Spatiotemporal perception of disasters based on social media data in the context of climate change: A case study of Shanghai

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Abstract
Extreme weather events are frequent in the context of climate change, which brings severe challenges to cities. Therefore, it is urgent to explore more adaptive planning methods to achieve climate resilience. Correspondingly, this paper conducts spatiotemporal perception research on typhoon disasters in Shanghai based on social media data. The results show that there are 3 types of disaster themes. Meanwhile, there presents different spatiotemporal characteristics among public concern index, negative sentiment intensity and positive sentiment intensity. Based on above situation, this paper proposes corresponding planning response strategies, and the purpose of this paper is to explore social media data in responding to climate change challenges and provide reference for resilient urban planning.

Keywords: climate change, resilient city, social media, spatiotemporal perception, typhoon disasters

1. Introduction

Due to the intensification of global climate change, various extreme climate disasters have occurred frequently, which poses a huge threat to urban safety. Typhoon is one of the most frequent and widespread natural disasters in the world, and the harm of hurricane and typhoon is becoming more prominent with the intensification of climate change. From the perspective of global cities, many cities in the world (such as New York, New Orleans, Tokyo, and Singapore) have experienced the impact of hurricane and typhoon disasters which caused a large number of casualties and property losses. China is one of the countries affected by typhoon disasters, and most of Chinese cities affected by typhoon disasters are located in the southeastern coastal area with highly concentrated industries and high-density population. Meanwhile, cities in the China's eastern coastal areas have accommodated more and more people with the advancement of urbanization, which means the impact of typhoon disasters will become increasingly serious. Therefore, it is urgent to enhance the climate resilience through urban spatial planning to cope with typhoon disasters.

In 2016, United Nations Conference on Housing and Sustainable Urban Development (Habitat III) advocated the construction of inclusive, safe, sustainable and resilient cities to meet the challenge of climate change. In recent years, city resilience improvement and resilient city development have received increasing attention and recognition with the advancement of Chinese new urbanization strategy and high-quality urban development strategy. For example, Shanghai has proposed the urban development goal of "responding to global climate change, enhancing the city's ability to resist natural disasters, and building a more sustainable and resilient ecological city". However, typhoons can bring secondary disasters such as strong winds and rainstorms which are characterized by high disaster intensity, rapid changes, and high uncertainty. Traditional urban disaster prevention planning methods (such as improving defense standards and formulating prevention planning) cannot respond to rapidly changing disaster situations in a timely manner. It is urgent for city planners to explore more adaptive planning methods to cope with the challenges brought about by climate change. In this context, urban planning should use dynamic models to improve the spatiotemporal governance paradigm and technical system except traditional static spatial strategies (Cai et al., 2018).

With the promotion and popularization of mobile Internet technology, disaster-stricken people can post real time disaster information on social media platforms at first time, such as disaster time, rescue request messages, and disaster locations. Social media data has become an emerging source of disaster situation information. Compared with traditional media reports, social media data has the advantages of large data volume, strong timeliness and wide spatial coverage (Allaire, 2016, Li et al., 2024). Based on identifying, extracting and analyzing relevant disaster information from social media data, urban planners and policymakers can better perceive disasters and dynamically optimize spatial elements according to changes in disaster characteristics to ensure the governance effectiveness of urban planning and achieve climate resilience.

This paper selects Shanghai as the research area and analyzes the spatiotemporal perception characteristics of typhoon disasters by the real time disaster information published on social media during the disaster. It explores the application path of big data technology and social media data in responding to climate change challenges in order to provide reference for exploring new technical methods for resilient urban planning.

2. Literature review

Disaster perception is the process of hazardous environment cognition and risk avoidance (Kieu and Senanayake, 2023). Due to global climate change, extreme weather intensifies the uncertainty and complexity of disaster risk, which leads to the weakened significance of accurate prediction, control and prevention for disaster reduction (Linkov et al., 2013). Correspondingly, it is more important for disaster response to obtain disaster information and conduct disaster perception. However, it is not enough to cope with complex and changeable disaster disturbances based on traditional methods of data acquisition and analysis. Firstly, comprehensive spatiotemporal data on disasters cannot be obtained through disaster information of traditional news media. Secondly, although statistical survey can provide direct disaster information, this method is costly and often accompanied by safety risks (Guo et al., 2025). Thirdly, it is also technically difficult for real-time emergency response to analyze remote sensing images (Shastry et al., 2023), because remote sensing cannot take into account both time and spatial resolution (Hou et al., 2024). In recent years, social media has increasingly become the main medium for information dissemination natural disasters (Chu et al., 2024). The widespread use of social media has promoted the rapid dissemination of real-time information during disasters (Liang and Ramirez-Marquez, 2024), which can integrate a large amount of spatiotemporal disaster information in a short time, and Therefore social media can make up for the method defects of traditional disaster information acquisition such as high cost and poor timeliness (Hou et al., 2024).

Social media can enhance situational perception during the disaster (Li et al., 2023a). Many scholars have paid attention to the role of urban public in disaster response, and try to conduct perception analysis through disaster information published on social media. At present, the application dimensions of social media in disaster mainly include temporal dimension, spatial dimension, text dimension and network dimension (Li et al., 2023a), and the analysis methods include sentiment analysis, text themes analysis, spatial correlation analysis and social network analysis. In the time dimension, social media data can be applied to analyze the changing characteristics of public sentiment and disaster themes. For example, Zhang et al. analyzed the public sentiment changes during typhoon disasters based on social media data, and find that typhoon disasters lead to a corresponding increase of negative sentiment (Zhang et al., 2024). Han and Wang identified 6 types of flood-related themes and 9 types of public sentiment reactions with text analysis on Sina microblog, and found that different types of themes and sentiment reactions closely corresponded to different development stages of flood disaster (Han and Wang, 2019). In the spatial dimension, social media data can be applied to analyze the distribution pattern of disaster vulnerability. For example, Forati and Ghose analyzed the spatial distribution characteristics of social media data during Hurricane Irma based on Twitter data and found the uneven characteristics of community vulnerability (Forati and Ghose, 2022). Zou et al. analyzed the geographical location of rescue requests on Twitter during Hurricane Harvey and found that communities with more rescue requests had more vulnerable environments and socioeconomic conditions (Zou et al., 2023). In the text dimension, social media data can be applied for sentiment recognition and disaster theme classification. For example, Karimiziarani et al. conducted sentiment recognition and topic classification of Twitter text with natural language processing (NLP) methods, and reveal the characteristics of social media responding to hurricanes (Karimiziarani et al., 2023). In the network dimension, social media data can be applied to analyze the relationship among Individual actors in social networks in order to identify important disaster information. For example, Lu and Brelsford applied Twitter data and the Infomap method to analyze the dynamic evolution of social networks during Japanese earthquake and tsunami in 2011, which reveals the change pattern of social interaction mechanisms under extreme events (Lu and Brelsford, 2014).

