

1 **Review article: Harnessing data driven methods for climate multi-**
2 **hazard and 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 assessment, focusing on four themes: (i) data processing and collection; (ii) hazard identification, prediction and analysis; (iii)
21 risk assessment; and (iv) future risk scenarios under climate change. Key findings highlight the extensive use of machine
22 learning to combine Earth observations and climate data for downscaling and land use and land cover characterisation; the
23 application of deep learning for hazard prediction; the use of ensemble methods for risk assessment; and the growing emphasis
24 on explainable AI frameworks. Supervised machine learning approaches trained on historical impact data to project future
25 climate risks have also emerged as a significant research area. Future research in this area should focus on modelling multi-
26 hazard interactions, particularly triggering and cascading effects, integrate dynamic vulnerability and exposure factors, and
27 address uncertainties associated with using machine learning for extrapolation. Advancements in Earth observations and
28 textual data integration, alongside the development of open-access disaster catalogues, will also be crucial for improving multi-
29 risk assessments and supporting AI-driven early warning systems tailored to regional needs.

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35 **1 Introduction**

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

45 Complex dynamics characterize socio-environmental and climate risk: applications may underestimate impacts if they do not
46 take into account the compounding, cascading and amplifying interactions of hazards and their effect on vulnerability and
47 exposure factors. In fact, (i) compounding hazards (co-occurring in the same location and at the same time) can lead to impacts
48 which may be substantially higher than the sum of the single events taken in isolation (Arosio et al., 2020; Zscheischler et al.,
49 2018), (ii) the occurrence of one hazard itself can modify vulnerability or resilience of the system, exposing assets or
50 communities to higher risks, such as in the case of consecutive hazards (de Ruiter & van Loon, 2022), and (iii) impacts and
51 risks can propagate across multiple scales and sectors, extending far beyond the area initially hit and affecting whole systems
52 (Arosio et al., 2021; Pescaroli & Alexander, 2018), such as in the case of high-impact and low-probability events (Linkov et
53 al., 2022). For these reasons, the international community (Intergovernmental Panel on Climate Change (IPCC), 2023;
54 UNDRR, 2020) has recently pledged for a paradigm shift from single hazard towards a more comprehensive representation of
55 multiple and interconnected climatic risks (AghaKouchak et al., 2020; De Angeli et al., 2022; Gallina et al., 2020; Šakić
56 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
57 data-driven methodologies that can analyse and predict the interactions and dependencies between multiple hazards, enabling
58 a more accurate characterisation of their compounding and cascading effects.

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

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

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

71 Integrating these heterogeneous data sources can help in capturing multi-hazard interactions and characterise their impacts on
72 social, economic, and natural systems, especially thanks to the introduction of new Deep Learning (DL) architectures and
73 models, specialized in capturing both spatial and temporal non-linear interactions (S. Park et al., 2023). As ML models have
74 become more complex, attention has shifted toward making these models more interpretable and explainable (Carvalho et al.,
75 2019). This is especially important for applications focussing on risk, where it is crucial to quantify the contribution of each
76 input feature to the model's prediction, making it easier to assess how different risk variables impact the overall risk. In this
77 context, explainability frameworks improve the robustness of risk assessments and enhance trust in the model's outputs by
78 providing insights into how the model arrives at specific conclusions (S. Jiang et al., 2024; McGovern et al., 2019), supporting
79 transparency and accountability for stakeholders.

80 In addition to ML methods, this review briefly considers the role of copulas as multivariate statistical tools in multi-risk
81 assessment. Copulas enable explicit modelling of the dependence structure between variables, making them particularly
82 valuable for analysing compound events in which multiple hazards occur simultaneously or sequentially (see, for example,
83 Agrawal, 2022; Hochrainer-Stigler et al., 2019). They have, for instance, been used to characterise the joint occurrence of
84 droughts and heatwaves, yielding insights into their combined impacts on agriculture and water resources (see e.g. Ribeiro et
85 al., 2020). Although their application is more specialised than most ML approaches, copulas provide critical information about
86 inter-hazard dependencies, supporting a deeper understanding of compounding and interacting risks. Their inclusion in this
87 review therefore highlights their importance in contexts requiring precise statistical modelling of hazard interactions and
88 underscores how they complement broader ML-based strategies in climate-risk analysis. To advance this field, there is a critical
89 need for predictive frameworks that can leverage these advanced methods to forecast long-term future multi-hazard and multi-
90 risk scenarios, addressing uncertainties and guiding adaptive risk management strategies under changing climatic conditions.
91 To support implementation, the development of a wide range of open-source libraries (e.g., *scikit-learn*, *TensorFlow*, *Keras*,
92 *PyTorch*, *VineCopulas* (Claassen et al., 2024), etc.), allows users to implement, train, validate, and deploy models with
93 minimal programming expertise, making it possible for non-experts or domain specialists with limited knowledge to efficiently
94 apply advanced techniques to risk modelling. This democratization of tools reduces the technical barriers for researchers and
95 practitioners, enabling more interdisciplinary collaborations and accelerating the adoption of data-driven methods in climate
96 risk management (Rolnick et al., 2019).

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

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103 al., 2020), and climate risk (Zennaro et al., 2021) – this paper takes a cross-cutting perspective on multi-hazard and multi-risk
104 assessment. By structuring the discussion around successive stages of risk analysis – data processing, hazard prediction, risk
105 assessment, and future scenarios – we connect climate risk and data-driven methods while also identifying critical gaps,
106 particularly in linking hazard interactions with vulnerability.▼
107 The review is structured as follows: Section 2 Methodology outlines the research questions, and the search methodology▼
108 employed. Section 3 Results and discussions summarises the literature review findings and discusses key insights related to
109 each of the research questions. Section 4 Conclusion provides a summary of the key insights and outlines the next steps for
110 research in this field. The Appendices provide an abbreviation dictionary (▲

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114 Appendix A: Abbreviations, as well as the summary tables of main articles collected for each research question (

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116 ~~Appendix B: Summary tables of the collected studies).~~

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117 **2 Methodology**

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

126 **2.1 Research questions**

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

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- 130 1. Data: How can Machine Learning improve data collection and processing?
- 131 2. Multi-Hazard: How can Machine Learning and statistical tools be used to analyse extreme events, and model hazard
132 interactions?
- 133 3. Multi-Risk: How can Machine Learning applications integrate vulnerability and exposure in multi-risk analysis?
- 134 4. Future: How can Machine Learning and statistical tools be used to predict long-term future multi-hazard and multi-
135 risk?
- 136



Figure 1: Research questions and sub-themes

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

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

154
155 The second research question investigates how ML and statistical tools improve the identification and modelling of hazard
156 dynamics by capturing complex spatio-temporal patterns, compounding effects, and non-linear interactions that traditional
157 approaches often overlook. This helps advance multi-hazard and multi-risk analysis by providing more accurate detection,
158 classification, and modelling of extreme events. In particular, the key sub-themes are:

- 159 I. Analyse which methods can be used to identify, classify and cluster extreme events, producing spatio-temporal
160 footprints of multi-hazard events (H. Yu et al., 2022).
- 161 II. The prediction of (multi-)hazard events, for example through early warning systems or seasonal predictions
162 (Bhowmik et al., 2023).
- 163 III. The analysis of hazard interactions, for example characterising joint distributions through copulas (Bevacqua et al.,
164 2021) or multi-hazard susceptibility maps (Pourghasemi et al., 2019).

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

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

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

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

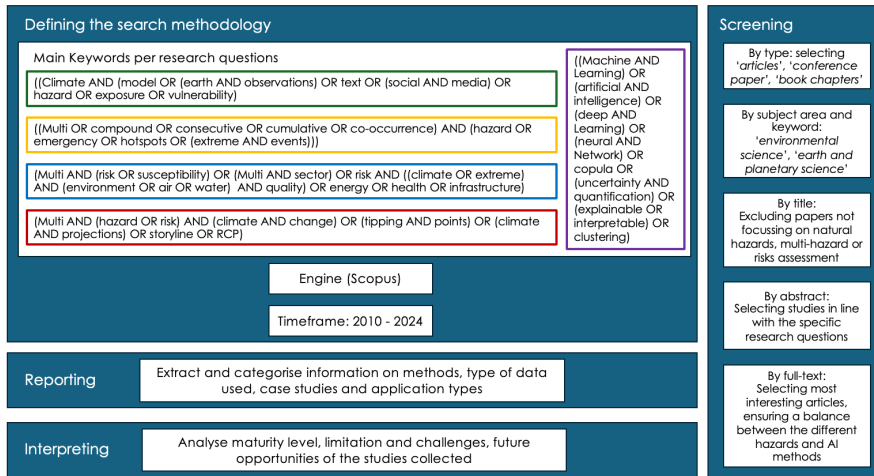
183 2.2 Methodological framework: search methodology, screening, reporting and interpreting

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

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194 **Figure 2: Literature review methodology**

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

201 2.3 Limitations and scope of the review

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

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

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

229 Finally, some considerations need to be taken on the geographical distribution of the 153 papers included in this review, which
230 reveal a marked concentration in a small number of regions. In terms of lead authorship, Europe (35.5%) and East Asia (27.0%)
231 together account for nearly two thirds of the corpus, followed by North America (21.1%), while the Global South is
232 substantially underrepresented: Africa, South America, and Oceania collectively contribute less than 5% of lead authors. A
233 similar pattern holds for co-authorship, though with a slight broadening of participation: South/SE Asia rises to 6.4% and
234 Middle East to 7.3%, suggesting that researchers from these regions participate more frequently as collaborators than as lead
235 investigators. The most pronounced shift occurs in the case study column: Global studies account for 14.9% of the corpus, and
236 South/SE Asia (10.6%), Middle East (6.8%), and Africa (5.0%) are more represented as study areas than as sources of
237 authorship, indicating that data-driven methods developed in high-income regions are frequently applied to, rather than
238 developed within, lower-income contexts. The full breakdown of lead author institution country, co-author countries, and case
239 study regions, together with a Sankey diagram illustrating the flows between these three dimensions, is provided in Appendix
240 B. These geographical imbalances should be borne in mind when interpreting the findings of this review, as the methods,
241 datasets, and risk priorities that dominate the literature inevitably reflect the institutional contexts in which the research was
242 produced.

