Achieving fine-grained urban flood perception and spatio-temporal evolution analysis based on social media

Zhiyu Yan, Xiaogang Guo, Zilong Zhao, Luliang Tang

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Highlights

- The novel framework for fine-grained flood perception and spatio-temporal analysis.
- Fine-grained flood location corpus construction.
- Multimodal data fusion for water depth information extraction.
- Spatio-temporal correlation of urban flooding in social and geographical spaces.
Achieving fine-grained urban flood perception and spatio-temporal evolution analysis based on social media

Zhiyu Yan *

a. State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China

Zhiyu Yan received her B.S. degree from Wuhan University, Wuhan, China, in 2022, where she is currently pursuing her M.S. degree at the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing. Her research interests include spatio-temporal big data analysis, text mining, and smart city.

Email: zhiyuy@whu.edu.cn

Xiaogang Guo **

a. State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China

Xiaogang Guo received his B.E. degree and M.S. degree from Beijing University of Civil Engineering and Architecture, Beijing, China, in 2017 and 2020. He is currently pursuing his Ph.D. degree at the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing. His research interests include human mobility, urban systems, and GIS.

Email: guoxg1006@whu.edu.cn

Zilong Zhao *

a. State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China

Zilong Zhao received his B.E. degree from Wuhan University, Wuhan, China, in 2021, where he is currently pursuing his M.S. degree at the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing. His research interests include spatio-temporal data mining, tensor imputation, and intelligent transportation systems.

Email: zilzhao@whu.edu.cn

Luliang Tang *

a. State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China

Luliang Tang received his Ph.D. degree from Wuhan University, Wuhan, China, in 2007. He is currently a Professor at Wuhan University. His research interests include spatio-temporal GIS, GIS for transportation, and change detection.

Email: tll@whu.edu.cn

*: Corresponding author

Abstract: Timely understanding of affected areas during disasters is essential for the implementation of emergency response activities. As one of the low-cost and information-rich volunteer geographic information,
social media data can reflect geographic events through human behavior, which is a powerful supplementary source for fine-grained flood monitoring in urban areas. However, the value of social media data has not been fully exploited as potential location and water depth information may be embedded in both text and images. In this study, we propose a novel framework for fine-grained information extraction and dynamic spatio-temporal awareness in disaster-stricken areas based on Sina Weibo. First, we construct a novel fine-grained location corpus specifically for urban flooding contexts. The corpus summarizes characteristics of address descriptions in flood-related Weibo texts, including standard address entities and spatial relationship entities, based on the named entity recognition (NER) model. Then, water depth information in texts and images is obtained based on different deep learning modules and fused at the decision level. Specifically, in text analysis module, we summarize and extract diverse descriptions of water depth, and in image analysis module, we develop a water level hierarchical mapping method. Finally, we analyze the spatio-temporal distribution characteristics and variation patterns of the extracted information to enhance situational awareness. Taking the urban flood occurred in Anhui, China as a case study, we find that the variation of flooding hotspot areas in Sina Weibo and rainfall centers show a significant spatial and temporal consistency, and the fusion of text and image-based information can facilitate dynamic perception of flood processes. The framework presented in this study provides a feasible way to implement refined situational awareness and spatio-temporal evolution analysis of urban floods at the city level in time.

Keywords: Urban floods; Social media; Water depth mapping; Spatio-temporal evolution; Flooding hotspot areas

1. Introduction

Extreme rainfall events are one of the most frequent disasters in the world, causing unprecedented flooding and significant losses of life, property and infrastructure (Ouyang et al., 2022). The disruptions brought on by flood events pose substantial obstacles to the sustainable economy and society development (Ye et al., 2019). The costly disasters have become more frequent and intense in the last decade as a result of global climate change (da Silva et al., 2022), especially in urban areas with high exposure to material wealth, poor surface water permeability, and intolerable drainage systems (Anni et al., 2020). For instance, on July 21, 2012, a rainstorm in Beijing, China, claimed the lives of 79 people, had an impact on nearly 1.9 million people, and caused a $16.94 billion economic loss (Wang, H. et al., 2021). A severe downpour in Henan Province on July 20, 2021, resulted in 302 fatalities, affected roughly 13.66 million people, and caused direct economic damage of $128.82 billion (Li et al., 2022). These damages highlight the significance of timely flood monitoring and implementation of emergency response measures.

Due to the wealth of information, the near real-time transmission route, and the low cost of data production, social media (e.g., Twitter, Facebook, Sina Weibo) is getting more and more attention in the field of disaster emergency management (Chen and Lim, 2021). For example, Wu et al. (2021) found a significant linear correlation between microblog counts and precipitation at daily and provincial scales. Wang et al. (2016) used spatial statistical analysis to find that the distribution pattern of Sina Weibo was related to emergencies but varied among topics. As social “sensors”, real-time and on-the-spot reports from the witnesses in disaster-stricken areas provide a feasible way to collect fine-grained flood location and water depth information (Rajput et al., 2020), which helps to improve situational awareness. However, extracting precise and comprehensive geographic events from social media to provide high-quality information services for flood monitoring still faces enormous challenges.

Urban flooding locations extracted based on social media are coarse-grained, and the accuracy is constrained by existing corpora, especially in Chinese. Location awareness of urban flooding zones is one of the critical components in disaster management (Roy et al., 2021). However, due to the lack of Chinese corpus for urban flood catastrophes, automated exploration and usage of location information in texts, during flood disasters...
remains a challenge (Kankanamge et al., 2020). First of all, the plurality and colloquiality of Chinese vocabulary expressions lead to the non-standard and complexity of Sina Weibo texts. Second, the resolution of estimated flood locations tends to be at the city or community level (Villegas and Martinez, 2022). However, the descriptions of flood locations from social media posts go beyond standard addresses and also involve the spatial relationships between standardized elements, such as the intersection of lines (“the intersection of Binhe Road and Mingde Road”), distance relationships (“100m in the direction of Five Group Road”), and directional relationships (“Wuzu Road from east to west”). So obtaining more detailed flood location information such as a street or a store, still requires further exploration.

The water depth information extraction based on social media is insufficient, and the single mode data mining is one-sided. Water depth information plays a significant role in urban flood situation awareness, which directly reflects the severity of flooding (Kanth et al., 2022). During the period of urban floods, the disaster-stricken areas impede community evacuation and ground rescue missions. In the last few years, the water depth information in flooding zones is mainly obtained from automatic water level gauges, hydrological models, traffic cameras, etc (Zhang et al., 2016; Zhang et al., 2014). However, these methods rely on the dispersion of already-existing sensors or demand a significant amount of data for evaluation (Gilmore et al., 2013; Kim et al., 2011; Nielsen et al., 2019; Song et al., 2019). Nowadays, many studies extract water depth information via social media, where texts and images are collected from citizen observations (Geetha et al., 2017; Pereira et al., 2020). These studies tend to employ a single data source (e.g., images) or model, and do not make maximum use of the available real-time social media data. In addition, text mining in social media focuses on physical damage classification and sentiment analysis (Shan et al., 2019), which led to the neglect of fine-grained descriptions of water depth in the texts.

To address the aforementioned issues, this study proposes a novel framework to extract fine-grained location and water depth information of flooding areas from social media texts and images, and analyze the spatio-temporal characteristics of the extracted information for the implementation of large-scale situational awareness at the city level. To summarize, the main contributions of this study are:

1. Fine-grained flood location corpus construction. By combining foundational geographic corpora, Sina Weibo data, and address databases, we extracted spatial relationships from flooding addresses that align with the expressions commonly found in social media, and fortified standard geographic entities within disaster-affected areas, achieving location annotations at the intersection level.

