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Spatiotemporal Study of Park Sentiments at Metropolitan Scale Using Multiple Social Media Data

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Abstract: Creating wonderful emotional experiences is the critical social function and cultural service of urban parks. Park sentiment patterns in rapidly urbanizing metropolitan areas need to be understood and interpreted thoroughly. This research aims to systematically study park sentiment patterns in metropolitan areas. By focusing on parks in Shanghai city and using the local mainstream social media data (SMD) of Dazhong Dianping, Ctrip, and Weibo, we created a series of score-related indicators to estimate park sentiment. We then applied statistical analyses to systematically interpret sentiment patterns in the spatial, temporal, and spatiotemporal domains, explored their related factors, and compared the performance of different SMD sources. The results proved that Shanghai parks generally bring positive emotions to visitors but showed uneven sentiment patterns citywide. Park sentiment distributions differed from various SMD sources, but the SMD sets of Dazhong Dianping and Ctrip showed significant correlations. For these two SMD sets, visitors have greater and more stable happiness in parks on a workday than on a non-workday and in spring than in other seasons. Parks with higher positive sentiments are scattered citywide, whereas those with lower emotions are clustered in the downtown area. For Weibo, more positive emotions occurred on non-workdays or in autumn, and the lower mood clustering did not exist. Moreover, the quality-related internal factors of the park itself, rather than external factors such as location and conditions, were identified to influence park sentiment. The innovations of park sentiment methods in this study included using multiple SMD sets, creating more accurate sentiment indexes, and applying statistics in temporal, spatial, and spatiotemporal domains. These enhanced sentiment analyses for urban parks to obtain more systematic, comprehensive, and thorough results. The defects and improvements for urban park construction were explored by interpreting park sentiment patterns and possible causes and effects. This motivates better park management and urban development, and enlightens urban planners, landscape designers, and policymakers.

Keywords: social media; sentiment analysis; sentiment pattern; park; green space; big data

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1. Introduction

Urban parks provide green spaces for recreation and social interactions, playing a crucial role in citizens' lives by improving health and well-being, arousing good feelings, and increasing happiness [1,2]. During the COVID-19 pandemic, citizens have more limitations on recreation activities that can be undertaken indoors. Urban parks have become more critical and necessary for people to undertake safe recreational activities, such as physical exercise, connecting with nature, and meeting people. This sustains their good mood and resists mental health issues [3]. Different urban parks trigger visitors to be in different moods [4]. There might be different patterns in temporal and spatial domains because of different factors [5]. These patterns might indicate urban characteristics and show strengths and weaknesses in urban park planning and management from the perspective of sentiment [6]. Temporally and spatially understanding visitors' emotions and studying the park sentiment patterns is critical to planning and managing urban parks and the whole city. Urban parks should deliver exciting experiences that fulfill citizens' emotional needs, improve the recreation quality of urban parks, and have a more effective and efficient social and cultural function.

With rapid development, social media data (SMD) have proven to be an effective proxy for traditional data in studies of human activities in green spaces [7,8]. They have been used more to understand various aspects of green space, such as visitation patterns [9], landscape perception [10], and tourist satisfaction [11]. Considering traditional survey methods, such as questionnaires, interviews, and site observations, are laborious, time-consuming, and costly, SMD have been considered as one of the most important and effective ways to collect data for green space research [12]. By covering much larger spatial and more extended temporal scales data than traditional data collection efforts, SMD have played a vital role in the spatial and temporal analyses of recreation activities in green spaces [13,14]. However, most previous studies focused on visitation estimation with geotagged posts or photographs and investigated park visitation patterns in the spatial and temporal domains [15,16].

Besides geolocation and time labels, SMD provide a venue for sharing green space-related content and posts on recreation experiences, conveying tourists' feelings, sentiments, and moods [17]. It has been proved that SMD could be used to better understand the interests and opinions of visitors through sentiment analysis and identifying meaningful implications for park planning and design [18]. SMD are increasingly being recognized for their potential as an effective, powerful, efficient, and readily available database of sentiment analysis for urban parks [19]. Besides photographs [20] and emojis [21] in posts, the most common SMD involved in previous studies of park sentiment analysis was the text in geolocated posts [14]. These data were used and applied to determine and quantify sentiment and emotion by techniques including lexicon-based and machine learning approaches [22]. For the informal and unstructured characteristics of a post's text for park sentiment analysis, the lexicon-based approach was used more as a standard and well-regarded methodology for accuracy and efficiency [23]. The sentiment analysis results obtained for each post of SMD were usually further used for analyses of green space visit sentiment distributions [24,25] and related factors [26,27].

Despite SMD's potential for sentiment analyses and spatiotemporal studies, only a small set of recent research has leveraged their capabilities to understand park emotions and sentiments in the spatial and temporal domains [28]. Most of the literature was in the temporal domain. They quantified park sentiment for each category and created statistics to show sentiment change for various time units, including hour, day, week, month, season, and year [29–31]. In the spatial domain, proportion and absence for each sentiment category were visualized and drawn using maps to show the sentiment geographical distributions of the parks in an area [27,32] and the attractions in a park [6]. Spatial statistics of hot-spot analysis were also applied to illustrate the sentiment clustering distributions for the attractions in the park [33]. In the spatiotemporal domain, the ratio of park emotion for each category during the day on weekdays and weekends was shown in the maps to identify visitors' spatial behavior characteristics [34]. By elaborately varying them over time and space, sentiments and emotions need quantification and systematic analysis to capture the preference and attitudes of visitors and interpret the distribution characteristics of varying levels of feelings in the parks. These are important for assessing green space conditions and implementing reasonable and effective urban planning and management measures. This subject is limited in the literature. Therefore, more research is needed to interpret park sentiment patterns systematically in the spatial, temporal, and spatiotemporal domains.

Green space studies widely extract knowledge from SMD platforms in western countries, such as Twitter, Flickr, and Instagram [35,36]. However, these SMD sources are quite different from the SMD platforms used in non-western countries, for instance, China. With the rapid development of networks and information, social media has very high coverage and penetration in China. Data from Chinese SMD platforms, such as Weibo, Ctrip, and Dazhong Dianping (DZDP), are proven to be a reliable data source for visitors' activities in green spaces [37–39], and have been increasingly used in green space research [35]. Of the previous studies on sentiment analysis of green space, most research was based on SMD sources from western countries instead of Chinese countries. Because of the differences between Chinese and English characters, existing English text preprocessing techniques cannot be applied to Chinese text. Fortunately, content analysis has achieved state-of-the-art results for Chinese big data applications, and it has obtained advanced techniques for Chinese text processing [17,40]. They have been used in a wide range of human activity-related research (Kern et al., 2019, Toivonen et al., 2019) and have created the foundation for text processing in sentiment analysis based on Chinese SMD in this study.

