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Social media insights on public perception and sentiment during and after disasters: The European floods in 2021 as a case study

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Abstract

Detecting and collecting public opinion via social media can provide near real-time information to decision-makers, which plays a vital role in urban disaster management and sustainable development. However, there has been little work focusing on identifying the perception and the sentiment polarity expressed by users during and after disasters, particularly regional flood events. In this article, we comprehensively analyze tweets data related to the "European floods in 2021" over time, topic, and sentiment, forming a complete workflow from data processing, topic modeling, sentiment analysis, and topic and sentiment prediction. The aim is to address the following research questions: (1) What are the public perception and main concerns during and after floods? (2) How does the public sentiment change during and after floods? Results indicate that there is a significant correlation between a flood's trend and the heat of corresponding tweets. The three topics that receive the most public concern are: (1) climate change and global warming; (2) praying for the victims: and (3) disaster situations and information. Negative sentiments are predominant during the floods and will continue for some time. We tested five different classifiers, of which

TextCNN-attention turned out to deliver the best predictions in topic and sentiment prediction, and performed well for sparse flood tweets, it can be used to predict the topic and sentiment polarity of a single tweet in real-time during the flood events. Our findings can help disaster agencies to better understand the dynamics of social networks and develop stronger situational awareness towards a disaster, which can contribute to scientifically justified decision-making in urban risk management and also meet the challenges associated with the global sustainable development goal 11 (SDGs) on Sustainable Cities and Communities.

1 | INTRODUCTION

Over the past few decades, extreme natural hazards have become more common as a consequence of climate change, which has posed severe challenges to disaster prevention and mitigation (Bhatt et al., 2015; Li, Zhu, Pirasteh, et al., 2022; Li et al., 2020; Ryan et al., 2020). Among them, floods are one of the most widespread natural disasters on Earth (Hong et al., 2007; Li et al., 2013). In July 2021, a series of summer storms and severe weather resulted in significant rainfall and floods. The catastrophic floods severely affected several European countries (e.g., Germany, Belgium, etc.) and many cities, caused more than 700 injuries and almost 200 deaths. The economic losses amount to approximately 35.3 billion euros (https://us.milliman.com/-/media/milliman/pdfs/2022-articles/3-28-22_europe-extreme-weather-report.ashx). Therefore, it is significant to carry out research on flood-related issues for improving disaster resilience in cities and meeting the challenges associated with the SDGs on Sustainable Cities and Communities (Cao et al., 2022).

The European Commission (EC) has been working on improving the level of flood risk management. For example, the European Flood Alert System (EFAS) was launched by the EC in 2002 and was the first operational European system monitoring and forecasting floods across Europe, intending to provide early warning information up to 10 days in advance to its partner countries (Smith et al., 2016). Subsequently, the European Union Floods Directive (FD) required the establishment of flood maps for high-risk cities in all member states by 2013 (Meyer et al., 2012). There is no doubt that warning systems and risk maps have greatly increased flood resilience for cities and public risk awareness in the last decade (Cools et al., 2016; O'Sullivan et al., 2012).

Floods will always occur and the public is the main body affected by floods (Li, Zhu, Gong, et al., 2022). Therefore, "people-centered" approaches should also be taken into account in addition to conventional techniques of flood control (Wolff, 2021). For example, it is important to detect and understand the public perception, concern, and sentiment during the floods, which represent the direct feedback from affected bodies on flood trends and relief progress (Alfarrarjeh et al., 2017; Camacho et al., 2021; Han & Wang, 2019; Roy et al., 2020; Yuan et al., 2020). The integration of the above valuable information into disaster management could assist the formulation of flood mitigation strategies, enhance situational awareness, and support post-disaster management, which also reflects a "people-centered" approach to disaster reduction services (Han & Wang, 2019; Neppalli et al., 2017; UNISDR, 2015).

Traditional public opinion and sentiment surveys (e.g., questionnaires, workshops, etc.) rely either on the participants' responses to hypothetical scenarios or on the affected citizens' memory of their responses during floods (Mandel et al., 2012; Yuan et al., 2021; Yuan & Liu, 2018). This approach has two shortcomings: (1) due to lagging, it is difficult to reflect the real reaction of the public during the flood response; and (2) the survey sample is in general too small to analyze most public concerns and sentiment changes. In recent years, social media have become a new channel of public information in disasters besides mass media (e.g., radio, television, newspapers, etc.). The advanced development of social media (e.g., Twitter, Facebook, Sina-Weibo, etc.) platforms provides the public with a channel to express their emotions and concerns during the crisis (Crooks et al., 2013; Hauthal et al., 2019; Mandel et al., 2012; Osorio-Arjona et al., 2021; Tagliacozzo & Magni, 2018; Yuan et al., 2021; Zhang et al., 2019). Particularly in the era of big data, these emerging social media have great potential for mining public opinion, concern and feeling during floods, thus providing unique opportunities to support urban disaster management from bottom to top (Chen et al., 2023).

Since 2019, there have been many research works on corona virus disease 2019 (COVID-19) topics by using natural language processing (NLP) and social media data (Boon-Itt & Skunkan, 2020; Han et al., 2020; Huang et al., 2022; Hung et al., 2020; Lyu et al., 2021). Some researchers have studied crisis communication efficiency and public sentiment change during hurricanes based on social media (Neppalli et al., 2017; Roy et al., 2020; Yuan et al., 2021). To the authors' knowledge, there has been little work focusing on identifying the perception and the sentiment polarity expressed by users during flood events. Furthermore, there is no work addressing the comprehensive utilization of unsupervised learning (e.g., Latent Dirichlet Allocation (LDA)) and supervised learning (e.g., TextCNN) in the case of urban flood applications. The combination of unsupervised and supervised learning has been however successfully applied in fraud detection (Carcillo et al., 2021), credit risk assessment (Wang et al., 2019), customer response sentiment prediction (Borg & Boldt, 2020), etc.

Here, the authors would like to explain the motivation of combining unsupervised and supervised learning for the detection of public perception and sentiment in flood events. (1) Unsupervised learning can automatically classify large unlabeled tweets into distinguished clusters without prior knowledge, and it may exhibit higher accuracy than human annotators, especially for short and less informative tweets (Vohra & Garg, 2022). Due to the lack of rule-based structural grouping, it does not perform well in the topic and sentiment polarity classification of a single tweet (Behl et al., 2021). (2) Supervised learning has shown great performance in text classification, but it requires large amounts of labeled data for model training (Chiny et al., 2021; Maokuan et al., 2004). Labeling is an expensive and time-consuming process, it is not feasible to manually label the data during floods. Therefore, the combination of the two methods can compensate for the inefficiency of unsupervised learning in text classification, and reduce the tediousness of supervised learning that requires manual labeling of training samples. Going beyond capturing the general trends in public perception and sentiment change during the floods, it is also meaningful to predict the topic and sentiment polarity of a single post in real-time during the events.

In this context, using the European floods in 2021 as a case study, this research seeks to explore the following two research questions (RQ) with social media data:

- RQ1: What are the public perception and main concerns during and after floods?
- RQ2: How does the public sentiment change during and after floods?

The main approach to answering the abovementioned research questions is shown in Figure 1. We start with the temporal analysis of public posts on social media during and after disasters, the LDA model is used to mine the topics that receive public concern (Blei, 2012; Blei et al., 2003). Then, using the Valence Aware Dictionary and sEntiment Reasoner (VADER) introduced by Hutto and Gilbert (2014) to analyze the public sentiment change during floods; Lastly, the topic extraction results and sentiment results are utilized as training samples for supervised learning as further topic and sentiment prediction. The supervised classifier provides decision-makers with real-time information, and a pre-trained model from the collected tweets in our experiments allows for predicting classes of new tweets never seen before.

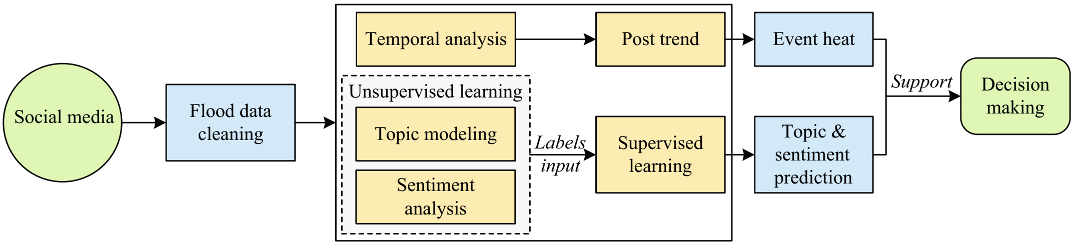

FIGURE 1 Overview of the main idea for public perception and sentiment analysis during and after floods. The data source is from public posts on social media, the analysis methods include temporal analysis, topic modeling, and sentiment analysis. The results of topic modeling and sentiment analysis are used as the label input for supervised learning to predict the public perception and sentiment polarity of each post.

The remainder of this article is organized as follows: Section 2 discusses the background and related work. In Section 3 the methodology is proposed, and the detailed study workflow and the corresponding core methods are introduced. In Section 4 the results are shown. Finally, Sections 5 and 6 present the discussion and conclusions, respectively.

2 | BACKGROUND AND RELATED WORK

2.1 | The European floods in 2021

From July 12th to 15th of 2021, a storm complex stalled over the European region, leading to heavy rain and catastrophic floods in western European countries, including Austria, Belgium, Croatia, Germany, Italy, Luxembourg, the Netherlands, and Switzerland. At least 700 injuries and 200 people died in the floods, where Germany and Belgium had been suffering the worst damage. In particular, more than 130 lives were lost in the Ahr valley to the south of Bonn, Germany. Across the whole of Europe, total economic losses from the flood are estimated at approximately 35.3 billion euros as of February 2022. It is worth noting that intensive floods occurred in China and the U.S. at almost the same time. This is a hint that the frequency and intensity of such events may increase in a rapidly warming climate and global fashion. It is also clear a signal that we should strengthen disaster management in cities.