2. Multimodal data fusion for water depth information extraction. We use multimodal data such as social media text and images to extract features related to flooding depth. Subsequently, decision-level information fusion is employed to enhance flooding perception. The proposed fusion method enables the generation of maps with wider coverage and higher spatio-temporal resolution.

3. Spatio-temporal evolution analysis of urban floods. We analyze the spatio-temporal correlation of urban flooding in social and geographical spaces, and explain the impact of geographical elements on social media geographic events. These help to explore the possibility of collaborative observation of urban floods in cyberspace and natural space.

The remainder of this article is organized as follows. Section 2 describes the collection and preprocessing of the Sina Weibo dataset. Section 3 introduces the framework of our study. Section 4 presents the empirical results. Section 5 discusses the findings and limitations of the study. Finally, Section 6 concludes this paper.

2. Related works

To collect and understand what is happening in the affected communities during disasters is known as situational awareness (Huang and Xiao, 2015). Researches using social media for situational awareness mainly focus on three dimensions of social media data: time, space, and content. 1) Temporal dimension. The temporal dimensional information of social media helps to detect the outbreak of disasters and to understand the process of disasters (Poblete et al., 2018; Wang et al., 2019). 2) Spatial dimension. Spatial dimensional information
from social media can be used for disaster location identification as well as disaster mapping (Li, Z.L. et al., 2018). 3) Semantic dimension. Semantic information in social media data can help disaster managers understand what is happening during a disaster event (Fu et al., 2020). Among these, the extraction of fine-grained spatial distribution of urban flooding and abundant water depth information is a challenging issue.

### 2.1 Extracting flood locations from social media texts

The geographic information carried by flood-related social media can provide disaster management and rescuers with detailed situation information of disaster-stricken areas (Arthur et al., 2018), which is the basis for flood monitoring and emergency management activities.

Among the existing studies related to the analysis of geographic information in social media, the sources of flood location information can be divided into two categories: 1) Social media with check-in locations (Arapostathis, 2021; Karimiziarani et al., 2022; Resch et al., 2018). This type of data is characterized by clear geographic labels (Kryvasheyeu et al., 2016; Wang and Taylor, 2018). However, the number of posts with check-in locations is less than 1% of all types of social media posts (Malik et al., 2015). A large number of social media posts containing valid information are ignored. 2) Descriptions of flood locations in texts. Keyword matching methods and deep learning methods are used to extract location information from the texts (Brouwer et al., 2017; Wang et al., 2020). A rich amount of location descriptions exists in unstructured texts, however, the lack of a fine-grained mining framework leads to the waste of information. Additionally, the spatial relations of locations in texts are ignored (Sattaru et al., 2021). Standard address elements and spatial relationship elements are two types of address entity components used in the geospatial context. The extraction of these two types of address entities from texts helps analyze at a more refined scale, not just at the city or community level.

### 2.2 Extracting water levels from social media texts and images

The depths of inundated areas can be computed based on social media texts and images from eyewitnesses and help improve the understanding and modeling of flood hazards (Lo et al., 2021).

The existing methods of estimating water level based on social media text can be divided into two types: 1) Text classification (Khan et al., 2022). Although this method can easily obtain the perception of water level, the fine-grained water depth descriptions in texts are directly ignored. 2) Keyword matching (Aarthysky et al., 2022). A dictionary-based mapping is proposed to get direct water depth descriptions and indirect water depth descriptions mentioned in texts. However, the extraction of fine-grained water depth descriptions depends on the quality of the dictionary, and the distance entity about disaster locations may also be mistaken for water depth information.

The majority of water level estimation methods are based on images. The automatic extraction of water level information from images based on deep learning methods can be roughly divided into three categories: 1) classification models. The flood-related images are classified into several classes according to the flooding severity. Then, the global deep features of the whole image are used to train classification models. For example, Nguyen et al. (2017) fine-tuned the VGG16 model to classify images as “severely damaged”, “mildly damaged”, and “almost undamaged”. However, the classifier is easily disturbed by the complex background in the images (Li et al., 2019). 2) object detection methods (Huang et al., 2020; Noto et al., 2022; Pally et al., 2022; Park et al., 2021). Images containing reference objects, such as persons, cars, buses, bicycles, and houses, are taken into account when estimating the flood level. By establishing the mapping strategy between reference objects and water levels, fine-grained water level estimation could be achieved. However, this interpretation is a nontrivial problem for computers. 3) Actual water depth detection methods. Recently, Li, J. et al. (2023) proposed an actual water depth detection method, which explored the possibility of estimating the true value of water depth from social media images, while many studies have obtained discrete water levels or severity levels.
Fusing text and image data allows for more effective flood severity mapping. However, it is challenging since the number of social media containing both texts and images is very small, and the content of texts and images is weakly related in many cases (Hao and Wang, 2020). The feature-level fusion of texts and images is less effective. It is more appropriate to analyze the texts and images using two different modules, and then combine the results at the decision level.

In summary, because of the massive popularity of social media networks and their real-time production of data, social media offers new opportunities for flood monitoring and situation awareness during emergencies. However, numerous studies have ignored characteristics of flood location descriptions in Sina Weibo texts, and the extraction of water level information focuses on a single data (e.g., images) or model, which causes the loss of fine-grained flood location and greatly limits the practical application of social media in assisting disaster management at the city level. Therefore, in this paper, we develop a novel framework for fine-grained information extraction and dynamic spatial-temporal awareness in disaster-stricken areas by the Chinese social media platform, Sina Weibo.

3. Study area and data

There are many rivers in Anhui province, and the Yangtze River flows through the southern of Anhui. Geographic location and climate make Anhui Province vulnerable to heavy rainfall and flooding. From July 15 to July 20, 2020, a large amount of precipitation fell in Anhui province. Many areas in Anhui were inundated by floodwaters. The main purpose of this study is to mine the location information as well as water level information of the flooding areas using social media data, and reveal the process of urban flooding disasters by analyzing the spatio-temporal characteristics of the extracted information. Therefore, the flood-related blogs posted on the Sina Weibo platform were collected from July 15 to July 20, 2020, including user ID, time, content, check-in location, and images. To protect user privacy, before crawling data, we applied for and authorized “Appkey” on Weibo platform1, which is used for relevant public opinion analysis (Tse et al., 2018). In addition, when crawling social media data, we did not collect user nicknames and ID fields and directly delete sensitive attributes from the data source (Löchner and Burghardt, 2023).

3.1. Social media data acquisition by a web crawler

The Sina Weibo platform provides an API (Application Programming Interface) for crawling blogs by keywords and dates, so the keywords need to be determined first. Since there are various expressions of urban floods on Sina Weibo, simply using “flooding” as the keyword will miss many flood-related posts. The flood-related keywords need to be expanded. Firstly, “flooding” and “rainstorm” were regarded as the basic words for crawling. Then the similarity between each word vector in the Wikipedia corpus and these basic word vectors was calculated, and the words with high similarity were selected as candidates for the flood-related keywords. Finally, the flood-related keywords were determined by manual analysis. The cosine similarity method was adopted to calculate the cosine of the angle between word vectors. Suppose X and Y are two n-dimensional word vectors of word A and word B respectively, where X is \([x_1, x_2, \ldots, x_i]\) and Y is \([y_1, y_2, \ldots, y_i]\) and the cosine similarity of word A and word B is calculated as follows:

\[
cos = \frac{\sum x_i \times y_i}{\sqrt{\sum x_i^2} \sqrt{\sum y_i^2}}
\]  

A larger cosine value means a greater similarity between the two words, and vice versa. The expanded flood-related keywords are shown in Table 1.

