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Extracting Disaster-Related Location Information through Social Media to Assist Remote Sensing for Disaster Analysis: The Case of the Flood Disaster in the Yangtze River Basin in China in 2020

Tengfei Yang [1], Jibo Xie [1,*], Guoqing Li [1], Lianchong Zhang [1], Naixia Mou [2], Huan Wang [1,2], Xiaohan Zhang [1,2] and Xiaodong Wang [3]

1 Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing 100094, China; yangtf@radi.ac.cn (T.Y.); ligq@aircas.ac.cn (G.L.); zhanglc@aircas.ac.cn (L.Z.); wanghuan9703@163.com (H.W.); zhangxiaohan156@gmail.com (X.Z.)
2 College of Geomatics, Shandong University of Science and Technology, Qingdao 266590, China; mounx@lreis.ac.cn
3 School of Mathematics and Statistics, Henan University of Science and Technology, Luoyang 471000, China; 9906208@haust.edu.cn
* Correspondence: xiejb@radi.ac.cn

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Abstract: Social media texts spontaneously produced and uploaded by the public contain a wealth of disaster information. As a supplementary data source for remote sensing, they have played an important role in disaster reduction and emergency response in recent years. However, social media also has certain flaws, such as insufficient location information, etc. This affects the efficiency of combining these data with remote sensing data. For flood disasters in particular, extensively flooded areas limit the distribution of social media data, which makes it difficult for these data to function as they should. In this paper, we propose a disaster reduction framework to solve these problems. We first used an approach that was based on search engine and lexical rules to automatically extract disaster-related location information from social media texts. Then, we combined the extracted information with the upload location of social media itself to construct location-pointing relationships. These relationships were used to build a new social network, which can be used in combination with remote sensing images for disaster analysis. The analysis integrated the advantages of social media and remote sensing. It can not only provide macro disaster information in the study area but can also assist in evaluating the disaster situation in different flooded areas from the perspective of public observation. In addition, the timeliness of social media data also improved the continuity and situational awareness of flood monitoring. A case study of the flood disaster in the Yangtze River Basin in China in 2020 was used to verify the effectiveness of the method described in this paper.

Keywords: social media; remote sensing; information mining; flood disaster; disaster reduction

1. Introduction

With the intensification of global climate change, meteorological disasters such as heavy rains and floods frequently occur [1,2]. This has caused a large number of casualties and property losses, which seriously affect the sustainable development of society [3]. Due to the development of science and technology, Earth observation methods represented by remote sensing have played an important role in disaster reduction [4,5]. They provide detailed snapshots of conditions that cover a wide range of disaster areas, which are convenient for disaster assessment and auxiliary rescue [6]. However, remote sensing also has some limitations. The revisit period of satellites is long, which makes it difficult to continuously monitor disaster-stricken areas [7]. Conversely, remote sensing is used more to describe the macro situation in the disaster-stricken area, such as the scope of the flooded area. It is difficult to learn the specific situation in these areas, and it is also difficult to assess which areas are most affected by a disaster. With the popularity of the internet and smart mobile devices [8], social media, as a kind of crowd-sourced data, has brought new opportunities for disaster reduction. Compared with traditional remote sensing, social media data from the public have the advantages of high timeliness and rich disaster information and can be used as an effective supplementary data source for remote sensing.

Social media has rich attribute features (e.g., space, time, content, and network), which have been well applied to disaster reduction [9]. Combining these attribute features with remote sensing data can effectively improve the effect of disaster reduction [10]. Many scholars have carried out research on this. For example, Denis et al. [11] developed a comprehensive system integrating remote sensing and social media data for decision making and rapid information dissemination. The system can help guide and evacuate people at risk in disasters in a timely manner. Qunying Huang et al. [12] proposed a framework that integrates multi-source data (e.g., social media, remote sensing, etc.) to help in the disaster analysis of historical and future events. Jun Li et al. [13] systematically discussed the key technologies used for integrating content and spatial information contained in social media with remote sensing data and showed the application effects of multi-source data integration in different fields with different examples. For the flood disaster mentioned in this paper, the fusion of multi-source data also showed great application potential. By introducing the spatiotemporal information contained on social media, the efficiency of flood inundation mapping can be improved [14–17]. The combination of location-marked pictures and remote sensing data can better judge the traffic conditions of urban roads under floods [18]. In [19], real-time data collected from social media were fused with remote sensing data for transportation damage assessment. Related studies have mostly relied on the tags of upload location on social media, which was also the basis for combining social media with remote sensing images. However, due to user habits (most users do not want to upload their location information to social media platforms), most social media data does not contain location tags [20]. Moreover, some disasters, especially floods, limit the spatial distribution of social media data (it is hard for people to upload social media in heavily flooded areas), which makes it difficult for us to keep abreast of detailed disaster information in hard-hit areas. This information is particularly important for disaster reduction. In this paper, we propose a framework that aims to improve the efficiency of combining social media data with remote sensing data in order to mine more disaster information from disaster-affected areas. We wanted to compensate for the insufficient location information of these data by extracting location information involving flooded areas from social media texts. On this basis, we constructed a new social network based on the relationship between different location information (uploading location information from social media and location information contained in text) in social media data to explore how to use multi-source data to assess and monitor disasters in severely affected areas.

1.1. Rapid Extraction of Disaster-Related Location Information Contained in Social Media Data

There are some studies [21,22] that have found that social media text contained a large number of locational words, which can effectively make up for the insufficient location information of the data. When an area was flooded, it usually attracted the attention of many people in the surrounding areas (these areas might not have been affected or might have been less affected by the flood), and these people would upload social media texts containing the location of the flooded area. We can then understand the disaster situation in the flooded area through this data. In addition, if an area was mentioned by more people, it might also mean that the area was more severely affected by disaster. There are three kinds of methods for extracting words with spatial attributes from Chinese texts, including dictionary-based [23,24], rule-based [25,26] and machine learning methods [27,28] (as well as deep learning [29]). These methods have their own advantages but all require certain labor costs. For example, the dictionary-based method is the most convenient, but the maintenance and update costs of dictionaries are high; the rule-based method has high accuracy, but it is difficult to apply to different scenarios, and the formulation of rules requires the participation of expert knowledge; machine learning methods have good flexibility, but the model requires a large amount of annotated corpus. Fortunately, there are some natural language processing tools available that integrate some existing methods to help identify locational words in text, such as "Stanford NLP (https://nlp.stanford.edu/ accessed on 15 January 2022)", "NLPIR (http://ictclas.nlpir.org/ accessed on 15 January 2022)" and "Hanlp (https://www.hanlp.com/, accessed on 15 January 2022)", etc. This saves a lot of labor for our work. However, through experiments, we found that some words were not well recognized, and they were often fragmented due to incorrect word segmentation. For example, the locational word "同马大堤 (Tongma Dyke)" was wrongly divided into "同 (Tong)", "马 (Ma)", "大堤 (Dyke)". Therefore, we used a method that combined the Internet search engines and Chinese lexical rules to effectively recall those locational words, which were not correctly recognized by natural language processing tools. It improved the recognition efficiency of locational words in social media texts and satisfied the requirements of subsequent experiments.