From an objective point of view, there are also certain challenges in applying social media data to disaster perception. In terms of data sources, disadvantaged groups may lack access to social media, resulting in "digital divide" problem (Xiao et al., 2015). Meanwhile, there may be low engagement in social media use in these area which suffer from severe disasters (Crawford and Finn, 2015). In terms of data processing, social media data may also present problems with the spread of misinformation (Erokhin and Komendantova, 2024). Therefore, it is still a major challenge to extract disaster information from massive social media messages (Hou et al., 2024). Fortunately, the analysis accuracy of social media can be improved through the improvement of analysis methods and the combination of multi-source data and it means that social media data can cope with the application challenges. At the same time, residents in different environments may suffer from differentiated disaster risks (Kaźmierczak and Cavan, 2011, Carvalho et al., 2022, Smiley et al., 2022, Nielsen et al., 2023). Therefore, as a type of real-time big data, social media data is essential for the efficiency improvement of disaster response in the case of disaster uncertainty challenge.

In general, the application of social media has profoundly changed the way of social communication and interaction. Correspondingly, social media has become an important element of "social perception", and it has become a research focus to conduct disaster perception based on social media data (Liu et al., 2015, Fang et al., 2019). In China, because of frequent and diverse disasters, social media is equally significant for the level improvement of urban disaster perception and the capability enhancement of disaster response. However, due to the complexity of Chinese semantics and the differences in social media type, it is under development to apply social media data to disaster perception in China (Jin et al., 2021). Therefore, there is still great application potential in the research on social media data such as city cases, disaster types, and research methods (Xie and Shao, 2024).

3. Research method

3.1. Study area

As the center of Chinese economic and technological innovation, Shanghai is a well-known megacity with a high population density and frequent economic activities. However, Shanghai is extremely vulnerable to typhoon disasters because of subtropical monsoon climate. According to statistics, Shanghai has suffered from typhoon disasters almost every year, which have had an impact on infrastructure damage, urban transportation, and social economy (Table 1). It means that typhoon disasters have become a challenge of resilient city development in Shanghai. Therefore, this paper selected Shanghai as the research object, the spatial scope covers the entire administrative region of Shanghai.

Table 1. Typhoon disasters statistics in Shanghai from 2010 to 2024

Year	Number of typhoon	Typhoon name and typhoon number
2010	0	/
2011	1	Typhoon Muifa (1109)
2012	1	Typhoon Haikui (1211)
2013	1	Typhoon Fitow (1323)
2014	2	Typhoon Fung-wong (1416), Typhoon Vongfong (1419)
2015	3	Typhoon Chan-hom (1509), Typhoon Goni (1515), Typhoon Dujuan (1521)
2016	1	Typhoon Meranti (1614)
2017	1	Typhoon Talim (1718)

2018	6	Typhoon Ampil (1810), Typhoon Jongdari (1812), Typhoon Yagi (1814), Typhoon Rumbia (1818), Typhoon Maria (1808), Typhoon Kongrey (1825)
2019	4	Typhoon Lekima (1909), Typhoon Mitag (1918), Typhoon Lingling (1913), Typhoon Tapah (1917)
2020	3	Typhoon Hagupit (2004), Typhoon Bavi (2008), Typhoon Maysak (2009)
2021	2	Typhoon In-Fa (2106), Typhoon Chanthu (2114)
2022	1	Typhoon Muifa (2212)
2023	0	/
2024	2	Typhoon Bebinca (2413), Typhoon Pulasan (2414)

Data sources: The data is collected from China Meteorological Disaster Yearbook, and China Climate Bulletin.

3.2. Analysis scenarios and data sources

3.2.1. Analysis scenarios

From September 14, 2024 to September 22, 2024, Typhoon Bebejia and Typhoon Prasang landed in Pudong New Area and Fengxian District of Shanghai respectively, and passed directly through the urban area. Typhoon Bebejia and Typhoon Prasang caused serious disasters in Shanghai such as rainstorm and waterlogging. Specifically, the central wind speed of Typhoon Bebiga reached level 14 (the range of wind speed is 41.5m/s - 46.1m/s) when it landed, making it the strongest typhoon to land in Shanghai since 1949. Typhoon Plasang brought a 500-year rainstorm to Shanghai especially Fengxian district and Pudong New Area. Furthermore, it was the first time that Shanghai was hit by two typhoon disasters in a week. Therefore, this paper selects Typhoon Bebejia and Typhoon Prasang as research scenarios, and conducts the spatiotemporal perception of typhoon disasters with the real time disaster information published on Sina microblog during the disaster (Figure 1).

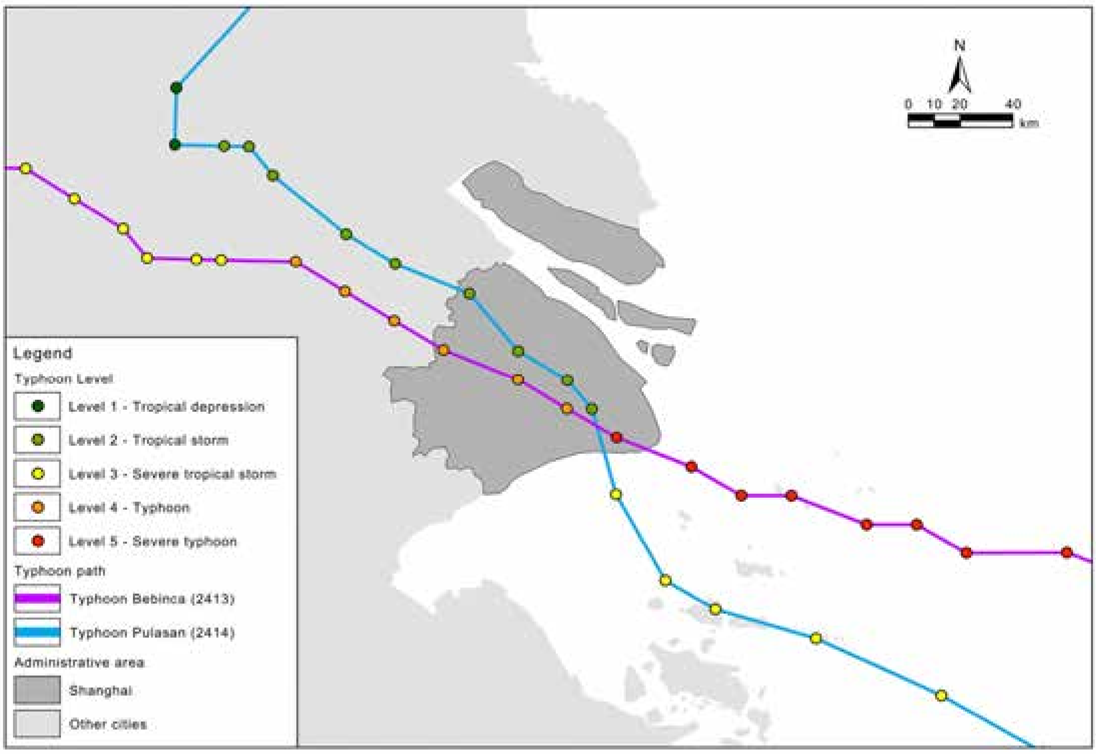

Figure 1. The paths of Typhoon Bebejia and Typhoon Prasang

3.2.2. Data sources

Sina microblog is a very popular social media in China which is equivalent to Twitter (Li et al., 2023b). Therefore, this paper collects typhoon disasters information from Sina microblog messages. Firstly, this paper collects Sina microblog messages in Shanghai area with a time range from September 14, 2024 to September 22, 2024. According to statistics, 27521 pieces of Sina microblog message are collected, which includes comment text, time and spatial location. Secondly, these Sina microblog messages are filtered based on keywords related to typhoon disasters (such as typhoon, Bebejia, Prasang, rainstorm, strong wind, waterlogging, water outage, and power outage). Thirdly, 2734 pieces of relevant messages are sorted out.