After matching with keywords such as “flooding”, “waterlogging” and “rainstorm”, we found that although some Sina Weibo posts contained such keywords, their semantic expressions were not related to urban floods.

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1 https://open.weibo.com/development/businessdata
Taking the blog “I went to Jishuitan Hospital today” as an example, in the Chinese expression, word “Jishui” in the blog and word “waterlogging” have the same Chinese spelling and pronunciation, yet the former lacks the semantics of the latter. TF-IDF (Term Frequency-Inverse Document Frequency) keyword extraction explores the theme of the whole text by identifying pivotal words that frequently occur in articles. From the Sina Weibo posts obtained in the previous step, we randomly selected 300 posts that were manually interpreted as unrelated to flooding. Then, TF-IDF keyword extraction method was conducted on these 300 posts, and the extracted keywords were further manually selected to obtain the reverse keyword Table 2. Finally, the reverse keywords were used to eliminate the crawled Sina Weibo posts to improve the quality of the dataset.

Table 1 Examples of flood-related keywords

<table>
<thead>
<tr>
<th>Keywords related to flooding</th>
<th>积水(ponding), 淹水(flooding), 水淹(water logging), 内涝(waterlogging)</th>
</tr>
</thead>
</table>

| Keywords related to heavy rainfall | 大雨(heavy rain), 暴雨(rainstorm), 大暴雨(downpour), 强降雨(heavy rainfall), 强降水(heavy precipitation) |

Table 2 Examples of reverse keywords

| The reverse keywords | 脑子(brain), 脑袋(head), 脑积水(hydrocephalus), 棉纶(cotton spandex), 池水(pool of water), 癌症(cancer), 医院(hospital), 厕所(toilet), 肺积水(hydrocephalus), 肾积水(hydrourephrosis), … |

3.2. Sina Weibo data Cleaning

The diversity and colloquiality of Chinese vocabulary expressions lead to the non-standard and complex Sina Weibo texts. Before performing the analysis, the collected texts must be pre-processed. First of all, sentence-level processing is performed. Texts with empty content are directly excluded. Moreover, there is retweeting behavior on Sina Weibo platform, and texts with similarity greater than 90% should be removed. Then the symbolic level processing is performed. The regular expressions are established to remove the special characters, emoticons, serial numbers and other parts of the texts that affect the recognition results. After cleaning the Sina Weibo content, the location information of check-in is considered as a part of the Sina Weibo texts.

Finally, we crawl a total of 95,723 Sina Weibo posts and get 75,868 flood-related posts after reverse keyword elimination, of which only 3.913% contained the location information of check-in.

4. Method

In this study, we propose a novel framework to extract fine-grained location and water level information of flooding areas from social media texts and images, and analyze the spatio-temporal characteristics of the extracted information based on geographic methods. The whole procedure is illustrated in Fig. 1. First, BERT–BiLSTM–CRF model (Tedeschi et al., 2021) trained on the constructed flood location corpus is used to identify the fine-grained location information. Secondly, Sina Weibo texts and images are fused to extract water level information in the flooding zones based on natural language processing and computer vision algorithms. Finally, kernel density estimation is used to detect flooding hotspot areas in Sina Weibo and geographic analysis methods such as Geodetector and statistical methods are adopted to analyze the spatial and temporal characteristics.
4.1. Extracting address entities in Sina Weibo texts

Extracting the location of the flooding areas is the basis of the whole framework, which consists of three main steps. First, we construct a flood location corpus. As sample datasets, they are converted from text to vector form. Secondly, the corpus is used to train the NER model for location extraction of flooding areas. Finally, the collected Sina Weibo posts of the study area are input to the trained NER model to extract the locations mentioned in the texts. The geographic coordinates are returned by searching the location names based on the Gaode Map Coordinate Picker API.

4.1.1. Address entities in the flood-related texts

Address entities represent small or large geographic regions with various types. By summarizing the characteristics of address descriptions in flood-related Sina Weibo texts, we divide address entities into two types, namely standard address entities and spatial relationship entities, based on the administrative division specification of the National Bureau of Statistics and the Chinese standard address element classification (Zhu et al., 2018). Standard address entities are divided into four main categories:

1) Administrative Divisions. Administrative Divisions are essential parts of the address, generally including five levels: provincial-level, city-level, county-level, town-level, and community/village committee level. For example, in the address “Fishery Planning Village, Taohua Town, West Lake District, Nanchang City, Jiangxi Province”, “Jiangxi Province” is a provincial area, “Nanchang City” is a prefecture level area, “West Lake
District” is a county level area, “Taohua Town” is a township level area, and “Fishery Planning Village” is a village committee level area.

2) Roads. Roads are the lifeblood of urban transportation. Generally speaking, roads are distributed in a linear pattern, including tunnels, elevated, streets, alleyways, roads, lanes, etc. For example, “Fuxin East Road” in the address “Fuxin East Road, Dongcheng District, Beijing”.

3) Local areas. Local areas generally describe a relatively small area, including the village group in the village committee, the development area in the city, the plot of land represented by the POI (Point of Interest), etc. For example, “Gushu Development Zone” in the address “Gushu Development Zone, Bao'an District, Shenzhen”, the village group name “Group 8” in the address “Group 8, Gejiache Village, Yuhang District, Hangzhou City”.

4) Buildings. The description of buildings in flood-related texts is sometimes accurate to the house number, unit number, and floor. For example, in the address “Floor 2, Unit 1, No. 122, Jiantao Road”, “No. 122” is the house number, “Unit 1” is the unit number, and “Floor 2” is the specific floor.

The spatial relationship entities are summarized into three major categories:

1) The intersection of lines described as roads in flood-related texts. Such as “the intersection of Binhe Road and Mingde Road”.

2) Distance relationship. Distance relationship indicates the distance between spatial entities, which provides a more detailed description of the spatial location, such as the “100 meters” distance in the address “People's Road 100 meters towards Group 5 Road”.

3) Directional relationship between spatial entities in a specific spatial coordinate system, which mainly has the following eight main directions, namely, east, south, west, north, east to west, west to east, south to north, and north to south, such as the address “Guanping Road east to west”.

4.1.2. Construction of flood location Sina Weibo corpus

For the construction of flood location Sina Weibo corpus and the recognition of Chinese Addresses, three data sources are used in this paper: 1) Chinese address element recognition dataset from CCKS 2021 Address NER Challenge, whose address data are obtained by crawling public address information. This data source provides 10826 addresses. 2) The address lexicon of the place where flooding occurs obtained based on Gaode API. This data source provides 652296 addresses. 3) Flood-related Sina Weibo data by a web crawler, which provides an opportunity to capture blog data (Li, Y. et al., 2023). There are 7173 Sina Weibo posts in total. According to the address description characteristics of the flood-related texts and the classification criteria established in Section 4.1.1, we manually label the address elements in the above datasets to construct the flood location corpus. The BIOSE annotation system mentioned in section 4.1.4 is adopted. In Table 3, the label body and label headers corresponding to 16 types of geographical entities are shown. If there is no label body (the last entity in the table), the label header will be treated as a separate label (O); Otherwise, combine the header and body of the labels (e.g., B-prov, I-prov, E-prov, S-cellno). Multiply the number of the two to obtain 52 labels. Finally, we annotate 658210 addresses totally.