1.2. Flood Disaster Assessment and Monitoring Combined with Multi-Source Data

We dealt with remote sensing and social media data separately. For remote sensing data, we obtained SAR images related to the study area before and after the disaster, and mapped the flooded areas based on these data. For social media, based on the different location information of social media (uploaded location information of social media and location information contained in the text), we constructed a new social network that can describe pointing relationships between spatial locations. These relationships can reflect the distribution of victims and their attention. Then, the social network and processed remote sensing images were comprehensively considered to mine disaster information. These multi-source data can not only provide the macro disaster situation in a study area but can also assess the disaster in different areas through public concern. Conversely, we used the continuous theme change information of social media data to dynamically monitor the severely flooded area, which effectively provided situational awareness to emergency responders, as well as assistance to disaster reduction. The flood disaster in the Yangtze River Basin in China in 2020 was used as a case study to verify the effectiveness of the method in this paper.

2. Study Area and Data

2.1. Study Area

Every year from mid-June, the Yangtze River Basin in China enters the "Meiyu" period, and there is continuous rainfall in this area. In 2020, the accumulated rainfall and duration days in the area exceeded the level in the same period over the years. In the southern Anhui Province in particular, due to the continuous torrential rain, many estuaries reached the upper limit of water volume on July 21, resulting in serious floods. In this paper, we took the central and southern regions of the Anhui Province as the study area, and the relevant scope is shown in Figure 1.

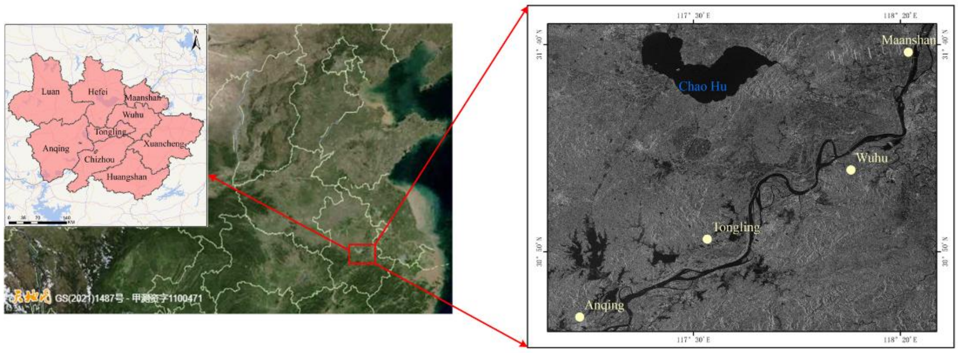
2.2. Data Collection

We collected multi-source data related to the disaster, including remote sensing data and social media data.

2.2.1. Remote Sensing Data

Unlike optical systems, SAR is an active sensor that utilizes microwaves, which can penetrate clouds and generate ground information regardless of atmospheric conditions [30]. Therefore, the "Sentinel-1" SAR was selected in this paper. We obtained the post-flood (on 27 July) images from the website "USGS" (https://earthexplorer.usgs.gov/

accessed on 15 January 2022). The study area is shown in Figure 1b. We also obtained pre-flood images (on 10 April) for the same area from this website.



(a) The cities related to the study area

(b) The SAR remote sensing images related to the study area

Figure 1. The study area shown in this paper. Among them, (**a**) depicts the cities involved in the study area; (**b**) shows the SAR remote sensing image covering the study area.

2.2.2. Social Media Data

The social media data used in this paper came from Sina microblog, which is the largest social media platform in China. We developed a crawler tool based on the advanced search platform of Sina microblog, which can obtain data related to this disaster in a specified area and a specified time period by setting search conditions. Through web page parsing, these data are stored in the database in a structured form, including fields such as time, location tags and content, etc. After de-duplication, the corresponding data totaled 10,839. The relevant data involved nine cities, including Hefei, Liuan, Ma'anshan, Wuhu, Tongling, Anqing, Chizhou, Xuancheng and Huangshan, as shown in Figure 1a. The time span of the data is from 21 to 30 July.

3. Methods

In this paper, we proposed a framework that integrated algorithms, including natural language processing, network analysis, etc., to extract locational words from social media texts and construct a new social network based on different kinds of locational information on social media. Then, we combined the network with processed remote sensing data to serve as disaster reduction. The structure of the proposed framework is shown in Figure 2.

3.1. Location Information Extraction Based on Social Media Text

Existing natural language processing tools have a certain ability to identify locational words contained in text. However, due to the limitation of Chinese word segmentation accuracy, some locational words are often destroyed such that they cannot be recognized by tools. In this paper, we introduce a method based on Chinese lexical rules and search engine knowledge discovery to recall the locational word form fragmented words. The method flow is shown in Figure 3.

3.1.1. Text Processing

We used the commonly used Chinese natural language processing tool "HanLP" to process social media text. The main processing flow included word segmentation, which is part of speech tagging and stop word removal. Among them, stopping word removal means discarding those words that have no practical meaning in the text, such as "的 (of)", "是 (is)" and so on. They contributed little to the semantics and affected the efficiency of the subsequent processing of the text.