3.3. Research design

3.3.1. Text features analysis

Text features analysis includes disaster themes determination and text sentiment evaluation according to the disaster information published on the Sina microblog.

In terms of disaster themes determination, this paper classifies the disaster themes that the public is concerned about based on the LDA (Latent Dirichlet Allocation) topic model. LDA is a commonly used topic model in natural language processing, which can identify different themes from a text collection. At the same time, this study determines the optimal number of disaster theme through the perplexity test and pyLDAvis (python library for Latent Dirichlet Allocation visualization). The perplexity test formula is:

$$\text{perplexity}(D)=\exp\left\{-\frac{\sum_{m=1}^{M}\log P(W_m)}{\sum_{m=1}^{M}N_m}\right\} \qquad \text{(a1)}$$

In the formula a1, D represents the text dataset, M represents the number of text items in the text dataset, N_m represents the number of words in the text item m, W_m represents the word sequence of the text item m, P(W_m) represents the appearance probability of each word in the text set.

In terms of text sentiment evaluation, this paper firstly applies the HowNet sentiment dictionary to identify and score the sentiment of Sina microblog text. Next this paper calculates the scores of positive or negative microblog texts respectively, and the range of sentiment score is limited to [0, 5] to avoid extreme values.

3.3.2. Analysis of disaster perception in the time Dimension
This research step mainly analyzes the change characteristics of Public Concern Index of Time Dimension (PCITD), Negative Sentiment Intensity of Time Dimension (NSITD) and Positive Sentiment Intensity of Time Dimension (PSITD) during the typhoon disasters. PCITD indicates the public attention to the event. Meanwhile, NSITD and PSITD reflect the overall change of the public sentiment towards the event.

(1) The formula of PCITD is:

$$\mathrm{PCITD}=\frac{\mathrm{NT}_{\mathrm{related}}}{\mathrm{NT}_{\mathrm{total}}} \tag{b1}$$

In the formula b1, $\mathrm{NT}_{\mathrm{related}}$ represents the number of Sina microblog messages related to typhoon disasters within the t time interval, $\mathrm{NT}_{\mathrm{total}}$ represents the total amount of Sina microblog messages within the t time interval, which can also be called background information.

(2) The formula of NSITD is:

$$\mathrm{NSITD}=\frac{\Sigma_1^t(\mathrm{ntmes}_i)}{\mathrm{nn}_t} \tag{b2}$$

In the formula b2, represents the sentiment score of each negative Sina microblog message within the t time interval, nn_t represents the total number of negative Sina microblog messages within the t time interval.

(3) The formula of PSITD is:

$$\mathrm{PSITD}=\frac{\Sigma_1^t(\mathrm{ptmes}_i)}{\mathrm{np}_t} \tag{b3}$$

In the formula b3, represents the sentiment score of each positive Sina microblog message within the t time interval, np_t represents the total number of positive Sina microblog messages within the t time interval.

3.3.3. Analysis of disaster perception in the spatial Dimension
Firstly, this research step mainly analyzes the characteristics of Public Concern Index of Spatial Dimension (PCISD), Negative Sentiment Intensity of Spatial Dimensions (NSISD), and Positive Sentiment Intensity of Spatial Dimensions (PSISD) based on ArcGIS in order to quantify the public perception level of typhoon disasters and the spatial distribution characteristics of the typhoon disasters impact on the public. Secondly, this paper performs spatial autocorrelation analysis and hotspot analysis on PCISD, NSISD, and PSISD.

Importantly, there will be few data in many grids due to the division of the 1km*1km grid which will result in small sample problems (Wang et al., 2020). Therefore, this paper applies a 2km*2km grid for spatial statistics.

(1) The formula of PCISD is:

$$\mathrm{PCISD}=\frac{\mathrm{NS}_{\mathrm{related}}}{\mathrm{NS}_{\mathrm{total}}} \qquad \text{(c1)}$$

In the formula c1, $\mathrm{NS}_{\mathrm{related}}$ represents the number of Sina microblog messages related to typhoon disasters in the grid, $\mathrm{NS}_{\mathrm{total}}$ represents the total amount of Sina microblog messages in the grid.

(2) The formula of NSISD is:

$$\mathrm{NSISD}=\frac{\sum(\mathrm{nsmes}_i)}{\mathrm{nn}_s} \qquad \text{(c2)}$$

In the formula c2, represents the sentiment score of each negative Sina microblog message in the grid, nn_s represents the total number of negative Sina microblog messages in the grid.

(3) The formula of PSISD is:

$$\mathrm{PSISD}=\frac{\sum(\mathrm{psmes}_i)}{\mathrm{np}_s} \qquad \text{(c3)}$$

In the formula c3, represents the sentiment score of each positive Sina microblog message in the grid, np_s represents the total number of positive Sina microblog messages in the grid.

4. Results

4.1. Text features

4.1.1. Disaster themes determination

This paper applies the perplexity test and pyLDAvis to determines the optimal number of disaster themes. In terms of the perplexity test, the optimal number of themes corresponds to the low perplexity. In terms of the overlap analysis among themes, each circle represents a theme, and the area of the circle is positively correlated with the frequency of the topic. The distance between different circles represents the independence between different topics, and the distance between circles is positively correlated with the independence between subjects. When the circle does not overlap, it means that the optimal number of disaster themes is determined. Combining the perplexity test and the overlap analysis among themes, this paper finally determined three disaster themes (Figure 2).

