integrate EO, in-probabilistic modeling for quantification and causal attribution situ, socio-economic and market data; driver attribution. often limited. use domain-adaptation/transfer learning for cross-region generalization.
3.3.2 Predicting Health			

768

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

773 3.4 Future

774 3.4.1 Predicting future hazards

775 Several studies focus on data-driven applications to predict long-term future multi-hazard and multi-risk scenarios.
776 Zscheischler et al. (2018) discuss the importance of compound events for future risk assessment and presents several
777 approaches and discusses the main challenges related to the use of future climate projections and weather simulations to analyse
778 future compound events. The role of bias correction and its connection to multi-hazard events and impact models is analysed:
779 future projections are often bias corrected to align the distribution of the modelled variables to the distribution of the observed
780 ones, in the reference timeframe. However, some issues can arise: the simplest approaches focus on adjusting the averages of
781 the variables and do not correct the tails of the distributions, thus modifying the behaviour of extreme events. Methods such
782 as quantile mapping, are needed to align the historical and future datasets before the application of any statistical or ML
783 methods. Sensitivity analysis can be performed to analyse how the model reacts to changes in inputs and the robustness of
784 future scenarios (Kim et al., 2023). Moreover, bias corrections are often univariate, and do not consider the effects on joint tail
785 distributions and consequently impact models based on these inputs are affected; multivariate bias correction models are then
786 encouraged (Sippel et al., 2016).

787 When dealing with the future of multi-hazard events, statistical methods are most often applied to identify hotspots and test
788 trends, similarly to the applications focussing on historical data. For example, Ridder et al. (2022) consider hot, dry, wet and
789 windy compound events by selecting cells which exceed the 99th percentile for wind and precipitation in the same day. Then
790 results are presented in changes in return period and annual event density, where the latter is a measure for how often an event
791 affects a region and how much of the region is affected, calculated from the number of grid cells affected. Similarly, Zhu et al.
792 (2023) investigate future compound wind and precipitation extreme at the global scale, analysing 14 CMIP6 models,
793 identifying compound events through the 95th percentile and discussing the sources of uncertainties via the HS09 statistical
794 method (Hawkins & Sutton, 2009) splitting between internal variability, model uncertainty and scenario uncertainty. Further
795 analyses discuss the spatial and temporal performances of future projections: Ridder et al., (2021) find good performances in
796 CMIP6 simulation for precipitation and wind compound extremes over North America, Europe and Asia, but poor
797 performances over Australia, probably linked to the limits in the modelling of tropical and extratropical cyclones and local
798 convection systems. Also, copulas are used to analyse spatial complementary patterns of compound events, such as in Ghanbari
799 et al. (2021), which analyse the joint return period of compound floods along the US coast, incorporating sea level rise and
800 peak river flows for future climate change risk scenarios with copulas. H. Wu et al., (2023, 2024), employ Vine copulas to
801 analyse hot & dry and pluvial & hot events in future scenarios, using the Single Model Initial Conditions Large Ensemble
802 (SMILE) approach.

803 Bevacqua et al., (2023) stress the importance of SMILE for a robust analysis of future compound climate events. In fact, a
804 SMILE consists of many simulations from a single climate model, each starting from slightly different initial states (differently
805 from classical model ensembles, like CMIP6, which consists of many different runs from different models). Each realization

806 differs solely due to internal climate variability and ensures a better quantification of future uncertainties, and at the same time
807 it provides a much larger dataset to analyse statistically compound events. Multiple SMILEs can then be combined to identify
808 model differences and distinguish between internal climate variability and structural model differences. Sometimes, especially
809 when dealing with unprecedented, High-Impact, Low-Probability events, climate projections or even SMILE or statistical
810 weather generation are not sufficient: in these cases, storyline approaches are often used as alternative to explore future multi-
811 risk patterns (Moezzi et al., 2017; Shepherd et al., 2018). These approaches fit well within common practices in disaster risk
812 management, which consider event-based scenarios for emergency preparedness, allowing for interaction with local
813 stakeholders to evaluate the effectiveness of selected measures (Sillmann et al., 2021) and to explore low-likelihood and high
814 impact plausibility events (Bevacqua et al., 2021).

