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Review

Advances in weather and climate extreme studies: a systematic comparative review

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Abstract
There is a growing evidence-based concerns pointing to global increase of weather and climate extreme events (WCEE). What decides whether these hazards become a disaster is how the society and humanity prepare and responds to it. Although various researchers have step up efforts through scholarly contributions in response to WCEE. However, the task of utilizing the needed tools, selecting the most suitable approach, and choosing appropriate techniques for WCEE studies can be daunting for researchers. Moreover, the technicality and complexity associated with the wide array of models and methods present additional challenges when it comes to their practical implementationF in disaster applications. This review comprehensively explores four approaches in WCEE studies: statistical analysis, geospatial modeling, MCDA, and AI-based techniques. It evaluates their effectiveness in assessing impacts within WCEE and highlights AI's (ML and DL's) superior performance compared to other conventional methods in disaster-related studies.

Keywords Weather and climate extremes · Disaster risk reduction · Approaches · Methods · Machine learning · Deep learning

1 Introduction

The increasing frequency, magnitude, and economic losses resulting from climatological, meteorological, hydrological, geophysical disasters have raised serious concerns globally [1–3]. Regardless of their economy or geography, millions of people and assets worth US$4 trillion will face the risk of devastating weather and climate extreme events (WCEE) by the year 2030 [4]. The alarming figures on predicted loss of lives and economic assets underscore the urgent need for effective strategies to mitigate and manage disasters [5–7]. The Intergovernmental Panel on Climate Change (IPCC) has also expressed concerns about the escalating occurrence of climate disaster, further highlighting the importance of disaster risk reduction (DRR) efforts [8, 9].

To address these challenges, the Sendai framework was developed as a global blueprint on DRR [10, 11]. This framework emphasizes the understanding and addressing of the multidimensional impact of disasters, recognizing the necessity of interdisciplinary approaches involving researchers, planners, policy makers and other relevant stakeholders [12, 13].

Recently, there has been an increasing adoption of innovative models and methods to address the challenges posed by disasters, with the aim of building resilient and sustainable societies [14–17]. These include climate modelling approaches both at regional (RCMs), atmospheric (AOGCMs) and earth systems (ESMs) levels [18]. Furthermore, studies on disaster

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risk reduction have made extensive use of a diverse range of tools, models, methods, and techniques to enhance their research efforts [19–23]. Others include geospatial tools such as GIS, remote sensing, and GPS, which have been widely utilized in carrying out disaster mapping using various spatial techniques [24–26]. Furthermore, statistical analysis techniques such as T-test, Chi-square, ANOVA, regression, and correlation have been applied for perception, descriptive, inferential and other kinds of analysis of disasters [27–31]. Additionally, multi-criteria decision analysis (MCDA) is an approach that has been utilized in both GIS and statistics [15]. Techniques such as the fuzzy logic, Analytical Hierarchy Process (AHP), and TOPSIS have been widely applied in WCEE studies [26, 32–34]. More recently, programming languages like R and AI-based techniques, such as machine learning and deep learning models, have become increasingly popular in WCEE studies. These approaches are particularly promising for predicting and modeling disaster risks [23, 35–38].

However, despite these diverse range of tools, approaches and techniques, researchers often encounter a set of challenges in the field of WCEE studies [39–41]. The task of utilizing the needed tools, selecting the most suitable approach, and choosing appropriate techniques for disaster risk reduction studies can be daunting, especially for new researchers [42]. Yet, the intricate nature of understanding their underlying principles and effectively integrating them into real-world scenarios further compounds the challenge.

Therefore, it is crucial to thoroughly examine the applicability and suitability of these models and methods in addressing the multi-dimensional issues within the context of disaster risk reduction [43–45]. This examination will facilitate significant progress in developing effective strategies for mitigating and managing disaster risks, while also enhancing our understanding of the complex dynamics associated with disasters [6, 46, 47].

The existing trend in WCEE literature reveals a limited number of studies exploring the principles and practical applications of methods, approaches, and techniques, as well as their suitability in WCEE, to guide researchers in making informed decisions. This results in a significant knowledge gap regarding their appropriate utilization based on their diverse applicability and reliability. Despite the growing scholarly interest in the field of disaster management [30, 48–51], comprehensive studies on techniques, models, and approaches within the context of disaster studies are scarce [52]. This highlights the need for extensive study to narrow the existing gap in the literature.

The study seeks to conduct a systematic review of recent literature on WCEE, evaluating the approaches, methods, and models used, and highlighting their broad suitability. By employing a comparative approach, the study will explore the principles of some of these most widely utilized approaches, methods, and models and discuss their diverse applications within WCEE study dimensions, highlight their effectiveness, and strengths in comparison to other methods and models. This analysis will provide valuable insights into the diversity, suitability, and limitations of different methods, enabling researchers and practitioners to make informed decisions regarding WCEE studies. Additionally, it will serve as a literature guide for decision-making processes in disaster risk reduction, leading to more efficient and impactful outcomes in reducing disaster risks.

2 Methodology

For the purpose of collecting data for this study, online database such as Google Scholar, Web of Science, ScienceDirect, Scopus, and SpringerLink etc., were utilized [53–55]. These databases were chosen for their broad coverage of scholarly literature across multiple disciplines, ensuring a thorough search for recent relevant articles and studies related to WCEE [6]. Figure 1 provides a detailed overview of the search and selection process, including the number of articles retrieved, screened, assessed, and included in the final review.

2.1 Search strategy

The data collection process in this study followed a two-step approach. The first step involved gathering relevant literature on the topic of disaster, while the second step focused on collecting data based on target sub-themes and technique-specific approaches within the field of DRR. To initiate the data collection process, the first step was deployed using general keywords, such as "weather and climate extremes", "climate change", "disaster studies," "DRR," and "disaster assessment," etc. were used to capture a broad range of literature on the topic and establish a foundational understanding of the field. This inclusive approach ensured that a comprehensive overview of the relevant literature was obtained [56].

The second step of the data collection process involved narrowing down the search by employing theme-specific and technique-specific keywords. Theme-specific keywords such as "disaster and gender," "urban resilience," "flood prediction and modelling," Windstorm assessment," and "extreme weather events" allowed for a targeted search, addressing specific

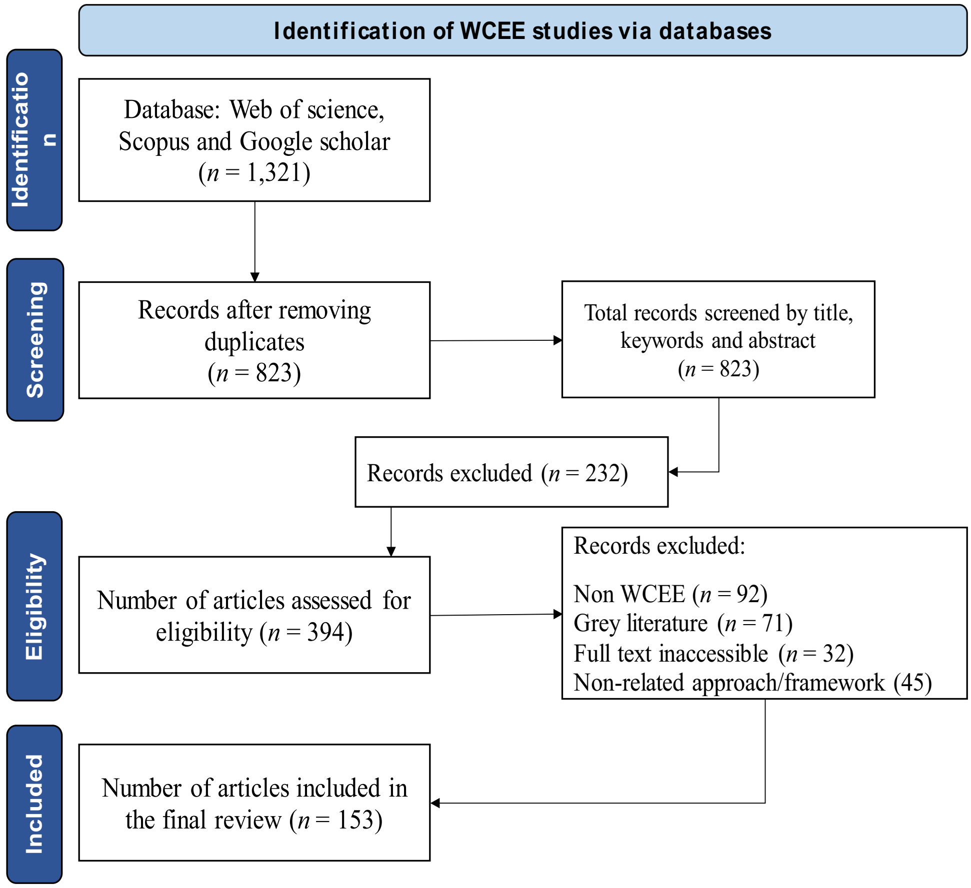

Fig. 1 Literature search and selection process based on PRISMA

themes and areas of interest within the broader field of DRR. Additionally, technique-specific keywords such as "AI-based disaster assessment," "machine learning in disaster," and "GIS-based mapping of disasters," fuzzy logic in disaster," "Deep learning model," etc., were used to identify articles that utilized these specific techniques in the context of DRR.

