https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Review article: Harnessing Machine Learning methods for climate multi-hazard and multi-risk assessment

Davide Mauro Ferrario[1,2,3], Marcello Sanò[1,2,4], Margherita Maraschini[1,2], Andrea Critto[1,2], Silvia Torresan[1,2]

[1]Department of environmental sciences, informatics and statistics, Ca' Foscari University Venice, 30170, Venice, Italy
[2]CMCC Foundation, EURO Mediterranean Center on Climate change, 73100, Lecce, Italy
[3] Institute for Advanced Study IUSS Pavia, 27100, Pavia, Italy
[4]Griffith University, 4222, Gold Coast, Australia

Correspondence to: Andrea Critto (critto@unive.it)

- Davide Mauro Ferrario, davide.ferrario@cmcc.it
- Marcello Sanò, marcello.sano@unive.it
- Margherita Maraschini, margherita.maraschini@cmcc.it
- Andrea Critto, critto@unive.it
- Silvia Torresan, silvia.torresan@cmcc.it

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

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

This review explores how Machine Learning (ML) can advance multi-hazard and multi-risk, going through four main themes: data processing, hazard prediction, risk assessment, and future climate scenarios. It shows how ML is widely used for Earth observations and climate data processing, with Deep Learning applied for hazard prediction and ensemble ML methods for risks, with future research moving towards analysis of multi-hazard interactions, dynamic vulnerability and early warning systems.

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Table of Contents

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

1 Introduction

The growing interconnectedness between socio-economic and natural systems, coupled with the escalating challenges presented by climate change, has led to increased complexities in climate risk analysis. At the same time, a wider availability of data on multiple risk drivers, including weather observations, Earth observations (EO), climate reanalyses and projections, socio-economic indicators, and social media, coupled with advances in machine learning (ML) and statistical methods, are increasing the potential of data-driven methodologies, which promise to revolutionise climate risk assessment (Kashinath et al., 2021; Reichstein et al., 2019). To unlock the full potential of this data, it is crucial to develop and apply advanced methods for processing, harmonizing, and integrating heterogeneous datasets. These efforts enable the generation of actionable insights essential for effective multi-hazard and multi-risk assessments, particularly in leveraging ML and statistical techniques.
Complex dynamics characterize socio-environmental and climate risk: applications may underestimate impacts if they do not take into account the compounding, cascading and amplifying interactions of hazards and their effect on vulnerability and exposure factors. In fact, (i) compounding hazards (co-occurring in the same location and at the same time) can lead to impacts which may be substantially higher than the sum of the single events taken in isolation (Arosio et al., 2020; Zscheischler et al., 2018), (ii) the occurrence of one hazard itself can modify vulnerability or resilience of the system, exposing assets or communities to higher risks, such as in the case of consecutive hazards (de Ruiter & van Loon, 2022), and (iii) impacts and risks can propagate across multiple scales and sectors, extending far beyond the area initially hit and affecting whole systems (Arosio et al., 2021; Pescaroli & Alexander, 2018), such as in the case of high-impact and low-probability events (Linkov et al., 2022). For these reasons, the international community (Intergovernmental Panel on Climate Change (IPCC), 2023; UNDRR, 2020) has recently pledged for a paradigm shift from single hazard towards a more comprehensive understanding of multiple and interconnected climatic risks (AghaKouchak et al., 2020; De Angeli et al., 2022; Gallina et al., 2020; Šakić 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 data-driven methodologies that can analyse and predict the interactions and dependencies between multiple hazards, enabling a more accurate understanding of their compounding and cascading effects.
To better navigate the many definitions surrounding multi-risk concepts, this papers refers to the terminology used in Zschau (2017), where *multi-layer single hazards* refers to applications focussing on more than one hazards, without considering hazard interactions; *multi-hazard* analyses hazard interactions; *multi-hazard risk* refers to applications considering risks in a multi-hazard framework, without discussing interactions at vulnerability level, and finally *multi-risk* refers to the most complex analysis comprising interactions at both hazard and vulnerability level.
The complex nature of multi-hazard events presents significant challenges to existing risk assessment methodologies, which treat hazards and risks singularly and often struggle to handle the non-linear interactions and feedback loops between multiple risk drivers (Tilloy et al., 2019). However, ML techniques have recently gained traction in climate science and risk analysis due to their capacity to address process and integrate large volumes of diverse and heterogeneous data (Zennaro et al., 2021).

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

In particular, learning from past historical data, they can identify underlying non-linear risk patterns, detect correlations across multiple spatial and temporal scales (Reichstein et al., 2019).

The increased availability of large and heterogenous datasets, coming from a wide array of sources, including weather observations, Earth Observations, climate reanalyses and projections, socio-economic indicators, social media and newspapers, is driving the increased use of ML for climate risk assessment tools. Integrating these heterogeneous data sources can help in capturing multi-hazard interactions and understanding their impacts on social, economic, and natural systems, especially thanks to the introduction of new Deep Learning (DL) architectures and models, specialized in capturing both spatial and temporal non-linear interactions (S. Park et al., 2023).

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

In addition to ML, this review briefly addresses the role of copulas as multivariate statistical methods in multi-risk assessment. Copulas are functions that allow us to model and analyse the dependence structure between multiple variables, making them particularly valuable for assessing compound events where multiple hazards occur simultaneously or sequentially (see, for example, Agrawal, 2022; Hochrainer-Stigler et al., 2019). For example, copulas have been applied to model the joint occurrence of droughts and heatwaves, providing insights into their combined impact on agriculture and water resources (see e.g. Ribeiro et al., 2020). While their application is more specialized compared to ML approaches, copulas offer critical insights into the dependencies between hazards, enabling a deeper understanding of cascading and interacting risks. Their inclusion in this review underscores their importance in scenarios requiring precise statistical modelling of hazard interactions, complementing the broader use of ML in climate risk analysis. To advance this field, there is a critical need for predictive frameworks that can leverage these advanced methods to forecast long-term future multi-hazard and multi-risk scenarios, addressing uncertainties and guiding adaptive risk management strategies under changing climatic conditions.

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

This paper aims to provide a comprehensive review of data-driven methods, with a specific focus on ML approaches, for multi-hazard and multi-risk assessment, exploring ongoing applications, current limitations and future perspectives, while also addressing the use of copulas, a non-ML statistical method, to highlight its role in modelling dependencies in compound hazard

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

events. Unlike other recent reviews that have focused on ML (particularly DL) for specific hazards or sectors – such as extreme events (Salcedo-Sanz et al., 2022), hydrology (Tripathy & Mishra, 2024), geophysics (S. Yu & Ma, 2021), wildfires (Jain et al., 2020), and climate risk (Zennaro et al., 2021) – this review highlights the potential of ML for multi-risk scenarios, connecting climate risk and data-driven methods across successive steps of risk analysis.

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

2 Methodology

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

2.1 Research questions

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

1. Data: How can data-driven applications improve data collection and processing?
2. Multi-Hazard: How can data-driven applications be used to analyse extreme events, and understand hazard interactions?
3. Multi-Risk: How can data-driven applications integrate vulnerability and exposure in multi-risk analysis?
4. Future: How can data-driven applications be used to predict long-term future multi-hazard and multi-risk?

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Figure 1: Research questions and sub-themes

The first research question examines how data-driven applications can help process diverse types of data, extracting and harmonising the information needed to analyse multi-hazard and multi-risk. In particular, the sub-themes are divided based on the type of data analysed:

I. Climate data, which provides input on the hazard characteristics, both in present and future scenarios. In order to prepare this data for multi-hazard and multi-risk applications, data-driven methods are required to increase the spatial and temporal resolution, extend and harmonise the timeframe of the analysis (often paired with EO) or correct biases (Schneider et al., 2023).
II. EO, such as satellite and drone images, which can be used to characterise exposure and vulnerability layers and extract information on impacts (Ghaffarian & Emtehani, 2021; Novellino et al., 2024).
III. Textual data, such as newspapers or social media, which in the last years have been leveraged for extracting information on diverse impacts (Sodoge et al., 2023).

The second research question investigates how data-driven applications improve the identification and understanding of hazard dynamics. In particular, the key sub-themes are:

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

The third research question concerns the application of data-driven methodologies for the integration of vulnerability and exposure into multi-risk analysis. In particular, the key themes are:

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

The fourth research question investigates the possible contribution of data-driven methodologies into the analysis of (long-term) future multi-hazard and multi-risk, where uncertainty associated with the representation of future extremes in climate projections further complicates risk modelling. In particular, the key sub-themes are:

I. Modelling future multi-hazard patterns using statistical methods to understand trends, such as those related with compound events (Zscheischler et al., 2018).

II. Assessing future impacts based on climate change projections, often using methods trained on historical data and applied to ensembles of RCP projections (S. J. Park & Lee, 2020).

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

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

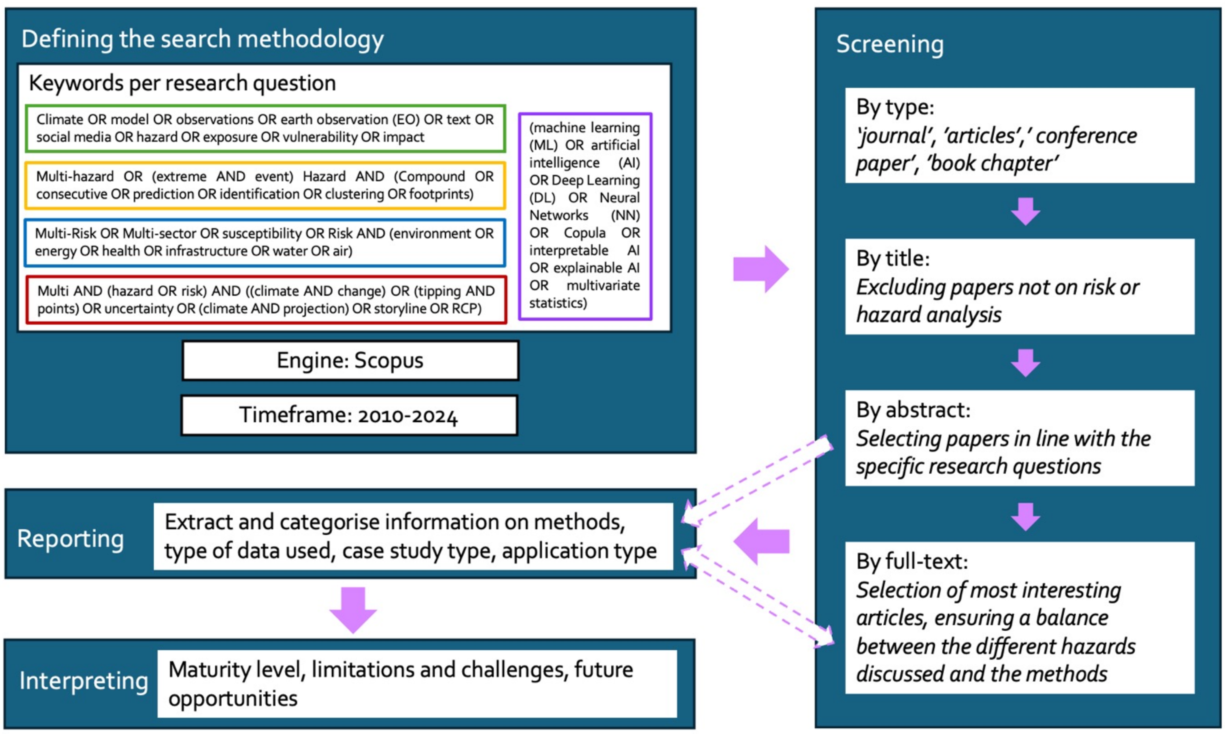

Figure 2: Literature review methodology

After collecting articles for each research question, the papers were first filtered by following typologies: *'journal articles'*, *'conference papers'*, and *'book chapters'*. Afterwards, for each research question, the papers were screened by title, then by

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

abstract, and finally by full text. The final screening selected 136 key papers to be analysed in the literature review. his information was then summarised into tables, identifying the type of applications, the type of data used, the case study and the methods used. Finally, for each research questions, the results were discussed to understand the maturity level of the applications, their limitations and possible future developments.

3 Results and discussions

3.1 Data

3.1.1 Climate datasets

The application of ML methods to produce new, complete, or high-resolution hazard datasets (either from meteorological observations, climate reanalyses or future projection) is quite established, and mainly focuses on data with sparse and irregular measurements. A typical indicator which is derived with ML methodologies is soil moisture: in-situ measurements are usually scarce and not uniformly distributed, satellite images (which will be discussed later) often presents temporal gaps and can only provide information on the first layer and struggles in complex topographies and it presents a complex dynamic that is influenced by many different drivers (similarly to multi-risk prediction) such as precipitation, temperature, evaporation, topography and land use. For example, Kang et al. (2018) and Orth (2021) investigate the complex interactions at different soil levels and temporal scales with a Long-Short Term Memory (LSTM) model that takes as inputs the topography, vegetation and atmospheric conditions and predicts each soil moisture layer in succession, using ERA-5 reanalysis as assessment endpoint. The same LSTM architecture (Entity-Aware LSTM) used in their research is modified by Kratzert et al. (2018) and by Kratzert, Klotz, Shalev, et al. (2019) to include both static and dynamic inputs allowing the algorithm to explicitly differentiate the two different types. This approach was widely applied to model the behaviour of other hydrological variables, such as snow, run-off and river catchments. Ghiggi et al. (2019) applies Random Forest (RF) regression to predict monthly runoff rates in the timeframe 1902-2020, based on antecedent precipitation and temperature from an atmospheric reanalysis, validating the results with in-situ streamflow observations. Other research focuses on different variables and in particular investigate the irregular distribution of sensors: Andersson et al. (2023), for example, applies Convolutional Neural Processes (ConvNPs), a probabilistic ML model, to suggest informative sensor placements by finding sites that maximally reduce prediction uncertainty, testing it for air temperature anomalies measurements in Antarctica. Typical ML and DL models, such as Convolutional Neural Networks (CNN) often struggle at this task because they require regularly distributed data, while Gaussian Processes (GP) or Bayesian probabilistic models present many challenges when modelling non-stationary multi-dimensional datasets and do not scale well to large datasets. ConvNP use neural networks to parameterise a joint Gaussian distribution at target locations, allowing them to scale linearly with dataset size while learning mean and covariance functions directly from the data and have been applied to the modelling of other environmental variables, such as the downscaling of

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

precipitation. DeepSensor[1], a specific GitHub python package, was developed to facilitate the application of Neural Processes in environmental sciences, especially for downscaling, interpolation, sensor placement and data imputation. Amato et al. (2020) introduces a multi-step methodology to interpolate irregularly distributed spatio-temporal timeseries, first decomposing the signal and then learning stochastic spatial coefficients which can be spatially modelled and mapped on a regular grid with Artificial Neural Networks (ANN), allowing the reconstruction of the complete spatio-temporal signal.