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245 **3 Results and discussions**

246 **3.1 Data**

247 **3.1.1 Climate datasets**

248 The application of ML methods to produce new, complete, or high-resolution hazard datasets (either from meteorological
249 observations, climate reanalyses or future projection) is quite established, and mainly focuses on data with sparse and irregular
250 measurements. A typical indicator which is derived with ML methodologies is soil moisture: in-situ measurements are usually
251 scarce and not uniformly distributed, satellite images (which will be discussed later) often presents temporal gaps and can only
252 provide information on the first layer and struggles in complex topographies and it presents a complex dynamic that is
253 influenced by many different drivers (similarly to multi-risk prediction) such as precipitation, temperature, evaporation,
254 topography and land use. For example, Kang et al. (2018) and O. & Orth, (2021) investigate the complex interactions at
255 different soil levels and temporal scales with a Long-Short Term Memory (LSTM) model that takes as inputs the topography,
256 vegetation and atmospheric conditions and predicts each soil moisture layer in succession, using ERA-5 reanalysis as
257 assessment endpoint. LSTM is widely applied to model the behaviour of other hydrological variables, such as snow, run-off
258 and river catchments. Entity-Aware LSTM was used for rainfall-runoff modelling by Kratzert et al., (2018); Kratzert, Klotz,
259 Shalev, et al., (2019), to include both static and dynamic inputs allowing the algorithm to explicitly differentiate the two
260 different types. Ghiggi et al. (2019) applies Random Forest (RF) regression to predict monthly runoff rates in the timeframe
261 1902-2020, based on antecedent precipitation and temperature from an atmospheric reanalysis, validating the results with in-
262 situ streamflow observations. Other research focuses on different variables and in particular investigate the irregular
263 distribution of sensors: Amato et al. (2020) introduces a multi-step methodology to interpolate irregularly distributed spatio-
264 temporal timeseries, first decomposing the signal and then learning stochastic spatial coefficients which can be spatially
265 modelled and mapped on a regular grid with Artificial Neural Networks (ANN), allowing the reconstruction of the complete
266 spatio-temporal signal.

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

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

295 In recent years, there has been growing interest in hybrid modelling: approaches that combine data-driven ML methods with
296 physical or process-based models or constraints, as a way to benefit from both high flexibility and physical realism. Such
297 hybrid / physics-informed ML methods help address several limitations of pure data-driven models: they can enforce
298 conservation laws, reduce overfitting to noise, improve generalization especially under conditions outside the training domain,
299 and provide more interpretable insights into underlying drivers. For instance, He et al., (2023) integrates ML corrections into
300 a land-surface / atmospheric model using data assimilation, remote sensing LAI and soil moisture to improve climate
301 simulations. Similarly, Huynh et al., (2025) combines process-based hydrological flux models with neural networks to correct
302 for scale mismatches and to better capture spatial heterogeneity. Also, (S. Yu et al., 2024) provides benchmarks for ML
303 emulators that mimic nested high-resolution physical simulations. Despite their promise, hybrid models also face important
304 limitations. They often require substantial domain and physical knowledge to be formulated appropriately and to ensure
305 physical consistency (Willard et al., 2022). Moreover, coupling ML architectures with numerical process models can remain
306 computationally demanding, particularly for high-resolution simulations or large spatio-temporal domains (Reichstein et al.,
307 2019). Calibration and validation can also be complex, as balancing the contributions of the physical and data-driven
308 components often involves ad hoc or case-specific tuning (Read et al., 2019). Finally, interpretability may still be reduced
309 when the ML component acts as a black box, obscuring how physical constraints shape predictions (Kashinath et al., 2021a).
310 These challenges are also relevant for hazard prediction, where process dynamics such as land–atmosphere feedback play
311 central roles and require models that are both physically credible and statistically robust. Thus, hybrid models represent an

312 emerging frontier at the interface of ML, process-based modeling, and data assimilation, particularly relevant for both climate
313 data reconstruction and hazard modelling and deserve explicit consideration in future reviews and benchmarking efforts.

314 Machine learning applications for climate and environmental datasets have greatly improved the reconstruction and
315 downscaling of variables from sparse and irregular observations. However, a critical yet often under-addressed aspect in this
316 field is uncertainty quantification (UQ), which is particularly relevant when these datasets are later used for hazard or risk
317 assessments (Beven, 2018). Uncertainty in ML-based arises from multiple sources: Aleatoric uncertainty stems from the
318 intrinsic variability and noise in the underlying measurements, such as sensor errors, missing satellite observations, or
319 inconsistent temporal coverage; epistemic uncertainty originates from limited or biased training data and model structural
320 choices (Xu et al., 2022). Several probabilistic approaches have been explicitly designed to represent spatial data uncertainty
321 by learning distributions rather than deterministic predictions, mainly involving Bayesian Networks (BN) and Gaussian
322 Processes (GP) (Siddique et al., 2022). For example, Multi-fidelity Gaussian Processes with a 5/2 Matern kernel in particular,
323 were used to downscale precipitation data from ERA-5 over high mountain terrain. Multi fidelity models combine low-fidelity
324 observations (which are usually more numerous and less expensive to obtain) with high-fidelity ones. This makes the model
325 more suited than other state-of-the-art machine learning methods for smaller datasets and able to quantify and narrow the
326 uncertainty associated with the precipitation estimates, which is especially needed over ungauged areas and can be used to
327 estimate the likelihood of extreme events that lead to floods or droughts (Tazi et al., 2024). Andersson et al., (2023) applies
328 Convolutional Neural Processes (ConvNPs), to suggest informative sensor placements by finding sites that maximally reduce
329 prediction uncertainty, testing it for air temperature anomalies measurements in Antarctica. Convolutional Neural Processes
330 (ConvNPs) extend the probabilistic framework of Gaussian Processes by learning flexible, data-driven covariance structures
331 through neural networks. While traditional GPs provide robust uncertainty estimates but suffer from scalability and stationarity
332 constraints (M. Jiang et al., 2022), ConvNPs maintain a probabilistic foundation while scaling linearly with data size and
333 accommodating irregular spatial inputs (Garnelo et al., 2018). DeepSensor¹, a specific GitHub python package, was developed
334 to facilitate the application of Neural Processes in environmental sciences, especially for downscaling, interpolation, sensor
335 placement and data imputation. Monte Carlo Dropout (MCD) enhances epistemic uncertainty quantification in climate data
336 and was tested on neural networks for probabilistic medium-range weather forecasting (Garg et al., 2022). Deep generative
337 models such as diffusion or GAN frameworks can further approximate uncertainty by generating ensembles of plausible
338 realisations that sample the predictive probability space (Ling et al., 2024b; Saha & Ravela, 2022). Despite these advances,
339 most studies still focus primarily on improving resolution and accuracy, while systematic approaches to quantifying and
340 propagating uncertainty through the modelling chain, from data to hazard and risk estimates, remain limited (Beven, 2018).
341 Addressing this challenge is crucial, as downstream risk assessments rely heavily on the reliability of the climate inputs that
342 feed them.

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

343 3.1.2 Earth observations

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

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

351 EO provides consistent, near-real time observations of environmental conditions that are critical for early warning and hazard
352 characterisation. For instance, indicators such as vegetation stress (Miyoshi et al., 2020; Schiefer et al., 2020; Veras et al.,
353 2022), surface temperature anomalies can enable the early detection of droughts (Barrett et al., 2020), floods (Dasgupta et al.,
354 2022) or wildfires (Jain et al., 2020) especially in remote and data scarce areas. DL and Physics Informed Neural Networks
355 can leverage radar (e.g., Sentinel-1 SAR), to estimate water levels for flood forecasting (Dasgupta et al., 2022; Gierszewska
356 & Berezowski, 2024) or fused into predictive models that refine hazard forecasts for severe weather and anticipate cascading
357 impacts (Flora et al., 2021). Remote sensing plays a crucial role in hazard dataset development by helping mitigate bias that
358 may be inherited by ML-based risk models. These models are often trained on datasets calibrated with data from resource-rich
359 regions, where the majority of weather stations are located. As a result, they may struggle to generalize effectively to
360 underdeveloped areas, which are frequently the most vulnerable to extreme events (McGovern et al., 2019, 2022).

361 EO combined with ML is also used in assessing environmental quality, such as water quality (Sagan et al., 2020; Sit et al.,
362 2020). These applications mainly showcase simpler models, such as short neural networks and SVM (Nazeer et al., 2017),
363 Decision Trees (DT), RF, Cubist Regression and Extreme Gradient Boosting (XGBoost), due to their ease of implementation
364 and relative scarcity of ground measurement data (J. Liu et al., 2023). They focus on optically parameters, such as chlorophyll-
365 a, turbidity and suspended solids, but also others such as of nutrients and other non-optical parameter) can be predicted relying
366 on models integrating meteorological and hydrological variables (S. Chen et al. 2022).

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

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

376 used EO and ML to track how rapidly services return to urban slums post disaster, highlighting which population remain
377 exposed and underserved (Ghaffarian & Emtehani, 2021). Similarly, UNET-based CNNs are used to identify deprivation
378 pockets from satellite images and track during their recovery process (J. Wang et al., 2019), or to derive proxy indicators for
379 poverty from satellite night lights (Jean et al., 2016), in combination with transfer learning to overcome scarcity of labelled
380 data (S. J. Pan & Yang, 2010). At longer timescales, techniques like K-Nearest Neighbour (KNN), SVM, ANN and RF are
381 used to classify urban and rural land cover, detect land use changes or informal settlements (Adam et al., 2014; Yuh et al.,
382 2023; Zerrouki et al., 2019).

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

385 3.1.3 Textual data

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

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

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

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409

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

414 **3.2 Multi-hazard**

415 **3.2.1 Identify, classify and cluster**

416 The initial step in conducting a comprehensive multi-risk assessment involves a thorough analysis of hazard factors, which is
 417 critical for effective climate risk evaluation and enhancing disaster preparedness. In this context, identifying various hazards,

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440 classifying them into distinct categories, and extracting their spatio-temporal footprints through clustering techniques are
441 fundamental processes.

