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Leveraging machine learning algorithms for improved disaster preparedness and response through accurate weather pattern and natural disaster prediction

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Globally, communities and governments face growing challenges from an increase in natural disasters and worsening weather extremes. Precision in disaster preparation is crucial in responding to these issues. The revolutionary influence that machine learning algorithms have in strengthening catastrophe preparation and response systems is thoroughly explored in this paper. Beyond a basic summary, the findings of our study are striking and demonstrate the sophisticated powers of machine learning in forecasting a variety of weather patterns and anticipating a range of natural catastrophes, including heat waves, droughts, floods, hurricanes, and more. We get practical insights into the complexities of machine learning applications, which support the enhanced effectiveness of predictive models in disaster preparedness. The paper not only explains the theoretical foundations but also presents practical proof of the significant benefits that machine learning algorithms provide. As a result, our results open the door for governments, businesses, and people to make wise decisions. These accurate predictions of natural catastrophes and emerging weather patterns may be used to implement pre-emptive actions, eventually saving lives and reducing the severity of the damage.

KEYWORDS

disaster preparedness, disaster response, machine learning, weather prediction, natural disaster forecasting

1 Introduction

In recent years, natural catastrophes and extreme weather events have increased in frequency and severity, posing a serious threat to people and governments throughout the globe (Leng et al., 2023). Such occurrences may result in fatalities, infrastructural damage, and interruptions of economic activity (Ruidas et al., 2022a; Chen et al., 2022). Therefore, mitigating the effects of these catastrophes depends on our capacity to properly forecast and prepare for them. In this context, the use of machine learning algorithms has shown promise for improving weather forecasting and natural catastrophe predictions, which may help in disaster preparation and response operations (Linardos et al., 2022, Powers et al., 2023). A

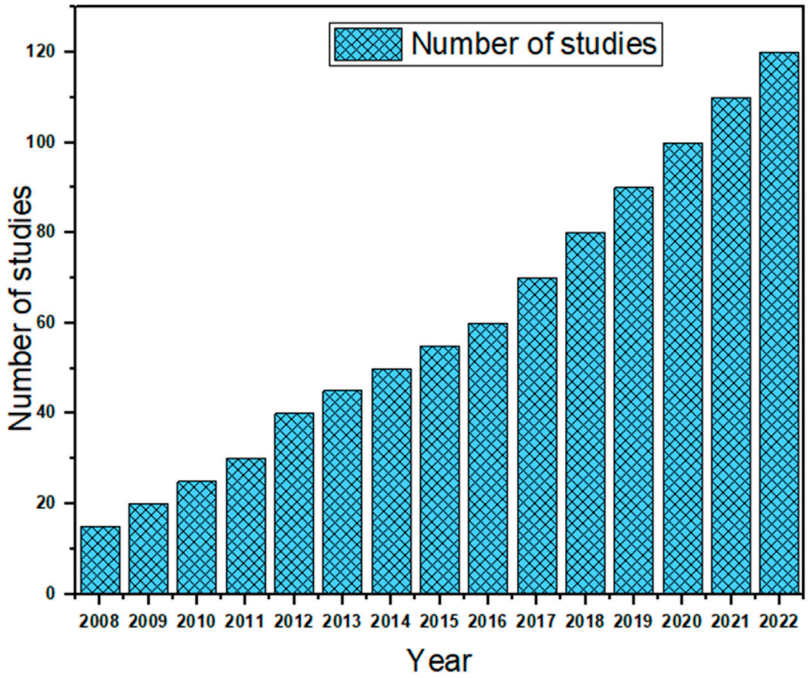

FIGURE 1
Number of studies on weather prediction using machine learning algorithms in the last 15 years. Source: The data was obtained using Scopus and Science direct database with exact keywords "Machine Learning" and "Weather Prediction."

subset of artificial intelligence (AI) known as machine learning algorithms (MLAs) enables computers to discover patterns in massive datasets without having to be explicitly programmed. These algorithms are able to scan large data sets and spot patterns that human analysts would miss. Machine learning algorithms may be used to examine a range of data sources, including satellite data, atmospheric data, and historical weather and catastrophe data, to provide precise forecasts in weather prediction and natural disaster forecasting (Aybar-Ruiz et al., 2016; Moosavi et al., 2021).

Weather prediction utilizing MLA's involves the use of different types of algorithms, such as neural networks (NN), decision trees (DT), and random forests (RF) (Fowdur and Nassir-Ud-Diin Ibn Nazir, 2022; Xu et al., 2023). The number of research on weather prediction using machine learning algorithms from 2008 to 2022 is shown in Figure 1. The data shows that the number of studies has been increasing over time, which has led to the noticeable increase in studies from 2014 to 2022. This pattern's conclusion demonstrates the increased interest in applying machine learning algorithms for weather forecasting, which might improve forecast accuracy and catastrophe preparation. These algorithms may look at a variety of data sources, including satellite photography and atmospheric data, to find trends and forecast weather. The possibility of a heatwave or a drought, for instance, may be predicted by MLAs by examining data on temperature, humidity, and precipitation (Ruidas et al., 2022c; Kim et al., 2022).

Various kinds of algorithms, including clustering algorithms, regression algorithms, and support vector machines, are used in the prediction of natural disasters (Zhang et al., 2022b). The number of works on utilising machine learning algorithms to predict natural disasters during the last 15 years is summarised in Figure 2. The figures show a consistent rise in the number of investigations every year, with the most research occurring in the most recent year (2022) (57). This shows that there is increased interest in and awareness of the potential advantages of using machine learning algorithms to anticipate natural disasters (Chakrabortty et al., 2023).

These algorithms can analyze various data sources, such as seismic data, historical disaster data, and weather data, to make predictions about natural disasters. For example, they can predict the likelihood of an earthquake or a hurricane by analyzing data such as seismic activity, wind speed, and sea surface temperature (Barrera-Animas et al., 2022). The use of these algorithms in catastrophe preparation and response may have a number of advantages. For instance, precise weather forecasts and natural catastrophe predictions may assist governments and organisations in taking preventive measures to be ready for and react to these occurrences. People may be informed of imminent natural catastrophes through early warning systems, allowing them to flee to safer areas (Karir et al., 2022). By focusing resources on the regions most likely to be impacted by natural disasters, resource allocation may be improved. Finding the most effective escape routes and organising the flow of people may both help with evacuation planning. The use of MLAs in disaster planning and response is not without its difficulties and restrictions, however. The precision with which these algorithms provide predictions is one of the major difficulties. False alarms brought on by inaccurate forecasts may erode public confidence in the system (Jia et al., 2022; Saha et al., 2023). The accuracy of the predictions may also be impacted by the quality of the data utilised to train these algorithms.

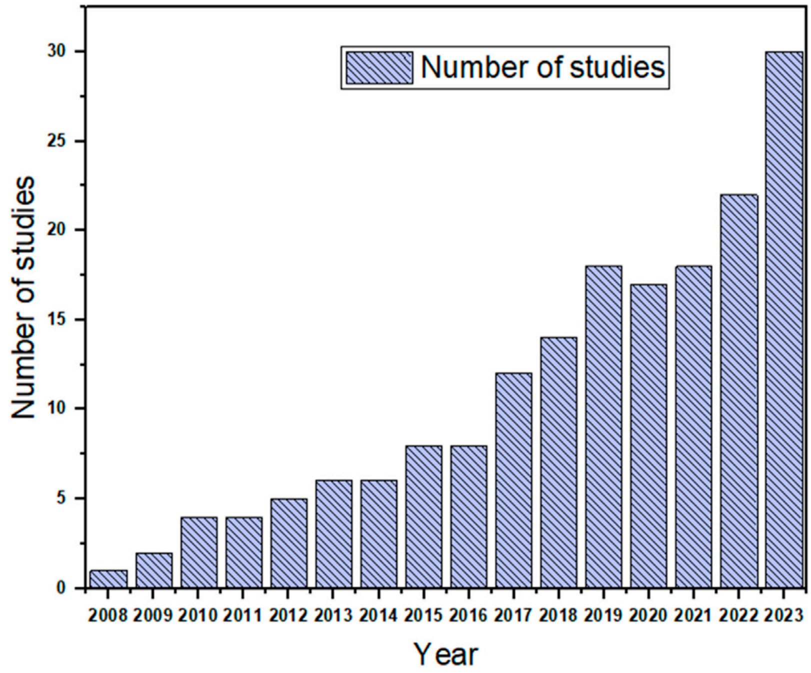

FIGURE 2
Number of studies conducted in the last 15 years on natural disaster forecasting using machine learning algorithms. Source: The data was obtained using Scopus and Science direct database with exact keywords "machine learning algorithms" and "disaster forecasting."

Additionally, if the data used to train them was biassed, they can be prejudiced as well. Their use in predicting weather and natural disasters has become a potential strategy to enhance disaster preparation and response operations (Esrafilian-Najafabadi and Haghighat, 2022). In this study, we adopt a robust methodology to explore the application of machine learning algorithms in forecasting weather patterns and predicting natural catastrophes, with a focus on enhancing global disaster preparedness and response efforts.

Using precise keywords and phrases linked to meteorological events, natural catastrophes, and machine learning, our method comprises a thorough literature analysis as depicted in Figure 3. From January 2012 to January 2023, we conduct a thorough search and analysis of peer-reviewed publications from renowned databases including SCOPUS, Science Direct, and Google Scholar. Multiple reviewers conduct the screening process, which guarantees consistency and relevance while upholding strict academic standards with the inclusion and exclusion criteria (Ruidas et al., 2022b). To offer a thorough overview of how machine learning algorithms contribute to effective catastrophe prediction, material from chosen papers is extracted and then synthesised (Ruidas et al., 2021; Ruidas et al., 2022a). This information includes technique specifics, input data sources, output results, case studies, and important conclusions (Jaydhar et al., 2022; Ruidas et al., 2023). This rigorous and thorough approach strengthens the reliability and validity of our conclusions, providing a current knowledge of the critical role that machine learning plays in reducing the effects of natural catastrophes on communities and nations throughout the globe.

