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Spatiotemporal Change Analysis of Earthquake Emergency Information Based on Microblog Data: A Case Study of the "8.8" Jiuzhaigou Earthquake

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Abstract: Information from social media microblogging has been applied to management of emergency situations following disasters. In particular, such blogs contain much information about the public perception of disasters. However, the effective collection and use of disaster information from microblogs still presents a significant challenge. In this paper, a spatial distribution detection method is established using emergency information based on the urgency degree grading of microblogs and spatial autocorrelation analysis. Moreover, a character-level convolutional neural network classifier is applied for microblog classification in order to mine the spatio-temporal change process of emergency rescue information. The results from the Jiuzhaigou (Sichuan, China) earthquake case study demonstrate that different emergency information types exhibit different time variation characteristics. Moreover, spatial autocorrelation analysis based on the degree of text urgency can exclude uneven spatial distribution influences of the number of microblog users, and accurately determine the level of urgency of the situation. In addition, the classification and spatio-temporal analysis methods combined in this study can effectively mine the required emergency information, allowing us to understand emergency information spatio-temporal changes. Our study can be used as a reference for microblog information applications within the field of emergency rescue activity.

Keywords: earthquake emergency; microblog; spatial autocorrelation; urgency degree; spatiotemporal change

1. Introduction

Effective measures at the earthquake emergency stage can reduce both disaster loss and casualties, while the acquisition of earthquake emergency data and the extraction of disaster information can form the basis of emergency decision-making [1]. The losses that can be caused by wrong or inaccurate emergency information may be even greater than those caused by the disaster itself. Traditional emergency management often acquires information through manual reports, and is unable to adapt in the face of continuous emergencies and any corresponding changes [2]. Therefore, the use of mining and the application of emergency information following an earthquake is necessary in order to effectively assist emergency decision-making.

Microblog platforms, such as Twitter and Sina Weibo in China, act as tools for individuals to share opinions, experiences and opinions, and can effectively reflect people's behavior characteristics and perception of the geographical environment [3]. Their application in the field of disasters, including disaster event detection [4,5], disaster process identification [6], and disaster loss assessment [7,8], are increasingly frequently being observed. In particular, microblogs have great potential in the field of disaster emergency management. Sakaki et al. [9] observed a faster release of earthquake emergency information from Twitter compared to the Japanese Meteorological Agency. Simon et al. [10] used a disaster exercise to prove that microblogs and other types of social media can effectively increase the search and rescue efficiency of medical workers and assist in emergency rescues. During disaster emergency rescues, help must be provided for disaster losses in different regions, while at the same time, the spatial-temporal changes of the disaster should be understood and used to modify the decisions of rescue operations. Many studies have proved that analyzing the space, time and content of microblog data can effectively reflect the spatial-temporal changes of disasters. Liang et al. [11] used the mining of typhoon disaster characteristics in order to prove that social media data can effectively reflect the spatio-temporal changes of disasters. Guan et al. [8] mined microblog data information based on a spatial and temporal Twitter model, and conducted a post-earthquake damage assessment, suggesting the potential of using microblog activities for rapid damage assessment.

However, in most cases, the release of emergency information is constant and changes over time. This paper aims to mine emergency information from several, disorganized datasets in real-time, as well as effectively determining the disaster and changes of relief activities in order to expand prior research. Based on spatial autocorrelation analysis and character-level convolutional neural networks, this study analyzes the spatiotemporal mode of emergency information from the Chinese Sina Weibo microblog following the Jiuzhaigou (Sichuan, China) earthquake on 8 August 2017. This study also investigates the time and precision of the processing of earthquake emergency information mining with respect to spatio-temporal disaster changes, in order to assist in disaster judgments and emergency rescue decision-making.

2. Related Work

2.1. Microblog Data for Disaster Damage Assessment

Previous studies have proved that semantic information analysis of microblogs and other social media data can be applied effectively and quickly for the assessment of disaster loss. For example, Wu [7] verified the spatio-temporal correlation between the number of disaster-related tweets, public emotion, and disaster loss. Faxi [12] et al. compared disaster-related tweets and loss-related tweets to demonstrate that it was possible for microblog data to rapidly determine county-level units suffering from serious disasters. To evaluate typhoon disaster losses, Qing [13] et al. applied Sina Weibo data to establish a disaster loss assessment index model using term frequency-inverse document frequency (TF-IDF), a classical term frequency weight method.

The number of disaster-related microblogs is often used as an important indicator for emergency damage, yet post-disaster microblogs and other social media usage is affected by the income, educational background, age and other aspects of the population [14]. Economically developed and highly populated areas tend to provide more data than rural areas, which subsequently affects the assessment of disaster information and leads to a bias in the experimental results. Although the degree of disaster loss has a certain association with the number of microblogs, social and economic factors such as average income and the percentage of educated individuals have a greater impact on the number of microblogs compared to the loss extent [14]. Many studies try to remove this influence in order to accurately reflect the loss of disasters using methods such as factor (e.g., population number) analysis [15] or normalization [7]. However, during the emergence stage of a critical situation, the accuracy and timeliness of information is more important, yet typical social and economic data may not be available in a timely manner. In the case of uneven number distributions of microblogs due to social and economic factors, disaster losses cannot be judged accurately simply by the number of microblogs. This study attempts to determine how to use the spatial distribution of microblogs for the quick assessment of the damage caused, and avoid the misjudgment caused by influence of factors other than disasters on the number of microblogs in different areas.

2.2. Microblog Data for Mining Spatio-Temporal Disaster Information

Microblog users often post content with geographical labels or provide location information. In addition, each message is published with a time stamp. Thus, microblog data possesses temporal and spatial characteristics. In the context of disasters, researchers believe that the integration of the geographical location, time characteristics and semantic information in microblog data can represent disaster information across space and time [15].

Using microblog data can often reflect the spatio-temporal evolution of disasters through the observed changes of public concern. Yan [16] classified Sina Weibo data following the Yushu (Qinghai, China) earthquake into the categories of emotion, opinion, situation, action and general, and found that the attention of individuals shifted to different topics with time. Kim et al. [17] investigated the communication characteristics of post-disaster emergency information among different users, such as news and meteorological agencies, and found that the information can be used to understand disaster event development trends over time. Huang [18] studied the change process of different information categories, and determined the spatial distribution of the number of microblogs in different disaster stages using geographical tags added by Twitter users. Results can assist disaster managers in deciding what actions to undertake during the change process of disasters.

