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Machine Learning and the Economic Losses in Disasters: Progress and Future Trends

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participated in SMR, ELITE, and SEMPOC, as well as ENGAGE projects funded by the European Commission in the H2020, FP7, and CIPS research programs, as well as in several national and regional funded projects.

Abstract. Climate change-induced disasters pose a significant global societal challenge, resulting in disruption and substantial economic losses. To combat such challenges, it is crucial to develop resilience and enhance the ability of any system (e.g., critical infrastructure, cities, or communities) to handle unforeseen events. Different approaches have been employed to support decision-makers in performing resilience assessments. For example, disaster loss estimation is an essential process for determining associated losses and supporting practical actions. However, these methods are resource- and time-consuming due to the data used. Machine learning (ML) techniques have emerged as powerful tools to overcome the challenge of analyzing vast amounts of data. Despite significant strides in applying ML techniques, more comprehensive reviews must be done on methodological development and ML applications in disaster loss estimation. This study aims to review the literature on ML techniques and their application in natural disaster loss estimations. A total of 676 studies were collected, and 56 were selected for detailed analysis. The study presents an overview of the ML techniques and applications for estimating economic losses in disaster scenarios. This review identifies the remaining challenges, limitations, and opportunities. Based on the outcomes of this review, a taxonomy was generated to characterize the various aspects of this area. The findings offer significant insights for policymakers, practitioners, and researchers, filling a critical void in current research.

Keywords: Loss Estimation, Machine Learning, Natural Disasters, Literature Review, Resilience, Disaster Management

1 Introduction

The rise in the number and severity of natural disasters caused by climate change is leading to new uncertainties and challenges for all systems, including any region, city, community, or critical infrastructure [1]. These disasters result in significant economic losses, including property damage and business disruptions. Such losses are associated with factors such as system characteristics, disaster magnitude, stress location, and the ability of affected systems to withstand stress [2–4]. The objectives of the Sustainable Development Goals (SDGs) and the European Union Disaster Resilience Goals emphasize the need to tackle rising disasters [5, 6]. A system's ability to withstand a disaster is related to its resilience level, defined as its capacity to prepare for, absorb, recover from, and adapt to unforeseen events [7].

Nowadays, most research focuses on resilience assessments based on stakeholders' perspectives to provide a complete picture of the system's resilience level [2, 4, 8, 9]. Such analyses are an essential and complex part of the decision-making process. To ensure practitioners take appropriate actions to enhance a system's responsiveness and maintain its functionality, these analyses must rely on accurate, reliable, and timely information. Further, there is a noticeable surge in the availability of data generated by field measurements related to disaster events, the system, and its surroundings [10–12]. Based on this measurable data, different methods, such as loss estimation, can be applied to support the assessment.

Loss estimation can identify and assess the economic impact of a disaster on a system. These estimations can assist in numerous aspects of disaster management, such as understanding past and current disasters, supporting the decision-making process, analyzing the cost-effectiveness of resources, assessing resilience, identifying vulnerabilities, and contributing to strategies to reduce possible risks and strengthen resilience [2, 13–18]. In this context, machine learning (ML) offers significant advancements in loss estimations by processing extensive datasets more rapidly and autonomously than traditional methods, such as on-site measurements or expert assessments [19, 20].

ML has been proven to be a reliable data-driven method in disaster research, with numerous studies reviewing its adoption in resilience and risk management[8, 21–26]. One example is the work of Wang et al. [8], which examines the application of ML in assessing disaster risk and resilience. Such work focuses on physical structural systems, the type of structural engineering (e.g., bridges, pipelines), the adopted ML, and the associated data to conduct the assessments [8]. Following that, Makhoul and Argyroudis [24] research assesses the use of loss estimation applications applied to seismic disasters, examining studies that either incorporate ML techniques or do not conduct their research. Furthermore, Hasik et al. [23] reviewed approaches that estimate seismic losses, considering life cycle assessments of building damage and repair impacts. Although recent literature has highlighted the benefits of incorporating ML in disaster management, a review of ML applicability in loss estimation and its potential to support evaluating resilience levels is still needed.

Therefore, it is essential to investigate current progress, uncover unexplored opportunities, identify potential challenges, and outline future directions related to the implementation of ML for loss estimation. This will advance and can ensure a reliable decision-making process, objectively estimate the resilience level, and promote data-driven approaches.

The objective of this study is to analyze the literature on estimating disaster economic losses using ML, thereby contributing to more effective and reliable resilience assessment and management strategies. In contrast to previous disaster management reviews, this study synthesizes the application of ML techniques in assessing economic losses across different disaster types and system characteristics.

Consequently, unlike the current review works, the present review provides key contributions to the topic of disaster loss estimation [8, 21–26]. First, it provides an analysis of the current state of adopting ML for estimating disaster losses, highlighting trends, data sources, and methodological approaches. Building on this foundation, a contribution of this work is the development of a taxonomy that classifies the relevant characteristics of ML-based loss estimation. This taxonomy provides a framework for the academic community to organize existing research, enabling systematic comparisons and facilitating future advances in this field. Finally, based on this review and taxonomy, the study offers recommendations to address open challenges and research opportunities, guiding both scholars and practitioners in developing more effective and data-driven resilience management strategies.

The paper is organized as follows: Section 2 explains the methodology, Section 3 presents the literature review results, discussion, and the generated taxonomy. Section 4 provides recommendations, and Section 5 presents the conclusions.

2 Research Methodology

This review delves into the current state of utilizing ML methods to support loss estimation when a system experiences any disaster event. From now on, the relationship between machine learning and loss estimation will be referred to as ML-LE. Additionally, the review explores how ML-LE contributes to resilience analysis. The following subsections outline the research questions and describe the processes for selecting studies, assessing their quality, and extracting data from the selected papers.

2.1 Research Questions

Our study aimed to achieve this paper’s objective by developing research questions (RQs) to answer how ML and loss estimation are adopted, the association between estimation and resilience assessment, and related future research challenges. By doing so, we identified accomplishments, unresolved issues, and challenges in this domain. Our analysis was conducted based on the following RQs:

RQ1 – What are the characteristics and purpose of the studies that adopt ML-LE?

RQ2 – What are the ML methods utilized to conduct these estimations?

RQ3 – What data sources are used for performing ML-LE?

RQ4 – How does loss estimation contribute to assessing the resilience level?

RQ5 – What are the current research challenges, directions, and recommendations when applying ML-LE?

2.2 Identifying and Selecting Primary Studies

Our review was based on the PRISMA guidelines to specify the selection process according to the predefined objectives and RQs [27]. This study used Scopus[1] and Web of Science[2] platforms as sources due to their precision in compiling scientific databases and journals [28]. In the initial search strategy, we extracted only English-language articles published between January 2019 and September 2025. Due to advances in ML, we limited the publication date to focus on the most recent and innovative ML approaches and to identify current research challenges and limitations.

We selected the keywords related to ML models, data, estimation goals, disaster scenarios, and the link between economic loss estimations and resilience. These keywords were formatted for a search string and applied to titles, abstract, and keywords fields. The terms were broad enough to capture relevant studies while excluding irrelevant ones. For example, terms related to reviews, cyber, mathematical, disaster, and food were excluded as they do not pertain to natural disasters. The following query was executed in the search engines of the selected platforms:

> (TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "supervised learning" OR "unsupervised learning" OR "deep learning" OR "semi-supervised learning" OR "reinforcement learning" OR "deep reinforcement learning") AND ALL ("data" OR "big data") AND TITLE-ABS-KEY ("loss estimation" OR loss OR estimation OR cost OR insurance) AND TITLE-ABS-KEY ("natural hazard" OR "natural disaster" OR "climate change") AND ALL ("disaster management" OR resilience OR "risk management") AND NOT TITLE-ABS-KEY ("cyber" OR "review" OR

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[1] https://www.scopus.com/

[2] https://www.webofscience.com/wos

"mathematical" OR "disease" OR food)) AND PUBYEAR > 2017 AND PUBYEAR < 2025 AND (LIMIT-TO (LANGUAGE, "english"))

After searching in the chosen databases, 676 studies were found, as presented in Figure 1. Subsequently, two rounds of visual examination were applied. The first round focused on visually examining paper titles, abstracts, and keywords. To perform such analysis, we adopted the Zotero[3] platform, an open-source reference management tool, to manage and organize the collected papers.

For this initial selection, we only considered studies that are strictly related to ML. Specifically, the studies must clearly state the use of ML or reference an ML method. While ML does not need to be the central focus, it should be employed to generate the study's output. Additionally, the article must explicitly associate its approach with the topic of natural disasters, including combinations of multiple disasters, thereby excluding disasters caused by human actions or cyber-attacks. Further, the economic losses topic must be cited, indicating that the study acknowledges the financial impacts on the analyzed systems during the disaster's occurrence. Finally, articles whose primary contribution was a literature review were excluded from this analysis to ensure the focus remained on original research studies.

This step helped to filter out irrelevant papers, leaving us with a total of 148. Finally, we performed the second round of examination, which was a qualitative analysis of the entire content of the selected papers. Each paper was carefully read and evaluated based on its relevance, accuracy, and reliability.

The criteria for the second round prioritize innovative contributions to disaster management and explicitly address topics related to ML, natural disasters, and economic losses. Each article must provide a clear and thorough description of its methodology, approach, results, limitations, and research gaps relevant to this review's

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[3] https://www.zotero.org/

focus. Specifically, the methodology section must detail the steps taken, the ML algorithms used (including a description of the models and their relevance to disaster management), and a summary of the input data, covering data categories, sources, open-access status, and the inclusion of economic loss data. Additionally, the article should specify the performance metrics used and the intended outcomes, along with a rationale justifying the selection of methods and approaches.

Furthermore, the articles must specify the type of disaster and describe the analyzed system (e.g., region, country, or company). They should also include the geographic context, mention any references to resilience concepts or related frameworks, and indicate the type of damage assessment performed (i.e., economic, social, or physical). Additionally, each study should explain how its approach improves decision-making and addresses links to climate change.

Finally, the criteria for this second screening also related to whether the papers aligned with the ML-LE topic, addressed the RQs, and met the literature review objectives. Appendix A Table A1 summarizes the inclusion and exclusion criteria, while Appendix A Table A2 lists the 56 papers that were included in the review.

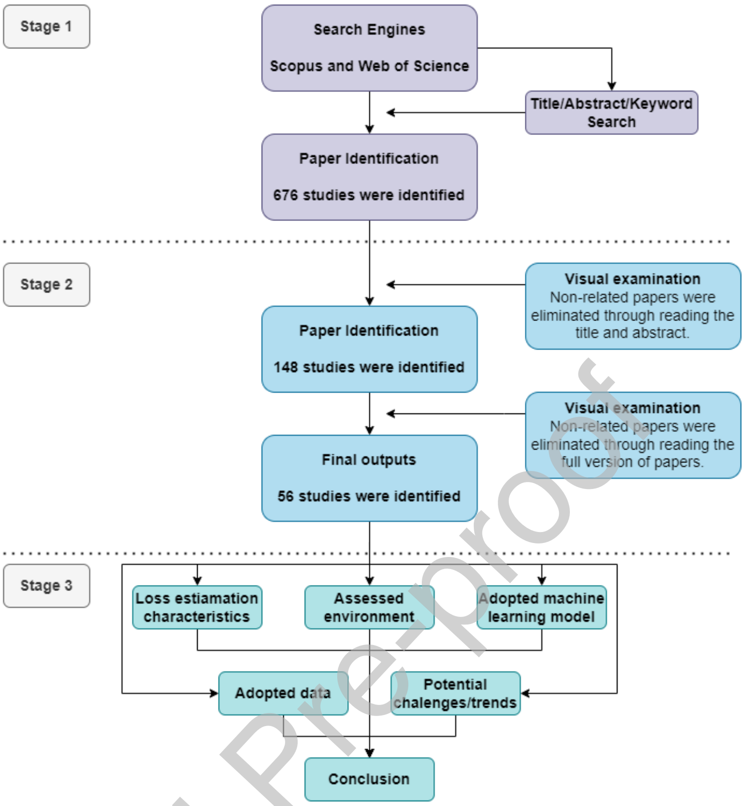

Figure 1: Diagram illustrating the review process conducted during this study

Relevant papers were screened to collect predetermined data, including publication year, publisher, and associated SDGs provided by SCOPUS. A data extraction workflow addressing each research question was conducted. For RQ1, environment characteristics, assessed losses, hazard type, and other characteristics were collected. For RQ2, ML models and related objectives were extracted. For RQ3, data features and preprocessing were collected. For RQ4, loss estimation and resilience concept relationship were analyzed. Lastly, in RQ5, reported challenges and potential improvements were identified.

In addition, a taxonomy was created to represent the ML-LE characteristics. Taxonomy is a useful tool for structuring information about a specific field, which is beneficial for researchers to comprehend and examine intricate domains [29].