Table 3 Description of address entities labeling

<table>
<thead>
<tr>
<th>Categories of entities</th>
<th>Examples</th>
<th>Body of labels</th>
<th>Header of labels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Provincial administrative divisions</td>
<td>Jiangxi province</td>
<td>prov</td>
<td>B, I, E</td>
</tr>
<tr>
<td>Municipal administrative divisions</td>
<td>Nanchang city</td>
<td>city</td>
<td>B, I, E</td>
</tr>
<tr>
<td>County administrative divisions</td>
<td>Wuchang district</td>
<td>district</td>
<td>B, I, E</td>
</tr>
<tr>
<td>Township administrative divisions</td>
<td>Huinan town</td>
<td>town</td>
<td>B, I, E</td>
</tr>
</tbody>
</table>

2 https://tianchi.aliyun.com/dataset/110146
4 https://s.weibo.com/weibo?q={keyword}&Refer=index
### 4.1.3. BERT-BiLSTM-CRF model

The BERT-BiLSTM-CRF model combines statistical and deep learning methods, and performs well in Chinese named entity recognition tasks. The overall process of the model is shown in Fig. 2, which can be summarized into three layers: the first layer adopts the Bert (Bidirectional Encoder Representation from Transformers) model pretrained using large-scale general text data, such as Wikipedia and bookcorpus. Then, based on the corpus of this paper, we further fine-tuned the parameters of the model to apply it to flooding address extraction tasks, and the texts were converted to vector form; the second layer uses BiLSTM (Bidirectional Long Short-Term Memory model) to extract the features required for entity recognition in the output vector. The position and direction information are critical in the sequence labeling task, so the BiLSTM is used to further learn the dependencies on the observed sequence; the third layer finally combines the CRF (Conditional random field) method to decode and compute the optimal labeling sequence. There is a particular combination pattern between adjacent entity labels, such as the B label (indicating the start character of the word) followed directly by the B label is incorrect. To further improve the prediction accuracy of the model, the CRF model is used to learn the transfer rules between adjacent entity labels.

![Fig. 2. Schematic diagram of BERT-BiLSTM-CRF model](image)

### 4.1.4. Model training and validation

There are three commonly used annotation systems: 1) BIO annotation system, where B identifies the beginning part of an entity, I identifies the middle part of an entity, and O identifies the non-entity part; 2) BMES annotation system. Add S to identify the entity composed of a single word; 3) BIOSE annotation system. Add E to identify the end part of the entity. Since the entity descriptions about the direction are often single words, the BIOSE annotation system is used in this paper. After annotation, the whole dataset contains 16
different types of named entities and a total of 52 labels. For data split, 60% of the labeled dataset is used for training, 20% of the labeled dataset is used for testing, with the rest for validating.

The evaluation of address element recognition can be analogous to classification models, and each annotation is considered as a category. The F1-score is used to evaluate the recognition effect. Precision and Recall are used to compute the F1-score, where Precision refers to the proportion of the actual positive samples among the predicted positive samples and Recall refers to the proportion of predicted positive samples among actual positive samples. The F1-score is the weighted average of Precision and Recall, as shown in Eq. (2):

$$F1\text{-}score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

The F1-score for each category is determined using the formula above. Due to the imbalance between the number of labels in each category, e.g., the number of road elements is significantly more than direction elements, the weighted average F1-score is used for the overall evaluation, which considers the proportion of the sample size of each category in the total sample.

4.1.5. Chinese address resolution

Considering the varied structures of point and line addresses, we integrate the address localization strategy proposed by Yang et al. (2022) and Li, L. et al. (2018) to standardize the extracted unstructured text, and locate it based on Gaode geocoding API5. Then the Gaode coordinate system is converted to the WGS84 coordinate system according to the coordinate conversion.

4.2. Extraction of Water depth information by fusing multimodal data

After obtaining the location information of the flooding areas, fine-grained water depth information can be further collected based on the texts and images in social media. In this paper, a multimodal water depth extraction method that contains two deep learning modules is proposed to analyze texts and images separately. Firstly, we construct sample datasets for texts and images separately. The water depth descriptions in the texts are labeled as entities and mapped to different water levels. In the images, we select the cars as our targets and annotate the processed images based on the constructed water depth hierarchical mapping method. Secondly, two deep learning modules are trained based on text and image datasets. The mined water level information is integrated from the image process module and text process module.

4.2.1. Dataset Preparation

• **Water depth descriptions and mapping in texts.** Generally speaking, there are two kinds of descriptions of water depth in the texts: 1) direct descriptions. The water depth is described in direct figures, such as “50 cm of water on the road” and “up to one meter of water”. 2) analogous descriptions. The most common reference is the body part. (Chaudhary et al., 2020) proposed a fine-grained mapping strategy between body parts and water levels, and the water depth was divided into 11 levels, from 0 (indicating no water) to 10 (indicating a person of average height who is fully submerged in water).

Table 4 displays the approximate water depth for each level based on the assumption that the average human height is 1.70 m tall. Based on the extracted flood-related Sina Weibo as mentioned in Section 3, we further manually selected Sina Weibo texts with water depth information for annotation. Given the limited sample size of our training dataset, we implemented the data augmentation technique introduced by Lai et al. (2022). We utilized the YEDDA annotation tool (Yang et al., 2017) to achieve semi-automatic annotation of water depth information in texts. After annotation, the direct and analogous descriptions are considered as two entity classes.

<table>
<thead>
<tr>
<th>Level</th>
<th>Body parts</th>
<th>Height range (m)</th>
<th>Estimation of water depth (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>None</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

---

5 [https://lbs.amap.com/api/webservice/guide/api/georegeo](https://lbs.amap.com/api/webservice/guide/api/georegeo)
Water level hierarchical mapping in images. According to the flooded part of the car, water depth is divided into three levels, namely “extremeFlood”, “mediumFlood”, and “smallFlood”. The levels “extremeFlood”, “mediumFlood” and “smallFlood” are mapped to the estimated water depth of 1.0~1.5 meters, 0.5~1.0 meters and 0.0~0.5 meters. The mapping strategy between car parts and water levels is shown in Fig. 3.

**Fig. 3.** The mapping strategy between car parts and water depth.

The process of filtering flood-related images including cars from Sina Weibo, involves two primary steps: initially, the original image datasets crawled from Sina Weibo are divided into two categories, namely “flooding” and “normal”, as training dataset of the VGG16 classification model which works effectively with complex backgrounds and small datasets (Liu et al., 2019; Simonyan and Zisserman, 2014). Images classified as “flooding” are flood-related and are considered as the valid dataset (as shown in Fig. 4a). Subsequently, the pre-trained Mask R-CNN (Faster, 2015) is adopted for instance segmentation on flood-related images. The instances with the category “car” are considered as reference objects. If there are “car” instances in the segmentation results, we extract the “car” instance alone from the flood-related images and then crop the images to a suitable size (as shown in Fig. 4b). The segmented car images are adopted as sample dataset for water level classification (as shown in Fig. 4c). Conversely, the image is excluded from the process of estimating water depth.

According to the water level hierarchical mapping method above, the segmented car images are manually labeled into three categories: “extremeFlood”, “mediumFlood” and “smallFlood”. After labeling, these images serve as the sample dataset for training the VGG16 model, which is used to estimate water depth.

