Spatiotemporal Patterns and Factors Associated with Online Attention to Shanghai Country Parks

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Abstract. Country parks are an important component of urban ecological networks and provide essential opportunities for recreation. Understanding how public attention to these parks varies across time and space can inform their planning and management. This study examines online attention to six country parks in Shanghai: Langxia, Guangfulin, Pujiang, Qingxi, Changxing Island, and Jiabei. For the temporal analysis, the natural logarithm of the 360 Search Index was used as the dependent variable in an entity fixed-effects panel model estimated with PanelOLS. The explanatory variables included the monthly numbers of statutory public holidays and weekend days, school-vacation periods, seasons, special events, public-health-emergency lockdowns, and precipitation. For the spatial analysis, kernel densities of bus stops, metro stations, residential areas, and road networks, together with distance from the city center, were examined through spatial visualization and exploratory univariate regressions. Online attention displayed a clear seasonal pattern, with generally higher levels in spring and autumn and lower levels in summer and winter. Spring and autumn were significantly positively associated with online attention. Lockdowns were significantly negatively associated with online attention, whereas precipitation was significantly positively associated with it. School vacations and special events showed marginal negative and positive associations, respectively, while statutory public holidays and weekend days were not statistically significant. None of the spatial indicators showed a statistically significant linear association with online attention. Because the spatial regressions included only six parks, these results should be interpreted as exploratory. The findings indicate that spatial variation in online attention is unlikely to be explained by any single spatial condition and may also reflect park-specific resources, activity programming, and promotional exposure. The study provides a spatiotemporal framework for examining online attention to country parks and offers evidence relevant to their planning and management.

Keywords: Online attention; Temporal patterns; Spatial patterns; Country parks.

1. Introduction

As urbanization continues worldwide, high-density cities face multiple challenges, including limited ecological space, growing demand for recreation, and increasing pressure to protect the environment [1]. As an important form of urban green infrastructure, country parks contribute to ecological security, provide recreational space, support physical and mental well-being, and promote regional sustainability [2]. Many countries and regions have therefore expanded their country-park systems as part of broader efforts to improve urban resilience and environmental quality, while public interest in these parks has continued to grow [3].

At the same time, widespread internet and mobile-device use has changed how people obtain tourism information and express travel intentions. Online searches, web browsing, and social-media interactions can provide timely indications of public interest in tourism destinations. Online attention has consequently become a useful indicator of destination visibility, public perception, and potential recreational demand [4]. Compared with conventional visitor statistics, online-attention data are relatively accessible, temporally continuous, and broad in coverage, offering an additional perspective on public behavior and changes in destination interest [5].

Research on country parks has focused primarily on planning and development, spatial configuration, ecological functions, and landscape evaluation. Using CiteSpace to map Chinese

country-park studies published between 1995 and 2019, Dai et al. found that the literature concentrated on planning models, ecological functions, greenway systems, and evaluation frameworks, whereas visitor behavior and online attention received comparatively little attention [2]. As internet-based data has become more widely used in tourism research, search indices have emerged as an important source for studying public interest in travel. International research began relatively early to examine digital traces in tourism-demand forecasting and recreation analysis. Yang et al. used Google and Baidu search volumes to forecast visitor arrivals in Hainan Province and found that search-engine data reduced the forecast errors of conventional time-series models, suggesting that search behavior may serve as a leading indicator of tourism demand [6]. Wood et al. estimated visitation at 836 natural recreation sites worldwide using geotagged photographs, demonstrating the potential of crowdsourced online data as a proxy for recreational activity [7]. Donahue et al. subsequently used geotagged social-media data to examine visits to urban and peri-urban parks and reported associations with water bodies, amenities, trail conditions, and surrounding population density [8]. These studies show that online-search and social-media data can support tourism-demand forecasting, park-use monitoring, and the analysis of spatial correlates. Evidence on the spatiotemporal dynamics of online attention to country parks in megacities, however, remains limited. Li et al. used the Baidu Index to identify temporal patterns in online attention to Chinese 5A tourist attractions and suggested that online attention may precede changes in visitor numbers [9]. Yuan and Sun examined the spatiotemporal evolution of online attention among Shanghai residents traveling to Thailand and found associations with holidays, seasonal change, and major events [10]. Yin and Huang used the Baidu Index, seasonal and geographical concentration indices, and the geographical detector to investigate online attention to virtual tourism, identifying marked seasonality and multiple socioeconomic and tourism-resource correlates [11]. Li et al. used the Baidu Index and spatial statistics to examine the spatial evolution of online attention to China's 5A attractions and reported spatial clustering associated with population size, economic development, and tourism resources [12]. Overall, previous work has emphasized the spatiotemporal differentiation and determinants of online attention to tourism destinations and attractions. The temporal dynamics of online attention to country parks, particularly in megacities, remain less well understood, as do the relationships between online attention and temporal or spatial conditions.