Researchers can hypothesize about these connections by studying relationships among concepts and understanding the subject matter [29]. To formulate this taxonomy, we utilized the framework proposed by Nickerson et al. [29]. This framework centers on creating a taxonomy that defines meta-characteristics to illustrate the features of the analyzed topic and the end conditions to represent it. It also involves identifying and examining the different concepts described in each meta-characteristic. This taxonomy defines the meta-characteristics as the RQs and the data extracted during the review. The information retrieved from the papers is the ending condition. Lastly, the extracted data are the concepts to be classified into the meta-characteristics. Through this taxonomy, we can identify trends and gaps, presenting a comprehensive picture of the subject matter.

3 Results and discussion

This section presents a summary of the selected ML-LE papers, a discussion of the obtained results with the identified RQs, and the taxonomy developed for ML-LE topic. As a first step of the analysis, the publication year, journal name, publisher, article keywords, and the associated SDG number were collected.

Figure 2 presents the distribution by publication year. In this case, an increase in ML-LE adoption from 2019 to 2022, as well as in the last two years, is perceived. Another observation pertained to the distribution of papers across various journals and publishers. As shown in Figure 3, the ML-LE publications are spread among fourteen publishers and 41 journals. Most publications were published by Elsevier, Multidisciplinary Digital Publishing Institute (MDPI), and Springer Nature publishers, with 40 papers among these three. The most popular journal was the "International Journal of Disaster Risk Reduction (IJDRR)" with six articles, followed by the "Sustainability" and "Natural Hazards and Earth System Sciences (NHESS)", with three articles each. The diversity of journals reflect the wide range of topics covered by ML-LE studies. Furthermore, this indicates an increase trend of researchers from various fields employing ML-LE techniques.

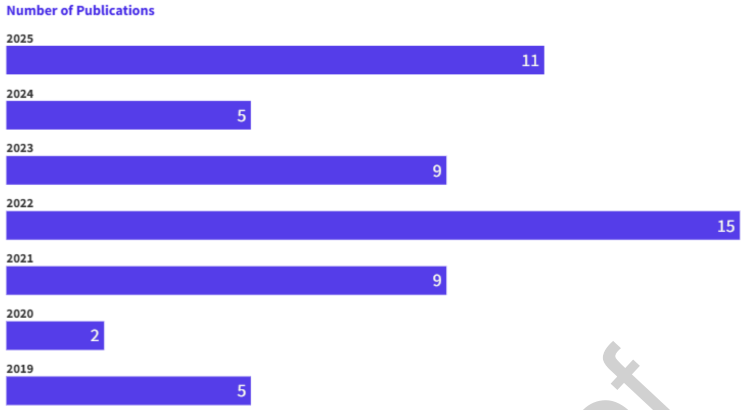

Figure 2: Quantity of publications per year

Another analysis of the collected data was based on the SDG classification. As presented in Figure 4, the analyzed papers cover ten of the seventeen goals proposed by the United Nations (UN). SDG 11 (Sustainable Cities and Communities) is the principal goal associated with 48 papers, followed by SDG 13 (Climate Action), which is related to 23 publications, and SDG 17 (Partnership for the Goals), which is represented by nine articles. Only four papers were not classified into the SDG categories. However, these works are highly related to SDG 11. With this categorization, the incorporation of ML-LE in alignment with the SDGs is significant, particularly in the domains of urban areas, communities, disasters, population, and environment. This classification further indicates that ML-LE is in accordance with improving and ensuring a more sustainable and secure future.

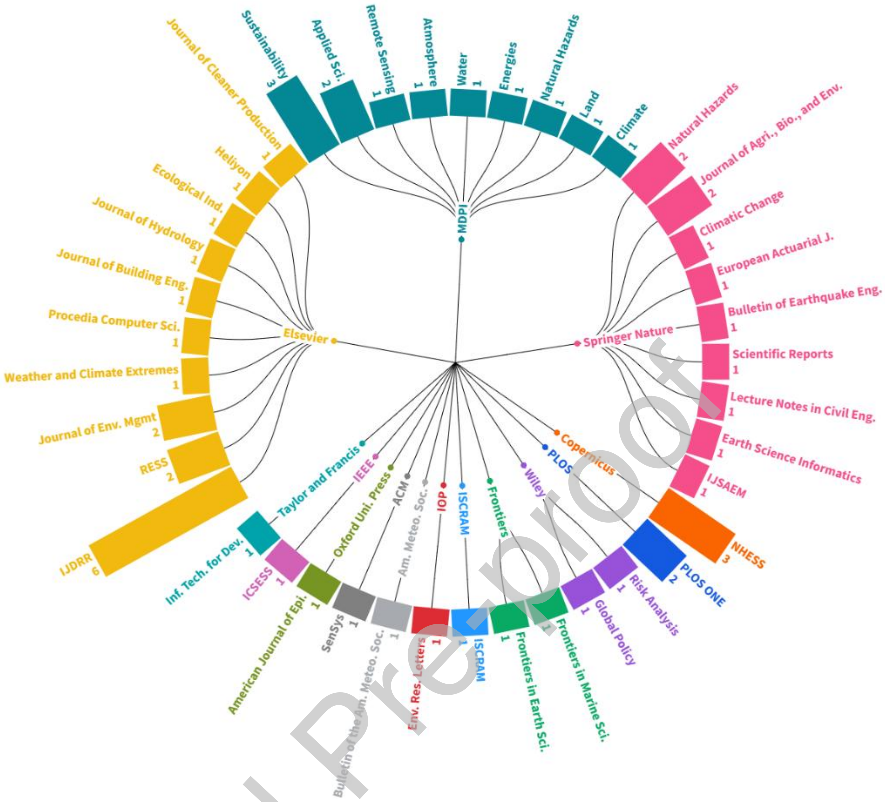

Figure 3: Distribution diagram showing publishers, their journals, and the frequency with which journal is related to the analyzed articles, with larger segments indicating more frequent journals.

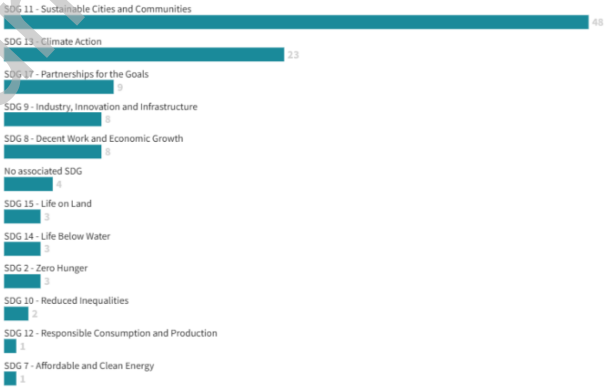

Figure 4: Papers classified based on the SDG goals tags

We also performed a keyword analysis. Eighteen keywords had more than one citation, and the central keyword was "machine learning", which was referenced in nineteen articles. The term "economic loss" was referenced nine times, "flood" eight times, "climate change" seven times, and "natural disaster" six times. "Resilience" appears five times, while "random forest", "insurance", and "extreme events" were mentioned four times each. Finally, nine keywords were cited twice each, associated with ML models, risk assessment, disaster events, and data topics. These keywords illustrate the diverse range of ML-LE adoption. When examining the connections between the keywords, it becomes apparent that "machine learning", "economic loss", and “flood” are the main keywords associated with the other keywords. These highly connected nodes illustrate the ML concept and its relationship to disasters.

3.1 RQ1 – What are the characteristics and purpose of the current studies that adopt ML-LE methods?

As previously mentioned, the studies exhibit a range of approaches and features, reflecting the nature of this field. These variations are based on factors such as the research focus, environment, loss assessment, hazard type, and supplementary characteristics. The following subsections delve into these characteristics, providing an overview of adopting ML-LE methods.

3.1.1 What are the purpose and methods for performing loss estimation?

In general, most of the selected papers propose different purposes and methods for estimating disaster losses [16, 30–36]. These approaches are mainly applied to single disasters and their association with the analyzed system. Losses can be classified into three categories: economic, social, and physical [32, 37–42]. Additionally, the review reveals that most studies concentrate on assessing economic damage.

During this analysis, it was perceived that the approaches share a similar workflow method for estimating losses, which involves data collection, filtering, analysis, transformation, normalization, and feature selection. The workflow initiates by determining the scope of their analysis, which may entail focusing, for example, on a single critical infrastructure, a particular sector or region, the population, or the economy of an entire city [43–46]. The disaster is also defined by the approaches, varying from a single disaster analysis to the influence of different disasters [31, 47, 48]. Finally, the workflow concludes based on the analysis of the results, which can be attributed to the performance of the ML model or its application in real-time or hypothetical situations [32, 49]. However, the existing approaches are mainly applied to specific scenarios rather than presenting an analysis adaptable to diverse situations, such as different types of disasters or systems.

Kim et al. [32] is one of the studies that follow a similar workflow. The presented approach focuses on predicting losses at construction sites using real data from insurance companies, particularly when these systems are affected by floods and windstorms. Chen et al. [43] also follow the same workflow of estimating the direct and indirect economic impacts in 42 industrial sectors. In general, most existing studies tend to apply their research to specific scenarios rather than presenting a universal analysis that can be adapted to diverse situations, such as different types of disasters or systems. However, these studies do not provide ways to extend their approach to this universal analysis or test their approach in other scenarios.

3.1.2 What are the characteristics of the adopted environment and system?

The existing literature performs loss estimation by considering the environment and supplementary characteristics. These characteristics are associated with the environment, hazard, loss estimation type, and supplementary characteristics, such as interdependence between systems, adopted policies, or geo-location analysis. Given the diversity of the systems, they can be grouped based on city and communities, critical infrastructures, industrial and economic sectors, and physical buildings. City and communities are the predominant systems, with 40 publications. The abundance of data concerning this system is attributed to its accessibility, with most of it being publicly available. One notable example is the Chinese census databases, which contain a vast amount of data regarding demographics, environment, and socio-economics [38, 39, 43, 50, 51]. The Korean government also provides a vast quantity of databases regarding socio-economic data, building characteristics, and economic damages [35, 46, 52]. Another example is the United States Emergency Management Agency platform, which provides information on natural hazards, socioeconomic factors, and geographic locations [14, 53–55].

Following that, physical buildings are covered by seven papers. These papers focus on the system's physical infrastructure, such as the type of construction and structure, number of floors and basements, building height, location, total construction cost, and insurance claims [30, 31, 56–58]. The critical infrastructures are also analyzed in seven publications and include flood supply, natural gas, transportation, and electric power distribution [30–32, 57, 59–62]. Lastly, three papers are associated with the industrial and economic sectors, related to manufacturing, commercial, and financial domains [16, 32, 42]. The scarcity of these papers could be due to the lack of data, which is usually private and proprietary [16, 34, 37, 43, 63].

Regarding the analyzed hazard, thirteen disaster types were identified and classified into hydrological, meteorological, climatological, and geophysical. By considering that one single article can explore one or more disasters, we identified 89 disaster analyses in the literature. For example, the work of Bae et al. [59] analyzes disasters related to floods, precipitation, snowstorms, heavy winds, thunderstorms, and fires. Based on this overview, was identified that floods and heavy winds are the predominant disasters cited on 26 occasions. Floods have high occurrences due to the considerable amount of data collected by national meteorological services and adopted in ML models [36, 48, 52, 55, 64].

Heavy wind group disasters relate to windstorms, typhoons, cyclones, hurricanes, and tornadoes. The publications on this disaster group tend to focus on the building infrastructures and the regions' general losses [30, 57–59]. Heavy precipitation is the third most adopted hazard, with ten citations. In this case, precipitation is different from the flood's properties, patterns, and analysis [32, 46, 51, 59, 60, 60, 63, 65–67]. Following that, earthquakes are present in seven citations focusing on regions and physical infrastructures. The data characteristics of this hazard range from peak ground acceleration, earthquake magnitude, and epicenter intensity, but also focus on qualitative data, such as social media and survey data [31, 38, 40, 56, 65, 68, 69].

On the other hand, hazards like droughts, sea level increase, snowstorms, thunderstorms, heatwaves, fires, and tsunamis have less than five papers each. The reason for this adoption rate is likely due these hazards are not so frequent and may have limited historical data, which becomes challenging to assess losses [68, 70, 71].

Figure 5 presents the association between hazards and systems. It is important to note that a system can be analyzed based on different disasters, as seen in the case of Kim et al. [32], which analyzed the effects of floods, heavy wind, and precipitation stresses in the construction sector. Therefore, the total number of relations presented in Figure 5 differ from the number of analyzed papers. The city and community systems are the principal analyzed for different disasters, with 53 cases. The second system associated with disasters was the critical infrastructure, with nineteen cases. Furthermore, city and community, and critical infrastructure systems share five different disaster types each. This demonstrates that they are highly vulnerable to various disasters and suggests their importance to researchers. Regarding critical infrastructures, it is important to note that this system is associated with disasters that do not have a higher representation in the analysis, i.e., drought, snowstorm, thunderstorm, fire, and temperature. This variety of disasters suggests that researchers should analyze all the potential risks a critical infrastructure can face.