Research into the application of microblog data in the field of disasters has placed a large amount of focus on the mining of spatio-temporal characteristics. However, existing research treats time and space as separate factors, without studying the changes of spatial information under different times. Moreover, the current literature fails to provide solutions for the application of microblogs to disaster emergency response. Most Chinese scholars do not attach enough importance to the application of microblog information across space and time in emergency rescue research, particularly in the emergency management of natural disasters. Thus, effectively using emerging microblog information as a data source to achieve accurate rescue missions during emergency situations still faces great challenges.

3. Data and Methods

3.1. Data

At 21:19:46 on 8 August 2017, a 7.0-magnitude earthquake occurred in Jiuzhaigou, Sichuan, China. The epicenter was located at 33.20° N and 103.82° E, 5 km west of the main scenic area of Jiuzhaigou (Figure 1). The earthquake occurred in the peak tourist season, and the disaster area was densely populated. Thus, it quickly triggered a heated discussion on Sina Weibo, which is China's largest, and the world's second largest, microblogging service [19], providing a data basis for the spatio-temporal change analysis of earthquake emergency information. A web crawler tool built using Python was used to capture Sina Weibo data from 8–14 August 2017 with the keyword "Jiuzhaigou earthquake" (in Chinese). The content of the crawled microblog data includes user ID, content and release time. After deweighting, a total of 22,813 pieces of microblog data related to the Jiuzhaigou earthquake were obtained. The amount of information obtained in different time periods is shown in Figure 2.

Although Sina Weibo and Twitter basically feature the same functionality, there are some differences in user behaviors. Compared to Sina Weibo users, Twitter users prefer hashtags [20], a word or an abbreviation starting with #, which is often used to mark the topic of the microblog. Some scholars use hashtags to distinguish microblogs related to or unrelated to disasters [21,22]. In this study, # was filtered out with other special symbols, and hashtags were not used as a basis for judging emergency information, because their usage is rare in Sina Weibo.

Sina Weibo provides a geotagging function, yet many microblogs that exhibit earthquake emergency information do not contain geotagging, and text semantics are inconsistent with the location of geotagging. This prevents the extraction of earthquake emergency information. In this study, word segmentation and part-of-speech tagging were conducted using the Natural Language

Processing & Information Retrieval Sharing Platform (Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China; v. 2.1) [23]. All the place names were marked as "ns" and could subsequently be extracted. By using Baidu Map API [24], geocoding was then used to convert place name information to the corresponding longitude and latitude coordinates (WGS84). A total of 36% of the microblogs were accurately located in units below the county level, and 91% of which were located in Sichuan province, concentrated in the vicinity of Zhangzha town and the Jiuzhaigou scenic area. The remaining microblogs were mainly located in provinces close to Sichuan, such as Gansu and Shanxi, and in Xinjiang, which also experienced an earthquake on 9 August 2017.

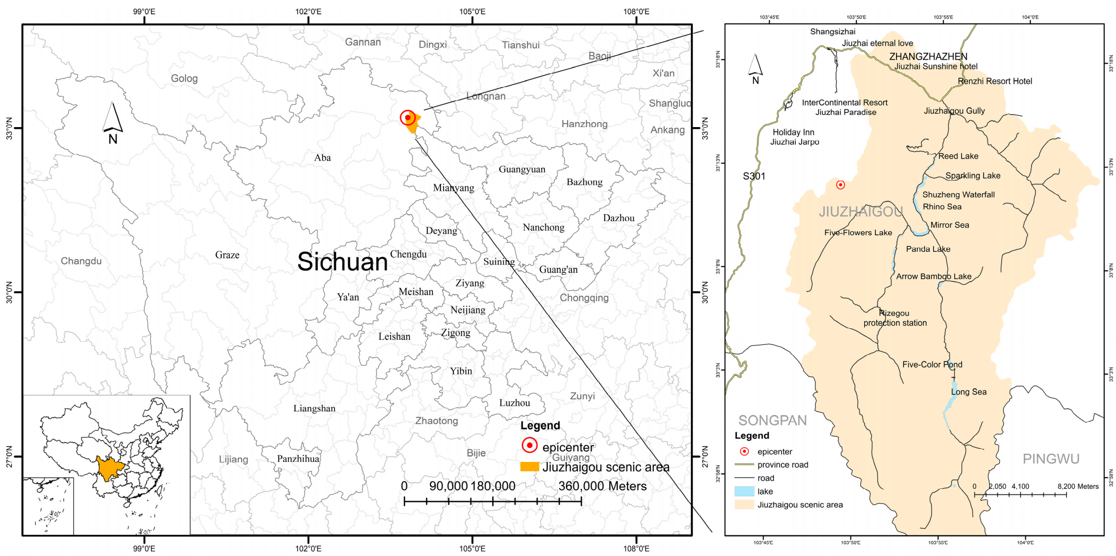

Figure 1. The administrative region of the Jiuzhaigou, Sichuan study area.

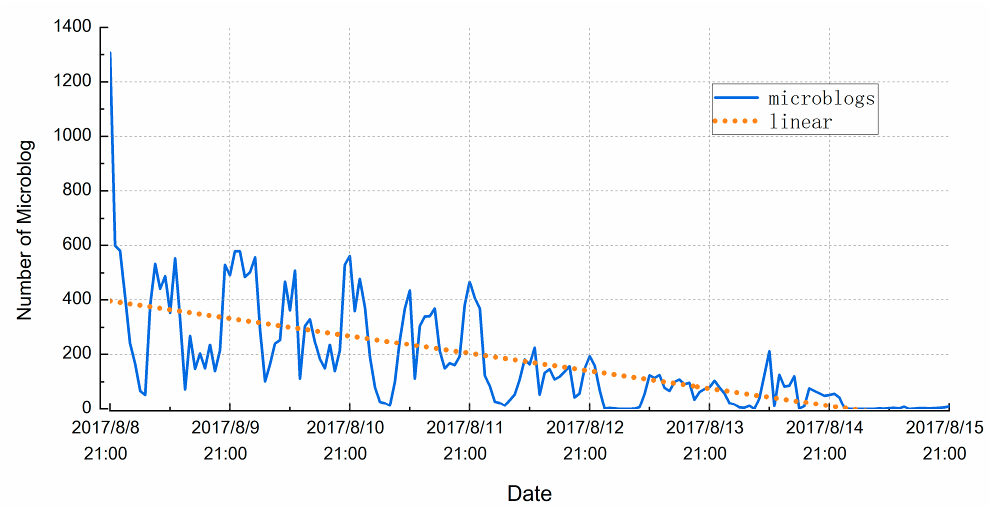

Figure 2. Number of Jiuzhaigou earthquake microblogs over time (after deweighting).