Against this background, the present study examines representative country parks, develops a set of indicators for factors potentially associated with online attention, and analyzes the temporal and spatial patterns of attention and their relationships with selected temporal and spatial variables. The aim is to provide quantitative evidence for country-park management and the planning of urban ecological recreation space.

2. Data Sources

Shanghai is a representative Chinese megacity in terms of population size, urban density, and the provision of green space. In recent years, the city has continued to develop its ecological-space system and has opened nine country parks, including Langxia, Qingxi, Changxing Island, Pujiang, Jiabei, and Guangfulin. Under the Shanghai Basic Ecological Network Plan and the Shanghai Ecological Space Special Plan (2021-2035), country parks serve not only ecological-protection functions but also as important settings for recreation, environmental education, and ecotourism [13]. As the country-park system has developed, its capacity to receive visitors and provide public services has increased, strengthening its contribution to the urban environment and residents' recreational needs [5]. Shanghai's stage of urban development, degree of population concentration, and approach to country-park development make it a useful case for understanding ecological recreation spaces in megacities [14].

Songnan, Heqing, and Caojing Country Parks had not formed stable search terms on the 360 Search platform, and their online-attention records lacked continuity and completeness. These three parks were therefore excluded to maintain a consistent sample. The final sample comprised six parks

with continuous observations: Langxia, Guangfulin, Pujiang, Qingxi, Changxing Island, and Jiabei. A balanced monthly panel was assembled for January 2022 to December 2025, comprising six parks observed over 48 months and yielding 288 park-month observations. The 360 Search Index (*360INDEX*) was used to represent online attention to each park.

Drawing on previous research on online tourism attention and considering data availability, the temporal variables included the monthly number of statutory public holidays divided by seven (*HOLIDAY_norm*), the monthly number of weekend days divided by seven (*WEEKEND_norm*), a school-vacation indicator (*VACATION*), a special-event indicator (*EVENT*), a public-health-emergency lockdown indicator (*COVID_lockdown*), and log-transformed precipitation (*LOG_rain*) [15][16]. Seasonal indicators for spring (*SPRING*), summer (*SUMMER*), and autumn (*AUTUMN*) were also included, with winter serving as the reference category.

The data were obtained primarily from an online-search platform and publicly available sources. The 360 Search Index was retrieved from the 360 Index platform. Precipitation data were compiled from the Shanghai Climate Bulletin issued by the Shanghai Meteorological Service, the Shanghai Water Resources Bulletin issued by the Shanghai Municipal Water Authority, and the Shanghai Statistical Yearbook. All temporal variables were organized at the monthly scale and coded consistently before analysis. An entity fixed-effects model was estimated with PanelOLS[17] to control for unobserved, time-invariant differences among the parks [19].

For the spatial analysis, kernel-density estimation was applied to metro stations, bus stops, road networks, and residential areas to characterize the spatial concentration of each feature. The resulting density surfaces were overlaid with the park locations to visualize differences in transportation facilities, residential development, and road networks around the parks. Because Shanghai's urban structure generally declines in intensity from the central city toward the periphery, People's Square has commonly been used as a reference point for measuring distance from the city center [18]. The Euclidean distance from each park to People's Square was therefore calculated and normalized as an indicator of location.