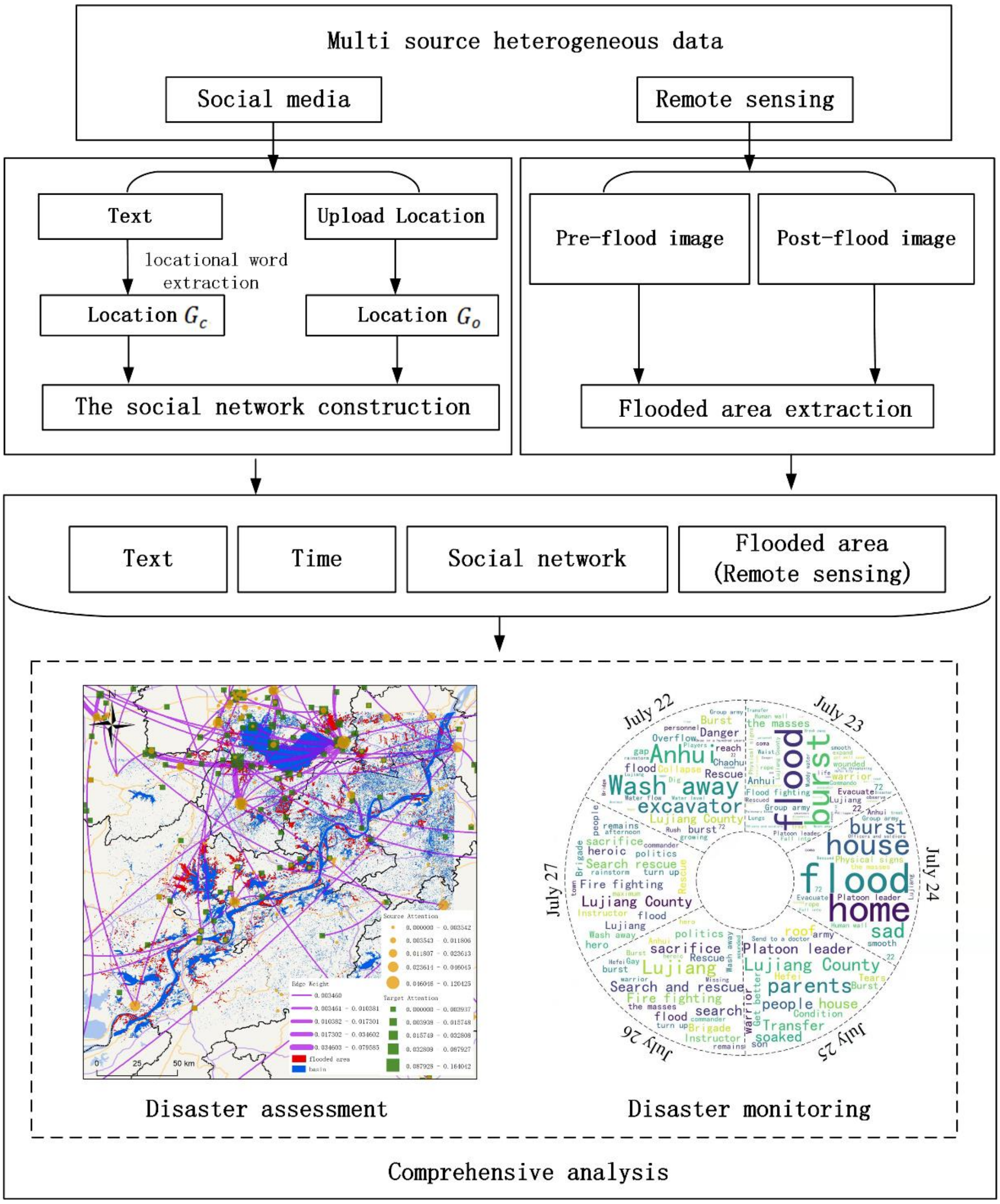


Figure 2. The structure of the proposed framework in this paper.

3.1.2. Part of Speech Selection and Word Set Construction

After word segmentation and part of speech tagging, we obtained those words with location tags. These tags were provided by the "HanLP" tool, such as "ns (place name label)", "nt (institution name label)", "ntcf (factory name label)", etc. Some common locational words were identified by filtering these tags. However, there were some potential words with spatial attributes that had not been correctly identified due to incorrect word segmentation. For example, after text processing, the sentence "暴雨使的附近同马大堤有崩溃的风险！ (the torrential rainstorm may break the nearby "Tongma dike"!)" can be converted into "(暴雨/n, 附近 /f, 同 /p, 马 /n, 大堤 /n, 有/vyou, 崩溃 /vg, 风险/n)". In the original text, "同马大堤 (Tongma dike)" was a locational word, which showed the area where the disaster occurred. However, it was broken into three words, including "同 (Tong)/p", "马 (Ma)/n" and "大堤 (Dyke)/n". We needed to restore these fragmented words correctly. In this paper, a suffix word vocabulary related to locational words was summarized based on the named entity library provided by "HanLP", such as "堤 (dyke)", " 路 (road)", etc. These suffix words can help us locate potential locational words in the fragmented words. When a word was matched successfully, we traced back from the position of the matched word. Each time an index position was traversed forward, the related words would be combined in order. For example, based on the processed sentence "(暴雨 /n, 附近/f, 同/p, 马 /n, 大堤 /n, 有 /vyou, 崩溃/vg, 风险/n)", we can match the word "大堤 (dyke)" and obtain the combined word set (大堤 (dyke), 马大堤 (ma dyke), 同马大堤 (tong ma dyke), 附近同马大堤 (near Tong ma dyke), and 暴雨附近同马大堤 (rainstorm near Tong ma dyke)) according to the rule. These combined words were regarded as potential locational words.

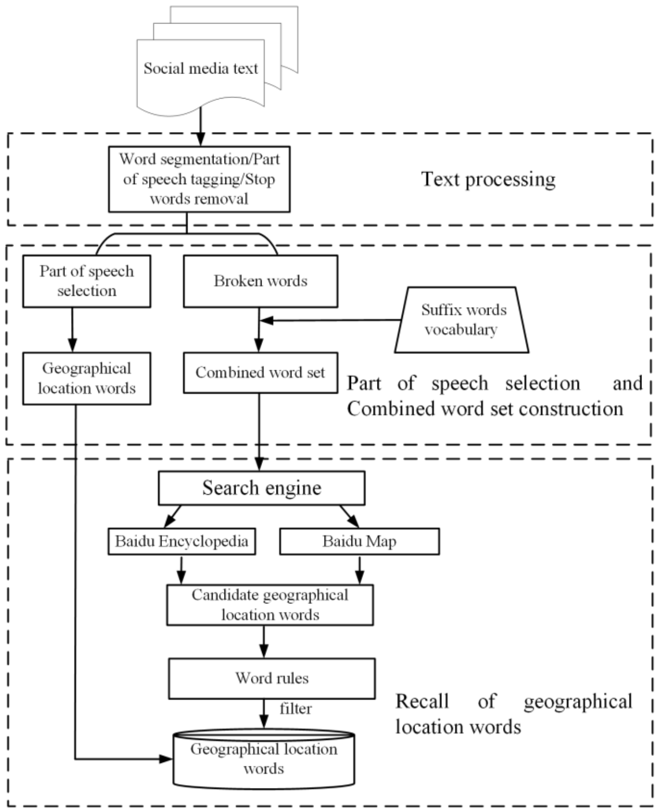


Figure 3. The process of extracting locational words in social media text.

3.1.3. Recalling the Locational Words

When using Internet search engines to retrieve words, we can obtain a lot of information related to them. This information will help us understand the attributes of these words, including judging whether the words have spatial attributes. This benefits from the explosive growth of information and even knowledge, and they are interconnected through the network. Due to using Chinese text, the Baidu search engine was selected in this paper. The related method was as follows.