2.2 | The role of social media in disaster management

The Sendai Framework for Disaster Risk Reduction (SFDRR) issued by United Nations Office for Disaster Risk Reduction (UNISDR) in 2015 specifically mentions the usage of social media and other communication channels to strengthen public education and awareness (Mavrodieva & Shaw, 2021; UNISDR, 2015). Since the terrorist attacks of 9/11 in 2001, social media has been established in many larger emergencies and crises (Kaufhold, 2021; Mavrodieva & Shaw, 2021). In the past 20 years, social media has not only become a part of daily life but also plays a critical role in disaster management, especially urban risk management. (Karimiziarani et al., 2022; Kavota et al., 2020; Mavrodieva & Shaw, 2021; Raza et al., 2020; Shiau et al., 2018). However, using social media as information sources for disaster management is highly problematic for reasons including rumors, misinformation, duplicated information, and inaccurate location (Li, Zhu, Pirasteh, et al., 2022; Martí et al., 2019; Neppalli et al., 2017). Still, researchers are optimistic about the value of using social media data in disaster management and crisis communication (Hughes & Palen, 2012; Neppalli et al., 2017).

In general, social media plays the following roles in disaster management: (1) Effective dissemination of disaster awareness information. The information on social media is updated almost in real-time, and the public can post their attitude, thought, judgment, or a specific view towards a disaster event (Dabner, 2012; Resnyansky, 2014; Zhang et al., 2019). (2) Establishing a two-way communication channel between disaster agencies and the general public. The aim is to establish a missing link between the public posting their opinions via social media and the agencies as well as decision-makers (Alamsyah et al., 2018; Neppalli et al., 2017; Reuter & Kaufhold, 2018; Tavra et al., 2021). (3) Providing support for post-disaster management. Previous studies have shown that people were likely to communicate situational updates and damages during disasters via social media. In this context, damage assessment and recovery can be carried out by analyzing the potential relationship between social media posts, disaster-related ratios, sentiment change of the public, and the social media activity of visitors (Yan et al., 2017; Yuan & Liu, 2020; Zou et al., 2018).

Among the many social media platforms, Facebook has over 2.6 billion monthly active users (MAUs) and Twitter had 330 million MAUs as of March 31, 2020 (Phengsuwan et al., 2021). Although Facebook has far more users than Twitter, Twitter is particularly popular with researchers and is the most widely-studied social media platform according to Zhang et al. (2019), which presents a greater potential in providing information in the management of emergencies due to the ease of use and its instant nature (Martnez-Rojas et al., 2018; Simon et al., 2015). Related studies using Twitter as a data source focus on earthquakes (Basu et al., 2019), hurricanes (Neppalli et al., 2017; Pourebrahim et al., 2019; Roy et al., 2021; Yuan et al., 2020, 2021), and typhoons (Zhang & Cheng, 2021). In this context, Twitter is chosen as the data source for this article.

2.3 | Topic modeling and sentiment analysis

Social media provides rich information sources about disaster situations. The extraction and analysis of social media information based on NLP are new means of assessing disaster phenomena and public opinion (Atefeh & Khreich, 2015; Fan et al., 2021; Mukherjee et al., 2022). Compared to traditional means (e.g., surveys, field interviews, etc.), NLP-based social media analytics can provide near real-time transitions of disaster situations, which can potentially improve the decision-making process for efficient disaster management (Fan et al., 2021). From the perspective of the research questions in this article, the authors would like to discuss two important applications in NLP: topic modeling and sentiment analysis (Lock & Pettit, 2020).

Topic modeling refers to techniques that infer or discover the hidden semantic structure in documents, which is often used as a text-mining tool to classify documents based on topic inference results (Alamsyah et al., 2018; Blei, 2012; Dahal et al., 2019; de Oliveira Capela & Ramirez-Marquez, 2019; Nolasco & Oliveira, 2019). The results of topic modeling are usually document-topics and topic-top words. Basically, there are many clustering algorithms (e.g., *k*-means clustering, principal component analysis, etc.) that can be used for topic modeling, but LDA is a popular topic modeling method that allows a word to simultaneously belong to several clusters with varying degrees rather than inducing only distinct clusters (Imran et al., 2015; Kowsari et al., 2019; Wang & Ye, 2018). LDA is currently considered as the state-of-the-art method for topic modeling (Nugroho et al., 2020). Especially since 2019, many researchers have mined and analyzed public opinion, vaccination intentions, and rumors related to COVID-19 based on LDA (AlAgha, 2021; Boon-Itt & Skunkan, 2020; Han et al., 2020; Lyu et al., 2021). However, compared to the global nature of epidemics, the impact of floods is regional and there is less social data available accordingly, which is why there are relatively few studies on the topic modeling of floods.

While topic modeling focuses on what the public is concerned about, sentiment analysis looks at changes in the public's mood during a big event (Hauthal et al., 2020; Yang et al., 2022). For disaster management, sentiment analysis is the process of identifying the public's feelings, concerns, and panic expressed on social media (Dahal et al., 2019; Neppalli et al., 2017; Yuan et al., 2021; Zhang et al., 2019). Labeling the posts with positive, neutral, and negative may help decision-makers to develop stronger situational awareness of the disaster (Zhang et al., 2019). Technically speaking, the methods used for sentiment analysis can be classified into two categories: lexicon- and classification-based analysis (Agarwal et al., 2011; Hauthal et al., 2020; Zou et al., 2018). Lexicon-based analysis assigns scores to the words based on a lexicon and returns a composite score representing the synthesis sentiment status of the text (Zou et al., 2018). Specifically, the open-source VADER rule-based model has been found one of the most suitable algorithms for sentiment analysis when compared to other available sentiment analysis tools, such as NRC Emotion Lexicon, and Wordnet (Hutto & Gilbert, 2014; Lock & Pettit, 2020; Zou et al., 2018). The classification-based analysis, however, uses supervised learning, such as support vector machine (SVM), logistic regression (LR), random forest (RF), to build classifiers from manually labeled samples and classify all datasets (Zhang et al., 2019; Zou et al., 2018). Supervised learning requires the labeling of massive samples which is expensive and time-consuming and hence does not present the best approach during disasters (Behl et al., 2021). Therefore, the combination of lexicon and supervised learning is useful for sentiment analysis during floods profiting from the strengths of both paradigms.

3 | METHODOLOGY

3.1 | Study workflow

This section introduces the detailed study workflow of this article, as shown in Figure 2. The first step is to collect and clean the tweets related to the European floods in 2021 from Twitter and further form a flood tweets dataset. The three core parts of this study workflow are temporal analysis, topic modeling, and sentiment analysis. Temporal analysis analyzes the trend of tweets as the flood changes. As mentioned, topic modeling is based on the LDA model to classify tweets, while supervised learning algorithms, such as SVM, LR, RF, TextCNN, and TextCNN-attention, are used to predict the topics of tweets to capture public perception. Sentiment analysis calculates the sentiment polarity of tweets and incorporates supervised learning to get the public sentiment changes during floods.

3.2 | Flood tweets collection and cleaning

Taking "Germany flood, Belgium flood, Netherlands flood, etc." as keywords, this research collects 34,731 English tweets about floods posted by verified users, this allows for omitting fake or robots accounts. The pre-filtered

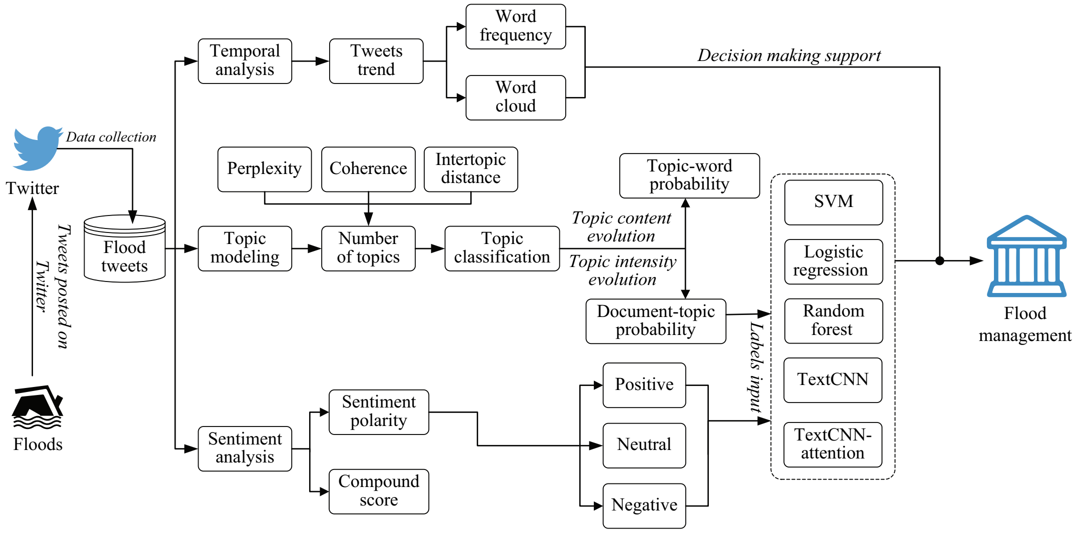

FIGURE 2 The study workflow includes three core parts: temporal analysis, topic modeling, and sentiment analysis. The workflow forms a basis for a subsequent flood management based on flood tweets.

tweets stem from July 1 to July 31, 2021. Flood tweets include the following information: user_id, username, date, tweet text, among others.

