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Analyzing the Reliability of Unstructured Data for Urban Rainfall Pattern Studies—A Case Study from Zhengzhou

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Abstract: Due to the insufficient number and uneven distribution of urban rainfall stations, research on urban flooding disasters is limited. With the development of big data research, many scholars have applied big data to natural disaster research. In this paper, we analyzed the reliability of unstructured data from the urban rainfall patterns studies using the measured rainfall data for Zhengzhou City. First, web crawler technology was used on Sina Weibo, one of China's largest social platforms, to obtain the unstructured data related to rainfall. The fuzzy recognition method was used to analyze the rain patterns of the measured rainfall data and the unstructured data, which verified the reliability of the unstructured data in the analysis of the urban rainfall patterns. Taking Zhengzhou City as an example, it was found that the matching degree of rain pattern recognition results was 45%, between the unstructured data and measured data. This showed that the application of the unstructured data in the analysis of the urban rainfall patterns has a certain degree of reliability.

Keywords: unstructured data; urban rainfall; rainfall patterns; fuzzy recognition method

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1. Introduction

With the continuous urbanization of the world, waterlogging caused by urban rainstorms has become a hot topic [1–3]. In 2002, torrential rain in central Europe resulted in most of the continent suffering the worst flood in a century. The torrential rain disrupted communications and washed away a large number of houses and roads, and more than 100 lives were lost in the flooding [4]. In 2013, eight states in the central United States were hit by historic floods, which caused urban public transportation failures, communication interruptions, and power interruptions, and left entire cities paralyzed [5]. In 2012, Beijing suffered the strongest torrential rains and floods in 61 years, affecting 1.602 million people and causing RMB 11.64 billion in economic losses [6]. On 20 July 2021, Zhengzhou City, Henan Province, experienced exceptionally heavy rainstorms. The maximum hourly cumulative precipitation value reached 201.9 mm, exceeding its historical extreme value on land. The cumulative precipitation at 24 h was up to 627.4 mm, far exceeding the defined threshold of heavy rain (250 mm accumulated in 24 h). This has caused serious urban waterlogging in Zhengzhou, inflicting huge losses of life and property on the people [7].

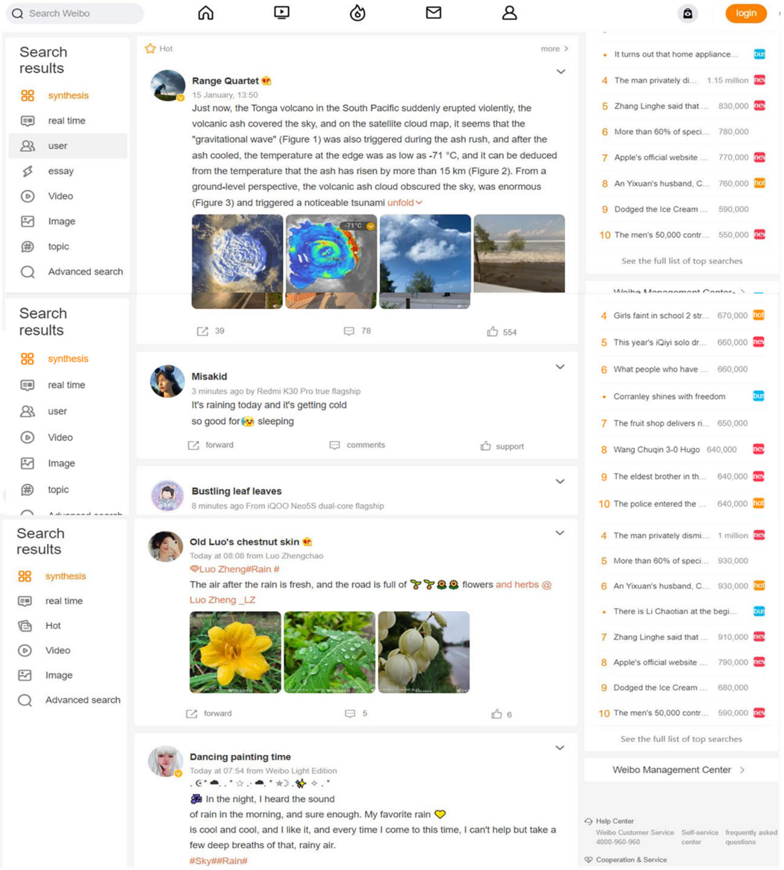
Urban rainfall data are important for the study of urban rain flood damage. [8]. However, the number of rainfall stations in cities is small and the distribution is uneven, so the measured data cannot reflect the urban rainfall situation well, which is unfavorable for the study of urban rainstorm patterns and disaster prevention. Following a long-term study, it was found that different rainfall patterns cause different geological disasters, and the relevant measures for disaster prevention can be developed by studying different types of rainfall.

Traditional research on rainstorm patterns is mainly based on the rainfall measured at rainfall stations. According to the existing research, the most commonly used rain patterns include the seven rain patterns identified by Bogomazova in the Soviet Union, including three unimodal rain patterns, one uniform rain pattern and three bimodal rain patterns [9,10]. The Chicago rain pattern was proposed by Keifer and Chu [11,12]. Ou et al. [13] verified the applicability of the Chicago rain pattern in the calculation of urban drainage and proposed that the use of this pattern can provide a reference for the analysis of the rain patterns in a short-duration urban storm. Rain pattern identification methods mainly include a visual estimation and a fuzzy recognition [14]. The visual estimation method is a method using the computer-generated histogram of the patterns, and then identifying the rainfall patterns visually. Although this method is simple and easy to implement, the process is of great variability and prone to human error. The fuzzy recognition method establishes seven kinds of rainfall pattern fuzzy matrices and then calculates the fit degree of each actual rainfall pattern with its respective fuzzy matrix, then it judges the rain pattern, according to the principle of proximity.

The above method uses the measured rainfall data for the calculation and analysis of the rainfall patterns, and it is inevitably affected by insufficient data when it is directly applied to urban storm and flood research. Rainfall data are the basic data for the study of rainstorm disasters. The adequacy of the rainfall data directly affects the accuracy of the rainstorm research [15].

With the continuous development of internet technology, a growing number of people are increasingly willing to reveal their lives on social platforms, which contain a lot of unstructured data that can be further explored. Unstructured data are data that have irregular or incomplete data structures, have no predefined data models, and are not conveniently represented by two-dimensional logic tables in a database. These data include office document formats, texts, images, XML, HTML, various reports, images, audio/video information, etc. [16]. The measured rainfall data and unstructured data belong to two different structures of big data, both of which can reflect the process of a rainfall, and the unstructured data is richer than the measured data. For example, whenever an emergency, such as a rainstorm, flood, or earthquake occurs, a large amount of unstructured data, including texts, pictures, and videos, will emerge on social platforms, as shown in Figure 1.

Using unstructured data to solve the problem of data limitation in urban flood disaster research, has become a hot topic for scholars [17]. Bruijn et al. [18] established a global database of historical and real-time flooding events, based on the Twitter social media platform. Saini et al. [19] analyzed 117 years (1901–2017) of rainfall trends in the West Coast Plain and Hill Agro-Climatic Region, using a rainfall grid dataset, indicating the rainfall regime shift in the region. By analyzing Sina Weibo data after the occurrence of rainstorms and waterlogging disasters, Chen [20] proposed a new idea of supplementing official observation data with Sina Weibo data. Li et al. [21] used web crawler technology to obtain Sina Weibo data with geographic location information. By analyzing the correlation between the number of rainfall-related Sina Weibo posts and the measured rainfall data, they found that by establishing simulated rainfall stations, they could effectively improve the interpolation accuracy of the traditional rainfall stations. Wu et al. [22] used big data to analyze the vulnerability of urban rainstorms and flood disasters. These studies provided new ideas for applying unstructured data to urban flood research. Unstructured data enrich the urban rainfall data and lays a data foundation for urban rainstorm research. The research demonstrates the scientific implications of collecting and using big data to study the urban rainfall patterns. Sina Weibo is a microblogging site in China. Similar to Twitter, it is a broadcast-style social media and networking platform that shares short, real-time information through a follow-up mechanism, based on the sharing, dissemination, and acquisition of user relationship information. Launched on August 14, 2009, Sina Weibo is one of the largest social media platforms in China, with 566 million monthly active users and an average of 246 million daily active users, as of June 2021. In this paper, taking Zhengzhou as an example, the feasibility of using unstructured data to identify the urban rain patterns was determined, based on data from Sina Weibo. Firstly, by editing the web crawler's code, user nicknames, the release times of blogs, user locations, blog content, and other information were retrieved in the Sina Weibo advanced search result page, and the retrieved pages were parsed and saved as CSV files. Secondly, the feasibility of applying unstructured data to the analysis of rain patterns was verified using the correlation coefficient method. Finally, the fuzzy recognition method was used to identify rainfall patterns, according to both the measured and unstructured rainfall data. The two results were comparatively analyzed, which verified the reliability of applying the unstructured data to the analysis of the urban rainfall patterns.