442 The identification of impacts from satellite images to discover hazard footprints, such as for landslides, earthquakes, floods
443 was discussed in the previous section because it is mainly an image processing task, where the goal is to identify differences
444 between two images. This section focuses on the identification of extreme events from climate datasets, which require specific
445 considerations on the typology of hazards and risk considered and is subject to different definitions and multiple interpretations.
446 The most common approach to identify multiple hazards from climate datasets is to use thresholds to identify univariate
447 extreme events and then combine them at a later stage into a multi-hazard database. In order to identify the thresholds, two
448 methods are applied: empirical thresholds (e.g., defining a max temperature over which an event is considered extreme) or
449 statistical thresholds (e.g., calculating a pixel-wise and/or day-wise percentile to identify events that exceeds a threshold that
450 can vary spatially and temporally). Empirical thresholds are usually fine-tuned to link extreme events to impacts on specific
451 sectors or local applications, and many applications focus on temperature extremes and health (Ray et al., 2021; X. Sun et al.,
452 2014). Statistical thresholds are preferred when analysing global trends and merging multi-hazard extremes because they allow
453 a more consistent and probabilistic robust comparison between different hazards. Percentiles can be easily adapted to model
454 spatial and temporal variations in data and are ideal for global application that cover multiple landscapes where a unique
455 empirical threshold cannot be univocally determined. For example, in Ionita et al. (2021), specific percentiles are used to
456 identify heatwaves and drought from temperature and SPI indicators respectively, before applying Empirical Orthogonal
457 Functions to investigate their drivers and their centre of actions over Europe; Similarly, Sutanto et al. (2020) is using
458 percentiles to identify heatwaves, droughts and wildfires from temperature, soil moisture and Fire Weather Index (FWI),
459 analysing spatial overlaps of the daily binary hazard maps to identify simultaneously occurrences of dry hazards and then
460 investigating cascading events by looking at different combinations of hazard sequences. Claassen et al. (2023), proposes a
461 methodology to identify multi-hazard events combining static footprints derived from the processing of satellite images (e.g.
462 for landslides, floods, tsunamis) with dynamic footprints (based on statistical percentiles) of climate hazards (e.g., heatwaves,
463 droughts, extreme precipitation, extreme wind, etc.), proposing a methodology to identify consecutive events using a specific
464 time lag and analysing the global distribution of the various multi-hazard events.

465 Return periods are another statistical technique used to identify extreme events, studying the likelihood of an event of a certain
466 magnitude occurring in a chosen timeframe (Liao et al., 2021). Return periods are most often applied in hydrology, when
467 dealing with flooding and storm surge events (G. Liu et al., 2020, 2023; Mattei et al., 2021; Zanini et al., 2020). These
468 applications fit a probability distribution (typically a Generalised Extreme Value Distribution, calculated over the number
469 exceeding of a threshold or over maxima) which allow for an estimation of the uncertainty of the threshold. Percentile
470 thresholds, returns periods and Generalised Extreme Value (GEV) distributions are also used conjunctly, such as in Orth et al.
471 (2022), where different hydrological hazards (floods, frost, heat waves, droughts, and storms) and their contrasting impacts
472 are analysed against multiple sectoral assessment endpoints (Gross Primary Productivity for vegetation, crop yields, human
473 mortality, damages to properties and public attention).

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

478 Other approaches focus on identifying and classifying extreme events from climate reanalyses using DL, especially in case of
479 cyclones or other hazards that are characterised by the interaction of multiple atmospheric drivers. Y. Liu et al. (2016) was one
480 of the first to apply CNN based on AlexNet to detect and classify tropical cyclones, atmospheric rivers and weather fronts
481 from climate datasets, such as ERA-5, CAM5.1. One of the main challenges in this domain is the scarcity of labelled data for
482 training supervised ML models. This is discussed by Racah et al. (2016), who expanded the previous approach, developing a
483 semi-supervised CNN model to overcome the lack of labelled data and created an extreme weather dataset as benchmark. In
484 general, the skewness of datasets is another common challenge for identifying climate anomalies with supervised approaches:
485 often data on which the ML models are trained on present very few samples of conditions leading to impacts (Dal Barco et al.,
486 2024).

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

495 3.2.2 Hazard forecasting and prediction

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

504 Applications that focus on predicting or forecasting hazards are still mainly focussed on single hazard approaches. However,
505 some single hazard approaches were included in this review because their multi-variate approach includes the combination of
506 different static (as land use, topography, socio-economic data) and dynamic (e.g., atmospheric and marine data) parameters

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509 and implicitly deal with multi-hazard interactions (e.g., a wildfire may be more probable when dry and hot conditions are
510 present, a drought can be influenced by temperature and soil moisture, etc.). For example, Haggag et al. (2021) propose an
511 ANN prediction model in a multi-hazard perspective, but then test it on past disaster records to predict only floods in Ontario
512 using indices for climate extremes inputs. Monte Carlo dropout techniques have been employed to quantify epistemic
513 uncertainty, for example in surge forecasts (Macdonald et al., 2025) and flood modelling (M. Nguyen et al., 2024).

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

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

536 CNN, ANN, LSTM are still popular for drought and heat events, which are characterised by longer scale spatio-temporal
537 dynamics. For example, Bonino et al. (2024) compare the performances of CNN, LSTM and RF for the prediction of marine
538 heatwaves; Patil et al. (2023) employ CNN to predict drought in East Africa 3 or 4 season ahead, analysing the contribution
539 of different climate drivers at multiple spatial and temporal scales; ANN are used for forecasting drought risk at near real time
540 in India, using Artificial Neural Network models (Singh et al., 2021). Other algorithms (SVM, Random Forest, XGBoost,
541 Extra Trees) are still often applied to analyse low probability extreme events in specific locations, where the lack of data

542 constrains the training of Deep Neural Networks, such as the storm surge height caused by tropical cyclones in New York
543 (Ayyad et al., 2022).

544 3.2.2 Modelling hazard interaction

545 Recent work has applied interpretable ML frameworks to hazard modelling, aiming not only at prediction but also at identifying
546 key drivers. For instance, S. Jiang, Bevacqua, et al. (2022) and S. Jiang, Zheng, et al. (2022) used LSTMs to study river
547 flooding in Europe, combining feature attribution methods such as Expected Gradients (Erion et al., 2021) and Additive
548 Decomposition (Du et al., 2019) to disentangle the roles of snowmelt and precipitation. By running models across decades,
549 they revealed shifts in dominant flood drivers, with precipitation becoming increasingly important. Other studies have applied
550 gradient-based methods (A. Y. Sun et al., 2021), CNN heatmaps (Patil et al., 2023), attention mechanisms (Castangia et al.,
551 2023), and sensitivity analysis (Bentivoglio et al., 2023; Bonino et al., 2024; Kratzert, Klotz, Shalev, et al., 2019). These
552 advances improve interpretability, yet ML approaches remain limited by high data demands, sensitivity to training biases, and
553 the difficulty of generalising beyond observed conditions (Bentivoglio et al., 2023). Their strength lies in prediction and
554 uncovering nonlinear relationships, but the black-box nature of many models complicates causal modelling (Freeman et al.,
555 2018).

556 While most ML studies focus on univariate hazards, compound events require methods that capture joint extremes. Copulas
557 offer a flexible statistical framework to model dependence structures between variables, such as the co-occurrence of high
558 river discharge, intense rainfall, and coastal surges (Hao & Singh, 2016; Nelsen, 2006). By decoupling marginal distributions
559 from their dependence structure, copulas can assess joint probabilities of rare events with more precision than traditional
560 multivariate models (Tilloy et al., 2019) Applications include pair copulas for compound flooding in Italy (Bevacqua et al.,
561 2017a), Joe copulas for concurrent river–coastal extremes (Sadegh et al., 2017), and copula-based Bayesian networks for
562 flood–drought interactions (Couasnon et al., 2018). However, several challenges remain: selecting appropriate copula families
563 is non-trivial (since different families imply different tail dependencies, yet many common families assume simplistic
564 dependency or exchangeability) (Oh & Patton, 2015); capturing joint tail dependence becomes increasingly difficult in high
565 dimensions (vines, mixtures, or hierarchical copulas may help but bring computational and inference burdens) (Simpson et al.,
566 2020); physical drivers (e.g. precipitation skew, changing climate forcings, watershed characteristics) are often only indirectly
567 represented through marginal or covariate models (Hochrainer-Stigler et al., 2019b). Therefore, while copulas are powerful
568 for probabilistic risk quantification, they are less suited to dynamic forecasting or process-based understanding without
569 additional model structure or ensembles (Tootoonchi et al., 2022).

570 **Comparison and complementarities.**

571 ML and copula methods approach hazard interactions from distinct perspectives. ML excels at prediction and feature
572 discovery but struggles with transparency and extrapolation, while copulas provide interpretable dependence structures and
573 joint probability estimates but scale poorly with dimensionality and lack causal interpretability. ML can identify critical
574 hazard predictors and generate inputs, while copulas rigorously quantify their joint occurrence. Yet, few studies combine

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575 these strengths; most rely on either predictive ML or probabilistic copulas in isolation. For example, an LSTM may forecast
576 river discharge under given precipitation and snowmelt conditions, while a copula model can then quantify the probability
577 that extreme discharge co-occurs with extreme rainfall or sea-level rise. Together, ML and copulas can provide a more
578 complete picture: ML enables forecasting and driver attribution, while copulas ensure rigorous treatment of dependence
579 structures and joint extremes (Sadegh et al., 2017; Tilloy et al., 2019). Combining both approaches offers a promising
580 pathway for advancing compound risk assessments. Some approaches, such as, T. Jiang et al., (2023) used a hybrid ML-
581 copula method to estimate the probability of consecutive drought events (in particular from meteorological to ecological
582 droughts), combining several ML classifiers (KNN, RF, SVM, ...) to estimate the propagation probability of meteorological
583 drought given its characteristics, and C-vine copulas to model conditional probability model of the paired meteorological
584 and ecological drought events. Closing this gap, for instance, by integrating ML-derived drivers into copula frameworks, or
585 benchmarking ML-learned dependencies against copula-based models, represents a promising but underexplored direction
586 for compound risk assessment.

