Zhu *et al. Computational Urban Science* (2024) 4:7
https://doi.org/10.1007/s43762-024-00119-z

Computational Urban Science

ORIGINAL PAPER

Open Access

Spatial heterogeneities of residents' sentiments and their associations with urban functional areas during heat waves– a case study in Beijing

Yanrong Zhu[1,2], Juan Wang[1,2*], Yuting Yuan[1,2], Bin Meng[1,2], Ming Luo[3], Changsheng Shi[1,2] and Huimin Ji[1,2]

Abstract

The intensification of global heat wave events is seriously affecting residents' emotional health. Based on social media big data, our research explored the spatial pattern of residents' sentiments during heat waves (SDHW). Besides, their association with urban functional areas (UFAs) was analyzed using the Apriori algorithm of association rule mining. It was found that SDHW in Beijing were characterized by obvious spatial clustering, with hot spots predominately dispersed in urban areas and far suburbs, and cold spots mainly clustered in near suburbs. As for the associations with urban function areas, green space and park areas had significant effects on the positive sentiment in the study area, while a higher percentage of industrial areas had a greater impact on negative SDHW. When it comes to combined UFAs, our results revealed that the green space and park area combined with other functional areas was more closely related to positive SDHW, indicating the significance of promoting positive sentiment. Subdistricts with a lower percentage of residential and traffic areas may have a more negative sentiment. There were two main combined UFAs that have greater impacts on SDHW: the combination of residential and industrial areas, and the combination of residential and public areas. This study contributes to the understanding of improving community planning and governance when heat waves increase, building healthy cities, and enhancing urban emergency management.

Keywords Geographical big data, Sentiment analysis, Urban functional area, Association rules analysis, Beijing

1 Introduction

In the context of continued global warming (Campbell et al., 2018, Intergovernmental Panel on Climate 2023), increases in the frequency, intensity, and duration of urban heat waves were observed at both the global scale and the regional scale (Sun et al., 2022). Urban heat waves not only lead to strain on urban resources and ecological degradation but also pose a serious threat to residents' health (Zhang et al., 2023). By 2019, the number of deaths associated with heat waves in China had reached nearly 30,000 over a thirty-year period (Cai et al., 2021). In addition, high temperatures can also affect human mood, behavioral disorders, mental health, and other related health indicators (Gao et al., 2019). Urban heat waves were significantly associated with suicide, acute illness, major depression and psychiatric admissions (Almendra et al., 2019). According to the Lancet Countdown to China Report released in 2022, rising temperatures have resulted in a 115% increase in heatwave-related mortality,

*Correspondence:
Juan Wang
wangjuan@buu.edu.cn
[1] College of Applied Arts and Science, Beijing Union University, Beijing, People's Republic of China
[2] Laboratory of Urban Cultural Sensing & Computing, Beijing Union University, Beijing, People's Republic of China
[3] School of Geography and Planning, Sun Yat-Sen University, Guangzhou, People's Republic of China

a 7.1% decrease in potential labor hours, and a 62.7% increase in wildfire exposure, and urbanization will further exacerbate heatwave risk (Cai et al., 2022). In order to give theoretical support and technical assistance for building healthy cities and enhancing urban emergency management, it is extremely vital to focus on the health effects of heat waves in rapidly urbanizing regions.

In recent years, research on the effects of urban heat waves on sentiments has received increasing attention (Romanello et al., 2021; Thompson et al., 2018). It has been widely recognized that urban heat waves have deleterious effects on health, leading to increased mortality and morbidity (Gasparrini et al., 2015; Green et al., 2019). However, the relationship between urban heat waves and sentiments was complex, with inconclusive results at different scales (Gao et al., 2020). For example, Huang et al. demonstrated that the irritability pattern of Beijing residents during heat waves has a distinct circle structure, showing a pattern of high centre and low periphery (Huang, Liu et al. 2022c). Wang et al. found that temperature was associated with more negative expressed sentiments in China by combining meteorological conditions with 400 million social media posts (Wang et al., 2020). The same results were found in the U.S., with sustained, statistically significant decreases in sentiments throughout the hot weather (Baylis, 2020). What's more, the risk areas for negative sentiments due to high temperatures were rapidly increasing (Huang, Li et al., 2022a). A study in Russia demonstrated that higher temperatures increase the frequency of positive sentimental expressions (Smetanin, 2022). Although the negative sentiments most likely to be triggered by global warming was fear, most people still expressed positive sentiments about it (Qiao & Williams, 2022). However, there are still research gaps on the spatial heterogeneities of sentiments during heat waves at the fine scale within the city.

The sentiments in urban environments were closely associated with the spatial structures and attributes at the intra-city scale (Shoval et al., 2018). As a geographical space where natural and social resources were concentrated, urban functional areas directly influenced the geospatial urban thermal environment and thus people's sentiments. Previous studies have tended to focus on exploring the association between a single urban functional area and residents' sentiment. For example, it has been demonstrated that green space and park areas could alleviate residents' negative sentiments during heat waves (Klemm et al., 2015). Rational allocation of public areas could enhance the city's ability to cope with heat waves and improve residents' thermal comfort (Santos Nouri et al., 2018). But the possible complex impacts on sentiments brought about by different combinations of functional land uses are ignored, which is crucial for revealing the diversity of emotion-functional area interactions at the inner-city scale. Other studies have focused on the relationship between emotional experience or well-being and functional area. The environmental quality, social security, and social interactions in urban residential areas can have different effects on residents' sentiments (Chen, Hall et al. 2019, Zhong et al., 2021). The larger, denser, and more accessible the commercial area is, the higher the shopping convenience and consumer satisfaction of residents, resulting in positive sentimental experiences (Rompay et al., 2012). In summary, a focus on the sentiments in conjunction with urban functional areas can help address urban socio-spatial inequalities and improve the well-being of residents. But most studies have ignored its association with high-temperature heat waves. There are still research gaps to explore the association between sentiments during heat waves and multiple urban functional areas at the intra-city scale.

In previous studies, medical data and questionnaire data were commonly used to study the comfort temperature range and the serious consequences of high temperature on emotional health. However, these data can hardly objectively reflect the real perceptions of the population on high temperatures. There were problems such as time lag, limited survey scope and coverage, and insufficient sample validity and diversity. In recent years, location-based social awareness data have been successfully applied to accurately measure the sentiment perception of large regional groups (Liu, 2016). Social media served as an important tool for public health surveillance (Kass-Hout & Alhinnawi, 2013). Due to its open, communicative, and participatory nature, social media contains a wealth of real-time group emotions and perceptions of the geographic environment (Zheng et al., 2019). It also allows emotional health research to break through the limitations of traditional questionnaires and psychiatric hospital visits to provide a more timely, comprehensive explanation of residents' emotional health. Weibo is the largest social media platform in China (Huang, Long et al., 2022b). By the end of 2022, the monthly active user count of Weibo had increased to 586 million. As a typical geographical big data, Weibo data not only contains information such as time and location, but also reflects the rich sentiments of users, providing great convenience for analyzing the emotional health of residents. Despite the potential biases and prejudices in the real numbers due to the different ages, occupations and geographical locations of users (Rabari & Storper, 2015), Weibo data remains one of the most useful data sources in the field of public health (Yang et al., 2019). It has been widely used to monitor affective states in real-time (Wang et al., 2022), measure well-being measures associated with events such as heat waves, sensitivity and studies of their health effects (Baylis, 2020; Clayton, 2020; Wang et al., 2021).

In recent years, significant progress has been made in sentiment analysis research focusing on social media data. Approaches primarily include methods based on sentiment lexicons, traditional machine learning, and deep learning. Lexicon-based methods face challenges in handling ambiguity, sensitivity to domain variations, and limited scalability (Hu & Liu, 2004). Traditional machine learning methods, such as Support Vector Machines (SVM) and Naive Bayes (NB), heavily rely on labeled data, necessitating intricate feature engineering with limited complexity handling capabilities (Pang, Lee et al. 2002). With the advancement of deep learning and big data technologies, an increasing number of researchers are turning to deep neural networks for sentiment analysis tasks. Deep learning methods excel in modeling contextual information within text, capturing intricate relationships between words. Techniques like Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Attention Mechanism, and Transformer models such as BERT and RoBERTa (Kim, 2014, Tang, Qin et al. 2015), have demonstrated superior capabilities in handling large-scale unstructured datasets, effectively enhancing the accuracy and efficiency of sentiment classification. These approaches find wide applications in exploring urban sentiments based on social media data (Chen et al., 2022; Cheng et al., 2023; He et al., 2023a, 2023b; Xia et al., 2023).