Range Quartet
15 January, 13:50
Just now, the Tonga volcano in the South Pacific suddenly erupted violently, the volcanic ash covered the sky, and on the satellite cloud map, it seems that the "gravitational wave" (Figure 1) was also triggered during the ash rush, and after the ash cooled, the temperature at the edge was as low as -71 °C, and it can be deduced from the temperature that the ash has risen by more than 15 km (Figure 2). From a ground-level perspective, the volcanic ash cloud obscured the sky, was enormous (Figure 3) and triggered a noticeable tsunami unfold

Misakid
3 minutes ago by Redmi K30 Pro true flagship
It's raining today and it's getting cold
so good for sleeping

Bustling leaf leaves
8 minutes ago From iQOO Neo5S dual-core flagship

Old Luo's chestnut skin
Today at 08:08 from Luo Zhengchao
Luo Zheng#Rain #
The air after the rain is fresh, and the road is full of flowers and herbs @ Luo Zheng _LZ

Dancing painting time
Today at 07:54 from Weibo Light Edition
. ☾ * . . * ☆ . · . * ★☽ . ✧ . *
In the night, I heard the sound
of rain in the morning, and sure enough. My favorite rain
is cool and cool, and I like it, and every time I come to this time, I can't help but take a few deep breaths of that, rainy air.
#Sky##Rain#

- It turns out that home appliance... bus
4 The man privately di... 1.15 million new
5 Zhang Linghe said that ... 830,000 new
6 More than 60% of speci... 780,000
7 Apple's official website ... 770,000 new
8 An Yixuan's husband, C... 760,000 hot
9 Dodged the Ice Cream ... 590,000
10 The men's 50,000 contr... 550,000 new
See the full list of top searches

Weibo Management Center >

4 Girls faint in school 2 str... 670,000 hot
5 This year's iQiyi solo dr... 660,000 new
6 What people who have ... 660,000
- Corranley shines with freedom bus
7 The fruit shop delivers ri... 650,000
8 Wang Chuqin 3-0 Hugo 640,000 new
9 The eldest brother in th... 640,000 new
10 The police entered the ... 640,000 hot

4 The man privately dismi... 1 million new
5 More than 60% of speci... 930,000
6 An Yixuan's husband, C... 930,000 hot
- There is Li Chaotian at the begi... bus
7 Zhang Linghe said that ... 910,000 new
8 Apple's official website ... 790,000 new
9 Dodged the Ice Cream ... 680,000
10 The men's 50,000 contr... 590,000 new
See the full list of top searches

Weibo Management Center >

Help Center
Weibo Customer Service 4000-960-960 Self-service center frequently asked questions
Cooperation & Service

Figure 1. Unstructured data about the contingencies on Weibo.

2. Materials and Methods

2.1. Study Area

Zhengzhou, in the north-central part of Henan Province, China, is located between 112°42′ and 114°14′ east longitude, and between 34°16′ and 34°58′ north latitude (Figure 2), with an area of about 1181.51 km^2. Zhengzhou is a northern temperate continental monsoon climate with a frequent alternation, due to cold and warm air masses. It is a high-risk area for flood disasters and one of the most intensive flood control towns [23]. The average annual precipitation is 625.9 mm. Heavy rains and floods are more frequent in summer, with the rainfall from July to September accounting for 60–70% of the total annual rainfall [24]. According to the statistics, Zhengzhou has suffered more than 15 rainstorms every year since 2006, and each flood disaster has caused more than USD 30 million in economic losses, resulting in serious disaster for the people of Zhengzhou.

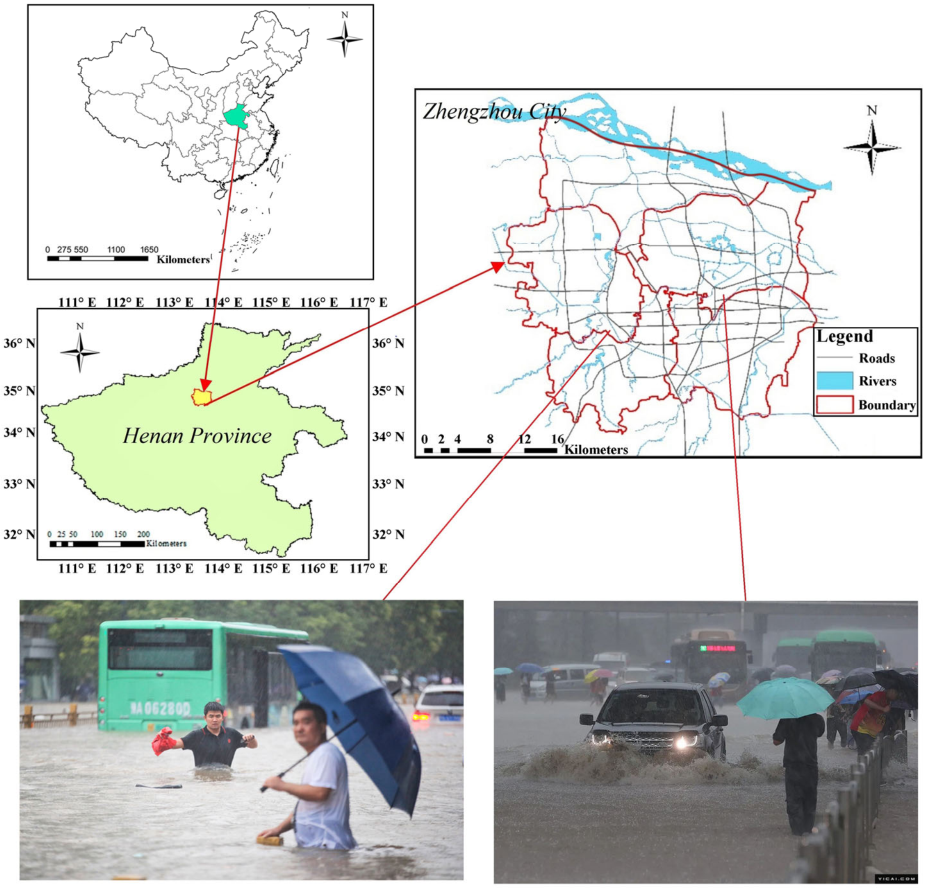


Figure 2. The geographical location of Zhengzhou and the heavy rain disaster that occurred in Zhengzhou on 20 July 2022.

In recent years, Zhengzhou has made significant progress in the construction of big data infrastructure. In 2013, it was identified as one of the first 10 pilot cities for the construction of a space–time information-based cloud computing platform for smart cities in China [25]. In 2015, Zhengzhou City achieved full coverage of the 4G mobile communications network in both urban and rural areas, and it completed the construction of a public information resource catalog system, a sharing platform, and a public service platform. In 2016, Zhengzhou ranked 19th among 335 "internet plus" cities in China. The Smart City Research Institute of Zhengzhou University, established in 2016, provides support for the construction, industrial development, and innovation of Zhengzhou's smart city technology.

2.2. Data Sources

2.2.1. Rainfall

Considering Zhengzhou as a case, the daily rainfall data of fourteen rainfall stations, taken from 2014 to 2018, were collected. The statistical interval of the rainfall data was ten minutes. The data were all digitized rainfall data. The point rainfall data of each station were analyzed using the arithmetic mean method, to obtain the areal rainfall data in Zhengzhou, and the rainfall accuracy was 0.5 mm.