(1) The construction of candidate locational word set

When the searched words have entity features, content such as Baidu Encyclopedia and Baidu Map may be fed back by the search engine. Baidu Encyclopedia and Baidu Map are two important applications that are closely related to the Baidu search engine. They have the ability to discover the attribute of the searched words, especially the spatial attribute. Then, we added those words with spatial attributes to the candidate locational word set.

- Spatial attribute judgment based on Baidu Encyclopedia

Similarly to Wikipedia, Baidu Encyclopedia is a Chinese information collection platform covering different fields of knowledge. As of October 2020, this platform contained more than 21 million entries [31]. When a word was included in Baidu Encyclopedia, and there were some attribute fields related to location information in the basic attribute list of the word, we considered that the word was a locational word. For example, by retrieving, we can obtain encyclopedic information (https://baike.baidu.com/item/%E4%B8%AD%E5%BA%99/24544? accessed on 15 January 2022) about the combined word "中庙寺 (Zhongmiao Temple)". The basic attribute list about it contained the " 地理位置 (location)" field, which proved that the word had spatial attributes. In addition, Baidu Encyclopedia provides a list of categories for different entities, and each category contains specific entity attribute fields (https://baike.baidu.com/editor/load/createload?lemmaTitle=baimasi, accessed on 15 January 2022). We obtained all of these entity categories and their attribute fields, and filtered out the attribute fields with spatial features, such as "地理位置 (location)", "发源地 (birthplace)", etc., to construct a spatial attribute list. When the attribute field in the basic attribute list of the searched word can match the attribute in the spatial attribute list, the word can be regarded as a candidate locational word.

- Spatial attribute judgment based on Baidu Map

Baidu Encyclopedia can confirm the spatial attribute of many commonly used words. However, the recognition effect of it on some ordinary POI (points of interest), such as a designated building or square, etc., and even some abbreviations of locational words were not positive. Therefore, Baidu Map, which is an electronic map that provides queries and positioning functions for geographical entities, was used to help identify the words with spatial attributes. When a word had spatial attributes, the retrieved results of the search engine would include the Baidu Map tag. For example, the word "石大圩 (Shi da wei)" was not included in Baidu Encyclopedia, but it was marked with a tag "百度地图 (Baidu Map)" when we retrieved it by search engine (https://www.baidu.com/s?wd=%E7%9F%B3%E5%A4%A7%E5%9C%A9, accessed on 15 January 2022).

(2) Recall of locational words

By using the search engine to link Baidu Encyclopedia and Baidu Map, we judged whether the combined word had spatial attributes. We proposed that there can only be, at most, one word in each combined word set as a recalled locational word. Some compound word sets also have multiple recognized locational words. For example, each word in the combined word sets "(石大圩 (shi da wei), 大圩 (da wei))" and "(大堤 (dyke), 同马大堤 (Tongma dyke))" had spatial attributes. We stated that the word with the longest byte was the final locational word, such as " 石大圩", "同马大堤 ", etc., because the word with a shorter byte may be a sub word of the word with a longer byte.

3.2. The Social Network Construction Based on Location Information

In this paper, we combined the locational words extracted from social media text and the tags of upload location of social media to construct the location-pointing relationship. The relationships can help us find the areas that were most concerned by people. These areas might be severely affected by disasters.

We removed the social media data that did not carry location tags and did not contain locational words in their texts. Then, we divided the other data into three categories, including:

- C_1: social media data themselves contained a location tag, but its text did not contain locational words.
- C_2: social media data themselves did not contain a location tag, but its text contained locational words.
- C_3: social media data themselves contained a location tag, and its text also contained locational words.

We used G_c to represent the locational words extracted from the text and G_o to represent the location tag of social media. The spatial scales of this location information were not the same. In this paper, the locations with large spatial scale, such as provinces and cities, were not considered.

We regarded the location information as nodes. Among them, $\boldsymbol{G_c}$ corresponded to the node $\boldsymbol{V_c}$, and $\boldsymbol{G_o}$ corresponded to the node $\boldsymbol{V_o}$. These nodes involved at least one piece of microblog, and the relationship between nodes was shown through these microblogs. We defined the location-pointing relationship between nodes pointed from $\boldsymbol{V_o}$ to $\boldsymbol{V_c}$. Based on the nodes and the relationship between nodes defined in this paper, we constructed a new social network. For example, there were three pieces of social media data, as shown in Table 1. The structure of the network can be described as shown in Figure 4. Among them, the circle represented $\boldsymbol{G_o}$ and the square represented $\boldsymbol{G_c}$. For the microblog $\boldsymbol{M_1}$, $\boldsymbol{G_o}$ was " 石头镇 (Shitou Town)" and $\boldsymbol{G_c}$ was "中庙寺 (Zhongmiao Temple)". It showed that the disaster in "中庙寺 (Zhongmiao Temple)" attracted the attention of the residents from " 石头镇 (Shitou Town)". The same was true of microblog $\boldsymbol{M_2}$. For microblog $\boldsymbol{M_3}$, it did not have $\boldsymbol{G_0}$, only $\boldsymbol{G_c}$. This meant that there was an implicit location-pointing relationship, pointing to $\boldsymbol{V_c}$ from an unknown node $\boldsymbol{V_o}$. This still indicated that the disaster in " 十字镇 (Shizi Town)" might be serious.

Table 1. Relationship between location information related to social media.

Microblog	Text	G_o	G_c
M_1	拥有700 多年历史的 **中庙寺** 被大水淹了。 (the **Zhongmiao Temple** with a history of more than 700 years was flooded by floods)	石头镇 (Shitou Town)	中庙寺 (Zhongmiao Temple)
M_2	据说 **同大镇**水淹严重。 (it is said that **Tongda Town** is seriously flooded)	石头镇 (Shitou Town)	同大镇 (Tongda Town)
M_3	**十字镇** 也受灾了。(**Shizi town** was also affected by the disaster)		十字镇 (Shizi Town)

