MINING METHOD OF TRAFFIC IMPACT AREAS OF RAINSTORM EVENT BASED ON SOCIAL MEDIA IN ZHENGZHOU CITY

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ABSTRACT:

Due to the influence of typhoon "fireworks" on July 20, 2021, there was a rare heavy rainfall in Zhengzhou, Henan Province, China, which caused severe urban waterlogged disasters and casualties. Take it as an example, using Web Crawler technology to obtain Weibo’s (Chinese Twitter) time and space data involved in the rare heavy rainfall in Zhengzhou. Through statistical analysis and spatiotemporal analysis to filter, classify, analyse and manipulate the crawled Weibo’s data, and then study the influence of the extreme rainstorm weather on the traffic areas from two aspects of address points and road networks. At the same time, to verify the effectiveness of the social media-based method for mining the traffic impact areas of the Zhengzhou extreme rainstorm, this experiment compares Weibo data with official data in various aspects according to four categories of waterlogging severity.

1. INTRODUCTION

With the severe changes in the global environment, the phenomenon of extreme natural disasters is also rampant around the world. In recent years, extreme rainstorms have occurred from time to time in China, resulting in disasters that have greatly affected urban transportation, which has caused people's safety and property to be lost (Chen et al., 2022). To reduce the loss, research on urban traffic areas affected by disasters has always been the focus of relevant scholars. Traditional methods mostly obtain data on the impact of disasters on traffic through fieldwork or remote sensing (Kong et al., 2020). The former way is time-consuming and laborious, although the latter can obtain a large-scale affected traffic area, it is limited by the weather and observation time, which cannot achieve the effect of timely and accurately to absorb the traffic impact information. To find a faster and more efficient method, some scholars have started to use social media platforms as a source of data acquisition, which can make up for the shortage of traditional traffic data acquisition methods by virtue of a large number of users and the richness of information released in real time on social media platforms.

On July 20, 2021, hit by typhoon "fireworks", Zhengzhou, Henan Province, China, experienced a hundred-year rare extreme rainstorm natural disaster, the maximum hourly rainfall reached 201.9 mm, breaking the historical extreme of 198 mm hourly rainfall in mainland China, as an important transportation hub in China, it has formed a transportation network consisting of 3 modes of transportation: railroad, road, and air. As of April 2022, Zhengzhou has 2 terminals, 2 runways, 162 air routes, 6 railroad stations, 2 main railway lines, 6 high-speed railway lines, 22 railways, 11 highways, and 37 BRT lines. This rainstorm led to flooding and mudslide disaster and a large number of houses collapsed. Local transportation was also greatly affected: railroads were stopped, highways were restricted, and city roads and subways were severely flooded, causing 292 people to be killed and direct economic losses of 53.2 billion RMB. In order to effectively respond to the impact of extreme rainstorms on urban traffic and ensure the safety of the commuting public (Wei et al., 2021), it is extremely important to conduct a timely and comprehensive survey of urban flooding at this time.

To be able to better cope with the impact of extreme rainstorms on urban traffic, to help urban traffic managers make better decisions, and to provide new ideas for troubleshooting urban flooding. Based on the advantages of obtaining data from social media platforms, this study takes the 7.20 heavy rain in Zhengzhou, Henan province as an example, and uses this method to research the influence areas of Zhengzhou traffic. In this work, we adopt social media platforms to obtain affected traffic information in Zhengzhou caused by heavy rains and combine geographical information technologies to actualize spatial analysis and visualization. The main contributions are as follows:

(1) Using the web crawler software, we crawled the data related to the 7.20 extraordinarily heavy rainfall event in Zhengzhou on Weibo at different times and obtained the address point data about urban flooding by eliminating redundancy, filtering, statistical classification, etc. In addition, we downloaded the traffic road network data of Zhengzhou City through the Ministry of Natural Resources of China's Geographic Information.

(2) For address point data use Python to write programs to achieve geocoding and coordinate conversion of address points

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for spatial and temporal analysis of data; for road network data use statistical classification and ArcMap software processing methods to achieve visual display of road network data.

(3) Through the visual analysis of address points and road network data, we obtained the five main areas affected by heavy rainstorms in Zhengzhou. In addition, we conducted a multi-dimensional comparison between Weibo and official data using the volume and overlap of flooding data as the judging criteria and found that Weibo flooding data can cover a wide range and complement the data released officially, reflecting the feasibility and accuracy of the Weibo-based method for mining the traffic impact areas in Zhengzhou.