ML methods have been applied also to climate reanalyses and models. Early applications, such as He et al. (2016), tested RF regression to statistically downscale spatially precipitation data, using few covariates and demonstrating how this approach is able to catch the non-linear relations between variables, minimising overfitting and collinearity issues between predictors. However, the algorithm struggled with skewed datasets and even the final model, which is the combination of two different RF models, trained respectively on high-precipitation and low-precipitation values, fails to detect the complex spatial and temporal complexity of precipitation data, overestimating the intensity and spatial distribution of low precipitation and underestimating high precipitation. Other applications are focussing on Deep Learning models: CNNs are used to downscale many variables from future climate models (among which, air temperature, precipitation, 10-m wind speed, 2-m relative humidity, downward shortwave radiation) (Lin et al., 2023). Generative models particularly Generative Adversarial Networks (GAN) and diffusion models, are widely used for this task. GANs consist of two neural networks – a generator and a discriminator - that are trained simultaneously in a competitive process. The generator attempts to create realistic fake data that can fool the discriminator, while the discriminator works to distinguish between real and fake data. For example, specific GANs based on Convolutional Neural Networks (CNNs) have been applied to post-process weather forecast outputs. These models can enhance the resolution of precipitation data by a factor of ten, producing more realistic and spatially coherent forecasts compared to the original input data (Harris et al., 2022). Diffusion models, on the other hand, learn to reverse a noise process: first the model adds sequentially noise to input data, then the model learns how to predict the noise at each step, and once trained, it can start with noisy data and work backwards, progressively removing the noise to generate a new, realistic dataset. Diffusion models are related to variational inference, where the forward process defines a probabilistic trajectory from data to noise, and the reverse process defines a generative path from noise back to data. Unlike other generative models like GANs, which learn through a "discriminative" process (trying to fool a discriminator network), diffusion models learn through this smooth diffusion and denoising process (Yeğin & Amasyalı, 2024). For example, diffusion models are applied to downscale multiple climate models, also providing information on the uncertainty downscaling, by generating a large number of ensemble members based on probability distribution sampling (Ling et al., 2024). Probabilistic ML methods, such as GP methods (Multi-fidelity Gaussian Processes with a 5/2 Matern kernel) are also used to downscale precipitation data from ERA-5 over high mountain terrain (Tazi et al., 2024). DL approaches are often used to downscale low-resolution future models to Convection Permitting (CP) climate models, where the main advantage of these techniques is their reduced computational costs compared to the development of a CP climate models (Bretherton et al., 2022; Clark et al., 2022). The role of Artificial

[1] https://github.com/alan-turing-institute/deepsensor

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Intelligence (AI) in climate predictions is discussed in Schneider et al. (2023). This study advocates for the development of global models at 10–50 km resolution, harnessing AI and EO for the calibration and development of higher-resolution regional simulations.

3.1.2 Earth observations

EO combined with ML have revolutionized the characterization of multi-hazard and multi-risk events, enhancing our ability to assess and respond to climate-related threats. The interest in leveraging remote sensing for this purpose has grown significantly, as evidenced by new initiatives from ESA and NOAA's Centre for AI, where particular attention is devoted to the use of EO to discovery of impacts in remote areas (such as in the Arctic region or over oceans) and the development of early warning systems.

Remote sensing images are used to improve climate datasets, for example increasing the spatial coverage in areas with sparse measurements or providing real data to bias-correct/downscale modelled data, with multiple AI methods, ranging from Support Vector Machine (SVM) (Ahmad et al., 2010; Jing et al., 2016a), Ridge Regression (Kang et al., 2018), RF (Han et al., 2023; Jing et al., 2016b) and LSTM (Fang et al., 2017) applied for developing soil moisture datasets. Remote sensing plays a crucial role in hazard dataset development by helping mitigate bias that may be inherited by ML-based risk models. These models are often trained on datasets calibrated with data from resource-rich regions, where the majority of weather stations are located. As a result, they may struggle to generalize effectively to underdeveloped areas, which are frequently the most vulnerable to extreme events (McGovern et al., 2019, 2022).

ML techniques are instrumental in assessing exposure, with many consolidated applications focussing on land use and land cover, with classical ML algorithms such as K-Nearest Neighbour (KNN), SVM, ANN and RF (Adam et al., 2014; Yuh et al., 2023; Zerrouki et al., 2019). The analysis of images follows typically three steps: first a pre-processing step, in which the different satellite images are merged and orthorectified; a segmentation step, in which common pixels are grouped together; and a classification or clustering step, to classify the elements of the image. Specific applications focus on vegetation, such as for identifying and mapping tree species (Miyoshi et al., 2020; Schiefer et al., 2020; Veras et al., 2022). Others focus on urban areas, analysing on socio-economic indicators, such as deprivation pockets, which are identified via UNET-based CNNs from RGB images and tracked during the recovery process (J. Wang et al., 2019), to derive proxy indicators for poverty from satellite night lights, in combination with transfer learning (S. J. Pan & Yang, 2010), to overcome scarcity of labelled data (Jean et al., 2016), or to track disaster recovery in urban deprived areas (Ghaffarian & Emtehani, 2021).

Another important aspect of the use EO in multi-risk is the detection of impacts on socio-economic assets, similarly to the methods also applied on longer timeframes to detect land use changes (Q. Wang et al., 2018). The general methodology consists in comparing images of the same location before and after the hazard, to identify changes that can convey information on damages following the occurrence of disaster (T. Bai et al., 2023). Many applications focus on identifying and estimating damages, mainly on buildings and infrastructures: Sublime & Kalinicheva (2019) applies Autoencoders and K-means algorithms to detect image changes after Tohoku earthquake and tsunami. In the same area, an SVM classifier is tested by Ji et al. (2018) and a CNN architecture is applied by Y. Bai et al. (2018). CNNs are particular popular, with many applications focussing on the identification of landslides events (Lei et al., 2019), wildfire footprints (Bo et al., 2022; Tran et al., 2020) or flooded areas (Munawar et al., 2021). The main challenges encountered in these applications are due to the return periods of satellites, which may limit their ability to detect fast changing impacts, the presence of clouds, which can hamper visibility especially during the occurrence of extreme events likely to cause damages, and to changes in luminosity or season, which may cause false positives (Faiza et al., 2012).

The application of ML methods in conjunction with EO is also playing a major role in the retrieval of impacts on indicators for environmental quality, with many literature reviews available on the topic, highlighting the potential of DL approaches (Sagan et al., 2020; Sit et al., 2020). Applications aimed at retrieving environmental and water quality parameters mainly showcase simpler models, such as short neural networks and SVM (Nazeer et al., 2017), Decision Trees (DT), RF, Cubist Regression and Extreme Gradient Boosting (XGBoost), due to their ease of implementation and the scarcity of ground measurement data (J. Liu et al., 2023). They usually focus on optically parameters, such as chlorophyll-a, turbidity and suspended solids, even if other applications, such as S. Chen et al. (2022) tested the application of RF, ANN and SVM for the estimation of nutrients and other non-optical parameters, for which other meteorological and hydrological variables (such as pH, and water temperature) are often included as input parameters of the models.

3.1.3 Textual data

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

transport etc.) by using different Supervised ML models (Naïve Bayes, Lasso Regression, RF, ANN). In general, rule-based methods are preferred to ML models when the number of samples is limited (X. Liu et al., 2018).

3.1 Multi-hazard

3.2.1 Identify, classify and cluster

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

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

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

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

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

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

3.2.2 Hazard forecasting and prediction

Before delving into more risk-based applications, it is worth noting that in the last few years, the application of DL models such as Transformers (Vaswani et al., 2017), Graph Neural Networks (GNN) (Veličković et al., 2017) and Physics Informed

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Neural Networks (Kashinath et al., 2021; Lütjens et al., 2021) has prompted a revolution in weather forecasting. Early applications of AI models, primarily using RF and SVM, were largely aimed at replacing specific steps within numerical weather forecasts. More recently, DL tools have gained prominence due to their ability to capture long-range dependencies, handle complex and irregular data structures and integrate the solutions of equations of physical systems into a unified framework, enabling DL to be successfully employed for modelling the whole medium range weather forecasting process (Bi et al., 2022; Chen et al., 2023; Keisler, 2022).

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

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

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

for river flood prediction, outperforming other RNNs in terms of computational costs and performances, also increasing the interpretability of the model (Castangia et al., 2023).

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

3.2.2 Modelling hazard interactions

Some applications are using interpretable ML frameworks to analyse the role played by each factor in hazard prediction. For example, S. Jiang, Bevacqua, et al. (2022) and S. Jiang, Zheng, et al. (2022) train a LSTM to study river flooding in Europe and combined Expected Gradients (EG) (Erion et al., 2021) to calculate feature importance scores and additive decomposition (AD) (Du et al., 2019) to evaluate the behaviour of internal nodes in the LSTM to characterise flooding drivers such as snow melting and precipitation. By running the model for different decades, they are able to identify flooding drivers changes in the last 70 years in Europe, with an increase of precipitation-cause flooding. Several applications mentioned in the previous chapter are also using methods to increase the interpretability of the DL models, even if the main focus is the prediction of the hazard; examples are gradient-based methods such as Integrated Gradients (IG), applied to a GNN (A. Y. Sun et al., 2021), visualising CNN heatmaps (Patil et al., 2023) or attention maps (Castangia et al., 2023), sensitivity analysis (Bentivoglio et al., 2023; Bonino et al., 2024; Kratzert, Klotz, Shalev, et al., 2019) and permutation/tree based feature importance (Freeman et al., 2018).

Copulas

Most of the previous analyses are focused mainly on univariate methods to identify single hazard anomalies. Extending such analyses to cover joint extremes in multi-dimensional datasets can be a challenging task but offers more insights in compound events dynamics (for example, when multiple rivers high discharges are combined with precipitation and high sea levels on the coast). Copulas are methods intended for investigating joint probabilities of extreme events (Joe, 2014), considering the interdependence of the tails of the distributions of relevant variables. Copulas are the preferred statistical framework when dealing with joint extremes: mathematically, copulas are multivariate probability distributions with uniform marginal distributions designed to model the dependence between multiple variables (Hao & Singh, 2016; Nelsen, 2006). Compared to other multivariate models, copulas describe the joint distribution of variables separately from their marginal distributions, allowing for a more flexible and comprehensive approach (Tilloy et al., 2019).

These applications usually follow five steps (Ming et al., 2022): (i) fitting the marginal distribution of each variable; (ii) testing multivariate independency, to understand whether a Copula function is needed to generate the joint distribution; (iii)

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

constructing the copulas, identifying the type and family of distributions; (iv) performing goodness-of-fit tests for copulas; (v) selecting the best copula to generate the joint distribution function.

Once the copula is defined, its parameters need to be estimated from data. Using a copula which does not capture adequately the dependence between two variables can lead to either underestimation or overestimation of the joint probability of these two variables (Mazas & Hamm, 2017). Usually, without prior knowledge on the studied hazards, several copulas are fitted to the data and compared (Sadegh et al., 2017). Different types of copulas exist, depending on their generator functions or the type of distributions associated to the marginal distributions. The simplest type of copulas are normal or Gaussian copulas, which assume that all the marginal distributions of the variables are standard normal. Their simplicity and ease of implementation make them popular, but they are not very flexible since they do not allow to model differently tail distributions from multiple variables. Student's t copulas, mixture copulas and Archimedean copulas, in particular Clayton, Gumbel, Frank and Joe copulas (Alhadlaq & Alzaid, 2020) are often used to model positive and negative dependencies and heavy-tail dependencies commonly associated to multi-risk (Bevacqua et al., 2021). Challenges may arise when building higher dimensional copulas (Aas et al., 2009): while the number of bivariate copulas is very large, the set of copulas in more than 3 dimensions is rather limited and lack the required flexibility to model multivariate distributions with different tail dependencies and distributions (Joe, 2014). Pair copulas allow to decompose an n-dimensional copula into the products of pair copulas, giving the opportunity to independently select distributions from the larger set of bivariate copulas, providing a higher flexibility (Bevacqua et al., 2017). Thus, complexities linked to the extension of copulas to large number of hazards limit their applicability to compound events.

Multiple concurrent or consecutive compound river and coastal hazards are analysed with Joe copulas (Joe, 2014), studying water level and river discharge extremes (Sadegh et al., 2018). Copula-based Bayesian Networks are applied to model flood and river hazards in a coastal location in Texas (Couasnon et al., 2018) and drought/floods combinations (Sadegh et al., 2017). Pair copulas are used to estimate the risk of compound flooding in Italy, with a 5-dimensional conditional model, considering the dependencies between meteorological predictors (precipitation on land and at sea) and water levels measured at two rivers gauges and one in the sea (Bevacqua et al., 2017). The role of meteorological predictors also allow to extend the analysis to past periods, where the water levels measurements were not directly available, and could in principle be extended to future risk analysis using climate projections, even if in this context the uncertainties of future climate projections may steer the adoption of other approaches, such as combining hydrodynamic models with storylines, to explore low-likelihood, high-impact future events, with a shift from probability to plausibility of the events (Bevacqua et al., 2021).

Susceptibility mapping

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

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

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

using a Random Forest model and are used to enhance the analysis of the multi-hazard maps. It is interesting to note 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 the 14 layers of predicting variables, producing an independent output pixel by pixel.

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

3.3 Multi-risk

3.3.1 Modelling risk combining susceptibility, exposure and vulnerability

Many studies are found to focus on modelling risk by combining hazard maps produced via susceptibility mapping with ML and vulnerability and exposure layers. Single hazards such as wildfires, floods and landslides are the often considered, and buildings, population and infrastructures are the most common assets. For example, Kotaridis & Lazaridou (2022) consider flooding risk in Tuscany and applied a 2D CNN to produce an urban flooding susceptibility map. Differently from Ullah et al. (2022) the CNN applied here makes use of the spatial context of each pixel, considering a 5x5 patch centred on a specific pixel (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 5x5x9 size, where the last number corresponds to the different predictors of the susceptibility mapping that are considered as channels in the CNN architecture. Thus, not only the selection of the initial samples, but also the selection of the size of the patch is a key hyperparameter to be considered: in this case, a cross validation is used to choose the best patch size. The vulnerability maps are created dividing the land use into 5 classes, which are then multiplied with the hazard layer to calculate the final risk map. Convolutional Neural Networks (CNNs) offer significant advantages over traditional algorithms in spatial

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

analysis due to their ability to process areas as 2D maps. This enables the model to leverage Max Pooling layers to capture and simplify the spatial context of events. Unlike models that focus on individual point characteristics, CNNs can better understand and integrate the broader spatial relationships. For example, Zhao et al. (2020) test CNN for urban flood susceptibility too but instead of producing separate maps for hazard and vulnerability, anthropogenic factors were used as predictors for the susceptibility map. The study compares the performances of different ML models: a simple (with 1 convolutional layer) CNN architecture, LeNet5 (Lecun et al., 1998), a slightly deeper CNN (with 2 convolutional layers), SVM and RF models. Different input strategies are tested: a point based strategy that only considers input at a given site; a partial spatial strategy that considers the surrounding pixels, flattening the 2D image to a 1D vector, thus loosing partially the spatial context, but allowing the neighbouring pixels to be fed to SVM and RF models as additional predictors; a patch strategy, similar to the one described before for the CNN models, which granted the best performances. This study also discusses the use of Deep CNNs, which is discouraged since the typical sample size and model is too small to tune the high number of parameters required by Deep CNNs.