This study aims to spatiotemporally assess sentiment patterns of parks in metropolitan areas with multiple SMD sources. It estimated park sentiment using sentiment analysis with a series of sentiment score-related indicators. Then, numerous statistical analyses were applied to systematically interpret the parks in the metropolitan area that make visitors happy and explore the distribution characteristics of park sentiment. Shanghai city was taken as the case study, and the SMD sets of DZDP, Ctrip, and Weibo were used to understand the following questions. (1) What is the park sentiment distribution by time? (2) What is the park sentiment distribution by space? (3) How do park sentiment patterns vary over time? (4) What factors impact park sentiment patterns? (5) What is the difference in park sentiment patterns by using different SMD sources? Through systematically investigating and addressing these five goals, sentiment analyses for urban parks were enhanced to obtain more systematic, comprehensive, and thorough results. The defects and improvements for urban park construction were explored by interpreting park sentiment patterns and possible causes and effects. This motivates better park management and urban development, and enlightens urban planners, landscape designers, and policymakers.

2. Study Site

As one of the most developed and attractive cities globally, the metropolitan area of Shanghai, China, has an advanced economy, is densely populated, rich in culture, and favorable in appearance [41]. It has 24.87 million permanent residents and covers an area of 6340.50 km^2 (http://tjj.sh.gov.cn/, accessed on 1 January 2020). With a per capita park green space area growing from approximately 7.6 m^2 in 2015 to 8.5 m^2 in 2020, Shanghai's green space quantity and quality are ever-improving [42]. However, its green space is limited and precious and needs good planning and management to improve citizens' recreation efficiency. In this study, Shanghai has been chosen as a testbed, given its need for an increased supply of green space, its world-class metropolitan area, and its favorable conditions for a data foundation for this study (i.e., excellent network coverage, a high level of urban digital information penetration, and widely used social media). This study focused on all the urban parks in Shanghai city (Figure 1). These 300 urban parks are located across the 16 districts of Shanghai and are the primary green spaces for recreation for citizens. They were rated with a star rating of urban parks on five levels (i.e., 5, 4, 3, 2, and 1 star) by the Shanghai Administration Department of Afforestation and City Appearance [43]. Their prospect as a tourist attraction was graded on five levels (i.e., 5, 4, 3, 2, and 1 A) by the Ministry of Culture and Tourism of the People's Republic of China (Table S1).

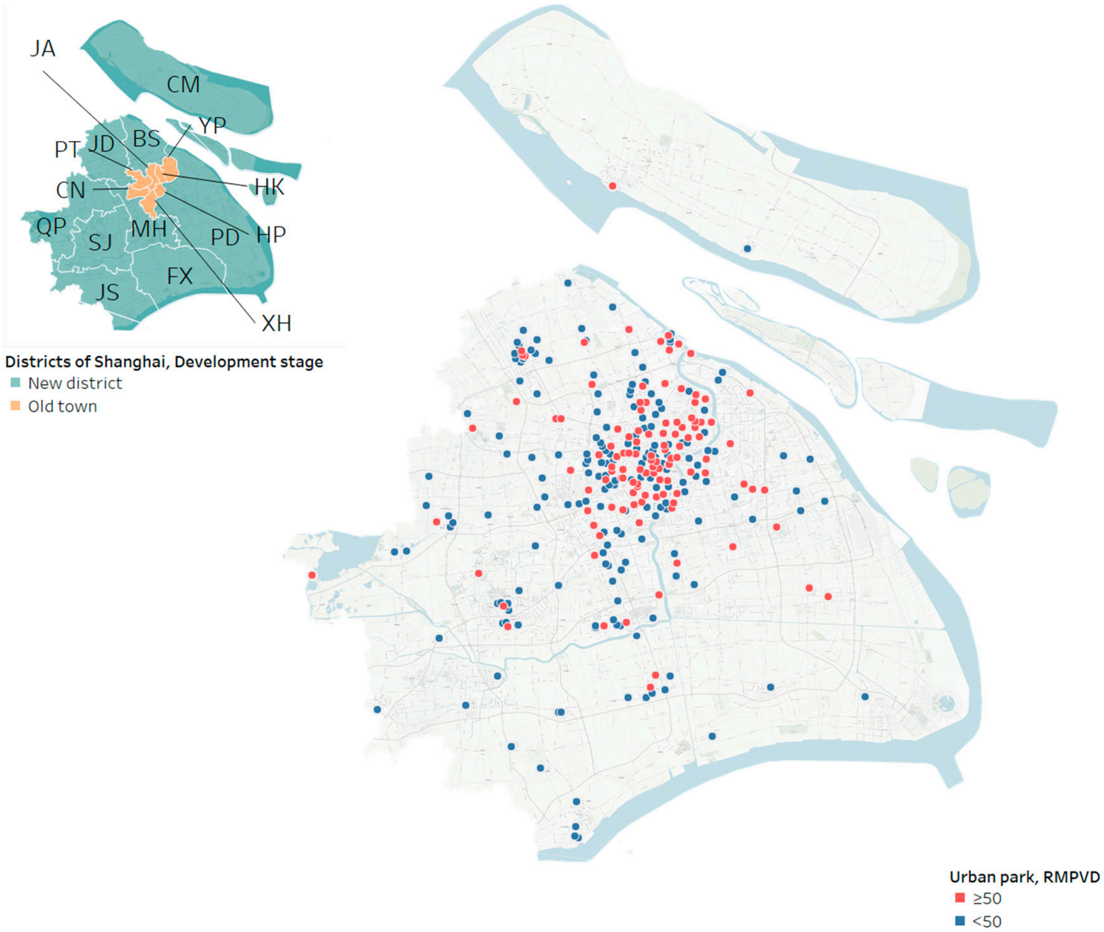

Figure 1. Study site.

3. Material and Methods

Three SMD sets from the most popular tourist attraction SMD platforms with multi-types in China [44], i.e., DZDP, Ctrip, and Weibo, were composed to study the patterns of urban park visit sentiment in Shanghai (see Supplementary Information for details on data collection and pretreatment). A lexicon-based approach was applied for sentiment analysis of microblogs/reviews in this study. Considering that the visitor repeating their reviews or microblogs might amplify their sentiment, the reviews/microblogs of the same park posted by the same visitor on the same day (RMPVD) are merged into one piece by calculating their average sentiment score (SSRMPVD) (see Supplementary Information for details on sentiment analysis).

After sorting and screening (see Supplementary Information for details on data sorting and screening), RMPVD pieces from three SMD platforms were used to calculate the average sentiment score by park (SSPVD) and average park sentiment scores on each day (SSDVD) using different time periods, such as year, workday/non-workday, and season for descriptive statistics (see Supplementary Information for details on statistical analysis of sentiment patterns). Global Moran's I and Getis-Ord Gi* statistics were conducted to study sentiment spatial distribution. 'Park average sentiment score' in each season (SSPSVD) and 'park average sentiment score on a workday or non-workday' (SSPWVD) were calculated. Spearman's coefficients were applied to explore whether the distribution of park sentiment has a significant correlation with the time period. Differences of SSPSVD for each season from the season average (DSSPSVD) and differences of SSPSVD between a workday and non-workday (DSSPWVD) were calculated and used to study how the spatial characteristics vary over time. A series of potential influential factors (Table S1) were involved in multiple linear regressions (MLRs) to explore their impacts on visitors' sentiment in Shanghai parks for the three SMD sets. Spearman's correlation coefficients were used to measure the relationships between each pair of the three SMD sources for the variables of SSPVD, SSPSVD, and SSPWVD at different time periods (see Supplementary Information for details on statistical analysis of related factors and SMD comparisons).