587 **Susceptibility mapping**

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

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

608 The most common approach for integrating susceptibility parameters into multi-risk assessment is by producing multi-hazard
609 susceptibility mapping, where susceptibility to multiple hazard (including factors for hazard, such as yearly precipitation, but
610 also vulnerability parameters, such as slope) can provide a valuable point of reference for decision makers in sustainable land-
611 use planning or infrastructure development. A number of studies are focusing on mountainous regions, using a range of ML
612 models, including Logistic Regression, ANN, DT, SVM, RF, Boosted Regression Trees (BRT), or Generalised Linear Models
613 (GLM) (Javidan et al., 2021; Karakas et al., 2023; Kariminejad et al., 2022; H. D. Nguyen et al., 2023; Pourghasemi et al.,
614 2019, 2020; Pouyan et al., 2021; Yousefi et al., 2020) The multi-hazard combination usually covers floods, landslides,
615 avalanches and forest fires, which have clear footprints that can be used to train single hazard susceptibility, and integrate other
616 risks which can be assessed through already available risk maps, such as seismic risk maps at a later stage (Bordbar et al.,
617 2022). Different hazards are included by Piao et al. (2022), who test BRT, RF and Classification And Regression Trees (CART)
618 in the Gangwon-do region in South Korea (an area rich in forests and ecological diversity) to establish a multi-hazard
619 probability map for forest fires and droughts; in this study the multi-hazard interactions are investigated, considering drought
620 as an amplifying hazard for forest fires. Mandal et al. (2022) focus instead on coastal areas, in particular in West Bengal
621 (India), considering tropical cyclones, embankment breaching, storm and tidal surge, inundations, extreme rainfall, salinization
622 and erosion; RF and ANN are applied to produce multi-hazard susceptibility maps. Ullah et al. (2022) test a CNN to produce
623 flash floods, landslides and debris flow multi-hazard susceptibility mapping, comparing its performances with Logistic
624 Regression and KNN methods in terms of accuracy, coefficient of determination, Mean Absolute Error and Root Mean Squared
625 Error. The input data consist of field surveys, topography, hydrology, and environmental data, while the locations of historical
626 flash flood, debris flow and landslide locations are extracted from Google Earth images. The feature importance scores are
627 derived using a Random Forest model and are used to enhance the analysis of the multi-hazard maps. It is interesting to note
628 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
629 the 14 layers of predicting variables, producing an independent output pixel by pixel.

630 While the literature on this topic is quite established, most of these applications propose a multi-layer single hazard risk, rather
631 than a full multi-hazard or multi-risk approach: in fact, the single hazard maps are often combined linearly or via a matrix
632 considering combined risk categories, without elaborating further on the hazard interactions. Another common challenge in
633 the development of susceptibility maps is the skewness of the training dataset, which are characterized by a predominance of
634 areas with no damage. These greatly affects the training and testing of the models, and specific sampling procedures are often
635 applied, rather than relying on balancing weights when training the ML model. Most often, all the positive samples (e.g., where
636 some impact was recorded) are included; a buffer area is applied to the positive samples and subtracted from the whole dataset
637 to exclude areas near recorded impacts; a number of points of comparable magnitude to the positive ones is sampled from the
638 difference dataset to ensure that the final training dataset includes a balanced representation of impacted and non-impacted
639 areas. This is a key step of the susceptibility mapping and can potentially add biases to the model, if the selected samples are
640 not representative of the whole dataset or if there is a high autocorrelation. Spatial or temporal autocorrelation needs to be
641 considered when splitting between training, validation and test data: random splitting methods assume data is independent and

642 identically distributed. Specific techniques, such as spatio-temporal block cross validation (Zanetti et al., 2022) need to be
 643 considered to account for this. For example, a recent paper by Sweet et al. (2023) shows the impact of different validation
 644 techniques in a RF model for the prediction of agricultural yield, and their implications on performances and robustness of the
 645 interpretation of the model.

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

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

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maps, then combined into multi-hazard maps;	<ul style="list-style-type: none"> • Sampling bias & autocorrelation; 	<ul style="list-style-type: none"> • Extend beyond the typical geohazards
<ul style="list-style-type: none"> • Feature importance to rank drivers. 	<ul style="list-style-type: none"> • Limited hazard breadth beyond fire/ landslide/ flood/ earthquake. 	

699

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

704 3.3 Multi-risk

705 3.3.1 Modelling risk combining susceptibility, exposure and vulnerability

706 Many studies are found to focus on modelling risk by combining hazard maps, produced via ML-based susceptibility mapping,
 707 with vulnerability and exposure layers. Single hazards such as wildfires, floods and landslides are often considered, and
 708 buildings, population and infrastructures are the typically included exposure elements. Kotaridis & Lazaridou (2022) consider
 709 flooding risk in Tuscany and applied a 2D CNN to produce an urban flooding susceptibility map. Differently from Ullah et al.
 710 (2022) the CNN applied here makes use of the spatial context of each pixel, considering a 5x5 patch centred on a specific pixel
 711 (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
 712 5x5x9 size, where the last number corresponds to the different predictors of the susceptibility mapping that are considered as
 713 channels in the CNN architecture. Thus, not only the selection of the initial samples, but also the selection of the size of the
 714 patch is a key hyperparameter to be considered: in this case, a cross validation is used to choose the best patch size. The
 715 vulnerability maps are created dividing the land use into 5 classes, which are then multiplied with the hazard layer to calculate
 716 the final risk map. Convolutional Neural Networks (CNNs) offer significant advantages over traditional algorithms in spatial
 717 analysis due to their ability to process areas as 2D maps. This enables the model to leverage Max Pooling layers to capture and
 718 simplify the spatial context of events. Unlike models that focus on individual point characteristics, CNNs can better model and
 719 integrate the broader spatial relationships. For example, Zhao et al. (2020) test CNN for urban flood susceptibility too but
 720 instead of producing separate maps for hazard and vulnerability, anthropogenic factors were used as predictors for the
 721 susceptibility map. The study compares the performances of different ML models: a simple (with 1 convolutional layer) CNN
 722 architecture, LeNet5 (Lecun et al., 1998), a slightly deeper CNN (with 2 convolutional layers), SVM and RF models. Different
 723 input strategies are tested: a point based strategy that only considers input at a given site; a partial spatial strategy that considers
 724 the surrounding pixels, flattening the 2D image to a 1D vector, thus losing partially the spatial context, but allowing the
 725 neighbouring pixels to be fed to SVM and RF models as additional predictors; a patch strategy, similar to the one described
 726 before for the CNN models, which granted the best performances. This study also discusses the use of Deep CNNs, which is

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736 discouraged since the typical sample size and model is too small to tune the high number of parameters required by Deep
737 CNNs.

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

761 A critical limitation of the studies reviewed in this section is the static treatment of vulnerability. Most applications use fixed
762 proxies – building footprints, land-use classifications, census-derived population density – that do not evolve in response to
763 hazard occurrence, adaptation measures, or broader socio-economic change (Haer et al., 2019, de Ruiter & van Loon, 2022).
764 This static framing can substantially underestimate risk in contexts where vulnerability is shaped by governance failures,
765 structural inequalities, or rapid urban expansion (Ward et al., 2022; Šakić Trogrlić et al., 2024). A particularly underexplored
766 challenge in multi-hazard risk assessment is that vulnerabilities do not simply add up across hazards: they interact. Synergies
767 and asynergies between vulnerabilities mean that the combination of hazards can fundamentally alter how exposed elements
768 are affected. For instance, adaptation measures designed to reduce risk from one hazard may increase vulnerability to another,
769 and damage caused by a first hazard event can leave a system more vulnerable to a subsequent one (Albulescu & Armas, 2024;

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772 de Ruiter & van Loon, 2022). Stolte et al. (2024) further demonstrate through a global systematic review of urban vulnerability
773 that the drivers of vulnerability differ substantially across hazard types, and explicitly call for research into multi-hazard
774 vulnerability dynamics as a necessary step beyond the current dominant paradigm of treating multiple hazards in parallel rather
775 than in interaction. Despite growing conceptual recognition of this problem, it remains essentially unaddressed in the data-
776 driven literature reviewed in this study, where vulnerability interactions are neither modelled nor discussed. Social justice
777 dimensions also remain largely absent from the reviewed multi-risk literature: only few of the papers analysed explicitly
778 consider vulnerability dimensions such as gender, while the question of how ML-based risk maps might inherit biases from
779 historically underinvested impact datasets remains largely unaddressed (McGovern et al., 2022).

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

787 3.3.2 Modelling risk predicting impacts

788 Another popular approach to model multi-risk with ML is to use impacts as a proxy and training supervised ML models on
789 past impacts. Examples of possible impacts are excess mortality for health risks, economic damages and monetary losses,
790 number of emergency signals or specific environmental indicators, such as ecological status. With regard to ML methodology,
791 approaches are similar to the ones applied for predicting hazard values, considering multiple predictors covering climate,
792 topography, land use and anthropogenic factors, but the final assessment endpoint, impact data, is very different from typically
793 hazard data, having a coarser resolution in time and space and resulting in much smaller datasets. Thus, most of the studies
794 focus on simpler and more interpretable ML methods like ensemble methods, rather than the DL approaches which are popular
795 for hazard prediction. Moreover, more attention is dedicated to the interpretation of the factors and the explainability of
796 methods (Ghaffarian et al., 2023), with most applications presenting some form of feature importance analysis, either as a
797 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
798 based on the sectors and type of impact considered, considering health, food security and crops, environmental quality &
799 biodiversity, physical damages and economic losses.