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

landslides and earthquake as hazards, and 25 indicators at the county level and Khatakho et al. (2021), focussing on population exposed to flooding, earthquakes and wildfires near Kathmandu (Nepal).

Compared to the publications focussing only on the multi-hazard aspect, the applications that also consider exposure and vulnerability do not test multiple ML algorithms, often rely on expert-based judgments or simple frequency analysis. Moreover, while these applications focus on multiple hazards, the analysis of vulnerability factors is often overlooked: in most cases, only exposure layers are used to produce risk maps. Even when vulnerability is explicitly considered, it is calculated only for single hazards and as a static parameter. Recent publications, such as de Ruiter & van Loon, (2022) highlight the importance of considering dynamic vulnerability factors, especially in multi-hazard and multi-risk contexts, where vulnerability can vary because of the changes cause on the system caused by the occurrence of the hazards of extreme events, or because of specific adaptation and responses. Even if the use of EO can help to inform the models of changes in the system (such as land cover changes due to wildfires and landslides, or new urbanisation patterns after reconstructions), these indicators are not yet integrated in multi-risk mappings.

3.3.2 Modelling risk predicting impacts

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

Health

Studies focussing on environmental-health risks often analyse the combination of heat and air quality stressors and use excess mortality as predicant variable. These applications aim at disentangling complex temporal patterns, consisting of a long-term trend, driven by multiple (and often unknown) factors, and short-term peaks, mainly driven by summer heatwaves; moreover, time-lags needs to be considered. Thus, statistical methods, such as Distributed Lag non-linear models have been widely applied (Gasparrini, 2014) to model exposure lag-response of mortality to environmental stressors. More recently, RF has been applied, analysing the role of humidity in urban mortality during heatwaves at the global scale (Guo et al., 2024) or predicting heat-stroke occurrence in China (Y. Wang et al., 2019), while SVM is applied for analysing previous diseases, population

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

density and urbanisation (X. Wang et al., 2021). One of the most interesting papers, Boudreault et al., (2023) test 9 different ML, DL and statistical methods (such as Generalised Additive Models – GAMs) in the Metropolitan City of Montreal, considering weekly all-cause mortality as predictand and air temperature, humidity, wind, Particle Matter (PM) 2.5, Ozone (O3), Nitrogen Dioxide (NO2), Sulphur Dioxide (SO2), Carbon Monoxide (CO) as predictors. Among the methods tested, Tree based methods (RF, XGBoost) usually perform better overall, while statistical methods (and GAM in particular) are more accurate in predicting the mortality peaks; Deep Learning approaches, such as MLP and LSTM have instead the worst performances. This is partially explained by the limited size of the dataset and the inclusion of non-climate causes in the predictand, likely to cause overfitting in the DL models. Another study also focussing on Canada proposes an AI-based framework to extrapolate vulnerability from health-heat relationship: Côté et al. (2024) test this approach considering two steps: first, a model to predict daily mortality from mean temperature for 3 days, age, income and period of the year as predictors and then a second model predicting annual mortality over aggregated areas with specific socio-economic and environmental (air quality, vegetation, …) characteristics. The model tested are AutoGluon (an automatic ML framework allowing to train and test ML models without expert knowledge[2]), GP and Deep Gaussian Process (Deep GP). The results shows that GP are able to model better the daily mortality trends, especially during extreme temperature, while AutoGluon is 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 better handle noise and small data samples (J. Wang, 2023), and their limit is their computational costs (M. Jiang et al., 2022); on the other hand, the more complex Deep GP handed the worst outcomes, highlighting the challenges in tuning more complex Deep GPs (Tazi et al., 2023). Other studies focus on predicting the influence of water quality parameters, such as turbidity, on the risk of cholera disease outbreaks in Indian Coastal municipalities using a RF predictor (Campbell et al., 2020).

Food security and crops

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

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

[2] https://auto.gluon.ai/stable/index.html

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

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

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

Environmental quality and biodiversity

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Economic losses and physical damages

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

3.4 Future

3.4.1 Predicting future hazards

Several studies focus on data-driven applications to predict long-term future multi-hazard and multi-risk scenarios. Zscheischler et al. (2018) discuss the importance of compound events for future risk assessment and presents several approaches and discusses the main challenges related to the use of future climate projections and weather simulations to analyse future compound events. The role of bias correction and its connection to multi-hazard events and impact models is analysed: future projections are often bias corrected to align the distribution of the modelled variables to the distribution of the observed ones, in the reference timeframe. However, some issues can arise: the simplest approaches focus on adjusting the averages of the variables and do not correct the tails of the distributions, thus modifying the behaviour of extreme events. Methods such

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

as quantile mapping, are needed to align the historical and future datasets before the application of any statistical or ML methods. Sensitivity analysis can be performed to understand how the model reacts to changes in inputs, to understand the robustness of future scenarios (Kim et al., 2023). Moreover, bias corrections are often univariate, and do not consider the effects on joint tail distributions and consequently impact models based on these inputs are affected; multivariate bias correction models are then encouraged (Sippel et al., 2016).

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

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

3.4.2 Modelling future impacts

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

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

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

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

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

4 Conclusion

This paper presents a comprehensive review of data-driven applications aimed at modelling and enhancing our understanding of climate-related multi-hazard and multi-risk events. Based on the selection of over 1,400 studies and an in-depth analysis of 136 key papers, the review addresses four research areas: (i) data processing and collection, (ii) hazard analysis, (iii) risk analysis, and (iv) future risk scenarios, each divided in several sub-topics. Figure 3 summarises the main methods used in each research question, illustrating the different approaches for each sub-topic. In particular, the figure highlights the strong

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

connections between Earth observations processing and ML techniques like CNN; on the other hand, RF, other ensemble methods and GAM are mostly applied for risk impacts and future risk assessment, while LSTM, ANN and other DL approaches are most common for hazard prediction, reflecting a growing trend toward leveraging sophisticated AI architectures for climate and hazards applications, and a focus on simpler, more interpretable models for risk applications.

Despite the current prevalence of single-hazard applications in ML research, there is growing recognition of the importance of multi-risk strategies. Notable advancements include copula-based compound event analyses and ML-driven multi-hazard susceptibility maps. Future research should prioritize a more comprehensive understanding of multi-risk interactions – such as triggering, cascading, or amplifying effects – by considering the interplay between hazard factors, vulnerability, and exposure dynamics. DL methods, with their capacity to capture complex, non-linear interactions across spatio-temporal dimensions, offer promising avenues for progress. However, these methods require high-resolution impact data, which remains a significant challenge. While EO and textual data can aid in generating new multi-risk disaster catalogues, traditional sensor-based and human-curated disaster catalogues remain essential for validation, representing a major bottleneck for advancing this research.

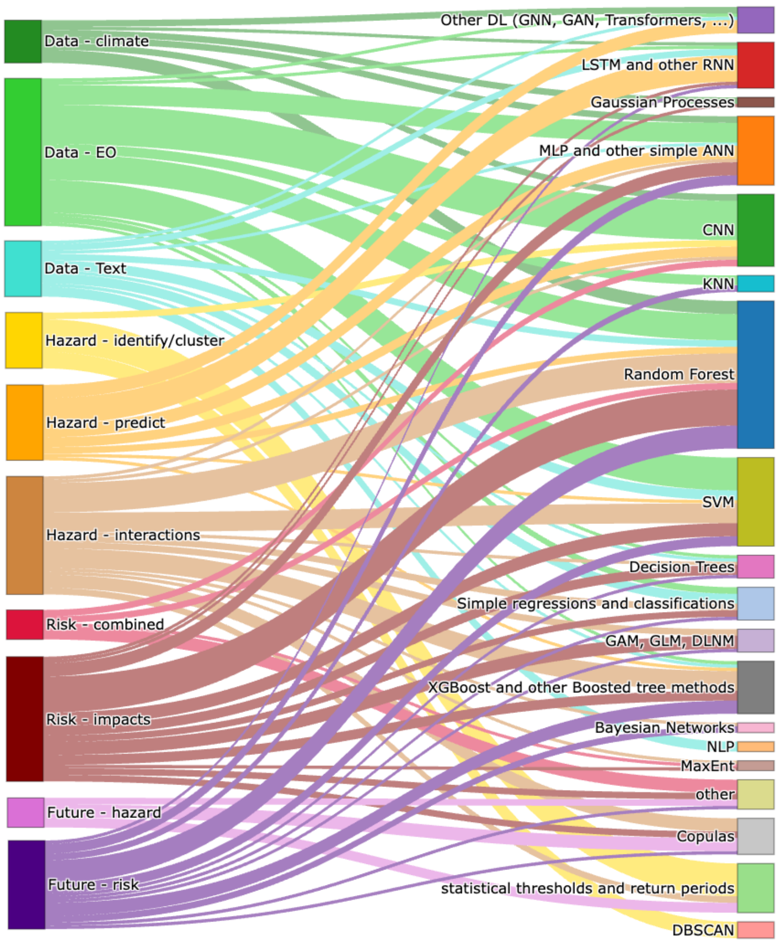

Figure 3: Main methods used for each research topic

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

Appendix A: Abbreviations

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

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

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

Appendix B: Summary tables of the collected studies

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Table B1: 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 understand 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	

Table B2: Final selection of studies for RQ1: Data

Reference	Year	Title	Hazards/ Main variable	ML methods

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Ling et al., 2024)	2024	Diffusion model-based probabilistic downscaling for 180-year East Asian climate reconstruction	atmospheric variables	Diffusion probabilistic models
(Bretherton et al., 2022)	2022	Correcting Coarse-Grid Weather and Climate Models by Machine Learning From Global Storm-Resolving Simulations	atmospheric variables	RF, ANN
(Clark et al., 2022)	2022	Correcting a 200 km Resolution Climate Model in Multiple Climates by Machine Learning From 25 km Resolution Simulations	atmospheric variables	RF, ANN
Topic 2: Data - Earth observations				
(Ahmad et al., 2010)	2010	Estimating soil moisture using remote sensing data: A machine learning approach	soil moisture	SVM, ANN, Linear regression
(Kang et al., 2018)	2018	Spatial Upscaling of Sparse Soil Moisture Observations Based on Ridge Regression	soil moisture	Ridge Regression
(Han et al., 2023)	2023	Global long term daily 1 km surface soil moisture dataset with physics informed machine learning	soil moisture	RF
(Jing et al., 2016a)	2016	A Comparison of Different Regression Algorithms for Downscaling Monthly Satellite-Based Precipitation over North China	precipitation	CART, KNN, RF, SVM

(Jing et al., 2016b)	2016	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)	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)	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)	2023	Application of machine learning approaches for land cover monitoring in northern Cameroon	LULC monitoring	RF, SVM, KNN, ANN
(Zerrouki et al., 2019)	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)	2020	A Novel Deep Learning Method to Identify Single Tree Species in UAV-Based Hyperspectral Images	Tree species mapping	CNN
(Schiefer et al., 2020)	2020	Mapping forest tree species in high resolution UAV-based RGB-imagery by means of convolutional neural networks	Tree species mapping	CNN

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Veras et al., 2022)	2020	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)	2019	Deprivation pockets through the lens of convolutional neural networks	Identify deprived urban areas	CNN
(Jean et al., 2016)	2016	Combining satellite imagery and machine learning to predict poverty	Track households' consumption and assets via nightlights	CNN
(Ghaffarian & Emtehani, 2021)	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)	2017	Evaluation of Empirical and Machine Learning Algorithms for Estimation of Coastal Water Quality Parameters	Water quality	ANN
(J. Liu et al., 2023)	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)	2022	Machine learning-based estimation of riverine nutrient concentrations and associated uncertainties caused by sampling frequencies	Water Quality (River Nutrients)	SVM, RF, ANN
(Q. Wang et al., 2018)	2018	Change detection based on Faster R-CNN for high-resolution remote sensing images	Change detection	CNN

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Sublime & Kalinicheva, 2019)	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)	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)	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)	2019	End-to-end Change Detection Using a Symmetric Fully Convolutional Network for Landslide Mapping	Change detection (landslide mapping)	CNN
(Bo et al., 2022)	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)	2020	Damage-Map Estimation Using UAV Images and Deep Learning Algorithms for Disaster Management System	Change detection (wildfire mapping)	CNN
(Munawar et al., 2021)	2021	UAVs in Disaster Management: Application of Integrated Aerial Imagery and Convolutional Neural Network for Flood Detection	Change detection (flood mapping)	CNN

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Topic 3: Data - Texts				
(Asinthara et al., 2022)	2022	Classification of Disaster Tweets using Machine Learning and Deep Learning Techniques	Classifying disaster tweets	SVM, Naïve Bayes
(Powers et al., 2023)	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)	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)	2021	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)	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

Table B3: Final selection of studies for RQ2: Hazard

Reference	Year	Title	Hazards/ Main variable	ML methods

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Topic 1: Hazard – identify, classify, cluster				
(Ionita et al., 2021)	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)	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)	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)	2021	Growing Threats From Unprecedented Sequential Flood-Hot Extremes Across China	consecutive flood - heatwave	Return periods
(Sfetsos et al., 2023)	2021	Multi-Hazard Extreme Scenario Quantification Using Intensity, Duration, and Return Period Characteristics	Heatwave, coldwave, precipitation, snowfall, wind extremes	Return periods
(Orth et al., 2022)	2022	Contrasting biophysical and societal impacts of hydro-meteorological extremes	Heatwave, Drought, Floods, Wildfire	Return periods, percentiles
(Y. Liu et al., 2016)	2016	Application of Deep Convolutional Neural Networks for Detecting Extreme Weather in Climate Datasets	Extreme weather (Tropical cyclones, atmospheric rivers, weather fronts)	CNN

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Racah et al., 2016)	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)	2023	A Generalized Density-Based Algorithm for the Spatiotemporal Tracking of Drought Events	Drought	DBSCAN, Percentile based thresholds
(J. Wang & Yan, 2021)	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)	2018	Spatiotemporal extended fuzzy C-means clustering algorithm for hotspots detection and prediction	earthquakes	DBSCAN
(Tilloy et al., 2022)	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)	2022	Hotspots, co-occurrence, and shifts of compound and cascading extreme climate events in Eurasian drylands	Drought, heatwave, coldwave, precipitation, wind	DBSCAN, Percentile based thresholds
Topic 2: Hazard - Predict				
(Haggag et al., 2021)	2021	A deep learning model for predicting climate-induced disasters	Multi-Hazard (flood tested)	ANN