4. Results

4.1. Park Sentiment Overview

Within the study period from 1 May, 2018, to 30 April, 2019, more than 99.00% of the RMPVDs with an SSRMPVD between −100 and 100 from all three SMD sets, covering more than 220 parks, were used as valid data for the analyses in this study (Figure 2a). Of these RMPVDs, there were 115 parks with an RMPVD count above 50 at all three platforms (Figure 1). In general, tourists have positive emotions at the three SMD sets. Visitors' RMPVDs appeared more positive on the platform, DZDP, with the greatest mean SSRMPVD of 3.96 (Figure 2a). By contrast, visitors' RMPVDs on the platform Weibo showed the most emotional calmness for the least mean SSRMPVD of 0.41. As for the proportion of emotions for each category, platform DZDP has the largest proportion of positive RMPVDs (with SSRMPVD > 0), 76.75%, which is slightly larger than that of Ctrip, 67.74%, but much larger than that of Weibo, 26.20%. Actually, Weibo RMPVDs were largely neutral (with SSRMPVD = 0) with a proportion of 63.41%. As shown in Figure 2a, the RMPVDs with an SSRMPVD from 0 to 10 accounted for the majority in all three SMD sets, not only for the RMPVD counts, but also for the number of park coverings. The distribution of SSPVDs for parks with valid data were shown in Figure 2b. Similar to distributions of SSRMPVDs, DZDP has the highest minimum, maximum, and mean SSPVD, and Weibo has the lowest. For Weibo, SSPVDs were mainly around 0, accounting for 70.43%.