The raw dataset contains interfering information, such as hyperlinks, hashtags, punctuation marks, and @users. These types of data are not required for machine learning and thus cleaning is needed, which deals with the data processing and transformation of the raw dataset to make the input data easier to decode and interpret. Initially, all the interfering information and any tweet that has less than three characters are eliminated using regular expressions. After that, to realize language simplification and efficient vectorization, stop words such as "a," "an," "do," and "in" are also removed using natural language toolkit (NLTK) (https://www.nltk.org/). In the end, all cleaned tweets are converted to lower case.

3.3 | Temporal analysis for flood tweets

Examining the volume of social media posts at a particular time is an important first step in exploring the data, and the data itself can provide some interesting results (Dahal et al., 2019). In particular, Achrekar et al. (2011), Nagel et al. (2013), and Wang et al. (2015) suggested that changes in the number of social media streams can be used to identify and even predict the evolution of specific events. Therefore, the overall temporal trend of the tweets related to the European floods in 2021 will be analyzed:

$$y = \{x_t \mid t \in T\} \tag{1}$$

where T represents a date set, t is a specific date, x_t indicates the number of tweets related to the floods that day, and y denotes the set of all tweets in the whole month.

3.4 | Topic modeling for public perception

3.4.1 | Topic modeling of flood tweets based on LDA model

Blei et al. (2003) proposed the LDA method. The latter represents a generative probabilistic model for document collections, which can be used to infer topics from unseen documents. LDA has become very popular, and it is currently considered as the state-of-the-art method for topic derivation (Nugroho et al., 2020). Figure 3 shows the framework of topic modeling of flood tweets based on LDA model.

The generative process can be described as follows:

- *Step 1: Parameter initialization*. Prepare the cleaned flood tweets D and initialization parameters M, K, N, α, and β. $D = \{d_1, \dots, d_m, \dots, d_M\}$ indicates a document collection, M is the number of documents. K is the number of topics, N is the number of words. α is the Dirichlet prior for the distribution of topics, and β is the Dirichlet prior for the distribution of words.
- *Step 2: Generation of word distribution for topics*. For the topic $z_k \in Z$. $Z = \{z_1, \dots, z_k, \dots, z_K\}$ indicates topic collection, z_k is the kth topic. A multinomial distribution parameter $\varphi_k \sim \mathrm{Dir}(\beta)$ is generated as the word distribution for the topic z_k, which is denoted as $p(w \mid z_k)$, $w \in W$. $W = \{w_1, \dots, w_n, \dots, w_N\}$ indicates word collection, w indicates a specific word.
- *Step 3: Generation of topic distribution for documents*. For the document $d_m \in D$. d_m is the mth document, D indicates document collection, as mentioned in Step 1. A multinomial distribution parameter $\theta_m \sim \mathrm{Dir}(\alpha)$ is generated as the topic distribution for the document d_m, which is denoted as $p(z|_m)$, $z \in Z$. Z indicates topic collection, z indicates a specific topic, as mentioned in Step 2.

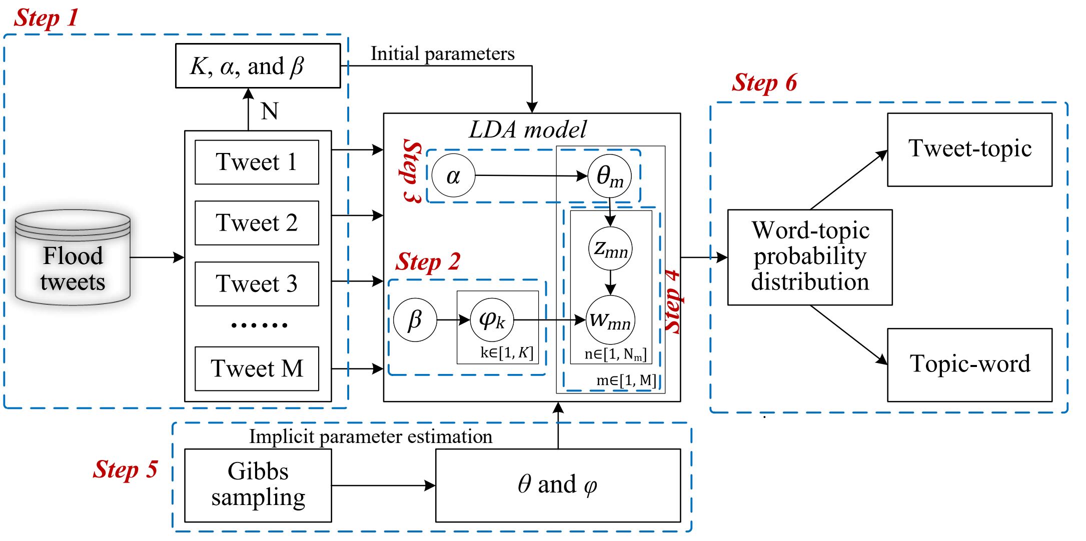

FIGURE 3 Topic modeling of flood tweets based on the LDA model. Each step of the process is consistent with the introduction below.

- *Step 4: Generation of word sequence for a specific document*. The generation process of the word w_{mn} (the nth word in the mth document) in the document d_m includes two steps. First, randomly generate a topic z_{mn} based on the multinomial distribution θ_m, which is denoted as the topic $z_{mn} \sim \mathrm{Multinomial}(\theta_m)$. Second, randomly generate a word w_{mn} based on $\mathrm{Multinomial}(\varphi_{z_{mn}})$, which is denoted as $w_{mn} \sim \mathrm{Multinomial}(\varphi_{z_{mn}})$.

Mathematically, the joint probability distribution of the LDA is formulated as follows:

$$p(w_m, z_m, \theta_m, \varphi | \alpha, \beta) = \prod_{k=1}^{K} p(\varphi_k | \beta) p(\theta_m | \alpha) \prod_{n=1}^{N_m} p(z_{mn} | \theta_m) p(w_{mn} | \varphi_{z_{mn}}) \quad (2)$$

where, w_m indicates the word sequence in document d_m, z_m indicates the topic sequence for the document, θ_m indicates the parameter of topic distribution for the document, φ denotes the parameter of word distribution for all topics, α and β are hyperparameters.

- *Step 5: Random sampling*. Gibbs sampling is used to estimate implicit parameters θ_m and φ_k, and to calculate the conditional probabilities of the word-topic distribution;
- *Step 6: Result output*. Count the proportion of each topic in documents and the proportion of all words under the topic, so that we can output the document-topic probability and topic-word probability.

3.4.2 | Determination of the optimal number of topics

LDA is an unsupervised topic model, in which the number of topics is an important input parameter. In this article, we combine the perplexity, coherence, and intertopic distance to determine the optimal number of topics. The three indicators are described as follows:

1. Perplexity: evaluates the model by comparing the theoretical word distributions represented by the topics with the actual distribution of words.
2. Coherence: measures the degree of semantic similarity between high-scoring words in the topic to determine the score of a single topic.

3. Intertopic distance: measures the similarity between different topics.

A low perplexity score indicates that one is close to an optimal number of topics. In general, the perplexity score will gradually decrease as the number of topics increases, but the more topics, the more expensive the LDA is to compute and the more likely it leads to overfitting. Conversely, a higher coherence score indicates an optimal number of topics. A larger intertopic distance, however, indicates lower similarity between topics. Theoretically, the inflection point of two scores and the large intertopic distance corresponds to the best optimal number of topics.

3.4.3 | Relevance-based ranking of words in a specific topic

The top words for a given topic output from LDA might not always be the best (Ramage et al., 2009), so this article uses the relevance proposed by Sievert et al. (2014) to rank the top words within topics. A weight parameter $(0 \leq \lambda \leq 1)$ is used to define the relevance of the word w to topic k:

$$r(w, k \mid \lambda) = \lambda \log\left(\varphi_{kw}\right) + (1 - \lambda)\log\left(\frac{\varphi_{kw}}{p_w}\right) \tag{3}$$

φ_{kw} indicates the probability of word w for topic k, which is estimated using Gibbs sampling, as described in Section 3.4.1; p_w denotes the marginal probability of term w in the corpus. When λ is set to 1, the ranking of top words is in decreasing order of the topic-specific probability, and when λ is set to 0, the order is just the opposite.

3.5 | Sentiment analysis during the floods

In this section, we employ VADER to label each flood tweet with sentiment polarity in three possible values: positive, neutral, and negative. According to Hutto and Gilbert (2014), VADER adopts a "normalized, weighted composite score" named compound score to describe a single unidimensional measure of sentiment for a given sentence. The compound score is the sum of all lexicon ratings and then normalized to be between −1 (most extreme negative) and +1 (most extreme positive). Therefore, three sentiment polarities can be defined according to the compound score as follows:

$$C = \begin{cases} 1\ (\text{positive tweet}), & \text{if compound score} \geq 0.05 \\ 0\ (\text{neutral tweet}), & \text{if} -0.05 < \text{compound score} < 0.05 \\ -1\ (\text{negative tweet}), & \text{if compound score} \leq -0.05 \end{cases} \tag{4}$$

3.6 | Prediction of public perception and sentiment polarity

LDA-based unsupervised learning is limited due to the lack of rule-based structural grouping, while supervised learning requires massive labeled tweet samples. Hence, it is difficult to complete such a time-consuming task during the floods (Behl et al., 2021). In this article, our idea is to use the results of topic extraction and sentiment analysis as training samples for the supervised algorithms to predict the topic and sentiment polarity of a single tweet in real-time during the flood events. We use three well-known supervised learning algorithms SVM, LR, and RF, and also use TextCNN and TextCNN-attention, currently the most dominant deep learning algorithm for text classification, the main process is shown in Figure 4.