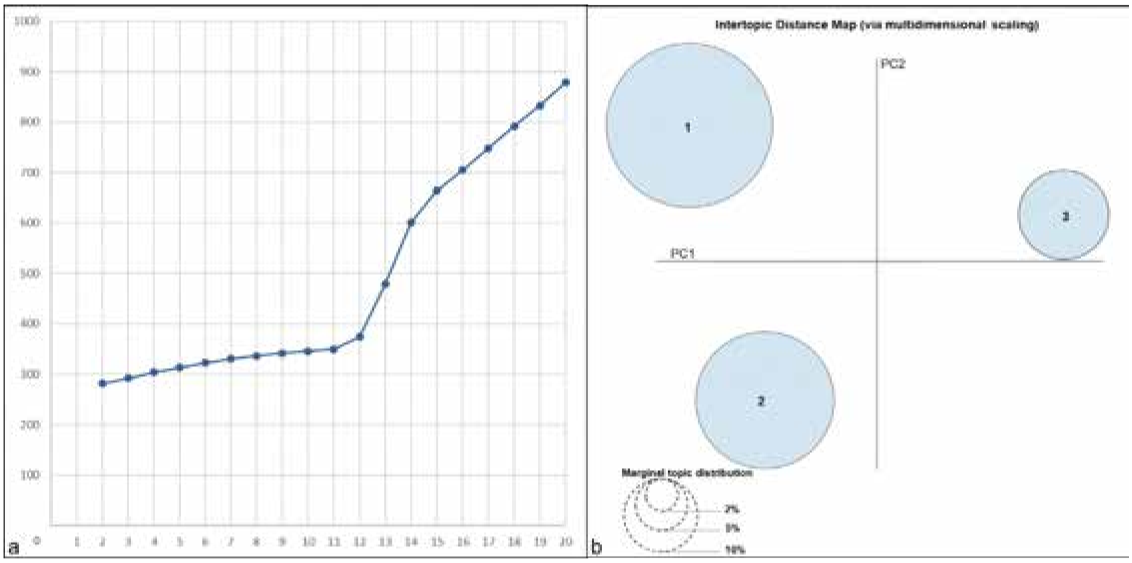

Figure 2. The perplexity test (a) and pyLDAvis (b)

At the same time, this paper screens the keywords within each disaster theme and filters out a total of 30 keywords by eliminating duplicates, unclear meanings and other invalid words. This paper finds that the keywords of each theme have different focuses. Among them, the keywords of theme 1 focus on the interference of typhoons in daily activities, especially the daily travel activities of urban residents. The keywords of theme 2 focus on the disaster-stricken places and people, especially Fudan University, ports and urban streets. The keywords of theme 3 focus on the status of public places after the disaster, such as campuses, hotels, squares, Shanghai Bund, subway stations and other public places (Table 2).

Table 2. Statistics of disaster themes determination

Number	Keywords	Disaster theme focus
Theme 1	Typhoon landfall (24.10%), garden (12.17%), impact (10.98%), life (10.04%), strong typhoon (9.35%), terminal building (8.55%), flight (7.10%), Pudong New Area (6.47%), outings (5.91%), community (5.33%)	Interference on daily activities
Theme 2	Fudan University (14.90%), rainstorm (13.84%), ferry (10.60%), Shanghai Port (10.43%), building (8.58%), wind and rain (8.58%), river bay (8.54%), road (8.35%), Suzhou River (8.32%), students (7.85%)	Affected locations and populations
Theme 3	After the disaster (16.15%), campus (14.61%), hotel (11.33%), square (10.89%), Bund (10.56%), notes (8.31%), power outage (8.24%), weather (7.67%), Baoshan district(6.39%), subway station (5.85%)	Post-disaster public places

Note: The value behind the keyword represents the discussion proportion of keyword in the disaster theme.

Combined with the actual situation of Shanghai, the characteristics of typhoon disasters can be summarized according to the disaster theme. Firstly, the typhoon disasters caused secondary disasters such as strong wind, rainstorm and waterlogging. These secondary disasters led to flight delays, subway suspension and public traffic interruption which had a great impact on travel activity of residents. Secondly, typhoon caused damage to houses and public service facilities. Therefore, affected places and people have become one of the focuses in the disaster. Finally, Typhoon Bebinca and Typhoon Pulasan landed in Shanghai consecutively within a week, which had a certain impact on the progress of post-disaster recovery, especially the restoration of the public places.

4.1.2. Text sentiment evaluation

According to the sentiment identification and sentiment score, there are 559 texts of negative sentiment (accounting for 20.45%), 1016 texts of positive sentiment (accounting for 37.16%), and 1159 texts of neutral sentiment (accounting for 42.39%). From the perspective of sentiment intensity, the average score of negative sentiment is -1.53, and the average score of positive sentiment is 1.71 (Table 3). From the perspective of the frequency distribution of the sentiment scores, there shows the characteristics of normal distribution among negative sentiment, positive sentiment and neutral sentiment (Figure 3). These statistics show that the sentiment intensity of positive sentiment is slightly higher than that of negative sentiment, which means the overall mood of urban residents was relatively optimistic during this typhoon.

Table 3. Statistics of text sentiment evaluation

Type	Quantity	Percentage	Average score
Sina microblog messages expressing negative sentiment	559	20.45%	-1.53
Sina microblog messages expressing positive sentiment	1016	37.16%	1.71
Sina microblog messages expressing neutral sentiment	1159	42.39%	0
Total	2734	100%	/

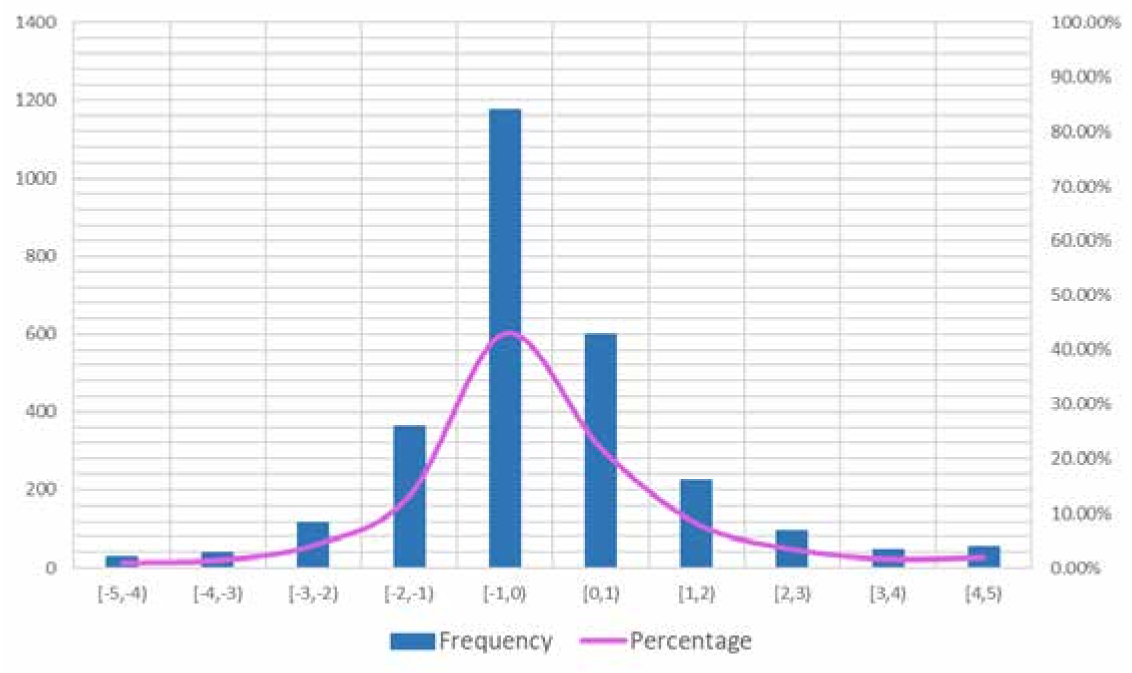

Figure 3. Frequency distribution of sentiment scores

4.2. Disaster perception in the time dimension

The entire period of typhoon disasters is from September 14, 2024 to September 22, 2024 which includes pre-disaster prevention stage, emergency response stage and post-disaster recovery stage (Table 4). The public perception and sentiment intensity also show obvious fluctuations and changes due to the impact of the typhoons.