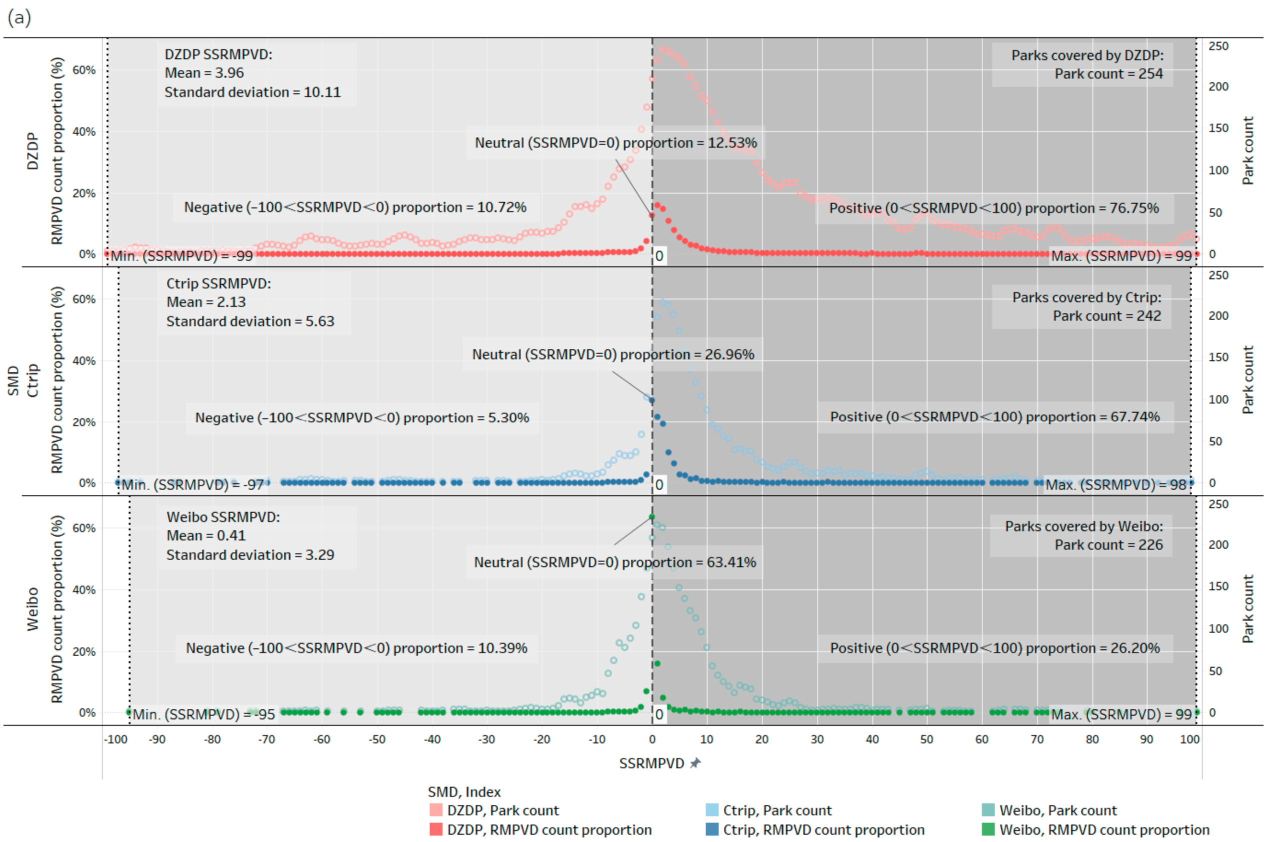

Figure 2. *Cont.*

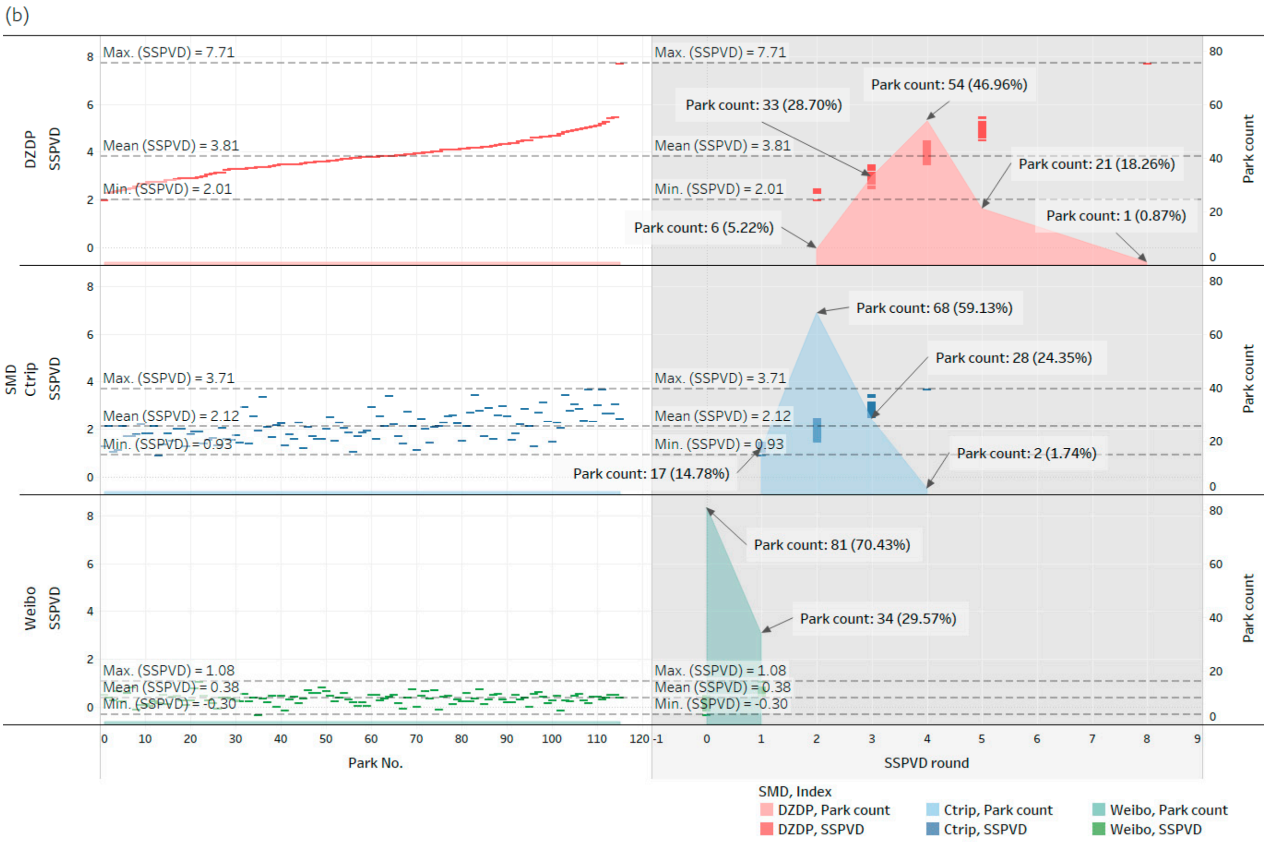

Figure 2. Descriptive statistics of SSRMPVD (1 May 2018–30 April 2019): (**a**) all SSRMPVDs between −100 and 100; (**b**) SSPVDs for the parks with an RMPVD number greater than 50.

4.2. Temporal and Spatial Park Sentiment Patterns

4.2.1. Temporal Sentiment Patterns

The results of the park sentiment temporal graphs reveal the distribution and variation characters of SSDVDs in different time periods, by year, season, and workday/non-workday (Figure 3). No matter which time period, the means of the SSDVDs for the three SMD sets were all positive. The platform DZDP has a higher SSDVD mean than the other SMD sources and maintains a 100% proportion of positive sentiment for any time period. By year, the three SMD sets all have higher means of SSDVD in 2019 than 2018 (Figure 3a). Standard deviations of SSDVD were smaller, showing less polarized emotions in 2019 than 2018. This indicated that visitors' emotions for the parks were becoming more positive and constant in 2019 than 2018. The platform Weibo has more days for positive emotion on non-workdays. The other SMD sets have almost the same days for positive emotion on workdays and non-workdays (Figure 3b). However, the standard deviations of SSDVD for all the three SMD sets were smaller on non-workdays than workdays. This indicated that park visitors tend to have less polarization in their emotions on non-workdays than workdays. By season, different platforms have different situations (Figure 3c). The SMD of DZDP and Ctrip have relatively high SSDVD means and more days and lower standard deviations of positive emotion in spring and winter. Similar pictures are presented in autumn for the SMD of Weibo. This indicates that more positive park moods occurred in spring and winter for DZDP and Ctrip and in autumn for Weibo.

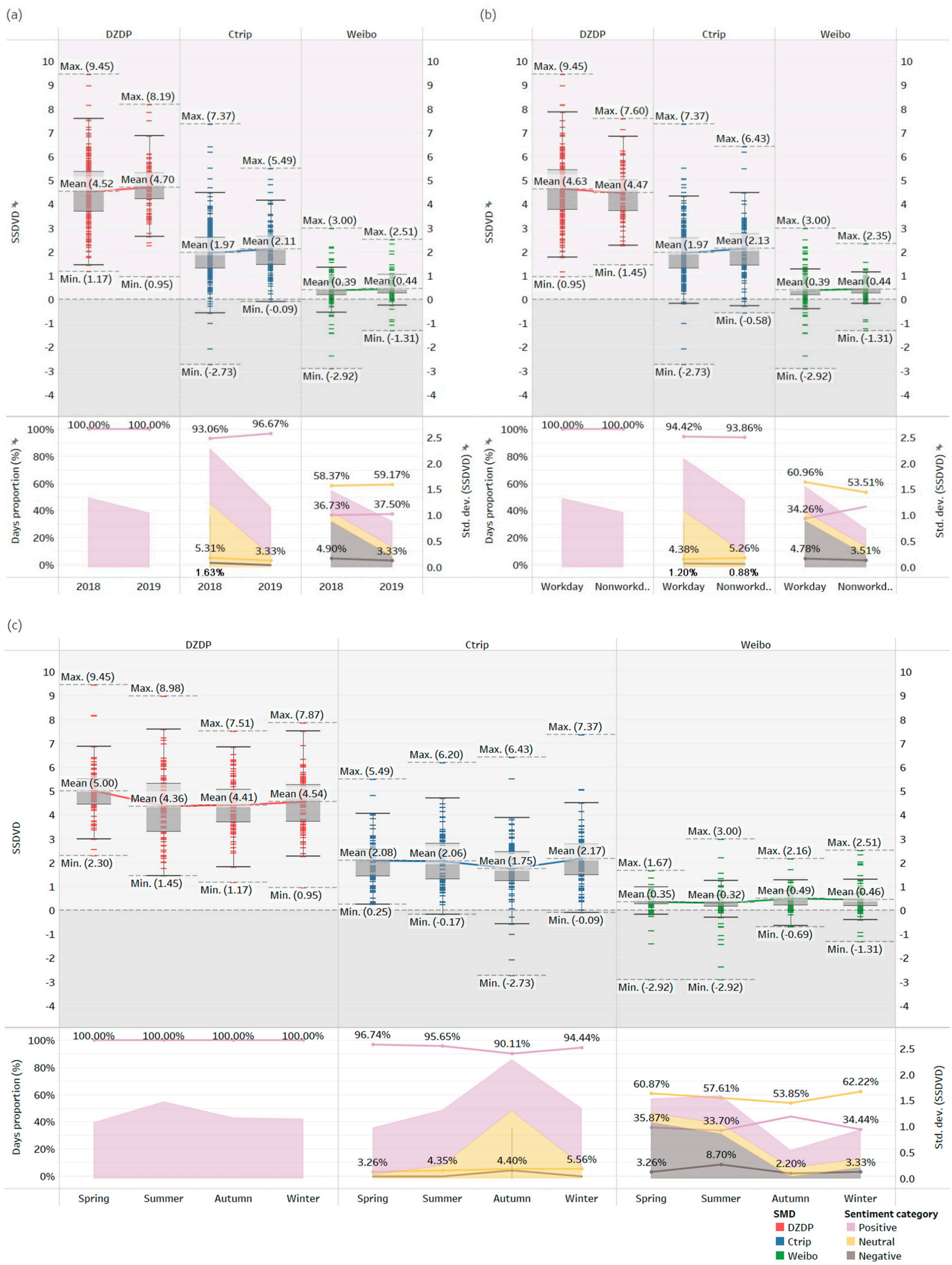

Figure 3. Temporal distribution of SSDVDs: (**a**) by year; (**b**) by workday/non-workday; (**c**) by season.