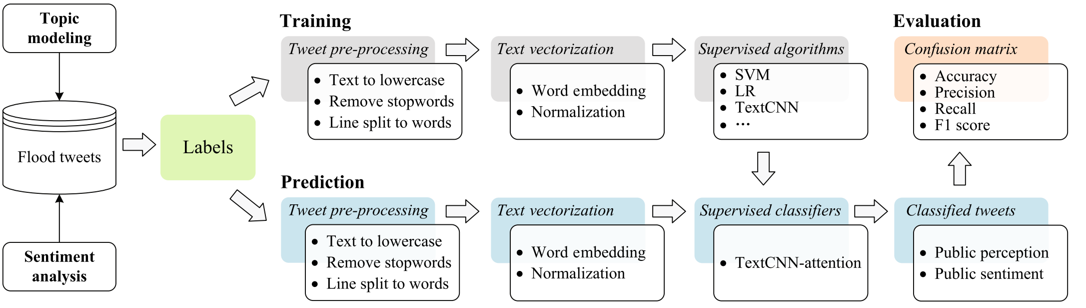

FIGURE 4 Flowchart of input data pre-processing, text vectorization, training, classification, and evaluation. The flood tweets and labels are provided by topic modeling and sentiment analysis. The TextCNN-attention model, used in the prediction step, proved to be the most outstanding classifier in the later topic and sentiment prediction compared to the other classifiers used in this article.

Then, accuracy, precision, recall, and F_1-score are used to evaluate the classification performance of flood tweets:

$$\begin{aligned} \text{Accuracy} &= \frac{(\text{TP}+\text{TN})}{(\text{TP}+\text{FP}+\text{FN}+\text{TN})} \\ \text{Precision} &= \frac{\text{TP}}{(\text{TP}+\text{FP})} \\ \text{Recall} &= \frac{\text{TP}}{(\text{TP}+\text{FN})} \\ F_1-\text{score} &= \frac{(\text{Precision}\times\text{Recall}\times 2)}{(\text{Precision}+\text{Recall})} \end{aligned} \tag{5}$$

Here, TP (True Positives) is the number of correctly classified positive flood tweets; TN (True Negatives) is the number of correctly classified negative flood tweets; FP (False Positives) is the number of incorrectly classified positive flood tweets; FN (False Negatives) is the number of incorrectly classified negative flood tweets.

4 | RESULTS

4.1 | Data source and description

As mentioned earlier, the data involved in the experiment were derived from public tweets related to the European floods from July 1 to July 31, 2021 from all over the word. A total of 34,731 tweets in English were collected, all of which were used to analyze tweet trends, as all tweets posted by the public were able to indicate the heat of flood topics. As duplicate tweets can affect the accuracy of topic modeling and sentiment analysis, we subsequently removed the duplicate tweets, and the remaining 20,962 tweets were used for word cloud analysis, topic modeling, sentiment analysis, and supervised learning-based prediction.

4.2 | Temporal analysis of Twitter trends during the floods

In this study, we found that there was a significant correlation between the trend of European floods and the change in tweets on the topic. Figure 5 illustrates the trend of the tweets related to the European floods, showing that the trend line began to increase on July 12, increased steeply by July 14, and peaked on July 16. According to Mohr et al. (2022) and Wikipedia, between July 12 and 15, 2021, heavy rain fell across the United Kingdom,

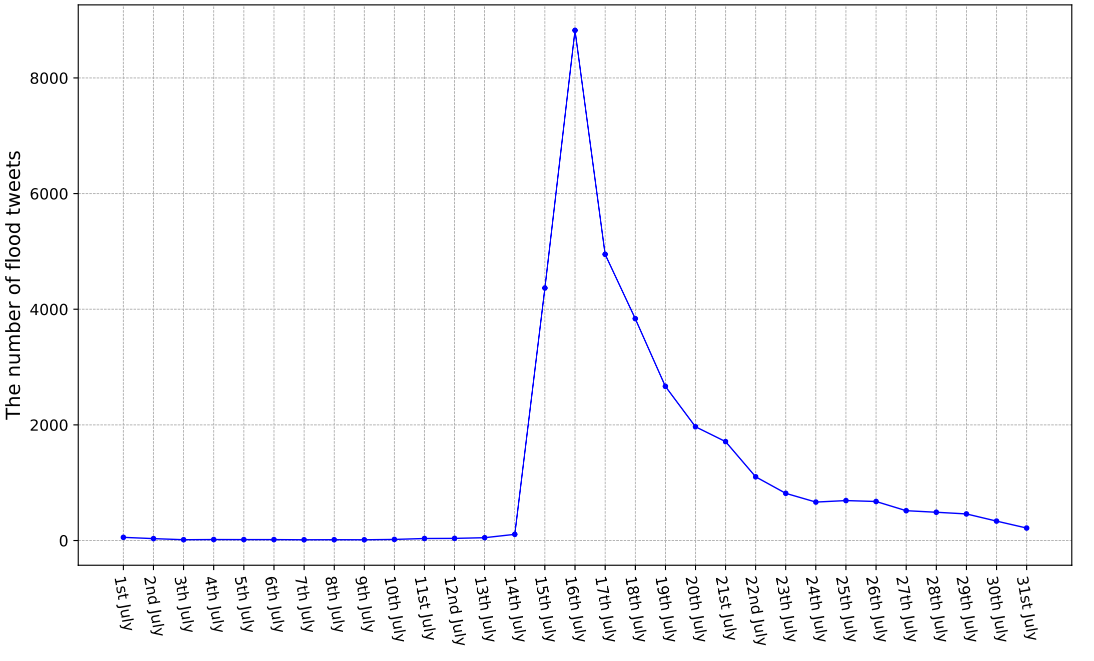

FIGURE 5 The trend of tweets related to the European floods from July 1, 2021, to July 31, 2021.

western Germany, the Netherlands, Belgium, and Luxembourg, severely affecting the aforementioned European regions on July 16 and July 17, which was consistent with the trend line of flood tweets. There was a clear downward trend in the number of flood-related tweets from July 17 to July 23, but a slight increase from July 24 to 26, due to renewed floods in Dinant, Friesland, and London on July 24, after which the topic of the European floods slowly leveled off.

4.3 | Frequency of keywords related to the floods

Predominant keywords in a corpus of tweet tokens can indicate the top topics discussed by users (Politis et al., 2021). In this context, word frequency analysis was used to infer the number of important words in the corpus, which can be also used to identify event hotspots and their changing trends. Visualizing these frequencies in the form of a word cloud in which the most frequent words are highlighted can provide a clearer understanding of dataset structure (Behl et al., 2021).

Before the word cloud analysis, topic modeling, and sentiment analysis, we removed duplicate tweets and merged words with the same meaning such as “flooding, flood” into “floods.” Figure 6 shows the keywords frequency and word cloud of flood tweets, respectively. It is obvious that the two topics of most concern to the public were climate change and human impact. The keywords (e.g., missing, dead, devastating) also reflect the dissemination of disaster awareness from the public. In addition, the word China was also a high-frequency word, because an intensive flood occurred in China at almost the same time, as mentioned in Section 2.3.

The word cloud is a simple way to make an initial assessment of topics in flood tweets, its results have to be further analyzed, since single keywords cannot easily provide a clear sense of a topic (Politis et al., 2021). The following section describes the topic modeling results of the public perception in detail.

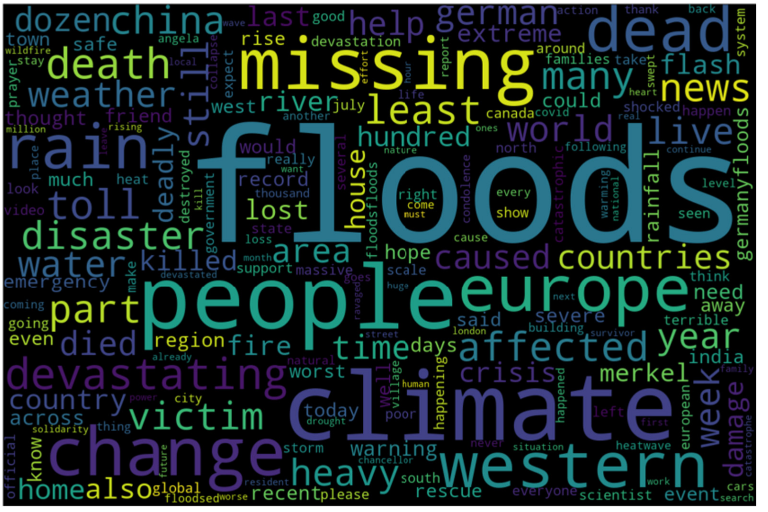

FIGURE 6 Word cloud of flood tweets.

4.4 | Topic analysis related to public perception

4.4.1 | The number of topics set

To determine the optimal number of topics, we plotted the trend of the perplexity and coherence with the number of topics, and inter-topic distance between topics, as shown in Figure 7. In Figure 7a, the perplexity value decreased as the number of topics K increased, and there was an inflection point when K was set at 7. Using the elbow method, we found that $K=7$ is close to the optimal number of topics. Figure 7b showed that the coherence was higher when K was set at 7, 9, or 11. However, Figures 7c,d showed that when $K=9$, the inter-topic distance was small and there was a certain degree of similarity between some topics, and the cluster effect was not as good as for $K=7$. Based on the above results and the explicability of each topic, the number of topics in our case was set at 7.

4.4.2 | Topic analysis

In this section, the topics and keywords identified using topic modeling are summarized. The objective of the topic modeling was to answer the first research question: What are the public perception and main concerns during and after the floods?