2 Weather prediction with MLA's

Agriculture, transportation, and the energy sector are just a few of the businesses that depend heavily on weather forecasting. To make wise judgments and avert weather-related problems, accurate weather forecasts are essential. MLA's have emerged as a viable strategy to increase the accuracy of weather forecasts in recent years (Fischer et al., 2023; Heddam, 2023). MLAs are capable of analysing enormous volumes of data to find patterns and make predictions. They come in several varieties, and each has advantages and disadvantages (Lan et al., 2020; Quan et al., 2022; Shafiei et al., 2022). Some of the most popular methods for predicting the weather include NN, DT, and RF (Figure 4).

NN are a type of MLA's inspired by the structure of the human brain (Yang et al., 2022). Applications for these techniques include picture recognition and natural language processing. A comparison of several algorithms for predicting weather and natural disasters is shown in Table 1. The algorithms fall into three primary categories: reinforcement learning, unsupervised learning, and supervised learning. Each algorithm's advantages and disadvantages are described, along with examples of how it has been used to forecast weather and natural disasters. It attempts to provide a thorough analysis of various machine learning algorithms and assist researchers and practitioners in choosing the best algorithm for their particular application.

In weather prediction, NN are used to analyze multiple data sources, such as satellite imagery, atmospheric data, and historical weather data, to identify patterns and make predictions (Brester et al., 2023). They can handle non-linear relationships between variables and make predictions with high accuracy (Buyrukoğlu

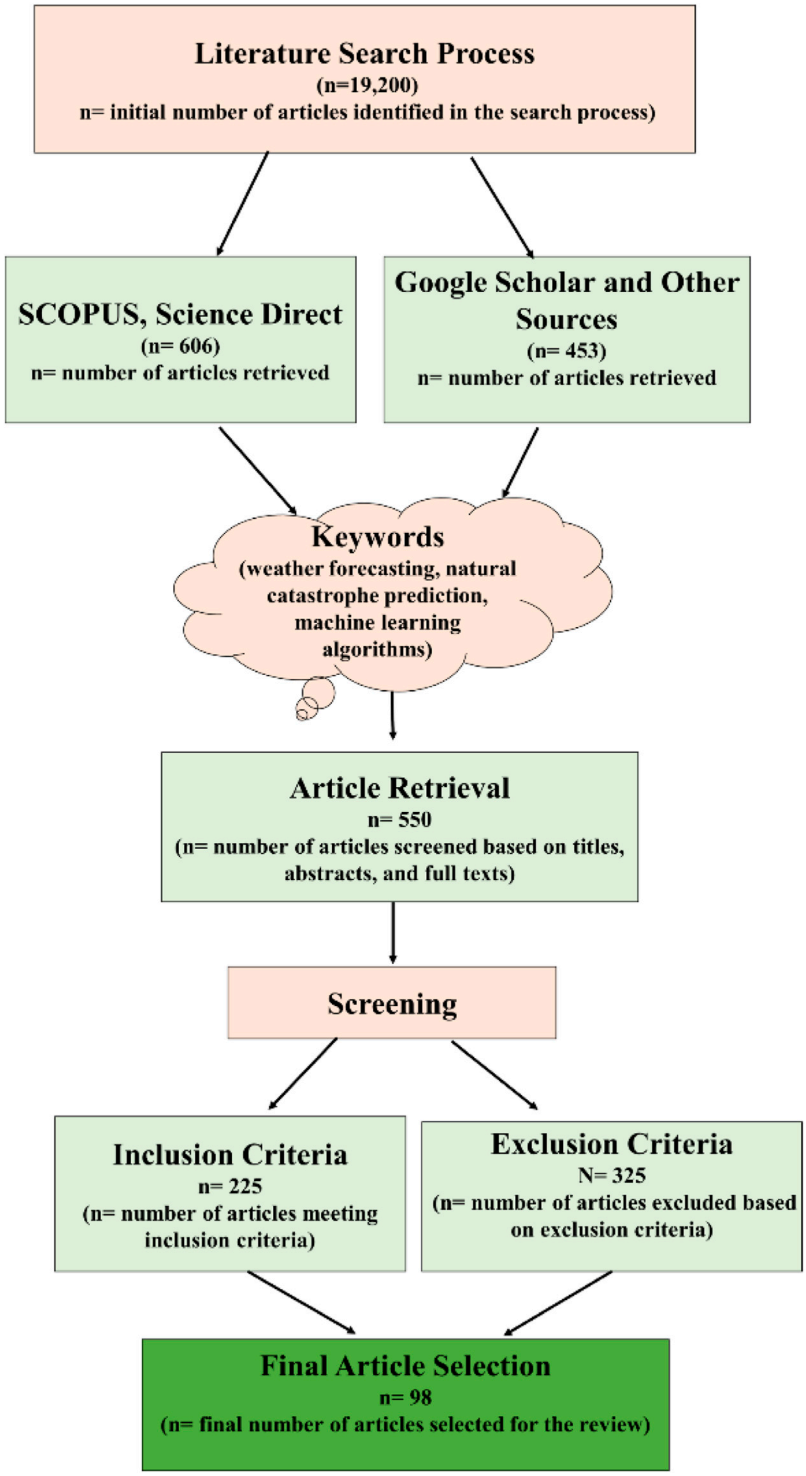

FIGURE 3
Schematic representation of the literature search process and article selection for the review.

et al., 2021; Seon Park et al., 2022). DT is another type used for weather prediction (Li et al., 2023a). These algorithms are built on a set of if-then rules that let the algorithm anticipate outcomes depending on certain circumstances (Pereira et al., 2022). Due to their simplicity and readability, they are great for a variety of applications. They may be used to analyse many data sources, including humidity, temperature, and precipitation, to provide weather predictions (van Blokland et al., 2021). Predictions are produced by RF, a collection of decision trees (He et al., 2022). This requires the development of several decision trees, each of which is trained on a distinct subset of the data. The agreement of each DT's projections forms the basis for the final projection. They can manage

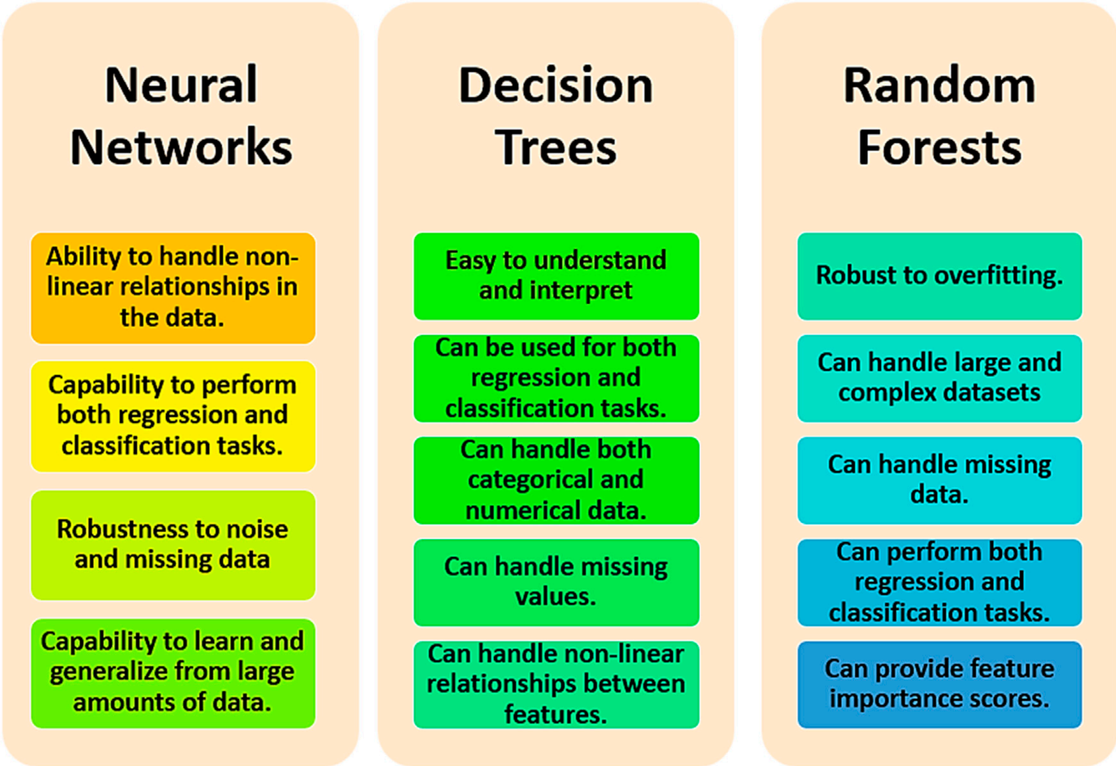

FIGURE 4
Advantages of NN, DT and RF.

complicated variable interactions and are extremely precise (Ghebleh Goydaragh et al., 2021). They may look at a variety of data sources to make weather forecasts. Satellite data is used to give information on temperature, cloud cover, and other weather-related factors. Weather forecasts for large regions may be made using this data, which includes specifics like temperature, pressure, and humidity. A further use of atmospheric data is the forecasting of local weather. Historical weather data offers details on previous weather conditions and may be used to spot patterns and forecast the weather in the future. One example of a successful MLA-based weather prediction model is the Global Ensemble Forecast System of the National Oceanic and Atmospheric Administration (NOAA) (GEFS). A collection of global weather models are used by the GEFS weather prediction model to provide predictions (Haver et al., 2018). In order to provide predictions, the model examines a variety of data sources, such as atmospheric data and historical weather data. GEFS has been used to forecast a variety of meteorological occurrences, including hurricanes, blizzards, and heatwaves (Jiang et al., 2022). A wide range of businesses, including agriculture, transportation, and energy, rely on GEFS projections. IBM's Deep Thunder is another reliable weather prediction tool (Afra et al., 2022). It is a very effective model for forecasting the weather, and it has been used to predict a variety of meteorological events, including thunderstorms, hurricanes, and snowstorms. It uses neural networks to evaluate a variety of data sources, including satellite and atmospheric data (Lu et al., 2022). Transportation and energy industries, among others, utilise Deep Thunder's forecasts.

2.1 Types of machine learning algorithms for weather prediction

Three general kinds of MLAs may be distinguished: supervised learning, unsupervised learning, and reinforcement learning (Table 2). Different approaches to weather prediction may be used with each of these sorts of algorithms.