815 **3.4.2 Modelling future impacts**

816 A common approach to estimate future risks involves using future climate projections as input data for ML models that have
817 been trained on historical data of past impacts, similar to applications that focus on assessing current risks by leveraging past
818 impacts. For example, the study of future cyclone impacts in New York and New Jersey, is feeding four General Circulation
819 models as input for a SVM / AdaBoost risk model (Ayyad et alPark & Lee (2020)rk & Lee (2020) test the performances of
820 three algorithms, K-NN, RF and SVM to analyse coastal risks in South Korea, considering rainfall, tides, topography and land
821 use, training the model on past floodings and then predicting future risks using monthly averages of rainfall and tidal values
822 from RCP 4.5 and 8.5 ensembles. Future risk scenarios are calculated aggregating the risk model outcomes for each decade
823 from 2030s to 2080s. In a successive publication, Park et al. (2023) apply a similar ML methodology to investigate adaptation
824 strategies for coastal flooding: in this case, the ML model is trained on historical data with two different adaptation strategies,
825 seawalls or green spaces, and then the future adaptation models are implemented, either maintaining current adaptation
826 infrastructures or increasing one specific strategy. To ensure comparability between the adaptation scenarios, infrastructure
827 construction costs are standardized, guaranteeing that the two distinct adaptation pathways incurred equal expenses.

828 In general, it is considered good practice to use ensemble projections and values calculated over multiple years, in order to
829 increase the robustness of the future scenarios; however, some risk analyses focus on just a few selected years: Lim & Kim
830 (2022) test RF for future rainfall induced landslides, also analysing different adaptation pathways and considering an increase
831 in forested or urban areas. Instead of using monthly or daily values for the ML model, yearly values are used in the model, for
832 specific years (2050, 2092), which are considered significative for representing future scenarios. This approach is valuable for
833 analysing specific extreme events that may be overlooked when averaging across multiple models or years, and it reduces
834 computational demands. However, it carries the risk of biasing the analysis, as the selection of specific years may result in
835 outcomes that are not fully representative of the broader range of future scenarios. Bayesian Networks were tested by Pham et
836 al., (2023) in a multi-model chain approach combining ocean hydrodynamics models, wind-wave models, and shoreline
837 extraction models to analyse sea water quality impacts and shoreline erosion under different RCP projections (4.5 and 8.5).
838 Bayesian Networks are applied due to their ability to integrate heterogeneous data sources, including quantitative and

839 qualitative inputs and several data fusion steps to harmonise different spatial coverage, temporal resolutions and data formats,
840 with a final risk assessment conducted at municipality level and yearly/ decadal scale.

841 With regard to the water-food nexus, ML is being progressively employed as an alternative to process or statistical methods
842 for future crop yield estimation, showing increased performances and higher computational efficiency: Leng & Hall (2020)
843 test a RF model for annual yield prediction in the US for a 2° C global warming scenario; while Khan et al. (2024) select
844 Gradient Boosting to model the relationships between daily climate variables, hazard indicators, such as Consecutive dry days
845 (CDD) and crop production with CMIP6 data. Tabari & Willems (2023) carry out a global risk assessment from hot and dry
846 events, employing Copulas and integrating data from Shared Socio-economic Pathways (SSP) scenarios, future land use
847 patterns population and governance. ML methods are used also to predict the risk of increased conflicts due to climate stressors:
848 a RF classifier is applied by Hoch et al., (2021) to predict water-related conflicts in Africa using different SSP future
849 projections, integrating socio-economic predictors (population, education, GDP, governance) and climate predictors
850 (precipitation, evaporation, flood volume, soil water). The model is trained on historical data up to 2015 and tested with
851 projections from 2016 to 2050. Future temperature-related mortality in different European regions is analysed by García-León
852 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
853 disparities between cold-related deaths and heat-related deaths and analysing the role of age, health infrastructure and climate
854 change with a Distributed Lag Non-Linear model. In particular, different scenarios are discussed: present climate and present
855 population, present climate with future population from EUROPOP 2019; future climate under different warming level with
856 future population exposure.