2.2.2. Unstructured Data

The unstructured data came from Weibo texts that reflected rainfall situations. By using Python programming, a web crawler code was written to crawl Weibo texts related to rainfall in Zhengzhou City, from 2011 to 2018, on the Sina Weibo platform. Then, it deleted the Weibo text that did not reflect rainfall information. The actual rainfall was reflected by the number of microblog texts related to rainfall, during the rainfall process. A geographical distribution map of the rainfall station location, compared to the unstructured data is shown in Figure 3.

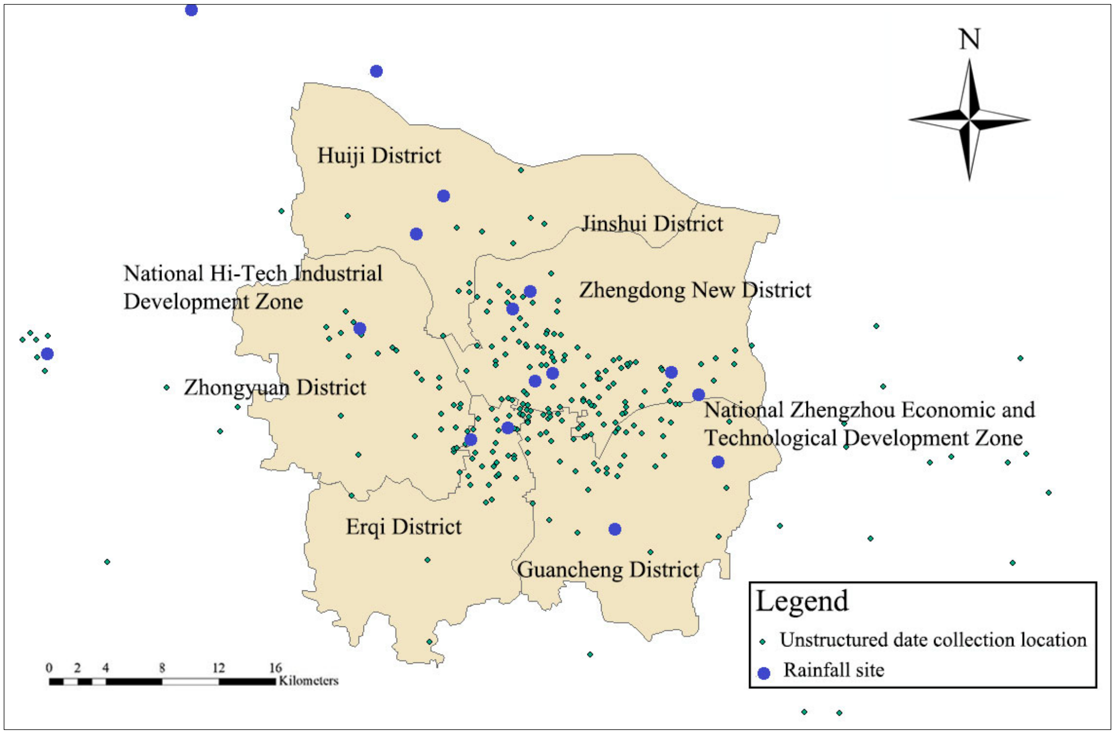


Figure 3. Geographic distribution of the rainfall unstructured data collection points, from 2011 to 2018, and the rainfall stations in Zhengzhou City.

2.3. Methodology

2.3.1. Unstructured Data Acquisition Method of the Rainfall Based on Web Crawler Technology

In this study, the web crawler code was written in Python programming, and then the unstructured data of the rainfall in Zhengzhou was crawled on Sina Weibo. A web crawler is a program or script that automatically grabs internet information according to certain rules [26–28]. A web crawler starts from an initial webpage URL. Then, it obtains a qualified new webpage URL from the webpage, according to the set criteria. Finally, it saves the qualified webpage, locally, and puts the newly acquired webpage URL in the queue to be crawled until the program ends, either when it reaches the system-set end criteria or no qualified webpage can be crawled. Then, it parses and analyzes the crawled webpage to obtain the data required [29–31].

Taking the Sina Weibo platform as an example, the rainfall data crawling steps were as follows: The first step was to simulate an individual account login on Sina Weibo; the second step was to enter the advanced search page of Sina Weibo; the third step was to analyze the advanced search page of Sina Weibo. Taking Zhengzhou as an example, the crawler entered the keyword rain and selected all types and content, the period selected was from 2011 to 2018, and the location was Zhengzhou, Henan. Then, it arrived at the search result page. The fourth step was to parse the search result page. Once all of the webpages on the search result page were obtained, each page was parsed and crawled, then keywords were set to exclude the interference of the irrelevant data, such as "meteor shower" and names with the word "rain". Finally, the page was written into the result file, which was stored in CSV format. The fifth step was to end the program after all of the search result pages were crawled. A flow chart of the steps taken by the Sina Weibo rainfall data crawler is shown in Figure 4.

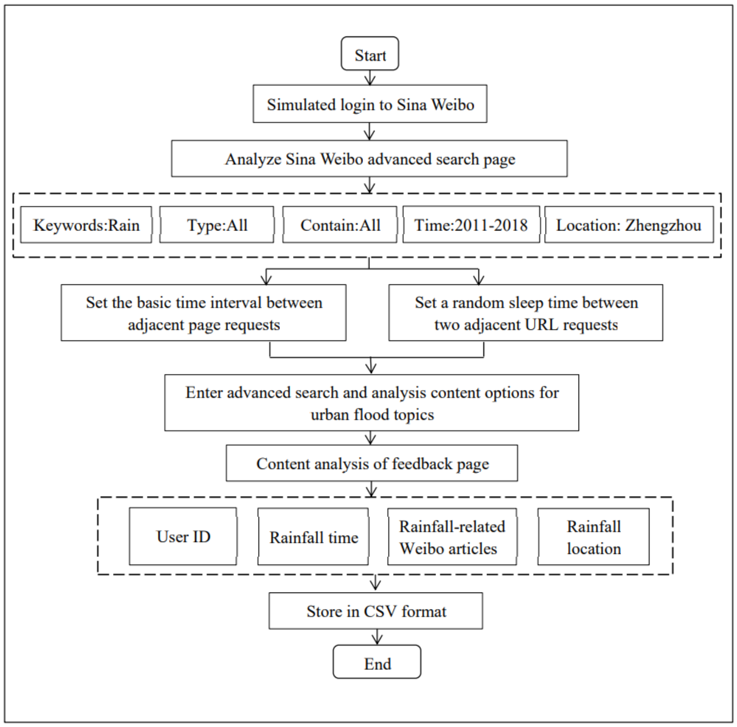
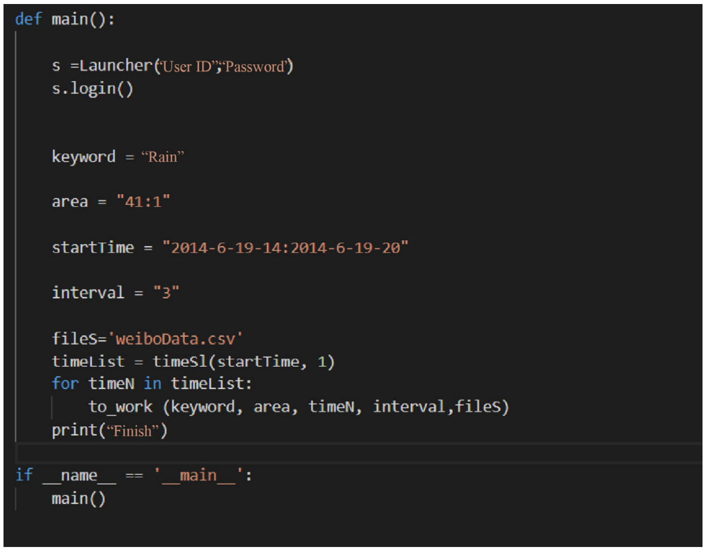

Start
Simulated login to Sina Weibo
Analyze Sina Weibo advanced search page
Keywords:Rain
Type:All
Contain:All
Time:2011-2018
Location: Zhengzhou
Set the basic time interval between adjacent page requests
Set a random sleep time between two adjacent URL requests
Enter advanced search and analysis content options for urban flood topics
Content analysis of feedback page
User ID
Rainfall time
Rainfall-related Weibo articles
Rainfall location
Store in CSV format
End

Figure 4. Flow chart of the Sina Weibo rainfall data crawler.