In order to model correlations between input factors (such temperature, humidity, pressure, and wind speed) and output variables, supervised learning techniques are often utilised in the field of weather prediction (such as precipitation, cloud cover, or temperature at a future time) (Ma et al., 2023). These techniques train a model using previous weather data so that it can forecast weather in the future. Regression algorithms (like linear regression and decision trees) and classification algorithms are some typical forms (such as support vector machines and random forests) (Alwindawi et al., 2022). Algorithms for unsupervised learning may be used to find patterns in big datasets of variables linked to the weather (Daneshvar et al., 2023). In order to identify regions that are expected to encounter similar weather conditions in the future, clustering algorithms, for instance, may group similar weather patterns together. The identification of odd weather patterns that can be a sign of severe weather occurrences can also be done using anomaly detection algorithms (Liu et al., 2023). Although less often utilised in weather forecasting, reinforcement learning techniques may be advantageous for improving weather-related

TABLE 1 Comparison of different types of MLA's, highlighting their strengths and weaknesses.

Algorithm type	Strengths	Weaknesses
Linear Regression	Simple to implement, computationally efficient	Only models linear relationships, prone to overfitting, assumes linear relationship between input and output variables (Kim et al., 2020)
Logistic Regression	Good for binary classification problems, interpretable results	Not suitable for non-linear data, may underperform on complex problems Wang et al. (2022a)
Decision Trees	Can capture non-linear relationships, easy to interpret and explain	Prone to overfitting, may not generalize well to new data (Li et al., 2023a)
Random Forests	High accuracy, can handle large datasets with high dimensionality, less prone to overfitting than decision trees	Computationally expensive, difficult to interpret and explain (He et al., 2022)
Support Vector Machines (SVM)	High accuracy, can handle non-linear data with high dimensionality	Computationally expensive, sensitive to choice of kernel function and parameters (Zheng et al., 2023)
Naive Bayes	Simple to implement, computationally efficient, can handle high dimensional data	Assumes independence between features, may not capture complex relationships (Shaheen et al., 2023)
Neural Networks	Can model complex relationships and non-linear data, high accuracy	Computationally expensive, requires large amounts of data and careful tuning of parameters (Yang et al., 2022)

TABLE 2 Categorization of machine learning algorithms based on learning type.

Algorithm type	Description
Supervised Learning	With this kind of approach, input features and output labels are supplied, and the model is trained using labelled data. By modifying its internal parameters to reduce the discrepancy between its predictions and the actual labels, the algorithm learns to map the input characteristics to the output labels. Examples include decision trees, support vector machines, and linear regression (Morales and Escalante, 2022)
Unsupervised Learning	In this kind of technique, just the input features are supplied, and the model is trained using unlabeled data. By grouping together related data points or by making the data less dimensional, the algorithm learns to spot patterns and correlations in the data. K-means clustering, principal component analysis, and autoencoders are a few examples (Morales and Escalante, 2022)
Reinforcement Learning	By interacting with its surroundings and getting feedback in the form of rewards or penalties, the model learns in this kind of algorithm. By doing activities that result in desired results and avoiding actions that result in bad consequences, the algorithm learns to maximise its rewards. Examples include deep reinforcement learning, policy gradients, and Q-learning (Morales and Escalante, 2022)

decision-making processes (Chen et al., 2023). These algorithms pick up new skills via interaction with their surroundings and feedback in the form of rewards or penalties. Reinforcement learning algorithms might be used to weather prediction to improve resource allocation, evacuation planning, or other decision-making procedures pertaining to catastrophe preparation and response (Duhem et al., 2023). There are other specific algorithms and approaches that may be utilised for weather prediction in addition to these general types of machine learning algorithms. Deep learning methods, for instance convolutional neural networks, have been used to analyse satellite pictures and provide very accurate weather forecasts. Similar to this, ensemble models, which aggregate the results of numerous models, may be used to increase the precision of weather forecasts by taking into consideration the advantages and disadvantages of various models.

2.2 Data sources for weather prediction

Large volumes of high-quality data are needed in order to correctly anticipate weather patterns using MLAs. There are several sorts of data sources available for weather forecasting (Table 3).

Table 3 details the many types of data sources that can be utilised for weather forecasting with MLAs. Satellite data, radar data, weather station data, atmospheric soundings, and numerical weather prediction models are among the sources (Brester et al., 2023). These data sources provide crucial information regarding temperature, humidity, wind speed and direction, pressure, and other meteorological characteristics (Payne et al., 2022). As it contains information about temperature, humidity, wind speed and direction, precipitation, cloud cover, and other weather-related variables at specific locations and times in the past,

TABLE 3 Table displaying numerous data sources for forecasting the weather (Gonçalves and Guedes Soares, 2022; Payne et al., 2022; Brester et al., 2023; Zhao et al., 2023).

Data source	Description
Satellites	Satellites may be used to track weather patterns, gauge atmospheric conditions, and measure temperature and humidity
Radars	Radars can identify precipitation, gauge wind direction and speed, and provide a three-dimensional (3D) image of storms
Surface Weather Stations	These provide on-the-ground observations of temperature, pressure, humidity, and wind speed and direction
Weather Balloons	These provide vertical profiles of the atmosphere, including temperature, pressure, and humidity
Aircraft	Aircraft can be used to collect data on atmospheric conditions, such as temperature, pressure, humidity, and wind speed and direction
Ocean Buoy Networks	These can provide information on sea surface temperature, wave heights, and ocean currents
Weather Prediction Models	These model the environment and forecast weather patterns using mathematical calculations

historical weather data is one of the most crucial data sources for training machine learning algorithms for weather prediction (Shin et al., 2022). Typically, weather stations, satellites, and other weather monitoring systems collect this information. Data from remote sensing is particularly valuable for predicting weather patterns across wide areas or in regions where there are no weather stations. Numerical Weather Prediction (NWP) models are computer models that replicate weather patterns using sophisticated mathematical equations. These physical-principles-based models are used to provide forecasts for future weather patterns (Voyant et al., 2012). NWP models can be used to provide input data for machine learning algorithms or to test the accuracy of weather predictions derived from machine learning. Social media and other crowdsourced data sources can be used to supplement conventional sources of meteorological information (Al-Yahyai et al., 2010). For instance, people may post about local weather conditions on social media, so contributing useful knowledge about local weather trends. Other environmental data, such as land use, vegetation cover, and topography information, can also be used to improve the precision of weather forecasts. For instance, vegetation cover can change temperature and humidity patterns, whereas terrain might affect wind patterns (Mayer and Yang, 2023b). By merging data from many sources, machine learning algorithms may produce extremely accurate weather forecasts that can be utilised to enhance catastrophe preparedness and response operations (Mayer and Yang, 2023a).

3 Natural disaster forecasting with MLA's

Accurate prediction and forecasting of natural disasters can aid in minimising their effects and enhancing disaster response. MLAs have demonstrated promise in accurately predicting natural calamities (Jiang et al., 2022; Singh et al., 2023). Random Forest (RF) builds a number of Decision Trees (DT) and then combines their outputs to form a final forecast (Figure 5). This algorithm can handle classification and regression issues. One of the primary benefits of is that it can handle huge datasets with high dimensionality and non-linear variable interactions (Bhoi et al., 2022). It can also manage missing data and outliers and is less susceptible to overfitting than other decision tree-based algorithms,

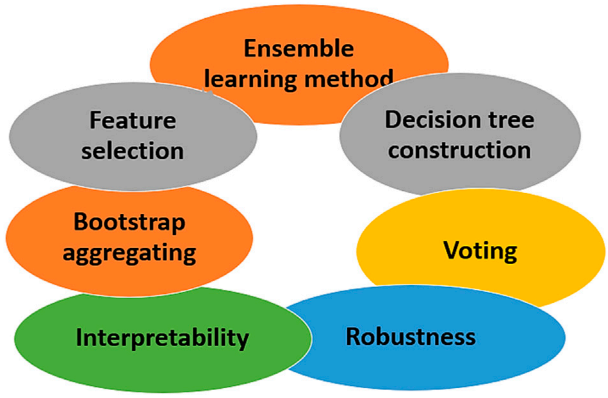

FIGURE 5
Characteristics of the random forest algorithm (Liu et al., 2020)

making it more accurate at predicting the outcomes of new data (Liu et al., 2020). In addition, it can provide estimates of variable relevance, which facilitates the identification of the most pertinent factors for producing correct forecasts (Wang et al., 2022b).

RF can analyse multiple data sources, such as satellite imagery, weather data, and historical disaster data, to predict the likelihood of a natural disaster occurring. For instance, an RF algorithm can analyse data on temperature, humidity, wind speed, and precipitation to predict the likelihood of a wildfire (Rahman et al., 2021). Support vector machine (SVM) is another technique often employed for natural catastrophe prediction. SVM is a supervised learning algorithm used to evaluate data and detect patterns. It may examine numerous data sources, such as past disaster data, weather data, and satellite images, to identify trends and predict the probability of a natural catastrophe occurring (Singh et al., 2023). It has various characteristics that make it effective for natural disaster forecasting, it can handle both linear and non-linear data by utilising different kernel functions, such as polynomial, Gaussian, and sigmoid (Li et al., 2023b) and can handle high-dimensional data and escape the curse of dimensionality (Chen and Li, 2020). Also, it is less affected by overfitting, as it tries to maximize the margin between classes (Liu et al., 2021a) and can handle imbalanced datasets, which are common in natural disaster

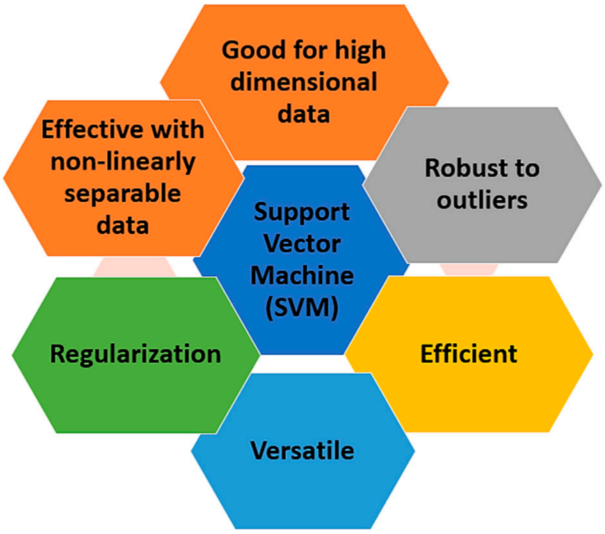

FIGURE 6
Advantages of the SVM model (Zhou et al., 2022).