800 **Health**

801 Studies focussing on environmental-health risks often analyse the combination of heat and air quality stressors and use excess
802 mortality as predicant variable. These applications aim at disentangling complex temporal patterns, consisting of a long-term
803 trend, driven by multiple (and often unknown) factors, and short-term peaks, mainly driven by summer heatwaves; moreover,
804 time-lags needs to be considered. Thus, statistical methods, such as Distributed Lag non-linear models have been widely

805 applied (Gasparrini, 2014) to model exposure lag-response of mortality to environmental stressors. More recently, RF has been
806 applied, analysing the role of humidity in urban mortality during heatwaves at the global scale (Guo et al., 2024) or predicting
807 heat-stroke occurrence in China (Y. Wang et al., 2019), while SVM is applied for analysing previous diseases, population
808 density and urbanisation (X. Wang et al., 2021). One of the most interesting papers, Boudreault et al., (2023) test 9 different
809 ML, DL and statistical methods (such as Generalised Additive Models – GAMs) in the Metropolitan City of Montreal,
810 considering weekly all-cause mortality as predictand and air temperature, humidity, wind, Particle Matter (PM) 2.5, Ozone
811 (O₃), Nitrogen Dioxide (NO₂), Sulphur Dioxide (SO₂), Carbon Monoxide (CO) as predictors. Among the methods tested,
812 Tree based methods (RF, XGBoost) usually perform better overall, while statistical methods (and GAM in particular) are more
813 accurate in predicting the mortality peaks; Deep Learning approaches, such as MLP and LSTM have instead the worst
814 performances. This is partially explained by the limited size of the dataset and the inclusion of non-climate causes in the
815 predictand, likely to cause overfitting in the DL models. Another study also focussing on Canada proposes an AI-based
816 framework to extrapolate vulnerability from health-heat relationship: Côté et al. (2024) test this approach considering two
817 steps: first, a model to predict daily mortality from mean temperature for 3 days, age, income and period of the year as
818 predictors and then a second model predicting annual mortality over aggregated areas with specific socio-economic and
819 environmental (air quality, vegetation, ...) characteristics. The model tested are AutoGluon (an automatic ML framework
820 allowing to train and test ML models without expert knowledge²), GP and Deep Gaussian Process (Deep GP). The results
821 shows that GP are able to model better the daily mortality trends, especially during extreme temperature, while AutoGluon is
822 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
823 better handle noise and small data samples (J. Wang, 2023), and their limit is their computational costs (M. Jiang et al., 2022);
824 on the other hand, the more complex Deep GP handed the worst outcomes, highlighting the challenges in tuning more complex
825 Deep GPs (Tazi et al., 2023). Other studies focus on predicting the influence of water quality parameters, such as turbidity, on
826 the risk of cholera disease outbreaks in Indian Coastal municipalities using a RF predictor (Campbell et al., 2020).

827 **Food security and crops**

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

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

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

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

852 **Environmental quality and biodiversity**

853 Numerous studies focus directly on environmental impacts, such as the influence of land use and urban planning on water
854 quality. For example, R. Wang et al., (2021) apply RF with SHAP values to model stream water quality and specific pollutants
855 based on four different urban planning scenarios in Texas. The model allows to correlate urban sprawl to water quality
856 degradation and was used to forecast environmental impacts under different urban development pattern scenarios. In Li et al.
857 (2022) the ensemble model XGBoost is used to predict water quality in beach locations in lake Eyre, paired with SHAP for
858 increased explainability. Other studies focus on ecosystem and biodiversity: for example, RF and Logistic regressions are
859 tested to predict forest loss in Borneo from topographical and anthropogenic variables (distance to urban areas, population,
860 etc.), highlighting the advantages of RF for modelling multi-scale spatial relationships between risk drivers (Cushman et al.,
861 2017). Similarly, in Islam et al. (2021), the spatio-temporal dynamics of wetlands in Bangladesh and their negative effects on
862 biodiversity are analysed using Decision trees, RF and SVM. RF and SVM are the best performing algorithms and in general,
863 the papers highlighted the role of remote sensing, for mapping wetlands variations in time. Species distribution is also
864 investigated, with many applications discussing the different spatial approaches for river network modelling. For example,
865 Schmidt et al. (2020) test the MaxEnt algorithm with two representations of rivers, highlighting how a high-resolution model
866 based on river reaches is better at discovering individual local habitat features, whereas lower resolution sub-catchment scale
867 models better account for more general drivers in fish distribution. Teichert et al. (2016) apply a RF model to identify the
868 dominant stressors for fish presence in estuaries, investigating the interactions among stressors evaluating ecological benefits
869 expected from reducing pressure. In particular, an RF model is trained to predict ecological status in 90 locations using 17

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871 predictors describing the different stressors (urbanisation, flow changes, water pollution, oxygen depletion, etc.). Then,
 872 simulations are run to analyse the benefit of restorations comparing the difference between the baseline model and a model
 873 where the intensity of stressors was varied. The difference between single and multiple restoration action is analysed,
 874 highlighting the importance of combined restoration schemes and the non-linearity of their effects.

875 **Economic losses and physical damages**

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

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

SECTION	METHODS	GAPS	OPPORTUNITIES
3.3.1 Risk via susceptibility + exposure + vulnerability	<ul style="list-style-type: none"> • Overlay of single-hazard susceptibility (RF, SVM, ANN, BRT, CART, MaxEnt, CNN with patch context) with exposure (buildings, 	<ul style="list-style-type: none"> • Vulnerability and exposure treated as static layers; • modelling only direct impacts and risks; 	<ul style="list-style-type: none"> • Dynamic vulnerability/exposure updates using EO and time-sequenced hazards;

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- Deleted: label imbalance and sampling bias; spatial/temporal autocorrelation leakage;

	<p>population, infrastructure) and simple vulnerability layers;</p> <ul style="list-style-type: none"> • AHP/MCDM weighting; • feature importance/_SHAP to rank drivers. 	<ul style="list-style-type: none"> • <u> Ignores cascading and indirect effects and their propagation across multiple spatial scales</u> 	<ul style="list-style-type: none"> • spatio-temporal block cross-validation; • interaction-aware fusion (graphs, learned weights); • extend to wind, hail, heat, storm surge; • probabilistic risk maps with uncertainty bands.
<p>3.3.2 Predicting impacts Health</p>	<ul style="list-style-type: none"> • Ensemble and hybrid ML approaches (RF, XGBoost, SVM, DL, copulas, causal ML) applied to health, food, environmental, and economic impacts; • explainable AI (SHAP) and probabilistic modelling for driver attribution. 	<ul style="list-style-type: none"> • Impact labels are sparse, coarse, biased, and confounded; • scale mismatches and aggregation blur signals; • extremes and tails poorly represented; • DL tends to overfit and transfer poorly across cities/regions/climates; • uncertainty quantification and causal attribution often limited. 	<ul style="list-style-type: none"> • <u>Data & catalogues</u>: build geocoded event-level cross-sector impact datasets and standardized labels (health, yields, biodiversity, losses); • <u>Causal & lag-aware stacks</u>: combine DLNM / explicit-lag models with ML and causal discovery to capture delayed and causal pathways; • <u>Multi-source fusion & transfer</u>: integrate EO, in-situ, socio-economic and market data; • use domain-adaptation/transfer learning for cross-region generalization.

904

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

909 **3.4 Future**

910 **3.4.1 Predicting future hazards**

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

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

932 When dealing with the future of multi-hazard events, statistical methods are most often applied to identify hotspots and test
933 trends, similarly to the applications focussing on historical data. For example, Ridder et al. (2022) consider hot, dry, wet and
934 windy compound events by selecting cells which exceed the 99th percentile for wind and precipitation in the same day. Then
935 results are presented in changes in return period and annual event density, where the latter is a measure for how often an event
936 affects a region and how much of the region is affected, calculated from the number of grid cells affected. Similarly, Zhu et al.
937 (2023) investigate future compound wind and precipitation extreme at the global scale, analysing 14 CMIP6 models,
938 identifying compound events through the 95th percentile and discussing the sources of uncertainties via the HS09 statistical
939 method (Hawkins & Sutton, 2009) splitting between internal variability, model uncertainty and scenario uncertainty. Further
940 analyses discuss the spatial and temporal performances of future projections: Ridder et al., (2021) find good performances in
941 CMIP6 simulation for precipitation and wind compound extremes over North America, Europe and Asia, but poor
942 performances over Australia, probably linked to the limits in the modelling of tropical and extratropical cyclones and local
943 convection systems. Also, copulas are used to analyse spatial complementary patterns of compound events, such as in Ghanbari
944 et al. (2021), which analyse the joint return period of compound floods along the US coast, incorporating sea level rise and
945 peak river flows for future climate change risk scenarios with copulas. H. Wu et al., (2023, 2024), employ Vine copulas to
946 analyse hot & dry and pluvial & hot events in future scenarios, using a ~~Single Model Initial Conditions Large Ensemble~~
947 (SMILE).

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

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962 3.4.2 Modelling future impacts

963 A common approach to estimate future risks involves using future climate projections as input data for ML models that have
964 been trained on historical data of past impacts, similar to applications that focus on assessing current risks by leveraging past
965 impacts. For example, the study of future cyclone impacts in New York and New Jersey, is feeding four General Circulation
966 models as input for a SVM / AdaBoost risk model (Ayyad et al. 2023). Park & Lee (2020) test the performances of three
967 algorithms, K-NN, RF and SVM to analyse coastal risks in South Korea, considering rainfall, tides, topography and land use,
968 training the model on past floodings and then predicting future risks using monthly averages of rainfall and tidal values from
969 RCP 4.5 and 8.5 ensembles. Future risk scenarios are calculated aggregating the risk model outcomes for each decade from
970 2030s to 2080s. In a successive publication, Park et al. (2023) apply a similar ML methodology to investigate adaptation
971 strategies for coastal flooding: in this case, the ML model is trained on historical data with two different adaptation strategies,
972 seawalls or green spaces, and then the future adaptation models are implemented, either maintaining current adaptation
973 infrastructures or increasing one specific strategy. To ensure comparability between the adaptation scenarios, infrastructure
974 construction costs are standardized, guaranteeing that the two distinct adaptation pathways incurred equal expenses.

975 In general, it is considered good practice to use ensemble projections and values calculated over multiple years, in order to
976 increase the robustness of the future scenarios; however, some risk analyses focus on just a few selected years: Lim & Kim
977 (2022) test RF for future rainfall induced landslides, also analysing different adaptation pathways and considering an increase
978 in forested or urban areas. Instead of using monthly or daily values for the ML model, yearly values are used in the model, for
979 specific years (2050, 2092), which are considered significative for representing future scenarios. This approach is valuable for
980 analysing specific extreme events that may be overlooked when averaging across multiple models or years, and it reduces
981 computational demands. However, it carries the risk of biasing the analysis, as the selection of specific years may result in
982 outcomes that are not fully representative of the broader range of future scenarios. Bayesian Networks were tested by Pham et
983 al., (2023) in a multi-model chain approach combining ocean hydrodynamics models, wind-wave models, and shoreline
984 extraction models to analyse sea water quality impacts and shoreline erosion under different RCP projections (4.5 and 8.5).
985 Bayesian Networks are applied due to their ability to integrate heterogeneous data sources, including quantitative and
986 qualitative inputs and several data fusion steps to harmonise different spatial coverage, temporal resolutions and data formats,
987 with a final risk assessment conducted at municipality level and yearly/ decadal scale.