3.2. *Overview of Research Methods*

In this study, microblog spatio-temporal and semantic information was mined to reflect the spatial distribution of the disaster impact and spatio-temporal changes of earthquake emergency information. A workflow diagram of the research methods is shown in Figure 3. First, by building text urgency grading and classification standards, the microblog data were graded according to the severity of the disaster (text urgent grading), and a subject classification for each microblog was conducted according to the need for mining emergency information (text classification). A character-level convolutional neural network classifier was used for text urgent grading and text classification (Section 3.3). This study then selected the microblog data published within 24 h after the earthquake and conducted spatial autocorrelation analysis based on the grading results of emergency degree, in order to determine the earthquake impact degree in different regions (Section 3.4). This was compared to kernel density estimates (Section 3.5) based on the number of microblogs. Moreover, the temporal and spatial analysis of earthquake emergency information was performed using data published 7 days after the earthquake. In particular, data on spatio-temporal changes of disaster victim help and rescue information were analyzed, according to earthquake emergency needs (Section 3.5). All map visualizations were implemented using ArcGIS 10.4.1.

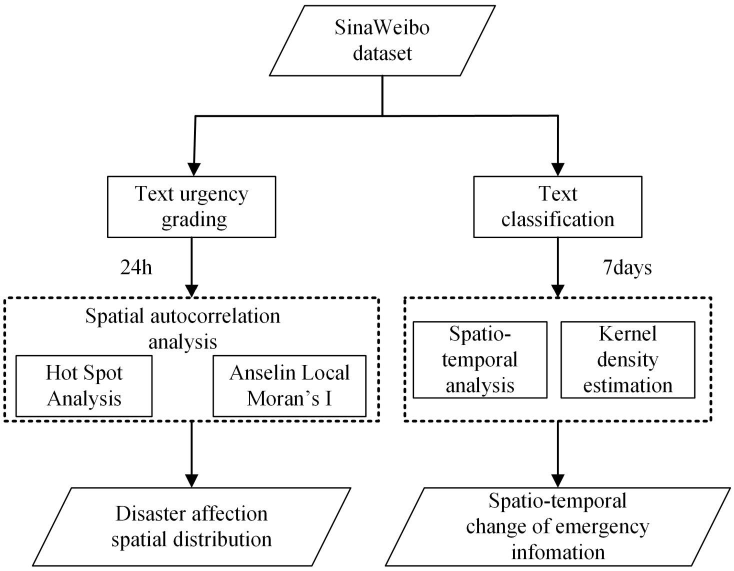

Figure 3. The process of research method.

3.3. *Text Urgency Grading and Classification for Earthquake Emergency Response*

As microblog information contains a large amount of public descriptive information and emotional expressions relating to emergencies, text grading and classification was performed to screen information that could specifically assist emergency rescue efforts. Text grading focuses on understanding the level of urgency and quantifying the disaster through the public's perception of the disaster. Classification aims to analyze earthquake emergency data in a more fine-grained qualitative way, so as to obtain the information required by different government departments or the public from a large volume of text.

The earthquake emergency phase performed by search and rescue personnel tends to focus on medical treatment and epidemic prevention for disaster victims, as well as the repairing of infrastructure [25]. Thus, with reference to the literature [16,18], and in order to meet the needs of disaster emergency management, 10 categories were created: feelings, emotional expression, seismic regime and losses, casualties, transportation, rescue operation, relief supplies, help seeking, disaster-reduction knowledge and donation. Moreover, the Chinese national earthquake emergency plan [25] divides earthquake disasters into three levels: special major, major, and larger. In this way, the semantic features of microblogs can also reflect the severity of earthquakes and the urgency of events. Thus, according to the semantic characteristics of the different categories shown in Table 1, the microblogs were divided into three levels: levels I, II and III, with values of 30, 60 and 90, respectively, denoting the urgency of the situation reflected on the microblog texts ordered from low to high.

Historical microblog data of earthquakes such as the Ya 'an (Sichuan, China) earthquake in 2013 and the Taiwan Hualien earthquake in 2018 were captured. These microblog data were manually divided as training samples according to the text grading and classification standard described in Table 1. Character-level convolutional neural network classifications [26] were applied to the training data, as this algorithm has been demonstrated to improve the mining of sparse features, thus increasing its accuracy. A convolutional neural network (CNN) is a deep learning algorithm containing convolution computation. We adopted a character-level CNN, which included an input, and one convolutional, one max pooling, two fully connected, softmax and output layers. A Chinese character table was used to construct a 64-dimensional character vector for the input of the convolutional neural network, with an input feature length of 100. Thus, as most microblogs have fewer than 140 characters, most of the texts of interest are likely to be contained within 100 characters. The character-level CNN was implemented using Tensorflow v.1.13.0 [27].

Table 1. Text urgency grading and classification standards.