The web crawler code was written in Python, and part of the code is shown in Figure 5.


```
def main():

    s =Launcher('User ID'';'Password')
    s.login()


    keyword = "Rain"

    area = "41:1"

    startTime = "2014-6-19-14:2014-6-19-20"

    interval = "3"

    fileS='weiboData.csv'
    timeList = timeSl(startTime, 1)
    for timeN in timeList:
        to_work (keyword, area, timeN, interval,fileS)
    print("Finish")

if __name__ == '__main__':
    main()
```

Figure 5. Part of the web crawler code that crawls the unstructured data.

2.3.2. Correlation Analysis Method of the Unstructured Data and the Measured Rainfall Data

A correlation analysis between the Sina Weibo crawling data and the measured rainfall data was carried out using the Pearson correlation coefficient method [32]. The measured rainfall was expressed as X, and the number of Sina Weibo posts involving rainfall was expressed as y. The formula for the correlation coefficient is as follows:

$$\mathrm{r} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{1}$$

In the formula, r represents the correlation coefficient, and its value range is ∣r∣ ≤ 1. A positive value of r means a positive correlation between the two directions; otherwise, a negative value means a negative correlation; ∣r∣ = means the two items are completely related; 0.8 ≤ ∣r∣ < 1 represents high correlations; 0.6 ≤ ∣r∣ < 0.8 represents strong correlations; 0.4 ≤ ∣r∣ < 0.6 represents moderate correlations; 0.2 ≤ ∣r∣ < 0.4 represents weak correlations; 0 < ∣r∣ < 0.2 represents very weak correlations; and ∣r∣ = 0 means the two items have no correlation [33,34].

2.3.3. Rainfall Pattern Identification Method Based on the Fuzzy Recognition Method

The fuzzy recognition method was used to identify rain patterns. Firstly, the ratio of the period rainfall to the total rainfall, was used as the rain pattern index, and a pattern matrix of seven rain patterns was established, which is shown in Table 1. Then, the proximity of each actual rainfall to the seven rain patterns (Figure 6), was calculated, and the rain pattern was identified according to the principle of proximity.

Table 1. Pattern matrix of the seven rainfall patterns.

Rainfall Pattern	**Period**					
	1	**2**	**3**	**4**	**5**	**6**
I	30.4%	26.1%	17.4%	13.0%	8.7%	4.3%
II	3.8%	7.7%	11.5%	23.1%	30.8%	23.1%
III	5.0%	20.0%	35.0%	25.0%	10.0%	5.0%
IV	14.3%	19.0%	14.3%	19.0%	14.3%	19.0%
V	25.0%	15.0%	5.0%	10.0%	25.0%	20.0%
VI	22.2%	11.1%	16.7%	27.8%	16.7%	5.6%
VII	8.7%	13.0%	30.4%	17.4%	8.7%	21.7%

Note: The data in the table are the percentage of the rainfall in one period compared to the total period.

The formula for calculating the closeness degree e_k between each rainfall and the seven modes is as follows:

$$e_k = 1 - \sqrt{\frac{1}{m}\sum_{i=1}^{m}(g_{ki} - x_i)^2} \qquad (k = 1,2\ldots,7) \tag{2}$$

where x_i is the rain pattern index of a rainfall event, $xi = \Delta H_i/H,\Delta H_i$ refers to the rainfall in each period, H is the total rainfall. g_{ki} is the rain indicator for the seven modes, $g_{ki} = \Delta H_{ki}$ / H_k, ΔH_{ki} is the rainfall in each period of the model, and H_k is the total rainfall of the model.

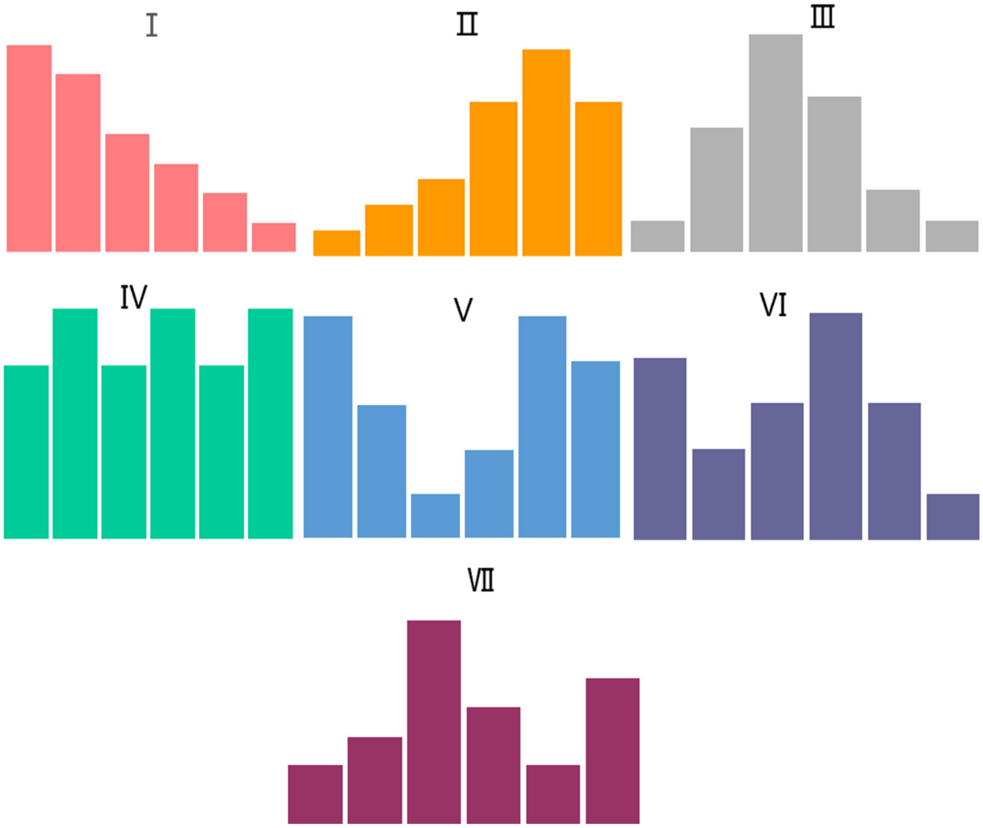


Figure 6. Seven modes of rainfall patterns. Rain pattern (**I**) is a single peak, and the rain peak is located in the front; Rain pattern (**II**) is a single peak, and the rain peak is located at the rear; Rain pattern (**III**) is a single peak, and the rain peak is in the middle; Rain pattern (**IV**) is a uniform rain pattern; Rain pattern (**V**) is bimodal, and the rain peaks are located at the front and rear; Rain pattern (**VI**) is bimodal and the rain peak is located at the front and in the middle; Rain pattern (**VII**) is bimodal and the rain peak is located in the middle and at the rear.

Based on the principle of proximity, if the closeness degree, e_k, to *k*th was the largest, the rain belonged to the *k*-th rain pattern. The division of work was performed automatically by computer, which avoided human error in the judgment.