857 Future risk patterns are also calculated implementing future multi-hazard susceptibility maps: for example, Rahman et al.,
858 (2024) analyse future coastal multi-hazard risks in Bangladesh, implementing an LSTM algorithm, in combination with RF
859 feature selection and a Genetic Algorithm (GA) optimiser. In particular, GA is used to identify optimal or near-optimal
860 solutions, searching the space of LSTM parameters through a process of selection, crossover and mutation. The combination
861 of the LSTM's ability to capture sequential patterns and long-term dependencies and GA's efficiency in navigating complex
862 search spaces, is proved to achieve better convergence, avoid local minima, and optimise both the architecture and parameters
863 of the LSTM model (Zamani et al., 2022). Other future multi-hazard susceptibility approaches include Ya et al., (2023), who
864 analysed future risks in the Tibetan plateau considering climate and land use changes. Logistic Regression is used to produce
865 susceptibility maps, while future climate scenarios were taken from CMIP6 future projections. In order to create future land
866 use, this paper focus on PLUS, a RF-based model analysing the relationship between influencing factors and land use changes
867 (Liang et al., 2021). Another approach for future land use is applied by Saha et al., (2021), which focus on modelling cultural
868 heritage site future multi-hazard susceptibility in the Sikkim state in India, considering different climate scenarios from CMIP5
869 and land use from an empirical model (Dyna-CLUE) incorporating spatial logistic regression (W. Jiang et al., 2015). Bayesian
870 Additive Regression Trees and Bayesian Generalised Linear models are applied to produce multi-hazard susceptibility maps,
871 considering extreme rainfall, landslides and earthquakes. Another dynamical model, a Cellular Automata- Markov model

872 (Clarke et al., 1997) is used to predict future land use changes in Iran to investigate flood risks, testing RF, XGBoost and
 873 Gradient Boosting as algorithms for producing susceptibility maps (Janizadeh et al., 2021).
 874

Section	Methods	Gaps	Opportunities
3.4.1 Predicting future hazards	Bias correction for projections (incl. quantile mapping); detection via percentile thresholds (e.g., 95th–99th), return periods; sources and propagation; vine copulas for joint tails; SMILE large ensembles; storyline event-based scenarios for HILP analysis.	hotspot/trend Univariate bias correction can distort extremes/joint tails; regional skill varies; limited direct detection of compound signals; uncertainty treatment often partial.	Adopt multivariate bias correction; combine SMILEs to separate internal variability vs. structural model differences; scale up vine copulas for compound events; embed storylines for preparedness.
3.4.2 Modelling future impacts	Trained on historical impacts and applied to future ensembles; ensemble methods (RF, XGBoost, ...) for coastal and sparse adaptation scenarios; Bayesian Networks for multi-model chains (hydrodynamics–waves–shoreline); distributed-lag models for future health impacts; future susceptibility land use changes	Impact data often coarse, biased, and sparse; studies often rely on risk, conflict risks, crop yield and few years → low representativeness; causal discovery hinges on strong assumptions; biases due to scale mismatch in climate–exposure–impacts; future susceptibility integrating impact data.	Use multi-model, multi-year ensembles and probabilistic models to quantify and propagate uncertainty.; evaluate adaptation portfolios with standardized costs; integrate dynamic land use + socio-economic pathways (SSPs); uncertainty-aware learning, and open, geocoded impact datasets.

875
 876 This section contributes to the field of multi-hazard and multi-risk analysis by reviewing how ML and statistical methods are
 877 applied to predict future hazards and impacts, highlighting the importance of bias correction, ensemble and SMILE approaches,
 878 and storyline methods, as well as the integration of socio-economic and land use projections. It emphasizes how these
 879 approaches can improve the robustness of long-term risk scenarios, support adaptation planning, and guide strategies to address
 880 uncertainties in future multi-risk patterns.