3. Methods

3.1. Data Preprocessing

To reduce the influence of skewed distributions on model estimation and improve parameter stability, the online-attention indicator and precipitation were transformed using natural logarithms. The 360 Search Index (360INDEX) was used to represent online attention, and the transformed variable LOG_360index was calculated as follows [9]:

$$LOG_360index = ln(360INDEX + 1) \tag{1}$$

Precipitation (RAIN) was transformed in the same manner to obtain LOG_rain:

$$LOG_rain = ln(RAIN + 1) \tag{2}$$

All temporal variables were constructed at the monthly scale. The numbers of statutory public holidays and weekend days were each divided by seven to express them in weeks and facilitate comparison of coefficient magnitudes, yielding *HOLIDAY_*norm and *WEEKEND_norm*. School vacations (*VACATION*), special events (*EVENT*), and lockdowns (*COVID_lockdown*) were coded as binary variables, with 1 indicating that the corresponding condition occurred and 0 otherwise. Seasonal indicators were defined for spring, summer, and autumn, with winter as the reference category.

Spatial variables were derived in ArcGIS 10.8. Kernel-density analysis was applied separately to bus stops, metro stations, residential-area points of interest, and road networks to represent the spatial concentration of each feature. Distance from each park to the center of Shanghai was calculated as a

locational indicator. Because the variables were measured on different scales, all spatial indicators were transformed using min-max normalization:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{3}$$

Where X is the original value, X' is the normalized value, and $X_{\min}$ and $X_{\max}$ are the minimum and maximum values in the sample. The normalized spatial indicators range from 0 to 1, facilitating comparison and visualization.

3.2. Entity Fixed-Effects Panel Model

The six country parks differ in location, landscape resources, and management in ways that are difficult to observe but relatively stable over time. To reduce confounding by this time-invariant heterogeneity, an entity fixed-effects panel model was used to examine temporal patterns in online attention and its associations with the selected temporal variables. The model controls for park-specific characteristics that remain constant over time [19].

The model is specified as follows:

$$\begin{aligned}\ln(360INDEX_{it}+1) = {} & \beta_0 + \beta_1 HOLIDAY_{it} + \beta_2 WEEKEND_{it} + \beta_3 VACATION_{it} + \\ & \beta_4 SPRING_{it} + \beta_5 SUMMER_{it} + \beta_6 AUTUMN_{it} + \beta_7 EVENT_{it} + \beta_8 COVID_{it} + \beta_9 LOGRAIN_{it} + \alpha_i + \varepsilon_{it}\end{aligned} \tag{4}$$

Where i indexes parks, t indexes months, α_i denotes the park fixed effect, and ε_{it} is the error term. The model was estimated using heteroskedasticity-robust standard errors.

3.3. Spatial Visualization and Exploratory Regression

To examine spatial differences in online attention among the parks, ArcGIS was used to visualize the spatial indicators and assess their relationships with online attention. Previous studies suggest that attention to and use of tourism destinations or urban parks may be related not only to landscape resources but also to transportation conditions, population concentration, and location [20][21][22]. Based on this literature and data availability, metro-station kernel density, bus-stop kernel density, residential-area kernel density, road-network kernel density, and distance from the city center were selected as spatial indicators.

Kernel density was calculated as follows:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{5}$$

Where $f(x)$ is the kernel-density estimate at location x, n is the number of spatial features included in the calculation, h is the search radius (bandwidth), $K(\cdot)$ is the kernel function, and x_i is the location of feature i. A higher kernel-density value indicates a greater concentration of the corresponding spatial feature.