3. Results

3.1. Calculation results of rain patterns in Zhengzhou City based on unstructured data

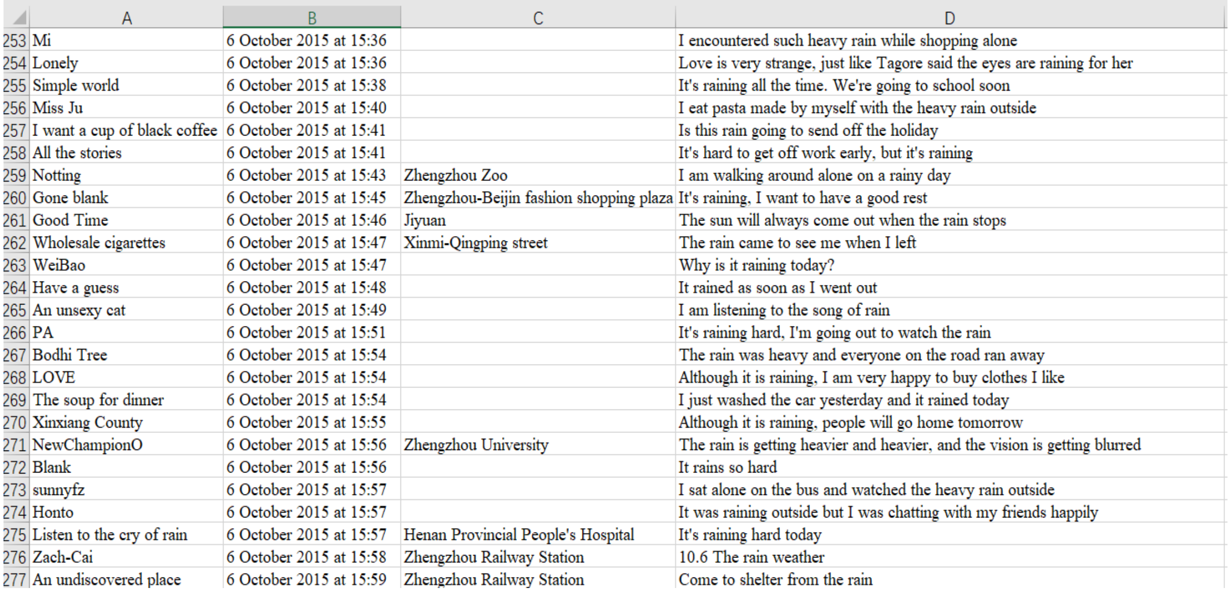
Taking Zhengzhou City as an example, the rainfall patterns of the unstructured data were analyzed. The unstructured data were obtained from the Sina Weibo platform with the web crawler program, and the unstructured data of 153 rainfall events, from 2011 to 2018, in Zhengzhou, were crawled. The measured data were the rainfall in the same 24 h periods at 14 rain stations in Zhengzhou, which was calculated in 1-h units. The period-by-period rainfall of the 14 rainfall stations, was arithmetically averaged, and a period-by-period rainfall table was established. Limited by the length of the article, only five rainfall data were shown in the table. The 20180730, 20170825, 20160605, 20150828, and 20140501 measured data tables for the rainfall, are shown in Table 2. Taking 20180730 as an example, 2018 is the year of the local rainfall, 07 is the month of the local rainfall, and 30 is the date of the local rainfall.

Table 2. Part of the measured rainfall data. Units of the measured rainfall are in millimeters.

Time Period	Session				
	30 July 2018	25 August 2017	5 June 2016	28 August 2015	1 May 2014
0	0	0	16.14	0	0
1	0	0	0.32	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0
5	0	0	0.04	0	0
6	0	0	0	0	0
7	0	0	0	0	0
8	0	0.04	0	0	0
9	0.07	1.36	1.71	0	0
10	0.07	6.25	12.07	0	0
11	0.21	9.04	1.54	0	0
12	3.82	2.89	0.07	0	0
13	0.43	0.43	0	0	0
14	0.07	0.14	0	0	2.14
15	0.07	0.11	0.04	0	0
16	0.18	0.07	0	0.57	0
17	0.11	0.04	0	4.64	0
18	0	0	0	0.32	0
19	0	0	0	0	0
20	0	0	3.57	0	0
21	0	0	12.89	0	0
22	0	0	11.04	0	0
23	0	0	3.5	0	0

3.1.1. Result and Analysis of the Unstructured Data Crawling

Figure 7 shows part of the data crawled, according to the keyword "rain" and the location is Zhengzhou, Henan.



	A	B	C	D
253	Mi	6 October 2015 at 15:36		I encountered such heavy rain while shopping alone
254	Lonely	6 October 2015 at 15:36		Love is very strange, just like Tagore said the eyes are raining for her
255	Simple world	6 October 2015 at 15:38		It's raining all the time. We're going to school soon
256	Miss Ju	6 October 2015 at 15:40		I eat pasta made by myself with the heavy rain outside
257	I want a cup of black coffee	6 October 2015 at 15:41		Is this rain going to send off the holiday
258	All the stories	6 October 2015 at 15:41		It's hard to get off work early, but it's raining
259	Notting	6 October 2015 at 15:43	Zhengzhou Zoo	I am walking around alone on a rainy day
260	Gone blank	6 October 2015 at 15:45	Zhengzhou-Beijin fashion shopping plaza	It's raining, I want to have a good rest
261	Good Time	6 October 2015 at 15:46	Jiyuan	The sun will always come out when the rain stops
262	Wholesale cigarettes	6 October 2015 at 15:47	Xinmi-Qingping street	The rain came to see me when I left
263	WeiBao	6 October 2015 at 15:47		Why is it raining today?
264	Have a guess	6 October 2015 at 15:48		It rained as soon as I went out
265	An unsexy cat	6 October 2015 at 15:49		I am listening to the song of rain
266	PA	6 October 2015 at 15:51		It's raining hard, I'm going out to watch the rain
267	Bodhi Tree	6 October 2015 at 15:54		The rain was heavy and everyone on the road ran away
268	LOVE	6 October 2015 at 15:54		Although it is raining, I am very happy to buy clothes I like
269	The soup for dinner	6 October 2015 at 15:54		I just washed the car yesterday and it rained today
270	Xinxiang County	6 October 2015 at 15:55		Although it is raining, people will go home tomorrow
271	NewChampionO	6 October 2015 at 15:56	Zhengzhou University	The rain is getting heavier and heavier, and the vision is getting blurred
272	Blank	6 October 2015 at 15:56		It rains so hard
273	sunnyfz	6 October 2015 at 15:57		I sat alone on the bus and watched the heavy rain outside
274	Honto	6 October 2015 at 15:57		It was raining outside but I was chatting with my friends happily
275	Listen to the cry of rain	6 October 2015 at 15:57	Henan Provincial People's Hospital	It's raining hard today
276	Zach-Cai	6 October 2015 at 15:58	Zhengzhou Railway Station	10.6 The rain weather
277	An undiscovered place	6 October 2015 at 15:59	Zhengzhou Railway Station	Come to shelter from the rain

Figure 7. Part of the original unstructured data.

In the above figure, column A is the user's nickname, column B is the time of the Sina Weibo post, column C is the address, and column D is the content of the Sina Weibo post.

When initially sorting out the original data, it could be found that some texts reflect real rainfall, but it was difficult to obtain the rainfall-related data, directly based on the content from Sina Weibo. It was found that, as the duration and volume of the rainfall gradually increased, the amount of unstructured data about the rainfall on social media platforms also increased. Therefore, by further analyzing the data, it was possible to study the amount of rainfall reflected in the microblogs.

Due to the existence of irrelevant data in the unstructured data, the unstructured data were not zero for the whole period, which made it difficult to judge the start and end time of the rainfall, directly based on the amount of data. Through a statistical analysis of the amount of data at the time when there was no rainfall in the unstructured data, the average value of the amount of data irrelevant to the period was 15. We tried to divide the process line with the average value of 15 as the data baseline and then used 25 and 30 as the baselines for the comparison process line. Taking the rainfall of 19 June 2014as an example, a processed comparison chart is shown in Figure 8. The larger the baseline selected, the more data that could be excluded. In this way, the unstructured data and the measured data process lines could be closer to each other before the rainfall began. However, the selection could not be too large, which would exclude the real data. Therefore, at twice the average value, 30 was selected as the baseline to process the unstructured data, to eliminate the interference of the irrelevant data as much as possible.