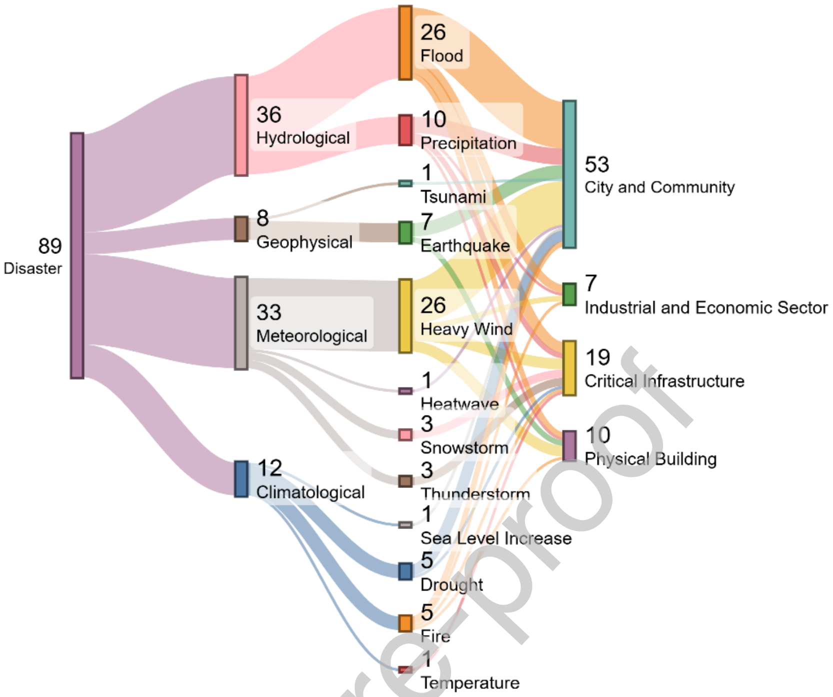

Figure 5: Diagram illustrating, from left to right, the categorization of 89 disaster events identified in the literature, their division into disaster categories, disaster types, and the connections to impacted systems. The width of each flow is proportional to the frequency of occurrence, providing a formal representation of the distribution and interconnection among disaster events and the system they impacted.

The type of estimated losses was also analyzed, distinguishing between direct and indirect losses. According to the analysis, 54 focused on direct losses, while only two explicitly addressed indirect ones. The first study analyzed short-term direct and indirect economic impacts of flood-induced flow disruptions across German economic sectors under uncertainty [16]. In this case, the ML-LE directly estimated a group of industries, and an input-output model estimated the indirect impacts [16]. The second work was applied to the Chinese economic sectors and flood events. In this case, the researchers also adopted ML-LE for the direct impacts and an input-output model for the losses to other sectors [43].The limited number of studies addressing indirect economic impacts is noteworthy, despite their fundamental role in comprehensively understanding the effects of supply chain interruptions, productivity declines, and the propagation of economic disturbances following disasters. For example, this deficiency could be related to the challenge of assessing the indirect impacts generated by the cascading disruptions of a transportation sector on other infrastructures. This complexity is related to persistent difficulties in collecting quantitative data and delineating sectoral interdependence. Both studies that assess indirect losses underscore the difficulty in quantifying these indirect effects, which include barriers such as sector dependency, restricted data access, and the necessity for expertise in identifying the indirect impacts[16, 43]. This gap poses a significant risk of undervaluing the actual economic impact of disaster events.

Furthermore, the publications also included supplementary characteristics. These characteristics focus on enhancing the analysis and cannot be categorized based on the mentioned characteristics due to their unique definitions. For instance, interdependencies between different systems and the associated losses during a hazard event were considered [16, 43]. Another topic was climate change, which may affect the intensity and frequency of disasters, and was also included in some of the reviewed approaches based on predicting future scenarios [35, 51, 60, 66]. Further, government policy adoption was identified as a crucial indicator for estimating losses [55]. Additionally, real-time analysis using social media data was suggested as a characteristic to enhance results [40, 44]. The adoption of geo-location was also implemented with a focus on understanding the influence and predicting the flow of floods, hurricanes, snowstorms, or tropical cyclones [33, 37, 58, 64, 72].

3.2 RQ2 – What are the ML methods utilized to conduct these estimations?

The review identified two main categories of ML models applied to loss estimation: supervised learning and unsupervised learning. Supervised learning uses labeled datasets to train algorithms and make predictions, while unsupervised learning focuses on finding patterns in unlabeled data. Figure 6 presents an overview of the adopted ML models associated with the disaster type. This analysis follows the same approach presented in Figure 5, which counts the times an ML model was used and not the quantity of papers associated with that. Most of the publications use supervised learning. This model type is associated with 207 occurrences across various disasters. Further, regression and classification tasks are the most associated with supervised learning. The regression focuses on estimating the correlation between the variables to predict a continuous numerical output [58]. On the other hand, the classification tasks are associated with categorizing data based on labeled data [33]. Conversely, unsupervised learning models were applied only 20 times.

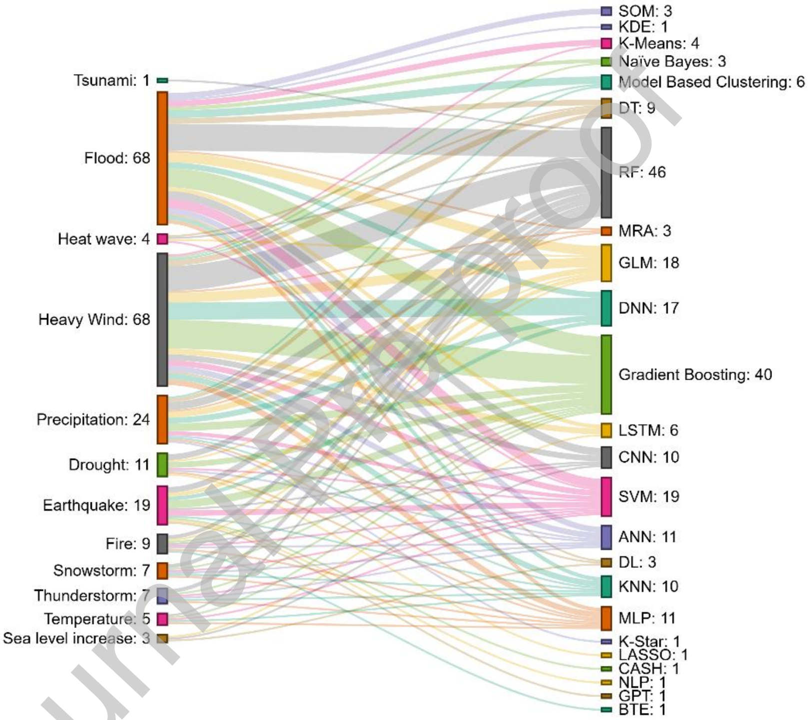

Figure 6: Sankey diagram illustrating, from left to right, the categorization of natural disaster types identified in the literature, their distribution by article appearance, and the association with corresponding ML algorithms. The width of each connecting flow reflects the frequency with which each algorithm is cited in relation to specific hazards.

Concerning supervised learning models, the Random Forest (RF) was applied in 46 disaster instances. However, it was not utilized in cases related to sea level rise disasters. RF is an ensemble learning algorithm that can be applied to regression and classification tasks. In regression, it computes a continuous output by taking the average of decision trees, while in classification, it provides the most frequent class among the trees, making it a flexible and reliable approach. [55]. Majority of the papers related to RF are associated with regressions tasks due to its versatility, ability to combine multiple decision trees for non-linear and outlier handling, robustness, feature selection, and effective management of missing values [14, 16, 33, 35, 46, 48, 51, 52, 55, 63, 64, 64, 72–74]. The RF can also be adopted in classification tasks, in such cases, the works focused on identifying the importance of the features in the losses but also classifying them for enhancing the inputs for other models or classifying the flood probability [2, 33, 34, 34, 37, 42, 50, 67–69, 75, 76].

The second most adopted supervised model was Gradient Boosting (GB), which encompasses eXtreme Gradient Boosting (XGBoost), Categorical Gradient Boosting (CatBoost), Light Gradient Boosting (LightGBM), Least-Squares Boosting (LSBoost), and Gradient Boosting Regression Trees (GBRT). GB was adopted 40 times. These studies support the use of GB for regression tasks as it can effectively model complex non-linear relationships and handle outliers and heterogeneous data. Its automatic feature interaction handling and regularization techniques contribute to robust predictions, making it a powerful and accurate tool for a wide range of regression problems [2, 14, 37, 38, 43, 46, 52, 54, 67, 69, 71–74, 77].

Considering unsupervised learning models, the most notable models related to ML-LE were the K-Means with four occurrences and the Self-Organizing Map (SOM) with three occurrences. These models prioritize clustering tasks, which may not be the primary focus when estimating losses but can still be used with other ML models. K-Means is a popular unsupervised clustering method that partitions a dataset into K clusters [49, 53, 54, 62]. In the ML-LE, K-Means has been applied in four studies related to floods and tropical storms. For flood events, K-Means was used to categorize regions based on economic and life losses and meteorological data [49, 53, 62] . In the case of tropical storms, K-Means was used to classify different disaster events, and, based on the results, used other methods like GB, RF, SVM, and Naïve Bayes to estimate losses [49, 53, 54, 62].

The SOM model, another highly cited unsupervised method, is a neural network that arranges input data on a low-dimensional grid while preserving topological relationships. It is usually used for clustering, visualization, feature mapping, and dimensionality reduction. It captures complex data structures and presents them in a structured, 2D format. Such a model was also used in the same flood categorization model, Abdel-Mooty et al. [49]. To generate the best output, this work tested various ML models to categorize and predict community losses, such as K-means, SOM, and Model-based clustering. The results demonstrated that K-means and SOM had the best performance, and based on the clusters, a category system was created to predict the resilience level. Notably, this practice of implementing diverse ML models is widely employed in literature to compare results and determine the best model performance.

After analyzing various articles on ML-LE, it was found that most models adhere to similar principles, mainly using supervised learning to analyze disaster-related losses. Additionally, many studies focused on selecting a set of ML models tailored to their research objectives and data, subsequently testing these models to identify the best performance. However, a significant number of these articles lack practical applications or use cases for the developed models or frameworks, limiting their contributions to performance analysis as the outcome.

The absence of practical applications or guidelines for incorporating these studies into real-world settings makes it challenging for decision-makers to apply these findings in disaster management strategies. This gap between academic research and its practical implementation must be bridged to ensure that research outcomes have a meaningful impact on real-world challenges. Nevertheless, some approaches do exhibit additional features, such as the use of SHAPLEY Additive Explanations (SHAP) utilized by Liu et al. and Wang et al. [54, 67].

The approach by Liu et al. [54] examines the financial costs associated with tropical cyclones, highlighting the influence of the adopted variables on the ML output. This method improves the interpretability of model results by highlighting variable importance, addressing a gap often overlooked in other studies that lack such detailed representations. Despite this advancement, current ML models are usually perceived as black-box models by non-expert users, which undermines trust in their output due to the unclear relationship between inputs and outputs.

The adoption of Explainable AI (XAI) can address this issue by increasing the transparency and reliability of the results for general knowledge [52, 54, 67]. XAI facilitates the analysis of ML processes and quantifies the contribution of each input factor to individual predictions, thereby promoting and enabling human understanding of model decisions [67]. Such approach is particularly appropriate when presenting the results of ML-LE approaches, as decision makers may lack the technical expertise to comprehend the decisions made by ML models fully. Delivering outcomes along with clear visualizations of the decision process can enhance interpretability, thereby increasing transparency and fostering greater trust in the results among end users.

3.3 RQ3 – What data sources are used for performing ML-LE?

As reported in various publications, ML-LE models are highly dependent on the adopted data [49, 61]. The related data can be classified into input and output for ML models. The input data is categorized into qualitative and quantitative, with quantitative data being the most representative. In addition, some articles adopt both data in a quali-quantitative approach. This considers the fact that qualitative data focuses on the results of questionnaires, manual analyses, or study groups [16, 33, 34, 45, 68, 77].

Regarding the outputs of such models, some studies have identified indicators and variables contributing to loss estimation. In such cases, approaches presented by Liu et al., Wu et al., and Zhang et al. [50, 51, 54, 67] adopt feature analysis after performing loss estimations related to urban environments. These studies aim to identify the most critical variables when performing ML-LE. A common objective of these studies is to use feature influence to identify the essential variables that can help stakeholders identify critical areas. However, these approaches acknowledge the need to improve the data used and to find a more effective way to interpret the results.