As shown in Table 1, we have induced seven topics. The percentage of topic 1 to topic 7 in flood tweets were 16.97, 14.41, 16.95, 10.78, 15.00, 15.23, and 10.66%, respectively. The top 15 keywords with the highest relevance (we set $\lambda=0.6$, which turns out to be the best parameter for interpreting the topics according to Sievert et al. (2014) to the topic were listed.

Topic_1 discussed the macro-level causes of the floods as climate change (Figure 8a). In the aftermath of the floods, scientists, activists, and reporters all highlighted the connection to global trends in extreme weather, especially more frequent heavy rainfall caused by climate change. Topic_2 showed the public sentiment, the keywords prayers, condolences, solidarity, and heart (Figure 8b) expressed people's deepest prayers for victims

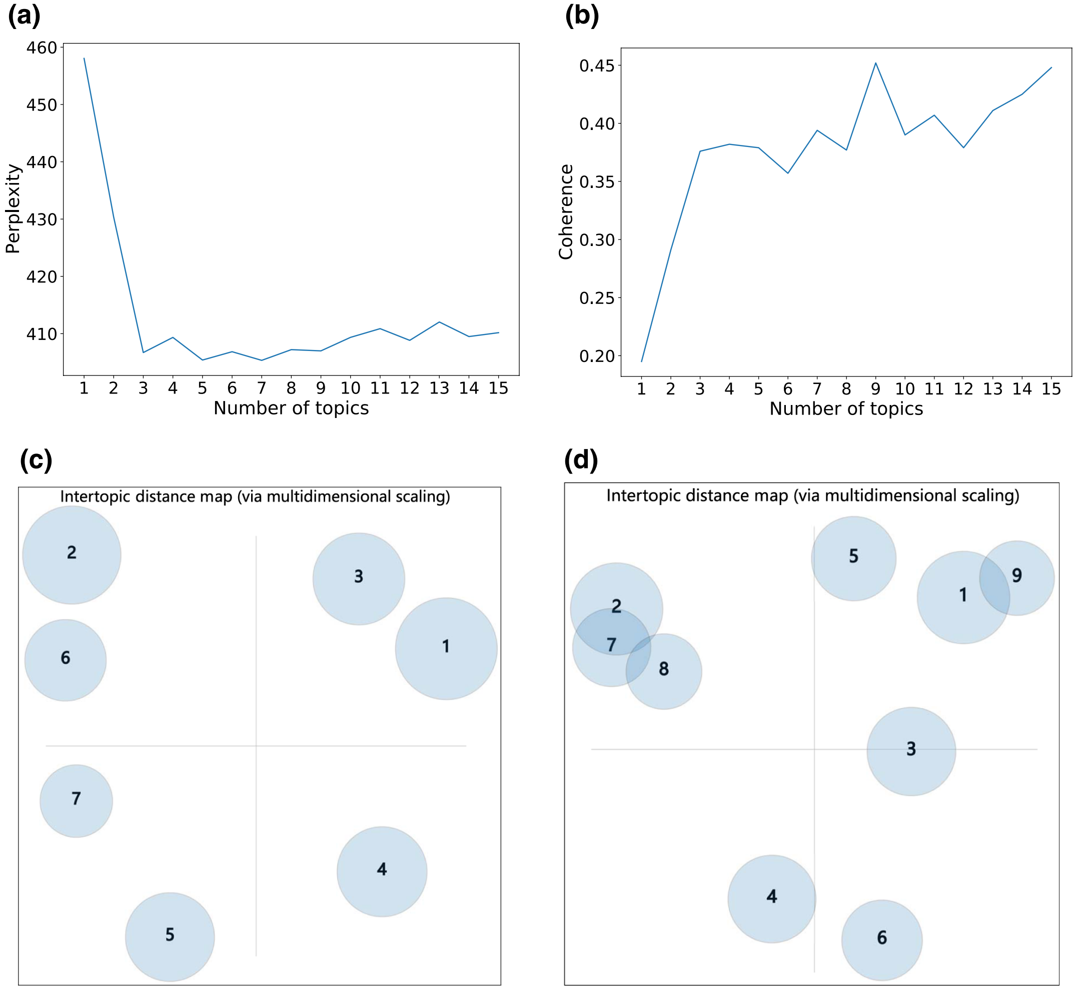

FIGURE 7 The perplexity, coherence, and inter-topic distance of topics. The visualization of inter-topic distance supported by LDAvis (Sievert et al., 2014). (a) The perplexity value. (b) The coherence value. (c) The inter-topic distance when $K = 7$. (d) The intertopic distance when $K = 9$.

affected by the floods. Topic_3 focused on disaster situation and information, some of the top keywords were missing, dead, people, dozens, houses, and cars (Figure 8c). Topic_4 highlighted the impact of floods on Germany, which was the country most seriously affected by the floods. The top keywords merkel, angela, rescue, search, and survivors (Figure 8d) expressed the German Chancellor Angela Merkel's concern about the floods. Topic_5 was weather warning and floods, the words with the highest probability were water, rain, weather, days, and china (Figure 8e), this topic showed that extreme weather and rain induced the floods warning and forecast. Topic_6 was somewhat similar to Topic_2 in that it showed that although the public felt sad about the floods, they still had hope, good, and positive expectations (Figure 8f). Topic_7 involved discussion related to the report on European floods, the words with the highest probability were death, toll, news, expect, europe, and rises (Figure 8g). This topic reflected the focus of new coverage on the casualties affected by floods, which was also a topic of primary concern to the public.

TABLE 1 The topics in tweets related to the European floods.

Topics	Description	Keywords	Percentage
Topic_1	Climate change and global warming	Climate, change, crisis, China, fires, extreme, global, shocked, heat, scientists, scale, Canada, weather, warming, action	16.97
Topic_2	Praying for the victims	Affected, victims, lost, thoughts, help, lives, prayers, support, families, condolences, solidarity, loss, devastating, goes, heart	14.41
Topic_3	Disaster situation and information	Missing, dead, people, dozens, heavy, died, killed, hundreds, houses, western, Europe, away, rain, collapse, cars	16.95
Topic_4	The floods in Germany	Merkel, western, deadly, German, Angela, chancellor, rescue, parts, search, worst, survivors, Rhine, Rhineland, aftermath, areas	10.78
Topic_5	Weather warning and floods	Water, rain, days, years, river, happened, weather, seen, year, happening, week, city, China, floodsed, past	15.00
Topic_6	Public expectation	Safe, hope, terrible, good, know, people, really, stay, countries, right, think, happen, heard, south, thought	15.23
Topic_7	Reports on the European floods	Death, toll, expect, rises, news, footage, warning, rose, countries, shows, poor, coming, number, Europe, amid	10.66

4.5 | Public sentiment analysis

4.5.1 | Sentiment status

We calculated the sentiment compound score of 20,962 flood tweets. A tweet was labeled as positive if the compound score was >0.05, as neutral if the compound score was between −0.05 and 0.05, and as negative if the compound score was <−0.05. The proportions of the sentiment polarity results are shown in Figure 9. Positive sentiment, neutral sentiment, and negative sentiment in flood tweets were 23.33% ($n\_1=4890$), 14.84% ($n\_2=3110$), and 61.83% ($n\_3=12{,}962$), respectively, indicating that negative sentiment remained dominant during the floods.

4.5.2 | Sentiment trend

Figure 10a shows the percentage of positive sentiment, neutral sentiment, and negative sentiment per day. Before July 11, 2021, public sentiment fluctuated but remained predominantly negative. Subsequently, the general sentiment towards floods was becoming more negative over time, the overall percentage of negative sentiment reached the maximum on July 16, 2021, which also corresponded to the report on the trend of floods. Negative sentiment remained high for the following half month, this suggests that flood disasters have immediate mental and physical harm, and also have long-term consequences, for instance, post-traumatic stress disorder (PTSD). So it is important to formulate effective post-disaster recovery policies and programs to help people return to normalcy (Jamali et al., 2019).

Figure 10b shows the compound score of sentiment per day. The green dotted line indicates the positive sentiment line (compound score ≥ 0.05), the orange dotted line indicates the negative sentiment line (compound score ≤ −0.05), and the area between the two lines indicates the neutral sentiment (−0.05 < compound score < 0.05). The public displayed negative sentiment during the floods, which was consistent with the results in Figure 10a. However, there appeared to be an abnormality in the compound score of sentiment for the day