Categories	Description	Level I	Lever II	Level III
Feelings	The somatosensory of earthquake shock, such as a house shaking	No feelings, no shaking, did not feel earthquake, slept like a log, did not feel anything	Felt the shake, felt the earthquake, felt the shaking for a while, slight shaking, shaking was obvious, woken up by the shaking	Strong feeling of earthquake, severe shaking, crazy shakes, roused from sleep, frightened to get up, heard a loud noise, heartbeat accelerating
Emotional expression	Personal thoughts or sentiment about earthquake, such as prayers and blessings	Calm, indifferent, smile, numb, peace of mind, bored, lucky	Worry, fear, uneasy, good, afraid, depressed, nervous, dare not sleep, unfortunately	Shivering, scared to death, urgent, scared to cry, highly panicking, shocked, collapsed, anxious, torn heart, difficult to breath
Seismic regime and losses	Earthquake level, secondary disasters and other reports and explanations	No reaction was observed	The lights are shaking, the table is shaking, the bed is shaking, the glass is falling, people are shaking, things are ringing	The lights fell down, building damage, a loud noise, the roof collapsed, barrier lake formed
Casualties	Reports on deaths and injures	No casualties	Injury, blood donation, mild illness	Lost contact, heavy casualties, many victims, bodies, dying, serious injuries
Transportation	Information related to traffic, electricity or network conditions	Communication and roads were unaffected by the earthquake	Road restrictions, partially damaged roads, telephone service slightly damaged	Road breaks, broken lifelines, road blockades, communication breakdown
Rescue operation	Rescue actions and medical treatment provided by government and society		Fire brigade, rescue team, search and rescue dogs, helicopter	
Relief supplies	Information on the delivery of supplies		Food, tents, quilts and other daily necessities	
Help seeking	Seeking help for shortages, trapped people, or finding relatives			Help, emergency medicine, emergency proliferation, blood bank emergency
Disaster-reduction knowledge	Common sense of earthquake preparedness and emergency response	Knowledge of earthquake prevention, first aid methods, resisting earthquakes, shock absorbers		
Donation	Release of donation information or description of donation amount	Donation information, donation amount		

3.4. Regional Spatial Autocorrelation Analysis Based on Text Urgency Grading

We used the results from the text urgency grading to conduct spatial autocorrelation analysis using hot spot analysis and Anselin's Local Moran's I implemented with the Spatial Statistics Tools in ArcGIS 10.4.1. By doing so, this paper aims to remove the influence of the number of microblogs in different regions on the accumulation of emergency information, thus allowing us to accurately determine areas in urgent need for rescue. The hot spot analysis and Anselin's Local Moran's I made it possible for us to evaluate the spatial distribution of the text urgency degree within 24 h after the earthquake, subsequently generating a hot spot distribution map. This map is able to reflect the disaster distribution mode within a short time period following the earthquake, thus quickly assessing the extent of the damage. Moreover, the microblog distribution was used to compare the derived map with the nuclear density analysis.

3.4.1. Getis-Ord G_i* Hot Spot Analysis

Getis-ord G_i* [28] is a statistic used to detect the statistical significance of the spatial autocorrelation of the aggregation space unit relative to the overall research scope. The statistic is calculated using the following Formula:

$$Gi^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

where x_j is the attribute value of factor j, that is, the urgency degree value following text classification, $w_{i,j}$ is the spatial weight between factor i and j, n is the total number of factors, $\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}$, and $S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\overline{X})^2}$.

The resultant value of the G_i* formula is the z score. A high spatial distribution clustering degree is implied for $z > 0$, that is, a high urgency degree of microblog clustering. For $z < 0$, a low spatial distribution clustering degree is implied, that is, a low urgency degree of microblog clustering.

3.4.2. Anselin's Local Moran's I

Anselin's Local Moran's I [29] is adopted in order to measure the heterogeneity in disaster emergency information space using the following Formula:

$$I_i = \frac{x_i - \overline{x}}{\sum_{j=1}^{n} \frac{(x_i - \overline{x})}{n}^2} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x}),$$

where I_i is the local autocorrelation value of microblogs, x_i represents the urgency of the situation reflected by the microblogs at different locations, $(x_i - \overline{x})$ represents the difference between the urgency of point i and all the points in the adjacent region and is used as a distance threshold ensuring that all points have at least one adjacent point, and $w_{i,j}$ is the spatial weight matrix. Here, we use the inverse distance-based spatial weight matrix.

The standard test value Z is determined as follows:

$$Z = \frac{I_i - E[I_i]}{\sqrt{V[I_i]}},$$

where $E[I_i] = -\frac{\sum_{j=1, j\neq i}^{n} w_{ij}}{n-1}$, $V[I_i] = E[I_i^2] - E[I_i]^2$. The Anselin's Local Moran's I is able to detect the clustering degree of urgent situations reflected in different microblogs trends. It divides spatial autocorrelation into the following four groups: high-value clustering (HH, where >0 and Z > 0); low-value clustering (LL, where >0 and Z < 0), high-value elements surrounded by low-value elements (HL, where <0 and Z > 0); and low-value elements surrounded by high-value elements (LH, where <0 and Z < 0).

3.5. Kernel Density Estimates

The spatial distribution characteristics of the microblog quantity are analyzed by using kernel density estimation. The kernel density estimate (KDE) method [30] calculates the density contribution value of each sample point within a specified radius range (here we use a search radius of 60 km) using a kernel function. The formula is as follows:

$$\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right),$$

for kernel function K, $K(x) = \begin{cases} 3\pi^{-1}\left(1^{-}x^{T}x\right)^{-2} & \text{if } x^{T}\text{x} < 1 \\ 0 & \text{otherwise} \end{cases}$. Here, h is the search radius, n represents the number of microblogs within the radius, x_i is the sample microblog point, x denotes the microblog points within the specified radius h, and $\hat{f}_h(x)$ is the kernel density function at x.

4. Results

4.1. Classification Accuracy Evaluation

The variable accuracy, recall rate and F1-score were used to measure the performance of the text urgency grading and classification results. Accuracy refers to the percentage of correctly predicted microblogs in a test sample for all microblogs predicted for that category. Recall is the percentage of a class that correctly predicts the total number of microblogs in the sample. The F1-score is the weighted average of the accuracy and recall rates, with values closer to 1 indicating higher accuracy levels. The classification accuracies of the text urgency grading, text classification, recall rate and F1-score were observed to be, on average, 95.4%, 87.4%, 83.9%, and 85.4%, respectively (Table 2). There is an observed information overlap between rescue operation, relief supplies and donation among the sample data. This reduces the clarity of the results. However, on the whole, each evaluation index of the classifier has a relatively high value.

Table 2. Precision, recall, and F1-score values character-level CNN text classifications.