To compare the parks' spatial attributes, metro-station density, bus-stop density, residential-area density, road-network density, distance from the city center, and mean online attention were min-max normalized and displayed in a radar chart. Separate univariate linear regressions were then estimated with mean online attention as the dependent variable and each spatial indicator as the independent variable. The coefficient of determination (R^2) and p value were reported on the thematic maps. Because these regressions contained only six parks, statistical power was limited; the results were treated as exploratory and were not interpreted causally.

The coefficient of determination was calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{6}$$

Where y_i is observed value i, $\hat{y}_i$ is its fitted value, and $\bar{y}$ is the mean of the observed values. R^2 ranges from 0 to 1, with larger values indicating better sample fit.

Model significance was assessed using the p value associated with the following F statistic:

$$F = \frac{SSR / k}{SSE / (n - k - 1)} \tag{7}$$

Where *SSR* is the regression sum of squares, *SSE* is the residual sum of squares, *n* is the sample size, and *k* is the number of independent variables. A *p* value below 0.050 was taken to indicate a statistically significant linear association between a spatial indicator and online attention.

The thematic maps, radar chart, and regression statistics provide complementary descriptions of differences among the six parks in transportation facilities, residential development, road networks, and location, and support an exploratory assessment of their relationships with online attention.

4. Temporal Patterns and Associated Factors

Figure 1 shows pronounced seasonal fluctuations in online attention to the six country parks, with generally higher levels in spring and autumn and lower levels in summer and winter. The three-month moving average smooths month-to-month variation and clarifies the longer-term pattern. Attention declined visibly during public-health-emergency lockdowns, whereas it rose in some months with heavier precipitation, suggesting possible contemporaneous relationships between online information seeking, public emergencies, and weather conditions. The park-specific time series in Figure 2 further show substantial differences among the six parks: Changxing Island and Pujiang generally received more online attention and displayed clearer spring and autumn fluctuations, whereas Guangfulin and Langxia received comparatively less attention.

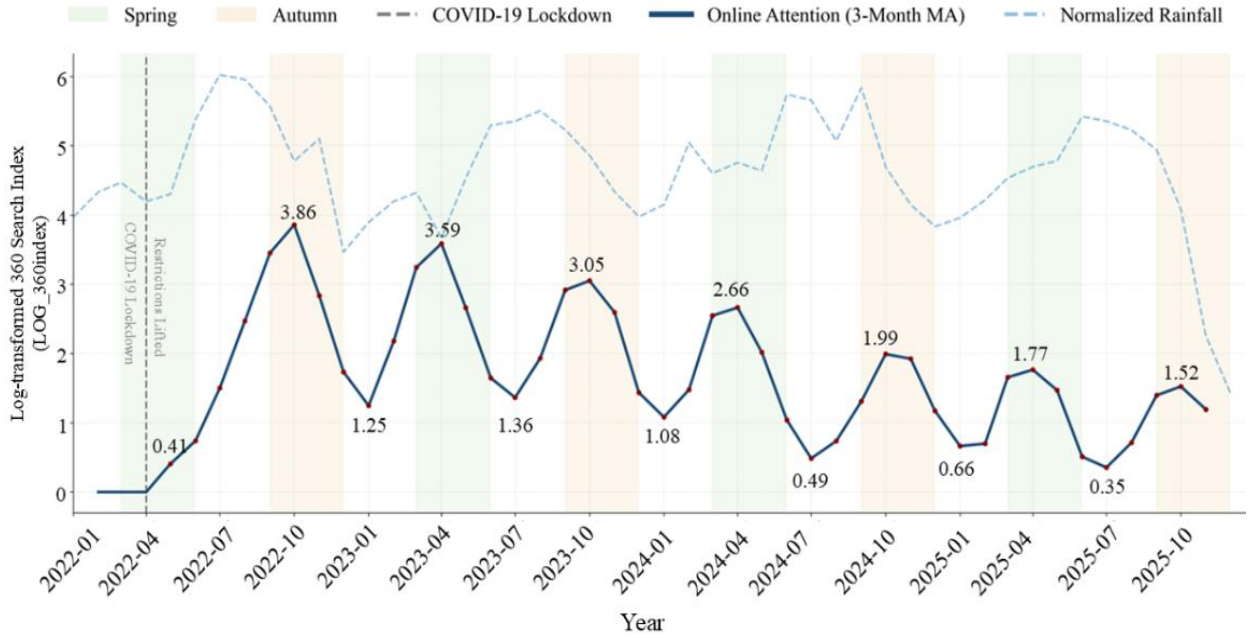


Figure 1. Three-month moving average of online attention to Shanghai country parks.