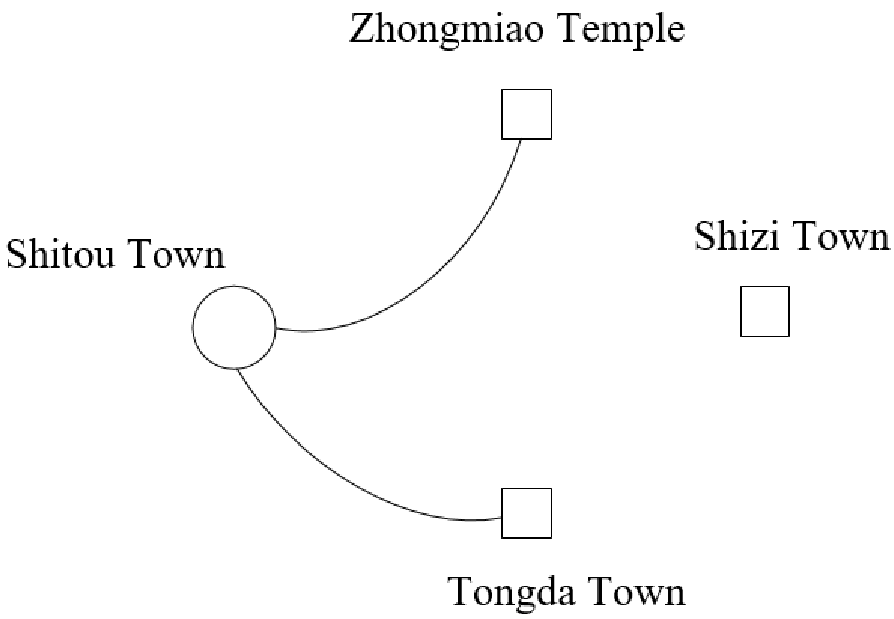


Figure 4. The structure of the reconstructed social network.

Furthermore, we set two indicators to quantify the network constructed in this paper, including node degree $\boldsymbol{D}$ and edge weight $\boldsymbol{W}$. The calculation formulas of related indicators are shown below:

$$\boldsymbol{D_o} = \frac{\boldsymbol{N_o}}{\boldsymbol{N}}$$

$$W_{oc} = \frac{N_{o\_c}}{N}$$

$$D_c = \sum_{i=0}^{N_e} W_{o_i c}$$

Among them, D_o was the node degree of V_o. It was related to the number of social media texts uploaded from node V_o, and we used N_o to represent the number of these social media texts. In addition, there were some data in these social media texts, which contained location information G_c. We used N_{o_c} to represent the number of such social media. The edge weight W_{oc} between nodes V_o and V_c was related to N_{o_c}. In order to better express indicators D_o and W_{oc}, we normalized them, and N was the number of all social media. D_c was the node degree of V_c. It was the sum of the edge weights of all edges (N_e) pointing to node V_c.

The larger the D_o, the more social media texts were uploaded in the area where V_o was located. The larger the D_c, the more people paid attention to the area where node V_c was located. Edge weight reflected the strength of the connection between two nodes. It showed the spatial distribution of people who paid attention to the disaster in the area where node V_c was located.

3.3. Flooded Area Extraction Based on Multi-Temporal Remote Sensing Images

There are two main commonly used strategies for extracting flooded areas based on remote sensing images [32], including directly classifying multi-temporal remote sensing images [15] and post-classification comparison (PCC) [33]. The former regards multi-temporal remote sensing images as a whole, and directly uses methods including machine learning, deep learning, etc., to extract a flooded area. The latter first identifies water bodies from multi-temporal remote sensing images, and then obtains the flooded area by comparing the differences between these processed images. In comparison, PCC is more intuitive and convenient. Therefore, PCC was selected to extract the flooded area. The flow is shown in Figure 5.

The Sentinel-1 GRD images involving the study area were used in this paper, including pre-flood images and post-flood images. These multi-temporal images were first preprocessed, and the process included co-registration, filtering and geocoding. In this paper, we used the pre-flood image as the main image for co-registration. "De Grandi spatio-temporal filtering" was selected to filter the noise of the images. The DEM data related to the study area from the Geospatial data cloud (http://www.gscloud.cn/#page1/2 accessed on 15 January 2022) was used to geocode the images, which facilitated spatial integration of remote sensing imagery with social media data. After the preprocessing operation, we performed an image mosaic on the images such that the images completely covered the study area.

There are many methods for extracting a water body from a remote sensing image, including classification [34,35], setting thresholds [18,36] and object-based image analysis [37,38], etc. In this paper, we selected the maximum likelihood method [39], which is a type of supervised classification and is one of the most commonly used methods. According to the Bayesian information criterion, this method assumes that the spectral characteristics of each object in the remote sensing image obey the orthonormal distribution. Then, the method evaluates the similarity between other pixels and the pixels in the training area by calculating the mean and variance of the pixels in the training area. The optimal parameters are obtained by learning and calculating the pixel features of the water body in the image by the classifier. Finally, the trained model can be directly used to calculate the category of specified pixels, so as to extract the water body in the image.