2. RELATED WORK

2.1 Natural Disaster Research

In recent years, with the deterioration of the global environment, such as changes caused by anthropogenic greenhouse gas emissions (Barthel and Neumayer, 2011), extreme natural hazards have occurred frequently in various countries, with weather-related natural disasters causing a significant increase in losses over the past decades (Mechler and Bouwer, 2014), as an important factor, climate changes can have an impact on hazard, disaster scale, frequency and space (Gallina et al., 2016). However, along with the adverse impacts of disasters, disaster risk research has also made significant progress in the last two decades (Gall et al., 2015). China, as one of the three major contributors to global disaster research (Shen et al., 2018), is also plagued by natural disasters, which cause countless casualties and economic losses every year. The extreme rainstorm in Zhengzhou in this study, for example, caused widespread paralysis of the transportation system and flooding everywhere, which resulted in 292 people killed and direct economic losses of 53.2 billion RMB.

2.2 Social Media Research

Due to the rapid development of network technology, social media is gradually being used more and more in scientific research activities as a new and important way to obtain data. Research on social media data has focused on four areas: natural disaster response, public sentiment survey, human activity research, and disease prevention and control. (1) Some of the studies related to natural disaster response include: the use of Twitter geolocation information to study the 2009 Red River floods in the United States and the prairie fires in Oklahoma (Vieweg et al., 2010). Disaster information related to space, time, content, and networks is analysed through social media to gain situational awareness and improve disaster response capabilities (Wang and Ye, 2017). Using the October 2015 South Carolina floods as a research case, (Fohringer et al., 2015; Li et al., 2017) proposed a new approach to extract potentially useful information from social media data (Twitter) to help quickly map floods, providing a new solution for scenario perception improvement in flood events. (Shan et al., 2019) proposed a disaster damage assessment model for large-scale disasters that cause severe damage and attract widespread social attention, enabling real-time and dynamic presentation of disaster damage assessment. By obtaining information posted by online Facebook users after a disaster, (Kim and Hastak, 2018) used social network analysis methods to study the aggregated interaction patterns adopted by users to help emergency response agencies develop their social media operational strategies to achieve disaster mitigation plans. (Laylavi et al., 2017) examined methods used to detect specific events and informational tweets that may be beneficial to emergency response, using the example of users posting cell phone messages and Twitter data during emergency disasters. (Wang et al., 2015) used the 2012 Beijing rainstorm as an example, investigating how to use social media to distribute timely emergency information during emergencies by targeting the classification and location of social media text stream information during emergencies. (Wu et al., 2018) used a storm in Nanjing as an example to study the acquisition of waterlogging points under heavy rain and the planning of an urban emergency logistics network using Weibo big data. (2) Related studies conducted for people emotion surveys include: (Tsou et al., 2013) investigated the correlation between the popularity of U.S. presidential candidates on Twitter and the actual election results by tracking and analysing the spatial content of social media and web pages. (Neppalli et al., 2017; Yang et al., 2019) used social media platforms to obtain users' post-disaster emotional information data, combined with the spatiotemporal analysis of GIS software, analysed the public's emotional changes, and provided corresponding help for post-disaster reconstruction. A study on suicide risk and emotional distress in Chinese social media platforms, using text mining and machine learning methods (Cheng et al., 2017). (Kryvasheyeu et al., 2015) studied the relationship between user sentiment and changes with hurricane geographic location by obtaining Twitter messages posted by users before, during, and after the arrival of Hurricane Sandy. (3) For human activity studies: (Li et al., 2013) explored the socioeconomic characteristics of the creators of geographic data by using geo-referenced tweets and photo data collected by Twitter and Flickr to study the relationship between tweets and photo density and the characteristics of local people, using California as an example. (Croitoru et al., 2013) used geospatial information obtained from social media feed to generate geosocial knowledge by building models to study larger scale and more accurate resolution to observe human landscapes, geosocial ecosystem formation, and their evolution over time. An activity-based analysis combined with a movement-based approach is used to study human mobility within the city, using check-in record data during a year in Shanghai as an example (Wu et al., 2014). (Gao et al., 2013) used cell phone data to study community communication interactions. (4) Studies conducted for disease prevention and control include: (Murzintcev and Cheng, 2017; Signorini et al., 2011) used Twitter data for classification of disaster information aggregation trend prediction and study of disease (H1N1) distribution and study of disease transmission patterns respectively. During the H1N1 flu, (Galvani et al., 2011) used Twitter to study the level of disease activity in the United States and the level of public concern about the disease. (5) In addition, there are other aspects of social media data that have been studied, such as (Hanna et al., 2011) used social media data to study the marketing strategies of companies, and product communication patterns. (Ji et al., 2016) proposed a new federated model for identifying informal location mentions from tweet content and linking the identified locations to well-defined location profiles to obtain relevant information such as the user's precise location.