(Kratzert, Klotz, Shalev, et al., 2019)	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)	2019	Using LSTMs for climate change assessment studies on droughts and floods	Floods, droughts	LSTM
(Tiggeloven et al., 2021)	2021	Exploring deep learning capabilities for surge predictions in coastal areas	Storm Surge	LSTM, CNN, ANN
(S. Jiang, Bevacqua, et al., 2022)	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)	2019	Identifying Dynamic Memory Effects on Vegetation State Using Recurrent Neural Networks	Hot and dry events (impacts on vegetation)	LSTM
(Freeman et al., 2018)	2018	Forecasting air quality time series using deep learning	Air quality (ozone)	LSTM
(Q. Wu & Lin, 2019)	2019	A novel optimal-hybrid model for daily air quality index prediction considering air pollutant factors	Air quality (various pollutants)	LSTM
(Chang-Hoi et al., 2021)	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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Bentivoglio et al., 2023)	2023	Rapid spatio-temporal flood modelling via hydraulics-based graph neural networks	Floods	GNN
(Kazadi et al., 2024)	2024	FloodGNN-GRU: a spatio-temporal graph neural network for flood prediction	Floods	GNN-GRU
(A. Y. Sun et al., 2021)	2021	Explore Spatio-Temporal Learning of Large Sample Hydrology Using Graph Neural Networks	Floods	GNN
(Castangia et al., 2023)	2023	Transformer neural networks for interpretable flood forecasting	Floods	Transformers
(Bonino et al., 2024)	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)	2023	Predicting extreme floods and droughts in East Africa using a deep learning approach	drought	CNN
(Singh et al., 2021)	2021	Drought risk assessment and prediction using artificial intelligence over the southern Maharashtra state of India	drought	ANN
(Ayyad et al., 2022)	2022	Machine learning-based assessment of storm surge in the New York metropolitan area	storm surge	RF, XGBoost, Extra Trees, SVM
Topic 3: Hazard - Interactions				

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Couasnon et al., 2018)	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)	2017	Multivariate Copula Analysis Toolbox (MvCAT): Describing dependence and underlying uncertainty using a Bayesian framework	droughts, floods	Copulas
(Bevacqua et al., 2017b)	2017	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)	2021	Guidelines for Studying Diverse Types of Compound Weather and Climate Events	compound flooding, precipitation/landslide	Copulas, regressions, percentile thresholds, clustering
(Cao et al., 2020)	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)	2021	Evaluation of multi-hazard map produced using MaxEnt machine learning technique	flood, landslide, gully erosion	MaxEnt
(Karakas et al., 2023)	2023	A Hybrid Multi-Hazard Susceptibility Assessment Model for a Basin in Elazig Province, Türkiye	Landslide, Flood, Earthquake	RF

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Kariminejad et al., 2022)	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
(Nguyen et al., 2023)	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)	2020	Assessing and mapping multi-hazard risk susceptibility using a machine learning technique	Flood, landslide, wildfire	RF
(Pouyan et al., 2021)	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)	2020	A machine learning framework for multi-hazards modeling and mapping in a mountainous area	avalanche, landslide, wldfire, subsidence, flood	SVM, BRT, GLM, FDA
(Piao et al., 2022)	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)	2022	Multi-hazard susceptibility mapping based on Convolutional Neural Networks	flash flood, debris flow, landslide	CNN, RF

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Mandal et al., 2022)	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

Table B4: Final selection of studies for RQ3: Risk

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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Luu et al., 2024)	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)	2018	Susceptibility of existing and planned Chinese railway system subjected to rainfall-induced multi-hazards	flood, landslide, debris flow	RF
(Arvin et al., 2023)	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)	2021	Multi-Hazard Risk Assessment of Kathmandu Valley, Nepal	flood, earthquake, wildfire	analytical hierarchy process
Topic 2: Risk – Predicting impacts				
(Gasparrini, 2014)	2014	Modeling exposure–lag–response associations with distributed lag non-linear models	heatwave, air pollution	Distributed Lag Non-Linear Models
(Guo et al., 2024)	2024	Regional variation in the role of humidity on city-level heat-related mortality	heatwave, humidity	RF
(Y. Wang et al., 2019)	2019	A random forest model to predict heatstroke occurrence for heatwave in China	heatwave, humidity	RF
(X. Wang et al., 2021)	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)	2023	Machine and deep learning for modelling heat-health relationships	heatwave, air pollution	DT, RF, GBM, SLP, MLP, LSTM,

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

				GLM, GAM, DLNM
(Côté et al., 2024)	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)	2024	Predicting Food-Security Crises in the Horn of Africa Using Machine Learning	Heatwaves, droughts, precipitation, conflict	XGB
(Tárraga et al., 2024)	2024	Causal discovery reveals complex patterns of drought-induced displacement	drought, precipitation, conflict	Granger Causality, PCMCI
(Zscheischler et al., 2017)	2017	Bivariate return periods of temperature and precipitation explain a large fraction of European crop yields	drought, heatwave, precipitation	Copulas
(Ribeiro et al., 2020)	2020	Risk of crop failure due to compound dry and hot extremes estimated with nested copulas	drought, heatwave	Copulas
(R. Wang et al., 2021)	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)	2022	Interpretable tree-based ensemble model for predicting beach water quality	water quality	DT, RF, CatBoost, GBM, XGBoost
(Cushman et al., 2017)	2017	Multiple-scale prediction of forest loss risk across Borneo	forest loss	RF, logistic regression

(Islam et al., 2021)	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)	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)	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)	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	ANN, SVM, RF, linear regression
(Pilkington & Mahmoud, 2017)	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)	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

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Carannante et al., 2024)	2024	Machine learning-based climate risk sharing for an insured loan in the tourism industry	wind, precipitation, heatwave	RF

865

Table B5: Final selection of studies for RQ4: future

Reference	Year	Title	Hazards/ Main variable	ML methods
Topic 1: Future: hazard				
(Zscheischler et al., 2018)	2018	Future climate risk from compound events	compound events	copulas, storylines
(Ridder et al., 2022)	2022	Increased occurrence of high impact compound events under climate change	drought, heatwaves, precipitation, wind	percentile threshold, return period
(Zhu et al., 2023)	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)	2021	Do CMIP6 Climate Models Simulate Global or Regional Compound Events Skillfully?	wind, precipitation	percentile threshold, return period
(Ghanbari et al., 2021)	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)	2023	Increasing Risks of Future Compound Climate Extremes with Warming Over Global Land Masses	drought, heatwave, precipitation	copulas

(H. Wu et al., 2024)	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)	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)	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)	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)	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)	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)	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)	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)	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)	2023	Increased flood susceptibility in the Tibetan Plateau with climate and land use changes	flood	logistic regression
(Liang et al., 2021)	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)	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)	2021	Mapping the spatial and temporal variability of flood hazard affected by climate and land-use changes in the future	flood	GBM, XGB

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

(Leng & Hall, 2020)	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)	2024	Association of precipitation extremes and crops production and projecting future extremes using machine learning approaches with CMIP6 data	precipitation, drought, heatwave	GBM, XGB
(Tabari & Willems, 2023)	2023	Global risk assessment of compound hot-dry events in the context of future climate change and socioeconomic factors	drought, heatwaves	Copulas

870

Author contribution

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

Competing interest

The authors declare that they have no conflict of interest.

Financial support

The research was carried out within the frame of *Myriad_EU project* (https://www.myriadproject.eu/), which has received fundings from the European Union's Horizon 2020 research and innovation programme call H2020-LC-CLA-2018-2019-2020 under grant agreement number 101003276.

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

References

Aas, K., Czado, C., Frigessi, A., & Bakken, H. (2009). Pair-copula constructions of multiple dependence. *Insurance: Mathematics and Economics*, *44*(2), 182–198. https://doi.org/10.1016/j.insmatheco.2007.02.001

Abu El-Magd, S. A., Ali, S. A., & Pham, Q. B. (2021). Spatial modeling and susceptibility zonation of landslides using random forest, naïve bayes and K-nearest neighbor in a complicated terrain. *Earth Science Informatics*, *14*(3), 1227–1243. https://doi.org/10.1007/s12145-021-00653-y

Adam, E., Mutanga, O., Odindi, J., & Abdel-Rahman, E. M. (2014). Land-use/cover classification in a heterogeneous coastal landscape using RapidEye imagery: evaluating the performance of random forest and support vector machines classifiers. *International Journal of Remote Sensing*, *35*(10), 3440–3458. https://doi.org/10.1080/01431161.2014.903435

AghaKouchak, A., Chiang, F., Huning, L. S., Love, C. A., Mallakpour, I., Mazdiyasni, O., Moftakhari, H., Papalexiou, S. M., Ragno, E., & Sadegh, M. (2020). Climate Extremes and Compound Hazards in a Warming World. *Annual Review of Earth and Planetary Sciences*, *48*(1), 519–548. https://doi.org/10.1146/annurev-earth-071719-055228

Agrawal, S. (UCLA). (2022). *The Effectiveness of Copulas for Modeling Compound Climate Extreme Events in Boulder County, Colorado.* [UCLA]. https://doi.org/ProQuest ID: Agrawal_ucla_0031N_21275. Merritt ID: ark:/13030/m59m1m6w.

Ahmad, S., Kalra, A., & Stephen, H. (2010). Estimating soil moisture using remote sensing data: A machine learning approach. *Advances in Water Resources*, *33*(1), 69–80. https://doi.org/10.1016/j.advwatres.2009.10.008

Ahmadlou, M., Al-Fugara, A., Al-Shabeeb, A. R., Arora, A., Al-Adamat, R., Pham, Q. B., Al-Ansari, N., Linh, N. T. T., & Sajedi, H. (2021). Flood susceptibility mapping and assessment using a novel deep learning model combining multilayer perceptron and autoencoder neural networks. *Journal of Flood Risk Management*, *14*(1). https://doi.org/10.1111/jfr3.12683

Alhadlaq, W., & Alzaid, A. (2020). Distribution Function, Probability Generating Function and Archimedean Generator. *Symmetry*, *12*(12), 2108. https://doi.org/10.3390/sym12122108

Amato, F., Guignard, F., Robert, S., & Kanevski, M. (2020). A novel framework for spatio-temporal prediction of environmental data using deep learning. *Scientific Reports*, *10*(1), 22243. https://doi.org/10.1038/s41598-020-79148-7

Andersson, T. R., Bruinsma, W. P., Markou, S., Requeima, J., Coca-Castro, A., Vaughan, A., Ellis, A.-L., Lazzara, M. A., Jones, D., Hosking, S., & Turner, R. E. (2023). Environmental sensor placement with convolutional Gaussian neural processes. *Environmental Data Science*, *2*, e32. https://doi.org/10.1017/eds.2023.22

Angelov, D. (2020). *Top2Vec: Distributed Representations of Topics*. http://arxiv.org/abs/2008.09470

Arosio, M., Cesarini, L., & Martina, M. L. V. (2021). Assessment of the Disaster Resilience of Complex Systems: The Case of the Flood Resilience of a Densely Populated City. *Water*, *13*(20), 2830. https://doi.org/10.3390/w13202830

Arosio, M., Martina, M. L. V., & Figueiredo, R. (2020). The whole is greater than the sum of its parts: a holistic graph-based assessment approach for natural hazard risk of complex systems. *Natural Hazards and Earth System Sciences*, *20*(2), 521–547. https://doi.org/10.5194/nhess-20-521-2020

Arvin, M., Beiki, P., Hejazi, S. J., Sharifi, A., & Atashafrooz, N. (2023). Assessment of infrastructure resilience in multi-hazard regions: A case study of Khuzestan Province. *International Journal of Disaster Risk Reduction*, *88*, 103601. https://doi.org/10.1016/j.ijdrr.2023.103601

Asinthara, K., Jayan, M., & Jacob, L. (2022). Classification of Disaster Tweets using Machine Learning and Deep Learning Techniques. *2022 International Conference on Trends in Quantum Computing and Emerging Business Technologies (TQCEBT)*, 1–5. https://doi.org/10.1109/TQCEBT54229.2022.10041629

Ayyad, M., Hajj, M. R., & Marsooli, R. (2022). Machine learning-based assessment of storm surge in the New York metropolitan area. *Scientific Reports*, *12*(1), 19215. https://doi.org/10.1038/s41598-022-23627-6

Ayyad, M., Hajj, M. R., & Marsooli, R. (2023). Climate change impact on hurricane storm surge hazards in New York/New Jersey Coastlines using machine-learning. *Npj Climate and Atmospheric Science*, *6*(1), 88. https://doi.org/10.1038/s41612-023-00420-4

Bai, T., Wang, L., Yin, D., Sun, K., Chen, Y., Li, W., & Li, D. (2023). Deep learning for change detection in remote sensing: a review. *Geo-Spatial Information Science*, *26*(3), 262–288. https://doi.org/10.1080/10095020.2022.2085633

Bai, Y., Mas, E., & Koshimura, S. (2018). Towards Operational Satellite-Based Damage-Mapping Using U-Net Convolutional Network: A Case Study of 2011 Tohoku Earthquake-Tsunami. *Remote Sensing*, *10*(10), 1626. https://doi.org/10.3390/rs10101626

Bentivoglio, R., Isufi, E., Jonkman, S. N., & Taormina, R. (2023). Rapid spatio-temporal flood modelling via hydraulics-based graph neural networks. *Hydrology and Earth System Sciences*, *27*(23), 4227–4246. https://doi.org/10.5194/hess-27-4227-2023

Bevacqua, E., De Michele, C., Manning, C., Couasnon, A., Ribeiro, A. F. S., Ramos, A. M., Vignotto, E., Bastos, A., Blesić, S., Durante, F., Hillier, J., Oliveira, S. C., Pinto, J. G., Ragno, E., Rivoire, P., Saunders, K., Wiel, K., Wu, W., Zhang, T., & Zscheischler, J. (2021). Guidelines for Studying Diverse Types of Compound Weather and Climate Events. *Earth's Future*, *9*(11). https://doi.org/10.1029/2021EF002340

Bevacqua, E., Maraun, D., Hobæk Haff, I., Widmann, M., & Vrac, M. (2017). Multivariate statistical modelling of compound events via pair-copula constructions: analysis of floods in Ravenna (Italy). *Hydrology and Earth System Sciences*, *21*(6), 2701–2723. https://doi.org/10.5194/hess-21-2701-2017

Bevacqua, E., Suarez-Gutierrez, L., Jézéquel, A., Lehner, F., Vrac, M., Yiou, P., & Zscheischler, J. (2023). Advancing research on compound weather and climate events via large ensemble model simulations. *Nature Communications*, *14*(1), 2145. https://doi.org/10.1038/s41467-023-37847-5

Bhowmik, R. T., Jung, Y. S., Aguilera, J. A., Prunicki, M., & Nadeau, K. (2023). A multi-modal wildfire prediction and early-warning system based on a novel machine learning framework. *Journal of Environmental Management*, *341*, 117908. https://doi.org/10.1016/j.jenvman.2023.117908

Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2022). *Pangu-Weather: A 3D High-Resolution Model for Fast and Accurate Global Weather Forecast*. http://arxiv.org/abs/2211.02556