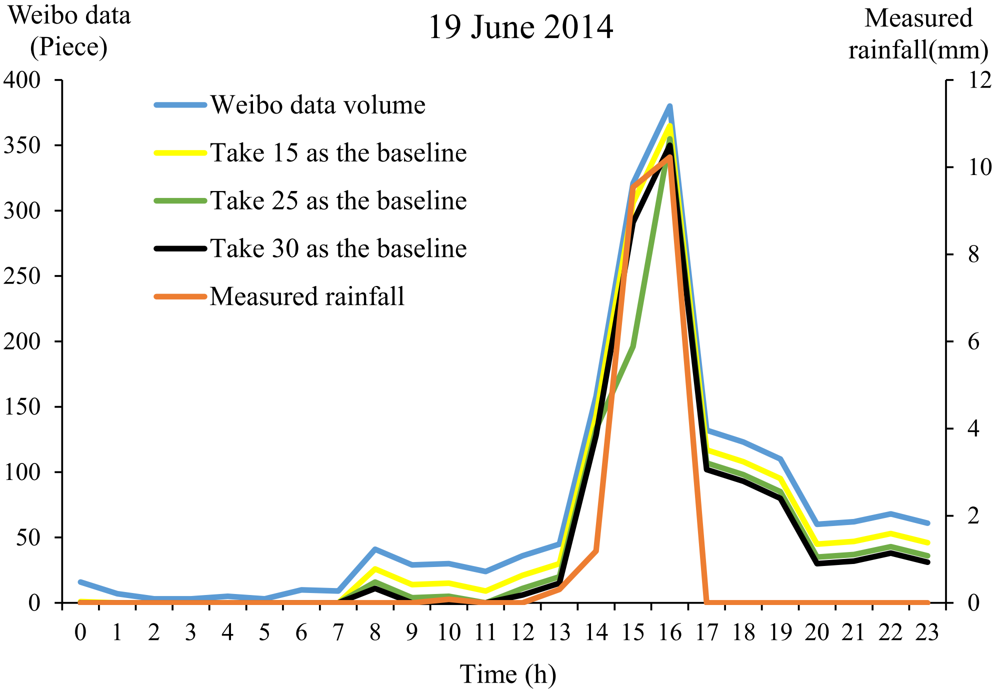


Figure 8. Data baseline selection.

The irrelevant data in the original data were removed, and the period's data volume table was established. Taking the rainfall of 20180730, 20170825, 20160605, 20150828, and 20140501, as examples, the period data volume is shown in Table 3.

Table 3. Unstructured data of the partial rainfall. Units of the unstructured data are pieces.

Time Period	Session				
	30 July 2018	25 August 2017	5 June 2016	28 August 2015	1 May 2014
0	13	6	645	10	12
1	3	6	100	5	7
2	1	3	19	2	3
3	5	1	12	2	2
4	0	1	16	2	3
5	2	4	6	1	10
6	9	8	16	5	9
7	14	18	47	23	12
8	16	29	63	11	8
9	25	52	136	16	15
10	18	98	388	10	9
11	38	103	173	21	20
12	78	84	128	5	14
13	70	33	82	14	16
14	38	43	76	12	105
15	34	42	53	26	78
16	34	30	46	31	31
17	31	32	46	139	20
18	23	26	66	63	34
19	31	25	90	26	24
20	28	37	160	32	27
21	24	39	407	26	27
22	31	38	505	27	28
23	25	43	119	29	18

The process line of the unstructured data was drawn, according to Table 2, and then, it was observed whether the process lines of the unstructured data reflected the rainfall characteristics. Some process lines are shown in Figure 9.

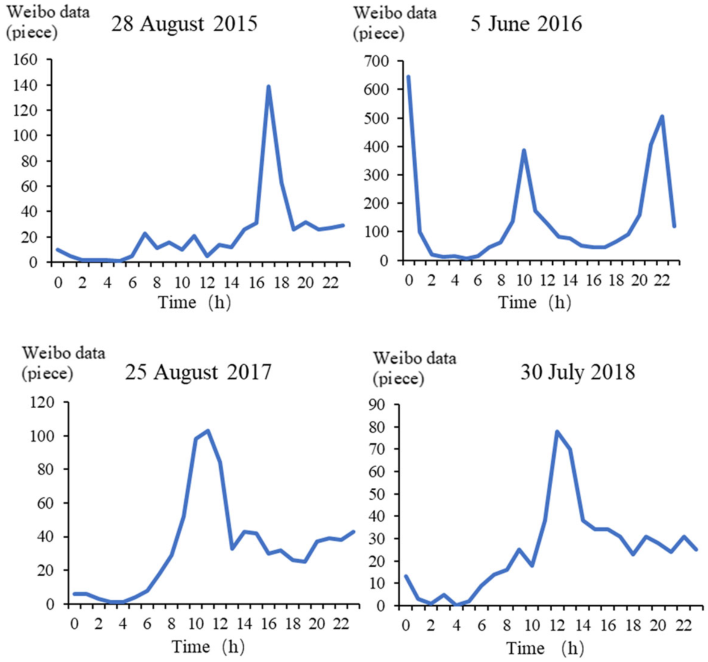


Figure 9. Process lines drawn from the unstructured data of the partial rainfall.

3.1.2. Correlation Analysis

From the beginning of the rain to the end of the rain, a large number of Sina Weibo users published rainfall-related blog posts in real-time, describing their current status. The number of posts varied with the duration and amount of rain [21]. These data were compared with the rainfall intensity process lines to draw a curve, based on the data volume and time, reflecting the change in rainfall intensity with time. Therefore, a correlation analysis between the measured data from the rainfall station and the unstructured data from Sina Weibo was carried out to verify the feasibility of applying the unstructured data to the rainfall pattern analysis.

The process line of the rainfall over time is the relation curve between the rainfall and the corresponding time, which can well reflect the rainfall of each period in the total rainfall duration [35,36]. Therefore, it is more intuitive to analyze whether the unstructured data can reflect the actual rainfall process, by comparing the process line drawn by the unstructured data with the rainfall process line drawn by the measured data in the same field. This is shown in Figure 10.

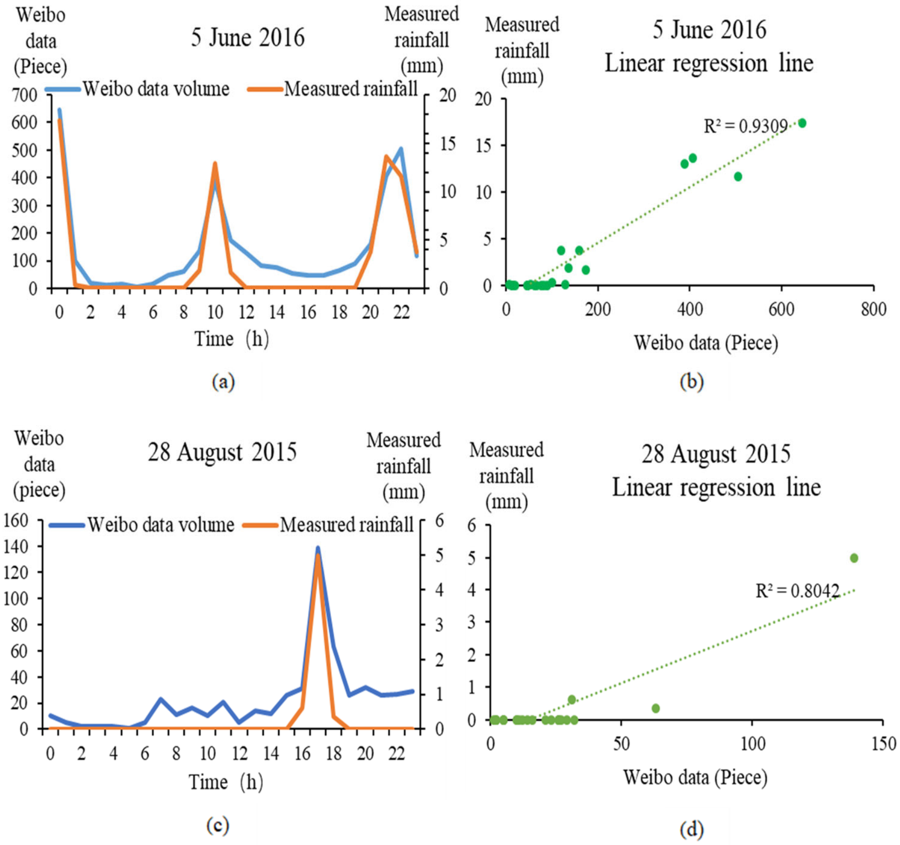


Figure 10. Comparison of two kinds of 24−h data process lines in Zhengzhou. (**a**) Process line drawn for the collected Weibo data and the measured rainfall data, during a rainfall event that occurred on 5 June 2016. (**b**) Linear regression line drawn for the Weibo data collected and the measured rainfall data, during a rainfall event that occurred on 5 June 2016. (**c**) Process line drawn for the collected Weibo data and the measured rainfall data, during a rainfall event that occurred on 28 August 2015. (**d**) Linear regression line drawn for the Weibo data collected and the measured rainfall data, during a rainfall event that occurred on 28 August 2015. The green circles indicate Weibo data and measured rainfall data.