In summary, we can see that fewer scholars have used social media to study the traffic impact conditions under natural disasters, and the traditional research on the traffic areas affected by natural disasters is mainly combined with remote sensing analysis, GIS software hydrological simulation calculation, and field survey, etc. Compared with the traditional disaster information acquisition methods, social media data have the advantages of strong real-time, wide sources, low acquisition cost, a large base, and a high degree of content synthesis.

3. METHOD AND DATA

3.1 Overview of Method

This paper uses Houyi Collector, a third-party web crawler software, to crawl Weibo's time and space data involved in the rare heavy rainfall in Zhengzhou. A Weibo is composed of a user profile, user name, posting time and source, topic, text, Weibo attached picture or video, retweet, comment, and likes, this article mainly obtains the text information at a specific time, so it crawls for Weibo time and Weibo text information. Then, crawled Weibo data needs to be filtered, classified, analysed and manipulated. After completing the work above, it is necessary to perform geocoding and coordinate transformation on the waterlogging points (Wu et al., 2021), and the data of the affected railway, high-speed and urban roads need to be manipulated for visualization by the ArcMap. After the data processing work is over, the spatiotemporal analysis of the waterlogging points and the road network data are performed by ArcMap. See Figure 1 for the specific process:

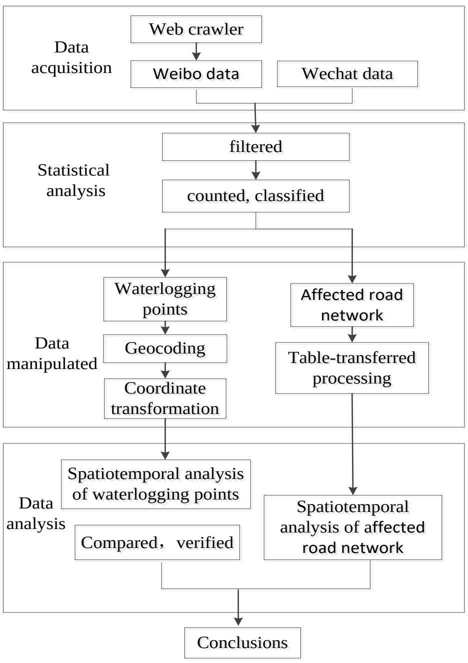


Figure 1. The framework of study.

3.2 Data Acquisition

In this paper, we need to obtain Weibo-based affected address points and traffic network data of Zhengzhou city. The so-called affected address points acquisition is to extract the data crawled from Weibo for waterlogging points extraction, exactly to extract roads (urban roads, highways, railroads) and physical spatial location information (such as residential building addresses, airports, shopping malls, etc.). At present, scholars for social media-specific data acquisition are mainly based on machine learning, rules, and purely geographic information elements extraction three kinds of Semantic segmentation. In our study, the data volume is not particularly large, and the best choice to ensure the quality of extracted data is to adopt the pure geographic information element extraction method by manual means. The traffic road network data is downloaded through the China Geographic Information Resources Catalogue Service System. Therefore, the process of data acquisition mainly revolves around the acquisition of waterlogged points.