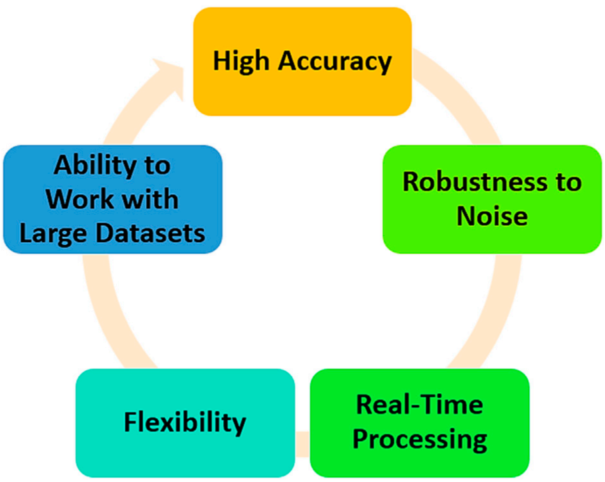

FIGURE 7
Advantages that make CNNs a promising tool for natural disaster forecasting and response efforts (Jörges et al., 2023).

forecasting, by adjusting the weights of the classes. Finally, SVM can be used for both classification and regression tasks, making it versatile for different types of forecasting problems (Chen et al., 2022) (Figure 6).

Deep learning algorithms, such as convolutional neural networks (CNNs), have also shown promise in natural disaster forecasting as it has several advantages when it comes to natural disaster forecasting like it can handle high-dimensional and complex data, such as satellite and radar images, which are often used in natural disaster monitoring (Ullah et al., 2022). They can extract relevant features from the images, such as cloud cover or precipitation, and use these features to predict the occurrence and intensity of natural disasters (Akter et al., 2021). It can learn

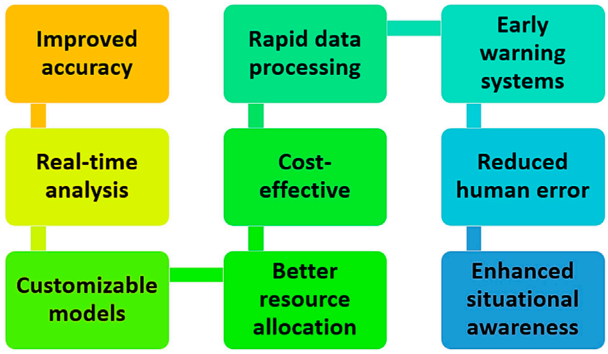

FIGURE 8
Advantages of using machine learning algorithms for natural disaster forecasting (Jiang et al., 2022).

spatial dependencies between the pixels in an image, allowing them to identify patterns and anomalies that may be indicative of an impending natural disaster and can be trained on large datasets, which can improve their accuracy and ability to generalize to new data (Guha et al., 2022) (Figure 7).

CNN can analyze satellite imagery to predict the likelihood of a hurricane occurring. One of the most critical applications of MLA's in natural disaster forecasting is predicting the intensity and path of hurricanes. Hurricane forecasting involves analyzing multiple data sources, including satellite imagery, atmospheric data, and historical hurricane data, to generate predictions (Najafi et al., 2022). NN and RF, for instance, can assess various data sources to generate accurate predictions of storm intensity and course, as well as the probability of floods (Najafi et al., 2022; Rani et al., 2022). Flooding is a significant natural disaster that can cause severe damage to life and property. SVM and DT can analyse various data sources, such as weather data and historical flooding data, to predict the likelihood of flooding occurring in a specific region (Danish, 2022). Similarly, SVM and DT can analyse various data sources, such as historical earthquake data, tectonic plate movements, and seismic activity, to predict the likelihood of an earthquake occurring in a specific region (Teodoro and Duarte, 2022).

3.1 Advantages of MLA's for natural disaster forecasting

MLAs have the capacity to enhance the precision and speed of natural catastrophe predictions (Jiang et al., 2022) (Figure 8). By enabling early warning systems and preemptive actions to alleviate the effects of these catastrophes, they can assist reduce the impact of natural disasters (Prodhan et al., 2022; Saravanan et al., 2023; Singh et al., 2023).

Depending on the nature of the data being studied and the forecasting task at hand, multiple MLAs may be utilised for this purpose (Singh et al., 2023). NN are a sort of artificial neural network inspired by the structure and function of the human brain that can be trained on massive historical datasets of weather and catastrophe data to detect patterns and correlations between variables. Once trained, the NN can be used to predict future weather trends and

TABLE 4 Types of data sources for natural disaster forecasting using machine learning algorithms.

Data source	Description
Remote sensing data	Data collected by satellites or other remote sensors that provide information on land, ocean, and atmospheric conditions (Kashtan Sundararaman et al., 2023)
Weather station data	Data collected from ground-based weather stations that measure temperature, humidity, pressure, wind speed, and other weather variables (Han et al., 2023)
Radar data	Data collected by radar systems that can detect precipitation, wind speed, and direction (Wang et al., 2023a)
Social media data	Data collected from social media platforms that can provide real-time information on natural disasters and their impacts (Platania et al., 2022)
Geospatial data	Data that includes information on terrain, land use, population density, and infrastructure (Stokes and Seto, 2019)
Historical data	Data from past natural disasters that can be used to train machine learning models for forecasting future events (Jiang et al., 2022)
Sensor data	Data collected by sensors deployed in disaster-prone areas that can measure seismic activity, water levels, and other variables (Wang et al., 2023b)
Mobile phone data	Data collected from mobile phone networks that can provide information on population movements and density during disasters (Yabe et al., 2022)

anticipate natural disasters. In natural disaster forecasting, DT can be used to simulate the likelihood of a disaster occurring depending on variables such as location, season, and weather conditions. This can assist emergency responders and disaster management teams with resource allocation and evacuation planning decisions. Based on factors like the region's geology and weather, SVMs may be used to locate areas that are at a high risk of a certain catastrophe, like floods or landslides (Zhang et al., 2022a; Prodhan et al., 2022).

3.2 Data sources for natural disaster forecasting

There are various types of data sources that can be used for natural disaster forecasting using MLA's (Table 4). One of the most crucial data sources for predicting natural disasters is satellite imaging, which can provide real-time information on weather patterns including the passage of storms and the amount of cloud cover (Han et al., 2023). Table 4 lists remote sensing, weather station, geospatial, historical, sensor, radar, social media and mobile phone data that may help anticipate natural catastrophes by providing information on atmospheric conditions, land use, population movements, and other characteristics (Jiang et al., 2022). These data may be used in the development of models that have the capability of predicting the likelihood of natural catastrophes such as droughts, heatwaves, and wildfires (Kashtan Sundararaman et al., 2023). And also it might include past disasters' frequency, intensity, location, and environmental causes (Zhang et al., 2022a). Combining data from numerous sources allows researchers to construct more complete models that can anticipate a variety of natural catastrophes (Prodhan et al., 2022).

3.3 Case studies of successful implementation of machine learning

There have been several successful implementations of MLA's in natural disaster forecasting and response efforts (Table 5). The National Oceanic and Atmospheric Administration (NOAA) uses machine learning algorithms to improve hurricane forecasting. They utilize deep neural networks to analyze satellite data and develop more accurate predictions of a hurricane's track, intensity, and timing. This technique was put to the test in 2018 during Hurricane Florence, when it precisely anticipated the storm's path and enabled more effective planning and reaction (Kaur et al., 2022). The Earthquake Research Institute at the University of Tokyo in Japan has created a machine learning algorithm that can anticipate earthquakes up to 10 s in advance (Liu et al., 2021b). The algorithm analyses seismic data and has an accuracy rate of 90 percent for predicting earthquakes of magnitude 3 or greater. This early warning system can provide individuals with precious seconds to evacuate or seek refuge. The Dartmouth Flood Observatory maps and forecasts floods using machine learning algorithms. They use satellite imagery to generate comprehensive flood maps that can be used to detect flood-prone locations and aid in evacuation preparations. During the 2015 floods in Chennai, India, this technology was utilised to prioritise rescue and relief efforts using flood maps (Laso Bayas et al., 2011). The US Forest Service uses machine learning algorithms to forecast the risk of wildfires. They provide predictions about potential wildfire locations by examining meteorological data, satellite imagery, and other environmental factors. This technology has made it possible to take more focused wildfire prevention actions, such as identifying areas where controlled burns might reduce the danger of wildfires. These case studies demonstrate how machine learning algorithms may be used for activities related to predicting and responding to natural disasters. By using these technologies, we may create early warning systems, develop more accurate forecasts of natural catastrophes, and improve our efforts to save lives and reduce damage. It gives several instances of how machine learning algorithms are successfully used for natural disaster prediction and response (Zhengru, 2015). The kind of natural catastrophe, the machine learning approach used, the application or use case, and the advantages of its usage are all listed in a row for each row. The examples highlight the potential of machine learning algorithms to improve damage assessment, early warning, proactive resource allocation, and evacuation planning in the event of a natural catastrophe (Kanbara and Shaw, 2022).

TABLE 5 Examples of successful implementations of machine learning algorithms in natural disaster forecasting and response efforts.