Bo, W., Liu, J., Fan, X., Tjahjadi, T., Ye, Q., & Fu, L. (2022). BASNet: Burned Area Segmentation Network for Real-Time Detection of Damage Maps in Remote Sensing Images. *IEEE Transactions on Geoscience and Remote Sensing*, *60*, 1–13. https://doi.org/10.1109/TGRS.2022.3197647

Bonino, G., Galimberti, G., Masina, S., McAdam, R., & Clementi, E. (2024). Machine learning methods to predict sea surface temperature and marine heatwave occurrence: a case study of the Mediterranean Sea. *Ocean Science*, *20*(2), 417–432. https://doi.org/10.5194/os-20-417-2024

Bordbar, M., Aghamohammadi, H., Pourghasemi, H. R., & Azizi, Z. (2022). Multi-hazard spatial modeling via ensembles of machine learning and meta-heuristic techniques. *Scientific Reports*, *12*(1), 1451. https://doi.org/10.1038/s41598-022-05364-y

Boudreault, J., Campagna, C., & Chebana, F. (2023). Machine and deep learning for modelling heat-health relationships. *Science of The Total Environment*, *892*, 164660. https://doi.org/10.1016/j.scitotenv.2023.164660

Bretherton, C. S., Henn, B., Kwa, A., Brenowitz, N. D., Watt-Meyer, O., McGibbon, J., Perkins, W. A., Clark, S. K., & Harris, L. (2022). Correcting Coarse-Grid Weather and Climate Models by Machine Learning From Global Storm-Resolving Simulations. *Journal of Advances in Modeling Earth Systems*, *14*(2). https://doi.org/10.1029/2021MS002794

Busker, T., van den Hurk, B., de Moel, H., van den Homberg, M., van Straaten, C., Odongo, R. A., & Aerts, J. C. J. H. (2024). Predicting Food-Security Crises in the Horn of Africa Using Machine Learning. *Earth's Future*, *12*(8). https://doi.org/10.1029/2023EF004211

Cammalleri, C., & Toreti, A. (2023). A Generalized Density-Based Algorithm for the Spatiotemporal Tracking of Drought Events. *Journal of Hydrometeorology*, *24*(3), 537–548. https://doi.org/10.1175/JHM-D-22-0115.1

Campbell, A. M., Racault, M.-F., Goult, S., & Laurenson, A. (2020). Cholera Risk: A Machine Learning Approach Applied to Essential Climate Variables. *International Journal of Environmental Research and Public Health*, *17*(24), 9378. https://doi.org/10.3390/ijerph17249378

Cao, J., Zhang, Z., Du, J., Zhang, L., Song, Y., & Sun, G. (2020). Multi-geohazards susceptibility mapping based on machine learning—a case study in Jiuzhaigou, China. *Natural Hazards*, *102*(3), 851–871. https://doi.org/10.1007/s11069-020-03927-8

Carannante, M., D'amato, V., Fersini, P., & Forte, S. (2024). Machine learning-based climate risk sharing for an insured loan in the tourism industry. *Quality & Quantity*. https://doi.org/10.1007/s11135-024-01958-y

Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine Learning Interpretability: A Survey on Methods and Metrics. *Electronics*, *8*(8), 832. https://doi.org/10.3390/electronics8080832

Castangia, M., Grajales, L. M. M., Aliberti, A., Rossi, C., Macii, A., Macii, E., & Patti, E. (2023). Transformer neural networks for interpretable flood forecasting. *Environmental Modelling & Software*, *160*, 105581. https://doi.org/10.1016/j.envsoft.2022.105581

Chang-Hoi, H., Park, I., Oh, H.-R., Gim, H.-J., Hur, S.-K., Kim, J., & Choi, D.-R. (2021). Development of a PM2.5 prediction model using a recurrent neural network algorithm for the Seoul metropolitan area, Republic of Korea. *Atmospheric Environment*, *245*, 118021. https://doi.org/10.1016/j.atmosenv.2020.118021

Chen, K., Han, T., Gong, J., Bai, L., Ling, F., Luo, J.-J., Chen, X., Ma, L., Zhang, T., Su, R., Ci, Y., Li, B., Yang, X., & Ouyang, W. (2023). *FengWu: Pushing the Skillful Global Medium-range Weather Forecast beyond 10 Days Lead*. http://arxiv.org/abs/2304.02948

Chen, S., Zhang, Z., Lin, J., & Huang, J. (2022). Machine learning-based estimation of riverine nutrient concentrations and associated uncertainties caused by sampling frequencies. *PLOS ONE*, *17*(7), e0271458. https://doi.org/10.1371/journal.pone.0271458

Claassen, J. N., Koks, E. E., de Ruiter, M. C., Ward, P. J., & Jäger, W. S. (2024). VineCopulas: an open-source Python package for vine copula modelling. *Journal of Open Source Software*, *9*(101), 6728. https://doi.org/10.21105/joss.06728

Claassen, J. N., Ward, P. J., Daniell, J., Koks, E. E., Tiggeloven, T., & de Ruiter, M. C. (2023). A new method to compile global multi-hazard event sets. *Scientific Reports*, *13*(1), 13808. https://doi.org/10.1038/s41598-023-40400-5

Clark, S. K., Brenowitz, N. D., Henn, B., Kwa, A., McGibbon, J., Perkins, W. A., Watt-Meyer, O., Bretherton, C. S., & Harris, L. M. (2022). Correcting a 200 km Resolution Climate Model in Multiple Climates by Machine Learning From 25 km Resolution Simulations. *Journal of Advances in Modeling Earth Systems*, *14*(9). https://doi.org/10.1029/2022MS003219

Clarke, K. C., Hoppen, S., & Gaydos, L. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B: Planning and Design*, *24*(2), 247–261. https://doi.org/10.1068/b240247

Côté, J.-N., Germain, M., Levac, E., & Lavigne, E. (2024). Vulnerability assessment of heat waves within a risk framework using artificial intelligence. *Science of The Total Environment*, *912*, 169355. https://doi.org/10.1016/j.scitotenv.2023.169355

Couasnon, A., Sebastian, A., & Morales-Nápoles, O. (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. *Water*, *10*(9), 1190. https://doi.org/10.3390/w10091190

Cushman, S. A., Macdonald, E. A., Landguth, E. L., Malhi, Y., & Macdonald, D. W. (2017). Multiple-scale prediction of forest loss risk across Borneo. *Landscape Ecology*, *32*(8), 1581–1598. https://doi.org/10.1007/s10980-017-0520-0

Dal Barco, M. K., Maraschini, M., Ferrario, D. M., Nguyen, N. D., Torresan, S., Vascon, S., & Critto, A. (2024). A machine learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy). *International Journal of Disaster Risk Reduction*, *108*, 104526. https://doi.org/10.1016/j.ijdrr.2024.104526

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

De Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., & Rudari, R. (2022). A multi-hazard framework for spatial-temporal impact analysis. *International Journal of Disaster Risk Reduction*, *73*, 102829. https://doi.org/10.1016/j.ijdrr.2022.102829

de Ruiter, M. C., & van Loon, A. F. (2022). The challenges of dynamic vulnerability and how to assess it. *IScience*, *25*(8), 104720. https://doi.org/10.1016/j.isci.2022.104720

Di Martino, F., Pedrycz, W., & Sessa, S. (2018). Spatiotemporal extended fuzzy C-means clustering algorithm for hotspots detection and prediction. *Fuzzy Sets and Systems*, *340*, 109–126. https://doi.org/10.1016/j.fss.2017.11.011

Du, M., Liu, N., Yang, F., Ji, S., & Hu, X. (2019). On Attribution of Recurrent Neural Network Predictions via Additive Decomposition. *The World Wide Web Conference*, 383–393. https://doi.org/10.1145/3308558.3313545

Erion, G., Janizek, J. D., Sturmfels, P., Lundberg, S. M., & Lee, S.-I. (2021). Improving performance of deep learning models with axiomatic attribution priors and expected gradients. *Nature Machine Intelligence*, *3*(7), 620–631. https://doi.org/10.1038/s42256-021-00343-w

Ester, M., Kriegel, H.-P., Sander, J., & Xu, X. (1996). A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise. *KDD-96 Proceedings*.

Faiza, B., Yuhaniz, S. S., Hashim, S. Z. M., & AbdulRahman, K. K. (2012). A Review and Analysis of Image Misalignment Problem in Remote Sensing. *International Journal of Scientific and Engineering Research*, *3*(3), 82–86.

Fang, K., Shen, C., Kifer, D., & Yang, X. (2017). Prolongation of SMAP to Spatiotemporally Seamless Coverage of Continental U.S. Using a Deep Learning Neural Network. *Geophysical Research Letters*, *44*(21). https://doi.org/10.1002/2017GL075619

Freeman, B. S., Taylor, G., Gharabaghi, B., & Thé, J. (2018). Forecasting air quality time series using deep learning. *Journal of the Air & Waste Management Association*, *68*(8), 866–886. https://doi.org/10.1080/10962247.2018.1459956

Fuchs, S., Keiler, M., & Zischg, A. (2015). A spatiotemporal multi-hazard exposure assessment based on property data. *Natural Hazards and Earth System Sciences*, *15*(9), 2127–2142. https://doi.org/10.5194/nhess-15-2127-2015

Gallina, V., Torresan, S., Zabeo, A., Critto, A., Glade, T., & Marcomini, A. (2020). A multi-risk methodology for the assessment of climate change impacts in coastal zones. *Sustainability (Switzerland)*, *12*(9). https://doi.org/10.3390/su12093697

García-León, D., Masselot, P., Mistry, M. N., Gasparrini, A., Motta, C., Feyen, L., & Ciscar, J.-C. (2024). Temperature-related mortality burden and projected change in 1368 European regions: a modelling study. *The Lancet Public Health*, *9*(9), e644–e653. https://doi.org/10.1016/S2468-2667(24)00179-8

Gasparrini, A. (2014). Modeling exposure–lag–response associations with distributed lag non-linear models. *Statistics in Medicine*, *33*(5), 881–899. https://doi.org/10.1002/sim.5963

Genkin, A., Lewis, D. D., & Madigan, D. (2007). Large-Scale Bayesian Logistic Regression for Text Categorization. *Technometrics*, *49*(3), 291–304. https://doi.org/10.1198/004017007000000245

Ghaffarian, S., & Emtehani, S. (2021). Monitoring Urban Deprived Areas with Remote Sensing and Machine Learning in Case of Disaster Recovery. *Climate*, *9*(4), 58. https://doi.org/10.3390/cli9040058

Ghaffarian, S., Taghikhah, F. R., & Maier, H. R. (2023). Explainable artificial intelligence in disaster risk management: Achievements and prospective futures. *International Journal of Disaster Risk Reduction*, *98*, 104123. https://doi.org/10.1016/j.ijdrr.2023.104123

Ghanbari, M., Arabi, M., Kao, S., Obeysekera, J., & Sweet, W. (2021). Climate Change and Changes in Compound Coastal-Riverine Flooding Hazard Along the U.S. Coasts. *Earth's Future*, *9*(5). https://doi.org/10.1029/2021EF002055

Ghiggi, G., Humphrey, V., Seneviratne, S. I., & Gudmundsson, L. (2019). GRUN: an observation-based global gridded runoff dataset from 1902 to 2014. *Earth System Science Data*, *11*(4), 1655–1674. https://doi.org/10.5194/essd-11-1655-2019

Guo, Q., Mistry, M. N., Zhou, X., Zhao, G., Kino, K., Wen, B., Yoshimura, K., Satoh, Y., Cvijanovic, I., Kim, Y., Ng, C. F. S., Vicedo-Cabrera, A. M., Armstrong, B., Urban, A., Katsouyanni, K., Masselot, P., Tong, S., Sera, F., Huber, V., … Honda, Y. (2024). Regional variation in the role of humidity on city-level heat-related mortality. *PNAS Nexus*, *3*(8). https://doi.org/10.1093/pnasnexus/pgae290

Haggag, M., Siam, A. S., El-Dakhakhni, W., Coulibaly, P., & Hassini, E. (2021). A deep learning model for predicting climate-induced disasters. *Natural Hazards*, *107*(1), 1009–1034. https://doi.org/10.1007/s11069-021-04620-0

Han, Q., Zeng, Y., Zhang, L., Wang, C., Prikaziuk, E., Niu, Z., & Su, B. (2023). Global long term daily 1 km surface soil moisture dataset with physics informed machine learning. *Scientific Data*, *10*(1), 101. https://doi.org/10.1038/s41597-023-02011-7

Hao, Z., & Singh, V. P. (2016). Review of dependence modeling in hydrology and water resources. *Progress in Physical Geography: Earth and Environment*, *40*(4), 549–578. https://doi.org/10.1177/0309133316632460

Harris, L., McRae, A. T. T., Chantry, M., Dueben, P. D., & Palmer, T. N. (2022). A Generative Deep Learning Approach to Stochastic Downscaling of Precipitation Forecasts. *Journal of Advances in Modeling Earth Systems*, *14*(10). https://doi.org/10.1029/2022MS003120

Hawkins, E., & Sutton, R. (2009). The Potential to Narrow Uncertainty in Regional Climate Predictions. *Bulletin of the American Meteorological Society*, *90*(8), 1095–1108. https://doi.org/10.1175/2009BAMS2607.1

He, X., Chaney, N. W., Schleiss, M., & Sheffield, J. (2016). Spatial downscaling of precipitation using adaptable random forests. *Water Resources Research*, *52*(10), 8217–8237. https://doi.org/10.1002/2016WR019034

Hoch, J. M., de Bruin, S. P., Buhaug, H., Von Uexkull, N., van Beek, R., & Wanders, N. (2021). Projecting armed conflict risk in Africa towards 2050 along the SSP-RCP scenarios: a machine learning approach. *Environmental Research Letters*, *16*(12), 124068. https://doi.org/10.1088/1748-9326/ac3db2

Hochrainer-Stigler, S., Balkovič, J., Silm, K., & Timonina-Farkas, A. (2019). Large scale extreme risk assessment using copulas: an application to drought events under climate change for Austria. *Computational Management Science*, *16*(4), 651–669. https://doi.org/10.1007/s10287-018-0339-4

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Ionita, M., Caldarescu, D. E., & Nagavciuc, V. (2021). Compound Hot and Dry Events in Europe: Variability and Large-Scale Drivers. *Frontiers in Climate*, *3*. https://doi.org/10.3389/fclim.2021.688991

Islam, A. R. Md. T., Talukdar, S., Mahato, S., Ziaul, S., Eibek, K. U., Akhter, S., Pham, Q. B., Mohammadi, B., Karimi, F., & Linh, N. T. T. (2021). Machine learning algorithm-based risk assessment of riparian wetlands in Padma River Basin of Northwest Bangladesh. *Environmental Science and Pollution Research*, *28*(26), 34450–34471. https://doi.org/10.1007/s11356-021-12806-z

Jain, P., Coogan, S. C. P., Subramanian, S. G., Crowley, M., Taylor, S., & Flannigan, M. D. (2020). *A review of machine learning applications in wildfire science and management*. https://doi.org/10.1139/er-2020-0019