4.2.2. Spatial Sentiment Patterns

Figure 4a–c shows park spatial distributions using SSPVD for the SMD sets of DZDP, Ctrip, and Weibo, respectively. It seems that parks with a high SSPVD are scattered throughout all areas of Shanghai, especially for platforms DZDP and Ctrip. However, Weibo only has parks with a higher SSPVD around the downtown area. Parks with a low SSPVD seem concentrated around the downtown area, especially for DZDP and Ctrip, less obviously for Weibo. The results of the global Moran's Indexes reveal global spatial autocorrelations for park emotion geographic distributions. There was a positive spatial autocorrelation with a significant spatial clustering tendency for DZDP and Ctrip (Moran's > 0 and $p < 0.001$). There was a negative spatial autocorrelation but with a weak spatial clustering tendency for Weibo (Moran's I < 0 and $p = 0.04$). This verified the clustering characteristics for parks in SSPVD in DZDP and Ctrip, which are roughly drawn in Figure 4a–c. Figure 4d,e shows the results of the spatial statistical analysis in the form of hot-spot maps for SSPVD clusters for DZDP and Ctrip. For these two platforms, similar spatial clustering situations for SSPVD occurred. Cold spots were highly concentrated in the downtown area, and hot spots were sporadically identified in the western areas of the city. This indicated that the downtown area, characterized by a dense population and a high density of smaller older parks, does not have such a cheerful and happy mood in its parks. However, the built-up areas in the west, located outside of but not far from the downtown area, have some larger and newer parks that generally make people happier.

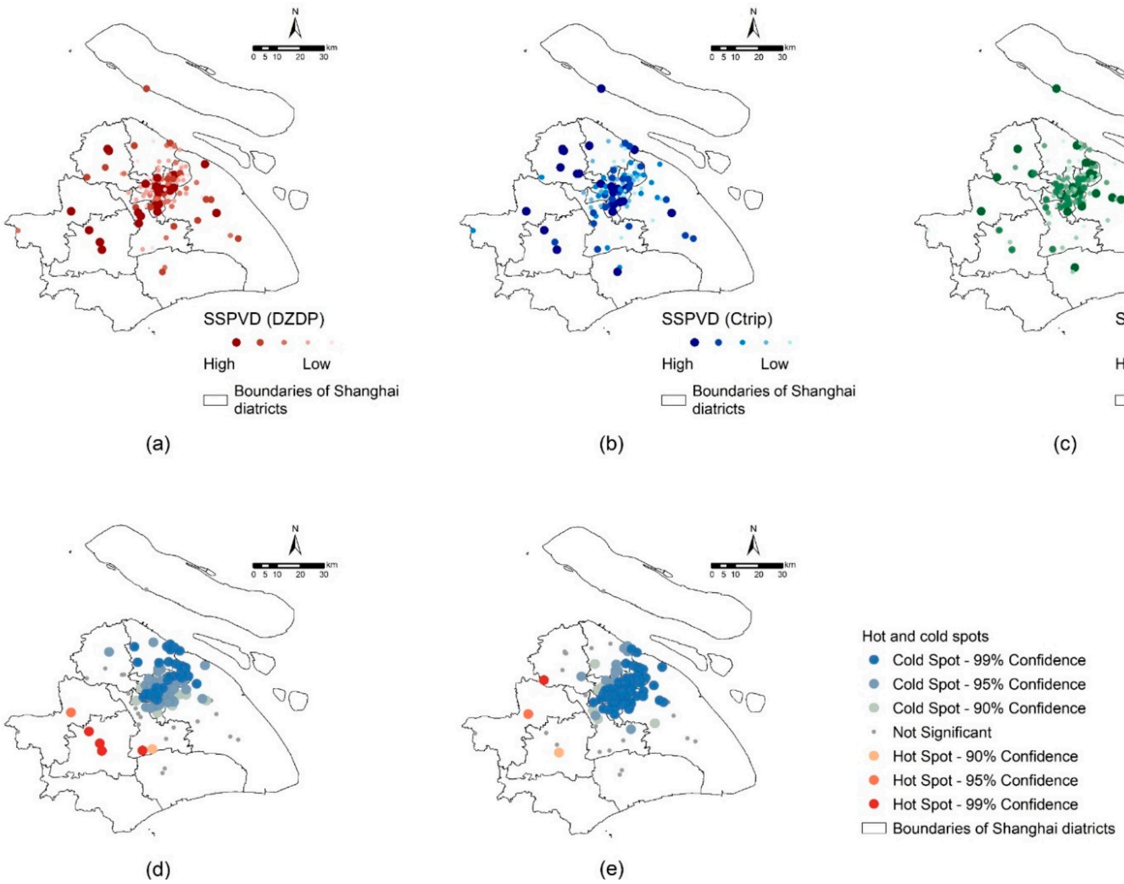

Figure 4. The spatial distribution of SSPVD: (**a**) geographic map for DZDP; (**b**) geographic map for Ctrip; (**c**) geographic map for Weibo; (**d**) hot-spot map for DZDP; (**e**) hot-spot map for Ctrip.

4.2.3. Spatiotemporal Sentiment Patterns

The results from Spearman's correlation analyses between the time unit of the season and SSPSVD, and between the time unit of the workday/non-workday and SSPWVD revealed that neither of the two pairs had a significant correlation for the parks according to DZDP, Ctrip, and Weibo SMD sets. Therefore, these data were used to make statistics by separately using different time units to obtain the results of spatiotemporal sentiment distributions for studying urban park sentiment characteristics that vary over time, as seen in Table 1 and Figure 5. Table 1 illustrates descriptive statistics of SSPSVD and SSPWVD by park from the three SMD sets. Figure 5a,b shows spatial distributions of DSSPSVD and DSSPWVD, respectively.

Table 1. Descriptive statistics of SSPSVD and SSPWVD by park.

SMD	Time Category	Time Period	SSPSVD/SSPWVD		Park Count (%)	
			Mean	Std. Dev.	<Mean	≥Mean
DZDP	Season	Spring	4.35	1.93	40.87	59.13
		Summer	4.10	3.48	62.61	37.39
		Autumn	4.11	2.29	59.13	40.87
		Winter	4.50	2.59	55.65	44.35
	Workday/Non-workday	Workday	4.42	1.79	40.87	59.10
		Non-workday	4.37	2.16	59.10	40.87
Ctrip	Season	Spring	2.42	1.76	47.83	52.17
		Summer	2.75	4.91	60.87	39.13
		Autumn	2.72	6.84	58.26	41.74
		Winter	2.35	2.90	60.00	40.00
	Workday/Non-workday	Workday	2.83	2.46	43.48	56.52
		Non-workday	2.77	3.28	56.52	43.48
Weibo	Season	Spring	0.36	0.61	56.52	43.48
		Summer	0.19	0.94	54.78	45.22
		Autumn	0.44	0.71	46.96	53.04
		Winter	0.34	0.75	58.26	41.74
	Workday/Non-workday	Workday	0.35	0.45	54.78	45.22
		Non-workday	0.37	0.51	44.35	55.65

Note (abbreviation): Standard deviation (Std. dev.).