2.2 Screening

Following the search process, the collected data went through a screening phase. The titles and abstracts of the articles were carefully reviewed to determine their relevance to the study objectives. Articles that did not align with the research focus were excluded from further analysis (see Fig. 1). This screening process ensured that the final selection of articles included in the study was appropriate and relevant, maintaining the coherence and integrity of the dataset.

2.3 Inclusion and exclusion criteria

In this study, we established specific inclusion and exclusion criteria to ensure a comprehensive and focused review of the literature on WCEE [57]. The inclusion criteria are as follows: (1) articles must be from peer-reviewed journals to ensure quality and reliability; (2) the main thematic focus of the articles must be relevant to WCEE, such as disaster risk reduction, prediction models, impact assessments, and mitigation strategies; (3) only articles published no earlier than 2013 were considered to include the most recent advances and developments in the field; and (4) only articles published in English were included to maintain consistency and accessibility. Conversely, the exclusion criteria are as follows: (1) articles published before 2013 were excluded to focus on contemporary research and methodologies; (2) articles that do not directly pertain to WCEE were excluded to maintain thematic relevance; (3) grey literature and unpublished studies were excluded to ensure the inclusion of rigorously vetted research; and (4) Articles employing frameworks or unconventional approaches not aligned with the study's focus were excluded from the review process.

3 Approaches and techniques in WCEE studies

3.1 Statistical models

Statistical models are essential in disaster management studies, facilitating the analysis, interpretation, and prediction of various variables related to disasters [58–60]. They help in understanding the complexities of disasters, assessing risks, evaluating vulnerabilities, and designing effective mitigation strategies etc. [61–63]. They are also vital in making informed decisions and guiding policy formulations for disaster preparedness, response, and recovery [64]. These statistical models can be broadly classified into bivariate and multivariate models:

3.1.1 Bivariate models

The bivariate statistical models focus on examining the relationship between two specific variables [65]. They are utilized to explore the association and impact that one variable may have on another within a specific context. Within the context of WCEE studies, the bivariate models can be utilized in investigating the relationship between two variables, or a variable and a construct. For example income levels and susceptibility to floods, gender and exposure [28, 66]. Similarly, they can be employed in behavioral pattern studies to analyze the correlation between education levels and behaviors related to disaster preparedness. See Fig. 2.

3.1.2 Multivariate models

The multivariate statistical models analyze the relationship between multiple variables simultaneously [67]. They consider the interactions and dependencies among various factors, providing a more comprehensive understanding [65]. These models have widespread applications in WCEE studies, allowing for the assessment of diverse factors encompassing physical, hydrological, lithological, demographic, geographic, and socio-economic conditions. Their utilization aids in the assessment and understanding various aspects of WCEE such as preparedness, exposure, vulnerability, risk, impact, or resilience [28, 63, 68–70].

3.2 Geospatial approach

Geospatial techniques have become increasingly popular in the field of WCEE, providing insights into the spatial patterns, vulnerabilities, risks, extent and magnitude of disaster severity [32, 71–75]. It includes operations like buffering, spatial queries, overlay analysis, image processing, interpolation and proximity analysis among others.

3.2.1 Satellite remote sensing

Remote sensing tools and techniques provide valuable and accurate assessment of disaster [24, 76]. It involves the utilization of data (satellite imagery) and software often referred to as geospatial technologies to manipulate and analyze the data using mathematical algorithms and techniques to extract useful information or enhance certain features within the imagery [77, 78]. For example satellite imagery, aerial photographs, RADAR, LiDAR and GPS data can be integrated within the GIS and other environment to assess and map pre-, during, and post-disaster events (flooding, windstorm, drought and forest fire), monitor changes in land cover, map extent, assess patterns, and analyze environmental factors contributing to disaster [79, 80]. These geospatial technologies significantly replaced labor-intensive and time-consuming traditional data collection methods [81], and provide a valuable resource for precise tracking and effective analysis of temporal shifts and spatial changes (change detection) in disaster occurrences across two or more distinct time frames [76].

3.2.1.1 Image classification approach **Pixel-based classification**: This approach classifies individual pixel in satellite data based on its spectral properties of the feature captured in the pixel [82]. This method is particularly valuable for mapping homogeneous land cover or land use classes and monitoring changes over time [81, 83]. By analyzing the spectral characteristics of pixels, pixel-based classification provides valuable insights into the distribution of land cover types and can help identify areas prone to specific hazards, such as forests susceptible to wildfires or urban areas prone to flooding [84].

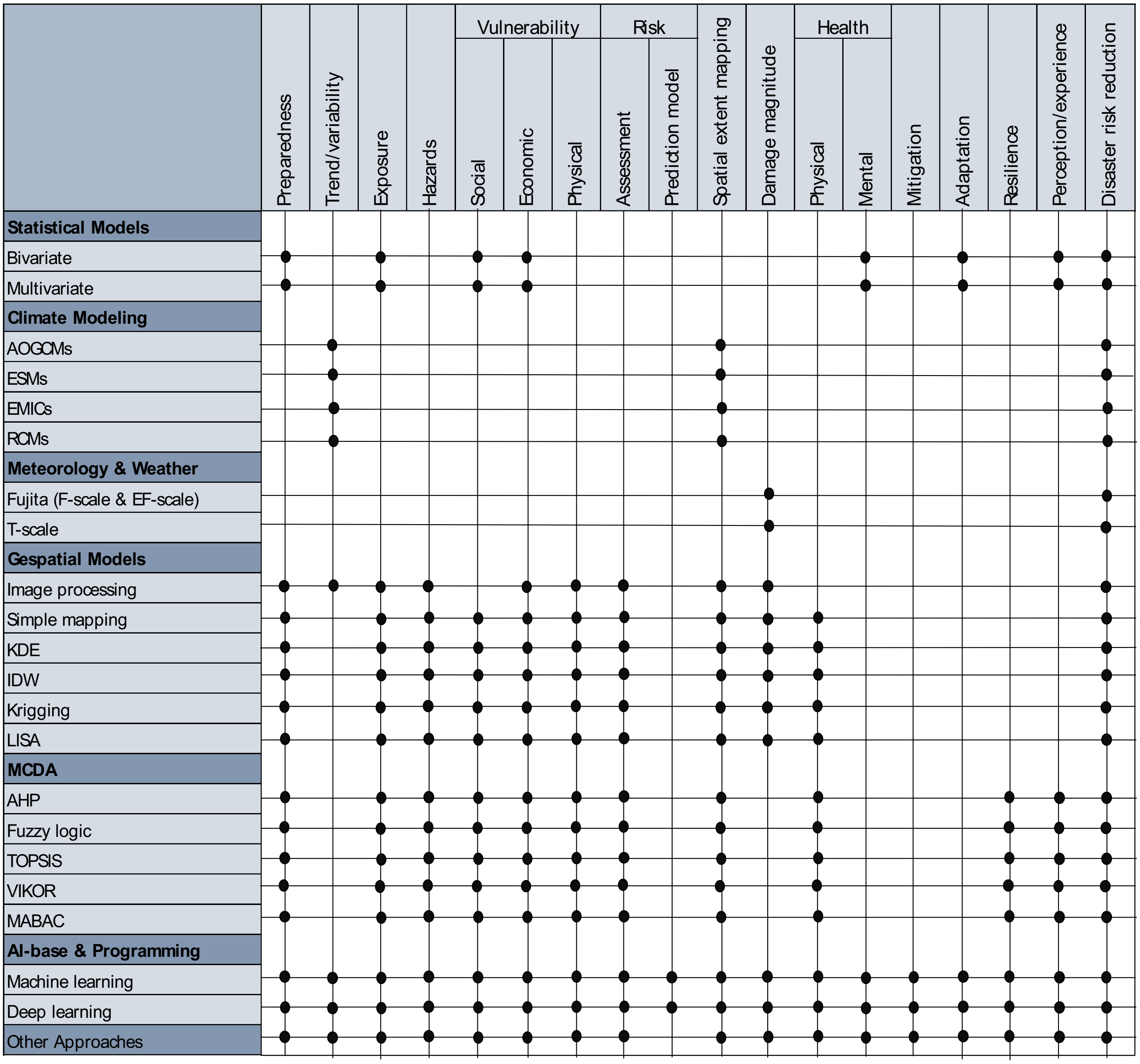

Fig. 2 Showing Matrix of various conventional and emerging approaches, methods and their multi-dimensional applications and suitability in WCEE studies

Object-based classification: This approach is more holistic because it considers not only the spectral properties of individual pixels of an imagery, but also their spatial relationships and contextual information, allowing for more accurate classification of complex features [85]. The object-based classification segments satellite data into meaningful objects or regions based on spectral, spatial, and contextual information [86]. This approach is especially useful for identifying and mapping specific features relevant to disaster risk reduction, such as buildings, infrastructure, and natural hazards. By considering the spatial context of features, object-based classification enables a more detailed and nuanced understanding of the landscape, which is crucial for effective disaster preparedness, response, and recovery efforts [87].