Natural disaster	Machine learning algorithm	Application/Use case	Benefits
Qin et al. (2020)	Convolutional Neural Networks (CNNs)	Flood inundation mapping and forecasting	Provided near real-time information to emergency responders and decision makers, allowing for more targeted rescue efforts and resource allocation (Nemni et al., 2020)
Moriguchi et al. (2021)	Random Forest Algorithm	Flood and landslide prediction	Successfully predicted areas at high risk of flooding and landslides, allowing for proactive evacuation planning and resource allocation (Kanbara and Shaw, 2022)
Goda et al. (2015)	Artificial Neural Networks (ANNs)	Earthquake damage assessment	Enabled rapid damage assessment of buildings and infrastructure, helping aid organizations prioritize rescue and relief efforts (Zhengru, 2015)
Wang et al. (2021)	Support Vector Machines (SVMs)	Wildfire detection and prediction	Provided early detection of wildfires, allowing for prompt response and evacuation planning (Pourghasemi et al., 2020)
Rubin et al. (2017)	Decision Trees	Tsunami detection and warning	Successfully detected the tsunami and provided timely warnings to people in affected areas, saving lives and minimizing damage (Laso Bayas et al., 2011)

4 Benefits of using MLA's in disaster preparedness and response

These algorithms analyse vast amounts of data from numerous sources to predict natural catastrophe frequency and severity. Therefore, emergency responders may be notified in advance and resources can be deployed properly, improving disaster response. Additionally, they may be used to keep track on natural catastrophes in real time, enabling quick and efficient response. Organizations involved in catastrophe planning and response may also achieve improved cooperation and communication by using these algorithms (Islam et al., 2020).

For effective emergency planning and response, accurate weather and catastrophe predictions are crucial. Accurate forecasts are essential for reducing the consequences of natural disasters since inaccurate or delayed predictions may cause significant losses in life and property. Planning your evacuation is an essential part of being prepared for and responding to a catastrophe. The planning of an evacuation may prevent fatalities and speed up the relocation of individuals from dangerous places. For instance, accurate forecasting may help emergency responders and authorities prepare shelter locations, evacuation routes, and other logistical issues in the event of storms or floods. Another way that accurate forecasting might help with disaster planning and response is via resource allocation (Johnson et al., 2022). Authorities may organise the distribution of resources like food, water, medical supplies, and rescue equipment by using accurate forecasting to make sure that they are delivered in a timely and efficient way to the areas that need them the most. As a result, there will be less waste and resources will be accessible when and where they are most needed. Exact predictions may help in disaster response in addition to organising evacuations and allocating resources. For example, accurate forecasting may help emergency responders plan and carry out suitable response strategies, including the deployment of fire-fighting gear or flood barriers to mitigate the consequences of the catastrophe. The ability to identify and locate people who may be trapped or stranded as a consequence of the catastrophe is another benefit of accurate forecasts for search and rescue operations. MLAs are an essential tool for emergency management organisations and first responders because their ability to increase forecast accuracy may significantly strengthen efforts to reduce the impact of catastrophes, react to them, and aid in recovery (Yu et al., 2021).

MLAs may help authorities allocate resources more effectively and efficiently by doing so. Machine learning algorithms can discover and distribute resources to areas with the largest resource needs by analysing data on previous catastrophes, available resources, and potential crisis scenarios. By doing this, waste may be decreased and resources will be distributed where they are most needed. Planning evacuations is another area where machine learning algorithms may be quite useful (Ganguly et al., 2019). These algorithms may help in the planning and execution of efficient evacuation procedures by analysing data on population density, infrastructure, and potential crisis circumstances. With the use of these algorithms, disaster response efforts, resource allocation, evacuation planning, and catastrophe forecast accuracy may all be improved. They should thus be promoted and used more often since they are an essential resource for disaster management organisations and first responders (Chamola et al., 2021).

One instance is the use of machine learning algorithms to predict floods in Vietnam. The Vietnamese government and the World Bank worked together to create a flood warning system that uses machine learning algorithms to analyse data from meteorological stations, river gauges, and satellite images. The technology sends out early warnings of impending floods, enabling authorities to evacuate citizens and more effectively allocate resources. Since its beginnings, the system has successfully lessened the impacts of floods on the local community. Using predictive analytics to find California wildfires is another useful use of machine learning techniques. The state's fire service uses machine learning algorithms to analyse data on weather patterns, vegetation, and other factors that affect the likelihood of wildfires. The algorithms provide early warnings of potential wildfires, enabling emergency responders to mobilise assets and create response strategies before the fire spreads (Linardos et al., 2022). The approach has been successful in protecting property and reducing the impact of wildfires on the neighborhood's residents.

The effective use of machine learning algorithms in earthquake prediction has also been noted. A system developed by the Japan Meteorological Agency analyses seismic data from hundreds of sensors spread around the country using machine learning techniques. The technology gives early warnings of potential earthquakes, enabling officials to deploy resources and carry out evacuation preparations more successfully. The technique has successfully lessened the impact of earthquakes on nearby populations and cut down on the likelihood of fatalities. Machine learning algorithms have been used in a range of disaster preparation and response projects, including hurricane forecasting, disease outbreak forecasting, and emergency response planning, in addition to these cases. Overall, the effective use of machine learning algorithms in planning and responding to disasters shows the potential advantages of these algorithms in reducing the consequences of natural disasters, saving lives, and protecting property.

5 Challenges and limitations of using MLA's in disaster preparedness and response

Massive amounts of data are needed for MLAs to analyse and provide accurate predictions, and the accuracy of the algorithm's predictions may be greatly influenced by the quality and completeness of the data. This may be particularly challenging in remote or rural places with poor data access. Another challenge is finding qualified personnel to design, operate, and maintain the systems (Algiriyage et al., 2021). This may be challenging in areas with little resources or skilled labour. Furthermore, machine learning algorithms are not foolproof and may still produce false positives or inaccurate predictions. For example, using algorithms to decide how to distribute resources or how to evacuate might cause issues with justice and equality, particularly if the system has biases against certain communities. In addition to these challenges, there are limitations to the use of machine learning algorithms in disaster planning and response (Johnson et al., 2022). It is difficult to predict the path of a hurricane since doing so requires the examination of a number of different factors, such as wind speed, temperature, and atmospheric pressure. If the criteria are too complex or the data is inadequate, MLAs may have trouble correctly forecasting the course of a cyclone. Despite these challenges and limitations, using machine learning algorithms to disaster prevention and response has significant advantages.

An algorithm created to predict the effects of flooding might be biassed towards low-income areas if it was trained on data that did not accurately represent their specific vulnerabilities and needs (Ganguly et al., 2019). Machine learning algorithms may be a useful tool for boosting disaster preparedness and response efforts, saving lives, and protecting property with careful planning and execution (Yu et al., 2021). Utilizing current, high-quality data that correctly represents current weather patterns and natural disaster occurrences is crucial to lowering the chance of inaccurate predictions. To counteract prejudice, it may be important to establish standards for data collection and analysis and to continuously evaluate the algorithm to find and remove any biases (Algiriyage et al., 2021). Additionally, to make sure that the algorithm truly represents the needs and priorities of the communities being served, it may be beneficial to engage community stakeholders in its design and implementation. In the event of natural disasters, we can better protect communities and save lives by using the potential of machine learning algorithms to enhance disaster planning and response (Islam et al., 2020).

6 Discussion

The use of MLAs emerges as a key element in enhancing our capacity to forecast and manage natural catastrophes as we look to the future of disaster planning and response. It is impossible to emphasise the importance of MLAs in this context; nonetheless, there are a number of critical areas that need more study and development in order to fully realise the potential advantages of this technology. For machine learning systems to be useful in predicting disasters, their accuracy must be improved. Future efforts should concentrate on creating algorithms that are more resistant to unforeseen circumstances, combining current data together with past data to improve accuracy. Additionally, in order to guarantee dependability in disaster prevention and response, efforts to improve the quality and completeness of training data are crucial (Jaydhar et al., 2022; Chakrabortty et al., 2023).

The possible bias that might be present in their algorithms is a serious issue when using MLAs. In order to lessen the effects of current biases, future research should adopt detailed criteria for data gathering and analysis. To make sure that algorithms are reflective of the particular needs and vulnerabilities of the communities they serve, engagement with community stakeholders is essential. It is crucial to ensure that the advantages of this technology are available to all communities, regardless of their financial or technical capacity, in order to maximise the social effect of MLAs. To promote the long-term use of these algorithms on a worldwide scale, creative finance methods and collaborations with the commercial sector might be investigated (Ruidas et al., 2022a; Ruidas et al., 2023).

MLAs may be equipped to provide up-to-date information on changing catastrophe situations by integrating real-time data from many sources, such as weather sensors, social media, and satellite imaging. Harmed communities are less affected as a result of the quick detection and reaction to potential dangers made possible by this real-time analysis. Emphasizing data fusion, the synthesis of several data sources, may result in a more thorough and precise knowledge of certain occurrences. MLAs may provide more accurate forecasts of upcoming catastrophic occurrences by merging information from meteorological forecasts, historical records, and real-time sensor data. There are fresh opportunities when MLAs are compared to other upcoming technology like drones and driverless cars. For instance, drones with sensors may gather information on catastrophe circumstances, which MLAs can then examine to provide insightful information that will guide response activities. It is essential to make sure that MLAs are useable and accessible to communities with little access to resources or technical know-how. These technologies may be made more accessible and effective at the community level by creating user-friendly interfaces and partnering with regional groups.

7 Conclusion

The need of precise weather and natural catastrophe forecasting in efficient disaster preparation and response operations is stressed in this article. Its worldwide repercussions highlight the need of using cutting-edge technology on a global basis. Machine learning algorithms have a revolutionary influence on disaster management because they allow efficient resource allocation and early warnings, thereby saving lives and reducing socio-economic effects. The ubiquitous application of machine learning techniques is what gives our research its worldwide significance. These algorithms, capable of assessing a variety of data sources, provide insights essential for well-informed response activities across various geographies and climatic conditions. They act as a cornerstone in dealing with natural catastrophes all over the globe, highlighting the need for a coordinated, technology driven strategy to global concerns. Our study emphasises the dynamic character of this subject, despite ongoing issues like accuracy and data quality. Continuous innovation and research serve as catalysts for addressing these issues, assuring ongoing advancement and resistance to unanticipated setbacks. By recognising the limits of the present, we open the door to a future in which technology adapts and develops to satisfy the needs of a constantly changing environment. Looking forward, there is a large and fascinating range of possible uses for machine learning algorithms in disaster planning and response. Critical components include prioritising innovation, encouraging cooperation, and interacting with communities. By doing this, we are able to safeguard communities from natural calamities and ultimately save lives by leveraging the revolutionary potential of this technology.