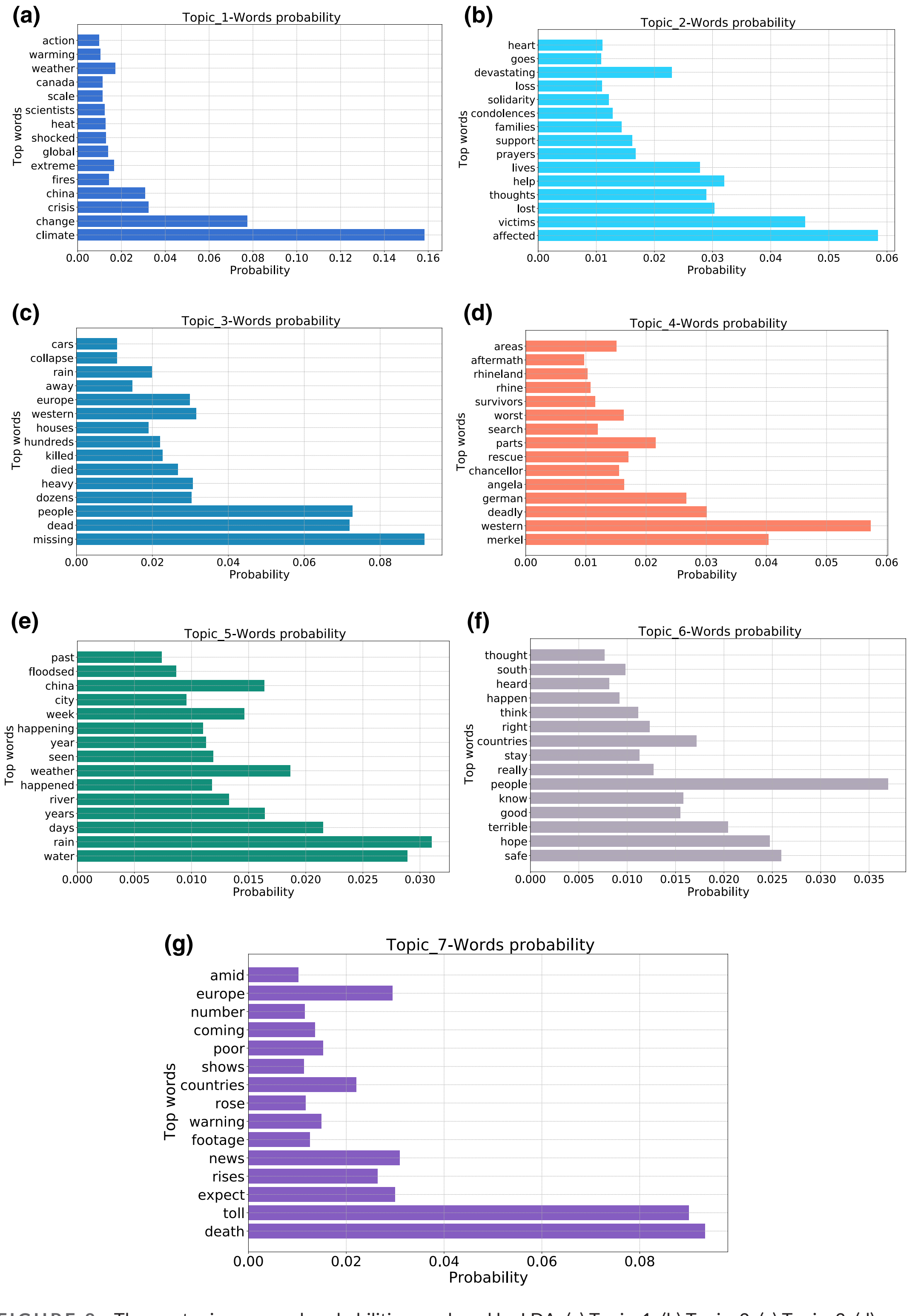

FIGURE 8 The per-topic-per-word probabilities produced by LDA. (a) Topic_1. (b) Topic_2. (c) Topic_3. (d) Topic_4. (e) Topic_5. (f) Topic_6. (g) Topic_7.

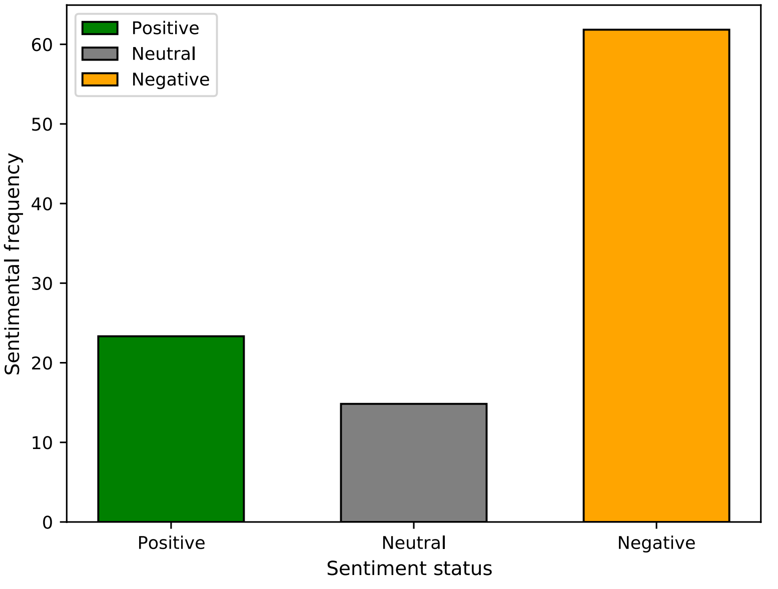

FIGURE 9 Sentiment frequency of the studied flood tweets.

of July 7, 2021, so we checked all tweets ($n=11$) related to the floods on that day. We found several tweets that contained the keyword "flood" but whose topic was not flooding and that had very low compound scores of sentiment. For example, "*I'm in floods of tears. This finally makes up for the loss to Germany at Italia90! I never thought I'd see England play in a major final!*", the compound score of this tweet is −0.6412, we realized that "flood" can be used to exaggerate the sentiment of extreme sadness. This is an intrinsic characteristic of human conversations called ambiguity. In the above case, this tweet used metaphor, which is the most difficult type of ambiguity that cannot be addressed by lexicon-based sentiment analysis models. The current approach of handling ambiguity is disambiguation, which remains a challenging research direction in NLP, and we discuss this point in Section 5.2.

4.6 | Topic and sentiment prediction

4.6.1 | Dataset division and parameter setting

There were 20,962 flood tweets used in this experiment, of which 19,962 tweets were used as the training set and 1000 tweets were used as the test set. The supervised algorithms were trained on Intel(R) Core(TM) i9-10850K CPU@3.60GHz and an NVIDIA RTX 3090 with 24GB memory. For the sake of replicability, the implementation framework and parameter setting are shown in Table 2.

4.6.2 | Feature extraction and selection

This module is responsible for extracting and selecting features from preprocessed flood tweets. In this article, the word2vec approach was used to convert training tweets into a numeric representation, which adopts a neural network model to learn word associations from a large corpus of text and demonstrates excellent performance in capturing the contextual information of words and understanding their meanings. Specifically, we computed

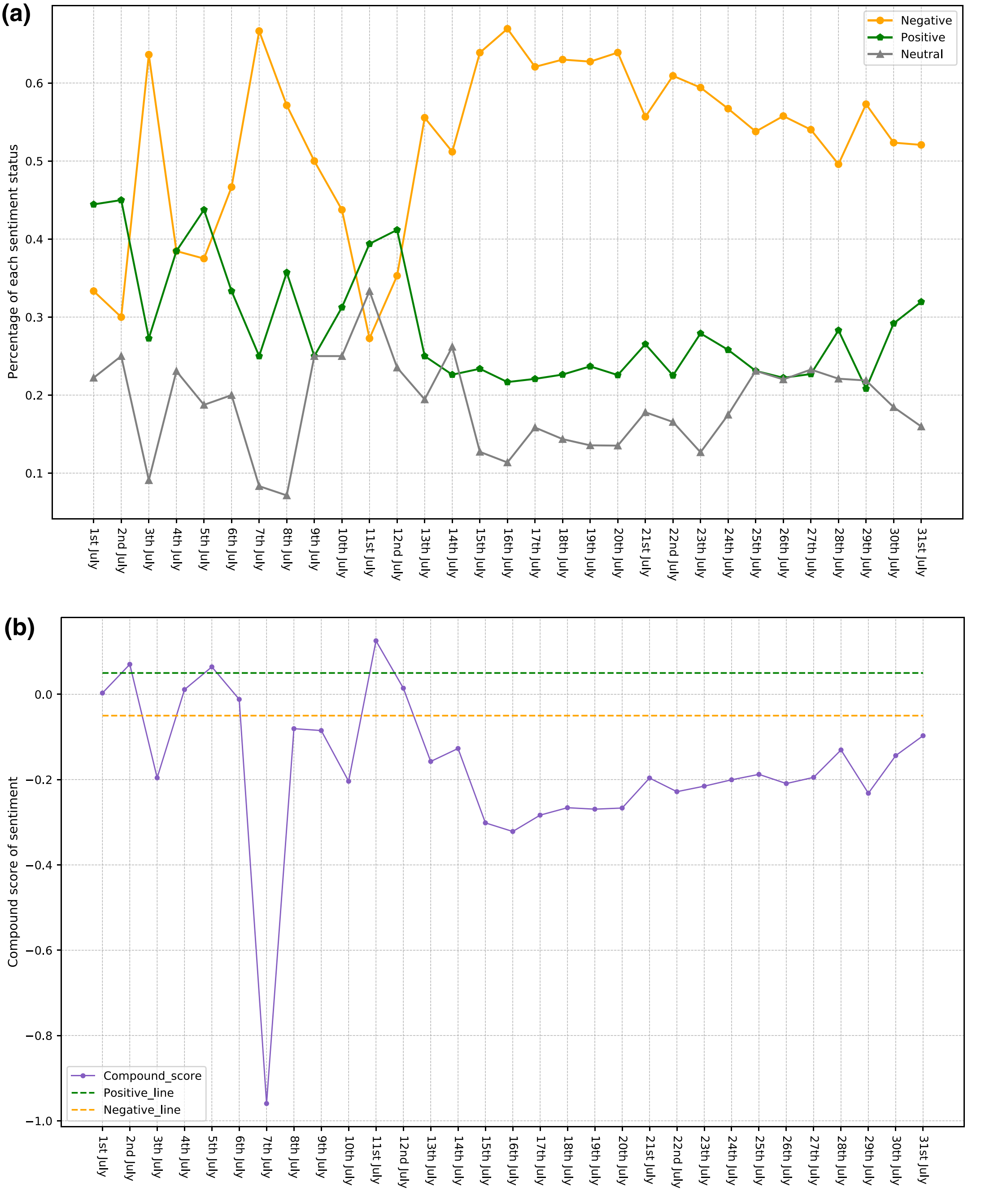

FIGURE 10 Trends in public sentiment over time. (a) The percentage of each sentiment status. (b) The compound score of each sentiment status.

the word vector of all cleaned words in each tweet and took its average value as the feature matrix of the tweets. Taking the feature representation of topics as an example, Figure 11a shows the feature representation of each topic after dimensionality reduction using principal component analysis (PCA), and it can be seen that the feature boundaries of each topic are distinct. Figure 11b shows the feature distribution of the top 20 keywords for each

TABLE 2 Description of implementation framework and parameter setting.