3.2.1.2 Image classification techniques **Supervised classification:** This digital image classification technique relies on labeled training data to train classifiers for assigning class labels to individual pixels or objects in the image [88]. This approach is highly effective for tasks such as mapping land cover or land use classes, where the classes of interest are known and identifiable spectral signatures exist [89]. By leveraging labeled training data, supervised classification enables accurate identification of features relevant to disaster risk reduction, aiding in hazard mapping, vulnerability assessment, and decision-making processes [83].

Unsupervised classification: offers a different approach by identifying natural groupings or clusters within the data without the need for labeled training samples [88]. This technique is particularly useful for exploratory analysis, identifying unknown patterns, and detecting anomalies in remote sensing imagery [90]. Unsupervised classification algorithms automatically partition the image data into clusters based on spectral similarities, providing insights into underlying patterns or structures that may not be apparent through visual inspection alone. While unsupervised classification is prone to misclassification errors [91], especially when dealing with low spatial resolution satellite data, it can still be useful in extracting valuable information relating to extreme events, especially in studies involving classification and assessment of discrete features, patterns, or trends in the data, facilitating hazard assessment and mitigation strategies.

3.2.1.3 Change detection approach The two most frequently utilized change-detection methods include spectrally based approaches, known as image-to-image methods, and classification-based methods, referred to as map-to-map methods [92]. Within this domain, the commonly employed techniques comprise the Algebra-based approach, Classification-based approach, and Other Methods. The Algebra-based Approach shares a common characteristic, which involves selecting thresholds to identify change areas. Examples of Algebra methods include Image differencing, Image rationing, and Image overlay.

The Classification based approach involves the division of image pixel into classes to produce a thematic representation [81]. In this technique image of single or multiple dates are separated and classified based on their different scattering or spectral signatures [93]. Supervised classification, Unsupervised classification and Post classification [83]. Other approaches encompass techniques for change detection (Land Use Land Cover) including decision rule-based and tree regression models, among others.

3.2.2 Spatial interpolation techniques

One key aspect of geospatial analysis is spatial interpolation, which enables the estimation of variable values at unmeasured locations based on the point data collected from known locations. The value of spatial interpolation is enhanced when there is a sufficient density of point data distributed across the study area [25]. The required density of the network depends on the specific variable being estimated. Therefore, achieving accurate and precise interpolated surfaces for any disaster mapping would likely necessitate a denser network of monitoring sites, as highlighted in the study by [94].

Various spatial interpolation techniques can be applied for disaster studies using the Geographic Information System (GIS) environment [26, 95–97]. These techniques encompass methods such as KDE, IDW, Kriging, Natural Neighbor, Spline etc. [71, 79, 98, 99]. By utilizing these diverse methods, accurate and comprehensive spatial estimates can be obtained, facilitating effective disaster planning, response, and mitigation strategies.

3.2.2.1 Kernel density estimation technique The Kernel Density Estimation (KDE) is an interpolation technique used to estimate the spatial density of events or phenomena [100]. It determines the intensity or concentration of events at different locations within a study area. The principle behind KDE is to use a kernel function to assign weights to neighboring events, creating a smooth density surface. The density at a particular location is influenced by the proximity and intensity of surrounding events [99].

To compute the KDE, the density of all damage incidents within a specified bandwidth (kernel radius) surrounding a focal point would be calculated. This computation involves a formula derived from methodologies outlined in prior studies [4, 101]. The mathematical equations commonly used for KDE are expressed as follows:

$$fh(x_j) = \sum_{i=1}^{n} \frac{1}{h^2} K\left(\frac{x_j - x_i}{h}\right) \tag{1}$$

In this equation, $f(x_j)$ denotes the estimation of intensity, h indicates the bandwidth, K represents the kernel function applied across dimensions of x, and $(x_j – x_i)$ signifies the Euclidean distance between the grid point x_j and event n_i. Here, x_j represents the location vector within the field R, and $x_1, x_2 \ldots\ldots x_n$ denote the location vectors of n events [101].

$$f_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{X_i - x}{h}\right) \tag{2}$$

In the Eq. (2), the kernel function, *K (x),* utilized in the KDE commonly employs a smooth and symmetrical function, like a Gaussian distribution [102]. The smoothing bandwidth, $h > 0$, governs the extent of smoothing applied. Essentially, the KDE process involves transforming each point data, *Xi*, into a localized density bump, and subsequently aggregating these individual bumps to derive the final density estimate [103].

3.2.2.2 Inverse distance weightage technique The Inverse Distance Weightage (IDW) is an interpolation technique that estimate the values at unknown locations based on values observed at known locations. It assumes that values closer to a target location have a stronger influence than those farther away. The principle behind IDW is to assign weights to known values based on their distance to the target location. These weights are inversely proportional to the distance, hence the name Inverse Distance Weightage [104]. The principle of IDW can be explained through several equations, with the commonly used equations known as the Shepard method. This method employs a weight function, denoted as *wi*, which is defined as follows [98].

$$w_i = \frac{\left[h_j^{(-p)}\right]}{\left[\sum_{i=0}^{n} h_j^{(-p)}\right]} \tag{3}$$

where, p represents a real positive number known as the power parameter (usually $p = 2$). Additionally, h_j represents the distance between the dispersion point and the interpolated point, which is calculated using the following equation:

$$h_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{4}$$

As shown in Eq. (2), values (x, y) represent the estimated coordinates of each interpolated (unknown) point, while (x_i, y_i) represents the coordinates of each dispersion point.

3.2.2.3 Kriging technique The Kriging technique is a geostatistical method used for spatial interpolation and modeling. They are widely applied in WCEE studies to estimate values at unmeasured locations based on observations from nearby locations [25, 105]. Kriging considers the spatial autocorrelation and variability of the data, yielding predictions that are more precise and dependable when contrasted with simpler interpolation techniques. Kriging, an algorithm utilizing linear least squares estimation, is employed to predict an unknown real-valued function E, at a specific point (x, y), based on the known values of the function at other points $(x_1, y_1), (x_2, y_2), \ldots\ldots (x_n, y_n)$. The Kriging estimator is considered linear since the predicted value, $E(x, y)$, is expressed as a linear combination of the known function values [98].

$$E(x, y) = \sum_{i=1}^{n} \lambda_j E\left(x_j - x_i\right) \tag{5}$$

$$E(x, y) = F(x, y) - \sum_{i=1}^{n} \lambda_j E\left(x_j, y_i\right) \tag{6}$$

The weights λ_j are derived by solving a set of linear equations, which stem from the assumption that E is a sample path of a random process $F(x, y)$. The goal is to minimize the prediction error in some manner. For instance, in simple kriging, where the mean and covariance of $F(x, y)$ are known, the Kriging predictor is selected to minimize the variance of the prediction error.

3.2.2.4 Spatial autocorrelation technique Spatial autocorrelation refers to the statistical relationship between spatially proximate observations within a dataset. It measures the degree to which values of a variable at one location are related to the values at neighboring locations. Spatial autocorrelation analysis is valuable in understanding spatial patterns, identifying clusters or hotspots, and detecting spatial dependencies in disaster studies [106]. It helps reveal whether similar values tend to cluster together (positive autocorrelation), exhibit dispersion (negative autocorrelation), or display no spatial pattern [104]. One of the most popular methods used in disaster studies is the Local Indicators of Spatial Autocorrelation (LISA). LISA technique identifies clusters, hotspots, or patterns of similarity and dissimilarity within a spatial dataset [102, 106]. It examines the degree of spatial autocorrelation, which measures how similar values at one location are to the values at nearby locations. The Moran's index, knowns as Moran's *I*. is the widely used measure of spatial autocorrelation. It measures the spatial relationship between a variable at one location and the values of neighboring locations. Usually, using the following Moran's *I* equation [102].