Using input data sourced from selected articles, the data can be classified into nine groups pertaining to disaster losses: demographic, socioeconomic, geological, physical infrastructure, geographic, meteorological, survey data, and social media. Figure 7 presents a heat map that shows the frequency of each category in the analyzed system. Among all the systems, the meteorological category has the highest occurrence, with 44 total occurrences, including 30 cases in the city and community systems. The disaster losses category follows with 36 occurrences, while geographic data has 34, socioeconomic data has 24, and physical infrastructure data has 22. As previously mentioned, most papers refer to city and community systems, which is also reflected in the data, with 124 cases across different categories. Demographic data is unique to the city and community system. Geological, survey, and social media data have low occurrences, with fewer than four occurrences.

Based on the articles analyzed, a comprehensive overview of the data sources utilized to assess losses was performed. Generally, open data, such as meteorological and geographic information, are more frequently employed due to their accessibility. In contrast, data that requires additional effort to obtain, such as survey and social media data, is less commonly utilized despite its potential to offer valuable insights.

	City and Community	Industrial and Economic Sector	Physical Building	Critical Infrastructure
Meteorological	30	2	5	7
Geographic	24	2	5	3
Socioeconomic	18	2	2	2
Demographic	11	0	0	0
Physical infrastructure	12	3	4	3
Disaster losses	22	2	6	6
Social media	3	0	0	0
Survey data	2	1	0	1
Geological	2	0	1	0

Figure 7: Occurrence of the defined data categories based on the analyzed system

As presented in Section 3.1, a common workflow for using such data is noticeable in the examined articles. This workflow includes filtering, collection, analysis, transformation, normalization, and future selection. This workflow begins with data filtering and collection, which can be done by extracting data from databases [59, 64, 78] or by collecting data in the field through tools that extract data from social networks [33, 40], or sensors to measure sea level rise data, for example [70]. The accessibility of existing data is associated with data collection, with most of the data being open and public [43, 54, 76].

However, it is noticeable that most publications mention the need for more precise data that is often private or cannot be used for such work. For example, data related to the cause of a car accident should be essential to track whether the accident was caused by human error or extreme weather conditions [68]. To address this issue, some existing studies, such as Sieg et al., employ a combination of public and private data, including the number and characteristics of companies associated with the flood characteristics [16]. The same combination is also evident in the work of Su et al. [48], which assesses flood disaster losses on the economy and population by utilizing public data such as rainfall characteristics and private data, including pipeline data network. Another example is the study by Torres and Vargas [66], which combines meteorological data from an open database with insurance data from companies to estimate future insured losses.

Once the data has been gathered, most studies follow a similar sequence of steps: conducting an analysis phase to detect any issues or discrepancies, checking the data provenance to ensure reliability, performing data normalization, and executing feature selection [61]. Regarding normalization, existing ML-LE approaches typically employ widely accepted methods, such as feature scaling tasks like the Z-score [57] or min-max [54], while some implement custom routines. For example, Abdel-Mooty et al. [49] propose a unique normalization routine for ML-LE related to communities and flood events. This study involves using two different socio-economic and meteorological datasets, standardizing variables by analyzing their averages and interdependencies. Feature selection is a crucial step in the ML process, with the existing research applying various techniques, including filter, wrapper, and embedded methods [14, 71]. Evaluating the significance of each variable is crucial when working with large, diverse datasets. However, it has been observed that most studies do not adopt such an analysis and instead directly perform ML-LE without considering the significance of each variable in the obtained results.

3.4 RQ4 – How does loss estimation contribute to assessing the resilience level?

The concepts of resilience and loss estimation are closely associated. This is because a higher resilience can be related to the attenuation of loss impacts generated by a disaster event. In contrast, loss estimation can provide valuable insights into a system's level of resilience. However, among the examined articles, only seven explicitly cite the use of the resilience concept or frameworks as a way for improving loss estimation or gaining a deeper understanding of system resilience. Such studies adopt a consistent approach by first defining the resilience concept in relation to the specific approach being presented, and subsequently aligning the selected data with the relevant resilience dimensions as previously established.

For example, the study by Abdel-Mooty et al. [53] focuses on the development of a flood resilience-based categorization based on an unsupervised ML model and on various resilience metrics related to the 4R’s resilience framework (an acronym for robustness, rapidity, resourcefulness, and redundancy). In such cases, the economic and social losses faced by regions in the USA are analyzed with additional features and incorporated into a clustering model to categorize the different areas based on the generated output, which represents the region's resilience level.

Another example is Zhang et al. [51], which focuses on estimating Storm Surge Disaster Loss (SSDL) grades based on ML. In their study, the authors collected 50 open-source features related to hazard, vulnerability, and resilience topics. Classified into distinct indicator categories, it then performs data improvement and applies different ML techniques to estimate the SSDL grades. The resilience features considered include the region's road network density, the availability of doctors and medical equipment, and the percentage of illiterate individuals. However, the adopted resilience variables are not supported by any resilience framework or concept. Liu et al. [54] present the same scenario using eXplainable AI algorithms. Their study evaluates tropical cyclone disaster loss using ML and identifies the impact of specific feature factors on the prediction model. In this case, the work adopts the same dataset as Zhang et al. [51], but without describing the resilience concept or framework adopted to choose such features.

Haggag et al. [14] provide an evolution of this resilience adoption scenario. In such cases, the proposed work develops a systematic framework for predicting climate change-induced damages based on the definition of different data analytics and machine learning techniques. The framework was deployed to predict wind-related property damages incurred in New York based on various datasets. Three regression models were tested, with the RF model demonstrating the highest accuracy. Furthermore, a series of insights was made considering the relationships between property damages and the model input variables, as well as their association with the resilience concepts, which are presented and discussed.

Another illustrative example is the study by Pedra et al. [62], which evaluates the resilience of the Spanish transportation system against flood events by integrating meteorological and insurance data. This work is grounded in the resilience concept that links infrastructure performance to the magnitude of disaster events. By combining infrastructure performance indicators derived from insurance data with event magnitude metrics from meteorological data, the authors develop a clustering-based approach that enables classification of the transportation system's resilience [62]. Consequently, a national resilience index is generated, providing comprehensive outputs and comparative analyses that offer valuable insights into the system's performance under varying hazard scenarios.

Based on the review, it is perceived that the association between the resilience concept and loss estimation remains unexplored, possibly due to challenges encountered by researchers. Specifically, these challenges include difficulties in aligning input data with established resilience concepts, as well as the lack of resilience frameworks that effectively bridge resilience attributes with quantitative data. Consequently, without grounding the selected features in recognized resilience theories, decision makers may struggle to understand the rationale behind the chosen data in ML-LE models. Furthermore, within the context of disaster management data, resilience represents the sole attribute that stakeholders can actively modify through the implementation of governmental actions, policies, and targeted interventions. Parameters such as disaster losses, meteorological records, and geological datasets remain immutable, as they are outcomes or inherent features not subject to direct alteration.

3.5 RQ5 – What are the current research challenges, directions, and recommendations when applying ML-LE?

As mentioned earlier, adopting loss estimation to assess resilience is a relatively new field, especially when using ML methods. This combination offers new directions, accomplishments, and challenges due to the range of ML models, data, systems, and additional characteristics. However, certain areas still need improvement to make significant progress in the field. Based on the publications obtained, the main challenges are data extraction and analysis, adopting accurate and reliable ML models, enhancing the model's interpretability, and its relation to the resilience concept.

The adopted data in ML-LE is critical to ensuring the reliability and practical application of estimation outcomes. As discussed in Section 3.3, most studies rely on public databases to collect this accurate data. The scarcity of data is commonly perceived as a significant issue in the literature, which can undermine the effectiveness of ML-LE models. To address this limitation, some works integrate proprietary data from insurance companies, critical infrastructure, and other private sectors. Nonetheless, it is important to note that competition in the financial sector and among companies can lead to restricted access to data. Facilitating access, however, could foster collaboration and help reduce potential disaster losses.

An additional strategy to avoid this scarcity is to merge different datasets, particularly those containing qualitative data. By combining these sources, expert opinions, policies, and legislation can be incorporated to bolster the robustness of ML-LE models. However, converting qualitative data into usable inputs presents significant challenges, requiring specialized techniques to quantify or appropriately adapt this information. Beyond data availability, another notable issue in the literature is the limited consideration of indirect losses. As previously presented, incorporating indirect impacts into ML-LE is inherently complex. However, doing so enhances the accuracy and comprehensiveness of the results, providing greater value for stakeholders' decision-making processes.

Additionally, it is crucial to have a resilience background to support the ML-LE input data and the adopted model. As presented in the literature, few studies adopt resilience concepts or frameworks in their approaches. Such integration is essential not only to demonstrate that the input data reflect the dynamics of how a disaster affects a system, but also to prevent the perception that any dataset could be arbitrarily used for ML-LE. Without this grounding, there is a risk of a trial-and-error approach to identify which data best correlates with the estimation.

Analysis of this topic suggests that the domains of data science and disaster resilience move in the same direction. However, deeper integration of these two fields remains uncommon in the literature. Employing resilience frameworks and concepts can support researchers in the development of ML-LE models, while simultaneously improving their comprehensibility and reliability for end users, who are often familiar with disaster resilience principles. In the absence of a precise definition of resilience, establishing a link to the concept becomes challenging, thereby adding an additional step for end users to comprehend the applicability of ML-LE to real-world issues.

In the realm of ML-LE models, numerous options are available depending on the project goals, data collected, and the system characteristics. Most ML-LE models are designed to achieve the same objective, with model accuracy and model selection often being the primary outcomes. When selecting the optimal model, these approaches should not rely on accuracy but also consider the real-world applicability and how they can assist in disaster management tasks. Additionally, current approaches often lack proper guidance for generalizing or adapting their approaches to different contexts.

Another critical problem related to the ML-LE is the prevalence of black-box models, which can be difficult for stakeholders to interpret. As noted in the literature, few models incorporate techniques to enhance the understandability and readability of the results after performing the estimations or assessments. The adoption of methods such as XAI and feature analysis can provide end-users with more information, thereby facilitating the decision-making process. This allows critical variables, areas, or features to be identified, enabling targeted actions to attenuate potential disaster effects, reduce economic losses, and enhance the system’s resilience. The development of more intuitive models and interpretability techniques requires further improvement.

In addition to these topics, some points need to be identified in the selected papers, such as the use of uncertainty ML-LE models, which recognize the unpredictability of disaster events. There is also a lack of real-time analysis, as evident in articles on social network analysis. Another area that needs to be addressed is the use of the results to contribute to enhancing resilience assessment models, helping to develop targeted resilience strategies. Finally, most of the identified models cannot be adapted to other scenarios beyond the configurations in the published work.

The use of ML-LE models has tremendous potential benefits. Researchers and stakeholders can achieve more comprehensive estimations when reliable and diverse datasets are combined with a resilient background and a robust and adaptable ML model. This offers in-depth knowledge that can be translated into highly effective risk management strategies, reducing both current and future losses while preserving systems and associated components. Evaluating and refining ML-LE models is crucial, as climate change can significantly impact the environment and increase the frequency of hazardous events. ML-LE approaches must be optimized to help address emerging risks by integrating advances and lessons from historical disasters.

3.6 ML-LE Taxonomy

Based on what was explored and extracted from the selected papers, a ML-LE topic taxonomy was developed, presented in Figure 8. By developing this taxonomy, we can provide an overview of the current approaches and settings used to estimate disaster economic losses. By adopting the work of Nickerson et al. [29], we defined the meta-characteristics based on the defined objectives, research questions, and the similarity of the selected papers. The meta-characteristics of this taxonomy are (i) machine learning model; (ii) machine learning task; (iii) type of loss; (iv) assessed system; (v) type of hazard; (vi) loss estimation type; (vii) data specifications; and (viii) supplementary characteristics. These meta-characteristics were classified into four main topics based on the defined objectives of this review and the identified characteristics found in the selected papers: environmental characteristics, machine learning, associated data, and supplementary characteristics. As mentioned earlier, the concluding criteria for creating this taxonomy were based on the content of the papers, as well as the objectives and concepts linked to the meta-characteristics of the data extracted from these papers.

For the first main topic, we analyzed the concepts associated with environmental characteristics. As presented in Section 3.1, the concepts related to the meta-characteristics of this main topic are the analyzed environment, evaluated losses, and the analyzed hazard, and the type of loss estimation. Machine learning is the second main topic, and the review presented in Section 3.2 was adopted to collect the necessary information. The ML model type and the associated task were inserted into the taxonomy identified. Our taxonomy prioritized the main ML models used in the papers, such as decision trees, ensembles, K-Means, SVM, and ANN. It also differentiated the various ML tasks based on clustering, regression, and classification. We also defined the third main topic based on the associated data category and the steps taken before utilizing the data. Additionally, we included any concept or specification found in the literature related to data characteristics, such as provenance to support the reliability of the adopted data, historical data for time-series analysis, or the use of quantitative or qualitative data. The last main topic was the supplementary characteristics, which encompass any topic or concept that did not fit into the previous meta-characteristics but was crucial for analyzing the research. For instance, this includes the climate change topic and policy relations that are inherently present in some papers and reflect the current scenario of the ML-LE topic. Using the developed taxonomy, we categorized the selected articles based on the main characteristics presented in Appendix A Table A2. This table includes only the primary features, while unique characteristics identified through the literature review were compiled and integrated into the taxonomy to reflect the full range of approach variations.