881 4 Conclusion

882 This paper presents a comprehensive review of data-driven applications aimed at modelling and enhancing our understanding
 883 of climate-related multi-hazard and multi-risk events. Based on the selection of over 1,400 studies and an in-depth analysis of

884 136 key papers, the review addresses four research areas: (i) data processing and collection, (ii) hazard analysis, (iii) risk
885 analysis, and (iv) future risk scenarios, each divided in several sub-topics. Figure 3 summarises the main methods used in each
886 research question, illustrating the different approaches for each sub-topic. In particular, the figure highlights the strong
887 connections between Earth observations processing and ML techniques like CNN; on the other hand, RF, other ensemble
888 methods and GAM are mostly applied for risk impacts and future risk assessment, while LSTM, ANN and other DL approaches
889 are most common for hazard prediction, reflecting a growing trend toward leveraging sophisticated AI architectures for climate
890 and hazards applications, and a focus on simpler, more interpretable models for risk applications. Despite the current
891 prevalence of single-hazard applications in ML research, there is growing recognition of the importance of multi-risk strategies.
892 Notable advancements include copula-based compound event analyses and ML-driven multi-hazard susceptibility maps.
893 Future research should prioritize a more comprehensive understanding of multi-risk interactions – such as triggering,
894 cascading, or amplifying effects – by considering the interplay between hazard factors, vulnerability, and exposure dynamics,
895 which are often overlooked or treated independently in current studies. DL methods, with their capacity to capture complex,
896 non-linear interactions across spatio-temporal dimensions, offer promising avenues for progress, yet remain underexplored in
897 operational multi-risk contexts. However, these methods require high-resolution impact data, which remains a significant
898 challenge due to limited availability, inconsistency across regions, and issues of data quality and standardization. While EO
899 and textual data can aid in generating new multi-risk disaster catalogues, traditional sensor-based and human-curated disaster
900 catalogues remain essential for validation, representing a major bottleneck that constrains model validation, transferability,
901 and ultimately the uptake of these methods in practice. By addressing these methodological and data gaps, the field can move
902 toward more robust, interpretable, and actionable multi-risk assessments, ultimately strengthening the integration of machine
903 learning into climate services that support adaptation, resilience, and disaster risk reduction.