Global Moran's *I*

$$I = \frac{\sum_i^n \sum_{j\neq 1}^n w_{ij}\left(x_i - \vec{x}\right)\left(x_j - \vec{x}\right)}{S^2 \sum_i^n \sum_{j\neq 1}^n w_{ij}} \tag{7}$$

The equation involves x_i and x_j, which respectively stand for the evaluation values of regions *i* and *j*. The parameter n denotes the number of spatial observation units, while S^2 indicates the variance of the evaluation values. Utilizing the spatial weight matrix, w_{ij}, adjacency relationships between regions *i* and *j* are established. If regions *i* and *j* are adjacent, w_{ij} is assigned a value of 1; otherwise, it is assigned 0. In this study, the Moran's *I* statistical test is conducted, with the Z statistic serving as the measure of association.

Local Moran's *I*

$$I_i = z_i \sum_{j=1}^{n} w_j z_j \tag{8}$$

The Moran's *I* value typically falls between -1 and 1, indicating negative correlation for values below 0, no correlation for 0, and positive correlation for values above 0. The standardized values of the evaluation values for region *i* and region *j* are represented by the variables z_i and z_j, respectively.

3.3 Multi-criteria decision analysis

The MCDA approach is used to systematically evaluate and compare multiple criteria or alternatives in decision-making processes [34, 107, 108]. It provides a structured framework for evaluating alternatives based on multiple criteria, assessing complex problems, and supporting informed decision-making under uncertainty. Many studies have utilized the MCDA including WCEE studies using techniques, such as AHP, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Fuzzy Logic.

3.3.1 Analytical hierarchy process

The AHP model, which is based on pairwise comparisons and hierarchical structures, allows for the evaluation of complex decision-making processes by considering attributes as indicators [109]. It was developed by Saaty in 1990 and employs an absolute number scale from 1 to 9 for pairwise comparisons [110, 111], see Table 1. With the AHP model, priorities of alternatives can be determined based on user judgments, and it provides a pairwise matrix, eigenvalue, and weighting coefficient. According to [112], if a decision maker considers alternative *i* to be equally

Table 1 Pairwise comparison scale rating

Scales	Judgement and preferences	Description
1	Equally important	Two factors contribute equally to the objective
3	Moderately important	One factor is slightly preferred over the other, based on experience and judgment
5	Strongly important	One factor is strongly preferred over the other, based on experience and judgment
7	Very strongly important	One factor is very strongly preferred over the other, based on experience and judgment
9	Extremely important	In practice, the evidence supporting one factor over the other is of the highest possible validity
2,4,6,8	Intermediate preference between adjacent scales	When compromise is necessary

important as alternative j, a comparison represented by $a_{ij} = a_{ji} = 1$is expected. However, if alternative i is considered significantly more important than alternative j, the score of the calculated matrix would be $a_{ij} = 9$ and $a_{ji} = 1/9$. These scores, distributed in a square matrix, form a reciprocal matrix [113]. The matrix A, denoted as $[a_{ij}]$, represents the preference intensity of the decision maker for one alternative over another, comparing a_{ij} for all $i, j = 1, 2, \ldots, n$ [110].

$$A = \left(a_{ij}\right) = \begin{bmatrix} 1 \; a_{ij\ldots} & a_{in} & \\ 1/a_{ij} & 1\ldots & a_{2n} \\ \vdots & \vdots & \vdots \\ 1/a_{in} & 1/a_{2n\ldots} & 1 \end{bmatrix} \tag{9}$$

Moreover, the AHP model guarantees consistency in priorities through the computation of the Consistency Ratio (CR). Using Eqs. 10 and 11 the Consistency Indices (CI) and CR for a specific choice can be calculated [111]. The CR helps to determine the acceptance of the decision maker's judgment scores or weights; a CR value less than or equal to 0.10 is deemed acceptable [110], as expressed in the following equation:

$$CI = \left(\frac{\lambda_{max} - n}{n - 1}\right) \tag{10}$$

$$CR = CI\left(\frac{1}{RI}\right) \tag{11}$$

The maximum eigenvalue, denoted as λ_{max}, is determined by averaging all individual eigenvalues, while n represents the random index (RI) and the number of elements or criteria that are subjected to a priority judgment [48, 114].

The AHP is widely recognized as one of the most popular techniques in DRR [26, 108, 111] due to its reliability and effectiveness in calculating weighted values and prioritizing variables. [109] utilized AHP in flood evaluation. [110] highlighted the effectiveness of AHP in selecting criteria and elements that accurately describe disaster-resilient coastal communities [34]. Applied AHP in to assess the social vulnerability of landslide. Overall, these studies highlight the reliability and usefulness of the AHP technique in WCEE studies and decision-making processes.

3.3.2 Fuzzy logic

Fuzzy logic, a technique developed by Zadeh in 1965 within the field of MCDA, emerged in response to the challenges posed by decision-making scenarios characterized by vagueness and uncertainty, where precise ranking of alternatives is elusive [115–118]. Fuzzy logic operates by employing linguistic variables and fuzzy sets to effectively represent and manage uncertainties and imprecisions in both data and decision-making processes [119]. Its fundamental concept revolves around assigning degrees of membership to elements within a set, with values ranging from 0 (indicating non-membership) to 1 (representing full membership) [26, 120, 121]. Given the intricacies and difficulties associated with decision-making scenarios that demand precise numerical values for evaluation criteria, fuzzy logic finds its relevance among various MCDA methods. In particular, within the realm of disaster management studies, where ranking is essential for tasks such as impact assessment, susceptibility and vulnerability assessment, and risk prediction, fuzzy logic has been widely employed, consistently yielding promising results [115, 117, 122–124]. Fuzzy technique works based on certain principles such as the fuzzy set, fuzzification, membership functions, and defuzzification etc. [125].

A review of the two commonly used fuzzy set A (for triangular and trapezoidal numbers), denoted by $[\mu_A]$, have their numbership functions defined by the mathematical equations as follows [117, 118, 126].

$$\mu_A = \begin{cases} \frac{x - a_l}{a_m - a_u}, a_l \le x \le a_m \\ \frac{a_u - x}{a_u - a_m}, a_l \le x \le a_m \\ o, Otherwise \end{cases} \tag{12}$$

The triangular fuzzy set A is denoted by a triplet $(a_{l,} a_{m,} a_u)$, Eq. (12)

$$\mu_A = \begin{cases} \frac{x-a_l}{a_{ml}-a_l}, a_l \le x \le a_{ml} \\ 1, a_{ml} \le x \le a_m \\ \frac{a_u-x}{a_u-a_m}, a_m \le x \le a_u \\ o, Otherwise \end{cases} \tag{13}$$

The trapezoidal fuzzy set A is denoted by a quartet $(a_{l,} a_{ml,} a_{m,} a_u)$, Eq. (13)

Where fuzzy member A is defined as an interval $\{a_{l,} a_{ml,} a_{m,} a_u\}$, where $a_{l,} a_{ml,} a_{m,}$ and $a_{u,}$ represent lower, middle-lower, middle and upper boundaries of A.

3.3.2.1 Fuzzification Fuzzification is the process in Fuzzy Logic by which precise data, often expressed as numerical values, is transformed into fuzzy data. This transformation is achieved by assigning degrees of membership to one or more fuzzy sets or linguistic terms [115, 127]. The primary purpose of fuzzification is to represent uncertainty or imprecision within the data and to facilitate reasoning within fuzzy logic systems. It serves as the initial step in many fuzzy systems and plays a pivotal role in managing vague or qualitative information during decision-making processes [107, 124, 128]. For instance, within the context of disaster severity assessment, fuzzification may involve the use of five linguistic terms: 'Severely damaged,' 'Significantly damaged,' 'Moderately damaged,' 'Lightly damaged,' and 'Minimally damaged.' See Table 2.

3.3.2.2 Fuzzy membership functions Within the Fuzzy Logic, a membership function is a mathematical curve or function that assigns a degree of membership (between 0 and 1) to each element in the input space of a fuzzy set or linguistic term. It defines how well an element belongs to a particular fuzzy set or category. The shape of the membership function determines the degree of membership for each input value [129–131]. Previous researchers have employed various types of membership functions, including triangular, trapezoidal, Gaussian, polynomial, and bell-shaped, to describe disaster severity, vulnerability, exposure and prediction process [34, 122, 132–134].

But the triangular and trapezoidal functions are the frequently employed due to their simplicity and ease of implementation within computer programs. They possess the capability to approximate a wide range of non-triangular functions, as noted by [118, 123, 135]. In contrast to Gaussian membership functions, which offer smoother transitions, trapezoidal and triangular membership functions, although common, exhibit sharp transitions that may not accurately represent uncertainties, as highlighted [125], see Fig. 3. This transformation of linguistic variables into numerical values is termed "fuzzification."