Waterlogging Points Extraction: Login to the Weibo page. The search time was set between 23:00 on July 19 and 23:00 on July 20, 2021, and the keywords "heavy rain, waterlogging, flooding, Zhengzhou" were searched. Since that time period was the worst of the rainstorm, the amount of information posted by users skyrocketed. However, only shows 50 pages because of the anti-crawl limit of Weibo, so to ensure the maximum number of pages obtained, we divided the research time into 6 different durations and used Houyi collector to crawl, and crawled a total of 11594 pieces of data, the actual 4141 valid data were obtained through de-duplication and human judgment (The analysis is mainly due to the performance of the crawler software itself and the fact that many important disaster information is forwarded by a large number of users at the same time when the rainstorm is severe). Then extracting valid waterlogging points and affected road networks by establishing a model of data screening indexes (such as time, waterlogging points, repeatability, severity, etc).

From the data obtained through Weibo, we know that the information on the time of the rainstorm is more accurate, and the description of the waterlogging information in the text of Weibo is also more detailed, but a few of the microblogs have "expand" or "......" at the end of the text, indicating that this part of the text information is not fully crawled, and it is necessary to find the Weibo again to accurately record the information about the location of the waterlogging points. In this paper, the data of a tweet includes the user's name, posting time, text, and the number of likes. The experiment needs to extract the time, address, and description of the severity of waterlogging from each tweet, and the number of likes can be used as another basis for the credibility of the data.

3.3 Storm Damage Points Classification and Processing

If we want to spatially analyse the storm damage points obtained from Weibo, we must classify, geocode and coordinate transformation on the semantic data.

Classification: Due to the need to verify the feasibility of the study on the influence of heavy rain events on traffic areas in Zhengzhou based on Weibo, this experiment also obtains the official traffic data of the same period. To avoid all data getting from Weibo and affecting the research conclusions, the official waterlogging points and affected road network data are obtained by the WeChat official account of "Zhengzhou Traffic Police". The Weibo address points and official address points were divided according to the severity of waterlogging, and the classification was used to compare the Weibo and official data in various aspects, as shown in Table 1, so as to enhance the credibility of data validation.

passable	barely passable	waterlogging (unknown depth)	impassable
Yangtze River Road West 3rd Ring Road	Jianshe Road Changchun Road	Dahe Road	North gate along Yanhe road

Lotus Street, West 4th Ring Road	Shangcheng Road Zijingshan Road	Fengyi Road	North Yousheng Road East
Suoling Road North 3rd Ring Road	Xiong'er River Road, South Agricultural Road	Yunfeng Road	South Agricultural Road,East 3rd Street

Table 1. Example of official classification data.

Processing: Geocoding refers to the process of converting information about location points into latitude and longitude information. The geocoding technology used in this paper is based on the API interface of Baidu Map on the Web, and the program is written by PyCharm in the Python environment to realize the conversion of the extracted address points into latitude and longitude, and the code should be written with "Zhengzhou" at the top of the address points to improve the positioning accuracy. The geocoded address points are shown in Table 2.

Location	Lon	Lat
Fengyi Road	113.725775	34.745621
Yunfeng Road	113.718384	34.767323
Dahe Road	113.660656	34.886095

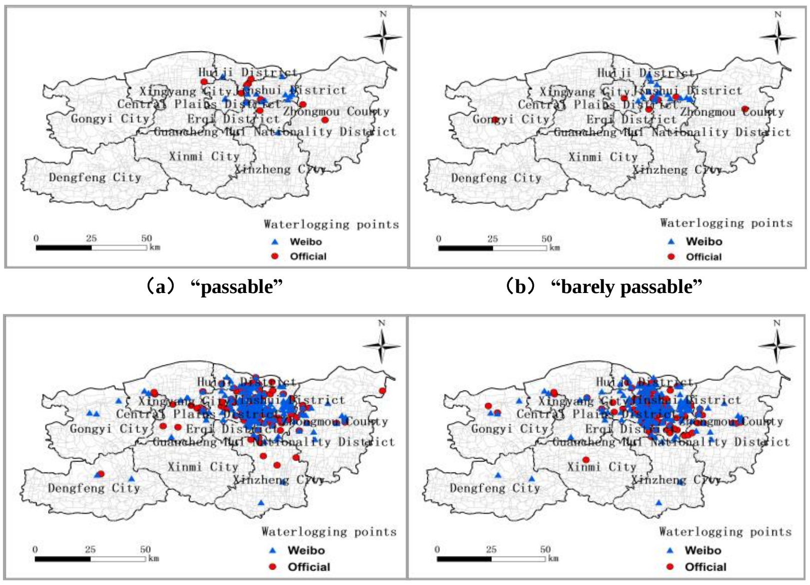
Table 2. Example of geocoded data.