Janizadeh, S., Chandra Pal, S., Saha, A., Chowdhuri, I., Ahmadi, K., Mirzaei, S., Mosavi, A. H., & Tiefenbacher, J. P. (2021). Mapping the spatial and temporal variability of flood hazard affected by climate and land-use changes in the future. *Journal of Environmental Management*, *298*, 113551. https://doi.org/10.1016/j.jenvman.2021.113551

Javidan, N., Kavian, A., Pourghasemi, H. R., Conoscenti, C., Jafarian, Z., & Rodrigo-Comino, J. (2021). Evaluation of multi-hazard map produced using MaxEnt machine learning technique. *Scientific Reports*, *11*(1), 6496. https://doi.org/10.1038/s41598-021-85862-7

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science*, *353*(6301), 790–794. https://doi.org/10.1126/science.aaf7894

Ji, Y., Sri Sumantyo, J., Chua, M., & Waqar, M. (2018). Earthquake/Tsunami Damage Assessment for Urban Areas Using Post-Event PolSAR Data. *Remote Sensing*, *10*(7), 1088. https://doi.org/10.3390/rs10071088

Jiang, L., Li, C., Wang, S., & Zhang, L. (2016). Deep feature weighting for naive Bayes and its application to text classification. *Engineering Applications of Artificial Intelligence*, *52*, 26–39. https://doi.org/10.1016/j.engappai.2016.02.002

Jiang, M., Pedrielli, G., & Ng, S. H. (2022). Gaussian Processes for High-Dimensional, Large Data Sets: A Review. *2022 Winter Simulation Conference (WSC)*, 49–60. https://doi.org/10.1109/WSC57314.2022.10015416

Jiang, S., Bevacqua, E., & Zscheischler, J. (2022). River flooding mechanisms and their changes in Europe revealed by explainable machine learning. *Hydrology and Earth System Sciences*, *26*(24), 6339–6359. https://doi.org/10.5194/hess-26-6339-2022

Jiang, S., Sweet, L., Blougouras, G., Brenning, A., Li, W., Reichstein, M., Denzler, J., Shangguan, W., Yu, G., Huang, F., & Zscheischler, J. (2024). How Interpretable Machine Learning Can Benefit Process Understanding in the Geosciences. *Earth's Future*, *12*(7). https://doi.org/10.1029/2024EF004540

Jiang, S., Zheng, Y., Wang, C., & Babovic, V. (2022). Uncovering Flooding Mechanisms Across the Contiguous United States Through Interpretive Deep Learning on Representative Catchments. *Water Resources Research*, *58*(1). https://doi.org/10.1029/2021WR030185

Jiang, W., Chen, Z., Lei, X., Jia, K., & Wu, Y. (2015). Simulating urban land use change by incorporating an autologistic regression model into a CLUE-S model. *Journal of Geographical Sciences*, *25*(7), 836–850. https://doi.org/10.1007/s11442-015-1205-8

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Jing, W., Yang, Y., Yue, X., & Zhao, X. (2016a). A Comparison of Different Regression Algorithms for Downscaling Monthly Satellite-Based Precipitation over North China. *Remote Sensing*, *8*(10), 835. https://doi.org/10.3390/rs8100835

Jing, W., Yang, Y., Yue, X., & Zhao, X. (2016b). A Spatial Downscaling Algorithm for Satellite-Based Precipitation over the Tibetan Plateau Based on NDVI, DEM, and Land Surface Temperature. *Remote Sensing*, *8*(8), 655. https://doi.org/10.3390/rs8080655

Joe, H. (2014). *Dependence Modeling with Copulas*. Chapman and Hall/CRC. https://doi.org/10.1201/b17116

Kang, J., Jin, R., Li, X., Zhang, Y., & Zhu, Z. (2018). Spatial Upscaling of Sparse Soil Moisture Observations Based on Ridge Regression. *Remote Sensing*, *10*(2), 192. https://doi.org/10.3390/rs10020192

Karakas, G., Kocaman, S., & Gokceoglu, C. (2023). A Hybrid Multi-Hazard Susceptibility Assessment Model for a Basin in Elazig Province, Türkiye. *International Journal of Disaster Risk Science*, *14*(2), 326–341. https://doi.org/10.1007/s13753-023-00477-y

Kariminejad, N., Pourghasemi, H. R., & Hosseinalizadeh, M. (2022). Analytical techniques for mapping multi-hazard with geo-environmental modeling approaches and UAV images. *Scientific Reports*, *12*(1), 14946. https://doi.org/10.1038/s41598-022-18757-w

Kashinath, K., Mustafa, M., Albert, A., Wu, J.-L., Jiang, C., Esmaeilzadeh, S., Azizzadenesheli, K., Wang, R., Chattopadhyay, A., Singh, A., Manepalli, A., Chirila, D., Yu, R., Walters, R., White, B., Xiao, H., Tchelepi, H. A., Marcus, P., Anandkumar, A., … Prabhat. (2021). Physics-informed machine learning: case studies for weather and climate modelling. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *379*(2194), 20200093. https://doi.org/10.1098/rsta.2020.0093

Kazadi, A., Doss-Gollin, J., Sebastian, A., & Silva, A. (2024). FloodGNN-GRU: a spatio-temporal graph neural network for flood prediction. *Environmental Data Science*, *3*, e21. https://doi.org/10.1017/eds.2024.19

Keisler, R. (2022). *Forecasting Global Weather with Graph Neural Networks*. https://doi.org/arXiv:2202.07575v1

Khan, F., Spöck, G., Liou, Y.-A., & Ali, S. (2024). Association of precipitation extremes and crops production and projecting future extremes using machine learning approaches with CMIP6 data. *Environmental Science and Pollution Research*, *31*(42), 54979–54999. https://doi.org/10.1007/s11356-024-34652-5

Khatakho, R., Gautam, D., Aryal, K. R., Pandey, V. P., Rupakhety, R., Lamichhane, S., Liu, Y.-C., Abdouli, K., Talchabhadel, R., Thapa, B. R., & Adhikari, R. (2021). Multi-Hazard Risk Assessment of Kathmandu Valley, Nepal. *Sustainability*, *13*(10), 5369. https://doi.org/10.3390/su13105369

Kim, Y., Evans, J. P., & Sharma, A. (2023). Correcting biases in regional climate model boundary variables for improved simulation of high-impact compound events. *IScience*, *26*(9), 107696. https://doi.org/10.1016/j.isci.2023.107696

Kipf, T. N., & Welling, M. (2016). *Semi-Supervised Classification with Graph Convolutional Networks*.

Koshy, R., & Elango, S. (2023). Multimodal tweet classification in disaster response systems using transformer-based bidirectional attention model. *Neural Computing and Applications*, *35*(2), 1607–1627. https://doi.org/10.1007/s00521-022-07790-5

Kotaridis, I., & Lazaridou, M. (2022). Integration of convolutional neural networks for flood risk mapping in Tuscany, Italy. *Natural Hazards*, *114*(3), 3409–3424. https://doi.org/10.1007/s11069-022-05525-2

Kraft, B., Jung, M., Körner, M., Requena Mesa, C., Cortés, J., & Reichstein, M. (2019). Identifying Dynamic Memory Effects on Vegetation State Using Recurrent Neural Networks. *Frontiers in Big Data*, *2*. https://doi.org/10.3389/fdata.2019.00031

Kratzert, F., Klotz, D., Brandstetter, J., Hoedt, P.-J., Nearing, G., & Hochreiter, S. (2019). *Using LSTMs for climate change assessment studies on droughts and floods*. https://doi.org/https://doi.org/10.48550/arXiv.1911.03941

Kratzert, F., Klotz, D., Brenner, C., Schulz, K., & Herrnegger, M. (2018). Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks. *Hydrology and Earth System Sciences*, *22*(11), 6005–6022. https://doi.org/10.5194/hess-22-6005-2018

Kratzert, F., Klotz, D., Shalev, G., Klambauer, G., Hochreiter, S., & Nearing, G. (2019). Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets. *Hydrology and Earth System Sciences*, *23*(12), 5089–5110. https://doi.org/10.5194/hess-23-5089-2019

Lam, R., Sanchez-Gonzalez, A., Willson, M., Wirnsberger, P., Fortunato, M., Pritzel, A., Ravuri, S., Ewalds, T., Alet, F., Eaton-Rosen, Z., Hu, W., Merose, A., Hoyer, S., Holland, G., Stott, J., Vinyals, O., Mohamed, S., Battaglia, P., & contribution, equal. (2022). *GraphCast: Learning skillful medium-range global weather forecasting*.

Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278–2324. https://doi.org/10.1109/5.726791

Lei, T., Zhang, Q., Xue, D., Chen, T., Meng, H., & Nandi, A. K. (2019). End-to-end Change Detection Using a Symmetric Fully Convolutional Network for Landslide Mapping. *ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 3027–3031. https://doi.org/10.1109/ICASSP.2019.8682802

Leng, G., & Hall, J. W. (2020). Predicting spatial and temporal variability in crop yields: an inter-comparison of machine learning, regression and process-based models. *Environmental Research Letters*, *15*(4), 044027. https://doi.org/10.1088/1748-9326/ab7b24

Li, L., Qiao, J., Yu, G., Wang, L., Li, H.-Y., Liao, C., & Zhu, Z. (2022). Interpretable tree-based ensemble model for predicting beach water quality. *Water Research*, *211*, 118078. https://doi.org/10.1016/j.watres.2022.118078

Liang, X., Guan, Q., Clarke, K. C., Liu, S., Wang, B., & Yao, Y. (2021). Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: A case study in Wuhan, China. *Computers, Environment and Urban Systems*, *85*, 101569. https://doi.org/10.1016/j.compenvurbsys.2020.101569

Liao, Z., Chen, Y., Li, W., & Zhai, P. (2021). Growing Threats From Unprecedented Sequential Flood-Hot Extremes Across China. *Geophysical Research Letters*, *48*(18). https://doi.org/10.1029/2021GL094505

Lim, C.-H., & Kim, H.-J. (2022). Can Forest-Related Adaptive Capacity Reduce Landslide Risk Attributable to Climate Change?—Case of Republic of Korea. *Forests*, *13*(1), 49. https://doi.org/10.3390/f13010049

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Lin, H., Tang, J., Wang, S., Wang, S., & Dong, G. (2023). Deep learning downscaled high-resolution daily near surface meteorological datasets over East Asia. *Scientific Data*, *10*(1), 890. https://doi.org/10.1038/s41597-023-02805-9

Ling, F., Lu, Z., Luo, J.-J., Bai, L., Behera, S. K., Jin, D., Pan, B., Jiang, H., & Yamagata, T. (2024). Diffusion model-based probabilistic downscaling for 180-year East Asian climate reconstruction. *Npj Climate and Atmospheric Science*, *7*(1), 131. https://doi.org/10.1038/s41612-024-00679-1

Liu, G., Gao, Z., Chen, B., Fu, H., Jiang, S., Wang, L., Wang, G., & Chen, Z. (2020). Extreme values of storm surge elevation in Hangzhou Bay. *Ships and Offshore Structures*, *15*(4), 431–442. https://doi.org/10.1080/17445302.2019.1661618

Liu, G., Yang, B., Nong, X., Kou, Y., Wu, F., Zhao, D., & Yu, P. (2023). Risk Level Assessment of Typhoon Hazard Based on Loss Utility. *Journal of Marine Science and Engineering*, *11*(11), 2177. https://doi.org/10.3390/jmse11112177

Liu, J., Qiu, Z., Feng, J., Wong, K. P., Tsou, J. Y., Wang, Y., & Zhang, Y. (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. *Remote Sensing*, *15*(23), 5559. https://doi.org/10.3390/rs15235559

Liu, K., Wang, M., Cao, Y., Zhu, W., & Yang, G. (2018). Susceptibility of existing and planned Chinese railway system subjected to rainfall-induced multi-hazards. *Transportation Research Part A: Policy and Practice*, *117*, 214–226. https://doi.org/10.1016/j.tra.2018.08.030

Liu, X., Guo, H., Lin, Y., Li, Y., & Hou, J. (2018). Analyzing Spatial-Temporal Distribution of Natural Hazards in China by Mining News Sources. *Natural Hazards Review*, *19*(3). https://doi.org/10.1061/(ASCE)NH.1527-6996.0000291

Liu, Y., Racah, E., Prabhat, Correa, J., Khosrowshahi, A., Lavers, D., Kunkel, K., Wehner, M., & Collins, W. (2016). *Application of Deep Convolutional Neural Networks for Detecting Extreme Weather in Climate Datasets*. https://doi.org/arXiv:1605.01156

Lütjens, B., Crawford, C. H., Veillette, M., & Newman, D. (2021). *PCE-PINNs: Physics-Informed Neural Networks for Uncertainty Propagation in Ocean Modeling*.

Luu, C., Forino, G., Yorke, L., Ha, H., Bui, Q. D., Tran, H. H., Nguyen, D. Q., Duong, H. C., & Kervyn, M. (2024). *Integrating multi-hazard susceptibility and building exposure: A case study for Quang Nam province, Vietnam*. https://doi.org/10.5194/egusphere-2024-57

Mandal, P., Maiti, A., Paul, S., Bhattacharya, S., & Paul, S. (2022). Mapping the multi-hazards risk index for coastal block of Sundarban, India using AHP and machine learning algorithms. *Tropical Cyclone Research and Review*, *11*(4), 225–243. https://doi.org/10.1016/j.tcrr.2023.03.001

Mattei, G., Di Luccio, D., Benassai, G., Anfuso, G., Budillon, G., & Aucelli, P. (2021). Characteristics and coastal effects of a destructive marine storm in the Gulf of Naples (southern Italy). *Natural Hazards and Earth System Sciences*, *21*(12), 3809–3825. https://doi.org/10.5194/nhess-21-3809-2021

Mazas, F., & Hamm, L. (2017). An event-based approach for extreme joint probabilities of waves and sea levels. *Coastal Engineering*, *122*, 44–59. https://doi.org/10.1016/j.coastaleng.2017.02.003

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

McGovern, A., Ebert-Uphoff, I., Gagne, D. J., & Bostrom, A. (2022). Why we need to focus on developing ethical, responsible, and trustworthy artificial intelligence approaches for environmental science. *Environmental Data Science*, *1*, e6. https://doi.org/10.1017/eds.2022.5

McGovern, A., Lagerquist, R., John Gagne, D., Jergensen, G. E., Elmore, K. L., Homeyer, C. R., & Smith, T. (2019). Making the Black Box More Transparent: Understanding the Physical Implications of Machine Learning. *Bulletin of the American Meteorological Society*, *100*(11), 2175–2199. https://doi.org/10.1175/BAMS-D-18-0195.1

Mehrotra, H., Mishra, A., & Pal, S. (2022). A Multi-stage Classification Framework for Disaster-Specific Tweets. *SN Computer Science*, *3*(1), 24. https://doi.org/10.1007/s42979-021-00930-z

Ming, X., Liang, Q., Dawson, R., Xia, X., & Hou, J. (2022). A quantitative multi-hazard risk assessment framework for compound flooding considering hazard inter-dependencies and interactions. *Journal of Hydrology*, *607*, 127477. https://doi.org/10.1016/j.jhydrol.2022.127477