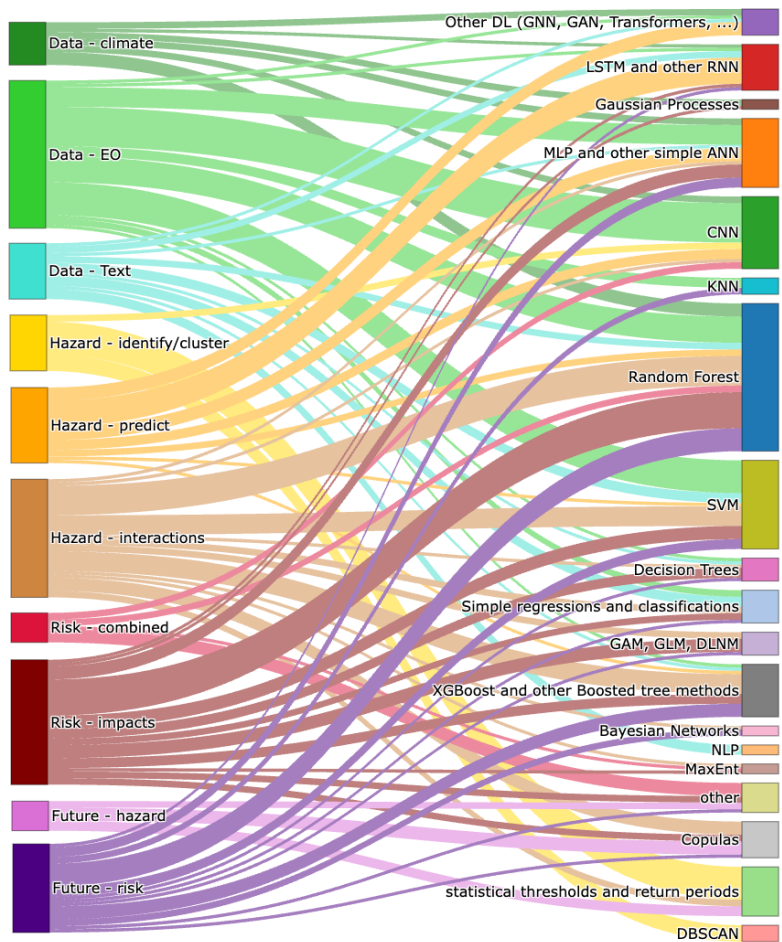


Figure 3: Main methods used for each research topic

904

905

906 Finally, this review highlights the importance of adopting a multidisciplinary approach that combines expertise in multivariate
 907 statistics, machine learning, big data, climate science, and risk assessment. Such collaboration is essential for leveraging new
 908 climate projections tailored to extreme events and their societal and ecological impacts. Advancements in AI and ML will
 909 further facilitate synthetic data generation, advanced pattern analysis, and AI-driven early warning systems. Stakeholder
 910 engagement – including policymakers, communities, and industries – is essential to ensure actionable and regionally tailored
 911 strategies for risk reduction and climate adaptation.

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913 **Appendix A: Abbreviations**914 **Table A2: Acronyms of methods (in alphabetical order)**

Acronym	Full Name
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
PCMRI	Peter and Clark Momentary Conditional Independence
RF	Random Forest
SHAP	Shapley Values
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting

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916 **Table A3: 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

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918 **Appendix B: Summary tables of the collected studies**

919 The literature review followed the PRISMA guidelines to ensure transparency and reproducibility in the identification,
920 screening, and selection of studies. The process is summarized in the PRISMA flow diagram and detailed as follows.
921 First, records were retrieved from major scientific databases (Scopus) and filtered by type, retaining only *articles, conference*
922 *papers, and book chapters* and language (English). Next, documents were filtered by subject area and keyword, selecting only
923 those classified under *Environmental Science* and *Earth and Planetary Science* as subjects and considering machine learning,
924 climate change, risk assessments (and their synonyms and variations) as keywords.
925 In the third step (title screening stage), studies not focusing on *natural hazards, multi-hazard, or risk assessment* were
926 excluded. During the abstract screening stage, each paper was evaluated for its relevance to the review's research questions,
927 focusing particularly on the use of machine learning (ML) techniques and their application to multi-hazard or multi-risk
928 contexts. Studies were retained if they explicitly applied ML, AI, or statistical learning methods to the modelling,

929 characterization, or assessment of natural hazards, or if they addressed interactions between multiple hazard types (e.g.,
 930 cascading or compound events) and their associated risks. Papers focusing solely on single hazards without methodological
 931 innovation or on unrelated environmental modelling were excluded. This step ensured that the final selection captured studies
 932 advancing methodological understanding of ML-driven hazard analysis, as well as those integrating multiple hazard processes
 933 or risk dimensions. Finally, the full-text review identified the most relevant and representative papers, ensuring balanced
 934 coverage across different hazard types and AI methodologies. The final selections were based on diversity in data sources,
 935 geographical coverage, hazard types and machine learning methods used. This process ensured that the resulting corpus reflects
 936 the breadth of current research at the intersection of AI, Earth observation, and multi-hazard risk assessment.
 937 The number of studies retained at each step is summarized below (numbers correspond to the four main research questions):
 938 Table B1: summary of the screening step results

Screening step	RQ1	RQ2	RQ3	RQ4
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

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940 **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),
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	NN (neural networks), multivariate statistics, regression, prediction, forecast, classification, anomaly detection, copulas,
Risk	How can data-driven applications integrate vulnerability and exposure in multi-risk analysis?	Multi-risk, climate-risk, multi-sector,	interpretability, explainability

		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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943 **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
(Ling et al., 2024a)	Diffusion model-based probabilistic downscaling for 180-year East Asian climate reconstruction	atmospheric variables	Diffusion probabilistic models
(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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946 **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 (Q. Wu & Lin, 2019) zone)	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, wildfire, 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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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, precipitation, heatwave,	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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955 **Table B5: 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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958 **Author contribution**

959 DMF: Conceptualisation, Methodology, Formal analysis, Investigation, Data curation, Visualisation, Writing – original draft.

960 MS: Conceptualisation, Methodology, Validation, Writing – review and editing.

961 MM: Conceptualisation, Data curation, Writing – review and editing.

962 AC: Funding acquisition, Supervision, Conceptualisation, Writing – review and editing.

963 ST: Funding acquisition, Supervision, Conceptualisation, Project administration.

964 **Competing interest**

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

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