Categories	Precision	Recall	F1-Score	Number
Feelings	82.0%	93.0%	87.0%	899
Disaster-reduction knowledge	88.0%	73.0%	80.0%	318
Seismic regime and losses	90.0%	84.0%	87.0%	1970
Transportation	85.0%	78.0%	81.0%	938
Casualties	92.0%	92.0%	92.0%	758
Help seeking	86.0%	88.0%	87.0%	527
Rescue operation	80.0%	83.0%	83.0%	1186
Relief supplies	94.0%	63.0%	75.0%	642
Emotional expression	93.0%	97.0%	95.0%	2379
Donation	84.0%	88.0%	87.0%	436
Total	87.4%	83.9%	85.4%	10,053

4.2. 24 h after the Earthquake

The first 24 h following the earthquake represent a golden period for rescue activities. Thus, by maximizing the use of the emergency information within this time period, disaster losses can be effectively detected and more lives can be saved. As shown in Figures 4 and 5, the kernel density analysis of the microblog data demonstrates that a large number of microblogs are concentrated in Chengdu and Jiuzhaigou county. The majority of the microblog posts in Chengdu are related to emotional expressions and feelings about the earthquake. In contrast, most of the emergency information, including help seeking, rescue operation and relief supplies, is concentrated in Jiuzhaigou county. Due to its relatively developed economy and dense population, a large number of Sina Weibo users are located in Chengdu, thus explaining the large amount of microblogging activity following the earthquake. The kernel density analysis is able to determine the number distribution of microblogs with interactions related to disaster events. However, it lacks the ability to identify emergency information distribution characteristics, which is key to avoiding the information outbreaks caused by non-homogeneous distribution of microblogging activity.

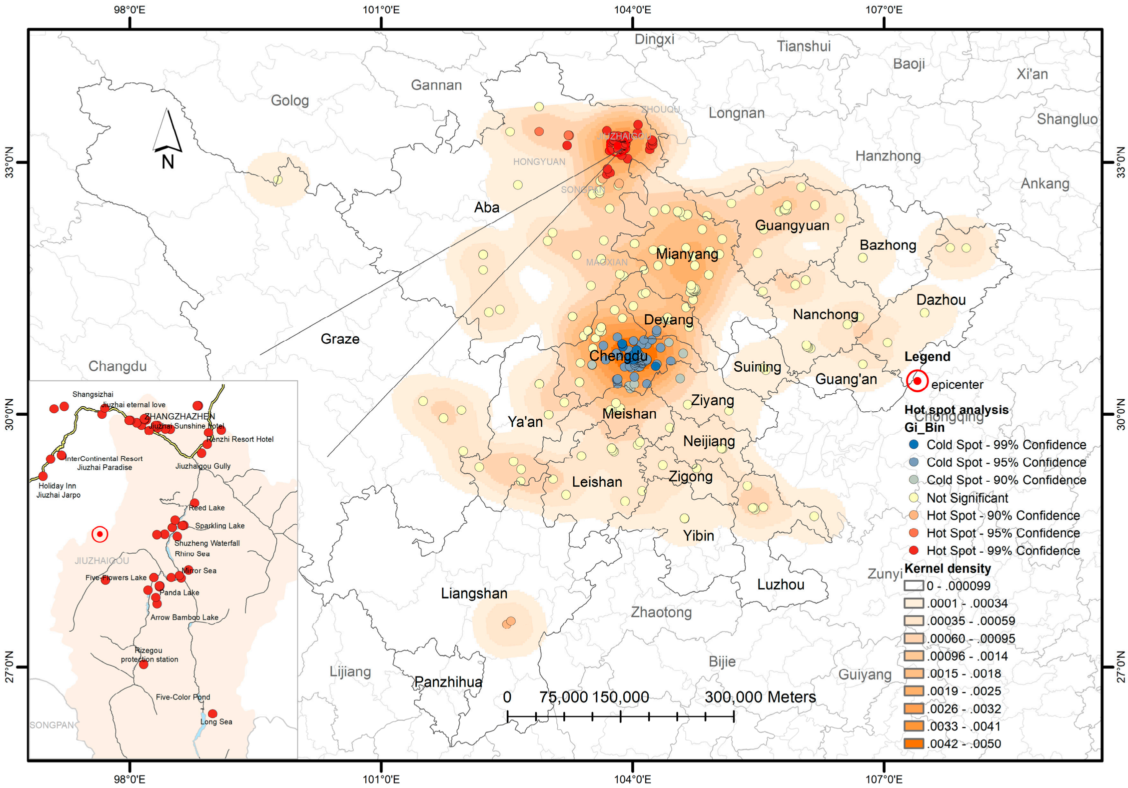

Figure 4. 24-h hot spot analysis and kernel density of microblogs.