Nos	Classifier	Implementation framework	Parameter setting
1	SVM	Scikit-learn 0.24.2	C = 1.0, kernel = "linear"
2	Logistic regression	Scikit-learn 0.24.2	Solver = "lbfgs," max_iter = 10,000
3	Random forest	Scikit-learn 0.24.2	n_estimators = 50, max_depth = 50
4	TextCNN	Tensorflow 2.6.0	Epochs = 2200, learning_rate = 0.001, optimization = "sgdm," batch_size = 512, keep_prob = 0.5
5	TextCNN-attention	Tensorflow 2.6.0	Epochs = 2200, learning_rate = 0.01, optimization = "sgdm," batch_size = 512, keep_prob = 0.5, attention_dim = 600

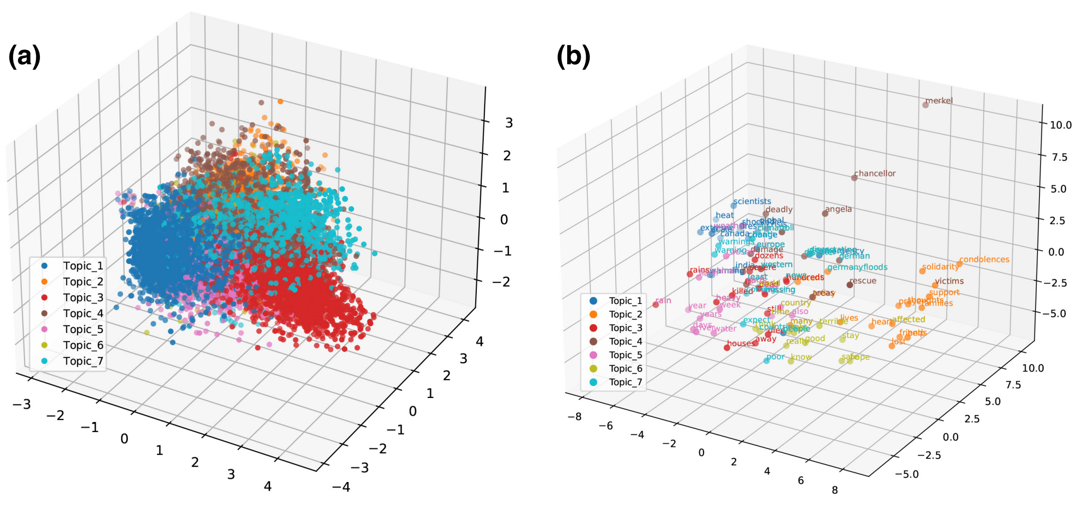

FIGURE 11 Feature representation of topics. (a) Each scatter point indicates the feature representation of one training tweet in three dimensions, which consist of the most promising features according to the PCA ranking; (b) each scatter point indicates the feature representation of one keyword in a specific topic.

topic, these keywords also show a certain degree of aggregation effect and have boundaries with each other, and they will play a key role in the subsequent topic prediction.

4.6.3 | Topic prediction

As mentioned before, the topic list of flood tweets computed by LDA was used as labels, and then SVM, LR, RF, TextCNN, and TextCNN-attention were used to predict the topics of the tweets to be classified, respectively. Table 3 shows the classification accuracy, precision, recall, and F_1-score of the topics.

From the classification results, the performance of SVM was slightly better than LR and RF classification. Overall speaking, these kinds of machine learning algorithms did not perform well in classifying flood tweets. In comparison, the deep learning algorithm TextCNN performed better, especially TextCNN-attention reached 88.09% accuracy, but it also required a longer training time.

Figure 12 shows the performance of classifiers on each topic. All classifiers perform well on Topic 1 (Climate change and global warming), Topic 2 (Praying for the victims), and Topic 3 (Disaster situation and information),

TABLE 3 Evaluation results of topic prediction related to flood tweets.

Algorithms	Accuracy (%)	Precision (%)	Recall (%)	F_1-score (%)
SVM	76.78	77.30	76.78	77.04
LR	76.48	77.01	76.48	76.74
RF	73.97	73.92	73.97	73.95
TextCNN	87.30	87.02	87.09	87.05
TextCNN-attention	**88.09**	**87.87**	**88.20**	**88.03**

TextCNN-attention turned out to deliver the best predictions in all classifiers are in bold.

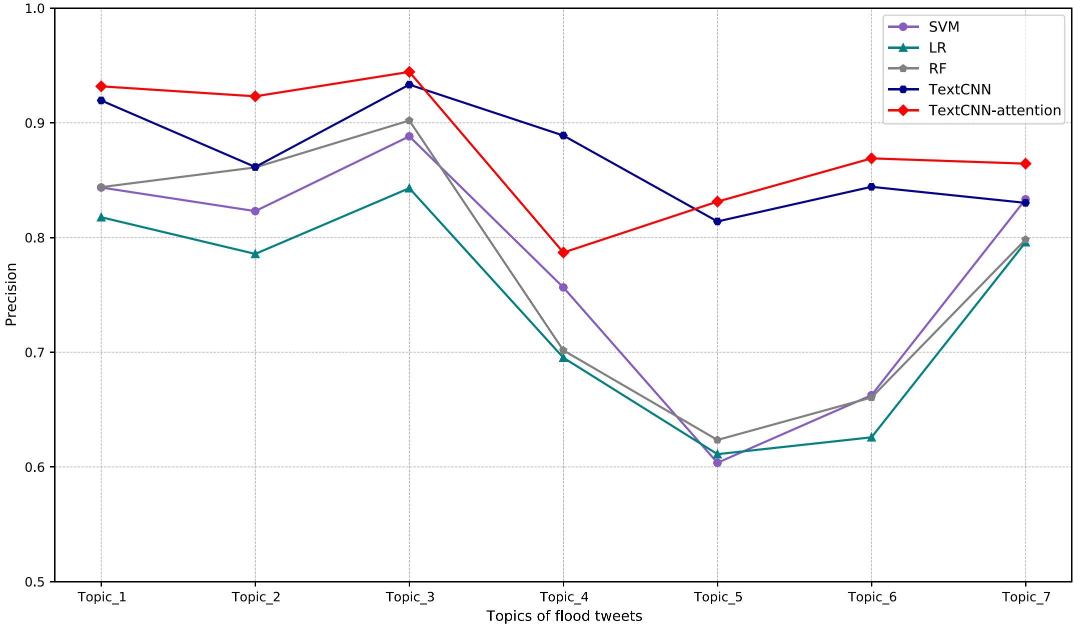

FIGURE 12 Comparison of prediction precision for each topic of flood tweet.

which were the three topics with obvious characteristics and better interpretation in the LDA topic modeling results. In contrast, topics 4, 5, and 6 had relatively low classification accuracy, and the clustering and interpretability of these three topics were not as good as the other topics.

To give readers a more intuitive representation of topic prediction, taking Topic 1 (Climate change and global warming) as an example, we visualized the keywords in the training dataset and the prediction results of TextCNN-attention, respectively, as shown in Figures 13a,b. The overall trend of both shows consistency, which fully illustrates the good performance of TextCNN-attention in topic prediction.

4.6.4 | Sentiment prediction

The label of sentiment prediction was derived from VADER analysis results, and then SVM, LR, RF, TextCNN, and TextCNN-attention were used to predict the sentiment of the tweets to be classified, respectively. Table 4 shows the classification accuracy, precision, recall, and F_1-score of the topics.

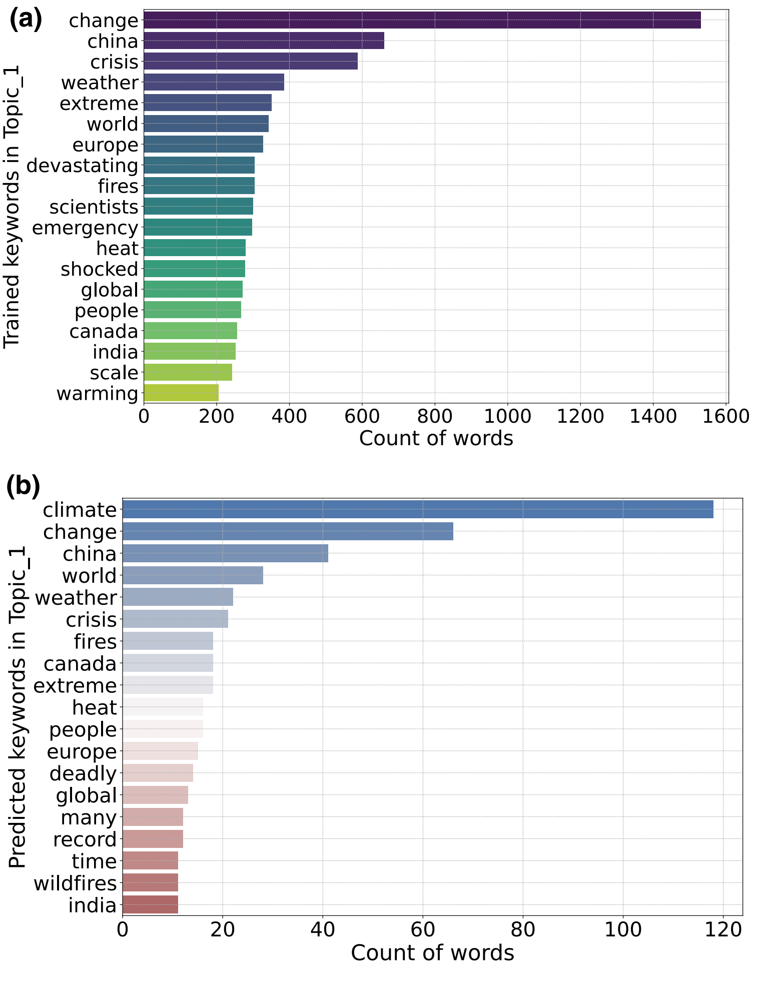

FIGURE 13 The comparison of keywords between the training dataset and the prediction results of TextCNN-attention. (a) Keywords extracted from the training dataset. (b) Keywords extracted from the prediction results.