**Fig. 4.** Example of water depth extraction of images. (a) the original flood-related image, (b) parts of cars that are not covered by water, (c) the estimation of water level from the segmented car images.
Fig. 5. Examples of image classification dataset of VGG16 model. (a) smallFlood, (b) mediumFlood, (c) extremeFlood.

4.2.2 Multimodal water depth extraction method

- **Text process module.** The texts tagged with named entities representing direct and analogous water level information are used as the sample dataset, with a total of 14618 annotated texts. Then the named entity recognition BERT-BiLSTM-CRF model mentioned in Section 4.1.3 and Section 4.1.4 is reused and fine-tuned based on the new sample dataset. For data split, 60% of the labeled dataset is used for training, 20% of the labeled dataset is used for testing, with the rest for validating.

- **Image process module.** According to Section 4.2.1, in the task of filtering flood-related images on Sina Weibo, the number of images collected for each category (“flooding” and “normal”) is about 300, which are adopted as the sample dataset for the VGG16 model. 80% of the image dataset is used for training, with the rest for testing. In the water level classification task, the number of images collected for each water depth category (1.0~1.5 meters, 0.5~1.0 meters and 0.0~0.5 meters) is about 230, which is adopted as the sample dataset for the VGG16 model. 80% of the image dataset is used for training, with the rest for testing. Considering that the number of samples of each type is relatively average, the accuracy rate is adopted as the accuracy evaluation index for the extraction of the water depth in images. The accuracy rate is the most common evaluation indicator, calculated as the ratio of correctly classified samples to all samples. Generally speaking, the higher the accuracy rate, the better the classifier.

- **Results fusion.** After extracting the water depth information in social media texts and images by using two models respectively, the results are fused at the decision level (Chen et al., 2022; Xiong et al., 2023). For blogs posted at the same time and place, if both texts and images contain the water depth information and the estimation ranges are the same, the more fine-grained estimation extracted from the texts is accepted. Conversely, if the estimation ranges of water depth extracted from the text and image are different, we compute the median of the range for each source separately. The final estimated water depth is then determined by averaging the two computed medians.

4.3 Analyzing the spatio-temporal characteristics of Sina Weibo data during flood disasters

4.3.1 Kernel density estimation

Hotspots are caused by the geographic order or geographical location of high-value objects (Hazaymeh et al., 2022). Kernel density estimation is a common method in hotspot analysis (Han et al., 2023; Wang et al., 2010). In the paper, we use the kernel density estimation method to detect flooding hotspot areas in Sina Weibo, and further explore the correlation between the hotspots and daily-scale county-scale rainfall in spatial and temporal dimensions. The kernel density \( f(s) \) at the spatial location \( s \) was calculated by Eq. (3):

\[
f(s) = \sum_{i=1}^{n} \frac{1}{\tau^d} e^{-\frac{(s-s_i)^2}{2\tau^2}}
\]

(3)

where \( \kappa \) is the spatial weight function, i.e., the kernel function; \( (s-s_i) \) is the distance from the valuation point \( s \) to the event \( s_i \); \( \tau \) is the distance decay threshold (i.e., bandwidth), and \( n \) is the number of element points whose distance from location \( s \) is less than or equal to \( \tau \).

4.3.2 Geodetector analysis
Spatial stratified heterogeneity (SSH) is one of the fundamental characteristics of geographic phenomena and refers to the fact that the value of an attribute differs between different regions (Song et al., 2020). The q-value in the Geodetector is often used to measure the spatially stratified heterogeneity of the variable Y, as well as to detect how much of the spatial variation in Y could be explained by a given factor X (Wang and Xu, 2017). In this paper, we use Geodetector to analyze the spatial variability of flood depth and explore the explanatory effects of terrain and rainfall factors on it. The q-value is calculated by Eq. (4):

\[ q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma^2}{N \sigma^2} = 1 - \frac{SSW}{SST} \]  

(4)

where \( h \) represents the classification or partition of variable Y or factor X; \( N \) and \( N_h \) respectively represent the number of cells in the whole region and the number of cells with category \( h \); \( \sigma_h \) and \( \sigma \) represent the variance of the variable Y in stratum \( h \) and the entire region, respectively; \( SSW \) and \( SST \) represent the sum of variance within strata and the total variance of the entire region.

The range of the q-value is [0, 1]. If the stratification of the variable Y is generated by the independent variable X, the larger the q-value, the stronger the explanatory power of the independent variable X on attribute Y. The p-value corresponding to the q-value of each factor X (independent variable) in the Geodetector represents the significance of this factor.

5. Results

The validity of the framework is tested with an urban flood from July 15 to July 20, 2020, in Anhui, China. The operation time of this framework is approximately 18.06 seconds (every 100 Sina Weibo posts). In Section 5, We introduce four modules respectively: fine location extraction of flood area, multimodal water depth information extraction, analysis of urban flood in geographical space and social space, and flooding process awareness.

5.1 The fine-grained location of flooding areas

5.1.1 The Performance of the NER model

The performance of the address recognition NER model is evaluated by using three evaluation indicators: Precision, Recall and weighted F1-score. As shown in Table 5, the weighted F1-score of the test set is high, reaching 0.929, which indicates the effectiveness of the model in Chinese text NER (Wang, C. et al., 2021). Nonetheless, three prevalent types of addresses are prone to being misidentified:

1) Confusing administrative division levels. For example, “Chaohu” may refer to both “Chaohu City” and the lake “Chaohu”. In the recognition results of the model, “Chaohu” is mostly recognized as a city category.

2) The accuracy of spatial relationship feature recognition is not high. Due to the relatively small amount of spatial relationship element corpus collected in the training samples, there is a problem of incomplete recognition of directional elements. Sometimes, the “west side” in the “west side road near the entrance” cannot be correctly extracted.

3) Confusing numerical characters with distance relationship elements. The distance relationship elements in the context of flooding should be expressed as the distances along the line or point elements, but irrelevant numerical descriptions are often extracted in the model. For example, “20 meters” in “water pipe rupture causing water to spread outward for 20 meters” will also be recognized as a distance type.

Table 5 The performance of the NER model in address recognition

<table>
<thead>
<tr>
<th></th>
<th>Precision</th>
<th>Recall</th>
<th>Weighted F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test set</td>
<td>0.928</td>
<td>0.929</td>
<td>0.929</td>
</tr>
</tbody>
</table>

5.1.2 The distribution of flooding areas in Sina Weibo
Based on the BERT-BiLSTM-CRF model and the local lexicon, we identified 8972 address information from the flood-related blogs posted by the public during the flooding from July 15 to July 20, 2020 in Anhui Province. The same address information was not eliminated in this paper, as the public can observe the same location at different times.

As shown in Fig. 6, we geocoded and visualized the extracted address information on the map. It can be observed that the flood areas extracted from Sina Weibo were widely distributed. The result reflects the great advantage of social media as a social sensor, which supplements the areas that cannot be monitored by traditional flood detection methods.

Further, we analyzed the spatial scales of the address information as shown in Table 6. A large portion of the address information in Sina Weibo is accurate to the street, POI, road intersections and other scales, which makes it easier to identify the location of urban flood zones so that emergency managers can respond quickly and effectively.