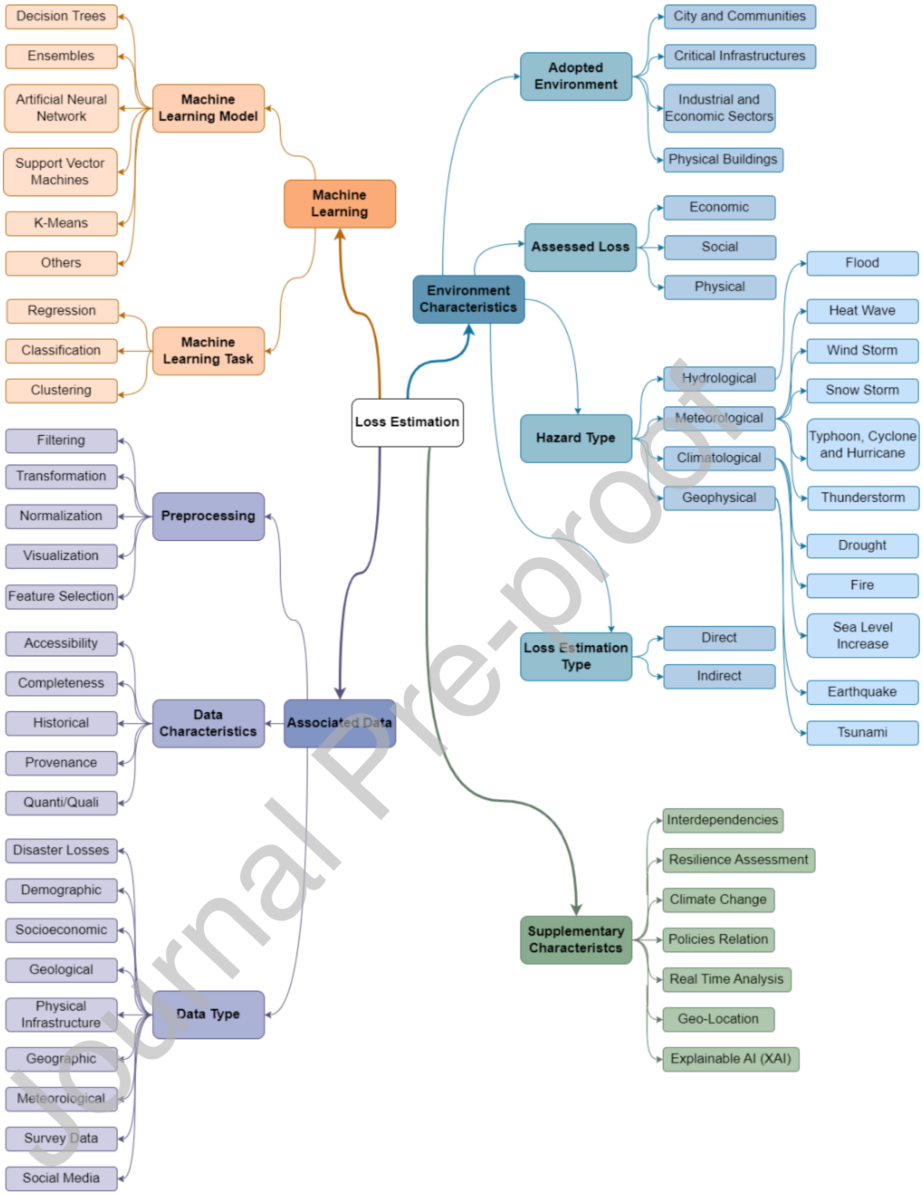

Figure 8: Visual representation of the generated taxonomy based on the ML-LE concepts

4 Recommendations

As presented in Section 3, the results and discussion provide an overview of the current literature scenario. However, it is important to note that this analysis does not cover all domains associated with ML-LE models, and there is room for improvement in this area. Therefore, this section delves deeper than the obtained results and offers recommendations to enhance the following ML-LE models and works.

Recommendation 1: Enhancing the data collection and storage

Using data for any ML model in any area is crucial, and this is no different from loss estimation. It is noticeable that the same problems encountered in this area, such as a lack of data, inconsistency, and private data, are commonly found in other areas. In addition, it was perceived that the current literature faces drawbacks in not considering the indirect impacts, heterogeneous data, data granularity, and the resilience concept.

Therefore, various approaches have been created to help solve this issue. One of the main approaches is to use the FAIR principles (from the acronym Findable, Accessible, Interoperable, and Reusable) [79]. These principles serve as guidelines that researchers and data protectors can adopt to improve the reusability of data in various research endeavors. Based on the goals to be achieved in each of the main areas, researchers can find the data more efficiently in any format, access the data, whether public or private, and promote the interoperability of the data so that it can be connected effortlessly and reused in their research and objectives. Various institutions have endorsed these principles, and in the context of disasters, one of the main applications is evident in the EM-DAT database. EM-DAT is used to record data about the human and economic impacts of natural disasters. By supporting the FAIR principles, EM-DAT can guarantee findable and accessible data in a way that is interoperable and reusable across different cases, thereby enhancing broader research [80].

The analysis of adopted data reveals a notable scarcity of social media and survey data. This situation is particularly unexpected considering the extensive volume of social media information generated and the prominence of surveys and qualitative data within disaster resilience research. Nevertheless, there appears to be no centralized repository or coordinated effort among researchers to compile such data into a unified platform.

Data granularity and diversity are essential for the effective implementation of ML-LE. Leveraging detailed, fine-grained data not only improves model accuracy but also enhances the interpretability of results [81, 82]. Granularity involves providing richly detailed data that ML-LE models can readily utilize, thereby boosting model credibility and delivering more specific, precise outcomes to end users. Examples of such fine-grained data include high-resolution satellite imagery, detailed characteristics of physical building structures, and economic information from insurance payouts, all of which can significantly improve loss estimation approaches.

This focus on granularity closely aligns with data heterogeneity. Many studies incorporate diverse datasets related to multiple domains to capture a comprehensive representation of the analyzed system. In this context, digital twin concepts can provide a virtual replica of real-world systems, facilitating simulations of disaster impacts [83]. By supporting scenario testing and improving the accuracy of loss predictions, digital twins play a key role in strengthening resilience planning and informing decision-making. Adopting such approaches can also address gaps in the literature related to the assessment of indirect losses. As highlighted in the results section, several works emphasize the need for more methods and techniques that explicitly account for these impacts, which can be directly linked to both data granularity and the application of digital twin concepts.

Another important aspect related to data is the adoption of a resilience assessment framework during data collection and its applications in the ML-LE models. Only a few studies attempt to establish this connection, as it is a challenging task that requires considerable effort in selecting or developing a framework grounded in well-established resilience concepts. Incorporating such resilience frameworks shifts the focus beyond evaluating only ML performance metrics. Instead, it emphasizes how end users can benefit from the developed methods and outputs of ML-LE models. For instance, resilience frameworks such as the 4Rs, People, and BRIC are commonly applied in qualitative assessments, and can also be adapted for quantitative models [84–86].

As shown in the results, studies that incorporate these frameworks offer more robust methods while remaining aligned with the core idea of disaster resilience. It is important to note that end users can only update resilience-related data based on the application of actions, policies, and interventions. On the other hand, variables such as meteorological conditions, geological factors, or disaster losses remain fixed. Focusing on resilience helps emergency managers identify which policies or interventions most effectively mitigate potential losses, enabling them to assess the impact of future measures and make more informed investment decisions. The adoption of resilience ensures that the underlying variables are relevant and comprehensive, and with that, the outputs can provide the stakeholders with reliable scenarios and results.

Future research should prioritize implementing FAIR principles to address current data deficiencies by fostering the development and enhancement of data repositories, as exemplified by the EM-DAT database. New studies with similar approaches will improve data reusability and significantly expand research opportunities. Additionally, efforts to centralize and integrate social media, survey data, or other data are crucial to enrich datasets. Emphasizing data granularity and heterogeneity will boost model accuracy and interpretability. The adoption of digital twin concepts can further enable realistic disaster simulations and improve assessments of indirect losses. Finally, integrating established resilience frameworks within ML-LE approaches will enhance methodological robustness and ensure outputs are relevant and actionable for stakeholders.

Recommendation 2: Exploring and improving the existing ML models

The analyzed ML-LE models are, in the vast majority, considered as black boxes. In this case, the review revealed a gap between model development and practical application guidance, which can lead to an unreliable scenario for end users. Therefore, exploring and improving existing ML models to embrace XAI frameworks and methods is essential for several reasons. With the increasing complexity of ML models and data heterogeneity, understanding the decision-making processes inside machine learning models is challenging.

With that in mind, XAI techniques are crucial as they provide transparency, allowing stakeholders and interested parties to comprehend how these models arrive at specific outcomes. By offering insights into how models utilize diverse inputs to generate loss predictions, XAI enables users to validate results, make informed decisions, and integrate models into operational tasks. XAI can transform the ML-LE outputs from black box predictions into actionable, reliable tools for estimating economic loss, managing resilience, and responding to emergencies. This transparency is essential and is already being adopted in disaster management research [22].

Emerging technologies related to XAI can enhance ML-LE models by increasing transparency and trust. For instance, digital twins enable real-time virtual simulations of disaster scenarios, which not only support proactive risk assessment but also provide a platform for testing different mitigation strategies [83]. When combined with XAI techniques, digital twins help identify key drivers and trends, such as demonstrating how nature-based solutions can cost-effectively reduce flood losses by mitigating hazards and enhancing resilience. Similarly, large language models generate human-readable explanations, making complex model outputs accessible to diverse stakeholders [87]. By integrating XAI with these advanced technologies, ML-LE models become more interpretable, reliable, and actionable for disaster management. To ensure effective adoption, it is crucial to develop domain-specific explanations, validate them with end users, and standardize workflows, thereby supporting adaptive and resilient disaster risk reduction.

Further, it is also important to establish a proper workflow when conducting ML-LE models to ensure that their outputs are standardized. This standardization makes the models robust, adaptable, and consistent, which helps stakeholders better understand their performance. Additionally, standardized workflows and explainability give stakeholders the power to make informed decisions based on the models' results.

This is vital for gaining trust and acceptance from end-users, regulatory bodies, and the broader community in the built models.

Furthermore, a gap was perceived between the academic research and the practical implementation of ML-LE approaches. It is crucial to bridge this by extending the developed ML-LE approaches and their outcomes so that decision-makers can effectively utilize them in real-world situations. The adoption of XAI techniques is just one example; researchers and decision-makers must collaborate to develop applications and guidelines for enhancing and incorporating various approaches into disaster management strategies.

Future directions regarding the ML-LE models should focus on enhancing the transparency and practical applicability through the integration of XAI frameworks. Emerging technologies, such as digital twins and large language models, combined with XAI, offer promising ways to facilitate real-time simulations and generate human-readable explanations, thereby enhancing interoperability and operational adoption. Establishing workflows and domain-specific explanation protocols will further ensure consistency, robustness, and stakeholder acceptance across applications. Moreover, bridging the gap between academic research and practice is crucial. Collaboration between researchers and decision-makers is needed to create practical guidelines for integrating ML-LE into disaster management. Future efforts should aim to make ML-LE models more reliable, transparent, and user-friendly to better support resilience planning, economic loss estimation, and emergency response.

Recommendation 3: Multi-scenario and multi-vision loss estimation

As presented in the review, most works focus on single disaster analysis and characteristics. A multi-scenario approach that integrates models for correlated or cascading effects (e.g., floods that impact power outages and consequently affect transportation and health services) is vital but not well explored. The current loss estimation scenario is a complex process that involves ML models, analyzed systems, natural disasters, adopted data, and supplementary characteristics. It has been observed that ensuring the accuracy and reliability of ML-LE models is a challenging task, especially when considering multi-hazards. However, the current work follows the same trend to conduct such an analysis. A multi-scenario approach with accurate and diverse datasets and robust ML models can improve estimation accuracy and reliability.

In addition to multi-scenario analysis, it is essential to consider other characteristics, particularly the role of uncertainty in disaster scenarios. These uncertainties often involve complex interactions between multiple hazards and critical infrastructure, and their combinations can lead to cascading effects, especially under climate change conditions [88]. Such cascading impacts may generate losses that are not adequately captured by existing ML-LE models, highlighting the need for more sophisticated approaches that account for these interdependencies. Furthermore, multi-scenario assessments should also incorporate the indirect and environmental impacts of disasters. While most studies focus on direct losses, indirect consequences, such as the carbon emissions or resource depletion associated with damaged infrastructure, are rarely quantified. Including both indirect and environmental impacts in ML-LE models would provide a more comprehensive understanding of disaster consequences, improve risk assessment, and support decision-making for mitigation and resilience planning.