TABLE 4 Evaluation results of sentiment prediction related to flood tweets.

Algorithms	Accuracy (%)	Precision (%)	Recall (%)	F_1-score (%)
SVM	77.30	77.87	77.30	77.58
LR	77.80	77.69	77.80	77.75
RF	72.80	73.65	72.80	73.22
TextCNN	91.54	88.29	88.81	88.55
TextCNN-attention	**91.54**	**91.84**	**88.44**	**90.11**

TextCNN-attention turned out to deliver the best predictions in all classifiers are in bold.

From the classification results of sentiment, the performance of LR and SVM was better than RF classification, but as with topic prediction, all three classifiers performed poorly. Both TextCNN and TextCNN-attention showed good performance in classification accuracy, which can reach 91.54%, TextCNN-attention performed slightly better than TextCNN from an overall performance perspective, at least in our case.

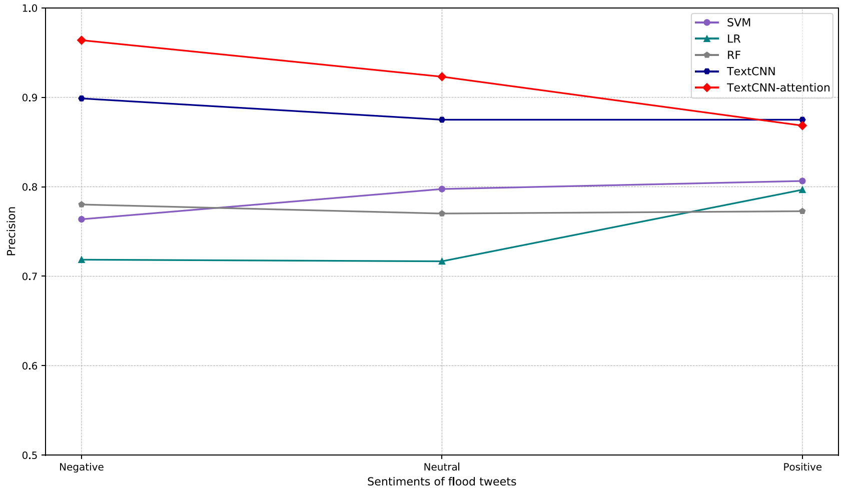

FIGURE 14 Comparison of prediction precision for each sentiment of flood tweets.

Figure 14 shows the performance of classifiers on each sentiment. The prediction precision of TextCNN-attention for negative sentiment, neutral sentiment, and positive sentiment are 96.39, 92.31, and 86.84%, respectively. It is obvious that the overall performance of TextCNN-attention is much higher than other classifiers, only for the precision is slightly lower than TextCNN in the prediction of positive sentiment, but its training time is also much longer than other classifiers.

5 | DISCUSSION

5.1 | Principal findings and practical implications

There have been lots of studies highlighting the significance of social media to support situation awareness during disasters, which can help the effective crisis response, scientific decision-making, and urban disaster management from bottom to top (Yuan et al., 2021). In this article, we demonstrated how social media can be used to improve the understanding of public perception and sentiment during and after floods. By implementing NLP methods such as the topic-based model LDA for investigating public perception, the rule-based model VADER for evaluating sentiment, and supervised learning algorithms for topic and sentiment prediction in real-time, this study illustrated how social media and data mining can be combined to capture the public's concerns and sentiment changes during disasters. These methods can be applied more generally to understand the public's reactions to disasters on social media, thus helping disaster agencies conduct "people-centered" mitigation actions. The principal findings and practical implications are discussed below.

First, we found that the changes in the number of the social media streams can indeed be used to identify how events evolved, and even to make predictions. In this study, there was a significant correlation between the trend of European floods and the change in tweets on the topic. For example, the worst situation for the European floods was on July 16, 2021, and it just so happened that the number of flood tweets reached a peak on that date. The floods rebounded from July 23 to July 26, and the corresponding number of flood tweets also increased slightly.

Second, the results of the topic modeling of tweets related to the European floods showed there were seven main topics: (1) climate change and global warming; (2) praying for the victims; (3) disaster situation and information; (4) the floods in Germany; (5) weather warning and floods; (6) public expectation; and (7) reports on the

European floods. Among them, topics 1, 2, and 3 had the highest interpretability and their keywords best reflect the meaning of the topics, indicating that the public has the most discussion and focus on these three topics. Especially the public was aware that climate change and global warming have become the biggest causal factors for extreme flood events, or at least discussing it.

Third, the results of the sentiment analysis of tweets related to the European floods showed negative sentiments were generally prevalent on social media during the floods. Starting with the unusual summer storms and heavy rain before the floods happened, the proportion of negative sentiments began to surge and reached a peak on July 16, 2021. Subsequently, the proportion of negative sentiments decreased over time but was still much higher than the number of positive and neutral sentiments, which also indicates that flood disasters have not only immediate mental and physical harm, but also have long-term consequences for the public.

Fourth, based on the labels generated by topic modeling and sentiment analysis, supervised learning performed well in further prediction. In particular, TextCNN-attention can reach 88.09% accuracy in topic prediction and 91.54% in sentiment prediction, which shows that TextCNN-attention can obtain good results from sparse flood tweets, and it can be used to predict the topics and sentiment of a single tweet in real-time. The reason is that TextCNN-attention can better capture global semantic information compared to TextCNN which rather extracts local text features. Remarkably, attention empowers the network to adaptively assign weights to different positions in the input word sequence, allowing the model to focus on keywords, thus boosting the model's performance (Alshubaily, 2021; Niu et al., 2021). The organic combination of unsupervised and supervised learning to mine public perceptions and sentiment has great potential in people-oriented disaster management.

Regarding the practical implications, disaster agencies and decision-maker should recognize that social media can be used to explore public perception and sentiments about floods (Boon-Itt & Skunkan, 2020). The recognition of the public concern and awareness can help disaster agencies understand what the public is thinking about the floods, the relevant information about peoples' perceptions is useful for formulating mitigation plans and improving resilience in cities (Ruz et al., 2020). The decision maker can better understand the public sentiments based on social media and then disseminate the information about the flood situation to the public, which can reduce the impact of negative sentiment and public panic. In addition, a return to normalcy is the ultimate goal of post-disaster recovery policies (Zhang et al., 2019). The public sentiment tracking of post-disaster helps mitigate the long-term consequences of disasters.

5.2 | Limitations and future research directions

For additional inspiration and information to consider, the limitations of and future research directions of this study are discussed below.

Topic modeling and sentiment analysis do not take into account contextual information. Although LDA is advantageous in extracting hidden topics, and VADER is the most popular sentiment analysis algorithm as well, they rely more on word frequency and do not take into account contextual information, which makes it difficult to mine deeper semantic information and leads to misjudgment of tweet topics and sentiment polarities, as described at the end of Section 4.5.2. A topic worth investigating is the mining of semantic structures and the automatic generation of knowledge graphs related to flood tweets using, for instance, hidden Markov models (HMM) or bi-directional long short-term memory (BiLSTM) (Minaee et al., 2021). Furthermore, we treated each word as equally important concerning the topic modeling in the current manuscript. However, it is indeed feasible to integrate weights into LDA, which is a subject of our ongoing work.

More comprehensive analysis and rich data sources should be adopted. In this study, our research more focuses on temporal analysis, topic analysis, and sentiment analysis due to the lack of tweets with geo-references, and the tweets available via the Twitter API, only 1–2% are geotagged (https://developer.twitter.com/en/docs/tutorials/advanced-filtering-for-geo-data). Therefore, we can try to use deep learning to infer the location of disaster events and users from non-geotagged tweets. The inferred geotagged tweets could be used as the potential dataset for disaster assessment in post-disaster management. In addition, although we have obtained good results from sparse data due to the locality of floods, a multi-source data analysis from the different social platforms (e.g., Facebook, Instagram, etc.) will have a more positive impact on disaster management (Kim & Hastak, 2018).

6 | CONCLUSION

The use of social media has many potentialities and applications during disasters. In this article, we comprehensively analyzed social media data related to the "European Flood in 2021" over time, topic, and sentiment, formed a complete workflow from flood tweets processing, topic modeling, sentiment analysis, and prediction. The findings indicate that the approach was accurate and viable for understanding public perceptions and opinions during floods. In the case of the European floods in 2021, there was a significant correlation between the trend of European floods and the change in tweets on the topic. The three topics that received the most public concern were climate change and global warming, praying for the victims, disaster situation and information. Negative sentiments were predominant during the floods and will continue for some time. Compared to other classifiers, the TextCNN-attention model turned out to deliver the best predictions in topic and sentiment prediction and performed well for sparse flood tweets, it can be used to predict the topic and sentiment polarity of a single tweet in real-time during the flood events. In short, social media can help understand the public's perception and sentiment towards a disaster event, which can contribute to enhancing situational awareness and also support post-disaster management.

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CONFLICT OF INTEREST STATEMENT
No potential conflict of interest was reported by the author(s).

DATA AVAILABILITY STATEMENT
The data and codes that support the findings of this study are available on request from the corresponding author.

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