For DZDP and Ctrip, spring has more parks with a higher SSPSVD than the other seasons on average (Table 1). These parks are not only located in the downtown area, but also in the built-up areas outside the downtown area (Figure 5a). Standard deviations of SSPSVD for the parks calculated in spring were lower than those of the other seasons (Table 1). This suggests that parks in Shanghai generally and more consistently bring more happiness to visitors in the season of spring than the other seasons from the SMD of DZDP and Ctrip. Similar conditions occurred in autumn for the SMD of Weibo, shown in Table 1 and Figure 5a, indicating that visitors have a higher mood in autumn in parks. Moreover, in summer from DZDP and Ctrip and winter from Weibo there are less parks with an SSPSVD above the season average (Table 1). These parks were all generally concentrated in the downtown area (Figure 5a). This suggests that parks in built-up areas outside the downtown area bring less happiness for the users of DZDP and Ctrip in summer and for the users of Weibo in winter than the other seasons.

Both DZDP and Ctrip have a higher mean and lower standard deviation of SSPWVD, and there are more parks with an SSPWVD above the average on workdays than on non-workdays (Table 1). The SMD of Weibo has the opposite conditions. This indicates that DZDP and Ctrip tourists generally showed a more positive park sentiment on workdays than non-workdays, but Weibo experienced the opposite. For all three SMD sets, parks with a higher mood on workdays/non-workdays were evenly located across the downtown area and built-up areas outside the downtown area (Figure 5b). This demonstrates that all SMD sets generally showed differences in park sentiment between workdays and non-workdays citywide.

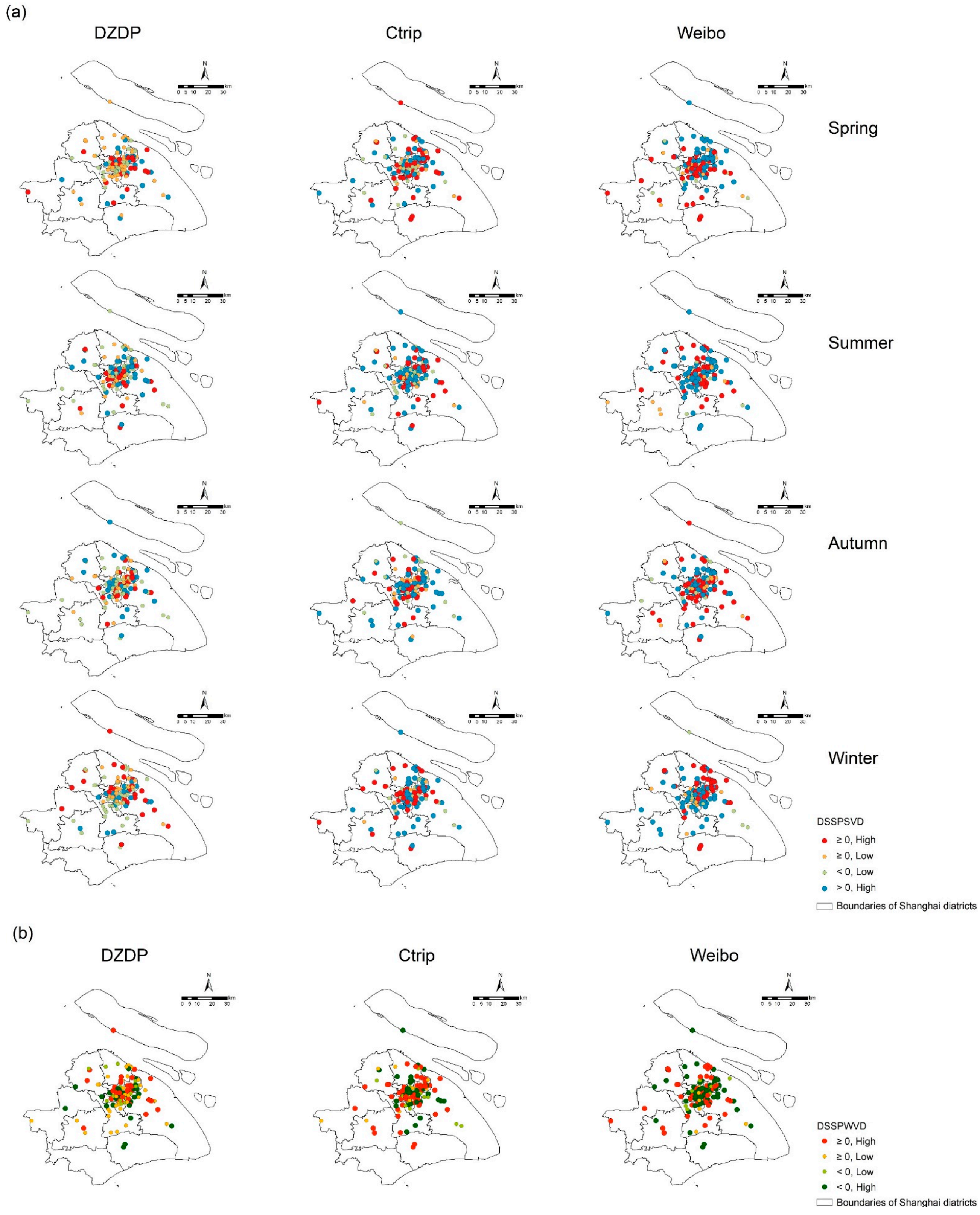

Figure 5. Spatiotemporal distribution of park sentiment according to DZDP, Ctrip, and Weibo SMD sets: (**a**) DSSPSVD; (**b**) DSSPWVD.

4.3. Relations between Park Sentiment Patterns and Related Factors

According to the results of the first MLR models for the three SMD sets, the variables of traffic convenience, commercial facilities, and service facilities were above 5 for VIF for all three SMD sets and were removed before further analyses. The impact of the potential factors left on SSPVD obtained in the second MLR models for the three SMD sets is shown in Table 2. Because the larger the absolute value of the standardized coefficient, the more important the variable is, factors with an important impact on park sentiment were among the potential influencers selected for the three SMD sources. These were identified as follows. For all three SMD sets, the factors that had a greater impact on park sentiment were internal factors, such as tourist attraction level, scenic spot count, and online reputation, instead of external factors, such as distance from the urban center, nearby residential areas, and nearby employment areas. This demonstrates that internal factors were the main impact on park sentiment compared with external factors. Among these internal factors with a higher influence, the factor of tourist attraction level was the only one with a relatively high positive impact on park sentiment compared with the other factors for all three SMD sets. As a complex set of normative and standardized quality rating systems to indicate the quality level of tourist attractions, the tourist attraction level was judged by rational and comprehensive considerations based on a variety of factors, such as security, accessibility, service, environment quality, maintenance, and management. This suggests that the factors most influencing visitors' sentiments in parks were the attributes of the parks themselves. The influences on park sentiment for the factors of visit number and visit density shown in Table 2 were ambiguous and hard to judge. Referring to the results of Spearman's correlation coefficient between SSPVD and visit number, and between SSPVD and visit density, it was revealed that neither visit number or visit density had a significant relationship with SSPVD. This indicates that the sentiment of visitors in parks with a higher visit number or density would not be better or less positive.