By quantitatively analyzing the correlation between the measured rainfall data and the unstructured data, using Pearson's correlation coefficient, as mentioned in Section

2.3.2, the feasibility of applying the unstructured data to the urban rainfall type analysis can be verified. According to formula (1), the correlation coefficient between the average rainfall data and the amount of Sina Weibo data, was calculated. The calculation results are shown in Figure 11. There were 20 rainfalls events with a high correlation (0.8 ≤ ∣r∣ < 1) and 44 rainfalls events with a strong correlation (0.6 ≤ ∣r∣ < 0.8).

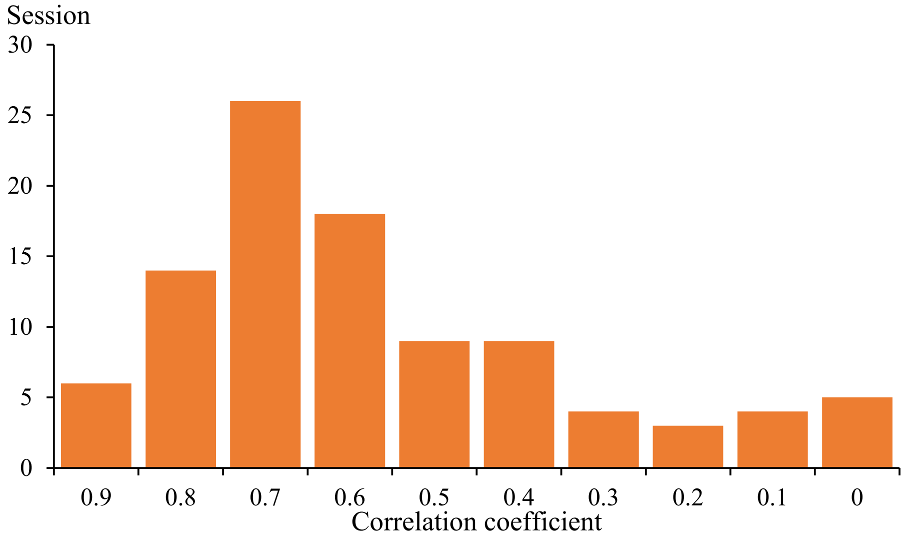


Figure 11. Distribution of the correlation coefficients between the unstructured data and the measured rainfall data.

3.1.3. Calculation Results of the Rain Pattern Analysis

According to the fuzzy recognition method, the rain patterns of 20 Sina Weibo rainfall data with a high correlation (0.8 ≤ ∣r∣ < 1) were identified. Then, the identified rainfall pattern results were linked to the rainfall events, as shown in Table 4.

Table 4. Rainfall pattern identified results of Weibo.

Correlation Coefficient	Session	Rainfall Pattern	Rain Peak Type	Rainfall Peak Location
0.8	26 August 2014	III	single peak	Central
0.8	27 August 2014	III		Central
0.8	7 July 2015	III		Central
0.8	22 July 2015	III		Central
0.8	3 August 2015	I		Front section
0.8	28 August 2015	III		Central
0.8	7 June 2016	II		Rear
0.8	25 August 2017	III		Central
0.9	19 June 2014	III		Central
0.9	29 July 2014	II		Rear
0.9	5 June 2016	III		Central
0.9	12 September 2016	III		Central
0.9	22 May 2017	I		Front section
0.8	19 April 2014	IV	uniform rain pattern	No peak
0.8	10 May 2014	IV		No peak
0.8	19 April 2015	IV		No peak
0.8	22 June 2017	IV		No peak
0.8	1 May 2015	VI	bimodal peak	Front and middle

0.8	26 June 2015	V		Front and back
0.9	6 October 2015	VI		Front and middle

The measured rainfall data from 13 rainfall stations were selected for the rain pattern analysis with reference to the geographic sources of the Sina Weibo data. The selection of the actual rainfall events data was the same as for the selection of the Sina Weibo rainfall events. Subsequently, the rain patterns, based on the fuzzy recognition method, were identified. The results are shown in Table 5.

Table 5. Identified rainfall pattern results from the measured data.

Session	Rainfall Pattern	Rain Peak Type	Rainfall Peak Location
19 April 2014	II	single peak	Rear
26 August 2014	III		Central
27 August 2014	I		Front section
1 May 2015	II		Rear
7 July 2015	II		Rear
22 July 2015	III		Central
28 August 2015	III		Central
22 June 2017	I		Front section
25 August 2017	III		Central
19 June 2014	II		Rear
6 October 2015	III		Central
5 June 2016	III		Central
12 September 2016	III		Central
22 May 2017	I		Front section
10 May 2014	IV	uniform rain pattern	No peak
19 April 2015	VI	bimodal peak	Front and middle
26 June 2015	V		Front and back
3 August 2015	VI		Front and middle
7 June 2016	VI		Front and middle
29 July 2014	VI		Front and middle

The two groups of data were compared and analyzed, and the results are shown in Table 5. The matching conditions of the two groups of data are shown in Table 6.

Table 6. Comparison results of the rainfall patterns identified by the two kinds of data.

	Session	Rain Pattern	
		Weibo Data	Measured Data
Match	10 May 2014	IV	IV
	26 August 2014	III	III
	26 June 2015	V	V
	22 July 2015	III	III
	28 August 2015	III	III
	25 August 2017	III	III
	5 June 2016	III	III
	12 September 2016	III	III
	22 May 2017	I	I
Does not match	19 April 2014	IV	II
	27 August 2014	III	I

19 April 2015	IV	VI
1 May 2015	VI	II
7 July 2015	III	II
3 August 2015	I	VI
7 June 2016	II	VI
22 June 2017	IV	I
19 June 2014	III	II
29 July 2014	II	VI
6 October 2015	VI	III

3.2. Analysis of the Results

As seen in Figure 11 and Figure 12, the correlation between the unstructured data and the measured rainfall data, was analyzed. Among the 98 rainfall events, the number of high correlations (0.8 ≤ ∣r∣ < 1) was 20, accounting for 20.41% of the total; the number of strong correlations (0.6 ≤ ∣r∣ < 0.8) was 44, accounting for 44.90% of the total; the number of moderate correlations (0.4 ≤ ∣r∣ < 0.6) was 18, accounting for 18.37% of the total; the number of weak correlations (0.2 ≤ ∣r∣ < 0.4) was 7, accounting for 7.14% of the total; the number of extremely weak correlations (0 < ∣r∣ < 0.2) was 4, accounting for 4.08% of the total; and the number of irrelevant (∣r∣ = 0) was 5, accounting for 5.10% of the total. More than half of the rainfall events had strong correlations between the Sina Weibo data and the measured data, indicating that there was a clear correlation between the crawled unstructured data and the rainfall. In the study by Li et al. [21], when the buffer radius was 2 km, the maximum correlation coefficient, between the rainfall and the Sina Weibo data, was 0.812, and the significance level was less than 0.01. This research also showed that there was an obvious correlation between the unstructured data and the precipitation.