Author contributions

HJ: Conceptualization, writing–original draft. RD: Resources, data curation, writing–review and editing. AS: writing–review and editing. MK: data curation, writing–review and editing, supervision. DK: Writing–review and editing. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Afra, B., Karimnejad, S., Amiri Delouei, A., and Tarokh, A. (2022). Flow control of two tandem cylinders by a highly flexible filament: lattice spring IB-LBM. *Ocean. Eng.* 250, 111025. doi:10.1016/j.oceaneng.2022.111025

Akter, R., Doan, V.-S., Lee, J.-M., and Kim, D.-S. (2021). CNN-SSDI: convolution neural network inspired surveillance system for UAVs detection and identification. *Comput. Netw.* 201, 108519. doi:10.1016/j.comnet.2021.108519

Algiriyage, N., Prasanna, R., Stock, K., Doyle, E. E. H., and Johnston, D. (2021). Multi-source multimodal data and deep learning for disaster response: a systematic review. *SN Comput. Sci.* 3, 92. doi:10.1007/s42979-021-00971-4

Alwindawi, A. F., Uçan, O. N., Ibrahim, A. A., and Abbas, S. A. (2022). Semi-supervised learning with ensemble deep learning networks for descriptor generation. *Optik*, 170450. doi:10.1016/j.ijleo.2022.170450

Al-Yahyai, S., Charabi, Y., and Gastli, A. (2010). Review of the use of numerical weather prediction (NWP) models for wind energy assessment. *Renew. Sustain. Energy Rev.* 14, 3192–3198. doi:10.1016/j.rser.2010.07.001

Aybar-Ruiz, A., Jiménez-Fernández, S., Cornejo-Bueno, L., Casanova-Mateo, C., Sanz-Justo, J., Salvador-González, P., et al. (2016). A novel Grouping Genetic Algorithm–Extreme Learning Machine approach for global solar radiation prediction from numerical weather models inputs. *Sol. Energy* 132, 129–142. doi:10.1016/j.solener.2016.03.015

Barrera-Animas, A. Y., Oyedele, L. O., Bilal, M., Akinosho, T. D., Delgado, J. M. D., and Akanbi, L. A. (2022). Rainfall prediction: a comparative analysis of modern machine learning algorithms for time-series forecasting. *Mach. Learn. Appl.* 7, 100204. doi:10.1016/j.mlwa.2021.100204

Bhoi, A., Balabantaray, R. C., Sahoo, D., Dhiman, G., Khare, M., Narducci, F., et al. (2022). Mining social media text for disaster resource management using a feature selection based on forest optimization. *Comput. Industrial Eng.* 169, 108280. doi:10.1016/j.cie.2022.108280

Brester, C., Kallio-Myers, V., Lindfors, A. V., Kolehmainen, M., and Niska, H. (2023). Evaluating neural network models in site-specific solar PV forecasting using numerical weather prediction data and weather observations. *Renew. Energy* 207, 266–274. doi:10.1016/j.renene.2023.02.130

Buyrukoğlu, G., Buyrukoğlu, S., and Topalcengiz, Z. (2021). Comparing regression models with count data to artificial neural network and ensemble models for prediction of generic *Escherichia coli* population in agricultural ponds based on weather station measurements. *Microb. Risk Anal.* 19, 100171. doi:10.1016/j.mran.2021.100171

Chakrabortty, R., Pal, S. C., Ruidas, D., Roy, P., Saha, A., and Chowdhuri, I. (2023). Living with floods using state-of-the-art and geospatial techniques: flood mitigation alternatives, management measures, and policy recommendations. *Water* 15, 558. doi:10.3390/w15030558

Chamola, V., Hassija, V., Gupta, S., Goyal, A., Guizani, M., and Sikdar, B. (2021). Disaster and pandemic management using machine learning: a survey. *IEEE Internet Things J.* 8, 16047–16071. doi:10.1109/jiot.2020.3044966

Chen, J.-Y., Feng, Y.-W., Teng, D., Lu, C., and Fei, C.-W. (2022). Support vector machine-based similarity selection method for structural transient reliability analysis. *Reliab. Eng. Syst. Saf.* 223, 108513. doi:10.1016/j.ress.2022.108513

Chen, G., and Li, S. (2020). Research on location fusion of spatial geological disaster based on fuzzy SVM. *Comput. Commun.* 153, 538–544. doi:10.1016/j.comcom.2020.02.033

Chen, X., Yao, L., Mcauley, J., Zhou, G., and Wang, X. (2023). Deep reinforcement learning in recommender systems: a survey and new perspectives. *Knowledge-Based Syst.* 264, 110335. doi:10.1016/j.knosys.2023.110335

Daneshvar, M. H., Sarmadi, H., and Yuen, K.-V. (2023). A locally unsupervised hybrid learning method for removing environmental effects under different measurement periods. *Measurement* 208, 112465. doi:10.1016/j.measurement.2023.112465

Danish, M. (2022). "Chapter 1 - artificial intelligence and machine learning in water resources engineering," in *Current directions in water scarcity research*. Editors M. ZAKWAN, A. WAHID, M. NIAZKAR, and U. CHATTERJEE (Elsevier).

Duhem, L., Benali, M., and Martin, G. (2023). Parametrization of a demand-driven operating model using reinforcement learning. *Comput. Industry* 147, 103874. doi:10.1016/j.compind.2023.103874

Esrafilian-Najafabadi, M., and Haghighat, F. (2022). Impact of predictor variables on the performance of future occupancy prediction: feature selection using genetic algorithms and machine learning. *Build. Environ.* 219, 109152. doi:10.1016/j.buildenv.2022.109152

Fischer, J., Wirtz, S., and Scherer, V. (2023). Random forest classifier and neural network for fraction identification of refuse-derived fuel images. *Fuel* 341, 127712. doi:10.1016/j.fuel.2023.127712

Fowdur, T. P., and Nassir-Ud-Diin Ibn Nazir, R. M. (2022). A real-time collaborative machine learning based weather forecasting system with multiple predictor locations. *Array* 14, 100153. doi:10.1016/j.array.2022.100153

Ganguly, K. K., Nahar, N., and Hossain, B. M. M. (2019). A machine learning-based prediction and analysis of flood affected households: a case study of floods in Bangladesh. *Int. J. Disaster Risk Reduct.* 34, 283–294. doi:10.1016/j.ijdrr.2018.12.002

Ghebleh Goydaragh, M., Taghizadeh-Mehrjardi, R., Golchin, A., Asghar Jafarzadeh, A., and Lado, M. (2021). Predicting weathering indices in soils using FTIR spectra and random forest models. *CATENA* 204, 105437. doi:10.1016/j.catena.2021.105437

Goda, K., Kiyota, T., Pokhrel, R. M., Chiaro, G., Katagiri, T., Sharma, K., et al. (2015). The 2015 Gorkha Nepal earthquake: insights from earthquake damage survey. *Front. Built Environ.* 1. doi:10.3389/fbuil.2015.00008

Gonçalves, M., and Guedes Soares, C. (2022). Local assimilation of wave model predictions for weather routing systems. *Ocean. Eng.* 266, 113126. doi:10.1016/j.oceaneng.2022.113126

Guha, S., Jana, R. K., and Sanyal, M. K. (2022). Artificial neural network approaches for disaster management: a literature review. *Int. J. Disaster Risk Reduct.* 81, 103276. doi:10.1016/j.ijdrr.2022.103276

Han, S., Park, Y., Noh, N., Kim, J.-H., Kim, J.-J., Kim, B.-M., et al. (2023). Spatiotemporal variability of the PM2.5 distribution and weather anomalies during severe pollution events: observations from 462 air quality monitoring stations across South Korea. *Atmos. Pollut. Res.* 14, 101676. doi:10.1016/j.apr.2023.101676

Haver, S. M., Gedamke, J., Hatch, L. T., Dziak, R. P., Van Parijs, S., Mckenna, M. F., et al. (2018). Monitoring long-term soundscape trends in U.S. Waters: the NOAA/NPS ocean noise reference station network. *Mar. Policy* 90, 6–13. doi:10.1016/j.marpol.2018.01.023

Heddam, S. (2023). "Chapter 18 - extremely randomized trees versus random forest, group method of data handling, and artificial neural network," in *Handbook of hydroinformatics*. Editors S. ESLAMIAN, and F. ESLAMIAN (Elsevier).

He, Y., Chen, C., Li, B., and Zhang, Z. (2022). Prediction of near-surface air temperature in glacier regions using ERA5 data and the random forest regression method. *Remote Sens. Appl. Soc. Environ.* 28, 100824. doi:10.1016/j.rsase.2022.100824

Islam, S., Goerlandt, F., Feng, X., Uddin, M. J., Shi, Y., and Hilliard, C. (2020). Improving disasters preparedness and response for coastal communities using AIS ship tracking data. *Int. J. Disaster Risk Reduct.* 51, 101863. doi:10.1016/j.ijdrr.2020.101863

Jaydhar, A. K., Chandra Pal, S., Saha, A., Islam, A. R. M. T., and Ruidas, D. (2022). Hydrogeochemical evaluation and corresponding health risk from elevated arsenic and fluoride contamination in recurrent coastal multi-aquifers of eastern India. *J. Clean. Prod.* 369, 133150. doi:10.1016/j.jclepro.2022.133150

Jia, D., Yang, L., Lv, T., Liu, W., Gao, X., and Zhou, J. (2022). Evaluation of machine learning models for predicting daily global and diffuse solar radiation under different weather/pollution conditions. *Renew. Energy* 187, 896–906. doi:10.1016/j.renene.2022.02.002

Jiang, Z., Yang, S., Liu, Z., Xu, Y., Xiong, Y., Qi, S., et al. (2022). Coupling machine learning and weather forecast to predict farmland flood disaster: a case study in Yangtze River basin. *Environ. Model. Softw.* 155, 105436. doi:10.1016/j.envsoft.2022.105436

Johnson, P. M., Barbour, W., Camp, J. V., and Baroud, H. (2022). Using machine learning to examine freight network spatial vulnerabilities to disasters: a new take on partial dependence plots. *Transp. Res. Interdiscip. Perspect.* 14, 100617. doi:10.1016/j.trip.2022.100617