Table 4. The impact of Typhoon Bebinca and Typhoon Pulasan on Shanghai

Time	Event	Disaster stage
September 14, 2024	Shanghai Central Meteorological Observatory issues typhoon warning for Typhoon Bebinca.	Pre-disaster preparation stage for Typhoon Bebinca
September 15, 2024	Shanghai Meteorological Bureau launches highest level typhoon emergency response.	
September 16, 2024	Typhoon Bebinca landed in Shanghai Pudong New Area.	Emergency response stage for Typhoon Bebinca
September 17, 2024	Typhoon Bebinca moved away from Shanghai, and Shanghai entered the post-disaster recovery stage.	Post-disaster recovery stage for Typhoon Bebinca
September 18, 2024	Shanghai Central Meteorological Observatory issues typhoon warning for Typhoon Pulasan.	Pre-disaster preparation stage for Typhoon Pulasan
September 19, 2024	Typhoon Bebinca landed in Fengxian District, Shanghai.	Emergency response stage for Typhoon Pulasan
September 20, 2024	Rainstorm occurs in Shanghai	

September 21, 2024	Typhoon Pulasan moved away from Shanghai, and Shanghai entered the post-disaster recovery stage again.	Post-disaster recovery stage for Typhoon Pulasan
September 21, 2024 - September 22, 2024	Post-disaster recovery work is basically completed.	

Source: The information is collected from news reports related to Typhoon Bebinca and Typhoon Pulasan

4.2.1. Change characteristics of PCITD

PCITD presents obvious double peak characteristics. The first peak occurs from 0:00 to 12:00 on September 16, 2024 (Emergency response stage for Typhoon Bebinca) and the second peak occurred from 0:00 to 12:00 on September 20, 2024 (Post-disaster recovery stage for Typhoon Pulasan). It shows that PCITD always reaches the peak when the typhoon landed in Shanghai, and the peak level of PCITD during the occurrence of Typhoon Bebinca was higher than that during the occurrence of Typhoon Pulasan (Figure 4).

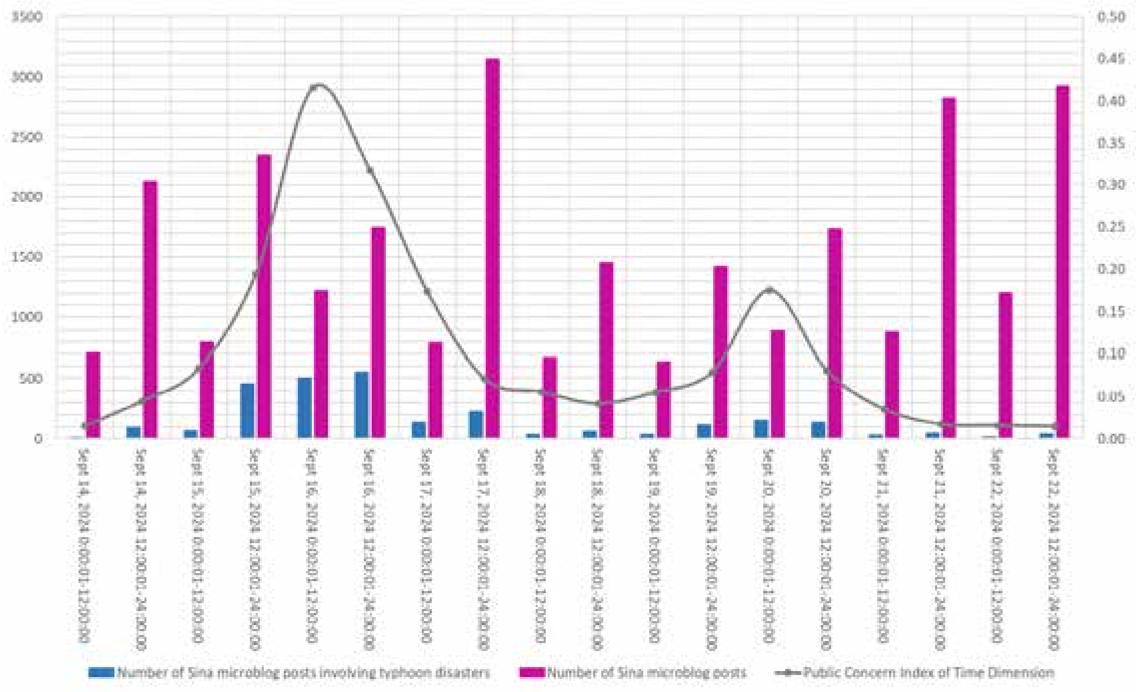

Figure 4. Change of PCITD

4.2.2. Change characteristics of NSITD and PSITD

NSITD and PSITD also presents double peak characteristics. The first peak occurred from 0:00 to 12:00 on September 18, 2024 (Post-disaster recovery stage for Typhoon Bebinca) and the peak of NSITD is higher than the peak of PSITD. The second peak occurred from 0:00 to 12:00 on September 22, 2024 (Post-disaster recovery stage for Typhoon Pulasan) and the peak of PSITD in this stage is higher than the peak of NSITD. At the same time, there is a significant difference between the NSITD and PSITD. The two peak levels of NSITD are basically the same, while the two peak levels of PSITD are quite different. The second peak level of PSITD is higher than the first peak level of PSITD (Figure 5).