### Table 6 Statistics of the scales of address information in Sina Weibo

<table>
<thead>
<tr>
<th>Address level</th>
<th>Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Province</td>
<td>27</td>
</tr>
<tr>
<td>City</td>
<td>1998</td>
</tr>
<tr>
<td>District</td>
<td>1329</td>
</tr>
<tr>
<td>Town</td>
<td>1443</td>
</tr>
<tr>
<td>Community</td>
<td>473</td>
</tr>
<tr>
<td>Village group</td>
<td>2</td>
</tr>
<tr>
<td>Road</td>
<td>754</td>
</tr>
<tr>
<td>Road intersection</td>
<td>927</td>
</tr>
<tr>
<td>House number</td>
<td>2</td>
</tr>
<tr>
<td>POI</td>
<td>2017</td>
</tr>
</tbody>
</table>

5.2 Water depth information in the flooding zones

5.2.1 Water depth information in texts

The direct and analogous descriptions of the water depth information were considered as entities in this paper. The performance of the NER model was evaluated by using three evaluation indicators: Precision, Recall and weighted F1-score. As shown in Table 7, the F1-score of the test set reached about 0.902, indicating the effectiveness of the model in extracting water depth descriptions from texts.

### Table 7 The performance of the NER model in the extraction of water depth description
A total of 422 Sina Weibo posts with water depth information were finally extracted from the texts, then we use the principle of proximity (Xu et al., 2022) to match the structured addresses obtained in Section 5.1.2 and water level entities. Some of the results are shown in Table 8.

Table 8 Example of water depth information in Weibo texts

<table>
<thead>
<tr>
<th>Post time</th>
<th>Address</th>
<th>Water depth description</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020/07/18 07:07</td>
<td>合肥市蜀山区安徽医科大学 (Anhui Medical University, Shushan District, Hefei)</td>
<td>(The water is already up to the knee)</td>
</tr>
<tr>
<td>2020/07/19 23:31</td>
<td>(Intersection of Ningxi Road and Hanghu Road, Feixi County, Hefei City)</td>
<td>水深达40厘米 (Water depth up to 40 cm)</td>
</tr>
<tr>
<td>2020/07/18 23:01</td>
<td>(Intersection of Yungu Road and Penglai Road, Feixi County, Hefei City)</td>
<td>积水超过胸口 (Accumulated water over the chest)</td>
</tr>
<tr>
<td>2020/07/19 07:57</td>
<td>合肥市巢湖市凤凰山路 (Fenghuang Mountain Road, Chaohu City, Hefei)</td>
<td>路面积水10公分 (10 cm of water on the road)</td>
</tr>
<tr>
<td>2020/07/19 12:41</td>
<td>(In front of Minsheng Building on Huining Road)</td>
<td>积水深度10厘米 (Ponded water depth 10 cm)</td>
</tr>
<tr>
<td>2020/07/19 15:42</td>
<td>合肥市庐江县文昌路 (Wenchang Road, Lujiang County, Hefei City)</td>
<td>淹到肚 (Flooding to the belly)</td>
</tr>
<tr>
<td>2020/07/19 17:27</td>
<td>(Intersection of Hongfeng Road and West Second Ring Road, Shushan District, Hefei)</td>
<td>大水漫过膝盖 (Water over the knee)</td>
</tr>
<tr>
<td>2020/07/20 20:15</td>
<td>(Xizang Road I High School, Baohe District, Hefei)</td>
<td>积水没过了学生的小腿 (The water was up to the student's calves)</td>
</tr>
<tr>
<td>2020/07/18 14:40</td>
<td>合肥市瑶海区造纸厂小区 (Hefei Yaohai District Paper Mill District)</td>
<td>积水最深处已没过大腿 (The deepest part of the water has reached the thigh)</td>
</tr>
<tr>
<td>2020/07/18 17:51</td>
<td>(Jinxin International Park, Jinzhai County, Lu’an City)</td>
<td>积水已淹过消防员的脖子位 (Accumulated water has flooded over the firefighters’ neck level)</td>
</tr>
<tr>
<td>2020/07/18 18:16</td>
<td>合肥市蜀山区安粮城市广场 (Anrong City Plaza, Shushan District, Hefei)</td>
<td>积水已退 (The stagnant water has receded)</td>
</tr>
</tbody>
</table>

For direct descriptions, the numbers in the entities were matched directly; for analogous descriptions, the body part descriptions in the entities were extracted first. Then the water depth was automatically estimated according to the mapping strategy between body parts and water levels mentioned in section 4.2.1. The mapping results of water depth description information within the texts are shown in Table 9.

Table 9 Example of mapping results of water depth information within the texts

<table>
<thead>
<tr>
<th>Water depth description (translate)</th>
<th>Keyword matching</th>
<th>Water depth mapping (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>The water is already up to the knee</td>
<td>knee</td>
<td>0.43</td>
</tr>
<tr>
<td>Water depth up to 40 cm</td>
<td>40 cm</td>
<td>0.40</td>
</tr>
<tr>
<td>Accumulated water over the chest</td>
<td>chest</td>
<td>0.13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test set</th>
<th>Precision</th>
<th>Recall</th>
<th>Weighted F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.909</td>
<td>0.895</td>
<td>0.902</td>
</tr>
</tbody>
</table>
5 cm of stagnant water 5 cm 0.05
10 cm of water on the road 10 cm 0.10
Ponded water depth 10 cm 10 cm 0.10
Flooding to the belly belly 1.06
Water over the knee knee 0.43
The water was up to the student's calves calves 0.21
The deepest part of the water has reached the thigh thigh 0.85
Water has flooded over the firefighters' neck level neck 1.49
The stagnant water has receded receded 0.00

5.2.2 Water depth information in images

The classification prediction result of VGG16 model includes the prediction probability of each output category of the image. If there are multiple car mask images in the image, the average value of the category probability of these car mask images is calculated, and the category with the largest probability is considered as the output result. Similarly, if the Sina Weibo post contains multiple images classified as flood-related, the average value of the category probability of these images is calculated, and the category with the highest probability is considered as the predicted output category for the Sina Weibo post. Then a total of 517 Sina Weibo posts with water depth information were finally extracted from the images. In addition, the original flood-related images were classified into “extremeFlood”, “mediumFlood” and “smallFlood” based on the VGG16 model as a comparison experiment to evaluate the effect of the method in this paper. The two methods were compared according to the accuracy indicator of the test set, as shown in Table 10. The results suggest that the accuracy of our method is significantly improved.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Category</th>
<th>Test result</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy of each category</td>
<td>Overall accuracy rate</td>
</tr>
<tr>
<td>Original image classification based on the VGG16 model</td>
<td>extremeFlood 0.80</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>mediumFlood 0.35</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>smallFlood 0.45</td>
<td>0.86</td>
</tr>
<tr>
<td>Our method</td>
<td>extremeFlood 0.80</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>mediumFlood 0.80</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td>smallFlood 0.86</td>
<td>0.86</td>
</tr>
</tbody>
</table>

5.2.3 Fusion of water depth information from multiple sources of data

By integrating water depth information extracted from Sina Weibo texts and images, only 31 blogs containing both kinds of data were found, which illustrates the necessity of using two models to process text and image data separately. The blogs with extracted water depth information were geocoded and visualized on a map, as in Fig. 7, where the red points represent the distribution of text data containing water depth information and the green points represent the distribution of image data containing water depth information. The distribution of flood locations from texts and images containing water depth information are different. The combination of these two parts of data provides richer information about urban flooding, highlighting the value of multimodal integration of social media. Moreover, compared to the spatial distribution of meteorological stations, the fusion of the two types of data is more sensitive to geographic events and facilitates urban flooding situational awareness, which enhances the efficiency of information utilization.
5. The spatio-temporal characteristics of Sina Weibo data

5.3.1 The relationship between Sina Weibo activity and precipitation

A heavy rainfall occurred from July 18 to July 19, 2020 in Anhui province. In the paper, the data of flooding areas extracted from Sina Weibo were aggregated and counted at the county level, and the correlation between Sina Weibo counts and precipitation at county and daily scales was examined based on Pearson correlation coefficients. As shown in Table 11, on July 18 and July 19, the correlation coefficients between Weibo counts and rainfall were 0.471 and 0.482 respectively, and the Sig values (significance test results) were both less than 0.001. The results indicated a highly significant moderate positive correlation between social media activity and precipitation at county and daily scales, which confirmed the reliability of the Sina Weibo data to some extent.