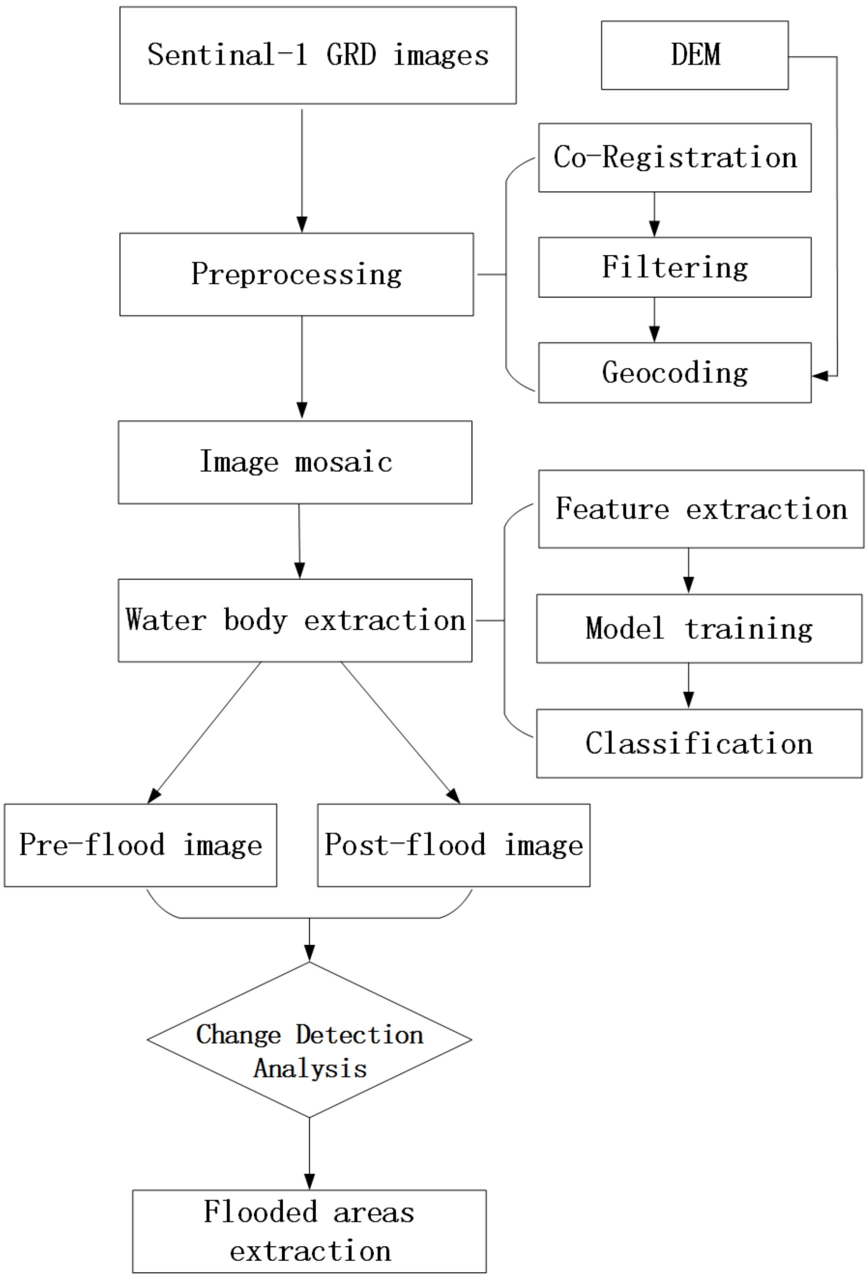


Figure 5. Process of flooded area extraction in this work using remotely sensed data.

Furthermore, we performed change detection on processed (water body extraction) pre- and post-disaster images. Among them, the pre-disaster image was used as the main image. We first kept only the water body part in the two images and then determined the area of change by taking the difference between the two images. Finally, based on the OSTU threshold segmentation method [40], we can extract the flooded area in the area of change.

3.4. Comprehensive Analysis

In order to combine social media data with remote sensing data, we need to convert the tags of upload location of social media and the extracted locational words into latitude and longitude coordinates. The API interface from AMAP (https://lbs.amap.com/api/javascript-api/guide/services/geocoder, accessed on 10 December 2021) was used in this paper to accomplish this purpose. Then, we performed a comprehensive analysis of the two types of data, which included disaster assessment and continuous disaster monitoring.

3.4.1. Disaster Assessment Combined with Multi-Source Data

We regarded the processed remote sensing images and the constructed social network as different spatial layers. These layers were then superimposed under one space to help assess disasters in different areas. Among them, the remote sensing image described the disaster situation in the study area from the macro perspective, including the extent and spatial distribution of the flooded area. Based on the relevant indicators of social networks, we can understand which flooded areas in the remote sensing image received more public attention. Generally speaking, the larger the flooded area and the more public attention it receives, the more severely affected the area is. Furthermore, the corresponding location-pointing relationship reflected the spatial distribution of people who paid attention to those flooded areas, and we can also learn about the situation in the flooded area through social media texts uploaded by those people. This is an effective illustration for disaster assessment.

3.4.2. Continuous Monitoring of Disaster in Flooded Areas Combined with Social Media Data

The long revisit cycle of satellites makes it difficult to provide continuous disaster monitoring. Moreover, it is difficult to perceive the specific disaster information in the flooded area simply by using remote sensing images. Therefore, we supplemented this information with social media data. We first selected the flooded area to be monitored and collected social media data related to this area based on the constructed social network. Then, we extracted keywords from these social media texts. These keywords reflected the disaster themes in the area that people were concerned about. By analyzing the change characteristics of these themes over time, the disaster reduction department can monitor and understand the disaster situation in the flooded area in detail. At the same time, it also improved the situational awareness of the disaster. The method of extracting keywords from social media texts used in this paper is "TF-IDF" [41], and its formulas are as follows:

$$\mathrm{TF}-\mathrm{IDF}=\mathrm{TF}\times\mathrm{IDF}$$
$$\mathrm{TF}(\mathrm{w})=\frac{n_{i,j}}{\sum_k n_{k,j}}$$
$$\mathrm{IDF}(\mathrm{w})=\log\left(\frac{|D|}{1+\left|\left\{j:w\epsilon d_j\right\}\right|}\right)$$

Among them, $\mathrm{TF}(\mathrm{w})$ is word frequency, which is a measure of the local importance of the word w; $n_{i,j}$ is the number of times the word w appears in the document (social media text) d_j; $\sum_k n_{k,j}$ is the sum of occurrences of all words in document d_j; IDF is the inverse document frequency, which represents the distribution of words in the entire corpus; $|D|$ is the total number of documents in the corpus; $\left|\left\{j:w\epsilon d_j\right\}\right|$ is the number of documents containing the word w.

4. Results

4.1. Locational Words Extraction

In this paper, we used three indicators, including P (precision), R (recall) and F-1 (comprehensive indicator), to evaluate the effect of the proposed method on extracting locational words from the social media text. The relevant calculation formulas are as follows:

$$\mathbf{P}=\frac{\mathbf{N\_Correct}}{\mathbf{N\_Correct}+\mathbf{N\_False}}$$

$$\mathbf{R}=\frac{\mathbf{N\_Correct}}{\mathbf{Num}}$$

$$\mathbf{F}-\mathbf{1}=\frac{\mathbf{2}\times\mathbf{P}\times\mathbf{R}}{\mathbf{P}+\mathbf{R}}$$

Among them, **N_Correct** represented the number of locational words that were correctly recognized, **N_False** represented the number of locational words that were not recognized correctly, and **Num** represented the number of locational words contained in the text.

We randomly selected 500 texts to evaluate the accuracy of the method in this paper (approximately 1000 locational words were contained in these texts). The experimental results showed that the indicators P, R and F-1 reached 89.32%, 83.64% and 86.39%, respectively. The relevant results met the requirements of subsequent disaster analysis in this paper.

4.2. Disaster Analysis Combined with Multi-Source Information

Based on the remote sensing data, we used the algorithm described above to extract the flooded area, as shown in Figure 6a. Among them, the blue area was the water body, and the red area was the flooded area. We superimposed the social media data with the remote sensing image, as shown in Figure 6b. We can see that there was little social media data in the flooded area. When the areas were being severely affected by floods, it was difficult for people in these areas to upload social media data. Conversely, the regional population distribution and the degree of economic development were also factors that caused the uneven distribution of social media data. Therefore, it was difficult to effectively assist remote sensing data to further mine disaster information by only using social media data with uploaded location information.