In the above process of combing through the literature, we found that scholars have begun to study the sentiments of residents during heat waves, as the health impacts of heat waves on residents have become more and more emphasized. Social media has become an important data source with its wide range, low access cost, high timeliness, and spatial location attributes for spatial difference analysis. However, there is still a research gap in detecting the pattern of residents' sentiments at the intra-city scale during heat wave events, as well as mining the associations between them and the functional areas of the city.

In summary, to fill the above-mentioned research gaps, this study was constructed to explore the spatial heterogeneities of residents' sentiments during heat waves and their associations with urban functional areas by taking Beijing as an example. Specifically, it has the following three objectives: 1) to do sentiment analysis on Weibo text data using deep learning-based sentiment analysis methods. 2) to explore the spatial pattern of residents' Sentiments During Heatwaves (SDHW) based on the location attributes of Weibo data by using spatialization methods as well as hotspot analysis. 3) to delineate the Urban Functional Areas (UFAs) at the intra-city scale in Beijing based on the POI data, and to explore their associations with SDHW by using the Apriori algorithm. It was found that SDHW in Beijing were characterized by obvious spatial clustering, with hot spots predominately dispersed in urban areas and far suburbs, and cold spots mainly clustered in near suburbs. There were two main combined UFAs that have greater impacts on SDHW: the combination of residential and industrial areas, and the combination of residential and public areas. This study contributes to the understanding of improving community planning and governance when heat waves increase, building healthy cities, and enhancing urban emergency management.

2 Study area

Beijing is the political center of China and has a long history of civilization and cultural integration. It covers an area of 16,410.54 square kilometers, of which 38.6% is plain and 61.4% is mountainous area (Xie et al., 2022). By the end of 2020, the population of Beijing 21.89 million, and the urbanization rate has reached 87.6% (Huang, Li et al., 2022a). Rapid urbanization has led to dramatic changes in land development and has significantly altered thermal environmental patterns (Peng et al., 2016). It has been estimated that Beijing experienced several heat events in the summer of 2019 (a heatwave event being defined as three or more days of high temperature in succession), with a total of 14 days of high temperature days (daily maximum temperature exceeding 35℃) in July. The study area is shown in Fig. 1, and there are 327 subdistricts and 16 districts in Beijing. The yellow dots in the figure represent the geographical locations of Weibo posts.

3 Data and method

3.1 Data

3.1.1 Social media Weibo data

Sina Weibo is one of the largest and most influential blogging websites in China. In July 2019, Beijing had 14 days of high temperature days (daily maximum temperature exceeding 35℃) and multiple prolonged heatwave events (a heatwave event being defined as three or more days of high temperature in succession) (http://www.tianqihoubao.com/lishi/beijing/month/201907.html). As such, in this research we selected Weibo posts from Beijing within July. Web crawling technology was used to obtain a total of 1,043,224 Weibo posts from the Weibo social media platform in July 2019. Each Weibo item includes the ID, textual content, time, latitude, and longitude. We found a significant positive correlation between the seventh census population and Weibo check-in population in 2019 of each subdistrict in Beijing (Fig. 2), suggesting that

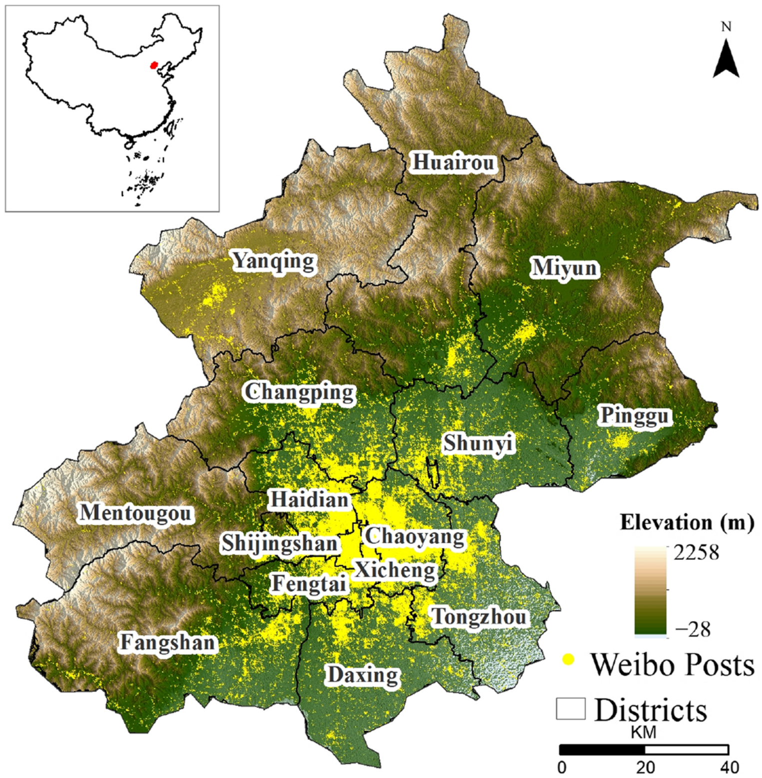

Fig. 1 Study area

Weibo data can be used to analyze the spatial distribution of residents' sentiments (He et al., 2023a, 2023b).

3.1.2 Point of interest (POI) data

Within cities, the spatial distribution of various functional activities creates small district differences, forming different single or mixed functional units such as residential, commercial, and industrial areas. Previous studies have shown that POI data can provide accurate information on urban functional land use and accurately reflect the spatial distribution of urban functional areas (Chen et al., 2016; Xiao et al., 2017).

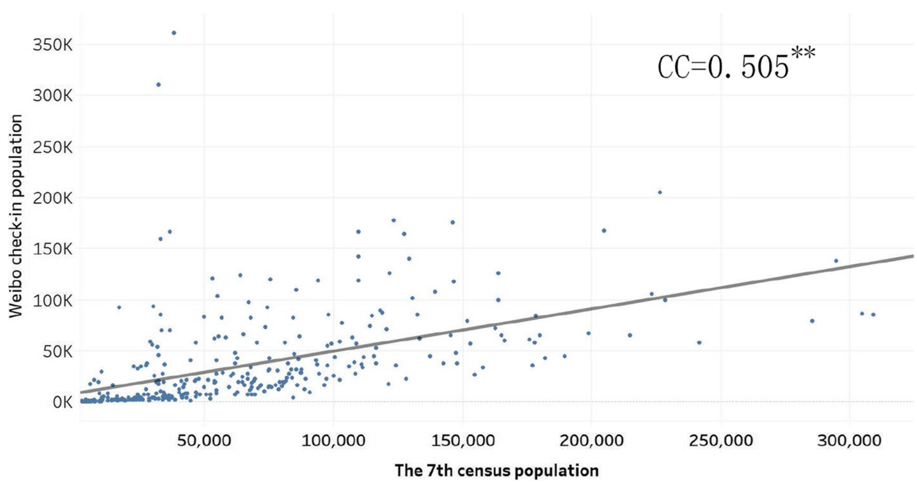

Fig. 2 Relationship between the total number of people in the 7th census and the total number of Weibo check-in in 2019 of each subdistrict in Beijing. ** means CC (correlation coefficient) is significant at the 0.01 level

The POI data used in this study was collected from AutoNavi Map, which contains nearly 918,441 points within the study area. The attributes of each POI include the name, latitude and longitude, address, category and administrative area. According to the type statistics, the POI data were classified into 13 categories, including catering services, scenic spots, public facilities, cultural and educational services, shopping services, government agencies and groups, car services, etc.

3.1.3 Fundamental geographic data

In addition, all the administrative boundaries on the scale of 1:4,000,000 maps were obtained from the National Earth System Science Data Center (http://www.geodata.cn/). These boundaries were used to separate subdistricts for the study area.

3.2 Method

3.2.1 Calculating SDHW based on Weibo data

This research used the Robustly Optimized BERT Pretraining Approach (RoBERTa) method to accomplish sentiment analysis of Weibo items (Lee & Toutanova, 2018, Liu, Ott et al. 2019). It is an improvement from the Bidirectional Encoder Representations from Transformers (BERT). It extends the key hyperparameters to train with much larger learning rates and mini-batches (Devlin, Chang et al. 2018, Barua, Thara et al. 2021). RoBERTa was fine-tuned using the UER-py framework in large-scale pretraining, incorporating diverse Chinese datasets from various domains, such as the Jingdong binary review dataset. This resulted in outstanding performance when adapting to sentiment analysis tasks in Chinese social media. The model's ability to better model the Chinese social media context is attributed to its adaptability to the unique characteristics of Chinese text. Moreover, RoBERTa-Base excels in handling long texts and capturing contextual information (Liu, Ott et al. 2019). These factors make it an ideal choice for sentiment analysis in Chinese social media in this study. The Chinese RoBERTa-Base Model used in this research was obtained from the Hugging face (https://huggingface.co/uer/roberta-base-finetuned-dianping-chinese) (Zhao, Chen et al. 2019).