Given the complexity of real-world situations, future work requires a comprehensive understanding of potential scenarios and varying perspectives to capture the intricacies of loss prediction accurately. Moreover, collaboration with domain experts and stakeholders can help incorporate expert data and qualitative information into the models. This approach enhances the system's resilience and aligns it with the evolving nature of real-world conditions characterized by climate change features. By synergizing ML capabilities with domain expertise and flexible workflows, we can establish a more comprehensive and adaptive framework for accurate loss estimation across various scenarios.

5 Conclusion

This study examines the use of ML to estimate economic losses incurred due to natural disasters. Based on the adopted methodology, we collected 676 publications on the topic and reviewed 56 in detail. We classified the ML-LE works based on defined research questions and analyzed the limitations and challenges addressed. We observed a growing trend in using ML-LE models, which can confirm the importance of automatically and reliably analyzing such losses.

Furthermore, the existing literature advances the field and facilitates stakeholders' understanding of how various disasters affect their respective systems. Notably, in the context of ML-LE, most studies assess the impacts on communities and urban areas, while also considering systems associated with physical and critical infrastructure, among others. Additionally, the approaches have been applied to twelve distinct disaster types, with floods and windstorms being the most frequently analyzed (RQ1). This study identified a range of ML models employed within these contexts. Specifically, random forest and gradient boosting models are predominantly adopted, though over twenty ML models are reported, demonstrating the diversity and richness of the evaluated approaches (RQ2). Another aspect examined was the nature of input data utilized by these approaches, where the majority rely on meteorological and disaster loss features, although some leverage data about geological characteristics, surveys, social media, socioeconomic indicators, and other variables (RQ3).

Based on this analysis, the intrinsic relationship between loss estimation and disaster resilience was identified. However, few studies explicitly incorporate this connection, despite its critical importance in enabling decision makers to select and prioritize actions that effectively enhance resilience and consequently reduce economic losses. Those approaches tend to utilize resilience concepts and frameworks primarily as a basis for selecting specific data inputs (RQ4). Furthermore, the review identified areas requiring improvement, primarily in data collection and analysis, ML model adoption, and the presentation of results in formats comprehensible to decision-makers (RQ5). Based on these findings, the principal ML-LE characteristics were identified, leading to the development of a comprehensive taxonomy that illustrates the current state of ML-LE. Additionally, key research directions were identified and synthesized into a series of recommendations to enhance future approaches (RQ5).

It is important to highlight several limitations of this review. First, studies published before 2019 were excluded, which may have overlooked foundational works or early advances that have shaped current research in the field. Second, the review focuses exclusively on scientific papers, without incorporating governmental reports or ongoing research projects, which could provide innovative perspectives on ML-LE. In addition, the review scope is limited to disaster resilience, rather than the broader domain of disaster management. This focus was chosen to maintain a precise and targeted analysis of the primary impacts on systems while ensuring a more coherent evaluation of relevant methodologies and findings.

This review has presented the relationship between ML and loss estimation, which can extract insightful information to assist stakeholders and lead to more efficient and effective decision-making. This can help reduce economic losses and possibly enhance a more resilient system in the face of ever-increasing natural disaster events.

Appendix A

Table 1: Summary of the inclusion and exclusion criteria used to identify relevant studies on machine learning models to perform economic loss estimations in natural disaster contexts

Criteria	Inclusion	Exclusion
Language	Articles written in English.	Non-English articles.
Publication Date	January 2019 – September 2025.	Published before 2019.
Source Databases	Scopus or Web of Science.	Articles not indexed.
Document Type	Peer-reviewed journal articles.	Conference papers, literature reviews, theses, and editorials.
Topic Domain	Studies addressing natural disasters, economic losses, and machine learning.	Studies on human-made disasters (e.g., cyber, war, disease, and food-related).
Methodology	Studies applying ML methods to generate results.	Studies with no ML component or only mathematical modeling without ML.
Economic Loss Focus	Studies acknowledge economic losses during disasters.	Studies without mentioning economic impacts.
Contribution Type	Research with empirical applications, or methods.	Literature reviews, surveys, or non-original research.
Detail Screening (Second Round)	Methodology (algorithms used, data described, metrics, outcomes), explicit disaster context, relation to resilience and decision-making, comparison with literature, and climate change consideration.	Studies lacking methodological detail, unclear or irrelevant context, or failing to connect ML, disasters, and economic loss.
Innovation & Relevance	Provides novel contributions, identifies gaps, and addresses the review's RQs and objectives.	Low-relevance studies without an innovative contribution.

Appendix A

Table 2: Classification of the selected articles collected during this literature review

Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	Hazard Type	Assessed Loss	ML Model	Data Type	Data Access	Real Case	Res. Asses	C.C
[76]	C&C	Flood	S	RF	GG, MR, PI, SE, DG	Public	Yes	No	Yes
[16]	I&E	Flood	E	RF	MR, PI, SE, GG, SD	Public and Private	Yes	No	Yes
[34]	CI	Drought	E	RF	MR, GG, SD	Public	Yes	No	Yes
[33]	C&C	Hurricane	E	LSTM; RF; Negative binomial regression	SM, DG, SE, DL	Public	Yes	No	No
[30]	PB	Tornado	E, P	ANN	MR, GG, SE	Public	Yes	No	Yes
[36]	C&C	Flood	E, S, P	Gaussian naïve bayes; DT; SVM; KNN; RF	MR		No	No	Yes
[35]	C&C	Heatwave	S	RF; Logistic Regression;	SE, DG, MR	Public	Yes	No	Yes

Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	**Hazard Type**	**Assessed Loss**	**ML Model**	**Data Type**	**Data Access**	**Real Case**	**Res. Asses**	**C.C**
				SVM; DT					
[31]	PB	Flood; Wind storm; Earthquake	E, P	DNN; Multiple regression	MR, GG, DL	Public and Private	Yes	No	Yes
[53]	C&C	Flood	E	Model-based clustering; K-Means; SOM-ANN	MR,DL	Public	Yes	Yes	No
[32]	I&E	Flood; Precipitation; Wind Storm	E	DNN; MRA	DL, PI, MR, GG	Public and Private	Yes	No	Yes
[48]	C&C	Flood	E, S	RF; Kernel Density	PI, GG, SE	Public and Private	Yes	No	Yes
[59]	CI	Fire; Flood; Heavy rain; Heavy snow; Hurricane; Storm;	E, P	ANN	PI, SE, MR, DL	Public	Yes	No	No

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Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	Hazard Type	Assessed Loss	ML Model	Data Type	Data Access	Real Case	Res. Asses	C.C
		Thunderstorm; Others							
[50]	C&C	Flood	E, P	RF	PI, SE, GG	Public	Yes	No	Yes
[75]	C&C	Flood	E	RF	GG, PI	Public	Yes	No	Yes
[43]	CI	Flood	E	GBRT; Bayesian Ridge; Line Linear; Elastic Net; XGB and GBR	MR, DL, PI	Public	Yes	No	Yes
[89]	C&C	Drought; Flood	E	ANN; SVM	MR, GG	Public	Yes	No	Yes
[38]	C&C	Earthquake	E, S	CASH; SVM; KNN; RF; XGBoost; CBoost; LGBM	DL, DG, SE, GL	Public	Yes	No	No
[73]	C&C	Drought	E	RF; GLM; XGBoost	GG, MR, SE	Public and Private	Yes	No	Yes
[47]	C&C	Flood	E	SOM-ANN	DL, MR	Public	Yes	Yes	Yes
[49]	C&C	Flood	E, S, P	K-means; SOM; Naïve Bayes; CT;	DL, MR	Public	Yes	Yes	Yes

Ref	**Environment Characteristics**			**Machine Learning**	**Associated Data**			**Supplementary Characteristics**	
	Adopted Env.	**Hazard Type**	**Assessed Loss**	**ML Model**	**Data Type**	**Data Access**	**Real Case**	**Res. Asses**	**C.C**
				SVM; ANN; Bagged DT; RF; NB					
[61]	PB	Earthquake	E, P	ARIMA-SVM	GL, PI, SE, GG, DL	Public and Private	Yes	No	No
[51]	C&C	Storm	E, P	RF; XGBoost; LMT; K-star	MR, GG, SE, DG, PI, DL	Public	Yes	Yes	Yes
[63]	CI	Hurricane; Winter storm; Thunderstorm; Storm; Heavy wind	E	RF	MR, DL, SE, GG	Public	Yes	No	Yes
[2]	C&C	Typhoon; Storm surge	E, P	RF-RFE; LSBoost; XGBoost; RF	MR, SE, DG	Public	Yes	Yes	Yes
[71]	PB	Fire	P	BTE	PI, MR, DL	Public	Yes	No	Yes
[14]	C&C	Windstorm	E, P	RF; RT; Bagging; Boosting.	GG, MR, SE, DG	Public	Yes	No	Yes

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Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	Hazard Type	Assessed Loss	ML Model	Data Type	Data Access	Real Case	Res. Asses	C.C
[39]	C&C	Storm surge	E	ANN-ELM	MR, DL, SE, PI	Public	Yes	No	Yes
[40]	C&C	Earthquake	S	Crisis NLP, GPT	SM	Public	Yes	No	No
[58]	PB	Tropical Cyclone; Flash Flood	E	DNN	DL, MR, GG, PI	Public	Yes	No	Yes
[64]	C&C	Flood	P	RF	GG, MR	Public	Yes	No	Yes
[55]	C&C	Flood	E	Hybrid RF	DL, MR, GG, PI	Public	Yes	No	Yes
[65]	C&C	Rainfall; Windstorm; Earthquake	E, P	DNN	DL, PI, MR, GL	Public	Yes	No	Yes
[57]	PB	Typhoon	P	DL; DNN	GG, MR, PI, DL	Public	Yes	No	Yes
[70]	C&C	Flood; Sea Level Increase	P	DL; CNN; LSTM	MR, GG	Public	Yes	No	Yes
[54]	C&C	Tropical Cyclone	P	K-means; LightGBM; RF; SVM; Naïve Bayes	MR, SE, GG, DL, PI	Public	Yes	No	Yes

Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	Hazard Type	Assessed Loss	ML Model	Data Type	Data Access	Real Case	Res. Asses	C.C
[60]	PB, CI	Precipitation	E, P	SVM	MR, DL	Public	Yes	No	Yes
[37]	CI	Snow; High winds; Temperature; Flood; Lightning.	P	KNN; MLP; RF; SVM; XGBoost	MR, PI, GG, DL	Public	Yes	No	No
[44]	C&C	Typhoon	P	CNN	MR, SM, SE, GG, DG	Public	Yes	No	Yes
[68]	C&C	Earthquake; Tsunami	E, S	RF	SD	Private	Yes	No	No
[45]	C&C	Drought	E, P	LASSO	DG, SE, DL, GG	Public and Private	Yes	No	Yes
[78]	C&C	Forest Fires	E	MLP	GG, DL, MR	Public	Yes	No	No
[66]	C&C	Precipitation; Wind	E	Clustering; GLM; GAM	DL, MR	Public	Yes	No	No

Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	Hazard Type	Assessed Loss	ML Model	Data Type	Data Access	Real Case	Res. Asses	C.C
[60]	C&C	Rainfall	E	Support vector regression; GLM; DNN	DL; MR	Public	Yes	No	No
[41]	C&C	Typhoon	E, P	DNN	DL; MR; GR	Public	Yes	No	No
[42]	I&E	Wind; Floods; Forest fires	E, S	RF	DL; SE; PI	Public	Yes	No	No
[67]	C&C	Floods; Heavy rainfall; Droughts	E	MLP; RF; XGBoost; LightGBM	DL; MR	Public	Yes	No	Yes
[69]	C&C	Floods; Earthquakes; Hurricanes; Wildfires	E	Hybrid CNN ; Logistic regression; SVM; GBoost; RF	GG	Public	Yes	No	No

Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	**Hazard Type**	**Assessed Loss**	**ML Model**	**Data Type**	**Data Access**	**Real Case**	**Res. Asses**	**C.C**
[52]	C&C	Floods	E	XGBoost; RF; LightGBM; CatBoost	MR; GG; SE; DG; PI	Public	Yes	Yes	No
[77]	C&C	Hurricane	E, P	XGBoost	PI; MR; SD; GG	Public	Yes	No	No
[72]	C&C	Typhoon	E, P	UProtoMLP; XGBoost; GBDT; RF; LightGBM; AdaBoost; MLP; LSTM; GRU; MetaNet+; TADAM; DN4++	MR; SE; DL; GG	Public	Yes	No	No
[46]	C&C	Heavy rainfall; Typhoons	E	RF; KNN; DT; XGBoost	MR; DL; PI	Public	Yes	No	No
[90]	C&C	Floods	E, P	CNN	GR; DL	Public	Yes	No	No