But this is not enough, because Baidu Map uses bd09 Baidu coordinate system, which cannot be displayed on ArcMap software, it must be converted from Baidu coordinate system to the WGS-84 coordinate system, and the actual conversion should be done by first converting Baidu coordinate system to Mars coordinate system, and then converting Mars coordinate system to WGS-84 coordinate system.

3.4 Storm Damage Road Network Classification and Processing

To understand more clearly the situations of different transportation modes affected by the rainstorm, the road network is divided into three parts according to road levels: railway, high-speed and urban roads. The urban roads are extracted from the waterlogged points and are divided into Weibo urban roads and official urban roads, while the rest is the data released by the official public number of "Zhengzhou Traffic Police" because the official data are more authoritative for railroad and high-speed disaster data.

For the processing of the road network data, the vector cropping tool of ArcGIS was used to obtain the road network data within Zhengzhou city, after which the Weibo data and official data were classified into excel tables according to the severity of waterlogging; then the attribute tables of railroad, highway and city roads were made by the transfer tool of ArcMap, which were associated with the total road network attribute table of Zhengzhou.



(a) "passable" (b) "barely passable"

(c) "waterlogging" (unknown depth) (d) "impassable"

Figure 2. Waterlogging points' comparison between Weibo and official.

4. EXPERIMENT

For the spatiotemporal analysis of data, the more commonly used geographic information software is ArcMap of Esri, Super Map of China, and QGIS used as open source, based on the powerful analysis function and easy operation of ArcMap, this experiment uses ArcMap as the spatiotemporal analysis software.

4.1 Spatiotemporal Analysis of the Waterlogging Points

Figure 2: To verify the reliability of Weibo data in multiple aspects, data from Weibo and official are divided into four categories according to the severity of the waterlogging: "passable", "barely passable", "waterlogging (unknown depth)" and "impassable". Under the premise of considering the detailed degree of waterlogging points description and geocoding positioning accuracy, we choose to use the points

exhibited in ArcMap as the basis of judgment and compare the number and overlap of Weibo and official waterlogging points.

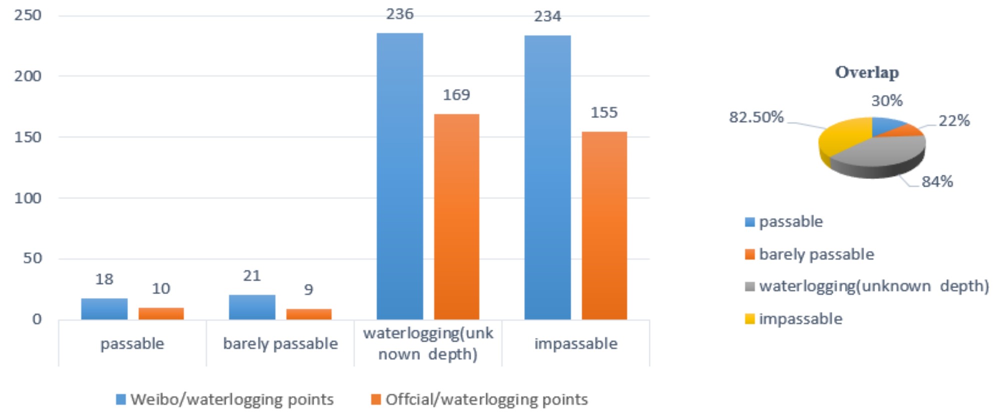


Figure 3. Comparison of the number and overlap of Weibo and official waterlogging points.