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

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996 a RF classifier is applied by Hoch et al., (2021) to predict water-related conflicts in Africa using different SSP future
 997 projections, integrating socio-economic predictors (population, education, GDP, governance) and climate predictors
 998 (precipitation, evaporation, flood volume, soil water). The model is trained on historical data up to 2015 and tested with
 999 projections from 2016 to 2050. Future temperature-related mortality in different European regions is analysed by García-León
 1000 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
 1001 disparities between cold-related deaths and heat-related deaths and analysing the role of age, health infrastructure and climate
 1002 change with a Distributed Lag Non-Linear model. In particular, different scenarios are discussed: present climate and present
 1003 population, present climate with future population from EUROPOP 2019; future climate under different warming level with
 1004 future population exposure.

1005 Future risk patterns are also calculated implementing future multi-hazard susceptibility maps: for example, Rahman et al.,
 1006 (2024) analyse future coastal multi-hazard risks in Bangladesh, implementing an LSTM algorithm, in combination with RF
 1007 feature selection and a Genetic Algorithm (GA) optimiser. In particular, GA is used to identify optimal or near-optimal
 1008 solutions, searching the space of LSTM parameters through a process of selection, crossover and mutation. The combination
 1009 of the LSTM's ability to capture sequential patterns and long-term dependencies and GA's efficiency in navigating complex
 1010 search spaces, is proved to achieve better convergence, avoid local minima, and optimise both the architecture and parameters
 1011 of the LSTM model (Zamani et al., 2022). Other future multi-hazard susceptibility approaches include Ya et al., (2023), who
 1012 analyse future risks in the Tibetan plateau considering climate and land use changes. Logistic Regression is used to produce
 1013 susceptibility maps, while future climate scenarios were taken from CMIP6 future projections. In order to create future land
 1014 use, this paper focus on PLUS, a RF-based model analysing the relationship between influencing factors and land use changes
 1015 (Liang et al., 2021). Another approach for future land use is applied by Saha et al., (2021), which focuses on modelling cultural
 1016 heritage site future multi-hazard susceptibility in the Sikkim state in India, considering different climate scenarios from CMIP5
 1017 and land use from an empirical model (Dyna-CLUE) incorporating spatial logistic regression (W. Jiang et al., 2015). Bayesian
 1018 Additive Regression Trees and Bayesian Generalised Linear models are applied to produce multi-hazard susceptibility maps,
 1019 considering extreme rainfall, landslides and earthquakes. Another dynamical model, a Cellular Automata- Markov model
 1020 (Clarke et al., 1997) is used to predict future land use changes in Iran to investigate flood risks, testing RF, XGBoost and
 1021 Gradient Boosting as algorithms for producing susceptibility maps (Janizadeh et al., 2021).

1022 **Table 4: Future related methods, gaps and opportunities.**

SECTION	METHODS	GAPS	OPPORTUNITIES
3.4.1 Predicting future hazards	<ul style="list-style-type: none"> Bias correction for projections (incl. quantile mapping); Hotspot/ trend detection via percentile thresholds (e.g., 95th–99th), return periods; Uncertainty sources and propagation; Vine copulas for joint tails; 	<ul style="list-style-type: none"> Univariate bias correction can distort extremes/joint tails; Regional skill varies; Limited direct detection of compound signals; 	<ul style="list-style-type: none"> Adopt multivariate bias correction; Combine SMILEs to separate internal variability vs. structural model differences;

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

1030

1031 This section contributes to the field of multi-hazard and multi-risk analysis by reviewing how ML and statistical methods are
1032 applied to predict future hazards and impacts, highlighting the importance of bias correction, climate ensembles, SMILEs, and
1033 storyline methods, as well as the integration of socio-economic and land use projections. It emphasizes how these approaches
1034 can improve the robustness of long-term risk scenarios, support adaptation planning, and guide strategies to address
1035 uncertainties in future multi-risk patterns.

1036 3.5 Limitations and future research directions

1037 Figure 3 summarises the distribution of ML methods across the ten research sub-topics identified in this review, providing a
1038 synthetic overview of the methodological landscape documented in the preceding sections. The figure reveals several patterns:
1039 CNNs and DL architectures dominate Earth observation processing tasks; LSTM and sequence-based models concentrate in
1040 hazard prediction, where temporal dynamics and memory effects are critical. Random Forest, ensemble methods, and simpler
1041 regression approaches prevail in risk and impact assessments and future scenario analysis, consistent with their interpretability,
1042 robustness to overfitting, and compatibility with tabular socio-environmental predictor sets. Statistical methods, including
1043 copulas and return period approaches, appear primarily in compound event characterisation. Taken together, these patterns
1044 confirm that data-driven methods have achieved meaningful penetration across the full multi-hazard risk assessment chain,
1045 with distinct methodological communities converging on appropriate tools for each sub-problem. At the same time, the figure
1046 shows that methods natively designed for multi-hazard interaction modelling, such as graph neural networks, remain marginal
1047 across all sub-topics, and no architecture yet bridges the full modelling chain in an integrated way.

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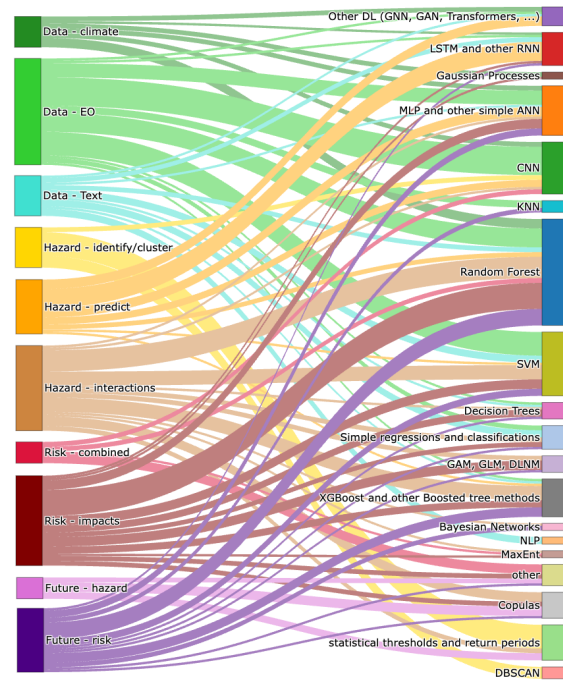


Figure 3: Main methods used for each research topic

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082 These gaps point to the limitations of the current ML applications and open research directions relevant to the operational
 083 uptake of data-driven approaches in multi-hazard risk management. A first and fundamental limitation is climate non-
 084 stationarity, as highlighted in Section 3.4 Future; ML models trained on historical hazard records implicitly assume that the
 085 statistical relationships between predictors and outcomes will remain stable into the future. As Reichstein et al. (2025) argue
 086 in the context of early warning systems, relying on past norms and training distributions will prove inappropriate under non-
 087 stationary risk conditions, where projected increases in hazard frequency and severity, combined with shifting exposure and
 088 vulnerability, create conditions that fall outside the range of any historical training set. This is particularly acute for compound
 089 and cascading events, which are by definition rare in the historical record yet are precisely the configurations that climate
 090 change is projected to intensify.

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1097 A second limitation is the gap between hazard prediction and impact prediction. Most ML applications reviewed optimise for
1098 hazard or susceptibility metrics, but impact prediction requires integrating physical hazard outputs with dynamic exposure and
1099 vulnerability data at sub-kilometre scales, a challenge that the reviewed papers largely sidestep by using static proxies. This
1100 gap between technical model performance and actionable risk information represents one of the most important unresolved
1101 challenges in translating ML-based risk assessment into operational decision-making (Tiggeloven et al., 2025, Reichstein et
1102 al., 2025).

1103 A third set of concerns relates to interpretability and trust. The black-box nature of deep learning models creates well-
1104 recognised barriers to adoption in high-stakes regulatory and emergency management contexts, where stakeholders need not
1105 only a prediction but a justification they can interrogate and contest. However, current XAI applications remain predominantly
1106 proof-of-concept and are rarely integrated into operational early warning or risk assessment workflows (Ghaffarian et al.,
1107 2023). Moreover, reproducibility and validation remain a persistent concern. In geoscientific applications, spatial
1108 autocorrelation means that random train-test splits routinely inflate apparent model skill relative to genuinely independent
1109 spatial holdouts (Sweet et al., 2023), and the reviewed literature shows limited adoption of spatially blocked cross-validation
1110 or independent regional test sets. These limitations do not invalidate the contributions reviewed here, but they do underscore
1111 the need for more rigorous validation protocols, realistic appraisal of out-of-sample performance, and explicit discussion of
1112 the conditions under which ML approaches can be expected to generalise beyond their training contexts.

1113 Another methodological gap identified by this review is the absence of end-to-end uncertainty quantification frameworks for
1114 multi-hazard risk assessment. Current practice addresses UQ in fragments: aleatory uncertainty in input data is handled at the
1115 start of the chain, epistemic uncertainty in ML models is occasionally addressed through Bayesian or ensemble methods at the
1116 hazard stage, and copula-based approaches characterise joint uncertainty for statistically correlated hazard pairs, but these
1117 efforts are rarely connected, and they do not extend to the full multi-hazard concept, which encompasses cascading and
1118 triggered hazards beyond the reach of shared statistical distributions. A genuinely integrated framework would propagate both
1119 aleatory and epistemic uncertainty continuously from input data through multi-hazard interactions, ML and statistical model
1120 outputs, and exposure and vulnerability components, to the final risk estimate (Beven et al., 2018).

1121 A further methodological consideration for future research is the development of data-driven frameworks that move beyond
1122 static representations of vulnerability and exposure. The reviewed literature overwhelmingly treats these components as fixed
1123 spatial layers, with limited engagement with their dynamic, socially differentiated, and governance-mediated dimensions.
1124 Addressing this gap will require closer integration of ML and statistical methods with approaches capable of representing how
1125 vulnerability evolves over time, including agent-based modelling, participatory data collection, and socially-informed
1126 frameworks that explicitly account for adaptive behaviour, equity, and governance processes. Progress in this direction would
1127 not only improve the realism of multi-risk assessments but also strengthen their relevance for policy and decision-making in
1128 contexts where social vulnerability is itself a driver of risk (Cannon 2017; Bankoff and Hilhorst 2022).