Miyoshi, G. T., Arruda, M. dos S., Osco, L. P., Marcato Junior, J., Gonçalves, D. N., Imai, N. N., Tommaselli, A. M. G., Honkavaara, E., & Gonçalves, W. N. (2020). A Novel Deep Learning Method to Identify Single Tree Species in UAV-Based Hyperspectral Images. *Remote Sensing*, *12*(8), 1294. https://doi.org/10.3390/rs12081294

Moezzi, M., Janda, K. B., & Rotmann, S. (2017). Using stories, narratives, and storytelling in energy and climate change research. *Energy Research & Social Science*, *31*, 1–10. https://doi.org/10.1016/j.erss.2017.06.034

Mukherjee, S., Nateghi, R., & Hastak, M. (2018). A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. *Reliability Engineering & System Safety*, *175*, 283–305. https://doi.org/10.1016/j.ress.2018.03.015

Munawar, H. S., Ullah, F., Qayyum, S., Khan, S. I., & Mojtahedi, M. (2021). UAVs in Disaster Management: Application of Integrated Aerial Imagery and Convolutional Neural Network for Flood Detection. *Sustainability*, *13*(14), 7547. https://doi.org/10.3390/su13147547

Nam, J., Kim, J., Loza Mencía, E., Gurevych, I., & Fürnkranz, J. (2014). *Large-Scale Multi-label Text Classification — Revisiting Neural Networks* (pp. 437–452). https://doi.org/10.1007/978-3-662-44851-9_28

Nazeer, M., Bilal, M., Alsahli, M., Shahzad, M., & Waqas, A. (2017). Evaluation of Empirical and Machine Learning Algorithms for Estimation of Coastal Water Quality Parameters. *ISPRS International Journal of Geo-Information*, *6*(11), 360. https://doi.org/10.3390/ijgi6110360

Nelsen, R. (2006). *An Introduction to Copulas*. Springer New York. https://doi.org/10.1007/0-387-28678-0

Nguyen, H. D., Dang, D., Bui, Q., & Petrisor, A. (2023). Multi-hazard assessment using machine learning and remote sensing in the North Central region of Vietnam. *Transactions in GIS*, *27*(5), 1614–1640. https://doi.org/10.1111/tgis.13091

Novellino, A., Pennington, C., Leeming, K., Taylor, S., Alvarez, I. G., McAllister, E., Arnhardt, C., & Winson, A. (2024). Mapping landslides from space: A review. *Landslides*, *21*(5), 1041–1052. https://doi.org/10.1007/s10346-024-02215-x

O., S., & Orth, R. (2021). Global soil moisture data derived through machine learning trained with in-situ measurements. *Scientific Data*, *8*(1), 170. https://doi.org/10.1038/s41597-021-00964-1

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

O'Dea, R. E., Lagisz, M., Jennions, M. D., Koricheva, J., Noble, D. W. A., Parker, T. H., Gurevitch, J., Page, M. J., Stewart, G., Moher, D., & Nakagawa, S. (2021). Preferred reporting items for systematic reviews and meta-analyses in ecology and evolutionary biology: a <scp>PRISMA</scp> extension. *Biological Reviews*, *96*(5), 1695–1722. https://doi.org/10.1111/brv.12721

Orth, R., O, S., Zscheischler, J., Mahecha, M. D., & Reichstein, M. (2022). Contrasting biophysical and societal impacts of hydro-meteorological extremes. *Environmental Research Letters*, *17*(1), 014044. https://doi.org/10.1088/1748-9326/ac4139

Pan, S. J., & Yang, Q. (2010). A Survey on Transfer Learning. *IEEE Transactions on Knowledge and Data Engineering*, *22*(10), 1345–1359. https://doi.org/10.1109/TKDE.2009.191

Pan, Y., Zeng, X., Xu, H., Sun, Y., Wang, D., & Wu, J. (2021). Evaluation of Gaussian process regression kernel functions for improving groundwater prediction. *Journal of Hydrology*, *603*, 126960. https://doi.org/10.1016/j.jhydrol.2021.126960

Park, S. J., & Lee, D. K. (2020). Prediction of coastal flooding risk under climate change impacts in South Korea using machine learning algorithms. *Environmental Research Letters*, *15*(9). https://doi.org/10.1088/1748-9326/ABA5B3

Park, S., Sohn, W., Piao, Y., & Lee, D. (2023). Adaptation strategies for future coastal flooding: Performance evaluation of green and grey infrastructure in South Korea. *Journal of Environmental Management*, *334*, 117495. https://doi.org/10.1016/j.jenvman.2023.117495

Patil, K. R., Doi, T., & Behera, S. K. (2023). Predicting extreme floods and droughts in East Africa using a deep learning approach. *Npj Climate and Atmospheric Science*, *6*(1), 108. https://doi.org/10.1038/s41612-023-00435-x

Pescaroli, G., & Alexander, D. (2018). Understanding Compound, Interconnected, Interacting, and Cascading Risks: A Holistic Framework. *Risk Analysis*, *38*(11), 2245–2257. https://doi.org/10.1111/risa.13128

Pham, H. V., Dal Barco, M. K., Cadau, M., Harris, R., Furlan, E., Torresan, S., Rubinetti, S., Zanchettin, D., Rubino, A., Kuznetsov, I., Barbariol, F., Benetazzo, A., Sclavo, M., & Critto, A. (2023). Multi-model chain for climate change scenario analysis to support coastal erosion and water quality risk management for the Metropolitan city of Venice. *Science of The Total Environment*, *904*, 166310. https://doi.org/10.1016/j.scitotenv.2023.166310

Piao, Y., Lee, D., Park, S., Kim, H. G., & Jin, Y. (2022). Multi-hazard mapping of droughts and forest fires using a multi-layer hazards approach with machine learning algorithms. *Geomatics, Natural Hazards and Risk*, *13*(1), 2649–2673. https://doi.org/10.1080/19475705.2022.2128440

Pilkington, S., & Mahmoud, H. (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. *Palgrave Communications*, *3*(1), 14. https://doi.org/10.1057/s41599-017-0016-1

Pourghasemi, H. R., Gayen, A., Panahi, M., Rezaie, F., & Blaschke, T. (2019). Multi-hazard probability assessment and mapping in Iran. *Science of The Total Environment*, *692*, 556–571. https://doi.org/10.1016/j.scitotenv.2019.07.203

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Pourghasemi, H. R., Kariminejad, N., Amiri, M., Edalat, M., Zarafshar, M., Blaschke, T., & Cerda, A. (2020). Assessing and mapping multi-hazard risk susceptibility using a machine learning technique. *Scientific Reports*, *10*(1), 3203. https://doi.org/10.1038/s41598-020-60191-3

Pouyan, S., Pourghasemi, H. R., Bordbar, M., Rahmanian, S., & Clague, J. J. (2021). A multi-hazard map-based flooding, gully erosion, forest fires, and earthquakes in Iran. *Scientific Reports*, *11*(1), 14889. https://doi.org/10.1038/s41598-021-94266-6

Powers, C. J., Devaraj, A., Ashqeen, K., Dontula, A., Joshi, A., Shenoy, J., & Murthy, D. (2023). Using artificial intelligence to identify emergency messages on social media during a natural disaster: A deep learning approach. *International Journal of Information Management Data Insights*, *3*(1), 100164. https://doi.org/10.1016/j.jjimei.2023.100164

Racah, E., Beckham, C., Maharaj, T., Kahou, S. E., Prabhat, & Pal, C. (2016). *ExtremeWeather: A large-scale climate dataset for semi-supervised detection, localization, and understanding of extreme weather events*. https://doi.org/https://doi.org/10.48550/arXiv.1612.02095

Rahman, M., Shufeng, T., Tumon, M. S. H., Hossain, M. A., Kim, H.-J., Islam, M. M., Alam, M., Sadiq, S., Ningsheng, C., Ullah, K., Zafor, M. A., & Raju, M. R. (2024). Multi-hazard could exacerbate in coastal Bangladesh in the context of climate change. *Journal of Cleaner Production*, *457*, 142289. https://doi.org/10.1016/j.jclepro.2024.142289

Ray, K., Giri, R. K., Ray, S. S., Dimri, A. P., & Rajeevan, M. (2021). An assessment of long-term changes in mortalities due to extreme weather events in India: A study of 50 years' data, 1970–2019. *Weather and Climate Extremes*, *32*, 100315. https://doi.org/10.1016/j.wace.2021.100315

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, *566*(7743), 195–204. https://doi.org/10.1038/s41586-019-0912-1

Ribeiro, A. F. S., Russo, A., Gouveia, C. M., Páscoa, P., & Zscheischler, J. (2020). Risk of crop failure due to compound dry and hot extremes estimated with nested copulas. *Biogeosciences*, *17*(19), 4815–4830. https://doi.org/10.5194/bg-17-4815-2020

Ridder, N. N., Pitman, A. J., & Ukkola, A. M. (2021). Do CMIP6 Climate Models Simulate Global or Regional Compound Events Skillfully? *Geophysical Research Letters*, *48*(2). https://doi.org/10.1029/2020GL091152

Ridder, N. N., Ukkola, A. M., Pitman, A. J., & Perkins-Kirkpatrick, S. E. (2022). Increased occurrence of high impact compound events under climate change. *Npj Climate and Atmospheric Science*, *5*(1), 3. https://doi.org/10.1038/s41612-021-00224-4

Rolnick, D., Donti, P. L., Kaack, L. H., Kochanski, K., Lacoste, A., Sankaran, K., Ross, A. S., Milojevic-Dupont, N., Jaques, N., Waldman-Brown, A., Luccioni, A., Maharaj, T., Sherwin, E. D., Mukkavilli, S. K., Kording, K. P., Gomes, C., Ng, A. Y., Hassabis, D., Platt, J. C., … Bengio, Y. (2019). *Tackling Climate Change with Machine Learning*. https://doi.org/https://doi.org/10.48550/arXiv.1906.05433

Rusk, J., Maharjan, A., Tiwari, P., Chen, T.-H. K., Shneiderman, S., Turin, M., & Seto, K. C. (2022). Multi-hazard susceptibility and exposure assessment of the Hindu Kush Himalaya. *Science of The Total Environment*, *804*, 150039. https://doi.org/10.1016/j.scitotenv.2021.150039

Sadegh, M., Moftakhari, H., Gupta, H. V., Ragno, E., Mazdiyasni, O., Sanders, B., Matthew, R., & AghaKouchak, A. (2018). Multihazard Scenarios for Analysis of Compound Extreme Events. *Geophysical Research Letters*, *45*(11), 5470–5480. https://doi.org/10.1029/2018GL077317

Sadegh, M., Ragno, E., & AghaKouchak, A. (2017). Multivariate Copula Analysis Toolbox (MvCAT): Describing dependence and underlying uncertainty using a Bayesian framework. *Water Resources Research*, *53*(6), 5166–5183. https://doi.org/10.1002/2016WR020242

Sagan, V., Peterson, K. T., Maimaitijiang, M., Sidike, P., Sloan, J., Greeling, B. A., Maalouf, S., & Adams, C. (2020). Monitoring inland water quality using remote sensing: potential and limitations of spectral indices, bio-optical simulations, machine learning, and cloud computing. *Earth-Science Reviews*, *205*, 103187. https://doi.org/10.1016/j.earscirev.2020.103187

Saha, A., Pal, S. C., Santosh, M., Janizadeh, S., Chowdhuri, I., Norouzi, A., Roy, P., & Chakrabortty, R. (2021). Modelling multi-hazard threats to cultural heritage sites and environmental sustainability: The present and future scenarios. *Journal of Cleaner Production*, *320*, 128713. https://doi.org/10.1016/j.jclepro.2021.128713

Šakić Trogrlić, R., Reiter, K., Ciurean, R. L., Gottardo, S., Torresan, S., Daloz, A. S., Ma, L., Padrón Fumero, N., Tatman, S., Hochrainer-Stigler, S., de Ruiter, M. C., Schlumberger, J., Harris, R., Garcia-Gonzalez, S., García-Vaquero, M., Arévalo, T. L. F., Hernandez-Martin, R., Mendoza-Jimenez, J., Ferrario, D. M., … Ward, P. J. (2024). Challenges in assessing and managing multi-hazard risks: A European stakeholders perspective. *Environmental Science & Policy*, *157*, 103774. https://doi.org/10.1016/j.envsci.2024.103774

Salcedo-Sanz, S., Pérez-Aracil, J., Ascenso, G., Del Ser, J., Casillas-Pérez, D., Kadow, C., Fister, D., Barriopedro, D., García-Herrera, R., Restelli, M., Giuliani, M., & Castelletti, A. (2022). *Analysis, Characterization, Prediction and Attribution of Extreme Atmospheric Events with Machine Learning: a Review*.