3.3.2.3 Defuzzification Defuzzification is the process in Fuzzy Logic that converts fuzzy data or fuzzy results into a crisp or precise form [129, 135]. Defuzzification aims to obtain a single, well-defined output or decision from these fuzzy values. It takes the fuzzy data, such as fuzzy sets or linguistic terms with varying degrees of membership, and produces a specific numerical or categorical result that can be easily understood and applied in practical application [136].

To defuzzify the fuzzy variables based on the mean of the weighted criteria, the process involves using the average weight criteria w_i, as shown in Eq. (14) [118].

$$w_i = \frac{a_1(+)a_2(+)\dots a_n}{n} \tag{14}$$

Fuzzy logic can be harnessed in MCDA within the domains of mapping, soft computing, and machine learning to address uncertainties and model complex, imprecise data, thereby enhancing the decision-making process [124,

Table 2 Representation of fuzzy linguistic terms and corresponding fuzzy values

Linguistic variables	Crips numbers	Membership functions (Triangular)	Membership functions (Trapezoidal)
Minimal damage	1	(0, 0, 0.25)	(0, 0, 0.25, 0.5)
Low damage	2	(0, 0.25, 0.5)	(0, 0.25, 0.5, 0.75)
Moderate damage	3	(0.25, 0.5, 0.75)	(0.25, 0.5, 0.75, 1)
Significant damage	4	(0.5, 0.75, 1)	(0.5, 0.75, 1, 1)
Severely damage	5	(0.75, 1, 1)	(0.75, 1, 1, 1)

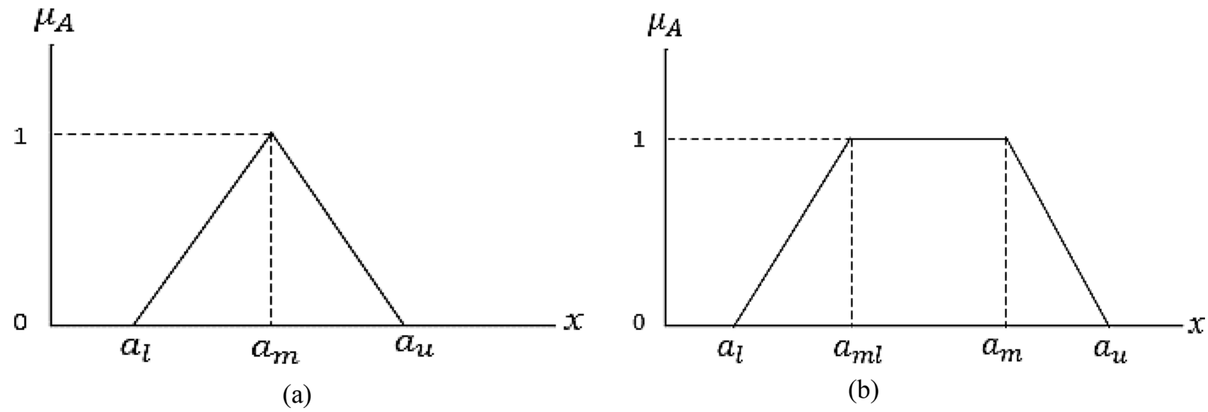

Fig. 3 Showing the schematic diagrams of (**a**) triangular fuzzy numbers and (**b**) Trapezoidal fuzzy numbers, given by $A = \{a_{l,}a_{ml,}a_{m,}a_u\}$

125, 128, 129, 135]. Fuzzy logic technique has showcased its adaptability in diverse aspects of disaster management. [117] developed a robust fuzzy optimization method to mitigate the risk of uncertainty such as travel time, relief times and severity of events during flood emergency response [137] predicted and modeled urban flood risk areas by combining machine learning techniques and fuzzy logic. Furthermore, [120] employed fuzzy in tracking typhoon trajectory by assigning fuzzy membership degrees to six typhoon track clusters. In another context, [127] utilized fuzzy logic for flood resilience mapping.

3.3.3 TOPSIS

The TOPSIS technique was first developed by Hwang and Yoon in 1981 [32, 107], is a popular multi-criteria decision-making technique known for its simplicity and ease of implementation. TOPSIS operates on the principle of determining the best alternative by finding the shortest distance to the positive-ideal solution and the longest distance to the negative-ideal solution among the evaluated options [138, 139]. It efficiently evaluates alternatives in a set of criteria and provides a clear representation of human decision-making logic.

The TOPSIS technique has been extensively applied in disaster management studies, offering a robust approach to assessing disaster events. For example [140, 141] applied TOPSIS to evaluate flood resilience based on community preparedness. Similarly, [123] utilized TOPSIS to assess stakeholders' perceptions of flood risk. Additionally, [142] utilized the technique to assess disaster loss based on economic impact and structural damage. Lastly, [47, 138] employed TOPSIS to evaluate flood risk based community's vulnerability, exposure factors. This collective evidence underscores the broad applicability of TOPSIS in contributing valuable insights across various dimensions of disaster management. A study by [143] on flood susceptibility modeling compared three MCDA techniques and reported that TOPSIS outperforms AHP and MABAC.

The implement the TOPSIS technique involves the following five steps [123, 134, 138, 139, 144].

Step 1. Establish the decision matrix $X = \{x_{ij}\}$, where x_{ij} is the value of the jth observation in the ith indicator;$i = 1, 2, \cdots, m; J = 1, 2, \cdots n$

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{15}$$

Step 2 involves standardizing the decision matrix X, considering various magnitudes and dimensions for the different indicators. The objective is to transform the decision matrix X into a standardized matrix $\hat{X} = \{\hat{x}_{ij}\}$. The process of calculating $\hat{X}$ through vector normalization can be represented as follows:

$$\hat{x}_{ij}^{\cdot} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}(x_{ij})^2}} i = 1, 2, \cdots, m; J = 1, 2, \cdots n \quad (16)$$

Step 3. A weighted standardized decision matrix $V = \{v_{ij}\}$, is obtained by multiplying the weights as follows:

$$v_{ij} = w_i x \hat{x}_{ij}, i = 1, 2, \cdots, m; j = 1, 2, \cdots n \quad (17)$$

Step 4 involves computing the positive and negative ideal solutions. The positive ideal solution (A +) and negative ideal solution (A-) are determined using the weighted standardized values in the following manner:

$$A^+ = \left[v_1^+ v_2^+ \cdots, v_n^+\right] \quad (18)$$

$$A^- = \left[v_1^- v_2^- \cdots, v_n^-\right] \quad (19)$$

where;

$$v_1^+ = \begin{cases} \text{max} v_{ij} \text{ if } j \text{ is a benefit attribute} \\ \text{min} v_{ij} \text{ if } j \text{ is a cost attribute} \end{cases}$$

$$v_1^- = \begin{cases} \text{min} v_{ij} \text{ if } j \text{ is a benefit attribute} \\ \text{max} v_{ij} \text{ if } j \text{ is a cost attribute} \end{cases}$$

Step 5. Calculate distance with ideal solution. The observations' Euclidean distance (S^+) from the positive ideal solution and the distance (S^-) from the negative ideal solution are calculated using Eqs. (20) and (21).

$$S_i^+ = \sqrt{\sum_{j=i}^{n} \left(v_i - v_j^+\right)^2}, i = 1, 2, \cdots m \quad (20)$$

$$S_i^- = \sqrt{\sum_{j=i}^{n} \left(v_i - v_j^-\right)^2}, i = 1, 2, \cdots m \quad (21)$$

Step 6. Calculate the closeness coefficient which represent the distance between positive ideal, A^+, and negative ideal, A^-. The closeness coefficient of each alternative (C_i) is given as;

$$C_i = \left(\frac{S_i^-}{S_i^- + S_i^+}\right) i = 1, 2, \cdots m \quad (22)$$

3.4 AI-based approach

3.4.1 Machine learning

Machine Learning (ML), a branch of Artificial Intelligence (AI), refers to the process of training computational models to learn patterns and make predictions from data [47, 132]. It operates on the principle that machines can learn from experience, improve over time, and perform tasks without explicit programming [145]. ML models can be broadly categorized into supervised, unsupervised, and reinforcement learning methods [52, 146, 147]. These models, when trained on datasets, learn underlying patterns and relationships to make predictions or decisions on new, unseen data [148]. The two main learning approaches are supervised and unsupervised learning.