1129 Finally, the geographical distribution of the reviewed studies, visualised in the Sankey diagram in Appendix B, points to an
1130 imbalance that is worth acknowledging explicitly. Europe, North America and East Asia together account for more than 80%

1131 of lead authorships, while Africa and South America contribute less than 5%. This pattern partly reflects the Scopus, English-
1132 only, 2010–2024 scope of the search strategy, which may systematically underrepresent research published in other languages
1133 or in regional journals not indexed by Scopus. At the same time, the decoupling between authorship geography and case study
1134 geography, with South/SE Asia, the Middle East, and Africa appearing more frequently as study areas than as sources of
1135 authorship, suggests that data-driven methods are in several cases developed in data-rich institutional contexts and
1136 subsequently applied to regions with different risk dynamics, data availability, and governance structures (Tiggeloven et al.,
1137 2025). While drawing strong conclusions about data colonialism or algorithmic bias from a bibliometric analysis alone would
1138 go beyond the scope of this review, these patterns do raise questions that the community should engage with: whether training
1139 datasets and validation benchmarks are representative of the contexts in which models are ultimately deployed, and whether
1140 the priorities shaping methodological innovation reflect the needs of the most exposed populations. Future work in this area
1141 should pay closer attention to the transferability of data-driven multi-risk frameworks across different socio-economic and
1142 data environments (Tiggeloven et al., 2025), and collaborative initiatives fostering locally-grounded research in currently
1143 underrepresented regions would strengthen both the scientific robustness and the equity dimensions of the field (Naudé &
1144 Viluesa, 2021).

1145 4 Conclusion

1146 This paper presents a comprehensive review of data-driven applications aimed at modelling and enhancing our understanding
1147 of climate-related multi-hazard and multi-risk events. Based on the selection and in-depth analysis of 153 key papers, the
1148 review addresses four research areas: (i) data processing and collection, (ii) hazard analysis, (iii) risk analysis, and (iv) future
1149 risk scenarios, each divided in several sub-topics. The results highlights the strong connections between Earth observations
1150 processing and ML techniques like CNN; on the other hand, RF, other ensemble methods and GAM are mostly applied for
1151 risk impacts and future risk assessment, while LSTM, ANN and other DL approaches are most common for hazard prediction,
1152 reflecting a growing trend toward leveraging sophisticated AI architectures for climate and hazards applications, and a focus
1153 on simpler, more interpretable models for risk applications. Despite the current prevalence of single-hazard applications in ML
1154 research, there is growing recognition of the importance of multi-risk strategies. Notable advancements include copula-based
1155 compound event analyses and ML-driven multi-hazard susceptibility maps. Future research should prioritize a more
1156 comprehensive understanding of multi-risk interactions – such as triggering, cascading, or amplifying effects – by considering
1157 the interplay between hazard factors, vulnerability, and exposure dynamics, which are often overlooked or treated
1158 independently in current studies. DL methods, with their capacity to capture complex, non-linear interactions across spatio-
1159 temporal dimensions, offer promising avenues for progress, yet remain underexplored in operational multi-risk contexts.
1160 However, these methods require high-resolution impact data, which remains a significant challenge due to limited availability,
1161 inconsistency across regions, and issues of data quality and standardization. While EO and textual data can aid in generating
1162 new multi-risk disaster catalogues, traditional sensor-based and human-curated disaster catalogues remain essential for

Deleted: of over 1,400 studies

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1169 validation, representing a major bottleneck that constrains model validation, transferability, and ultimately the uptake of these
1170 methods in practice. By addressing these methodological and data gaps, the field can move toward more robust, interpretable,
1171 and actionable multi-risk assessments, ultimately strengthening the integration of machine learning into climate services that
1172 support adaptation, resilience, and disaster risk reduction.

1173 The gap between hazard prediction and impact prediction remains largely unresolved and bridging it will demand closer
1174 integration of data driven model outputs with dynamic representations of exposure and vulnerability, including human
1175 behaviour, adaptive responses, and the social and governance dimensions that determine how risk is distributed across
1176 communities. Explainability is a further priority: XAI methods need to move beyond their current role as exploratory tools and
1177 be embedded into operational early warning and risk assessment workflows, where their ability to illuminate driver interactions
1178 and build stakeholder trust is most consequential. End-to-end uncertainty quantification across the full modelling chain remains
1179 absent and developing integrated frameworks that propagate both aleatory and epistemic uncertainty from inputs through
1180 multi-hazard interactions to the final risk estimate is one of the most important open methodological challenges for the field.
1181 Underlying all of these challenges is the problem of non-stationarity: as climate change intensifies hazard frequency and
1182 severity, shifts exposure and vulnerability, and increases the likelihood of compound and cascading configurations that fall
1183 outside any historical training set, the assumption that past conditions are a reliable guide to future risk becomes increasingly
1184 untenable, with direct consequences for the validity of ML-based projections of multi-risk evolution.

1185 Addressing these gaps, alongside the geographic and equity imbalances documented in this review, will require not only
1186 methodological innovation but also more inclusive research practices: collaborative frameworks that bring together physical
1187 scientists, social scientists, and communities in currently underrepresented regions, co-producing knowledge that is robust,
1188 transferable, and genuinely relevant to those most exposed to the evolving risks of a changing climate.

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1191 **Appendix A: Abbreviations**

1192 **Table A1: 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
PCMCi	Peter and Clark Momentary Conditional Independence
RF	Random Forest
SHAP	Shapley Values
SVM	Support Vector Machine
XGBoost	Extreme Gradient Boosting

1193

1194 **Table A2: Other acronyms (in alphabetical order)**

Acronym	Full Name
AHP	Analytical Hierarchy Processes
CO	Carbon Monoxide
CDD	Consecutive Dry Days
CMIP	Coupled Model Intercomparison Project
DynaCLUE	Dynamic Conversion of Land Use and its Effect
EO	Earth observations
FWI	Fire Weather Index
GEV	Generalised Extreme Value (distributions)
HKH	Hindu-Kush and Himalaya (Region)
NO2	Nitrogen Dioxide
O3	Ozone
RCP	Representative Concentration Pathways
PLUS	Patch-generating Land Use Simulation
PM	Particle Matter
SO2	Sulphur dioxide
SMILE	Single Model Initial-condition Large Ensemble
SPEI	Standardised Precipitation and Evapotranspiration Index
SPI	Standardised Precipitation Index

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1197 **Appendix B: Summary tables of the collected studies**

1198 The literature review followed the PRISMA guidelines to ensure transparency and reproducibility in the identification,
 1199 screening, and selection of studies. The process is summarized in the PRISMA flow diagram and detailed as follows.
 1200 First, records were retrieved from major scientific databases (Scopus) and filtered by type, retaining only *articles, conference*
 1201 *papers, and book chapters* and language (English). Next, documents were filtered by subject area and keyword, selecting only
 1202 those classified under *Environmental Science* and *Earth and Planetary Science* as subjects and considering machine learning,
 1203 climate change, risk assessments (and their synonyms and variations) as keywords.
 1204 In the third step (title screening stage), studies not focusing on *natural hazards, multi-hazard, or risk assessment* were
 1205 excluded. During the abstract screening stage, each paper was evaluated for its relevance to the review’s research questions,
 1206 focusing particularly on the use of machine learning (ML) techniques and their application to multi-hazard or multi-risk
 1207 contexts. Studies were retained if they explicitly applied ML, AI, or statistical learning methods to the modelling,
 1208 characterization, or assessment of natural hazards, or if they addressed interactions between multiple hazard types (e.g.,
 1209 cascading or compound events) and their associated risks. Papers focusing solely on single hazards without methodological
 1210 innovation or on unrelated environmental modelling were excluded. This step ensured that the final selection captured studies
 1211 advancing methodological understanding of ML-driven hazard analysis, as well as those integrating multiple hazard processes
 1212 or risk dimensions. Finally, the full-text review identified the most relevant and representative papers, ensuring balanced
 1213 coverage across different hazard types and AI methodologies. The final selections were based on diversity in data sources,
 1214 geographical coverage, hazard types and machine learning methods used. This process ensured that the resulting corpus reflects
 1215 the breadth of current research at the intersection of AI, Earth observation, and multi-hazard risk assessment.
 1216 The number of studies retained at each step is summarized in Table B1 (numbers correspond to the four main research
 1217 questions):

1218 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

1219
 1220
 1221 Figures B1 and B2 provide an overview of the geographic characteristics of the reviewed literature and together contextualise
 1222 some of the limitations discussed in the main text. Figure B1 illustrates the geographic distribution of reviewed papers across
 1223 lead author country, all author countries, and case study region, revealing that research output is heavily concentrated in China,
 1224 the USA, and Western Europe. Figure B2 further summarises this regional imbalance: Europe and North America together
 1225 account for over 55% of lead authorships, while regions such as Africa, South/SE Asia, and South America remain substantially

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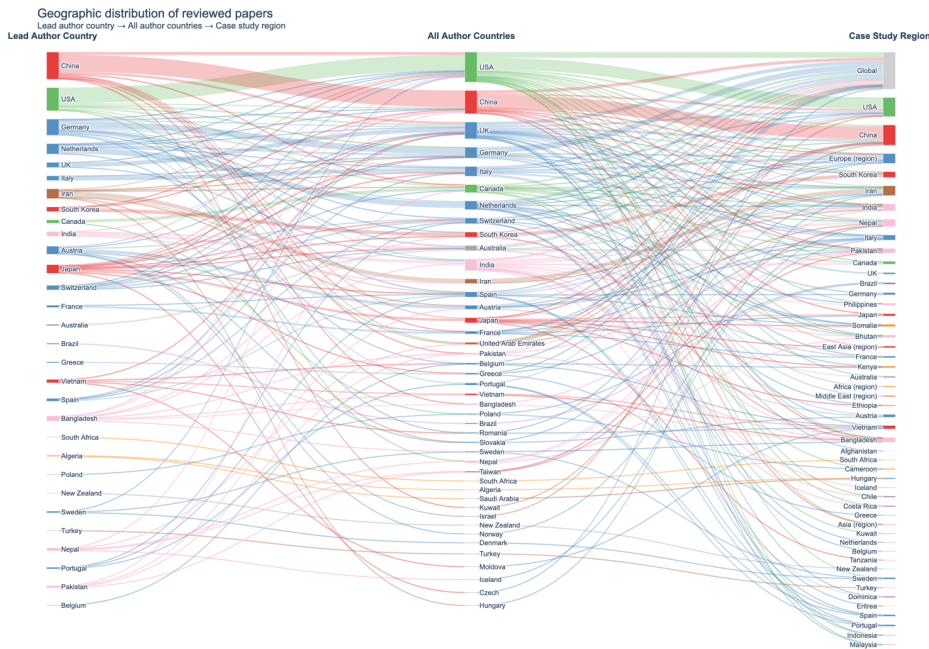
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Deleted: Figure B1 shows the distribution of ML methods across application domains: CNNs dominate EO-processing applications, reflecting their architectural suitability for gridded spatial data. Random Forest and other ensemble methods are the predominant choice for risk impact modelling and future risk assessment, consistent with their interpretability, robustness to overfitting, and compatibility with tabular socio-environmental predictor sets. LSTM and other sequence-to-sequence deep learning architectures concentrate in hazard prediction tasks where temporal dynamics and memory effects are critical. Notably, methods specifically designed for multi-hazard interaction modelling – such as graph neural networks or multi-output probabilistic models – are conspicuously absent from the reviewed literature, confirming that the methodological frontier lies in adapting or designing architectures that natively represent inter-hazard dependencies rather than applying single-hazard models independently. ¶