<table>
<thead>
<tr>
<th>Pearson correlation coefficient</th>
<th>Weibo activity</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Precipitation</td>
<td></td>
</tr>
<tr>
<td>0.471**</td>
<td>July 18, 2020</td>
<td></td>
</tr>
<tr>
<td>0.482**</td>
<td>July 19, 2020</td>
<td></td>
</tr>
</tbody>
</table>

Note: ** indicates significant correlation at the 0.01 level (bilateral); * indicates significant correlation at the 0.05 level (bilateral).

5.3.2 Spatially stratified heterogeneity of the water level in flooding zones

Spatially stratified heterogeneity is one of the fundamental characteristics of geographic phenomena. Geodetector is a useful tool to detect spatially stratified heterogeneity and reveal the driving factors. Based on the water depth information, rainfall, and elevation data at the flooding areas on July 19, 2020, we used the factor detection module in Geodetector to analyze the effects of rainfall and elevation on the severity of flooding. As shown in Table 12. The results illustrate that the rainfall factor and the elevation factor respectively explain about 28.0% and 35.2% of the spatially stratified heterogeneity of water depth. The spatially stratified heterogeneity of the severity of flooding is significantly influenced by elevation and rainfall.
Table 12 Results of Spatially stratified heterogeneity detection

<table>
<thead>
<tr>
<th></th>
<th>Rainfall factor</th>
<th>Elevation factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>q-value</td>
<td>0.280**</td>
<td>0.352**</td>
</tr>
</tbody>
</table>

Note: ** indicates significant correlation at the 0.01 level (bilateral); * indicates significant correlation at the 0.05 level (bilateral).

5.3.3 Spatio-temporal variability of flooding hotspot areas in Sina Weibo

In this paper, the Jenks natural breaks classification method (Stefanidis and Stathis, 2013) was used to classify the county-scale rainfall into five classes, and the kernel density estimation method was used to detect flooding hotspot areas in Sina Weibo based on the locations of waterlogging.

![Fig. 8](image1.png)

We analyzed the rainfall data from July 15 to July 20, 2020 with the flooding hotspot data in Sina Weibo, as shown in Fig. 8. The distribution of flooding hotspot areas in Sina Weibo and rainfall shows significant spatial and temporal consistency. The detected flooding hotspot areas in Sina Weibo were concentrated in places with higher rainfall, and the changes in the spatial distribution of the two are synchronous on a daily scale. Specifically speaking, from July 15 to July 20, the flooding hotspot areas in Sina Weibo moved with the change of rainfall center. From July 15 to July 17, the rainfall center shifted from the south-central region of Anhui...
Province to the north and east, and the hotspot areas in Weibo also moved to the north and east; from July 17 to July 19, the rainfall center shifted to the west-central region of Anhui Province, and the hotspot areas in Sina Weibo were obviously distributed in the west-central region of Anhui Province; from July 19 to July 20, the rainfall center shifted from central and western to the southeast of Anhui Province, and the hotspot areas in Sina Weibo also moved significantly to the southeast. In addition, there were flooding hotspots in areas with relatively low rainfall (e.g. in the lower part of Fig. 8(c) and upper part of Fig. 8(f)), the accumulated water in flooding areas, due to the accumulated water in flooding areas that had not subsided or the time lag of social media discussions (Li, Z. et al., 2018; Shoyama, Kikuko et al., 2021).

In general, the distribution of flooding areas in Sina Weibo and the spatio-temporal variation of flooding hotspot areas in Sina Weibo were closely consistent with the spatio-temporal distribution of rainfall at county and daily scales.

5.3.4 Flooding process awareness

Social media data was used to extract fine-grained water level information in the flooding zones. During urban flooding, the public perceives the changes in their communities from the first perspective, and at different moments, the public may observe the same area and post the current disaster situation of the area on social media platforms promptly. As shown in Table 13, we unearthed the public’s descriptions about water depth of the same flooded areas at different moments, such as in Jinzhai County, Lu’an City, where we learned that on July 19, 2020, the water depth of this spot was from waist to chest to knee level and eventually receded, revealing the whole process from severe damage to recovery in the spot. While on the North First Ring Road in Luyang District of Hefei City, the extent of flooding was getting worse.

<table>
<thead>
<tr>
<th>Time</th>
<th>Water level</th>
<th>Address</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020/07/19 10:20</td>
<td>淹水到腰 (Flooding to the waist)</td>
<td>六安市金寨县</td>
</tr>
<tr>
<td>2020/07/19 17:48</td>
<td>洪水齐胸 (Flood water at chest level)</td>
<td>(Jinzhai County, Lu’an City)</td>
</tr>
<tr>
<td>2020/07/19 19:34</td>
<td>淹到膝盖 (Flooding to the knees)</td>
<td></td>
</tr>
<tr>
<td>2020/07/19 22:01</td>
<td>已无积水 (No longer waterlogged)</td>
<td></td>
</tr>
<tr>
<td>2020/07/18 23:01</td>
<td>积水超过胸口 (Accumulated water over the chest)</td>
<td>云谷路与蓬莱路交叉口</td>
</tr>
<tr>
<td>2020/07/20 18:41</td>
<td>积水最深两米 (The deepest water is two meters)</td>
<td>(Intersection of Yungu and Penglai Road)</td>
</tr>
<tr>
<td>2020/07/19 21:18</td>
<td>水位十公分 (The water level is ten centimeters)</td>
<td>庐阳区北一环路</td>
</tr>
<tr>
<td>2020/07/19 23:18</td>
<td>水位齐膝 (Water level at knee level)</td>
<td>(North First Ring Road, Luyang District)</td>
</tr>
<tr>
<td>2020/07/20 08:28</td>
<td>积水过膝 (Accumulated water over the waist)</td>
<td></td>
</tr>
<tr>
<td>2020/07/19 10:18</td>
<td>漫过车身 (Diffuse over the body)</td>
<td>庐阳区北一环与肥西路交口</td>
</tr>
<tr>
<td>2020/07/20 16:14</td>
<td>积水已退 (The stagnant water has receded)</td>
<td>(Intersection of North First Ring Road and Feixi Road, Luyang District)</td>
</tr>
<tr>
<td>2020/07/15 06:00</td>
<td>齐膝水 (Knee-water)</td>
<td>马鞍山市雨山区石矶风景区采石矶-三元洞</td>
</tr>
<tr>
<td>2020/07/15 03:28</td>
<td>齐膝水 (Knee-water)</td>
<td>(Caishiji-Sanyuan Cave, Shiji Scenic Area, Yushan District, Maanshan City)</td>
</tr>
<tr>
<td>2020/07/17 15:39</td>
<td>积水最深两米 (The deepest water of two meters)</td>
<td></td>
</tr>
</tbody>
</table>

6. Discussion

6.1. significance and contributions

Social media has provided new approaches to the acquisition of time-sensitive information (Yao and Wang, 2020). Due to the challenges of inaccurate location extraction and incomplete water depth information retrieval, the application of social media faces enormous obstacles (Roy et al., 2021). Compared with existing research,
the framework proposed in this paper fully utilizes multimodal data, extracts detailed disaster information, and reveals the spatiotemporal correlation of geographic events in real and social spaces. This framework can achieve large-scale flood monitoring, emergency rescue positioning, and disaster assessment.