Figure 3: We can find that the waterlogging points of urban roads caused by heavy rainfall by tabulating and comparing the data of waterlogging points obtained: (1) For "passable", the overlap between Weibo and official data is only 30%, and the analysis considers that the situation is critical when a heavy rainstorm, for safety reasons, so the official data may be more inclined to the serious waterlogging roads, and less consider the "passable" roads. (2) For "barely passable", the overlap between Weibo and official data is 22%. The analysis considers that "barely passable" is a classification for experimental research, and the actual waterlogging data officially released does not distinguish between them but is unified with waterlogging roads to release them. Also, the large user base of Weibo and the artificial factors in data classification, resulted in a large difference in the number of "barely passable" waterlogging points between Weibo and official data but the overlap was not high. (3) For "waterlogged (unknown depth)", the overlap between Weibo and official data can reach 84%. It can be seen that both official and Weibo users are very concerned about the city's waterlogging points, and Weibo has an obvious advantage in the number of waterlogging points with high overlap due to their large user base and real-time data release. (4) For "Impassable", Weibo and official data overlap up to 82.5%. From Figure 2, we can see that the flooding areas are concentrated in five districts: Jinshui District, Guancheng Hui Nationality District, Erqi District, Central Plains District, and Huiji District, which are the areas with the largest amount of heavy rainfall on that day, and the dense building construction and low terrain in these districts, resulting in the paralysis of the urban drainage system and serious flooding in these areas.

4.2 Spatiotemporal Analysis of the Affected Road Network

Since the official and authoritative vector map of the Zhengzhou traffic road network was made in 2017, but the heavy rainstorm occurred in 2021, the railroads, highways, and city roads affected by the rainstorm in Zhengzhou built after 2017 cannot be displayed because they cannot be found in the attribute table of the traffic road network vector map. Due to the imprecise description of some of the road network data and the vector map attribute table of high speed, railroads are mostly segmented restrictions, the display process may appear a high speed originally only a section or a few sections of "impassable" but show the whole, or originally display a whole but show a part of the roads. The following four maps do not demonstrate all the official road network data of the disaster, so they can only be used for the analysis of the rainstorm-affected traffic areas under this experimental data.

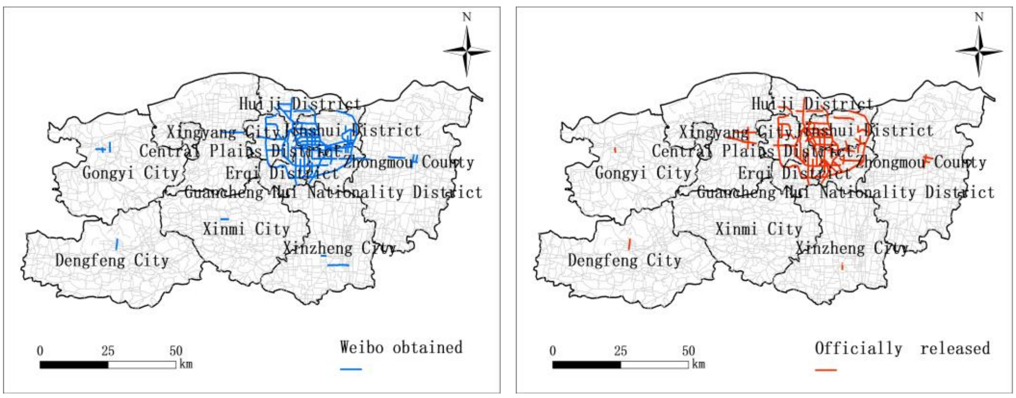


Figure 4. Waterlogging urban roads' comparison between Weibo and official.

Figure 4: By visualizing the road network of waterlogged urban roads, Weibo has 427 segments, a total of 438 km; the official has 399 segments, a total of 398 km; the Weibo data is 1.07 times more than the official data in terms of segments, and 1.1 times more than the official data in terms of mileage. This data corresponds to the experiment in Figure 2 "waterlogging (unknown depth)", and the analysis of the data shows that the overlap between Weibo and official data is 89% according to the number of waterlogging road segments, which is 84% higher than the overlap between Weibo and official data of "waterlogged (unknown depth)" waterlogging points. It can be seen that the waterlogging points are presented in the form of a road network, which can reflect the disaster situation more intuitively and further verify the feasibility of Weibo data.

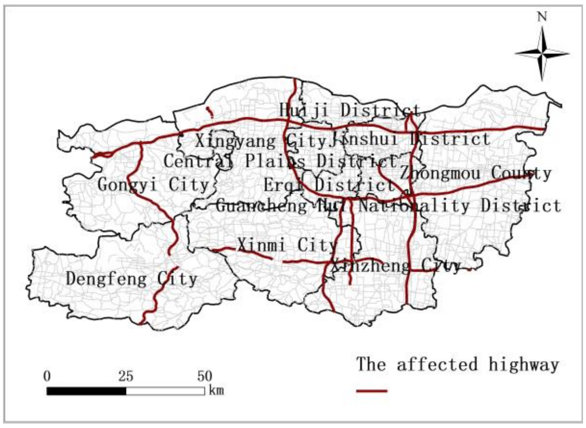


Figure 5. Highway affected by rainstorm.