Jörges, C., Berkenbrink, C., Gottschalk, H., and Stumpe, B. (2023). Spatial ocean wave height prediction with CNN mixed-data deep neural networks using random field simulated bathymetry. *Ocean. Eng.* 271, 113699. doi:10.1016/j.oceaneng.2023.113699

Kanbara, S., and Shaw, R. (2022). Disaster risk reduction regime in Japan: an analysis in the perspective of open data, open governance. *Sustainability* 14 (1), 19. doi:10.3390/su14010019

Karir, D., Ray, A., Kumar Bharati, A., Chaturvedi, U., Rai, R., and Khandelwal, M. (2022). Stability prediction of a natural and man-made slope using various machine learning algorithms. *Transp. Geotech.* 34, 100745. doi:10.1016/j.trgeo.2022.100745

Kashtan Sundararaman, H. K., Shanmugam, P., and Nagamani, P. V. (2023). Robust extension of the simple sea-surface irradiance model to handle cloudy conditions for the global ocean using satellite remote sensing data. *Adv. Space Res.* 71, 1486–1509. doi:10.1016/j.asr.2022.10.009

Kaur, S., Gupta, S., Singh, S., Koundal, D., and Zaguia, A. (2022). Convolutional neural network based hurricane damage detection using satellite images. *Soft Comput.* 26, 7831–7845. doi:10.1007/s00500-022-06805-6

Kim, B.-Y., Lim, Y.-K., and Cha, J. W. (2022). Short-term prediction of particulate matter (PM10 and PM2.5) in Seoul, South Korea using tree-based machine learning algorithms. *Atmos. Pollut. Res.* 13, 101547. doi:10.1016/j.apr.2022.101547

Kim, M. K., Kim, Y.-S., and Srebric, J. (2020). Predictions of electricity consumption in a campus building using occupant rates and weather elements with sensitivity analysis: artificial neural network vs. linear regression. *Sustain. Cities Soc.* 62, 102385. doi:10.1016/j.scs.2020.102385

Lan, T., Hu, H., Jiang, C., Yang, G., and Zhao, Z. (2020). A comparative study of decision tree, random forest, and convolutional neural network for spread-F identification. *Adv. Space Res.* 65, 2052–2061. doi:10.1016/j.asr.2020.01.036

Laso Bayas, J. C., Marohn, C., Dercon, G., Dewi, S., Piepho, H. P., Joshi, L., et al. (2011). Influence of coastal vegetation on the 2004 tsunami wave impact in west Aceh. *Proc. Natl. Acad. Sci.* 108, 18612–18617. doi:10.1073/pnas.1013516108

Leng, P., Yang, Z., Yan, Q.-Y., Shang, G.-F., Zhang, X., Han, X.-J., et al. (2023). A framework for estimating all-weather fine resolution soil moisture from the integration of physics-based and machine learning-based algorithms. *Comput. Electron. Agric.* 206, 107673. doi:10.1016/j.compag.2023.107673

Linardos, V., Drakaki, M., Tzionas, P., and Karnavas, Y. L. (2022). Machine learning in disaster management: recent developments in methods and applications. *Mach. Learn. Knowl. Extr.* 4, 446–473. doi:10.3390/make4020020

Li, P., Wu, W., and Pei, X. (2023a). A separate modelling approach for short-term bus passenger flow prediction based on behavioural patterns: a hybrid decision tree method. *Phys. A Stat. Mech. its Appl.* 616, 128567. doi:10.1016/j.physa.2023.128567

Liu, D., Fan, Z., Fu, Q., Li, M., Faiz, M. A., Ali, S., et al. (2020). Random forest regression evaluation model of regional flood disaster resilience based on the whale optimization algorithm. *J. Clean. Prod.* 250, 119468. doi:10.1016/j.jclepro.2019.119468

Liu, D., Li, M., Ji, Y., Fu, Q., Li, M., Abrar Faiz, M., et al. (2021a). Spatial-temporal characteristics analysis of water resource system resilience in irrigation areas based on a support vector machine model optimized by the modified gray wolf algorithm. *J. Hydrology* 597, 125758. doi:10.1016/j.jhydrol.2020.125758

Liu, W., Fujii, K., Maruyama, Y., and Yamazaki, F. (2021b). Inundation assessment of the 2019 typhoon hagibis in Japan using multi-temporal sentinel-1 intensity images. Remote Sens. *[Online]* 13, 639. doi:10.3390/rs13040639

Liu, Y., Mazumdar, S., and Bath, P. A. (2023). An unsupervised learning approach to diagnosing Alzheimer's disease using brain magnetic resonance imaging scans. *Int. J. Med. Inf.* 173, 105027. doi:10.1016/j.ijmedinf.2023.105027

Li, Y., Zhou, S., Liu, J., Tong, J., Dang, J., Yang, F., et al. (2023b). Multi-objective optimization of the Atkinson cycle gasoline engine using NSGA III coupled with support vector machine and back-propagation algorithm. *Energy* 262, 125262. doi:10.1016/j.energy.2022.125262

Lu, M., Wang, M., Zhang, Q., Yu, M., He, C., Zhang, Y., et al. (2022). A vision transformer for lightning intensity estimation using 3D weather radar. *Sci. Total Environ.* 853, 158496. doi:10.1016/j.scitotenv.2022.158496

Ma, J., Yu, G., Xiong, W., and Zhu, X. (2023). Safe semi-supervised learning for pattern classification. *Eng. Appl. Artif. Intell.* 121, 106021. doi:10.1016/j.engappai.2023.106021

Mayer, M. J., and Yang, D. (2023a). Calibration of deterministic NWP forecasts and its impact on verification. *Int. J. Forecast.* 39, 981–991. doi:10.1016/j.ijforecast.2022.03.008

Mayer, M. J., and Yang, D. (2023b). Pairing ensemble numerical weather prediction with ensemble physical model chain for probabilistic photovoltaic power forecasting. *Renew. Sustain. Energy Rev.* 175, 113171. doi:10.1016/j.rser.2023.113171

Moosavi, A., Rao, V., and Sandu, A. (2021). Machine learning based algorithms for uncertainty quantification in numerical weather prediction models. *J. Comput. Sci.* 50, 101295. doi:10.1016/j.jocs.2020.101295

Morales, E. F., and Escalante, H. J. (2022). "Chapter 6 - a brief introduction to supervised, unsupervised, and reinforcement learning," in *Biosignal processing and classification using computational learning and intelligence*. Editors A. A. TORRES-GARCÍA, C. A. REYES-GARCÍA, L. VILLASEÑOR-PINEDA, and O. MENDOZA-MONTOYA (Academic Press).

Moriguchi, S., Matsugi, H., Ochiai, T., Yoshikawa, S., Inagaki, H., Ueno, S., et al. (2021). Survey report on damage caused by 2019 Typhoon Hagibis in Marumori Town, Miyagi Prefecture, Japan. *Soils and Foundations* 61 (2), 586–599. doi:10.1016/j.sandf.2021.01.009

Najafi, Z., Pourghasemi, H. R., Ghanbarian, G., and Fallah Shamsi, S. R. (2022). "Chapter 39 - identification of land subsidence prone areas and their mapping using machine learning algorithms," in *Computers in earth and environmental sciences*. Editor H. R. POURGHASEMI (Elsevier).

Nemni, E., Bullock, J., Belabbes, S., and Bromley, L. (2020). Fully convolutional neural network for rapid flood segmentation in synthetic aperture radar imagery. Remote Sens. *[Online]* 12, 2532. doi:10.3390/rs12162532

Payne, H. J., Hemming, S., Van Rens, B. A. P., Van Henten, E. J., and Van Mourik, S. (2022). Quantifying the role of weather forecast error on the uncertainty of greenhouse energy prediction and power market trading. *Biosyst. Eng.* 224, 1–15. doi:10.1016/j.biosystemseng.2022.09.009

Pereira, S., Abreu, E. F. M., Iakunin, M., Cavaco, A., Salgado, R., and Canhoto, P. (2022). Method for solar resource assessment using numerical weather prediction and artificial neural network models based on typical meteorological data: application to the south of Portugal. *Sol. Energy* 236, 225–238. doi:10.1016/j.solener.2022.03.003

Platania, F., Hernandez, C. T., and Arreola, F. (2022). Social media communication during natural disasters and the impact on the agricultural market. *Technol. Forecast. Soc. Change* 179, 121594. doi:10.1016/j.techfore.2022.121594

Pourghasemi, H. R., Gayen, A., Lasaponara, R., and Tiefenbacher, J. P. (2020). Application of learning vector quantization and different machine learning techniques to assessing forest fire influence factors and spatial modelling. *Environ. Res.* 184, 109321. doi:10.1016/j.envres.2020.109321

Powers, C. J., Devaraj, A., Ashqeen, K., Dontula, A., Joshi, A., Shenoy, J., et al. (2023). Using artificial intelligence to identify emergency messages on social media during a natural disaster: a deep learning approach. *Int. J. Inf. Manag. Data Insights* 3 (1), 100164. doi:10.1016/j.jjimei.2023.100164

Prodhan, F. A., Zhang, J., Hasan, S. S., Pangali Sharma, T. P., and Mohana, H. P. (2022). A review of machine learning methods for drought hazard monitoring and forecasting: current research trends, challenges, and future research directions. *Environ. Model. Softw.* 149, 105327. doi:10.1016/j.envsoft.2022.105327

Qin, R., Khakzad, N., and Zhu, J. (2020). An overview of the impact of Hurricane Harvey on chemical and process facilities in Texas. *Int. J. Disaster Risk Reduct.* 45, 101453. doi:10.1016/j.ijdrr.2019.101453

Quan, H. D., Khai, H. D., and Huynh, H. T. (2022). Ordinary differential equation based neural network coupled with random forest in the quality assessment of hand hygiene processes. *Appl. Soft Comput.* 130, 109627. doi:10.1016/j.asoc.2022.109627

Rahman, M. A., Hokugo, A., and Ohtsu, N. (2021). Household evacuation preparation time during a cyclone: random Forest algorithm and variable degree analysis. *Prog. Disaster Sci.* 12, 100209. doi:10.1016/j.pdisas.2021.100209

Rani, A., Kumar, N., Kumar, J., Kumar, J., and Sinha, N. K. (2022). "Chapter 6 - machine learning for soil moisture assessment," in *Deep learning for sustainable agriculture*. Editors R. C. POONIA, V. SINGH, and S. R. NAYAK (Academic Press).