Firstly, the process of performing sentiment analysis required textual input in a machine-readable format. Pre-processing was required, such as clean text, stopword removal, stemming, removal of punctuation, etc. Subsequently, the roberta-base-finetuned-jd-binary-chinese corpus was called to perform semantic sentiment analysis on the pre-processed Weibo texts. The final score value is obtained for the sentiment of each Weibo post. The score ranges from 0–1, the closer to 1 the more positive the sentiment. Lastly, 2,000 Weibo items were selected as the validation set for manual validation, achieving an accuracy of 87%, which is basically credible.

After clipping the Weibo posts of each subdistrict based on the administrative division, the mean value of sentiment score within each subdistrict was summarized and this value was used as the sentiment value-SDHW for each subdistrict. The SDHW of each subdistrict was converted into categorical data. And then the principle of equal quantity distribution was used to divide the values into five categories: worst, bad, medium, good, and best (He et al., 2018). We also use Hotspot Analysis for grid detection of SDHW on subdistricts. Hotspot analysis in ArcGIS is a spatial statistical method designed to identify significant clustering and dispersion patterns in spatial data. It quantifies and spatializes the identification of clustering patterns within a region. We use hotspot analysis to detect in which regions SDHW will be clustered with high/low values. See specifically Sect. 4.1.

3.2.2 Calculating UFAS based on POI data

The urban function areas were mapped following Wang and Zhang (Wang & Xu, 2012; Zhang, 2012). According to the principle of universality and consistency of POI classification, POI data were divided into six major categories, including residential area (RA), public area (PA), commercial area (CA), industrial area (IA), green space and park area (GPA), and traffic area (TA). It was mentioned that POI data do not have area information of geographic entities, and there were differences in the influence range of different types of geographic entities. In this research, two indicators, general area and public awareness were introduced to give weights (Li et al., 2020; Xue et al., 2020; Zhao et al., 2011). In addition, some categories of POIs, such as public toilets and newsstands, were not significant in functional areas and were therefore excluded. After reorganization, the final urban functional areas were mapped at the subdistrict scale with the percentage of the six categories. That is, the percentage of the six functional areas in each subdistrict were obtained: the percentage of residential area (PRA), the percentage of public area (PPA), the percentage of commercial area (PCA), the percentage of industrial area (PIA), the percentage of green space and park area (PGPA), and the percentage of traffic area (PTA). As with the Weibo data mentioned above, all data were also converted to categorical variables, divided into lowest, low, medium, high, and highest.

3.2.3 Association rule mining based on the Apriori algorithm

Association rule analysis is one of the most important techniques used in data mining research (Witten & Frank, 2002). Association rules reflect the influence of the occurrence of one thing on the occurrence of other things. It is an unsupervised learning data mining method to discover and extract frequently occurring or interesting knowledge from large databases. Association rule mining is suitable for handling data with fuzzy relationships (Zhang & Zhang, 2002). The relationships between sentiments and urban functional areas are complex and influenced by many factors, therefore the deep-seated and multi-dimensional relationship between urban functional areas and sentimental health can be explored by the association rules.

In this research, the classic Apriori algorithm in association rule mining was used to explore the relationship between SDHW and UFA_S (Agrawal & Srikant, 1994). The algorithm involves three metrics, namely Support, Confidence, and Lift. The indicators are explained below:

(1) Support: Support represents the frequency of occurrence of an itemset in the entire dataset.

$$Support(X) = \frac{Transactions\ containing\ itemset\ X}{Total\ transactions}$$

(2) Confidence: Confidence represents the probability of itemset Y occurring when itemset X occurs.

$$Confidence(X \Rightarrow Y) = \frac{Support(X \cup Y)}{Support(X)}$$

(3) Lift: Lift measures how much more likely itemset Y is to occur when itemset X occurs, compared to when Y occurs independently.

$$Lift(X \Rightarrow Y) = \frac{Confidence(X \Rightarrow Y)}{Support(Y)}$$

To perform the Apriori algorithm, information about the SDHW for each subdistrict was combined with UFAs to create a database of itemset. There were a total of 327 itemsets in our research. Each itemset contains the following information:

$$\mathrm{I} = (\mathrm{SDHW};\ \mathrm{PRA}, \mathrm{PPA}, \mathrm{PCA}, \mathrm{PIA}, \mathrm{PGPA}, \mathrm{PTA})$$

The Apriori algorithm identifies relationships between SDHW and UFAs (PRA, PPA, PCA, PIA, PGPA, PTA) based on information from all subdistricts. Thresholds need to be set before running the algorithm. In this research, we found the minimum threshold that can cover the basic valid rules by setting the initial minimum confidence and support and then gradually changing the minimum threshold. The minimum support was 0.02 and the minimum confidence was 0.3. As a result, we extracted a total of 128 rules, some of which were shown in Table 2 in Sect. 4.3.2. The measures of each rule include Support, Confidence, and Lift. Figure 3 illustrated the distribution of the above three metrics for all 128 rules. The Lifts were more than 1, indicating that the rules were basically valid.

In order to clearly clarify the relationships between urban functional areas and SDHW, all the association rules were analyzed from two aspects. First, in Sect. 4.3.1. we filtered out the combined UFAs with only one functional area as a way to analyze the impact of a single UFA on SDHW. We use Sankey diagrams to show the correlation between single UFA and SDHW. The Sankey diagram is a graphical tool used to visualize processes, resource allocations, and interrelationships. Its distinctive feature lies in representing the quantity of flows through arrows of varying widths, effectively illustrating the connections and interactions between multiple steps. The effects of other combined UFAs with more than one on SDHW were described in 4.3.2.

4 Result

4.1 Spatial patterns of SDHW

There were obvious spatial differences in SDHW in Beijing which was shown in Fig. 4. The SDHW was averaged within each subdistrict and then reclassified into five categories using the equal quantity distribution, that is, worst, bad, medium, good, and best (Fig. 4 left). The percentage of subdistricts with positive (good, best) SDHW and negative (bad, worse) SDHW in each district was counted, as shown in the right column of Fig. 4. Positive SDHW was mainly located in urban areas and far suburbs, specifically Dongcheng, Xicheng, Shijingshan, Yanqing, and Mentougou Districts. For example, 65% of subdistricts in Dongcheng District had positive SDHW, and 54% in Mentougou District. Negative SDHW was dominated by near suburbs, respectively Changping, Fangshan, and Tongzhou Districts. For example, 68% of subdistricts in Changping District had negative SDHW, and 61% in Fangshan District. Specifically, negative SDHW occurred in the subdistricts of Xinzhen, Xiangyang, and Junzhuang Town.

To further explore the characteristics of its spatial heterogeneities, the Hotspot Analysis was done for the SDHW of Beijing, and the results are shown in Fig. 5. Hotspot analysis helps correlate sentiment values with their spatial distribution. Subsequently, examining their geographical clustering patterns, such as observing whether areas with high sentiment values form clusters, becomes possible. By considering the spatial relationships of different sentiments, trends in their distribution