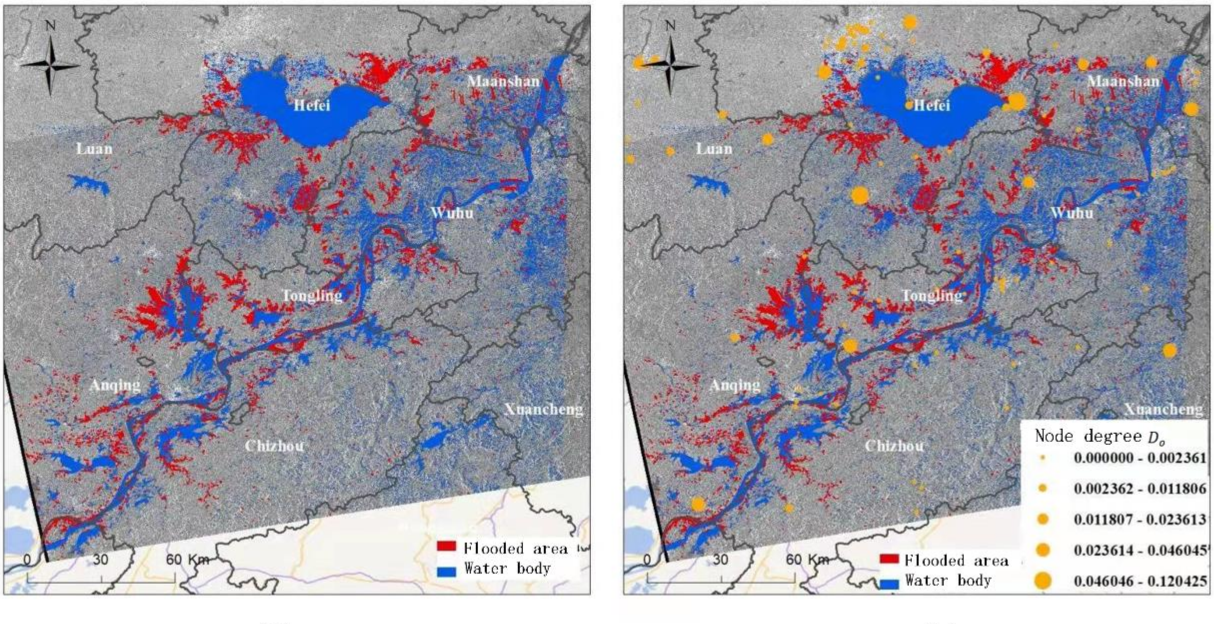


Figure 6. The spatial distribution relationship between social media data and flooded areas. Among them, (**a**) shows the flooded area based on remote sensing images; (**b**) overlays social media data, which have location tags, on a remote sensing image.

4.2.1. Disaster Assessment Combined with Multi-Source Data

Based on social networks constructed in this paper and remote sensing data, we superimposed them to carry out disaster assessments for different disaster-affected areas. The analysis results are shown in Figure 7. In this figure, the yellow circular node represents the upload location of the social media data, and the green square node represents the location of the disaster mentioned in the social media text. We can see that most of the green square nodes are located in the flooded area, such as area 1, area 2 and area 3, etc. The larger the green square node, the more attention the area it was in received, which meant that the disaster in these areas was serious. Based on the remote sensing image, it can be seen that there are some areas which were less affected by floods. However, these areas still received more attention, such as area 4. This area is "Zhongmiao Temple", which is a famous scenic spot. Combined with social media data related to this area, we found that this area was greatly affected by the disaster, and the base under the temple had been flooded. The relevant disaster situation had attracted the attention of people in many other areas. We checked the official news reports and confirmed the information mined by social media (https://www.thepaper.cn/newsDetail_forward_8404872, accessed on 15 January 2022). Perhaps due to factors such as resolution or ground occlusion, the remote sensing images failed to reflect this disaster information.

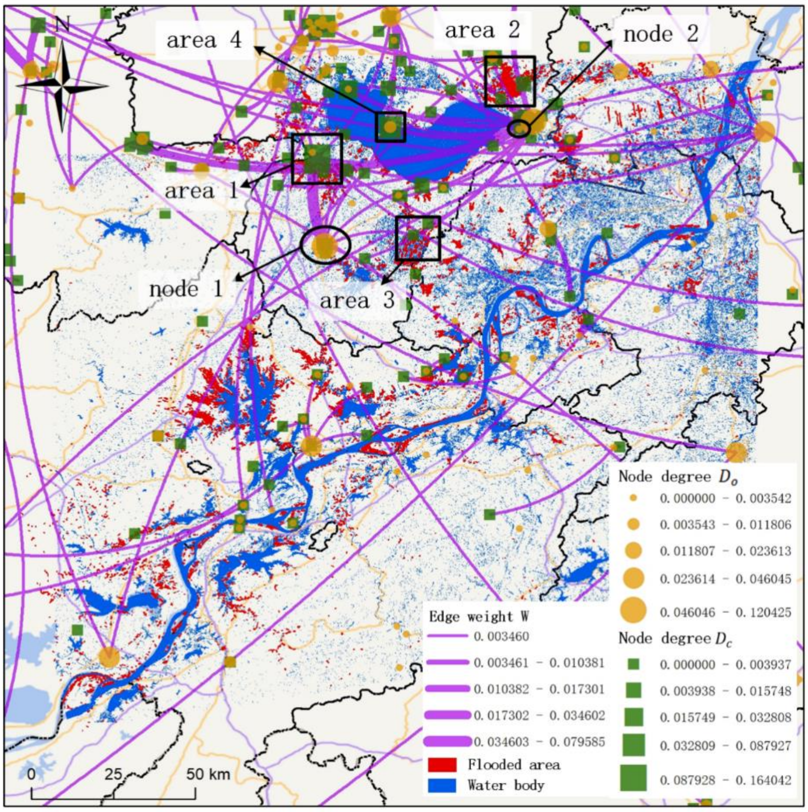


Figure 7. Superposition analysis of multi-source disaster information.

In addition, the edges between nodes described the spatial distribution characteristics of people who were concerned about those affected areas. Combined with the corresponding social media data, we can understand why people paid attention to these affected areas and even what requirements people wanted. Using area 1 in Figure 7 as an example, this area is "Tongda Town", which had been seriously affected by a flood. We marked two yellow circular nodes (node 1 and node 2) that were linked to area 1. Among them, node 1 was closer to area 1. The two nodes were less affected by the disaster according to remote sensing images. We checked some social media data at node 1 and found that some people were worried about the disaster in area 1 and even felt nervous and anxious. Because their property (such as houses, farmland, etc.) and relatives were located in area 1, they were curious to know how the disaster was progressing in this area. Although these people were not directly affected by the flood, their bad emotions (nerves and anxiety) might have triggered some other disaster losses [42,43]. For example, anxious people are more sensitive to negative information about disaster, and are more likely to be induced and deceived by bad information such as rumors [44]. Therefore, the disaster reduction department can take some measures, such as pushing more disaster information in the flooded area to the people in a timely manner, etc. In contrast, people at node 2 were only concerned about the disaster situation in area 1. It indicated that more disaster reduction measures may not be required for this area. Therefore, understanding the themes that people in different areas pay attention to in flooded areas is conducive to reasonably allocating disaster relief resources.