Rubin, C., Horton, B., Sieh, K., Pilarczyk, J., Daly, P., Ismail, N., et al. (2017). Highly variable recurrence of tsunamis in the 7,400 years before the 2004 Indian Ocean tsunami. *Nat. Commun.* 8, 16019. doi:10.1038/ncomms16019

Ruidas, D., Chakrabortty, R., Islam, A. R. M. T., Saha, A., and Pal, S. C. (2022a). A novel hybrid of meta-optimization approach for flash flood-susceptibility assessment in a monsoon-dominated watershed, Eastern India. *Environ. Earth Sci.* 81, 145. doi:10.1007/s12665-022-10269-0

Ruidas, D., Pal, S. C., Islam, A. R. M. T., and Saha, A. (2021). Characterization of groundwater potential zones in water-scarce hardrock regions using data driven model. *Environ. Earth Sci.* 80, 809. doi:10.1007/s12665-021-10116-8

Ruidas, D., Pal, S. C., Saha, A., Chowdhuri, I., and Shit, M. (2022b). Hydrogeochemical characterization based water resources vulnerability assessment in India's first Ramsar site of Chilka lake. *Mar. Pollut. Bull.* 184, 114107. doi:10.1016/j.marpolbul.2022.114107

Ruidas, D., Pal, S. C., Towfiqul Islam, A. R. M., and Saha, A. (2023). Hydrogeochemical evaluation of groundwater aquifers and associated health hazard risk mapping using ensemble data driven model in a water scares plateau region of eastern India. *Expo. Health* 15, 113–131. doi:10.1007/s12403-022-00480-6

Ruidas, D., Saha, A., Islam, A. R. M. T., Costache, R., and Pal, S. C. (2022c). Development of geo-environmental factors controlled flash flood hazard map for emergency relief operation in complex hydro-geomorphic environment of tropical river, India. *Environ. Sci. Pollut. Res.* doi:10.1007/s11356-022-23441-7

Saha, S., Bera, B., Shit, P. K., Bhattacharjee, S., and Sengupta, N. (2023). Prediction of forest fire susceptibility applying machine and deep learning algorithms for conservation priorities of forest resources. *Remote Sens. Appl. Soc. Environ.* 29, 100917. doi:10.1016/j.rsase.2022.100917

Saravanan, S., Abijith, D., Reddy, N. M., Kss, P., Janardhanam, N., Sathiyamurthi, S., et al. (2023). Flood susceptibility mapping using machine learning boosting algorithms techniques in Idukki district of Kerala India. *Urban Clim.* 49, 101503. doi:10.1016/j.uclim.2023.101503

Seon Park, H., Hong, T., Lee, D.-E., Kwan Oh, B., and Glisic, B. (2022). Long-term structural response prediction models for concrete structures using weather data, fiber-optic sensing, and convolutional neural network. *Expert Syst. Appl.* 201, 117152. doi:10.1016/j.eswa.2022.117152

Shafiei, A., Tatar, A., Rayhani, M., Kairat, M., and Askarova, I. (2022). Artificial neural network, support vector machine, decision tree, random forest, and committee machine intelligent system help to improve performance prediction of low salinity water injection in carbonate oil reservoirs. *J. Petroleum Sci. Eng.* 219, 111046. doi:10.1016/j.petrol.2022.111046

Shaheen, M., Naheed, N., and Ahsan, A. (2023). Relevance-diversity algorithm for feature selection and modified Bayes for prediction. *Alexandria Eng. J.* 66, 329–342. doi:10.1016/j.aej.2022.11.002

Shin, J.-Y., Kim, K. R., and Lee, Y. H. (2022). Spatial prediction of outdoor thermal comfort using an operational NWP model for city and regional scales: a case study in Korea. *Urban Clim.* 45, 101286. doi:10.1016/j.uclim.2022.101286

Singh, S., Bansal, P., Hosen, M., and Bansal, S. K. (2023). Forecasting annual natural gas consumption in USA: application of machine learning techniques- ANN and SVM. *Resour. Policy* 80, 103159. doi:10.1016/j.resourpol.2022.103159

Stokes, E. C., and Seto, K. C. (2019). Characterizing urban infrastructural transitions for the Sustainable Development Goals using multi-temporal land, population, and nighttime light data. *Remote Sens. Environ.* 234, 111430. doi:10.1016/j.rse.2019.111430

Teodoro, A. C., and Duarte, L. (2022). "Chapter 10 - the role of satellite remote sensing in natural disaster management," in *Nanotechnology-based smart remote sensing networks for disaster prevention*. Editors A. DENIZLI, M. S. ALENCAR, T. A. NGUYEN, and D. E. MOTAUNG (Elsevier).

Ullah, K., Wang, Y., Fang, Z., Wang, L., and Rahman, M. (2022). Multi-hazard susceptibility mapping based on convolutional neural networks. *Geosci. Front.* 13, 101425. doi:10.1016/j.gsf.2022.101425

Van Blokland, J., Nasir, V., Cool, J., Avramidis, S., and Adamopoulos, S. (2021). Machine learning-based prediction of surface checks and bending properties in weathered thermally modified timber. *Constr. Build. Mater.* 307, 124996. doi:10.1016/j.conbuildmat.2021.124996

Voyant, C., Muselli, M., Paoli, C., and Nivet, M.-L. (2012). Numerical weather prediction (NWP) and hybrid ARMA/ANN model to predict global radiation. *Energy* 39, 341–355. doi:10.1016/j.energy.2012.01.006

Wang, C., Chen, Y., Chen, M., and Huang, X.-Y. (2023a). Evaluation of two observation operator schemes for wind profiler radar data assimilation and its impacts on short-term forecasting. *Atmos. Res.* 283, 106549. doi:10.1016/j.atmosres.2022.106549

Wang, D., Guan, D., Zhu, S., Kinnon, M. M., Geng, G., Zhang, Q., et al. (2021). Economic footprint of California wildfires in 2018. *Nat. Sustain.* 4, 252–260. doi:10.1038/s41893-020-00646-7

Wang, J., Song, H., Fu, T., Behan, M., Jie, L., He, Y., et al. (2022a). Crash prediction for freeway work zones in real time: a comparison between Convolutional Neural Network and Binary Logistic Regression model. *Int. J. Transp. Sci. Technol.* 11, 484–495. doi:10.1016/j.ijtst.2021.06.002

Wang, L., Mao, Z., Xuan, H., Ma, T., Hu, C., Chen, J., et al. (2022b). Status diagnosis and feature tracing of the natural gas pipeline weld based on improved random forest model. *Int. J. Press. Vessels Pip.* 200, 104821. doi:10.1016/j.ijpvp.2022.104821

Wang, Q., Geng, P., Chen, C., Chen, J., and He, C. (2023b). Determination of seismic response of reinforced tunnel portal slope using shaking table tests. *Tunn. Undergr. Space Technol.* 136, 105072. doi:10.1016/j.tust.2023.105072

Xu, D., Wang, Y., Huang, J., Liu, S., Xu, S., and Zhou, K. (2023). Prediction of geology condition for slurry pressure balanced shield tunnel with super-large diameter by machine learning algorithms. *Tunn. Undergr. Space Technol.* 131, 104852. doi:10.1016/j.tust.2022.104852

Yabe, T., Jones, N. K. W., Rao, P. S. C., Gonzalez, M. C., and Ukkusuri, S. V. (2022). Mobile phone location data for disasters: a review from natural hazards and epidemics. *Comput. Environ. Urban Syst.* 94, 101777. doi:10.1016/j.compenvurbsys.2022.101777

Yang, H., Yan, J., Liu, Y., and Song, Z. (2022). Statistical downscaling of numerical weather prediction based on convolutional neural networks. *Glob. Energy Interconnect.* 5, 217–225. doi:10.1016/j.gloei.2022.04.018

Yu, J., Liu, J., and Choi, Y. (2021). Review and prospects of strategies and measures for typhoon-related disaster risk reduction under public emergencies in TC region. *Trop. Cyclone Res. Rev.* 10, 116–123. doi:10.1016/j.tcrr.2021.05.002

Zhang, S., Zhang, J., Li, X., Du, X., Zhao, T., Hou, Q., et al. (2022a). Estimating the grade of storm surge disaster loss in coastal areas of China via machine learning algorithms. *Ecol. Indic.* 136, 108533. doi:10.1016/j.ecolind.2022.108533

Zhang, X., Sun, Y., Gao, D.-C., Zou, W., Fu, J., and Ma, X. (2022b). Similarity-based grouping method for evaluation and optimization of dataset structure in machine-learning based short-term building cooling load prediction without measurable occupancy information. *Appl. Energy* 327, 120144. doi:10.1016/j.apenergy.2022.120144

Zhao, X., Yin, Y., Zhang, S., and Xu, G. (2023). Data-driven prediction of energy consumption of district cooling systems (DCS) based on the weather forecast data. *Sustain. Cities Soc.* 90, 104382. doi:10.1016/j.scs.2022.104382

Zhengru, T. Artificial Neural Network attempts for long-term evaluation of great earthquakes. 2015 11th International Conference on Natural Computation (ICNC), 15-17 Aug. 2015 2015. 1128–1132.

Zheng, Y., Ge, Y., Muhsen, S., Wang, S., Elkamchouchi, D. H., Ali, E., et al. (2023). New ridge regression, artificial neural networks and support vector machine for wind speed prediction. *Adv. Eng. Softw.* 179, 103426. doi:10.1016/j.advengsoft.2023.103426

Zhou, S.-Y., Huang, A.-C., Wu, J., Wang, Y., Wang, L.-S., Zhai, J., et al. (2022). Establishment and assessment of urban meteorological disaster emergency response capability based on modeling methods. *Int. J. Disaster Risk Reduct.* 79, 103180. doi:10.1016/j.ijdrr.2022.103180