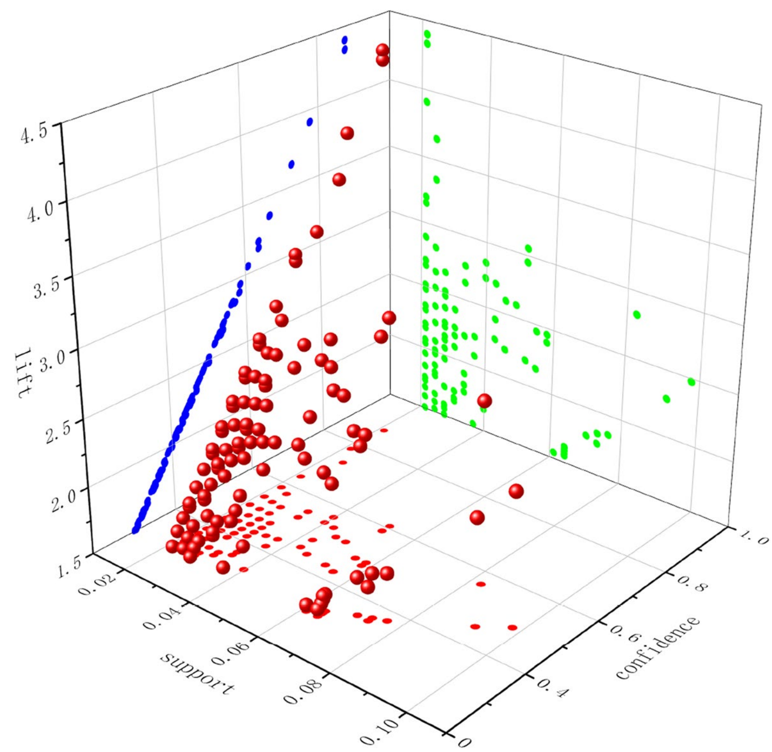

Fig. 3 Support, confidence, lift of 128 rules extracted by the Apriori algorithm

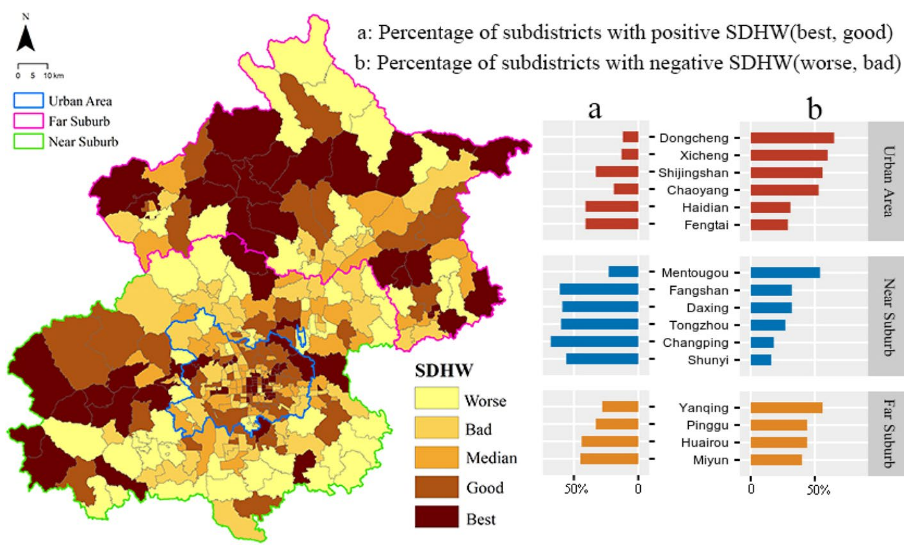

Fig. 4 Spatial distribution and regional statistics of SDHW. *SDHW means Sentiment During Heat Waves

can be identified, contributing to a deeper understanding of the spatial trends and variations in the sentiment distribution among residents across different subdistricts in Beijing. In the results of the hotspot analysis, hotspots and coldspots reflect significant differences in the spatial distribution of the data. As shown in Fig. 5, hotspots indicate areas with relatively high values, while coldspots represent areas with relatively low values. Confidence levels of 90%, 95%, and 99% are used to denote different statistical significance levels for hotspots and coldspots. It can be seen that the SDHW distribution in Beijing had a spatial clustering of high and low values of statistical

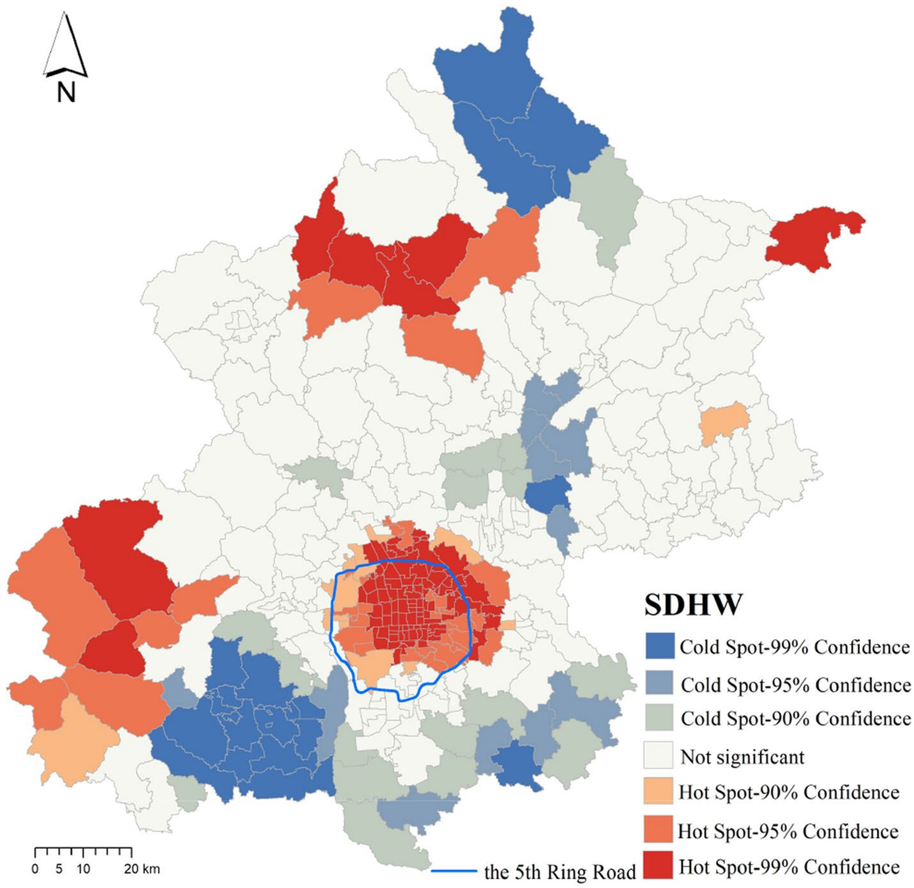

Fig. 5 The hot spot analysis of SDHW

significance. Within the 5th Ring Road of the central city, SDHW showed a clear clustering of high values, indicating that during heat waves, residents in these areas were relatively more positive in their emotional performance. Further south, Fangshan District, Daxing District, Tongzhou District and other subdistricts showed cold clustering of sentiments, i.e., residents' sentiments were more negative. In addition, the Mentougou District also exhibited clustering of high values of residents' emotions. The northern suburbs also showed different patterns of clustering, with Yanqing District being positively emotionally clustered, while some streets in Huairou and Shunyi Districts showed negative emotional clustering.

4.2 Spatial patterns of UFAs

Based on the UFA division of POI data, we obtained the percentage of six functional areas for 327 subdistricts, as shown in Fig. 6. The spatial pattern of six urban functional areas was pronounced. The percentage of green space and park areas was larger in the suburbs of Beijing, and smaller in the urban areas. The pattern for residential areas was far different. Industrial areas showed a pattern of high in the southeast and low in the northwest. Public areas also had roughly quite another spatial pattern. Commercial areas were generally higher in the urban areas than in the suburbs. Notably, traffic areas showed a pattern of high suburban percentage. After that, all data were also converted to categorical variables the same as SDHW, divided into lowest, low, medium, high, and highest. The interval for each range of indicator values was shown in Table 1.

4.3 Associations between UFAs and SDHW

4.3.1 Associations between a single UFA and SDHW

The impacts of a single UFA varied for different SDHW. We measured the impact of the six UFAs on SDHW based on Lift values, as shown in Fig. 7. The left side represents different proportions of urban functional area, and the right side represents different levels of sentiment during heat waves. The thickness represents the correlation between the two. The thicker the correlation, the stronger the correlation. The effects of

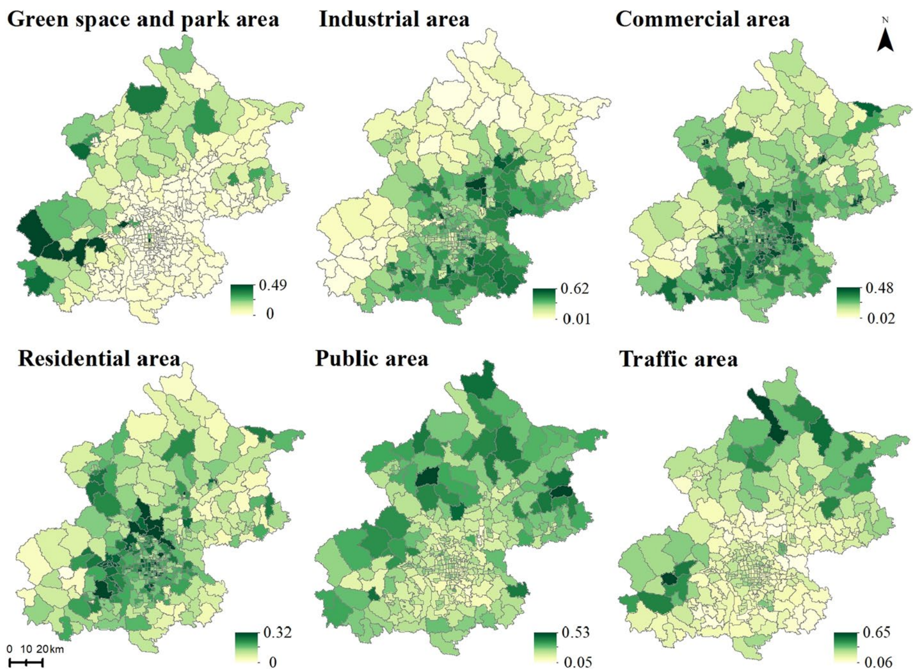

Fig. 6 Percentages of six urban functional areas of each subdistrict

Table 1 The interval for each indicator value

UFA	lowest	low	medium	high	highest
PGPA*	0–0.006	0.006–0.010	0.010–0.019	0.019–0.060	0.060–0.486
PIA*	0–0.111	0.111–0.189	0.189–0.248	0.248–0.329	0.329–0.618
PCA*	0–0.162	0.162–0.209	0.209–0.254	0.254–0.309	0.309–0.475
PRA*	0–0.045	0.045–0.063	0.063–0.083	0.083–0.103	0.103–0.324
PTA*	0–0.158	0.158–0.194	0.194–0.227	0.227–0.280	0.280–0.649
PPA*	0–0.155	0.155–0.178	0.178–0.204	0.204–0.252	0.252–0.530