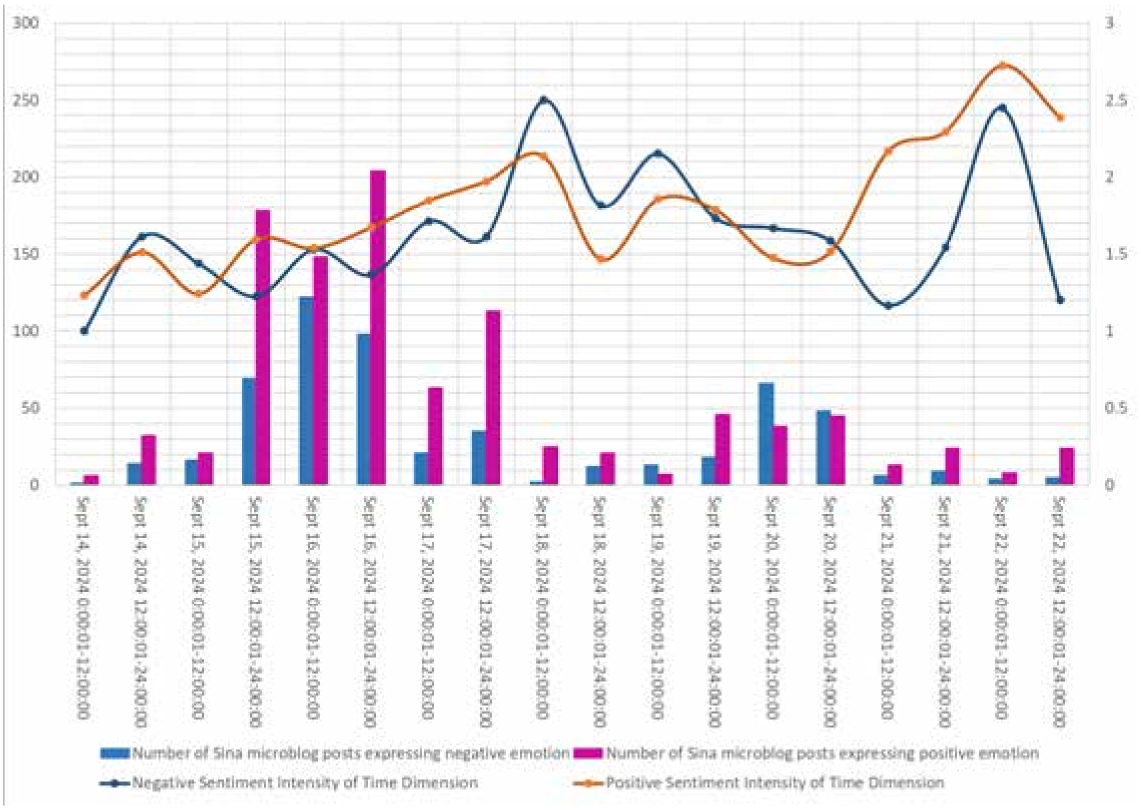

Figure 5. Change of NSITD and PSITD

4.2.3. Comparative analysis of PCITD, NSITD and PSITD

Although PCITD, NSITD and PSITD have two peaks, they have different characteristics. Firstly, the peak of NSITD and PSITD lags behind the peak of PCITD. The peak of PCITD occurs in the emergency response stage, while the peak of NSITD and PSITD occurs in the post-disaster recovery stage. Secondly, the time curve of PCITD is relatively smooth with obvious upward and downward trends, while the time curves of NSITD and PSITD show the fluctuating characteristics. In view of this disaster period, Typhoon Bebinca is stronger than Typhoon Pulasan, and Typhoon Bebinca causes greater damage to the city than Typhoon Pulasan. Therefore, PCITD during the Typhoon Bebinca is higher than that during the Typhoon Pulasan, which also causes the NSITD to be significantly higher than PSITD during the Typhoon Bebinca. At the same time, the continuous disaster impact also caused NSITD to reach two peaks. Fortunately, PSITD rises faster during the Typhoon Pulasan, which also shows the high efficiency of post-disaster recovery work in Shanghai.

4.3. Disaster perception in the spatial dimension

4.3.1. Distribution characteristics of PCISD

The areas with high value of PCISD are mainly distributed around the Shanghai Suburban Ring Road, especially in the southern coastal areas. While, the value of PCISD is relatively low in the areas within the Outer Ring Road (Figure 6).

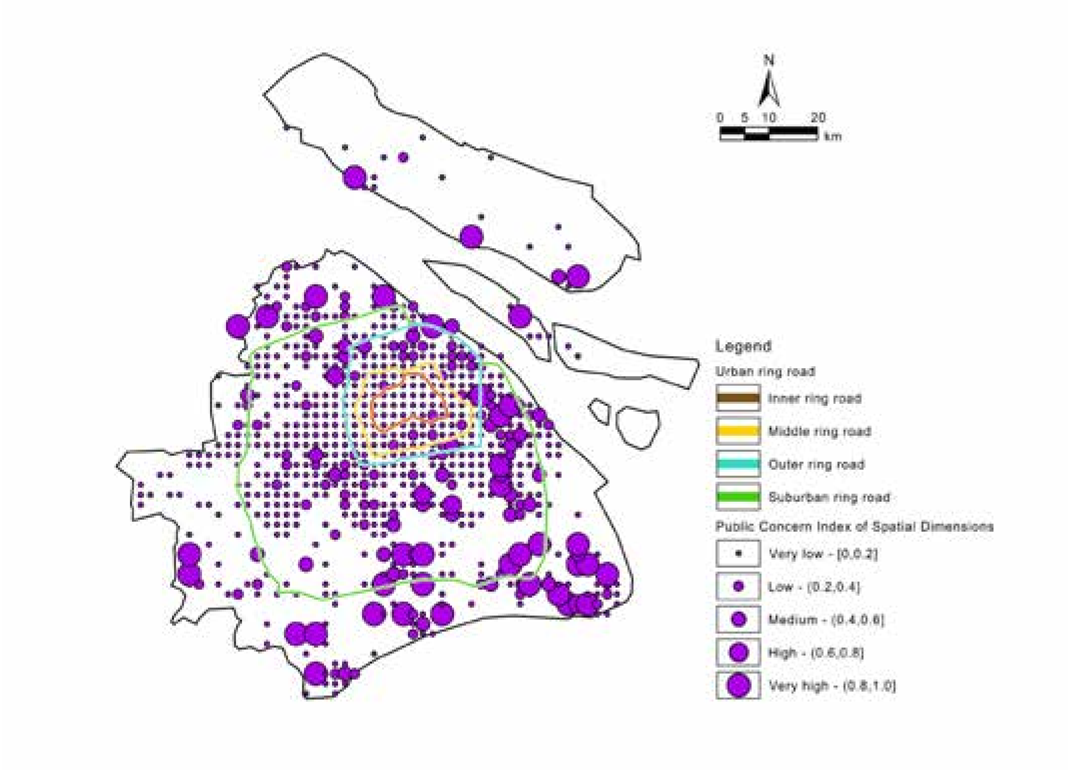

Figure 6. Spatial distribution of PCISD

According to spatial autocorrelation analysis, it shows that the spatial distribution of PCISD has obvious spatial clustering characteristics. For example, the hotspots are distributed in the coastal areas near the south of suburban ring road which are close to the typhoon landing sites and subject to typhoon disasters. While, the cold spots are distributed in the inland areas which are relatively less affected by typhoon disasters (Figure 7).