Sammonds, P., Alam, A., Day, S., Stavrianaki, K., & Kelman, I. (2023). Hurricane risk assessment in a multi-hazard context for Dominica in the Caribbean. *Scientific Reports*, *13*(1), 20565. https://doi.org/10.1038/s41598-023-47527-5

Sarkis-Onofre, R., Catalá-López, F., Aromataris, E., & Lockwood, C. (2021). How to properly use the PRISMA Statement. *Systematic Reviews*, *10*(1), 117. https://doi.org/10.1186/s13643-021-01671-z

Schiefer, F., Kattenborn, T., Frick, A., Frey, J., Schall, P., Koch, B., & Schmidtlein, S. (2020). Mapping forest tree species in high resolution UAV-based RGB-imagery by means of convolutional neural networks. *ISPRS Journal of Photogrammetry and Remote Sensing*, *170*, 205–215. https://doi.org/10.1016/j.isprsjprs.2020.10.015

Schmidt, H., Radinger, J., Teschlade, D., & Stoll, S. (2020). The role of spatial units in modelling freshwater fish distributions: Comparing a subcatchment and river network approach using MaxEnt. *Ecological Modelling*, *418*, 108937. https://doi.org/10.1016/j.ecolmodel.2020.108937

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Schneider, T., Behera, S., Boccaletti, G., Deser, C., Emanuel, K., Ferrari, R., Leung, L. R., Lin, N., Müller, T., Navarra, A., Ndiaye, O., Stuart, A., Tribbia, J., & Yamagata, T. (2023). Harnessing AI and computing to advance climate modelling and prediction. *Nature Climate Change*, *13*(9), 887–889. https://doi.org/10.1038/s41558-023-01769-3

Shah, K., Patel, H., Sanghvi, D., & Shah, M. (2020). A Comparative Analysis of Logistic Regression, Random Forest and KNN Models for the Text Classification. *Augmented Human Research*, *5*(1), 12. https://doi.org/10.1007/s41133-020-00032-0

Shepherd, T. G., Boyd, E., Calel, R. A., Chapman, S. C., Dessai, S., Dima-West, I. M., Fowler, H. J., James, R., Maraun, D., Martius, O., Senior, C. A., Sobel, A. H., Stainforth, D. A., Tett, S. F. B., Trenberth, K. E., van den Hurk, B. J. J. M., Watkins, N. W., Wilby, R. L., & Zenghelis, D. A. (2018). Storylines: an alternative approach to representing uncertainty in physical aspects of climate change. *Climatic Change*, *151*(3–4), 555–571. https://doi.org/10.1007/s10584-018-2317-9

Sillmann, J., Shepherd, T. G., van den Hurk, B., Hazeleger, W., Martius, O., Slingo, J., & Zscheischler, J. (2021). Event-Based Storylines to Address Climate Risk. *Earth's Future*, *9*(2). https://doi.org/10.1029/2020EF001783

Singh, T. P., Nandimath, P., Kumbhar, V., Das, S., & Barne, P. (2021). Drought risk assessment and prediction using artificial intelligence over the southern Maharashtra state of India. *Modeling Earth Systems and Environment*, *7*(3), 2005–2013. https://doi.org/10.1007/s40808-020-00947-y

Sippel, S., Otto, F. E. L., Forkel, M., Allen, M. R., Guillod, B. P., Heimann, M., Reichstein, M., Seneviratne, S. I., Thonicke, K., & Mahecha, M. D. (2016). A novel bias correction methodology for climate impact simulations. *Earth System Dynamics*, *7*(1), 71–88. https://doi.org/10.5194/esd-7-71-2016

Sit, M., Demiray, B. Z., Xiang, Z., Ewing, G. J., Sermet, Y., & Demir, I. (2020). A comprehensive review of deep learning applications in hydrology and water resources. *Water Science and Technology*, *82*(12), 2635–2670. https://doi.org/10.2166/wst.2020.369

Sodoge, J., Kuhlicke, C., & de Brito, M. M. (2023). Automatized spatio-temporal detection of drought impacts from newspaper articles using natural language processing and machine learning. *Weather and Climate Extremes*, *41*, 100574. https://doi.org/10.1016/j.wace.2023.100574

Sublime, J., & Kalinicheva, E. (2019). Automatic Post-Disaster Damage Mapping Using Deep-Learning Techniques for Change Detection: Case Study of the Tohoku Tsunami. *Remote Sensing*, *11*(9), 1123. https://doi.org/10.3390/rs11091123

Sun, A. Y., Jiang, P., Mudunuru, M. K., & Chen, X. (2021). Explore Spatio-Temporal Learning of Large Sample Hydrology Using Graph Neural Networks. *Water Resources Research*, *57*(12). https://doi.org/10.1029/2021WR030394

Sun, X., Sun, Q., Zhou, X., Li, X., Yang, M., Yu, A., & Geng, F. (2014). Heat wave impact on mortality in Pudong New Area, China in 2013. *Science of The Total Environment*, *493*, 789–794. https://doi.org/10.1016/j.scitotenv.2014.06.042

Sutanto, S. J., Vitolo, C., Di Napoli, C., D'Andrea, M., & Van Lanen, H. A. J. (2020). Heatwaves, droughts, and fires: Exploring compound and cascading dry hazards at the pan-European scale. *Environment International*, *134*, 105276. https://doi.org/10.1016/j.envint.2019.105276

Sweet, L., Müller, C., Anand, M., & Zscheischler, J. (2023). Cross-Validation Strategy Impacts the Performance and Interpretation of Machine Learning Models. *Artificial Intelligence for the Earth Systems*, *2*(4). https://doi.org/10.1175/AIES-D-23-0026.1

Tabari, H., & Willems, P. (2023). Global risk assessment of compound hot-dry events in the context of future climate change and socioeconomic factors. *Npj Climate and Atmospheric Science*, *6*(1), 74. https://doi.org/10.1038/s41612-023-00401-7

Tárraga, J. M., Sevillano-Marco, E., Muñoz-Marí, J., Piles, M., Sitokonstantinou, V., Ronco, M., Miranda, M. T., Cerdà, J., & Camps-Valls, G. (2024). Causal discovery reveals complex patterns of drought-induced displacement. *IScience*, *27*(9), 110628. https://doi.org/10.1016/j.isci.2024.110628

Tazi, K., Lin, J. A., Viljoen, R., Gardner, A., John, S., Ge, H., & Turner, R. E. (2023). Beyond intuition, a Framework for Applying GPs to Real-World Data. *ICML Workshop on Structured Probabilistic Inference and Generative Modelling*.

Tazi, K., Orr, A., Hernandez-González, J., Hosking, S., & Turner, R. E. (2024). Downscaling precipitation over High-mountain Asia using multi-fidelity Gaussian processes: improved estimates from ERA5. *Hydrology and Earth System Sciences*, *28*(22), 4903–4925. https://doi.org/10.5194/hess-28-4903-2024

Teichert, N., Borja, A., Chust, G., Uriarte, A., & Lepage, M. (2016). Restoring fish ecological quality in estuaries: Implication of interactive and cumulative effects among anthropogenic stressors. *Science of The Total Environment*, *542*(Part A), 383–393. https://doi.org/10.1016/j.scitotenv.2015.10.068

Terzi, S., Torresan, S., Schneiderbauer, S., Critto, A., Zebisch, M., & Marcomini, A. (2019). Multi-risk assessment in mountain regions: A review of modelling approaches for climate change adaptation. *Journal of Environmental Management*, *232*(February), 759–771. https://doi.org/10.1016/j.jenvman.2018.11.100

Tiggeloven, T., Couasnon, A., van Straaten, C., Muis, S., & Ward, P. J. (2021). Exploring deep learning capabilities for surge predictions in coastal areas. *Scientific Reports*, *11*(1), 17224. https://doi.org/10.1038/s41598-021-96674-0

Tilloy, A., Malamud, B. D., & Joly-Laugel, A. (2022). A methodology for the spatiotemporal identification of compound hazards: wind and precipitation extremes in Great Britain (1979–2019). *Earth System Dynamics*, *13*(2), 993–1020. https://doi.org/10.5194/esd-13-993-2022

Tilloy, A., Malamud, B. D., Winter, H., & Joly-Laugel, A. (2019). A review of quantification methodologies for multi-hazard interrelationships. *Earth-Science Reviews*, *196*, 102881. https://doi.org/10.1016/j.earscirev.2019.102881

Tran, D. Q., Park, M., Jung, D., & Park, S. (2020). Damage-Map Estimation Using UAV Images and Deep Learning Algorithms for Disaster Management System. *Remote Sensing*, *12*(24), 4169. https://doi.org/10.3390/rs12244169

Tripathy, K. P., & Mishra, A. K. (2024). Deep learning in hydrology and water resources disciplines: concepts, methods, applications, and research directions. *Journal of Hydrology*, *628*, 130458. https://doi.org/10.1016/j.jhydrol.2023.130458

Ullah, K., Wang, Y., Fang, Z., Wang, L., & Rahman, M. (2022). Multi-hazard susceptibility mapping based on Convolutional Neural Networks. *Geoscience Frontiers*, *13*(5), 101425. https://doi.org/10.1016/j.gsf.2022.101425

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). *Attention Is All You Need*. https://doi.org/arXiv:1706.03762v7

Veličković, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., & Bengio, Y. (2017). *Graph Attention Networks*. https://doi.org/1710.10903

Veras, H. F. P., Ferreira, M. P., da Cunha Neto, E. M., Figueiredo, E. O., Corte, A. P. D., & Sanquetta, C. R. (2022). Fusing multi-season UAS images with convolutional neural networks to map tree species in Amazonian forests. *Ecological Informatics*, *71*, 101815. https://doi.org/10.1016/j.ecoinf.2022.101815

Wang, J. (2023). An Intuitive Tutorial to Gaussian Process Regression. *Computing in Science & Engineering*, *25*(4), 4–11. https://doi.org/10.1109/MCSE.2023.3342149

Wang, J., Kuffer, M., Roy, D., & Pfeffer, K. (2019). Deprivation pockets through the lens of convolutional neural networks. *Remote Sensing of Environment*, *234*, 111448. https://doi.org/10.1016/j.rse.2019.111448

Wang, J., & Yan, Z. (2021). Rapid rises in the magnitude and risk of extreme regional heat wave events in China. *Weather and Climate Extremes*, *34*, 100379. https://doi.org/10.1016/j.wace.2021.100379

Wang, Q., Zhang, X., Chen, G., Dai, F., Gong, Y., & Zhu, K. (2018). Change detection based on Faster R-CNN for high-resolution remote sensing images. *Remote Sensing Letters*, *9*(10), 923–932. https://doi.org/10.1080/2150704X.2018.1492172

Wang, R., Kim, J.-H., & Li, M.-H. (2021). Predicting stream water quality under different urban development pattern scenarios with an interpretable machine learning approach. *Science of The Total Environment*, *761*, 144057. https://doi.org/10.1016/j.scitotenv.2020.144057

Wang, X., Ma, Z., & Dong, J. (2021). Quantitative Impact Analysis of Climate Change on Residents' Health Conditions with Improving Eco-Efficiency in China: A Machine Learning Perspective. *International Journal of Environmental Research and Public Health*, *18*(23), 12842. https://doi.org/10.3390/ijerph182312842

Wang, Y., Song, Q., Du, Y., Wang, J., Zhou, J., Du, Z., & Li, T. (2019). A random forest model to predict heatstroke occurrence for heatwave in China. *Science of The Total Environment*, *650*, 3048–3053. https://doi.org/10.1016/j.scitotenv.2018.09.369

Ward, P. J., Daniell, J., Duncan, M., Dunne, A., Hananel, C., Hochrainer-Stigler, S., Tijssen, A., Torresan, S., Ciurean, R., Gill, J. C., Sillmann, J., Couasnon, A., Koks, E., Padrón-Fumero, N., Tatman, S., Tronstad Lund, M., Adesiyun, A., Aerts, J. C. J. H., Alabaster, A., … de Ruiter, M. C. (2022). Invited perspectives: A research agenda towards disaster risk management pathways in multi-(hazard-)risk assessment. *Natural Hazards and Earth System Sciences*, *22*(4), 1487–1497. https://doi.org/10.5194/nhess-22-1487-2022

Wu, H., Su, X., & Singh, V. P. (2023). Increasing Risks of Future Compound Climate Extremes With Warming Over Global Land Masses. *Earth's Future*, *11*(9). https://doi.org/10.1029/2022EF003466

Wu, H., Su, X., Singh, V. P., & Niu, J. (2024). Predicting compound agricultural drought and hot events using a Cascade Modeling framework combining Bayesian Model Averaging ensemble with Vine Copula (CaMBMAViC). *Journal of Hydrology*, *642*, 131901. https://doi.org/10.1016/j.jhydrol.2024.131901

Wu, Q., & Lin, H. (2019). A novel optimal-hybrid model for daily air quality index prediction considering air pollutant factors. *Science of The Total Environment*, *683*, 808–821. https://doi.org/10.1016/j.scitotenv.2019.05.288

Wubalem, A. (2022). Landslide Inventory, Susceptibility, Hazard and Risk Mapping. In *Landslides*. IntechOpen. https://doi.org/10.5772/intechopen.100504

Ya, R., Wu, J., Tang, R., & Zhou, Q. (2023). Increased flood susceptibility in the Tibetan Plateau with climate and land use changes. *Ecological Indicators*, *156*, 111086. https://doi.org/10.1016/j.ecolind.2023.111086

Yeğin, M. N., & Amasyalı, M. F. (2024). *Theoretical research on generative diffusion models: an overview*. https://doi.org/10.1016/j.neucom.2024.128373

Yousefi, S., Pourghasemi, H. R., Emami, S. N., Pouyan, S., Eskandari, S., & Tiefenbacher, J. P. (2020). A machine learning framework for multi-hazards modeling and mapping in a mountainous area. *Scientific Reports*, *10*(1), 1–14. https://doi.org/10.1038/s41598-020-69233-2

Yu, H., Lu, N., Fu, B., Zhang, L., Wang, M., & Tian, H. (2022). Hotspots, co-occurrence, and shifts of compound and cascading extreme climate events in Eurasian drylands. *Environment International*, *169*, 107509. https://doi.org/10.1016/j.envint.2022.107509

Yu, S., & Ma, J. (2021). Deep Learning for Geophysics: Current and Future Trends. *Reviews of Geophysics*, *59*(3). https://doi.org/10.1029/2021RG000742

Yuh, Y. G., Tracz, W., Matthews, H. D., & Turner, S. E. (2023). Application of machine learning approaches for land cover monitoring in northern Cameroon. *Ecological Informatics*, *74*, 101955. https://doi.org/10.1016/j.ecoinf.2022.101955

Zanetti, M., Allegri, E., Sperotto, A., Torresan, S., & Critto, A. (2022). Spatio-temporal cross-validation to predict pluvial flood events in the Metropolitan City of Venice. *Journal of Hydrology*, *612*, 128150. https://doi.org/10.1016/j.jhydrol.2022.128150

Zanini, E., Eastoe, E., Jones, M. J., Randell, D., & Jonathan, P. (2020). Flexible covariate representations for extremes. *Environmetrics*, *31*(5). https://doi.org/10.1002/env.2624

Zennaro, F., Furlan, E., Simeoni, C., Torresan, S., Aslan, S., Critto, A., & Marcomini, A. (2021). Exploring machine learning potential for climate change risk assessment. *Earth-Science Reviews*, *220*, 103752. https://doi.org/10.1016/j.earscirev.2021.103752

Zerrouki, N., Harrou, F., Sun, Y., & Hocini, L. (2019). A Machine Learning-Based Approach for Land Cover Change Detection Using Remote Sensing and Radiometric Measurements. *IEEE Sensors Journal*, *19*(14), 5843–5850. https://doi.org/10.1109/JSEN.2019.2904137

Zhao, G., Pang, B., Xu, Z., Peng, D., & Zuo, D. (2020). Urban flood susceptibility assessment based on convolutional neural networks. *Journal of Hydrology*, *590*, 125235. https://doi.org/10.1016/j.jhydrol.2020.125235

https://doi.org/10.5194/egusphere-2025-670
Preprint. Discussion started: 3 March 2025

Zhu, X., Yang, Y., & Tang, J. (2023). Compound wind and precipitation extremes at a global scale based on CMIP6 models: Evaluation, projection and uncertainty. *International Journal of Climatology*, *43*(16), 7588–7605. https://doi.org/10.1002/joc.8281

Zschau. (2017). *Where are we with multihazards, multirisks assessment capacities?, in: Science for disaster risk management 2017: knowing better and losing less, edited by: Poljansek, K., Marin Ferrer, M., De Groeve, T., and Clark, I., European Union, Brussels, Belgium.* https://drmkc.jrc.ec.europa.eu/knowledge/science-for-drm/science-for-disaster-risk-management-2017

Zscheischler, J., Orth, R., & Seneviratne, S. I. (2017). Bivariate return periods of temperature and precipitation explain a large fraction of European crop yields. *Biogeosciences*, *14*(13), 3309–3320. https://doi.org/10.5194/bg-14-3309-2017

Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., AghaKouchak, A., Bresch, D. N., Leonard, M., Wahl, T., & Zhang, X. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3