* *PGPA* means the percentage of green space and park area, and *PIA* means the percentage of industrial area, and *PCA* means the percentage of commercial area, and *PRA* means the percentage of residential area, and *PTA* means the percentage of traffic area, and *PPA* means the percentage of public area

green space and park areas on extreme sentiments were greater. During urban heat waves, residents living in subdistricts with a higher percentage of green space and park areas had the highest possibility to show positive sentiments. The same was true for residents living in subdistricts with the lowest percentage of industrial areas. Meanwhile, a high percentage of industrial areas may lead to worse-SDHW. The effects of transportation areas on sentiments were not significant, but an overall higher percentage of transportation areas was more associated with positive SDHW. Also, residents were in more positive sentiments during heat waves when the percentage of commercial areas was lowest or public areas was highest. The negative sentiments during heat waves were more related to the lowest percentage of residential areas.

4.3.2 Associations between combined UFAs and SDHW

This section focused on the effects of combined UFAs on SDHW. Table 2 listed part of the most important rules showing the effects of combined UFA on the five SDHW. The combined UFAs associated with the worse-SDHW were dominated by low percentage of residential areas, as shown in rules 1–3 in Table 2. When there was the lowest percentage of residential areas and traffic areas, it was more likely to lead to worse-SDHW. Similarly, worse SDHW also occurred when there were the lowest percentage of residential areas and the highest percentage of industrial areas. In addition, the combination of the lowest PRA, highest PPA, and lowest PCA also had a higher likelihood of worse-SDHW when it occurs simultaneously in the subdistrict. Subdistricts were more likely to be bad-SDHW when the percentage of green space and park was low while the percentage of public areas was high. There was also a high degree of correlation between bad-SDHW and these two UFAs: the lowest percentage of green space and park, and highest percentage of industrial area. Good-SDHW was more associated with two types of combined UFAs. Good-SDHW was more likely to occur in subdistricts that have a high percentage of both commercial and traffic areas. Similarly, residents living in subdistricts with a high percentage of residential areas and a low percentage of public areas mainly show good-SDHW. Meanwhile,

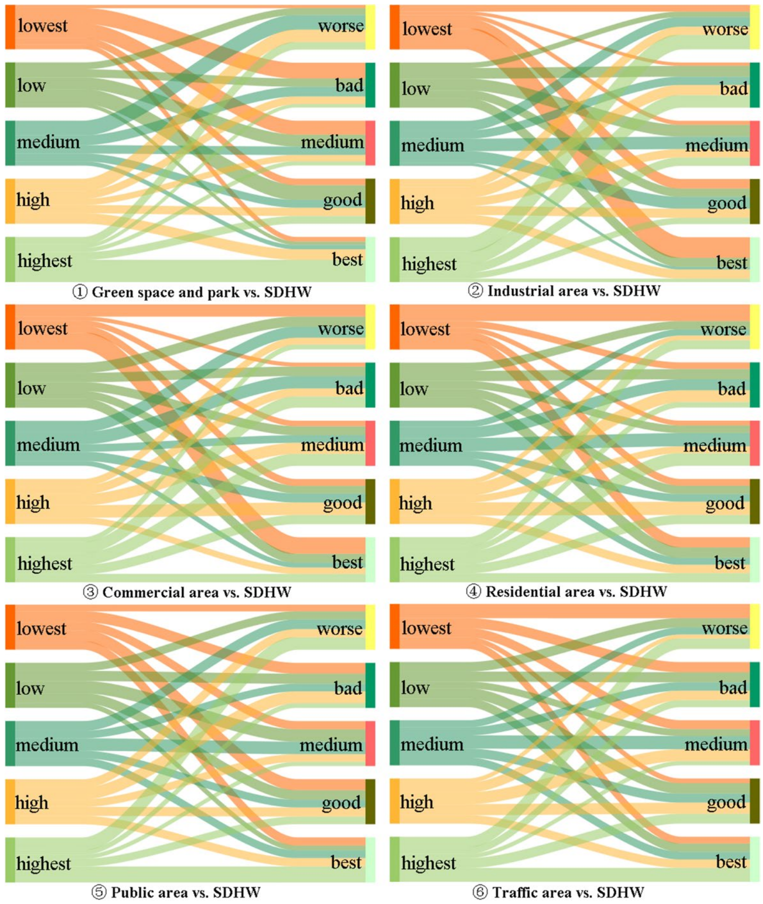

Fig. 7 Associations between single UFA and SDHW

Table 2 Associations between combined UFAs and SDHW

ID	Combined UFAs		SDHW	Support	Confidence	Lift
1	lowest-PRA*, lowest-PTA*	→	Worse	0.02	0.64	3.15
2	lowest-PRA*, highest-PIA*	→	Worse	0.03	0.43	2.12
3	lowest-PRA*, highest-PPA*, lowest-PCA*	→	Worse	0.02	0.38	1.88
4	lowest-PGPA*, high-PPA*	→	Bad	0.02	0.58	2.89
5	highest-PIA*, lowest-PGPA*	→	Bad	0.02	0.40	1.98
6	medium-PRA*, medium-PIA*	→	Medium	0.02	0.50	2.52
7	high-PCA*, high-PTA*	→	Good	0.02	0.54	2.71
8	high-PRA*, low-PPA*	→	Good	0.02	0.50	2.52
9	low-PRA*, lowest-PIA*	→	Best	0.02	0.87	4.40
10	lowest-PIA*, highest-PGPA*	→	Best	0.08	0.56	2.83
11	low-PCA*, lowest-PIA*, highest-PGPA*	→	Best	0.02	0.72	3.65

* *PGPA* means the percentage of green space and park area, and *PIA* means the percentage of industrial area, and *PCA* means the percentage of commercial area, and *PRA* means the percentage of residential area, and *PTA* means the percentage of traffic area, and *PPA* means the percentage of public area

best-SDHW occurred most frequently when the subdistrict had a high percentage of green space versed a low percentage of industrial areas. In addition, the low PCA, PIA, and high PGPA also had a greater impact on best-SDHW.

5 Discussion

5.1 Summary of key findings

This study aims to investigate the effects of different urban functional areas within Beijing on residents' sentiments during heat waves (SDHW), and the spatial heterogeneities of these effects. By studying 327subdistricts, we found a clear spatial clustering of SDHW in Beijing, with relatively more positive affect in the central city and more negative affect in the southern area. Green areas and industrial areas are the functional areas with the most significant influence on sentiment, with the combination of a high percentage of green areas and a low percentage of industrial areas contributing to more positive sentiment. There was more divergence from the impacts of commercial and traffic areas, with environmental changes in different zones also leading to different emotional experiences.

5.2 Analysis and Comparison with other studies

5.2.1 About SDHW

As mentioned above, there were obvious spatial clustering characteristics of SDHW in Beijing, with several relatively obvious hot and cold spot areas. SDHW in the central city (within the 5th Ring Road) was relatively more positive. This are consistent with a number of studies that urban areas typically have more services and critical resources that are conducive to helping residents cope with extreme heat and promoting emotional stability (Harlan et al., 2007, Gallegos, Lerman et al. 2016). Previous research documented that positive sentiments were closely related to economic indicators, and residents may be happier in high-income areas (Van de Vliert et al., 2004; Mitchell et al., 2013, He, Wang et al. 2023). But there were also studies that point out that residents of areas with higher economic incomes are usually more sensitive to high temperatures in summer (Cheng et al., 2023).