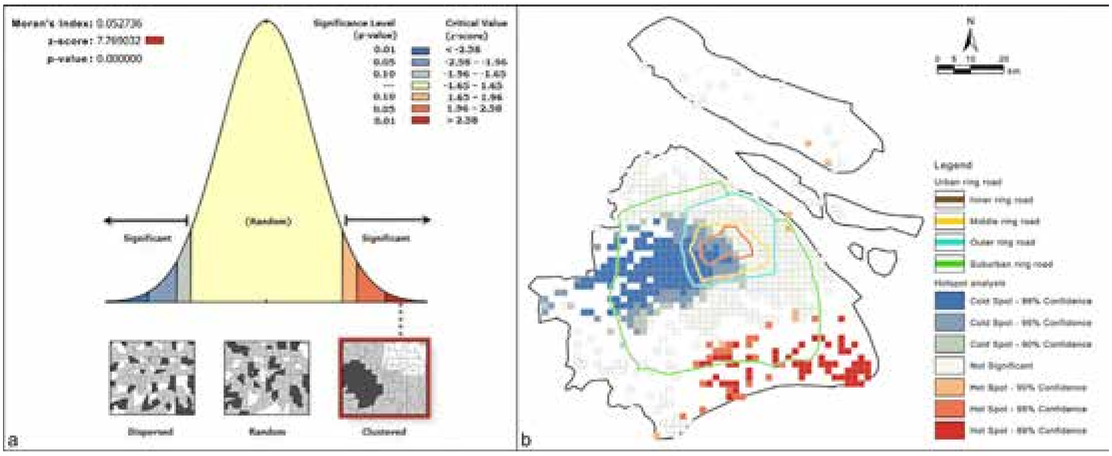

Figure 7. Spatial autocorrelation analysis of PCISD (a) and hot spot analysis of PCISD (b)

4.3.2. Distribution characteristics of NSISD and PSISD

In terms of NSISD, the areas with high value of NSISD are generally located within the outer ring road, while the areas outside the outer ring road present low high value of NSISD, with a small number of high value points of NSISD (Figure 8). In terms of PSISD, the spatial distribution of high value of PSISD is dispersed, the areas with high value of PSISD includes the area within the outer ring road, the area between the outer ring road and suburban ring road, the area near the southern coast (Figure 9).

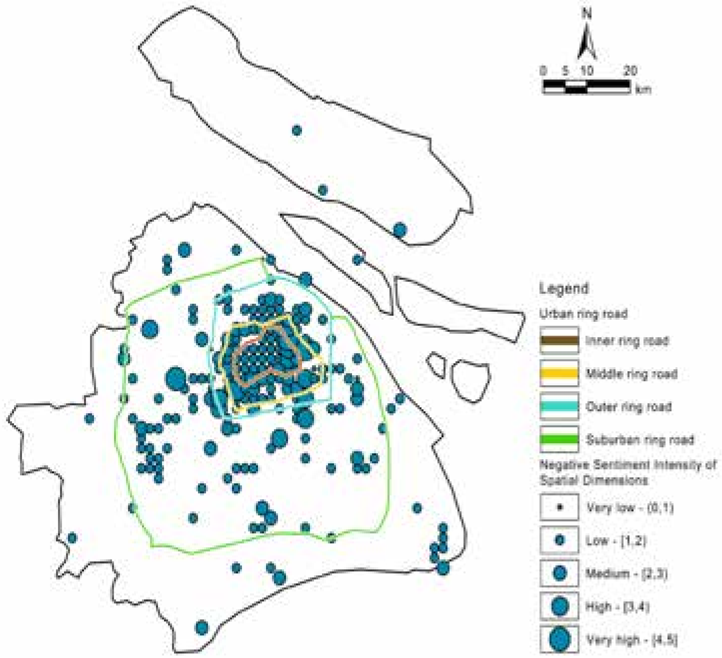

Figure 8. Spatial distribution of NSISD

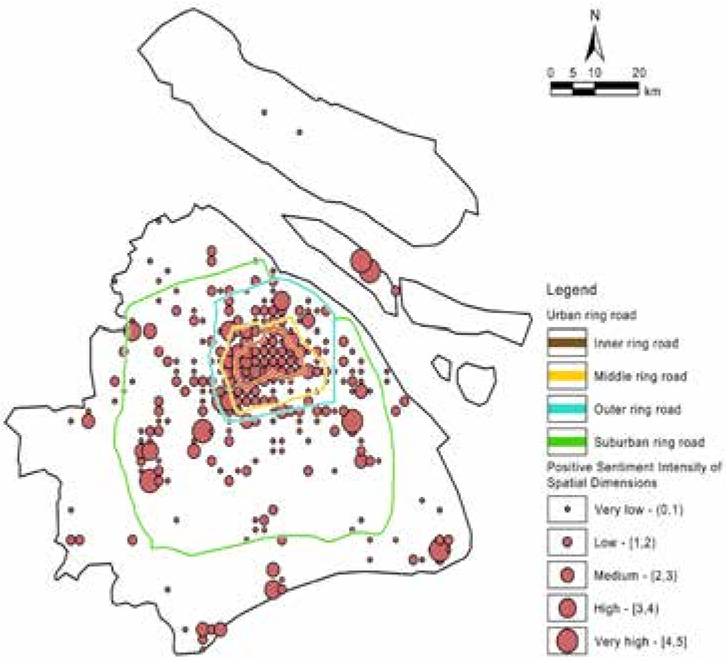

Figure 9. Spatial distribution of PSISD

According to spatial autocorrelation analysis, NSISD and PSISD present different spatial clustering characteristics. In terms of NSISD, NSISD exhibits obvious spatial clustering characteristics. Meanwhile, hotspots of NSISD concentrated within the middle ring road and cold spots of NSISD located in the western area of the suburban ring road (Figure 10). In terms of PSISD, PSISD exhibits random distribution characteristics (Figure 11). Furthermore, there are densely populated population and public service facilities within the middle ring road, which are highly vulnerable to typhoon disasters. Therefore, negative sentiment easily gathers in these areas and becomes hotspots.

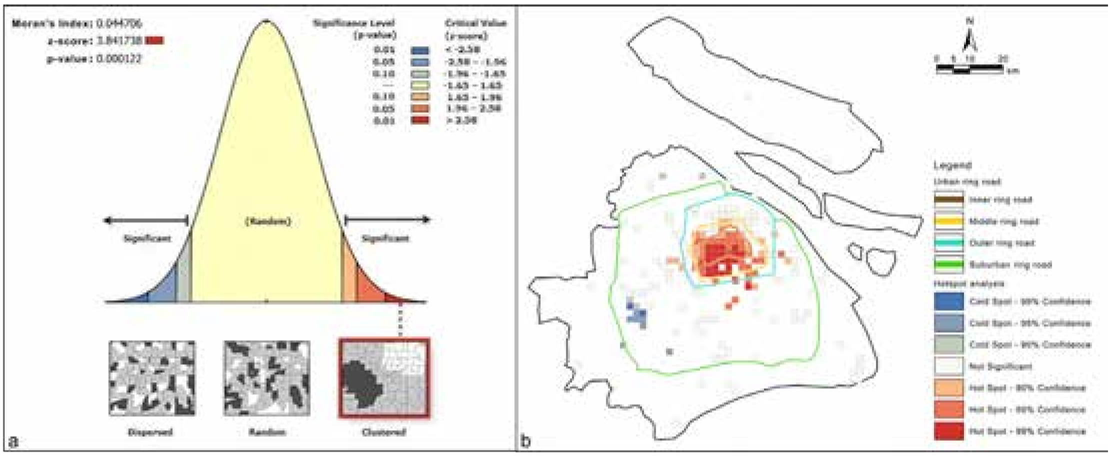

Figure 10. Spatial autocorrelation analysis of NSISD (a) and hot spot analysis of NSISD (b)