Table 2. Results from the MLR of SSPVD on potential factors.

Variable	DZDP			Ctrip			Weibo		
	Cof.	Std. Cof.	VIF	Cof.	Std. Cof.	VIF	Cof.	Std. Cof.	VIF
Size	0.20 *	0.12 *	2.32	0.05	0.04	2.01	−0.04	−0.08	2.10
Scenic spots count	−0.01 ***	−0.45 ***	4.21	0.00	0.09	3.99	0.01	0.11	4.02
Star rating	0.03	0.05	1.63	−0.06 *	−0.10 *	1.63	0.00	0.02	1.74
Tourist attraction level	0.17 ***	0.36 ***	2.20	0.07 *	0.17 *	2.09	0.02 *	0.16 *	2.59
Visit number	-5.39×10^{-5}	−0.07	4.61	0.00 *	−0.20 *	2.60	0.00 *	0.17 *	2.99
Visit density	7.00×10^{-6} *	0.13 *	1.35	-4.04×10^{-6}	−0.11	1.48	4.23×10^{-6} *	0.10 *	1.50
Entrance fee	−0.02	−0.04	3.13	−0.00	−0.05	2.94	−0.00	0.00	2.41
Online reputation	1.04 ***	0.44 ***	1.46	0.74 ***	0.39 ***	1.43	−0.09 *	−0.13 *	1.45
Distance from the urban center	1.12×10^{-5} **	0.18 **	1.55	8.53×10^{-6} **	0.17 **	1.45	5.98×10^{-7}	0.03	1.68
Residential places	-9.30×10^{-5}	−0.07	1.63	0.00 **	−0.24 **	1.55	2.13×10^{-6}	0.01	1.73
Employment places	0.00 *	0.11 *	1.47	0.00 *	0.13 *	1.44	-1.03×10^{-5}	−0.01	1.51

Note: * indicates significance at the 0.1 level, ** indicates significance at the 0.05 level, *** indicates significance at the 0.001 level.

4.4. Comparisons between Different SMD Sets

Table 3 shows the results of the coefficients calculated by Spearman's bivariate correlations (R_s) of SSPVD, SSPSVD, and SSPWVD between each pair of SMD sources, revealing the degree of park sentiment association between each pair of the three SMD sets. For the SSPVD involved in this study, the results indicated significant correlations between the datasets of DZDP and Ctrip (R_s = 0.539 **), while neither had a significant relationship with the SMD of Weibo. Similar conditions occurred with the results of SSPSVD and SSPWVD. For the correlations of SSPSVD and SSPWVD between the SMD of DZDP and Ctrip, different time periods showed different degrees of association. This might present a tendency that the higher the park positive sentiment the time period has, the more significant the correlation between these two SMD sets. SSPWVD showed more significant relationships between the SMD of DZDP and Ctrip on workdays than on non-workdays. As for the significant correlations of SSPSVD between the SMD of DZDP and Ctrip in different seasons, spring occupied first place, autumn came second, and summer and winter had no significant relationship. The spatial and spatiotemporal domain sentiment conditions shown in Figures 4 and 5 also proved the results obtained above—the platforms of DZDP and Ctrip were more similar to each other than with Weibo for both the geographic distribution of SSPVD, SSPSVD, SSPWVD, and the spatial clustering of SSPVD.

Table 3. Spearman's correlation coefficient for SSPVD, SSPSVD, and SSPWVD.

Variable	Time Class	Time Unit	R_s		
			DZDP vs. Ctrip	**DZDP vs. Weibo**	**Ctrip vs. Weibo**
SSPVD	-	-	0.539 **	0.069	0.158
SSPSVD	Season	Spring	0.401 **	0.122	0.111
		Summer	0.119	−0.011	0.074
		Autumn	0.228 *	0.114	0.006
		Winter	0.172	0.037	0.124
SSPWVD	Workday/Non-workday	Workday	0.393 **	0.052	−0.119
		Non-workday	0.251 **	0.027	0.031

Note. ** significant to 0.001, * significant to 0.01. The bold values represent statistically significant correlations.

5. Discussions

5.1. Park Sentiment Patterns

The sentiment conveyed by park visitors was mostly positive by SSRMPVD and entirely positive by SSPVD and SSDVD at the three SMD sets; this proved the importance and necessity parks have on citizens' health and happiness. The main account of RMPVDs for all three SMD sets has an SSRMPVD concentrated from 0 to 10, indicating that most visitors conveyed sensible and rational emotions for the parks studied, guaranteeing the reliability of the research. The findings showed that park sentiment patterns in Shanghai were uneven in intemporal, spatial, and spatiotemporal domains. Visitors have higher positive sentiments for parks in 2019 than in 2018 in all three SMD sets. This could be because the time periods studied in 2019 were the seasons of spring and winter, which showed that these seasons exhibit more happiness than the other seasons. The more joyful park emotions in spring and winter for the SMD of DZDP and Ctrip and in autumn for the SMD of Weibo might be because of the weather and festival spirit. Spring and autumn have more favorable weather and climate for outdoor recreation in Shanghai. Winter has the Spring Festival (Chinese New Year), the most important traditional Chinese festival. Citizens often like to go to parks for cheerful family activities during the Spring Festival, and therefore, they obtain more positive sentiments from park visitation. For all three SMD sets, non-workdays have more consensus for park emotions than workdays from these three SMD sets. This could be because people often have a more consistent purpose for park visitation on non-workdays for family activities. Visitors often have lower positive emotion in the parks in the downtown area, especially for the SMD of DZDP and Ctrip. This could be because most of these parks were built earlier and have a slightly more dated appearance, limited area, and the city environments are often more crowded, noisy, and have poor air quality. The park attributes of a dated appearance and limited space might play the leading role, since internal factors have a greater impact on park emotion than external ones as mentioned previously. On the other hand, newly built parks in built-up areas outside of the downtown area bring people more happiness, mainly because of their nicer landscape and scenery, and better facilities and services. The parks outside of the downtown area have less positive park emotions in the summer for the SMD sets of DZDP and Ctrip and in the winter for the SMD of Weibo. This could be because these seasons were less favorable in weather and climate for outdoor recreation.