3.4.2 Deep learning

Deep Learning (DL), is a subset of ML that focuses on training deep neural networks [23, 148, 149]. It involves complex neural architectures with multiple layers (often referred to as deep neural networks), enabling the automatic extraction of hierarchical representations from raw data [6]. DL models, particularly artificial neural networks, excel in processing unstructured data like images, text, and audio. While some ML models are less complex and offer better interpretability compared to DL models (e.g., decision trees, RF, LR and SVM) [150]. However, DL models often outperform traditional ML models in terms of accuracy and handling large, high-dimensional datasets due to their ability to capture intricate patterns and relationships within the data [151, 152].

3.4.3 ML/DL approaches

3.4.3.1 Supervised learning Supervised Learning involves training models using labeled data, where the algorithm learns from input–output pairs [75]. In this approach, the model is trained to generate predictions or decisions by analyzing input features alongside their corresponding output labels or target variables. The objective is to correctly translate the input data with the corresponding output through the utilization of this training dataset [147]. Examples of supervised learning models in ML are decision trees, linear regression, random forest and support vector machines [6, 153]. Examples of supervised learning models in DL are artificial neural networks (ANN), long short-term memory (LSTM), convolutional neural networks (CNN), and recurrent neural networks (RNN) [38, 133, 154].

3.4.3.2 Unsupervised learning Unsupervised Learning is a ML/DL approach where the model learns from unlabeled data, seeking to discover hidden patterns or structures within the data without explicit guidance or supervision [146, 155]. Unlike supervised learning, there are no predefined target labels for the algorithm to predict. Instead, unsupervised learning algorithms aim to discover inherent patterns, relationships, or structures within the data. Clustering, dimensionality reduction, and association mining are common unsupervised learning tasks [6]. K-Means clustering, Hierarchical clustering and Principal Component Analysis (PCA) are the most popular unsupervised learning models [147]. Unsupervised learning is particularly useful for exploratory data analysis, uncovering hidden patterns, and gaining insights from large and complex datasets.

3.4.4 ML/DL models

3.4.4.1 Support vector machine Support Vector Machine (SVM) is a powerful ML method that is based on nonlinear transformations [156]. This method utilizes powerful classifiers that finds the hyperplane with the maximum margin of separation between different classes in the feature space [6, 157]. SVM are particularly useful for identifying complex relationships and analyzing weather and climate extreme phenomena based on multidimensional dataset to assess, forecast, predict and model extreme events [150, 158]. Many studies on WCEE have utilized SVM and reported the model's promising results. For example, [159] conducted a comparative analysis of multiple ML models for urban flood prediction. Their research revealed that SVM demonstrated superior performance compared to Logistic Regression and Decision Tree classifiers. Similarly, [160] compared various machine learning models for monitoring drought conditions. The study found that SVM outperformed other models, including Random Forest, in predicting soil moisture levels, indicating SVM's effectiveness in drought monitoring and management strategies.

3.4.4.2 Logistic regression Logistic regression (LR) is a statistical method used in ML to undertake binary classification tasks, where the outcome variable is categorical and binary [156, 159]. LR models the probability of occurrence of an event based on one or more predictor variables [114]. Within the context of WCEE, LR method can be employed to model the likelihood of extreme events based on environmental variables and climatic factors, aiding in understanding impact or probability of occurrence (risk prediction) and decision-making processes [159]. Various studies on WCEE have utilized LR method in DRR and report promising results. For example, [161] investigated the effectiveness of various ML models in developing an early warning system for heavy rain prediction. Their study found that LR outperformed other classifiers among the ML models considered, showcasing its superiority in accurately predicting heavy rainfall events. This emphasizes the effectiveness of LR in weather-related forecasting and its potential for enhancing early warning systems for extreme weather events.

3.4.4.3 Random forest Random Forest is a versatile ML algorithm widely used for both classification and regression tasks [145]. It constructs multiple decision trees during training and combines their predictions through a process called "bagging" (bootstrap aggregating) to improve accuracy and robustness [162]. Each decision tree in the forest is trained on a random subset of the training data and a random subset of features, reducing overfitting and capturing diverse patterns in the data [158]. The final prediction is determined by aggregating the predictions of individual trees, often through a simple averaging or voting mechanism [145]. In a study by [163], ML and DL models were utilized to predict lake water levels. Among the models evaluated, Random Forest emerged as the top-performing model, surpassing Support Vector Regression, Linear Regression, and ANN approaches. Because of its scalability and ability to handle high-dimensional data with complex relationships, many researchers have utilized Random Forest in their various WCEE studies [36, 162].

3.4.4.4 Convolution neural network (CNN) Convolution Neural Network (CNN) is a DL architecture designed for processing structured grid data, such as images [151]. They use convolutional layers to automatically learn hierarchical representations of features, making them highly effective for tasks such as image classification, object detection, and image segmentation [76]. CNN is ideally suited for tasks involving complex image pattern recognition and modeling, making them a suitable option for understanding events or phenomena with intricate visual characteristics [162]. These architectures are robust in automatically learning hierarchical representations of features from images, enabling them to capture spatial dependencies which are essential for accurate modeling. Due to their ability to detect complex visual patterns at multiple levels of abstraction, CNN model have made the utilization of satellite data and aerial imaging systems in disaster assessment and prediction crucial [6]. For example, [133] employed CNN to predict the occurrence of extreme weather events based on temporal and spatial dimensions. The study reported the CNN model to be robust and effective in extreme event predictions.

3.4.4.5 Recurrent neural networks Recurrent Neural Networks (RNN) are a DL architecture within the class of neural networks designed for processing sequential data [6]. The model has recurrent connections that allow them to capture temporal dependencies in the data, making them suitable for tasks such as time series prediction, natural language processing, and speech recognition. [164] conducted research on drought projection by applying RNN to unravel the intricate relationship between short, intense wet periods and the long-term trend of dryness. Their findings demonstrated that the RNN model yielded promising results, revealing statistically significant correlations with drought occurrences, thereby enhancing our understanding of drought dynamics.

3.4.4.6 Long short-term memory (LSTM) Long Short-Term Memory (LSTM) models are a type of RNN architecture within the DL models designed to tackle the challenge of learning long-term dependencies in sequential data [162]. They incorporate specialized units called "memory cells" that enable them to selectively store, update, and retrieve information over time [165]. LSTMs are equipped with three gates—input, forget, and output—that regulate the flow of information within the network. These gates control which information is retained, discarded, or passed on to the next time step, allowing LSTMs to effectively capture temporal patterns and context in the data [166, 167]. Recently, the LSTM architecture has been increasingly used by researchers and applied in various WCEE studies focusing on time series modeling due to its superior performance compared to traditional RNN [154]. For example, [168], reported that LSTM outperformed SVM models in predicting lake water levels in China. Similarly, [35] reported how LSTM models yielded promising results in detecting extreme wind speed and rainfall patterns, thereby enhancing our understanding of climate change impacts and supporting decision-making processes for disaster preparedness and adaptation measures.

3.4.4.7 Other ML/DL models There are other state-of-the-art models underpinning recent advances in the domain of WCEE. For example, Graph Neural Networks (GNNs) are leveraged for their ability to model spatial and temporal dependencies in climate data [169]. Physics-Informed Neural Networks (PINNs) integrate physical laws into neural networks, enhancing model accuracy by respecting known physics constraints [170]. Transformers, known for their efficiency in handling sequential data, have shown promise in time-series forecasting of extreme weather events. Generative AI models like GANs and Diffusion Models are also utilized for generating realistic climate scenarios, aiding in risk assessment and planning [6]. Gradient Boosting Trees (GBTs), Naïve Bayes Tree, and Bayesian Additive

Regression Trees (BART) provide robust predictive performance and uncertainty quantification, making them valuable for probabilistic forecasting and decision-making in WCEE [6, 171] among a host of other models.

3.4.5 Modeling process

3.4.5.1 Model selection The choice of ML/DL algorithms is essential in modeling any phenomenon of interest [16]. Within the domain of disaster management, selecting the right ML/DL algorithms plays a crucial role in understudying any impact or addressing any issue in the pre-, during-, and post-disaster phases. It is essential to balance between model accuracy, complexity, and interpretability based on the context of the disaster management scenario. Additionally, the choice of ML/DL algorithms should align with the nature of the problem, the characteristics of the available data, and the objectives of the study. For example, ANN present a powerful approach in predicting extreme meteorological events due to their ability to capture complex, nonlinear relationships inherent in weather patterns, especially those characterized by temporal and spatial variabilities [35, 147].

In scenarios involving satellite and aerial image analysis, CNNs stand out due to their proficiency in extracting features from visual data [76]. For trend analysis of extreme weather and climate events, RNNs and LSTM models are preferred, given their ability to capture temporal dependencies [151, 167]. Logistic regression is particularly valuable in binary classification tasks within the realm of DRR. SVM find application in various areas within the WCEE studies, such as flood prediction, drought monitoring, due to their capability to handle non-linear relationships and high-dimensional data [150, 159].