Figure 5: As of 2021, Zhengzhou City has 11 transit highways, affected by heavy rainfall, expressways of Beijing-Hong Kong-Macao, Lian Huo, Zheng Shao, Zheng Min, Shang Deng, Zheng Jiao Jin, Jiao Tong, and other highways are affected to varying degrees, the overall situation of the affected highway shows the characteristics of a wide range of radiation over a large distance span.

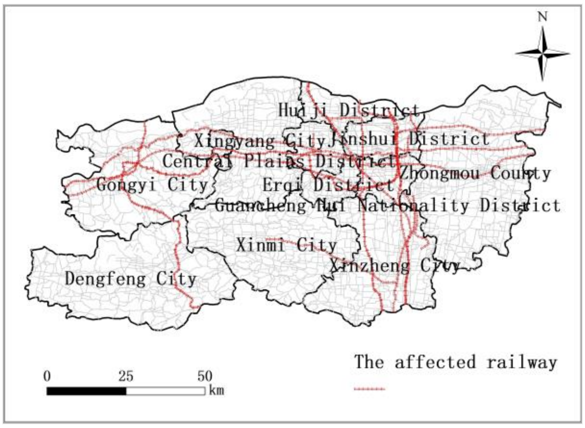


Figure 6. Railway affected by rainstorm.

Figure 6: Zhengzhou is a transportation hub in the Central Plains region of China, the railroad currently has 4 operating railroad stations, 2 railroad main lines, 6 high-speed rail lines, and 7 subway lines in operation, July 20, 2021, one of the largest passenger stations in Asia Zhengzhou station and China's second-largest high-speed railway station Zhengzhou East Station 2 railway stations in addition to some trains all out of service due to the impact of heavy rainfall, railways of Long Hai, Beijing-Guangzhou, Xu Lan High-speed Railway, and many trips trains of other railway lines were affected to different degrees, including Zhengzhou West, Beijing-Guangzhou and Xu Lan 3 high-speed railway lines were soaked by the rainstorm, and all 7 metro lines were out of service. As of February 2022, the total length of metro operation in Zhengzhou City is 206.4 km, and the total length of Line 1 metro and Line 2 metro lines obtained in this study is 72.3 km, accounting for about 35% of the total length of metro lines. The railroad affected by heavy rainfall is 1040 km, accounting for about 26% of the total operational railroad mileage (3939.2 km) released by Zhengzhou Railway Bureau in 2017, and the overall railroad is more severely affected than the highway, especially in the hardest-hit areas in the northeast low terrain of Zhengzhou, with dispersion to areas with high terrain such as the west, south of Zhengzhou. Trains are highly susceptible to brake failure or overturning under heavy rainfall, which can lead to major casualty accidents. The traffic department may have stricter control over railroads compared to highways for safety reasons.

5. RESULTS AND DISCUSSIONS

In this paper, three main conclusions can be shown: (1) The severe waterlogged areas were mainly concentrated in the five areas of Jinshui District, Guancheng Hui Nationality District, Erqi District, Central Plains District, and Huiji District with high rainfall and low terrain (see Figure 2). (2) According to the analysis data, 1040 km of railways and 634 km of highways are affected by the rainstorm, the railway disaster is dominated by the severe disaster-stricken areas with low terrain in the northeast, spreading to the areas with high terrain in the west and south; The high-speed disaster situation presents the characteristics of a large distance span and wide radiation range (see Figure 5 and Figure 6). (3) Through various visual analyses and comparisons, the number of waterlogging information obtained by Weibo is not only greater than that released officially; but the coincidence degree of the two data is as high as 84% (see Figure 2 and Figure 4).

The mining method of traffic impact areas of rainstorm event based on social media in Zhengzhou city, as a faster and more efficient method, which will provide new ideas for urban waterlogging, help urban traffic managers make better decisions, and offer strong support for disaster prevention and reduction, to effectively prevent and reduce the impact of disasters, protect people's safety and reduce property losses.

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