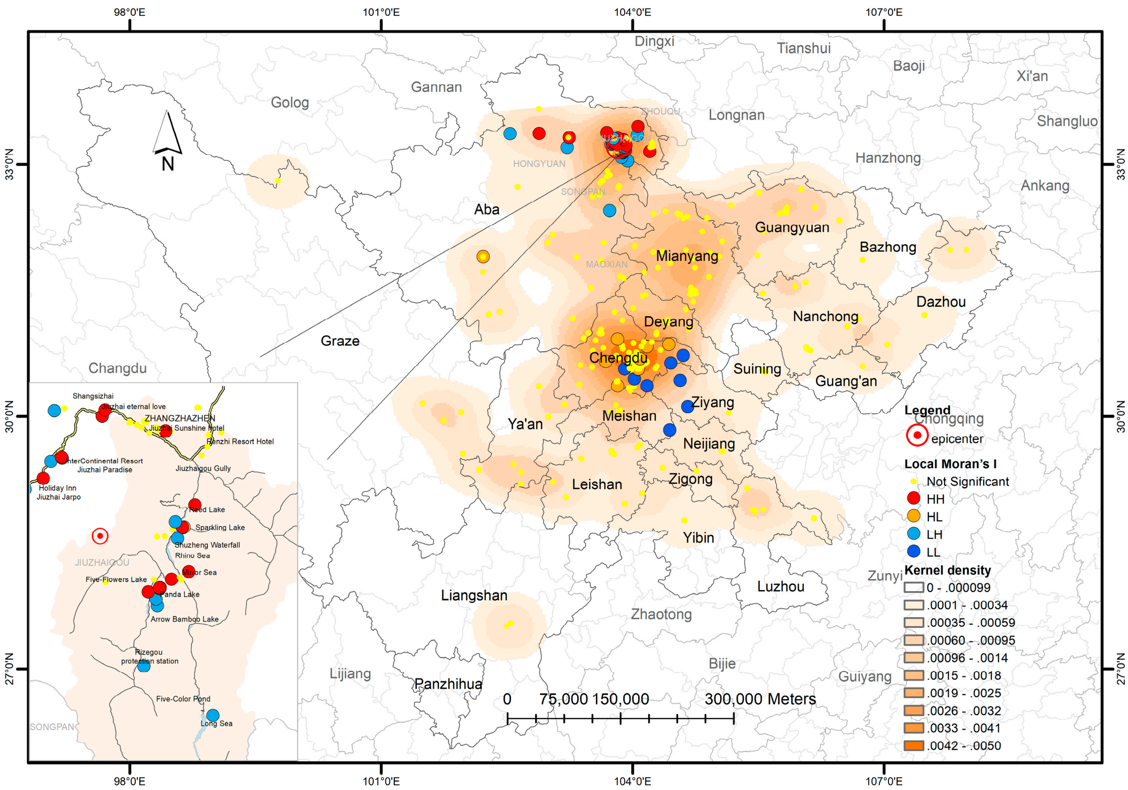

Figure 5. 24-h Anselin's Local Moran's *I* and kernel density of microblogs.

According to the hot spot analysis of the text grading results (Figure 4), both the Jiuzhaigou scenic spot and Zhangzha county were determined to be hot spot gathering areas, while Chengdu was a cold point gathering area. This indicates a low degree of urgency for microblogs with smaller disaster losses close to Chengdu, although there were a lot of microblogs. Meanwhile, disasters in the vicinity of Jiuzhaigou were considered to be more serious, and thus emergency information was gathered for this zone. Moreover, Xichang was a moderate hotspot area. In particular, on the day of the Jiuzhaigou earthquake, Liangshan prefecture in Xichang suffered a huge mud-rock flow disaster, causing a great amount of loss.

We applied two spatial weight matrices to calculate Anselin's Local Moran's I. When the adjacency matrix and K proximity analysis were used, few low-value clustering regions were observed. Moreover, the number of neighborhood sets in the K neighborhood analysis has a great influence on the results. We consequently chose the inverse distance weight matrix, as it avoids the aforementioned problems. From Anselin's Local Moran's I statistics (Figure 5), the Jiuzhai InterContinental Paradise Hotel, close to the Jiuuzhaigou scenic spot, and Shangsizhai village, in Zhangzha county, were both high urgency value aggregations. This implies that serious disasters were suffered at these two locations. The Jiuzhaigou scenic spot, as with the spark sea, the panda sea, and the arrow bamboo sea, also exhibit high value aggregations. However, several low value outliers can be observed around the high values for the Jiuzhaigou scenic spot, representing emotional expression texts describing memories while lamenting the disappearance of the beautiful scenery. In addition, a small number of low value outliers around the high values were located in Chengdu, as several critically ill patients were transferred there for treatment.

The hot spot analysis essentially demonstrates a more significant degree of cold hot spot aggregation compared to the Anselin's Local Moran's I, while the latter focuses on detecting abnormal data that reflects special disasters. Meanwhile, compared with kernel density analysis, spatial autocorrelation analysis based on urgency degree classification can more accurately reflect central emergency information trends, exclude uneven spatial distribution influences of microblog activities, and determine emergency rescue focus areas.

4.3. Seven Days after the Earthquake

4.3.1. Temporal Changes and Spatial Distribution of Different Categories

Figure 6a and Table 3 show that in the seven days following the earthquake, the number of emotional expression texts was the largest of all categories, with no significant temporal changes. This was followed by the feelings and rescue operation categories. Moreover, the feelings and seismic regime and losses categories experienced a decrease with time, while donations gradually increased. Public descriptions related to earthquake feeling were mainly published within a short period following the earthquake. However, from the gradual reduction of seismic regime and losses, we can assert that the disaster was controlled, to a certain extent, with no large aftershocks following the main incident. There was an observed rise in donations following the spread of information. However, help-seeking information, which emerged on 9 August, had a smaller presence over time. In contrast, information on rescue operations peaked on 12 August, partially indicating that the rescue efforts had a certain lag. Information on casualties appeared mostly in reports on the total number of casualties, with an increasing and then falling temporal trend. This trend reflects the increasing number of casualties with time and the advance in emergency rescue activities. Please note that such reports on the number of casualties do not contain spatial information.

As shown in Figure 6b, in most prefecture-level cities, emotional expression microblogs account for a large proportion, particularly in Chendu, Guangyuan and Dazhou. The distribution of rescue operation microblogs is more widespread. Help seeking, casualties and transport microblogs tend to occur in the most affected areas or at the source of victims. Moreover, debris flow occurred in Liangshan on the same day as the Jiuzhaigou earthquake, and thus many users posted the situation of both the earthquake and debris flow in the same microblog. This led to a large number of microblogs under the seismic regime and losses and casualties categories.

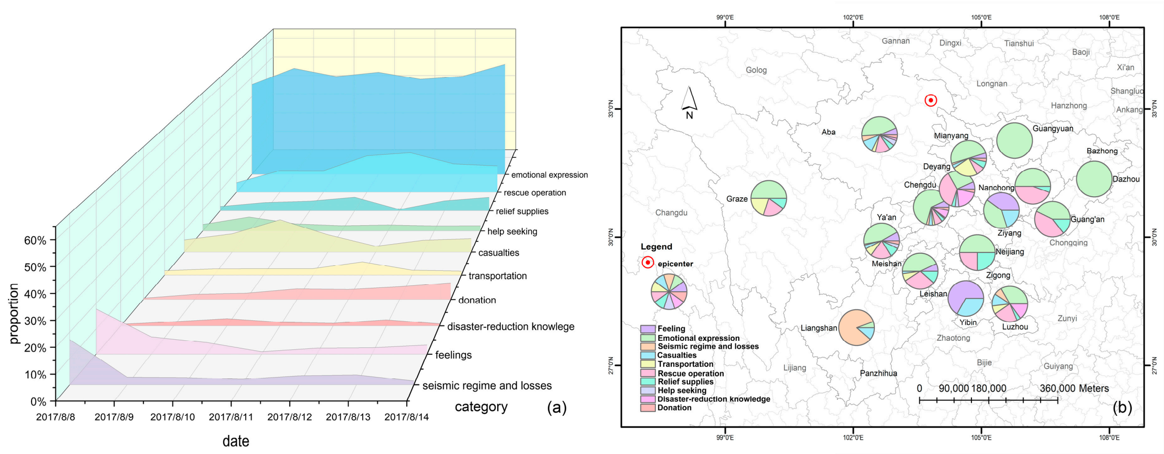

Figure 6. Temporal variation (**a**) and spatial distribution (**b**) of the quantity of the types of information. The percentage of each type of information was calculated per day. In addition, the pie charts show the types in different prefecture-level cities.