Social media is now often considered as one of the crucial data sources for emergency response. When a disaster occurs, people in the affected areas share critical information on social media platforms (Shoyama, K. et al., 2021). However, most studies extract flood location information only at a large spatial scale, which may hinder emergency response operations (Njue et al., 2019). In this paper, the multi-spatial resolution corpus for Chinese text can achieve fine-grained location extraction such as roads, intersections, and POIs, which is helpful for flood control positioning. When the public posts tweets related to requests or assistance on social media platforms, the fine-grained locations help to quickly locate the affected people and provide assistance.

During urban flood disasters, water depth is one of valuable information for flood monitoring. Compared to most studies that used a single data source, the proposed method, based on multimodal data fusion, can effectively extract comprehensive water depth information from social media, offering a way for widespread disaster monitoring. These help traffic management make timely judgments about road accessibility.

The correlation between geographical events in cyberspace and real space has always been a concern (Qian et al., 2022). Previous studies focused on social media response analysis of a single time series. In this paper, we analyze the spatio-temporal evolution of urban flooding in social space and geographical space, and reveal the spatio-temporal correlation between them, offering essential insights for evaluating the quality of geographic event perception derived from social media data. Moreover, we analyze the interpretability of geographical elements. Further, the time of Sina Weibo posting can be accurate to the minute, and the integration of water depth observations at different moments can reveal the flooding process, which means that it is possible to observe the process of flood accumulation and receding in disaster areas at the minute level through the analysis of real-time social media stream data.

6.2. Limitations and future research

However, from the perspective of urban flood perception based on social media, the method proposed in this paper has some limitations. Firstly, Sina Weibo data was retrieved and filtered based on the expanded keywords and reverse keywords. However, due to the complexity of Chinese texts, we can not cover all the relevant blogs, and some blogs that have nothing to do with urban floods might not be removed. Secondly, in the address recognition model, although spatial relationships of geographic entities such as “500 meters of roads” were extracted, it is still difficult to accurately locate addresses containing spatial relationships in geocoding through Gaode API. Thirdly, in the process of creating the text training datasets, named entities were manually annotated. In the future, it is expected to construct an automatic annotation method to reduce labor costs. Fourthly, the water level is estimated by taking 1.70 m as the average human height, ignoring the differences in height between individuals, especially children and adults. Finally, regarding the water level estimation in flood-related images, the current method also has some defects: 1) The correlation between waterlogging location and water depth. 2) Single reference object. 3) Rough water depth mapping strategy for images (Feng et al., 2020).

The integration of traditional monitoring data and social media data can effectively compensate for the shortcomings of existing monitoring methods, improve the spatio-temporal resolution of disaster information and widen the scope of monitoring. However, this domain confronts numerous challenges, such as uneven data information quality, complex and diverse data structures, and discrepancies in spatiotemporal references. We believe that multi-source data assimilation (Xing et al., 2023), point-surface data fusion (Liu et al., 2023), and disaster knowledge graph construction (Zhang et al., 2022) may be effective approaches and future research priorities.

7. Conclusion
Social media data have been widely used as a powerful supplementary data source for situational awareness during disasters. Therefore, a novel framework was proposed to extract fine-grained location and water level information and perceive the spatio-temporal variation in disaster-stricken areas based on the Chinese social media platform, Sina Weibo. The validity of the framework was tested with an urban flood from July 15 to July 20, 2020, in Anhui, China.

Several important results were found. First, social media provide a feasible way to obtain real-time information in disaster-stricken areas. The location information could be refined to the address-level of neighborhoods, roads and intersections, and the water depth information could describe the specific water depth at flooding areas. Second, from the perspective of time and space, the moving of flooding hotspots in Sina Weibo showed significant consistency with the change of rainfall centers at county and daily scales. Third, the observed information about water depth at the same location in Sina Weibo helps to reveal the specific process of flood accumulation and receding at the area. Fourth, in the example of flooding in Anhui, both rainfall and topographic factors were correlated with the severity of flooding, with the rainfall factor and elevation factor respectively explaining about 28.0% and 35.2% of the spatially stratified heterogeneity of water depth at flooding areas.

Regarding future work, we will focus on two aspects. First, during the flooding period, the public also uploaded many videos related to the affected areas on social media. Videos as another important data could also be used to extract relevant information. Second, multi-source data integration, specifically the combination of social media data with other data sources such as road sensor data and remote sensing images, enables a more comprehensive understanding of urban flood events.

Appendix A
A.1 A few typical samples to reveal the annotation of addresses

<table>
<thead>
<tr>
<th>Source of samples</th>
<th>Original text</th>
<th>Text after annotation</th>
</tr>
</thead>
<tbody>
<tr>
<td>From first data source</td>
<td>环城路与东城路接壤处 (Intersection of Huancheng Road and Dongcheng Road)</td>
<td>B-road I-road E-road O B-road I-road I-road E-road B-intersection I-intersection E-intersection</td>
</tr>
<tr>
<td>From second data source</td>
<td>安徽省阜阳市阜南县 (Funan County, Fuyang City, Anhui Province)</td>
<td>B-prov I-prov E-prov B-city I-city E-city B-district I-district E-district</td>
</tr>
<tr>
<td>From third data source</td>
<td>笔者下午四时行至中山路与新兴街交界开始出现积水 (At about 4:00 p.m., the author walked to the intersection of Zhongshan Road and Xinxing street, and then there began to be ponding)</td>
<td>O O O O O O O B-road I-road E-road O B-road I-road E-road B-intersection I-intersection E-intersection</td>
</tr>
</tbody>
</table>

A.2 The description patterns of intersections

<table>
<thead>
<tr>
<th>The description pattern of intersection</th>
<th>Text after annotation</th>
</tr>
</thead>
<tbody>
<tr>
<td>中环路和花园路交叉口 (Intersection of Zhonghuan Road and Huayuan Road)</td>
<td>B-road I-road E-road O B-road I-road E-road B-intersection I-intersection E-intersection</td>
</tr>
</tbody>
</table>
CRediT authorship contribution statement

Zhiyu Yan: Conceptualization, Methodology, Software, Writing - original draft.
Xiaogang Guo: Conceptualization, Data curation, Writing - Review & Editing.
Ziling Zhao: Formal analysis, Visualization, Writing - Review & Editing.
Luliang Tang: Conceptualization, Writing - Review & Editing, Funding acquisition.

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Conflict of interest statement

The manuscript entitled “Achieving fine-grained urban flood perception and spatio-temporal evolution analysis based on social media” has not been published before and is not being considered for publication elsewhere. All authors have contributed to the creation of this manuscript for important intellectual content and read and approved the final manuscript. There are no conflicts of interest to declare.