Sentiments in the southern subdistricts were significantly more negative during heat waves. In addition to economic factors, southern areas, such as Daxing and Tongzhou District, typically face higher temperatures and humidity during summer. It has been suggested that the compounding effects of factors such as rainfall and humidity that accompany high temperatures in the south may lead to relatively poor adaptation to extreme heat for residents of the southern region (Cheng et al., 2023; Morrissey et al., 1996). In addition, compared to several suburban districts, SDHW was more active in the distant suburbs, such as Yanqing and Huairou Districts. Some studies have also pointed out that staying in the suburbs makes people happier (Adams, 1992). This may also have more to do with the natural environment of far suburbs, which were more mountainous and had relatively cooler temperatures in extreme heat, and where people may have a more positive emotional experience (De Vos & Witlox, 2016).

5.2.2 About associations between UFAs and SDHW

Subdistricts hold different site combinations and spatial layouts, and the correlations between sentiments and combined functional areas were site-specific. Green space and industrial areas are usually the common functional areas that have a high and opposite impact on mood (Klemm et al., 2015, HE, SUN et al., 2022). We reached a similar conclusion that the combination of a high percentage of green space and low percentage of industrial areas contributed to greater positive sentiments during the heatwaves (Rule 5 and Rule 10 in Table 2). Positive sentiments during heat waves were associated with a high percentage of green space areas, such as in far suburban areas. In contrast, negative sentiments were associated with a low percentage of green space areas. Industrial areas were usually areas with a high concentration of factories and industrial facilities, which were prone to noise, pollution, traffic congestion and other problems, and usually had a negative impact on sentiments (Cao et al., 2018). Thus, a low percentage of industrial areas would tend to promote the emergence of more positive sentiments. For example, the low percentage of industrial areas in Yanqing and Huairou streets located in the northern suburbs was more associated with best-SDHW. Most of the negative sentiments during heat waves in the central city as well as in the southern subdistricts was associated with high percentage of industrial areas.

The simultaneous presence of a high percentage of commercial and industrial areas in Dongcheng District could exacerbate the negative sentiments of residents during heat waves. Positive sentiments in Yanqing and Huairou Districts were also related to the low percentage of commercial areas. These results seem to indicate that people in denser commercial areas have more negative sentiments. From the perspective of urban planning and design, studies have shown that areas with a low percentage of commercial areas tend to give residents a sense of relaxation and tranquillity. Areas with a high percentage of commercial areas were often noisy and busy, and more likely to produce feelings of stress and anxiety. Therefore, many studies have shown that positive sentiments cluster near commercial areas (Gao et al., 2022; Park et al., 2021). However, there was disagreement about the impact of commercial areas on sentiments (Lin et al., 2022; Yang et al., 2022).

Our results show that the high percentage of traffic areas was more associated with positive sentiments. Previous research had found that the results of using transportation and residents' well-being tend to be mixed (Páez & Whalen, 2010; Pfeiffer & Cloutier, 2016). The number of bus stops may be a negative factor (Park et al., 2021), but residents with better access to transportation may be happier (Leyden et al., 2011). On the other hand, our results may be influenced by the bias of POI data in suburban areas, where there was a lack of data for other functional areas and thus a high percentage of traffic areas. Besides, the negative sentiments of subdistricts in Shunyi and Miyun Districts during heat waves were related to the lack of green space and park areas, as well as the lack of public areas. In contrast, Changping, Daxing, and Shijingshan Districts were associated with insufficient green space and park areas, but more public areas. This indicated that the influence of functional areas on SDHW was not absolute, but there were spatial heterogeneities. Different environmental changes and their potential impacts on residents should be taken into account to develop urban planning solutions that better meet residents' needs.

5.3 Policy implication

In an in-depth study of the impact of urban functional areas on residents' emotions, the following recommendations are made to enhance the overall social well-being of the city:

For the southeastern areas of Beijing, such as Tongzhou and Daxing Districts, it is recommended to moderately increase residential areas and strategically plan public spaces in urban development. Equally important is attention to the layout of industrial areas, as an increased proportion adversely affects the emotional well-being of residents in these regions. The government can reduce the negative impact on residents' sentiments and improve the quality of life by guiding industrial upgrading and structural adjustment. In the suburban areas, such as Changping and Shunyi Districts, considering an augmentation of green space proportions and judicious utilization of public areas to create a more pleasant community environment is advised. Additionally, in outlying districts like the Huairou District, enhancing residential land and facilitating the use of public spaces to encourage social interactions holds promise for improving residents' positive emotional experiences during heat waves. In the central city, a crucial focus should be placed on preserving public areas and establishing a rational layout for residential areas. Building upon this foundation, a modest increase in green space could enhance the emotional experiences of residents. However, caution is advised when contemplating an expansion of commercial areas, as the correlation between commercial districts and residents' emotional states during heat waves is not definitively established. Government planning for commercial zones should comprehensively consider factors such as noise levels and business activity to craft a tranquil and habitable urban environment. These recommendations aim to adjust land use structures and create a more livable urban environment, ultimately enhancing residents' emotional experiences during heat waves.

5.4 Limitation and further research

Limitations and uncertainties in this study need to be mentioned. First, although the sentiments expressed on social media can reflect the underlying sentiments in real time (Settanni & Marengo, 2015). However, social media users were mainly young people and cannot represent all people (Ilieva & McPhearson, 2018). Especially the elderly and children may be sentimentally more susceptible to the effects of bad weather (Obradovich et al., 2017). Therefore, our results were not sufficiently comprehensive to respond to residents' sentiment. The negative emotional impact of heat waves on residents may be underestimated. Therefore, this paper is more conservative in the inference of the results. Besides, the deep learning-based sentiment exploration method in this study may not be the best choice for measuring the sentiments expressed in social media posts. Regarding the results of sentiment measurement, the results can be extended to fine-grained sentiment exploration in subsequent studies, such as further classifying negativity into anger, sadness, etc. In addition, future research should consider residents' individual characteristics such as occupation, income, age, etc., and conduct a more in-depth analysis of how the emotional well-being of different demographic groups is affected by heat waves. In the selection of influencing factors, future studies could also explore the impact of various urban environmental factors on residents' sentiments during heat waves. Factors such as urban greenery levels, air quality, noise levels, etc., could be investigated for their short-term and long-term effects on residents' emotional states. The research scope could be further extended to encompass various types of urban environments, including but not limited to large cities, medium-sized cities, as well as cities situated in different geographic and climatic conditions. Such comprehensive studies would contribute to providing a more nuanced understanding, enabling urban planners and policymakers to optimize urban environments effectively and enhance residents' emotional experiences during high temperatures.

6 Conclusion

This research explored the spatial differentiation of Beijing residents' sentiments during urban heat waves based on social media big data. The associations between them and functional areas were also analyzed by using the association rule mining based on the Apriori algorithm. This research can help identify urban spatial problems, enhance urban emergency management and build healthy cities.

The results show that SDHW has obvious spatial clustering characteristics, with hot spots dominated by the urban areas and far suburbs, and cold spots mainly distributed in the near suburbs. The combination of PGPA and other functional areas (PIA, PTA, PCA) was more associated with positive SDHW, indicating the importance of green space and park in promoting positive sentiments. In contrast, the lowest percentage of residential areas was relatively important and was frequently combined with other areas to influence poorer sentiments. In addition, the combination of green space and industrial areas had a significant impact on SDHW. The following two combinations also had a greater impact on SDHW: a combination of residential and industrial areas, and a combination of residential and public areas. This research revealed the associations between sentiments and a single UFA during heat waves, in addition to revealing which kinds of combined functional areas were associated with sentiments in different subdistricts. It helps to understand the spatial heterogeneities of residents' sentimental health and improves the planning and governance of communities in an environment of increased heat waves. Future research should aim to improve the accuracy and granularity of sentiments and provide additional insights into the heterogeneities of associations with urban functional areas.

Acknowledgements
We thank the editors and the anonymous reviewers for their valuable comments to improve the quality of this manuscript.

Authors' contributions
All authors contributed to the study conception, design, and original draft writing. Conceptualization of the study involved Yanrong Zhu, Juan Wang, and Bin Meng. Data curation was performed by Yanrong Zhu, Yuting Yuan, Huimin Ji, and Changsheng Shi. The original draft preparation was carried out by Yanrong Zhu with subsequent modifications made by Juan Wang and Ming Luo. Project administration responsibilities were shouldered by Juan Wang and Bin Meng. All authors have read and agreed to the published version of the manuscript.

Funding
The research is supported by the R&D Program of Beijing Municipal Education Commission (KM202211417015), the Academic Research Projects of Beijing Union University (No. ZK10202209), and the Academic Research Projects of Beijing Union University (No. ZKZD202305).

Availability of data and materials
There are no data made available from this work for public access.