Ref	Environment Characteristics			Machine Learning	Associated Data			Supplementary Characteristics	
	Adopted Env.	Hazard Type	Assessed Loss	ML Model	Data Type	Data Access	Real Case	Res. Asses	C.C
[74]	C&C	Wind	E, P	Regression tree; Bagging; RF; GBoost; XGBoost	MR; GR; DL; DG; SE	Public	Yes	No	No
[91]	C&C	Flood	E, P	LSTM; CNN	GR; MR; DL	Public	Yes	No	No
[92]	C&C	Typhoon	E	KNN	GR; DL	Public	Yes	No	No
[62]	CI	Floods	E	K-Means; DBSCAN; OPTICS; Gaussian Mixture	MR; DL	Public	Yes	Yes	No

Note: In the Adopted Env. column, the C&C, CI, I&E, and PB represent city and communities, critical infrastructures, industrial and economic sectors, and physical buildings, respectively. In the data column, the Disaster Losses is represented by DL, Demographic by DG, Socioeconomic by SE, Geological by GL, Physical Infrastructure by PI, Geographic by GG, Meteorological by MR, Survey Data by SD, and Social Media by SM. Regarding the Assessed Type column, the Economic losses is represented by E, the Social by the S, and the Physical by P.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Grammarly in order to improve the readability and language of the work. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. OECD (2021) Managing Climate Risks, Facing up to Losses and Damages. Organisation for Economic Co-operation and Development, Paris

2. Du X, Li X, Zhang S, Zhao T, Hou Q, Jin X, Zhang J (2022) High-accuracy estimation method of typhoon storm surge disaster loss under small sample conditions by information diffusion model coupled with machine learning models. Int J Disaster Risk Reduct 82:103307. https://doi.org/10.1016/j.ijdrr.2022.103307

3. Jia C, Zhang C, Li Y-F, Li Q-L (2023) Joint pre- and post-disaster planning to enhance the resilience of critical infrastructures. Reliab Eng Syst Saf 231:109023. https://doi.org/10.1016/j.ress.2022.109023

4. Zhang X, Mao F, Gong Z, Hannah DM, Cai Y, Wu J (2023) A disaster-damage-based framework for assessing urban resilience to intense rainfall-induced flooding. Urban Clim 48:101402. https://doi.org/10.1016/j.uclim.2022.101402

5. European Commission (2023) Civil Protection: EU outlines Disaster Resilience Goals. In: Eur. Comm. - Eur. Comm. https://ec.europa.eu/commission/presscorner/detail/en/ip_23_599. Accessed 1 Feb 2024

6. United Nations (2023) The Sustainable Development Goals Report 2023: Special Edition. United Nations

7. Bruneau M, Chang SE, Eguchi RT, Lee GC, O’Rourke TD, Reinhorn AM, Shinozuka M, Tierney K, Wallace WA, von Winterfeldt D (2003) A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. Earthq Spectra 19:733–752. https://doi.org/10.1193/1.1623497

8. Wang X, Mazumder RK, Salarieh B, Salman AM, Shafieezadeh A, Li Y (2022) Machine Learning for Risk and Resilience Assessment in Structural Engineering: Progress and Future Trends. J Struct Eng 148:03122003. https://doi.org/10.1061/(ASCE)ST.1943-541X.0003392

9. Huang H, Li R, Wang W, Qin T, Zhou R, Fan W (2023) Concepts, models, and indicator systems for urban safety resilience: A literature review and an exploration in China. J Saf Sci Resil 4:30–42. https://doi.org/10.1016/j.jnlssr.2022.10.003

10. Aruväli T, De Marchi M, Rauch E (2023) Analysis of quantitative metrics for assessing resilience of human-centered CPPS workstations. Sci Rep 13:2914. https://doi.org/10.1038/s41598-023-29735-1

11. Witt E, Lill I (2018) Methodologies of contemporary disaster resilience research. Procedia Eng 212:970–977. https://doi.org/10.1016/j.proeng.2018.01.125

12. Paltrinieri N, Comfort L, Reniers G (2019) Learning about risk: Machine learning for risk assessment. Saf Sci 118:475–486. https://doi.org/10.1016/j.ssci.2019.06.001

13. Bendimerad F (2001) Loss estimation: a powerful tool for risk assessment and mitigation. Soil Dyn Earthq Eng 21:467–472. https://doi.org/10.1016/S0267-7261(01)00022-7

14. May Haggag, Yosri A, El-Dakhakhni W, Hassini E (2022) Interpretable data-driven model for Climate-Induced Disaster damage prediction: The first step in community resilience planning. Int J Disaster Risk Reduct 73:102884. https://doi.org/10.1016/j.ijdrr.2022.102884

15. Neumann JE, Emanuel K, Ravela S, Ludwig L, Kirshen P, Bosma K, Martinich J (2015) Joint effects of storm surge and sea-level rise on US Coasts: new economic estimates of impacts, adaptation, and benefits of mitigation policy. Clim Change 129:337–349. https://doi.org/10.1007/s10584-014-1304-z

16. Sieg T, Schinko T, Vogel K, Mechler R, Merz B, Kreibich H (2019) Integrated assessment of short-term direct and indirect economic flood impacts including uncertainty quantification. PLOS ONE 14:e0212932. https://doi.org/10.1371/journal.pone.0212932

17. Tian N, Lan H (2023) The indispensable role of resilience in rational landslide risk management for social sustainability. Geogr Sustain 4:70–83. https://doi.org/10.1016/j.geosus.2022.11.007

18. Maiti M, Kayal P (2024) Exploring innovative techniques for damage control during natural disasters. J Saf Sci Resil 5:147–155. https://doi.org/10.1016/j.jnlssr.2024.02.004

19. Bixler RP, Lieberknecht K, Atshan S, Zutz CP, Richter SM, Belaire JA (2020) Reframing urban governance for resilience implementation: The role of network closure and other insights from a network approach. Cities 103:102726. https://doi.org/10.1016/j.cities.2020.102726

20. Iturriza M, Labaka L, Hernantes J, Abdelgawad A (2020) Shifting to climate change aware cities to facilitate the city resilience implementation. Cities 101:102688. https://doi.org/10.1016/j.cities.2020.102688

21. Albahri AS, Khaleel YL, Habeeb MA, Ismael RD, Hameed QA, Deveci M, Homod RZ, Albahri OS, Alamoodi AH, Alzubaidi L (2024) A systematic review of trustworthy artificial intelligence applications in natural disasters. Comput Electr Eng 118:109409. https://doi.org/10.1016/j.compeleceng.2024.109409

22. Ghaffarian S, Taghikhah FR, Maier HR (2023) Explainable artificial intelligence in disaster risk management: Achievements and prospective futures. Int J Disaster Risk Reduct 98:104123. https://doi.org/10.1016/j.ijdrr.2023.104123

23. Hasik V, Chhabra JPS, Warn GP, Bilec MM (2018) Review of approaches for integrating loss estimation and life cycle assessment to assess impacts of seismic building damage and repair. Eng Struct 175:123–137. https://doi.org/10.1016/j.engstruct.2018.08.011

24. Makhoul N, Argyroudis S (2018) Loss estimation software: Developments, limitations and future needs. In: 16th European Conference on Earthquake Engineering, Thessaloniki, Greece

25. Samarakkody A, Amaratunga D, Haigh R (2023) Technological Innovations for Enhancing Disaster Resilience in Smart Cities: A Comprehensive Urban Scholar's Analysis. Sustainability 15:12036. https://doi.org/10.3390/su151512036

26. Liang B, van der Wal CN, Xie K, Chen Y, Brazier FMT, Dulebenets MA, Liu Z (2023) Mapping the knowledge domain of soft computing applications for emergency evacuation studies: A scientometric analysis and critical review. Saf Sci 158:105955. https://doi.org/10.1016/j.ssci.2022.105955

27. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, Chou R, Glanville J, Grimshaw JM, Hróbjartsson A, Lalu MM, Li T, Loder EW, Mayo-Wilson E, McDonald S, McGuinness LA, Stewart LA, Thomas J, Tricco AC, Welch VA, Whiting P,

Moher D (2021) The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ 372:n71. https://doi.org/10.1136/bmj.n71

28. Mongeon P, Paul-Hus A (2016) The journal coverage of Web of Science and Scopus: a comparative analysis. Scientometrics 106:213–228. https://doi.org/10.1007/s11192-015-1765-5

29. Nickerson RC, Varshney U, Muntermann J (2013) A method for taxonomy development and its application in information systems. Eur J Inf Syst 22:336–359. https://doi.org/10.1057/ejis.2012.26

30. Diaz J, Joseph MB (2019) Predicting property damage from tornadoes with zero-inflated neural networks. Weather Clim Extrem 25:100216. https://doi.org/10.1016/j.wace.2019.100216

31. Kim J-M, Yum S-G, Park H, Bae J (2021) A deep learning algorithm-driven approach to predicting repair costs associated with natural disaster indicators: The case of accommodation facilities. J Build Eng 42:103098. https://doi.org/10.1016/j.jobe.2021.103098

32. Kim JM, Bae J, Son S, Son K, Yum SG (2021) Development of Model to Predict Natural Disaster-Induced Financial Losses for Construction Projects Using Deep Learning Techniques. Sustain 2021 Vol 13 Page 5304 13:5304. https://doi.org/10.3390/SU13095304

33. Ma G, Surakitbanharn C (2019) Predicting Hurricane Damage Using Social Media Posts Coupled with Physical and Socio-Economic Variables

34. Mann ML, Warner JM, Malik AS (2019) Predicting high-magnitude, low-frequency crop losses using machine learning: an application to cereal crops in Ethiopia. Clim Change 154:211–227. https://doi.org/10.1007/s10584-019-02432-7

35. Park M, Jung D, Lee S, Park S (2020) Heatwave Damage Prediction Using Random Forest Model in Korea. Appl Sci 2020 Vol 10 Page 8237 10:8237. https://doi.org/10.3390/APP10228237

36. Snehil, Goel R (2020) Flood Damage Analysis Using Machine Learning Techniques. Procedia Comput Sci 173:78–85. https://doi.org/10.1016/J.PROCS.2020.06.011

37. Awuku B, Huang Y, Yodo N (2023) Predicting Natural Gas Pipeline Failures Caused by Natural Forces: An Artificial Intelligence Classification Approach. Appl Sci 13:4322. https://doi.org/10.3390/app13074322

38. Chen W, Zhang L (2022) An automated machine learning approach for earthquake casualty rate and economic loss prediction. Reliab Eng Syst Saf 225:108645. https://doi.org/10.1016/j.ress.2022.108645

39. Guo H, Yin K, Huang C (2022) Modeling of Direct Economic Losses of Storm Surge Disasters Based on a Novel Hybrid Forecasting System. Front Mar Sci 8:

40. Hou J, Xu S (2023) Near-Real-Time Seismic Human Fatality Information Retrieval from Social Media with Few-Shot Large-Language Models. In: Proceedings of the 20th ACM Conference on Embedded Networked Sensor Systems. Association for Computing Machinery, New York, NY, USA, pp 1141–1147

41. Kim J-M, Bae J, Adhikari MD, Yum S-G (2024) Building loss assessment using deep learning algorithm from typhoon Rusa. Heliyon 10:e23324. https://doi.org/10.1016/j.heliyon.2023.e23324

42. Mingyue J, Yuxuan C, Siyu Z (2024) The Application of Artificial Intelligence in Exploring New Economic Growth in the Insurance Industry in the Context of Increased Natural Disasters. In: 2024 IEEE 15th International Conference on Software Engineering and Service Science (ICSESS). pp 104–110

43. Chen A, You S, Li J, Liu H (2021) The Economic Loss Prediction of Flooding Based on Machine Learning and the Input-Output Model. Atmosphere 12:1448. https://doi.org/10.3390/atmos12111448

44. Li S, Wang Y, Huang H, Huang L, Chen Y (2023) Study on typhoon disaster assessment by mining data from social media based on artificial neural network. Nat Hazards 116:2069–2089. https://doi.org/10.1007/s11069-022-05754-5

45. Nordmeyer EF, Mußhoff O (2023) Understanding German farmers' intention to adopt drought insurance. J Environ Manage 345:118866. https://doi.org/10.1016/j.jenvman.2023.118866

46. Song Y, Song YH, Park M, Kim SY (2025) Development of Prediction Model for Damage Costs of Heavy Rainfall Disasters Using Machine Learning in the Republic of Korea. Climate 13:72. https://doi.org/10.3390/cli13040072