Table 3. Number of microblogs per category in the seven days after the earthquake.

Categories	Number
Feelings	2487
Disaster-reduction knowledge	231
Seismic regime and losses	526
Transportation	1101
Casualties	231
Help seeking	2832
Rescue operation	873
Relief supplies	221
Emotional expression	12,120
Donation	650

4.3.2. Spatial-Temporal Variation Analysis of Rescue Operation and Help-Seeking Microblogs

The most important task of earthquake emergency rescue work is to minimize casualties; thus, the set-up and management of rescue activities is crucial in the allocation of operations to different rescue forces. For the effective functioning of rescue operations, the needs of the victims and rescue activities of various organizations must be understood.

During 10–12 August, many rescue microblogs were recorded, and the corresponding microblogs were divided into four categories—search and rescue, source of rescue force, source of victims, and hospital—according to their keywords (Table 4) in order to learn more about existing rescue efforts. Spatial and temporal analysis (Figure 7) showed that many rescue microblogs were distributed in the area close to the Jiuzhaigou scenic area, as well as in Chengdu, Songpan county, and Wenchuan county, among others, on 10 August. This implies that the rescue force mentioned on microblogs originates mainly from the area around Jiuzhaigou county. Moreover, some microblogs described the gathering of rescue forces, and many injured people were sent to areas that included Mianyang and Chengdu. After 11 August, rescue microblogs focused on the Jiuzhaigou scenic area and Zhangzha county, mainly describing the rescue efforts and assistance provided to trapped individuals, with a small number of descriptions being related to rescue forces. Rescue efforts were still active on 12 August, and microblogs in regions other than Jiuzhaigou mostly described the earthquake disaster situation in terms of the local people.

Help-seeking information reflects the disaster situation and the needs of the victims. These factors need to be quickly addressed in order to proceed with decision-making in the rescue process. Most help-seeking information was located near the Jiuzhaigou scenic area (Figure 8), Jiuzhai InterContinental Paradise Hotel and Zhangza county, indicating more serious disasters and trapped individuals in these areas. Following the publishing of several help-seeking microblogs, corresponding rescue microblogs were observed. For example, on 9 August, individuals were trapped in Shansizhai village and were in urgent need of supplies. On 10 August, corresponding reports appeared that were able to provide these individuals with mineral water, food and other supplies. However, for the Jianzhuhai area, although there were many microblogs asking for help, most of which related to casualties or a loss of contact due to housing damage, no related rescue microblogs appeared. Through the spatial distribution of the mining of disaster victim help and rescue information, both the locations in need for rescue efforts and the information of trapped victims can be effectively determined. This can significantly aid decision-making for rescue teams.

Table 4. Rescue microblog categories and keywords.

Category	Key Word
Search and rescue	Rescue; search; evacuate; be rescued; be saved
Source of rescue force	Assemble at; rush to; fly to; firemen/rescue team from
Source of victims	Residents of;tourists/visitor from
Hospital	Transporting the wounded; hospital; medical treatment; cure

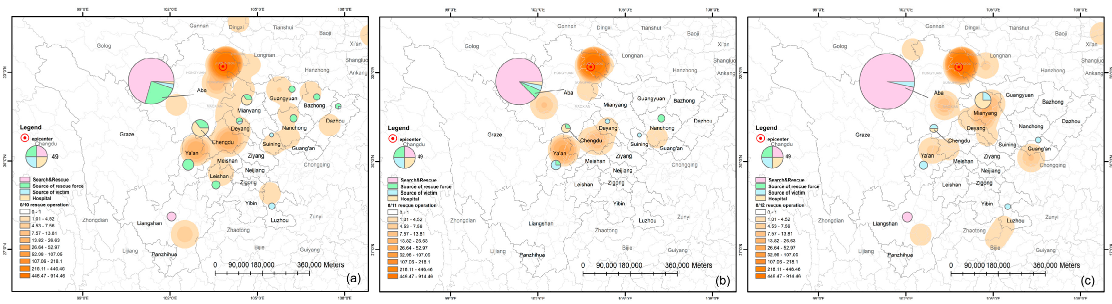

Figure 7. Spatial distribution of rescue microblogs. (**a**–**c**) Spatial distribution of rescue microblogs on 10 to 12 August, with a darker color indicating more rescue microblogs. Pie charts show the types and numbers of rescue microblogs in different prefecture-level cities.