Declarations

Competing interests
The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Received: 22 November 2023 Revised: 8 February 2024 Accepted: 16 February 2024
Published online: 11 March 2024

References

Adams, R. E. (1992). Is happiness a home in the suburbs?: the influence of urban versus suburban neighborhoods on psychological health. *Journal of Community Psychology, 20*(4), 353–372.

Agrawal, R. and R. Srikant (1994). Fast algorithms for mining association rules. Proc. 20th int. conf. very large data bases, VLDB, Santiago, Chile.

Almendra, R., Loureiro, A., Silva, G., Vasconcelos, J., & Santana, P. (2019). Short-term impacts of air temperature on hospitalizations for mental disorders in Lisbon. *Science of the Total Environment, 647*, 127–133.

Barua, A., S. Thara, B. Premjith and K. Soman (2021). Analysis of contextual and non-contextual word embedding models for Hindi ner with web application for data collection. Advanced Computing: 10th International Conference, IACC 2020, Panaji, Goa, India, December 5–6, 2020, Revised Selected Papers, Part I 10, Springer.

Baylis, P. (2020). Temperature and temperament: evidence from twitter. *Journal of Public Economics, 184*, 104161.

Cai, W., Zhang, C., Suen, H. P., Ai, S., Bai, Y., Bao, J., Chen, B., Cheng, L., Cui, X., & Dai, H. (2021). The 2020 China report of the Lancet Countdown on health and climate change. *The Lancet Public Health, 6*(1), e64–e81.

Cai, W., Zhang, C., Zhang, S., Bai, Y., Callaghan, M., Chang, N., Chen, B., Chen, H., Cheng, L., & Cui, X. (2022). The 2022 China report of the Lancet Countdown on health and climate change: leveraging climate actions for healthy ageing. *The Lancet Public Health, 7*(12), e1073–e1090.

Campbell, S., Remenyi, T. A., White, C. J., & Johnston, F. H. (2018). Heatwave and health impact research: a global review. *Health & Place, 53*, 210–218.

Cao, X., MacNaughton, P., Deng, Z., Yin, J., Zhang, X., & Allen, J. G. (2018). Using twitter to better understand the spatiotemporal patterns of public sentiment: a case study in Massachusetts, USA. *International Journal of Environmental Research and Public Health, 15*(2), 250.

Chen, W., Liu, L., & Liang, Y. (2016). Retail center recognition and spatial aggregating feature analysis of retail formats in Guangzhou based on POI data. *Geographical Research, 35*(4), 703–716.

Chen, N. C., C. M. Hall, K. Yu and C. Qian (2019). "Environmental Satisfaction, Residential Satisfaction, and Place Attachment: The Cases of Long-Term Residents in Rural and Urban Areas in China." Sustainability.

Chen, S., Liu, L., Chen, C., & Haase, D. (2022). The interaction between human demand and urban greenspace supply for promoting positive emotions with sentiment analysis from twitter. *Urban Forestry & Urban Greening, 78*, 127763.

Cheng, Y., Yu, Z., Xu, C., Manoli, G., Ren, X., Zhang, J., Liu, Y., Yin, R., Zhao, B., & Vejre, H. (2023). Climatic and economic background determine the disparities in urbanites' expressed happiness during the summer heat. *Environmental Science & Technology, 57*(30), 10951–10961.

Clayton, S. (2020). The insidious impacts of climate change: Mood, mental health, and psychosocial well-being. *One Earth, 2*(6), 530–531.

De Vos, J., & Witlox, F. (2016). Do people live in urban neighbourhoods because they do not like to travel? analysing an alternative residential self-selection hypothesis. *Travel Behaviour and Society, 4*, 29–39.

Devlin, J., M.-W. Chang, K. Lee and K. Toutanova (2018). "Bert: Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Gallegos, L., K. Lerman, A. Huang and D. Garcia (2016). Geography of emotion: Where in a city are people happier? Proceedings of the 25th International Conference Companion on World Wide Web.

Gao, J., Cheng, Q., Duan, J., Xu, Z., Bai, L., Zhang, Y., Zhang, H., Wang, S., Zhang, Z., & Su, H. (2019). Ambient temperature, sunlight duration, and suicide: a systematic review and meta-analysis. *Science of the Total Environment, 646*, 1021–1029.

Gao, W., Tu, R., Li, H., Fang, Y., & Que, Q. (2020). In the subtropical monsoon climate high-density city, what features of the neighborhood environment matter most for public health? *International Journal of Environmental Research and Public Health, 17*(24), 9566.

Gao, Y., Chen, Y., Mu, L., Gong, S., Zhang, P., & Liu, Y. (2022). Measuring urban sentiments from social media data: a dual-polarity metric approach. *Journal of Geographical Systems, 24*(2), 199–221.

Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, É., Zanobetti, A., Schwartz, J. D., Tobías, A., Tong, S., Rocklöv, J., Forsberg, B., Leone, M., De Sario, M., Bell, M. L., Guo, Y.-L.L., Wu, C.-F., Kan, H.-D., Yi, S.-M., de Sousa Zanotti, M., Stagliorio Coêlho, P. H. N., … Armstrong, B. G. (2015). Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *Lancet (london, England), 386*, 369–375.

Green, H., Bailey, J. L., Schwarz, L., Vanos, J. K., Ebi, K. L., & Benmarhnia, T. (2019). Impact of heat on mortality and morbidity in low and middle income countries: a review of the epidemiological evidence and considerations for future research. *Environmental Research, 171*, 80–91.

Harlan, S. L., Brazel, A. J., Darrel Jenerette, G., Jones, N. S., Larsen, L., Prashad, L., & Stefanov, W. L. (2007). *In the shade of affluence: The inequitable distribution of the urban heat island* (pp. 173–202). Emerald Group Publishing Limited.

He, Q., He, W., Song, Y., Wu, J., Yin, C., & Mou, Y. (2018). The impact of urban growth patterns on urban vitality in newly built-up areas based on an association rules analysis using geographical 'big data.' *Land Use Policy, 78*, 726–738.

He, H., Sun, R., Li, J., & Li, W. (2023a). Urban landscape and climate affect residents' sentiments based on big data. *Applied Geography, 152*, 102902.

He, Q., Wang, Y., Qiu, Q., Su, Y., Wang, Y., Wei, H., & Li, J. (2023). Joint effects of air PM2.5 and socioeconomic dimensions on posted emotions of urban green space visitors in cities experiencing population urbanization: a pilot study on 50 cities of East China. *Science of The Total Environment, 861*, 160607.

Hu, M. and B. Liu (2004). Mining and summarizing customer reviews In: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining (KDD'04), 168–177.. ACM, New York.

Huang, H., Li, Y., Zhao, Y., & Zhai, W. (2022a). Analysis of the impact of urban summer high temperatures and outdoor activity duration on residents' emotional health: Taking hostility as an example. *Frontiers in Public Health, 10*, 955077.

Huang, H., Long, R., Chen, H., Sun, K., & Li, Q. (2022b). Exploring public attention about green consumption on Sina Weibo: using text mining and deep learning. *Sustainable Production and Consumption, 30*, 674–685.

Huang, H., Liu, X., & Ren, L. (2022c). Analysis of the spatiotemporal mechanism of high temperature on residents' irritability in Beijing based on multiscale geographically weighted regression model. *Frontiers in Ecology and Evolution, 10*, 973365.

Ilieva, R. T., & McPhearson, T. (2018). Social-media data for urban sustainability. *Nature Sustainability, 1*(10), 553–565.

Intergovernmental Panel on Climate, & C. (2023). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Kass-Hout, T. A., & Alhinnawi, H. (2013). Social media in public health. *British medical bulletin, 108*(1), 5–24.

Kim, Y. (2014). "Convolutional neural networks for sentence classification." arXiv preprint arXiv:1408.5882.

Klemm, W., Heusinkveld, B. G., Lenzholzer, S., Jacobs, M. H., & Van Hove, B. (2015). Psychological and physical impact of urban green spaces on outdoor thermal comfort during summertime in The Netherlands. *Building and Environment, 83*, 120–8.

Lee, J. and K. Toutanova (2018). "Pre-training of deep bidirectional transformers for language understanding." arXiv preprint arXiv:1810.04805.

Leyden, K. M., Goldberg, A., & Michelbach, P. (2011). Understanding the pursuit of happiness in ten major cities. *Urban Affairs Review, 47*(6), 861–888.

Li, Q., Zheng, X., & Chao, Y. (2020). Research on function identification and distribution characteristics of Wuhan supported by big data. *Science of Surveying and Mapping, 45*(5), 119–125. [in Chinese].