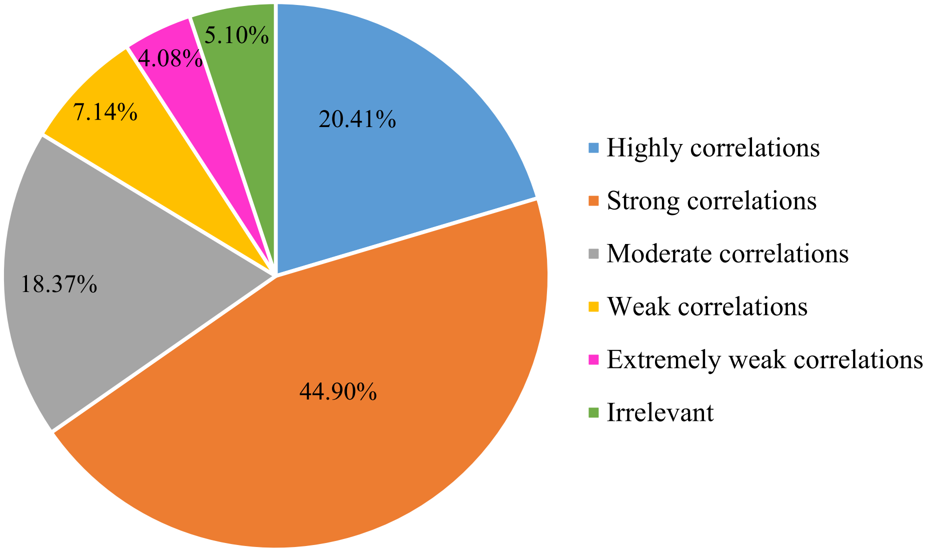


Figure 12. Proportion of the different correlation coefficients between the unstructured data and the measured rainfall data.

According to Tables 6 and 7, in the 20 selected rainfall events, the matches between the two groups of data accounted for 45%, nearly half, meaning that the use of the unstructured data to analyze the urban rainfall patterns may have a certain degree of reliability. Wu et al. [22] combined the text data with the traditional statistical data, to assess the vulnerability of cities to flood disasters. The results showed that research on rainstorm and flood disasters, based on big data, has a certain degree of reliability.

Table 7. Matching results of the rainfall patterns identified by two kinds of data.

Rainfall Pattern	Matching Number	Mismatch Number	Total	Proportion of Rain Pattern	Proportion of Matching	Percentage of Mismatches	Matching Degree
I	1	2	3	15%	11%	18%	33%
II	0	4	4	20%	0%	36%	0%
III	6	1	7	35%	67%	9%	86%
IV	1	0	1	5%	11%	0%	100%
V	1	0	1	5%	11%	0%	100%
VI	0	4	4	20%	0%	36%	0%
VII	0	0	0	0%	0%	0%	
Total	9	11	20	100%	100%	100%	

According to Table 7 and Figure 13, we know that, among the matching results, the number of rain pattern III matches was the largest, accounting for 67% of the total, while 86% of all rain pattern III fields matched. This showed that, among the seven rain patterns, the unstructured data had the best response to rain pattern III.

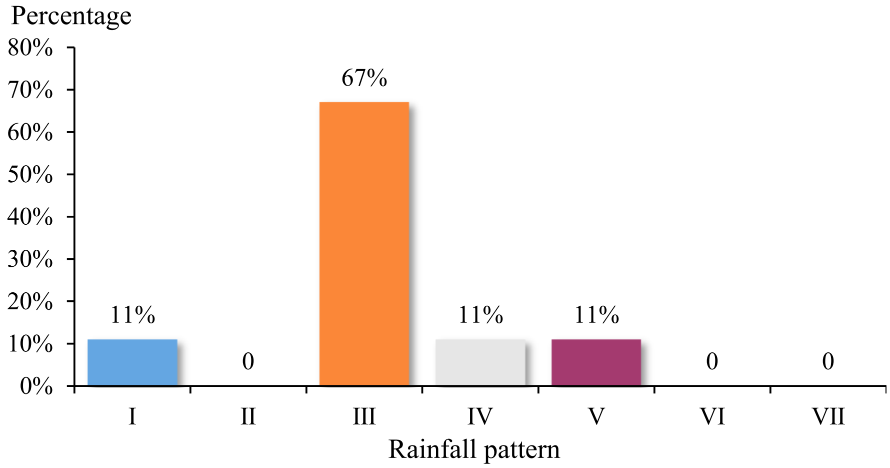


Figure 13. Matching results of the rain patterns identified by the unstructured data and the measured data.

Table 7 also shows that the results of the unstructured data correspond to four measured rain patterns of pattern VI, two of patterns II, one of pattern I, and one of pattern IV. This discrepancy was caused by the hysteresis in the unstructured data. The amount of rainfall in the early stages was relatively large, and the amount of unstructured data was also relatively large. The amount of rainfall in the middle of the rainfall becomes smaller, but the amount of unstructured data did not decrease or decrease significantly, due to hysteresis in the unstructured data. The rainfall in the later stages became larger, and the unstructured data continued to increase. Therefore, the rain pattern identified by the unstructured data was a unimodal rain pattern with the rain peak behind, or a uniform rain pattern, and it was difficult to divide it into a bimodal rain pattern

4. Discussion

The application of the unstructured data in the urban rainstorm disaster research has attracted the attention of scholars. For example, Xiao et al. [37] presented a real-time identification method for the urban-storm disasters, using Weibo data. The experiments showed that the naive Bayes algorithm had the highest macro-average accuracy. However, that research was focused on identifying storm hazards and failed to alleviate the problem of insufficient rainfall data in cities. Wu et al. [22] used a combination of textual data and traditional data to evaluate the ability of cities to resist flood disasters and showed that the use of unstructured data in the study of urban rainstorms and flood disasters has a certain degree of reliability.

This paper focused on the reliability of the unstructured data for the study of urban rainfall patterns. However, there are still some limitations in this study. The selection of end times for the rainfall events has a great influence on the results of the rain pattern identification because of the potential hysteresis in the unstructured data. Therefore, the primary problem to improving the reliability of the unstructured data in the urban rainfall pattern research is finding a way to reduce the hysteresis in the unstructured data. In addition, the unstructured data in this article were only obtained through Sina Weibo, because WeChat, QQ, and Facebook are relatively private and their data are difficult to obtain. Future researchers can further study ways to use more platforms to enrich the methods of obtaining unstructured data and to make the data more sufficient. In the analysis of the Sina Weibo data, it is found that it is difficult to crawl data that have both geographic locations and rainfall conditions, which makes it impossible to accurately reflect the specific location of the Sina Weibo data; thus, it is impossible to explore the specific effects of the spatial distribution on the unstructured data for the rain pattern analysis. As a result, future researchers should further study the spatial distribution of the unstructured data, to make the research contents more complete.

5. Conclusions

Rainfall data are very important for urban rainfall research. However, it is easy to not have enough rainfall data, due to an insufficient number or uneven distributions of urban rainfall stations. This paper studied the feasibility of using unstructured data in the urban rainfall pattern recognition. The unstructured precipitation data of Zhengzhou, from 2011 to 2018, were collected using web crawler technology, and the measured rainfall data from 14 rain measuring stations in Zhengzhou were collected and sorted out. First, the Pearson correlation coefficient method was used to calculate the correlation coefficient between the unstructured data and the measured rainfall data from the same field. Second, several rainfall events with strong correlations were selected, and the fuzzy identification method was used to identify them with the seven rainfall patterns. The matching degree between the rainfall patterns, identified by using two different datasets, was calculated, and the reliability of the unstructured data used in the study of the urban rainstorm patterns was analyzed. Using Zhengzhou as a case study, it was found that the matching degree of the rainfall pattern recognition results was 45% between the unstructured data and the measured data. It can find that the application of unstructured data in the analysis of the urban rainfall patterns has a certain degree of reliability; rainfall pattern III was the best match, indicating that the unstructured data are best at identifying this rainfall pattern. The results showed that the application of the unstructured data in the analysis of the urban rainfall patterns, not only has a certain degree of reliability, but it can also alleviate the problem of insufficient measured rainfall data, caused by insufficient rainfall stations and their unequal distribution.

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