Compared with some existing studies, including flood disaster assessments based solely on social media [45,46] or remote sensing [47,48], and flood disaster analysis combined with multi-source data such as that shown in the literature [14–17], the method in this paper fully considered disaster-related location information contained in social media texts, constructing the relationship between them and uploading location tags of social media. This not only improves the fusion efficiency of the two kinds of data but also effectively integrates the respective advantages of multi-source data. Remote sensing images show the macroscopic disaster situation in the study area; conversely, social media (especially the constructed social network) further assess the disaster situation in different flooded areas. In addition, through the method in this paper, more disaster information, such as the spatial distribution of people who pay attention to the disaster area and the detailed disaster situation of the flooded areas, are also effectively excavated.

4.2.2. Continuous Monitoring of Disaster in Flooded Areas Combined with Social Media Data

Figure 7 not only showed the spatial distribution and extent of flooded areas but also reflected the degree to which these areas were affected by disasters from the public perspective. Among them, areas 1, 2 and 3 were severely affected by the disaster, especially area 1. Therefore, we took area 1 as an example and combined social media texts to continuously monitor this area. The analysis results are shown in Figure 8.

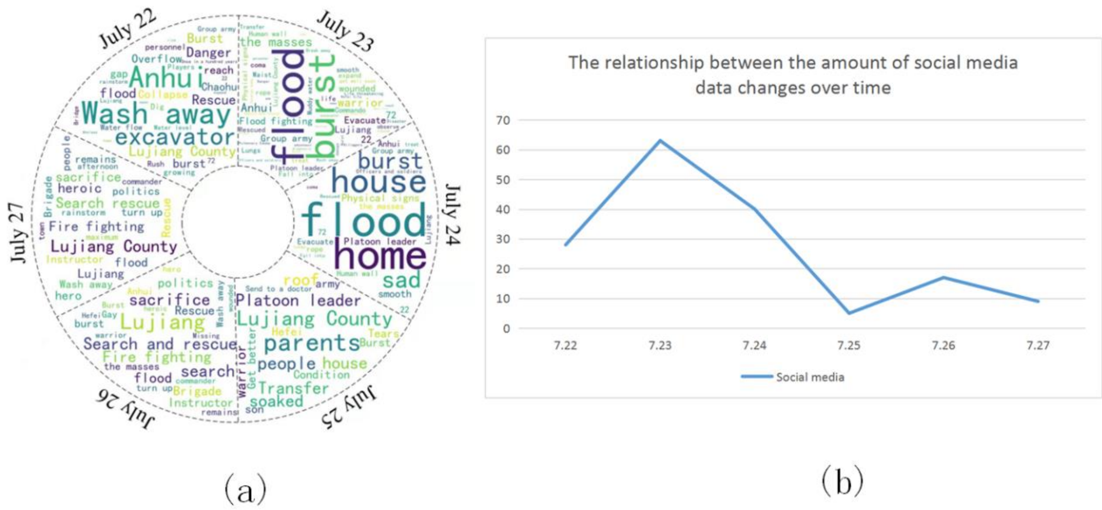


Figure 8. Monitoring the disaster in "Tongda Town" based on social media data. Among them, (**a**) depicts how the themes of social media data related to "Tongda Town" changed over time; (**b**) depicts how the amount of social media data related to "Tongda Town" changed over time.

In Figure 8, it can be seen that "Tongda Town" received more attention from 22 to 24 July. Among them, the keyword "22" indicated the specific date when the disaster occurred. Keywords such as "burst", "overflow", "collapse" and "danger" described the main causes of the flood disaster. It was reported that due to heavy rains over the past few days, a section of the dam in the area broke, causing several villages to be submerged. Almost at the same time as the disaster occurred, the disaster reduction departments had already started rescue operations, and the keywords "flood fighting", "rescue", etc., could explain it. With the progress of disasters and rescue, more and more people began to pay attention to this area, especially on 23 and 24 July. During this period, related disaster themes were abundant, and we could learn about the specific progress of the disaster, including property damage (through the keywords "home", "houses", "sad", etc.), rescue casualties (through the keywords "wounded", "coma", "sign", etc.) and effectiveness of disaster reduction (through the keywords "rescued", "evacuate", "transfer", etc.), etc.

Since 25 July, although the disaster in "Tongda Town" still existed, the attention of people to this area had dropped significantly. This might show that the disaster in the area was no longer serious. Keywords such as "transfer" and "get better" accounted for a relatively large proportion, indicating that the public had received better assistance during this period. On 26 and 27 July, people once again focused their attention on "Tongda Town". By combining keywords such as "search", "sacrifice", etc., we could learn that some rescuers were sacrificed in this disaster, and their remains were not found until 26 July. This information attracted widespread attention. Keywords such as "heroic" and "hero", etc., showed how grateful people were to rescuers. The same method can be used for disaster monitoring in other areas.

Social media data enhance temporal continuity of flood monitoring, which is an important complement to remote sensing data. Moreover, based on the social network constructed in this paper, we can obtain more social media data about the flooded area (only a small amount of these data were from the local flooded area, and more were from other areas). The information mined from social media effectively reflected the entire disaster process and improved the situational awareness of disasters.

5. Conclusions

Social media and remote sensing data serve disaster reduction from different perspectives. They complement each other and enrich the expression of disaster-related information. However, the limitations of social media data, such as insufficient geotags and uneven spatial distribution, make it difficult to efficiently combine them with remote sensing data. Thus, in this paper, we tried to solve this problem by extracting disaster-related location information in social media texts and constructing a social network based on the pointing relationship between different types of location information (uploaded location information of social media and location information contained in the text). We combined the processed social media data with remote sensing image data to verify the advantages of our method in disaster analysis. We found that: (1) It is difficult to dig out more disaster information in the flooded area by simply using the social media data with only uploaded location tags because some hard-hit areas may exist little or no social media. (2) The social network constructed in this paper can be effectively combined with remote sensing image data and can help us to mine more disaster information, such as assessing the disaster situation in different areas and analyzing the spatial distribution of people who pay attention to flooded areas. (3) The effective combination of multi-source data can make better use of the advantages of different data sources, helping to fully describe the progress of the disaster.

The method in this paper still has some aspects that need to be improved in the future: (1) We will consider optimizing the location information extraction method proposed in this paper. Although this method had low labor costs and high automation, it depended on the suffix words of the locational word. It is difficult for us to list all the suffix words exhaustively. Therefore, we can consider introducing the semantic similarity calculation of words to try to automatically identify these suffix words in the future. (2) More data sources will be introduced, including population distribution data, land use data, and road network data. These data can feed back disaster information from different aspects. In a word, this paper has made an effective attempt to improve the efficiency of multi-source data combinations to enhance disaster information mining and proved the great potential of multi-source data combination in disaster reduction.

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