Overall, previous studies employing ML/DL methods, especially those conducting comparative assessments, have not identified a clear dominance or consensus regarding the best algorithm [148]. Nonetheless, certain models are specifically tailored to specialized in learning and training for certain complex tasks i.e., the neural networks, rendering them more suitable for such applications.

3.4.5.2 Data preparation

1.1.1.Data Splitting: The implementation of any ML/DL models requires data for calibration and validation [154]. Data splitting involves dividing the dataset into two or three subsets: training, validation, and test sets. The training set is utilized to train the models on training data, employing algorithms that minimize the disparity between predicted and actual values. The validation set aids in fine-tuning hyperparameters, while the test set assesses the model's performance on unseen data. Normalization and Standardization: This involves the process of rescaling the data to a standard range or distribution. Normalization scales the values between 0 and 1, while standardization transforms data to have a mean of 0 and a standard deviation of 1. Given by the given by the equation [35].

$$x_{norm} = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{23}$$

2.2.2.Data Augmentation (DL-specific): In DL, augmenting the dataset by generating new synthetic data from the existing samples [6]. Techniques include rotation, flipping, cropping, and adding noise to images.

3.4.5.3 Model training and evaluation Model evaluation is a pivotal process in machine learning, as it serves as a critical checkpoint for assessing the performance and reliability of trained models [137]. It provides insights into how well a model generalizes to new, unseen data, enabling the determination of its predictive or classification accuracy [39, 52, 153]. Evaluation metrics help compare different algorithms or variations of the same algorithm, aiding in the selection of the most suitable model for a specific task. Additionally, it guides the fine-tuning of model hyperparameters to optimize its performance, ensures quality assurance, and supports decision-making regarding the model's deployment or improvements, thereby enhancing its applicability and usefulness in real-world scenarios. Metrics used in evaluating the trained ML/DL model performance for validation and testing are confusion matrices, ROC-AUC, accuracy, precision, and F1-score etc. The evaluation metrics are calculated using the equations given by [145].

Confusion Matrix: A table representing the model's performance in tabular form, displaying actual versus predicted values. It includes True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

ROC (Receiver Operating Characteristic) is a graphical representation used in binary classification to analyze the performance of a classifier model. It illustrates the trade-off between the true positive rate (sensitivity) and the false positive rate (1—specificity) across various threshold values.

$$Sensitivity = \frac{TN}{TN + FP} \tag{24}$$

$$Specificity = \frac{TN}{TN + FN} \tag{25}$$

The AUC (Area Under the ROC Curve) quantifies the overall performance of a classifier by computing the area under the ROC curve. The AUC value ranges between 0 and 1, where a higher AUC indicates better model performance. It provides a single scalar value to compare different classifiers, with an AUC of 1 suggesting a perfect classifier, while an AUC of 0.5 represents a classifier performing randomly.

$$AUC = \sum TP \sum \frac{TN}{P} + N \tag{26}$$

Accuracy: It measures the overall correctness of predictions and is computed as the ratio of correctly predicted instances to the total number of instances within the dataset [145].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{27}$$

3.4.5.4 Uncertainty in ML/DL measurements Uncertainty in ML/DL refers to the absence of complete certainty or predictability in outcomes due to limited knowledge, incomplete data, variability, or inherent randomness in a system or process [172, 173]. It represents the degree to which a result, measurement, or prediction deviates from the true value or expected outcome. Similarly, applying ML/DL models in WCEE involves making inferences for informed decision-making [174]. Therefore, it is essential to assess the reliability and effectiveness of AI systems before they are implemented in real-world applications, as predictions made by these models are subject to inference errors [175]. Beyond the uncertainty from inductive inference, other sources like incorrect model assumptions and noisy or imprecise data also contribute to overall uncertainty [176]. Therefore, it is crucial to represent uncertainty accurately and transparently in AI-based systems to ensure the trustworthiness of predictions and the accuracy of outcomes.

3.4.5.5 Sources of uncertainty These uncertainties are broadly categorized into aleatoric and epistemic uncertainties [177]. Aleatoric uncertainty, often referred to as statistical uncertainty, arises from inherent randomness or noise in the data, such as measurement errors, data entry mistakes, or natural variability in processes. This type of uncertainty can be reduced with more data or better data quality, among other methods [176]. Epistemic uncertainty, also known as model uncertainty, stems from a lack of knowledge about the best model or the most appropriate way to model the data. This includes uncertainties related to model parameters and the choice of model architecture and can be mitigated by improving the model, using more comprehensive datasets, or incorporating expert knowledge, etc. [178].

3.4.5.6 Modeling uncertainty There are various approaches and methods for quantifying and modeling uncertainty in ML/DL. For instance, probabilistic approach, such as Bayesian methods using Bayesian Neural Networks (BNNs), which model uncertainty by assigning probability distributions to model parameters [179]. The simulation and resampling approach, exemplified by Monte Carlo simulations, generates multiple possible outcomes by sampling from input distributions to estimate prediction uncertainty [180, 181]. The ensemble approach**,** like bagging and boosting, combines outputs from multiple models to capture variability and provide uncertainty bounds [175]. The fuzzy theory-based approach uses Fuzzy Logic Systems to handle ambiguity by representing data with degrees of membership rather than fixed values [180]. Additionally, the prediction interval approach employs models like interval regression to estimate prediction ranges, providing bounds that account for measurement and model uncertainty [180].

3.4.5.7 Challenges in modeling uncertainty Modeling uncertainty in WCEE prediction presents several challenges. One major challenge is quantifying and accounting for uncertainties in model inputs, parameters, and structure [182]. The selection and implementation of suitable mathematical structures for aleatory and epistemic uncertainties, as these often differ, pose another challenge [181]. Additionally, identifying and distinguishing between sources of uncertainty [183], accurately quantifying these uncertainties, and integrating uncertainty models into WCEE with vast amounts of data [173], all pose significant challenges. Furthermore, calibration and validation of uncertainties further complicate WCEE prediction and assessment.

4 Technique applications and their suitability in WCEE

4.1 Statistical models

The statistical models, whether bivariate or multivariate, measure the relationships, behavior, attitude, knowledge, practice, perception, or experience of people or target groups within disaster contexts [184–187], see Fig. 2. Therefore, the choice between bivariate and multivariate models in disaster research depends on the complexity of the variables under study [188]. Bivariate models, such as linear regression, T-test, and Chi-square, are suitable when analyzing two variables or a variable and a construct, as demonstrated in studies examining income levels and susceptibility to floods, or gender and disaster exposure [28, 66]. Similarly, they are valuable in behavioral pattern studies, elucidating the relationship between education levels and attitudes, adaptation practices, or preparedness. For example, [189] employed Chi-square to evaluate preparedness and response behaviors concerning floods, while [61] investigated the economic vulnerability of women and their resilience to urban floods in Lagos, Nigeria.

On the other hand, multivariate models, such as Structural Equation Modeling (SEM), Principal Component Analysis (PCA), Probit, MANOVA, and Multiple Linear Regression, are more suitable when analyzing multiple variables or constructs. Therefore, disaster studies involving the examination of multiple conditioning factors in relation to disaster impact or risk reduction are best suited using multivariate models. For instance, [190] utilized a combination of T-tests and SEM to evaluate various factors associated with disaster exposure in the Deepwater Horizon oil spill. Similarly, [63] employed multivariate models to study perceptions of climate risk policies related to floods, droughts, and temperature changes. In another study, [191] utilized the Probit model to understand the perception, adaptation, and mitigation strategies of flood and windstorm victims, while [64] employed the Probit model to investigate adaptation strategies against droughts, floods, and bushfires. This selection of models enhances the depth and breadth of analysis, contributing to a comprehensive understanding of disaster dynamics and informing effective disaster risk management strategies.

4.2 Spatial interpolation techniques

Spatial interpolation techniques are generally effective in a wide range of WCEE studies that involve assessment using mapping models, such as spatial extent of impact, exposure, or risk assessment, coldspot-hotspot mapping, and target vulnerability mapping [71, 72, 192], see Fig. 2. While KDE is suitable for estimating the density of points [4], Kriging is appropriate for modeling spatial variability and accounting for spatial autocorrelation in data [193]. On the other hand, IDW is particularly suitable for well-scattered data [194]. However, there is no consensus on a single technique with ultimate superior performance in the field of WCEE [25]. For instance, a study by [195] found that ordinary kriging outperformed IDW with dense point data, while IDW performed better than ordinary kriging for interpolating phenomena with scattered point data. In another study, [196] compared six interpolation techniques for understanding rainfall magnitude under different climatic conditions and reported that IDW performed the least effectively. In contrast, [197] compared four interpolation methods to analyze changes in rainfall patterns in Malaysia and found that Multi-scale Geographical Regression (MGWR) and IDW demonstrated better performance compared to the other models. Therefore, comparative studies on the effectiveness and suitability of geospatial techniques reveal that one method may outperform another depending on factors such as data availability, clustering, linearity, density, and sparsity patterns [195].