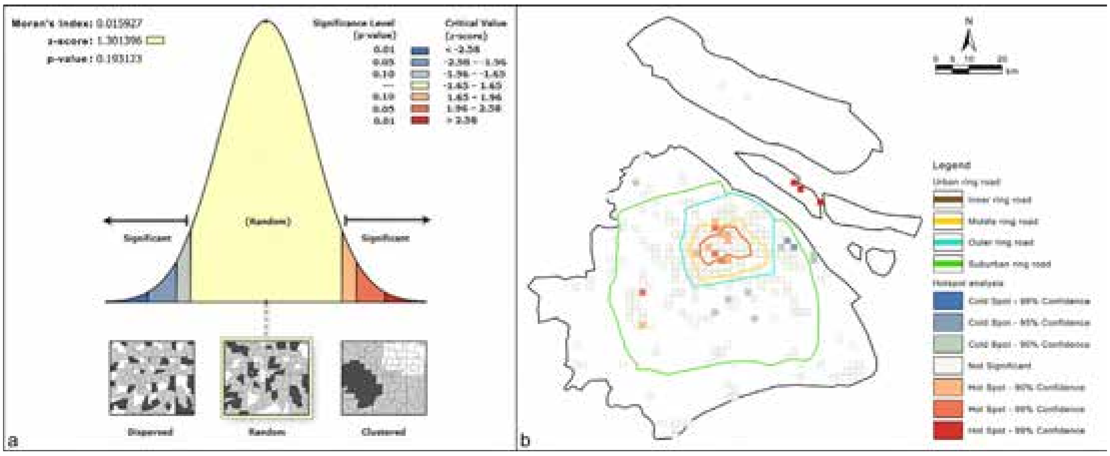

Figure 11. Spatial autocorrelation analysis of PSISD (a) and hot spot analysis of PSISD (b)

4.3.3. Comparative analysis of PCISD and NSISD

By comparing the hotspots of PCISD and NSISD, there is spatial differentiation between PCISD and NSISD. The area with high attention (high value of PCISD) distributes in the southern coast where the negative sentiment is not obvious (low value of NSISD). However, the area with low attention (low value of PCISD) distributes within the middle ring road where negative sentiment concentrated (high value of NSISD). Because low density of population and facility distributes in the southern coast with the greatest typhoon disasters impact, negative sentiment are not concentrated. Meanwhile, high density of population and facility distribute in the area within the middle ring road, but typhoon disasters have different impacts on people in different neighborhoods, which may cause public attention to be dispersed. This phenomenon shows that extreme weather events have greater uncertainty and cause different impacts on different parts of the city.

5. Discussion and conclusion

5.1. Discussion

Based on social media data, this paper conducts spatiotemporal perception analysis on typhoon disasters in Shanghai. Firstly, during the typhoon disasters, residents mainly focused on three themes, including daily travel activities, disaster-stricken locations and people, and post-disaster public places. It means that the focus of typhoon disasters prevention should include urban transportation, highly vulnerable neighborhoods and people, and public spaces. Secondly, the peak of PCITD occurs during the emergency response stage, while the peak of PSITD and NSITD occurs during post-disaster recovery stage. It means that PCITD can reflect the changing trend of the disaster impact, and disaster recovery effects can be evaluated based on NSITD and PSITD. Thirdly, PCISD can reflect the spatial distribution of disasters impact, and NSISD can reflect the spatial distribution of disaster-stricken conditions.

Typhoon disaster is the main type of natural disasters that affect the resilience level of cities in the China's eastern coastal areas. With the intensification of climate change, it is urgent to strengthen the ability of typhoon disaster prevention and improve the effectiveness of planning response. According to the above analysis, this paper proposes the following planning strategies.

(1) Construction of disaster intelligent perception platform for planning support system
Social media data provides a data source matching the dynamic change of disaster events, which can establish the disaster intelligent perception platform to achieve intelligent monitoring of typhoons. On the one hand, social media data can be applied to determine the impact and changing trend of the typhoon disasters based on the analysis of the disaster themes, the change of public perception, and the evolution of sentiment intensity. On the other hand, the disaster intelligent perception platform should integrate multiple data resources such as social media data, mobile signaling data and remote sensing data in order to identify disaster hotspots, delineate risk zones, and determine the location of disaster-stricken people.

(2) Layout optimization of emergency facilities based on disaster perception
In the pre-disaster preparation stage, urban planners can timely strengthen the refunction of emergency facilities and plan emergency evacuation routes based on hotspots of public concern on the social media. In the emergency response stage, urban planners can identify the location of disaster-stricken areas and provide decision-making support for the allocation of emergency relief resources through the text features analysis of social media. In the post-disaster recovery stage, urban planners can determine the spatial distribution characteristics of disaster damage, allocate relief supplies and set up emergency rescue sites and emergency hospitals based on the analysis of disaster themes and public sentiment intensity.

(3) Integration social media analysis tools into resilient urban planning
In order to cope with the uncertain challenges of disasters, resilient urban planning needs to incorporate dynamic analysis models to enhance adaptability. In terms of spatial dimension, social media data can be applied to conduct spatial distribution analysis of disaster hotspots and sentiment intensity. Meanwhile, these analysis results can be incorporated into disaster risk maps to support shelters selection and evacuation routes organization. In terms of temporal dimension, social media data can be applied to conduct the analysis of disaster themes and sentiment intensity, which can help determine the risk level of typhoon disasters and the key disaster response tasks at different stages.

5.2. Conclusion

As one of the most significant stakeholders in urban governance system, citizens are important force in resilient city construction. In the process of disaster response, it is crucial to analyze the disaster impact on citizens for the formulation of disaster response strategies and the improvement of urban emergency response capabilities. This paper shows that disaster perception through social media data can help reveal the characteristics of typhoon disasters impact on urban residents, which can provide reference for disaster management departments and explore new technical methods for resilient city planning.

With the development of social media and the advancement of messages dissemination, social media data contains multiple data formats such as sound, pictures, and videos in addition to text data, which contain a large amount of disaster information. This paper focuses on text data. In the future, we will further explore the potential of social media data in disaster perception, and conduct comprehensive analysis in combination with multiple data formats to improve the accuracy of disaster perception.

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Statements and declarations
All figures in this paper are created by the authors. Meanwhile, this paper adopts the 2024 version of China's administrative divisions map published by the National Geographic Information Public Service Platform (https://www.tianditu.gov.cn/), and the approval number of China's administrative division maps used in this paper is GS(2024)0650.

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