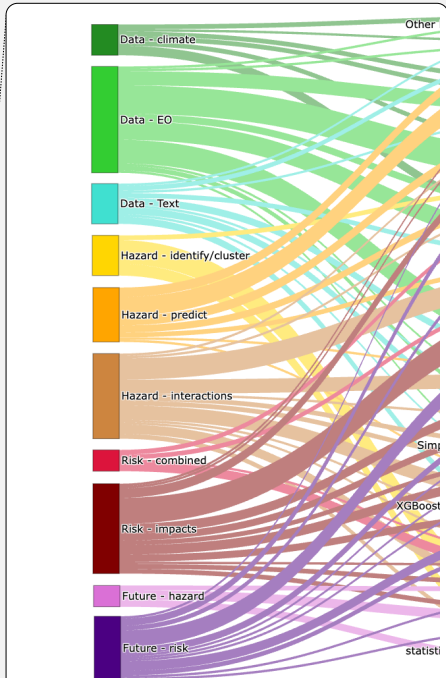
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1248 underrepresented both as producers and subjects of research. This geographic skew has direct methodological implications:
 1249 the predominance of country-level aggregated indicators, and the limited availability of sub-national spatially resolved
 1250 datasets, partly reflects the data infrastructure of the regions where most studies are conducted and may systematically
 1251 underrepresent the vulnerability dynamics of lower-income contexts where disaster impacts are most severe.



252
 253 **Figure B1: Geographic distribution of reviewed papers: Sankey diagrams between main authors countries, co-author countries and**
 254 **analysed case studies.**



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 Figure B1: Main methods used for each research topic

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

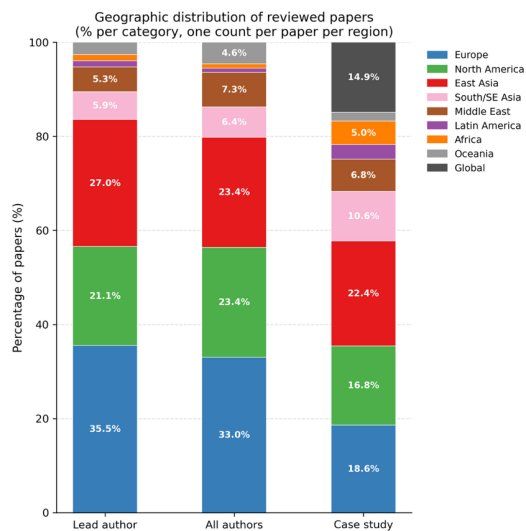


Figure B2: Summary statistics of geographic distribution of reviewed papers

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1268 **Table B2: Summary of the research questions and their keywords**

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

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1272 **Table B3: Final selection of studies for RQ1: Data**

Reference	Title	Hazards/ Main variable	ML methods
Topic 1: Data - Climate			
(Orth et al., 2022)	Global soil moisture data derived through machine learning trained with in-situ measurements	Soil moisture	LSTM
(Ghiggi et al., 2019)	GRUN: an observation-based global gridded runoff dataset from 1902 to 2014	run-off	RF
(Anderson et al., 2019)	Environmental sensor placement with convolutional Gaussian neural processes	air temperature	CONVNP
(Tazi et al., 2024)	Downscaling precipitation over High-mountain Asia using multi-fidelity Gaussian processes: improved estimates from ERA5	precipitation	GP
(He et al., 2016)	Spatial downscaling of precipitation using adaptable random forests	precipitation	RF
(Lin et al., 2023)	Deep learning downscaled high-resolution daily near surface meteorological datasets over East Asia	Air temperature, humidity, wind, radiation	CNN

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

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

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

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

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

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

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

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1276 **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			

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(Haggag et al., 2021)	A deep learning model for predicting climate-induced disasters	Multi-Hazard (flood tested)	ANN
(Kratzert, Klotz, Shalev, et al., 2019)	Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets	Floods	LSTM
(Kratzert, Klotz, Brandstetter, et al., 2019)	Using LSTMs for climate change assessment studies on droughts and floods	Floods, droughts	LSTM
(Tiggeloven et al., 2021)	Exploring deep learning capabilities for surge predictions in coastal areas	Storm Surge	LSTM, CNN, ANN
(S. Jiang, Bevacqua, et al., 2022)	River flooding mechanisms and their changes in Europe revealed by explainable machine learning	River floods, pluvial floods, snowmelt floods	LSTM
(Kraft et al., 2019)	Identifying Dynamic Memory Effects on Vegetation State Using Recurrent Neural Networks	Hot and dry events (impacts on vegetation)	LSTM
(Freeman et al., 2018)	Forecasting air quality time series using deep learning	LSTM	
(Q. Wu & Lin, 2019)	A novel optimal-hybrid model for daily air quality index prediction considering air pollutant factors	Air quality (various pollutants)	LSTM

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(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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1280 **Table B5: Final selection of studies for RQ3: Risk**

Reference	Title	Hazards/ Main variable	ML methods
Topic 1: Risk - Combining hazard, exposure and vulnerability			
(Kotaridis & Lazaridou, 2022)	Integration of convolutional neural networks for flood risk mapping in Tuscany, Italy	flood	CNN
(Zhao et al., 2020)	Urban flood susceptibility assessment based on convolutional neural networks	flood	CNN
(Rusk et al., 2022)	Multi-hazard susceptibility and exposure assessment of the Hindu Kush Himalaya	flood, landslide, wildfire	MaxEnt
(Fuchs et al., 2015)	A spatiotemporal multi-hazard exposure assessment based on property data	river flood, snow avalanche, torrential flood	Frequency ratio
(Sammonds et al., 2023)	Hurricane risk assessment in a multi-hazard context for Dominica in the Caribbean	hurricane, landslides, floods	Frequency ratio, analytical hierarchy process
(Luu et al., 2024)	Integrating multi-hazard susceptibility and building exposure: A case study for Quang Nam province, Vietnam	flood, wildfire	RF, CART
(K. Liu et al., 2018)	Susceptibility of existing and planned Chinese railway system subjected to rainfall-induced multi-hazards	flood, landslide, debris flow	RF

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

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

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

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1285 **Table B6: Final selection of studies for RQ4: future**

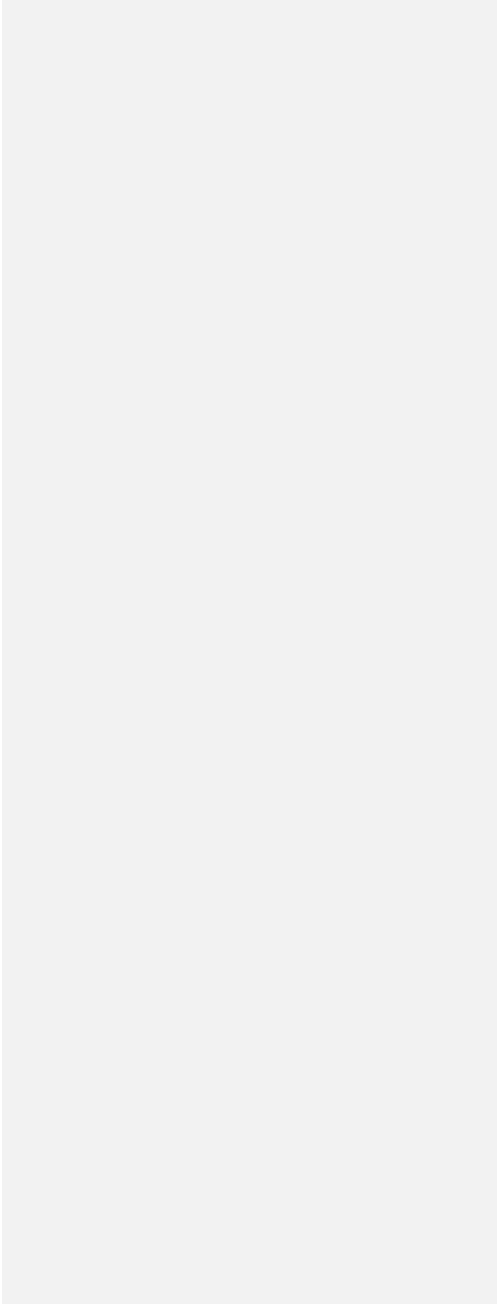
Reference	Title	Hazards/ variable	Main	ML methods
Topic 1: Future: hazard				
(Zscheischler et al., 2018)	Future climate risk from compound events	compound events		copulas, storylines
(Ridder et al., 2022)	Increased occurrence of high impact compound events under climate change	drought, heatwaves, precipitation,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

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

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

(Tabari & Willems, 2023)	Global risk assessment of compound hot-dry events in the context of future climate change and socioeconomic factors	drought, heatwaves	Copulas
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1300 **Author contribution**

1301 DMF: Conceptualisation, Methodology, Formal analysis, Investigation, Data curation, Visualisation, Writing – original draft.

1302 MS: Conceptualisation, Methodology, Validation, Writing – review and editing.

1303 MM: Conceptualisation, Data curation, Writing – review and editing.

1304 AC: Funding acquisition, Supervision, Conceptualisation, Writing – review and editing.

1305 ST: Funding acquisition, Supervision, Conceptualisation, Project administration.

1306 **Competing interest**

1307 The authors declare that they have no conflict of interest.

1308 **Financial support**

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1314 **References**

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