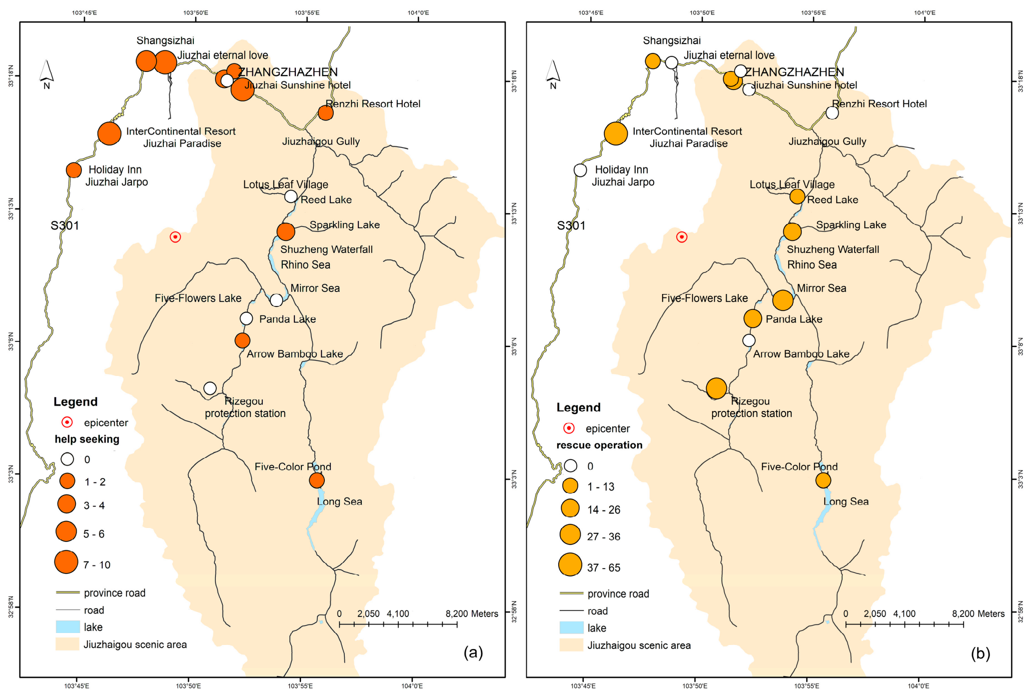

Figure 8. Spatial distribution of help-seeking (**a**) and rescue operation (**b**) microblogs. The circle size shows the number of microblogs.

5. Discussion and Conclusions

In this study, an emergency information spatial distribution detection method, combining both microblog information urgency grading and spatial autocorrelation analysis, was established to mine and analyze the emergency information contained in post-earthquake microblogs. This study conducted spatial autocorrelation analysis of microblogs 24 h after the earthquake using hot spot analysis and Anselin's Local Moran's *I*, and compared the results with kernel density analysis based on the number of microblogs. Post-disaster areas with an active use of micro-blogs tend to produce more post-disaster microblogs, and thus analysis using just density values based on quantities will be biased. However, the combination of hot spot analysis and Anselin's Local Moran's *I* based on urgency degree classification can exclude the bias caused by the normal microblog quantity distribution, thus enabling us to understand the actual disaster loss distribution. Anselin's Local Moran's *I* is similar to hot spot analysis, but the former focuses on detecting abnormal points in spatial distributions. These results demonstrate that the detection range of cold hot spots is smaller than that of hot spot analysis, which is consistent with the description in the literature [31–33]. Moreover, in the process of spatial autocorrelation analysis, the spatial weight matrix is of great importance. Different spatial weight matrices define different adjacency relations of spatial objects and thus affect spatial autocorrelation judgments. In general, the adjacency matrix, the distance matrix and K proximity analysis are adopted as the spatial weight matrix. We found that although the general trend of different spatial weight matrices was similar, the Anselin's Local Moran's *I* was still greatly affected by this matrix. Compared with the adjacency matrix and K proximity analysis, the inverse distance weight matrix used in this paper can more accurately detect areas with higher urgency values, as well as areas with higher urgency values surrounding those with lower values. These properties make the inverse distance weight matrix suitable for the evaluation of the impact of disasters, as well as the identification of special disasters. Moreover, the number of neighborhood sets have little effect on the results of the inverse distance weight matrix, such that adjustment parameters process becomes easier and can adapt to the emergency phase. In practical applications, it is necessary to comprehensively consider the specific situation of the research area in order to select the appropriate spatial weight matrix. Furthermore, the application of different weight matrices as a disaster develops is a topic for future research.

In the process of disaster emergency response, members of the public release information, such as help-seeking information and people searches, through microblog platforms. Meanwhile, the news reported by microblogs and relevant descriptions of disaster victims can effectively reflect the spatial-temporal change characteristics of disaster and emergency rescue activities. In this paper, microblogs were divided into 10 categories: feelings, emotional expression, seismic regime and losses, casualties, transportation, rescue operation, relief supplies, help seeking, disaster-reduction knowledge and donation. These categories can help determine valuable information during earthquake emergency rescue efforts. A character-level CNN was used to classify the categories, with a classification accuracy of 87.4%, a recall rate of 83.9%, and an F1-score of 85.4%. Thus, the character-level CNN met the requirements of earthquake emergency information classification. This allows the establishment of microblog categories to adapt to different stages of disasters, so as to take into account longer disaster management time series. For example, in the post-disaster reconstruction stage, the infrastructure construction or psychological needs of disaster victims can be determined, which has rarely been featured in previous studies.

This paper used the classified microblogs published 7 days after the earthquake in order to analyze temporal and spatial distribution changes. Most public descriptions emerged within 24 h of the earthquake, and many victims released help messages through microblog platforms. Information relating to rescues and donations appeared relatively late. This is in line with disaster information dissemination following the earthquake. Moreover, temporal and spatial differences between rescue operations and help requests from disaster victims were observed. On the one hand, this may be attributed to information dissemination, while on the other hand, it may be due to rescue operation delays. The results imply that conducting spatial-temporal analysis based on microblog classification results can help comprehensively understand the rescue operations and the needs of disaster victims in different regions, so as to provide information service to emergency management department.

There are several limitations in this study. First, this study only used the geographical name information extracted from microblogs for spatial analysis, without considering the geo-tagged data published by users. Although many scholars [6,34] believe that geo-tagged data is insignificant or inaccurate, the accuracy of such data can be evaluated in the future as the integration of two spatial information sources may lead to more accurate positioning. Furthermore, only Sina Weibo was considered as the data source in this paper. Additional social media, such as WeChat and BBS, can be included in the analysis to obtain more comprehensive and accurate earthquake emergency information. However, data from social media, including microblogs, exhibits a certain bias. Research based on social media data is affected by the communication interruption caused by disasters and other such factors, which may lead to neglecting areas without relevant data. In future research, multi-source data, such as remote sensing, should be considered to further verify the reliability of microblog data in effectively helping disaster.

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Abbreviations

The following abbreviations are used in this manuscript:

TF-IDF	Term Frequency-inverse Document Frequency.
WGS84	World Geodetic System 1984 Datum.
CNN	Convolutional Neural Network.

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