5.2. SMD Comparisons

The significant correlation of park sentiment that exists between the SMD of DZDP and Ctrip might be because they were consistent in the website features of the travel product. DZDP is the oldest and leading website providing independent consumer reviews of local services with efficient, professional, and trustworthy travel data including park travel and reviews. Ctrip is the largest and most popular Chinese travel website with the most travel users and the largest number of park travel comments in China. However, neither of them was significantly correlated to park sentiments from the SMD of Weibo. This might be because Weibo is not a website for tourism products focusing on park evaluation. Weibo is the core social media and the most used microblog product in China with park check-in microblogs well reflecting the visitations of parks in Chinese cities. It is accessible for daily life and where people convey real-time emotion. The higher park sentiment the time period has, the more significant the correlation that exists between the SMD sets of DZDP and Ctrip. This might be because stronger park emotions were given in the reviews of these two platforms presented, and the consistency was more obvious for evaluating travel characteristics.

The differences in park sentiment results between different SMD sets might also be because of their different website features. DZDP showed the strongest positive emotions from the three SMD sets, possibly because its users often describe park visit experiences with words of more rich emotion to make their tourism reviews more distinctive and vivid. Weibo had the calmest park emotions because its users conveyed more comprehensive and closer to daily life occasions, including life perceptions and daily moods expressed from within the park. The spatial clustering of parks with a lower positive visit sentiment in the downtown area was apparent for the SMD sets of DZDP and Ctrip, rather than Weibo. This might be because DZDP and Ctrip have more comments about tourism evaluation factors, such as landscape and scenery, facilities, and environments. As for the other park sentiment conditions different SMD sets have in different seasons, the SMD sets of DZDP and Ctrip have better park emotions in spring because these two are more travel-related websites. They have more positive travel emotions expressed in these two seasons, which is possible because of the weather and festivals as mentioned previously. Weibo exhibited better everyday emotions for parks in autumn because autumn had nicer weather for daily walks in neighborhood parks in Shanghai. As for workdays and non-workdays, the SMD sets of DZDP and Ctrip showed stronger positive travel emotions on workdays because tourists have better experiences on workdays with fewer visitors and less congestion. Citizens expressed a higher positive park sentiment on Weibo because they were inherently in a better mood during non-workdays in their daily lives.

5.3. Related Factors and Relations to Visitation

The results obtained were that park internal attributes, especially the factor of tourist levels, rather than external attributes, influenced visitors' sentiments more for parks in Shanghai for all three SMD sets. This suggests that the measures for improving the qualities of the parks themselves, such as landscape and scenery, facilities, and service quality, rather than those that make changes to the outdoor environment, such as relocation, improving traffic, and developing commerce, are more effective and efficient for bringing more happiness to visitors in parks. The insignificant relationships between SSPVD and visit numbers or density demonstrate no statistical relationship between park sentiment and visitation, but not mean no meaningful. After comparisons between the results of park sentiment patterns and visitation distributions in previous research [44], some interesting coincidences were found. According to the results of temporal and spatiotemporal park visitation in previous studies, people were more likely to go to parks in spring. Coupled with a better mood than other seasons, this demonstrates that spring is really a wonderful season for visiting parks in Shanghai city. If the authorities want to enhance park tourism, trying to find ways to improve park experiences in other seasons might be a more effective and achievable endeavor. For the results of spatial autocorrelation, both park visitation and sentiment in Shanghai have a spatial clustering situation, but opposite tendency, in the downtown area, in which there were highly concentrated hot spots for park visitation and cold spots for park sentiment. In other words, a fair number of parks concentrated in the downtown area were highly visited, aggravating the city's congestion and bringing relatively weak happiness. This might point to a defect in city development in the past and an improvement for park planning in the future. This study proved that internal factors, such as scenery, service quality, and management level, instead of external factors, such as distance from city center, commercial facilities, and distance from employment locations, better determine park visitors' emotions. Therefore, more parks oriented as tourist attractions with characteristics such as a big size, more attractive scenic spots, and room for recreation activities could be built in the dense areas outside of the downtown area. The styles of green space, such as street gardens, attached green spaces, and pocket parks, might be more appropriate for parks located in the city center for meeting citizens' environmental and mental needs in their everyday lives. This could not only alleviate congestion in the downtown area, but also improve the experience for parks in the city.

5.4. The Method Innovations and Limitations

This research bridges the gap between the systematic and comprehensive study of park sentiment analysis in a series of spatial, temporal, and spatiotemporal domains focusing on urban parks in such municipal areas using multiple SMD sources. The notion of RMPVD and a series of related indexes were creatively involved for avoiding sentiment exaggeration, caused by repeating posts, to enhance the reasonability and reliability of park sentiment calculation. As mentioned previously, spatiotemporal sentiment related to previous studies was not only limited, but also generally only in the temporal [29–31] or spatial domain [6,27,32]. With these indicators, we pioneered a series of systematic statistics in the spatial, temporal, and spatiotemporal domains, by using multiple approaches, such as Spearman's coefficient, MLR, and the Getis-Ord Gi* statistic, to obtain more comprehensive, thorough, and deep results. To avoid the bias caused by a single SMD source [5,31], it took innovative ideas to choose multiple widely used SMD sources from SMD platforms of multi-types. Besides analyzing each SMD source separately, comparisons between results obtained based on these different SMD sets were conducted and reasons were explored and discussed to obtain comprehensive and in-depth research on sentiment patterns. These results from different SMD sources were not merged into one. This might be a limitation of this research. Since simply combining the results from different platforms was unreasonable for a large number of overlapped users and data between different SMD sources [44,45], more complicated and detailed research, such as overlapped data filtering, and assigning weights for different SMD sets and algorithms for data merging, could be done in the future to conduct more advanced park sentiment pattern studies. Moreover, few previous studies have been conducted for such a representative metropolitan area on such a continuous series of research, including both visitation and sentiment in multiple consistent conditions, such as study periods, multiple SMD sources, and spatiotemporal domains.

6. Conclusions

By focusing on urban parks in Shanghai, this research systematically studied park sentiment patterns in the spatial, temporal, and spatiotemporal domains using multiple SMD sources of SMD sets from DZDP, Ctrip, and Weibo. The results demonstrated the parks' positive impact on visitors' emotions, and showed the uneven sentiment patterns in Shanghai. For the SMD sets of Dazhong Dianping and Ctrip, visitors have greater and more stable happiness in parks on a workday than on a non-workday and in spring than in other seasons. Parks with higher positive sentiments are scattered citywide, whereas those with lower emotions are clustered in the downtown area. For the SMD set of Weibo, more positive emotions occurred on non-workdays or in autumn, and the lower mood clustering did not exist. The results also found that the quality-related internal factors of the park itself, rather than external factors such as location and conditions, were identified to influence park sentiment. Use of multiple SMD sources was proven to confirm the achievement of better understanding of park sentiment. Using the creative park sentiment methods in this study would enhance sentiment analyses for urban parks to obtain more systematic, comprehensive, and thorough results. This study helps to explore the defects in the past, possible improvements that can be made in the future for urban park construction, and motivates better park management and urban development.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land11091497/s1, Table S1: Factors that might be related to park sentiment. References [23,27,38,43,44,46–53] can be found in Supplementary Materials.

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