Lin, Y., Wood, S. A., & Lawler, J. J. (2022). The relationship between natural environments and subjective well-being as measured by sentiment expressed on Twitter. *Landscape and Urban Planning, 227*, 104539.

Liu, Y. (2016). Revisiting several basic geographical concepts: a social sensing perspective. *Acta Geographica Sinica, 71*(4), 564–575. [in Chinese].

Liu, Y., M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer and V. Stoyanov (2019). "Roberta: A robustly optimized bert pretraining approach." arXiv preprint arXiv:1907.11692.

Mitchell, L., Frank, M. R., Harris, K. D., Dodds, P. S., & Danforth, C. M. (2013). The geography of happiness: connecting twitter sentiment and expression, demographics, and objective characteristics of place. *PLoS ONE, 8*(5), e64417.

Morrissey, S. A., Raggatt, P. T., James, B., & Rogers, J. (1996). Seasonal affective disorder: some epidemiological findings from a tropical climate. *Australian and New Zealand Journal of Psychiatry, 30*(5), 579–586.

Obradovich, N., Migliorini, R., Mednick, S. C., & Fowler, J. H. (2017). Nighttime temperature and human sleep loss in a changing climate. *Science Advances, 3*(5), e1601555.

Páez, A., & Whalen, K. (2010). Enjoyment of commute: a comparison of different transportation modes. *Transportation Research Part a: Policy and Practice, 44*(7), 537–549.

Pang, B., L. Lee and S. Vaithyanathan (2002). "Thumbs up? Sentiment classification using machine learning techniques." arXiv preprint cs/0205070.

Park, Y., Kim, M., & Seong, K. (2021). Happy neighborhoods: Investigating neighborhood conditions and sentiments of a shrinking city with Twitter data. *Growth and Change, 52*(1), 539–566.

Peng, J., Xie, P., Liu, Y., & Ma, J. (2016). Urban thermal environment dynamics and associated landscape pattern factors: a case study in the Beijing metropolitan region. *Remote Sensing of Environment, 173*, 145–155.

Pfeiffer, D., & Cloutier, S. (2016). Planning for happy neighborhoods. *Journal of the American Planning Association, 82*(3), 267–279.

Qiao, F., & Williams, J. (2022). Topic modelling and sentiment analysis of global warming tweets: evidence from big data analysis. *Journal of Organizational and End User Computing (JOEUC), 34*(3), 1–18.

Rabari, C., & Storper, M. (2015). The digital skin of cities: urban theory and research in the age of the sensored and metered city, ubiquitous computing and big data. *Cambridge Journal of Regions, Economy and Society, 8*(1), 27–42.

Romanello, M., McGushin, A., Di Napoli, C., Drummond, P., Hughes, N., Jamart, L., Kennard, H., Lampard, P., Rodriguez, B. S., & Arnell, N. (2021). The 2021 report of the Lancet Countdown on health and climate change: code red for a healthy future. *The Lancet, 398*(10311), 1619–1662.

Rompay, T. J. L. V., Krooshoop, J., Verhoeven, J. W. M., & Pruyn, A. T. H. (2012). With or without you: Interactive effects of retail density and need for affiliation on shopping pleasure and spending. *Journal of Business Research, 65*, 1126–1131.

Santos Nouri, A., Costa, J. P., Santamouris, M., & Matzarakis, A. (2018). Approaches to outdoor thermal comfort thresholds through public space design: a review. *Atmosphere, 9*(3), 108.

Settanni, M., & Marengo, D. (2015). Sharing feelings online: studying emotional well-being via automated text analysis of Facebook posts. *Frontiers in Psycholog, 6*, 1045.

Shoval, N., Schvimer, Y., & Tamir, M. (2018). Tracking technologies and urban analysis: adding the emotional dimension. *Cities, 72*, 34–42.

Smetanin, S. (2022). How weather impacts expressed sentiment in Russia: evidence from Odnoklassniki. *PeerJ Computer Science, 8*, e1164.

Sun, S., Zhang, Q., Singh, V. P., Shi, C., Wang, G., Wu, W., & Shen, Z. (2022). Increased moist heat stress risk across China under warming climate. *Scientific Reports, 12*(1), 22548.

Tang, D., B. Qin and T. Liu (2015). Document modeling with gated recurrent neural network for sentiment classification. Proceedings of the 2015 conference on empirical methods in natural language processing.

Thompson, R., Hornigold, R., Page, L., & Waite, T. (2018). Associations between high ambient temperatures and heat waves with mental health outcomes: A systematic review. *Public Health, 161*, 171–191.

Van de Vliert, E., Huang, X., & Parker, P. M. (2004). Do colder and hotter climates make richer societies more, but poorer societies less, happy and altruistic? *Journal of Environmental Psychology, 24*(1), 17–30.

Wang, J., Obradovich, N., & Zheng, S. (2020). A 43-million-person investigation into weather and expressed sentiment in a changing climate. *One Earth, 2*(6), 568–577.

Wang, J., Meng, B., Pei, T., Du, Y., Zhang, J., Chen, S., Tian, B., & Zhi, G. (2021). Mapping the exposure and sensitivity to heat wave events in China's megacities. *Science of the Total Environment, 755*, 142734.

Wang, J., Fan, Y., Palacios, J., Chai, Y., Guetta-Jeanrenaud, N., Obradovich, N., Zhou, C., & Zheng, S. (2022). Global evidence of expressed sentiment alterations during the COVID-19 pandemic. *Nature Human Behaviour, 6*(3), 349–358.

Wang, K. and Y. Xu (2012). "Questions and Answers to the Code for Classification of Urban Land Use and Planning standards of Development Land(GB 50137–2011)(I) " City Planning Review(4): 69–70 [in Chinese].

Witten, I. H., & Frank, E. (2002). Data mining: practical machine learning tools and techniques with Java implementations. *Acm Sigmod Record, 31*(1), 76–77.

Xia, X., Zhang, Y., Jiang, W., & Wu, C. Y. (2023). Staying home, tweeting hope: mixed methods study of twitter sentiment geographical index during US stay-at-home orders. *Journal of Medical Internet Research, 25*, e45757.

Xiao, Y., Chen, X., Li, Q., Yu, X., Chen, J., & Guo, J. (2017). Exploring determinants of housing prices in Beijing: An enhanced hedonic regression with open access POI data. *ISPRS International Journal of Geo-Information, 6*(11), 358.

Xie, S., Liu, L., Zhang, X., & Yang, J. (2022). Mapping the annual dynamics of land cover in Beijing from 2001 to 2020 using Landsat dense time series stack. *ISPRS Journal of Photogrammetry and Remote Sensing, 185*, 201–218.

Xue, B., Zhao, B., Xiao, X., Li, J., Xie, X., & Ren, W. (2020). A POI data-based study on urban functional areas of the resources-based city: a case study of Benxi, Liaoning. *Human Geography, 35*(4), 81–90. [in Chinese].

Yang, F., Wendorf Muhamad, J., & Yang, Q. (2019). Exploring environmental health on Weibo: a textual analysis of framing haze-related stories on Chinese social media. *International Journal of Environmental Research and Public Health, 16*(13), 2374.
Yang, L., Duarte, C. M., & Ciriquián, P. M. (2022). Quantifying the relationship between public sentiment and urban environment in Barcelona. *Cities, 130*, 103977.
Zhang, H., Luo, M., Pei, T., Liu, X., Wang, L., Zhang, W., Lin, L., Ge, E., Liu, Z., & Liao, W. (2023). Unequal urban heat burdens impede climate justice and equity goals. *The Innovation, 4*(5), 100488.
Zhang, C. and S. Zhang (2002). Association Rule Mining: Models and Algorithms.
Zhang, L. (2012). Research on POI Classification Standard. *Bulletin of Surveying and Mapping, 10*, 82–84. [in Chinese].
Zhao, W., Li, Q., & Li, B. (2011). Extracting hierarchical landmarks from urban POI data. *National Remote Sensing Bulletin, 15*(5), 973–988. [in Chinese].
Zhao, Z., H. Chen, J. Zhang, X. Zhao, T. Liu, W. Lu, X. Chen, H. Deng, Q. Ju and X. Du (2019). "UER: An open-source toolkit for pre-training models." arXiv preprint arXiv:1909.05658.
Zheng, S., Wang, J., Sun, C., Zhang, X., & Kahn, M. E. (2019). Air pollution lowers Chinese urbanites' expressed happiness on social media. *Nature Human Behaviour, 3*(3), 237–243.
Zhong, W., Suo, J., Ren, X., & Li, G. (2021). The influence of emotional health on the activity characteristics of the elderly and the selection of environmental quality factors in residential areas. *International Journal of Environmental Research and Public Health, 18*(23), 12618.

Publisher's Note