4.3 MCDA techniques

The utilization of MCDA techniques in DRR studies is crucial as it enables the systematic evaluation of complex decision-making scenarios, aiding in the selection of optimal strategies [15, 198]. Through the use of ranking criteria and the integration of various techniques such as Machine learning, spatial interpolation etc. [137, 199], MCDA techniques can be suitable for many WCEE applications. For example, MCDA has been widely utilized in understanding community or target group preparedness, vulnerability, or exposure to disasters [200, 201]. Additionally, it has been found to be promising in comprehensively mapping spatial susceptibility, risk and extent of disaster impact [143, 202], see Fig. 2.

Various MCDA techniques, such as VIKOR, SIR, MABAC, etc., also exist [203]. However, AHP, Fuzzy Logic, and TOPSIS are the most widely used in disaster studies [123]. These methods effectively assess social, economic, and physical dimensions of disasters across all stages [108, 204]. Although each MCDA technique has its inherent limitations, researchers are using hybrid approach by integrating methods such as Fuzzy-AHP, Fuzzy-TOPSIS, and AHP-TOPSIS [122]. These approaches replace crisp values with fuzzy numbers and introduce linguistic terms to better evaluate the importance of attributes and their values, enhancing their ability to handle vagueness [136]. Generally, the suitability and effectiveness of a particular MCDA technique can vary across different areas of application, depending on the available conditioning factors and how they are objectively ranked to assess disasters.

4.4 ML/DL techniques

AI-based techniques have emerged as formidable tools in WCEE modelling due to their capability to analyze large and complex datasets and discern intricate patterns [133, 205]. Unlike certain methods that have compatibility limitations, which further hinder their suitability and scope of application, ML/DL methods offer extensive compatibility with various techniques including statistical models, geospatial modeling, and MCDA across a diverse range of applications, encompassing all dimensions of disaster studies [125, 148, 206], see Fig. 2. ML/DL can handle nonlinear relationships and intricate patterns in data, enabling more precise predictions. They can seamlessly integrate with statistical techniques, such as regression analysis and hypothesis testing, to augment predictive capabilities [159]. Furthermore, ML/DL methods can be integrated with GIS techniques, such as Kriging and IDW, KDE, etc. to enhance spatial interpolation and accuracy of model maps [207]. Additionally, ML/DL can process various data types, including satellite imagery, remote sensing data [171], socioeconomic data, and sensor data, facilitating a comprehensive understanding of disaster dynamics [52].

Furthermore, ML/DL have emerged as a fundamentally effective methods for overcoming dataset limitations through data fusion and assimilation techniques [208, 209]. For example, satellite data from Landsat can be fused with other satellite data or ground-based observations to enhance spatial resolution and accuracy, leveraging the broad coverage of satellites while addressing their coarse details [210]. Assessing and predicting extreme weather conditions typically involve large areas and numerous climate variables, making data fusion essential. Additionally, ML/DL methods can assimilate data by integrating observational data into numerical models to improve their accuracy and reliability [211]. This technique enhance traditional data assimilation by efficiently handling vast datasets and uncovering patterns that conventional approaches might miss [212, 213]. For instance, DL models can integrate real-time weather data into predictive models, continuously refining forecasts for more accurate and timely predictions of events such as floods, droughts and heatwaves [214, 215]. By Assimilating appropriate observational data into numerical weather prediction models, even for mesoscale atmospheric conditions, it can substantially reduce initial condition

errors in mesoscale models, thereby significantly enhancing the accuracy of model forecasts [216]. It also helps in identifying and correcting model biases, resulting in better long-term climate projections.

However, despite the numerous advantages and suitability of ML/DL in WCEE studies, these models have inherent limitations. WCEE prediction and modeling is prone to measurement uncertainties, making them susceptible to errors from data variability, model assumptions, parameter estimation, and environmental changes [173]. Uncertainty in ML/DL can affect the reliability of WCEE model predictions by reducing accuracy and increasing forecast errors. For instance, Aleatoric and epistemic uncertainties can lead to inaccurate and less reliable predictions due to data noise, overlaps or gaps (see Fig. 4), particularly for complex and rare events. Uncertainty can misrepresent the probability of extreme event

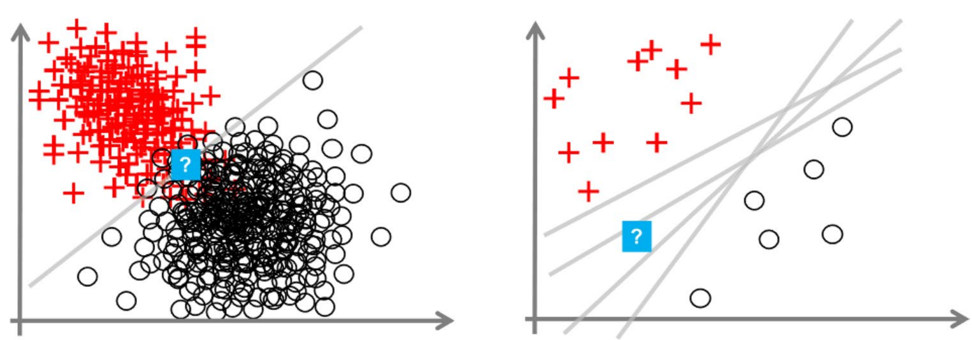

Fig. 4 Left: Aleatoric uncertainty due to overlapping classes at certain region. Right: Epistemic uncertainty occurs from a lack of data. Sourced [176]

occurrence by skewing risk assessments, leading to either overestimation or underestimation of event likelihood [175, 180]. This misrepresentation undermines the reliability of forecasts and can misguide preparedness efforts. Furthermore, it can impacts the calibration and validation of models, making it difficult to fine-tune predictions for effective disaster risk reduction and response strategies [179].

Additionally, choosing the right ML algorithm and tuning hyperparameters for optimal performance can be challenging [154]. Experimenting with different models, hyperparameters, and validation techniques is often necessary to find the best combination. Additionally, ML/DL models are prone to overfitting during training, where the model memorizes the training data instead of capturing underlying patterns, leading to poor generalization to unseen data [145, 162]. Despite these challenges, the versatility and effectiveness of ML/DL make them invaluable tools for enhancing DRR efforts and refining disaster management strategies.

5 Conclusion

This study comprehensively reviewed, examine, and explored four distinct approaches utilized within WCEE studies, encompassing statistical models, geospatial techniques, MCDA, and AI-based models. The systematic examination of these diverse approaches and their techniques provided insights into their effectiveness and limitations in assessing a wide array of impacts and addressing multifaceted issues related to WCEE. Additionally, the study employs a detailed matrix to illustrate how different techniques and methods within each approach are applicable to various aspects of WCEE study dimensions.

Within spatial interpolation techniques, the study reveals that the performance of these methods is largely influenced by the density, sparsity, and clustering of the model data. For instance, ordinary kriging performs better when mapping phenomena with dense and clustered point data, whereas IDW is more appropriate for interpolating phenomena with scattered point data. Within the decision-making approach, hybrid techniques such as Fuzzy-AHP, Fuzzy-TOPSIS, or AHP-TOPSIS have been found to overcome the limitations of individual MCDA techniques, resulting in better accuracy and more robust decision-making. Regarding AI models, while some models have demonstrated superior performance in certain applications, the effectiveness of ML/DL models largely depends on the datasets used. ML models, such as decision trees and support vector machines, are often more utilized for structured data and smaller datasets due to their interpretability and relatively lower complexity. On the other hand, DL models, like neural networks, excel in handling large, unstructured datasets and complex pattern recognition tasks, making them particularly suitable for analyzing and predicting time series data, as well as for image and speech recognition in disaster contexts.

Overall, while each approach and technique has its strengths and specific applications, ML/DL methods offer unparalleled versatility and integration capabilities with other techniques, such as statistical methods, spatial interpolation, and MCDA. The ability to handle complex and large-scale datasets, combined with advanced pattern recognition and predictive analytics, positions AI as a cornerstone for future DRR strategies. The synthesis of these findings underscores the importance of leveraging the strengths of each method while moving towards more integrated and AI-enhanced frameworks for effective disaster risk management.

Furthermore, the study has highlighted that, given the evolving landscape of disaster events intensified by climate change and other natural and anthropogenic factors, there is a critical need for ongoing innovation in WCEE research. The complex nature of WCEE stress the need for ongoing exploration and advancement in methodologies to enhance DRR strategies.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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