47. Abdel-Mooty MN, El-Dakhakhni W, Coulibaly P (2023) Community Resilience Classification Under Climate Change Challenges. In: Walbridge S, Nik-Bakht M, Ng KTW, Shome M, Alam MS, el Damatty A, Lovegrove G (eds) Proceedings of the Canadian Society of Civil Engineering Annual Conference 2021. Springer Nature, Singapore, pp 227–237

48. Su X, Shao W, Liu J, Jiang Y, Wang K (2021) Dynamic Assessment of the Impact of Flood Disaster on Economy and Population under Extreme Rainstorm Events. Remote Sens 13:3924. https://doi.org/10.3390/rs13193924

49. Abdel-Mooty MN, El-Dakhakhni W, Coulibaly P (2022) Data-Driven Community Flood Resilience Prediction. Water 14:2120. https://doi.org/10.3390/w14132120

50. Wu M, Wu Z, Ge W, Wang H, Shen Y, Jiang M (2021) Identification of sensitivity indicators of urban rainstorm flood disasters: A case study in China. J Hydrol 599:126393. https://doi.org/10.1016/j.jhydrol.2021.126393

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

52. Lee E, You Y-W, Jung Y-H, Kam J (2025) Explainable AI-based risk assessment for pluvial floods over South Korea. J Environ Manage 385:125640. https://doi.org/10.1016/j.jenvman.2025.125640

53. Abdel-Mooty MN, Yosri A, El-Dakhakhni W, Coulibaly P (2021) Community Flood Resilience Categorization Framework. Int J Disaster Risk Reduct 61:102349. https://doi.org/10.1016/j.ijdrr.2021.102349

54. Liu S, Liu Y, Chu Z, Yang K, Wang G, Zhang L, Zhang Y (2023) Evaluation of Tropical Cyclone Disaster Loss Using Machine Learning Algorithms with an eXplainable Artificial Intelligence Approach. Sustainability 15:12261. https://doi.org/10.3390/su151612261

55. Yang Q, Shen X, Yang F, Anagnostou EN, He K, Mo C, Seyyedi H, Kettner AJ, Zhang Q (2022) Predicting Flood Property Insurance Claims over CONUS, Fusing Big Earth Observation Data. Bull Am Meteorol Soc 103:E791–E809. https://doi.org/10.1175/BAMS-D-21-0082.1

56. Hu Q, Xiong F, Zhang B, Su P, Lu Y (2022) Developing a novel hybrid model for seismic loss prediction of regional-scale buildings. Bull Earthq Eng 20:5849–5875. https://doi.org/10.1007/S10518-022-01415-X/TABLES/10

57. Kim J-M, Bae J, Adhikari MD, Yum S-G (2023) A study of deep learning algorithm usage in predicting building loss ratio due to typhoons: the case of southern part of the Korean Peninsula. Front Earth Sci 11:

58. Kim J-M, Bae J, Park H, Yum S-G (2022) Predicting financial losses due to apartment construction accidents utilizing deep learning techniques. Sci Rep 12:5365. https://doi.org/10.1038/s41598-022-09453-w

59. Bae J, Yum S-G, Kim J-M (2021) Harnessing Machine Learning for Classifying Economic Damage Trends in Transportation Infrastructure Projects. Sustainability 13:6376. https://doi.org/10.3390/su13116376

60. Dey AK, Lyubchich V, Gel YR (2023) Multivariate Modeling of Precipitation-Induced Home Insurance Risks Using Data Depth. J Agric Biol Environ Stat. https://doi.org/10.1007/s13253-023-00554-1

61. Hu Q, Xiong F, Zhang B, Su P, Lu Y (2022) Developing a novel hybrid model for seismic loss prediction of regional-scale buildings. Bull Earthq Eng 20:5849–5875. https://doi.org/10.1007/s10518-022-01415-x

62. Puime Pedra M, Hernantes J, Labaka L (2025) Data-driven disaster resilience assessment: a case study in the Spanish transportation system. Inf Technol Dev 0:1–26. https://doi.org/10.1080/02681102.2025.2502418

63. Ali R, Khosa I, Armghan A, Arshad J, Rabbani S, Alsharabi N, Hamam H (2022) Financial Hazard Prediction Due to Power Outages Associated with Severe Weather-Related Natural Disaster Categories. Energies 15:9292. https://doi.org/10.3390/en15249292

64. Collins EL, Sanchez GM, Terando A, Stillwell CC, Mitasova H, Sebastian A, Meentemeyer RK (2022) Predicting flood damage probability across the conterminous United States. Environ Res Lett 17:034006. https://doi.org/10.1088/1748-9326/AC4F0F

65. Kim J-M, Yum S-G, Park H, Bae J (2022) Strategic framework for natural disaster risk mitigation using deep learning and cost-benefit analysis. Nat Hazards Earth Syst Sci 22:2131–2144. https://doi.org/10.5194/nhess-22-2131-2022

66. Oquendo-Torres FA, Segovia-Vargas MJ (2024) Sustainability risk in insurance companies: A machine learning analysis. Glob Policy 15:47–64. https://doi.org/10.1111/1758-5899.13440

67. Wang Y, Chou J, Zhao W, Li Y, Jin H (2025) Exploring the economic loss characteristics of meteorological disasters in China based on CGE model improved loss function. J Clean Prod 524:146385. https://doi.org/10.1016/j.jclepro.2025.146385

68. Shiba K, Daoud A, Hikichi H, Yazawa A, Aida J, Kondo K, Kawachi I (2023) Uncovering Heterogeneous Associations Between Disaster-Related Trauma and Subsequent Functional Limitations: A Machine-Learning Approach. Am J Epidemiol 192:217–229. https://doi.org/10.1093/AJE/KWAC187

69. J T T (2025) An enhanced discovery of multiple natural disasters using machine learning model. Earth Sci Inform 18:324. https://doi.org/10.1007/s12145-025-01793-1

70. Memarian Sorkhabi O, Shadmanfar B, Al-Amidi MM (2023) Deep learning of sea-level variability and flood for coastal city resilience. City Environ Interact 17:100098. https://doi.org/10.1016/j.cacint.2022.100098

71. Wang N, Xu Y, Wang S (2022) Interpretable boosting tree ensemble method for multisource building fire loss prediction. Reliab Eng Syst Saf 225:108587. https://doi.org/10.1016/J.RESS.2022.108587

72. Zhou S, Zhao Z, Hu J, Liu F, Zheng K (2025) Impacts of Spatial Expansion of Urban and Rural Construction on Typhoon-Directed Economic Losses: Should Land Use Data Be Included in the Assessment? Land 14:924. https://doi.org/10.3390/land14050924

73. Heranval A, Lopez O, Thomas M (2023) Application of machine learning methods to predict drought cost in France. Eur Actuar J 13:731–753. https://doi.org/10.1007/s13385-022-00327-z

74. Haggag M, Rezk E, El-Dakhakhni W (2025) Machine learning prediction of climate-induced disaster property damages considering hazard- and community-related attributes. Nat Hazards 121:2895–2917. https://doi.org/10.1007/s11069-024-06871-z

75. Mobley W, Sebastian A, Blessing R, Highfield WE, Stearns L, Brody SD (2021) Quantification of continuous flood hazard using random forest classification and flood insurance claims at large spatial scales: a pilot study in southeast Texas. Nat Hazards Earth Syst Sci 21:807–822. https://doi.org/10.5194/nhess-21-807-2021

76. Terti G, Ruin I, Gourley JJ, Kirstetter P, Flamig Z, Blanchet J, Arthur A, Anquetin S (2019) Toward Probabilistic Prediction of Flash Flood Human Impacts. Risk Anal 39:140–161. https://doi.org/10.1111/risa.12921

77. Habibnia M, van de Lindt JW (2025) Enhanced risk mapping for hurricane surge losses using synthesized probabilistic and machine learning models. Int J Disaster Risk Reduct 123:105523. https://doi.org/10.1016/j.ijdrr.2025.105523

78. Huang MS, Wichmann B (2024) Machine learning estimates on the impacts of detection times on wildfire suppression costs. PLOS ONE 19:e0313200. https://doi.org/10.1371/journal.pone.0313200

79. Wilkinson MD, Dumontier M, Aalbersberg IjJ, Appleton G, Axton M, Baak A, Blomberg N, Boiten J-W, da Silva Santos LB, Bourne PE, Bouwman J, Brookes AJ, Clark T, Crosas M, Dillo I, Dumon O, Edmunds S, Evelo CT, Finkers R, Gonzalez-Beltran A, Gray AJG, Groth P, Goble C, Grethe JS, Heringa J, ’t Hoen PAC, Hooft R, Kuhn T, Kok R, Kok J, Lusher SJ, Martone ME, Mons A, Packer AL, Persson B, Rocca-Serra P, Roos M, van Schaik R, Sansone S-A, Schultes E, Sengstag T, Slater T, Strawn G, Swertz MA, Thompson M, van der Lei J, van Mulligen E, Velterop J, Waagmeester A, Wittenburg P, Wolstencroft K, Zhao J, Mons B (2016) The FAIR Guiding Principles for scientific data management and stewardship. Sci Data 3:160018. https://doi.org/10.1038/sdata.2016.18

80. CRED (2025) EM-DAT is FAIR. https://www.emdat.be/news/2025/01/emdat-is-fair/. Accessed 15 Sept 2025

81. Jayawardene V, Huggins TJ, Prasanna R, Fakhruddin B (2021) The role of data and information quality during disaster response decision-making. Prog Disaster Sci 12:100202. https://doi.org/10.1016/j.pdisas.2021.100202

82. Le DC, Zincir-Heywood N, Heywood MI (2020) Analyzing Data Granularity Levels for Insider Threat Detection Using Machine Learning. IEEE Trans Netw Serv Manag 17:30–44. https://doi.org/10.1109/TNSM.2020.2967721

83. Lagap U, Ghaffarian S (2024) Digital post-disaster risk management twinning: A review and improved conceptual framework. Int J Disaster Risk Reduct 110:104629. https://doi.org/10.1016/j.ijdrr.2024.104629

84. Bruneau M, Reinhorn A (2007) Exploring the Concept of Seismic Resilience for Acute Care Facilities. Earthq Spectra 23:41–62. https://doi.org/10.1193/1.2431396

85. Renscheler CS, Frazier AE, Arendt LA, Cimellaro GP, Reinhorn AM, Bruneau M (2010) Developing the “PEOPLES” resilience framework for defining and measuring disaster resilience a the community scale. Proc 9th US Natl 10th Can Conf Earthq Eng

86. Scherzer S, Lujala P, Rød JK (2019) A community resilience index for Norway: An adaptation of the Baseline Resilience Indicators for Communities (BRIC). Int J Disaster Risk Reduct 36:101107. https://doi.org/10.1016/j.ijdrr.2019.101107

87. Xu F, Ma J, Li N, Cheng JCP (2025) Large language model applications in disaster management: An interdisciplinary review. Int J Disaster Risk Reduct 127:105642. https://doi.org/10.1016/j.ijdrr.2025.105642

88. Šakić Trogrlić R, Reiter K, Ciurean RL, Gottardo S, Torresan S, Daloz AS, Ma L, Padrón Fumero N, Tatman S, Hochrainer-Stigler S, de Ruiter MC, Schlumberger J, Harris R, Garcia-Gonzalez S, García-Vaquero M, Arévalo TLF, Hernandez-Martin R, Mendoza-Jimenez J, Ferrario DM, Geurts D, Stuparu D, Tiggeloven T, Duncan MJ, Ward PJ (2024) Challenges in assessing and managing multi-hazard risks: A European stakeholders perspective. Environ Sci Policy 157:103774. https://doi.org/10.1016/j.envsci.2024.103774

89. Cesarini L, Figueiredo R, Monteleone B, Martina MLV (2021) The potential of machine learning for weather index insurance. Nat Hazards Earth Syst Sci 21:2379–2405. https://doi.org/10.5194/nhess-21-2379-2021

90. Clark AS, Collins T, Grineski S, Brewer S, Flores A (2025) Comparative assessment of residential property values at risk to flooding: The case of Utah, USA. Int J Disaster Risk Reduct 118:105247. https://doi.org/10.1016/j.ijdrr.2025.105247

91. Situ Z, Zhong Q, Zhang J, Teng S, Ge X, Zhou Q, Zhao Z (2025) Attention-based deep learning framework for urban flood damage and risk assessment with improved flood prediction and land use segmentation. Int J Disaster Risk Reduct 116:105165. https://doi.org/10.1016/j.ijdrr.2024.105165

92. Zhao B (2025) Adaptive strategies for predicting economic impacts of natural disasters using hybrid optimization methods. Int J Syst Assur Eng Manag. https://doi.org/10.1007/s13198-025-02915-0

CRediT authorship contribution statement

Matheus Pedra: Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Josune Hernantes:** Writing – review & editing, Supervision, Investigation, Conceptualization. **Leire Labaka:** Writing – review & editing, Supervision, Investigation, Conceptualization.

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly in order to improve its readability and language of the work. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of Interest Statement

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.