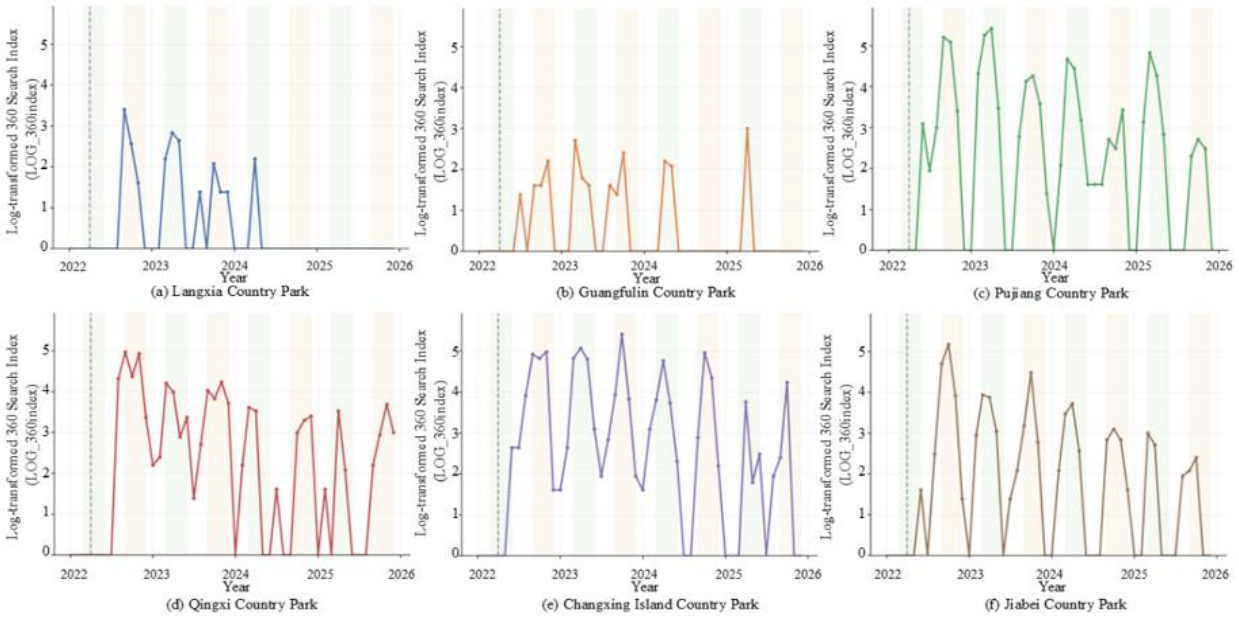


Figure 2. Time series of online attention to the six Shanghai country parks.

The coefficient estimates from the entity fixed-effects panel model are presented in Table 1. The model was jointly significant (p<0.001), indicating that the included temporal variables had joint explanatory value. The poolability test, $F(5,273)=24.227$, p<0.001, supported the inclusion of park fixed effects. Relative to winter, spring (β=1.205, p<0.001) and autumn (β=1.238, p<0.001) were significantly positively associated with online attention, whereas the summer coefficient was not significant. Lockdowns were significantly negatively associated with online attention (β=-1.804, p<0.001), while log precipitation was significantly positively associated with it (β=0.325, p=0.019). School vacations (β=-0.430, p=0.056) and special events (β=0.548, p=0.068) showed marginal negative and positive associations, respectively, but neither reached the 5% significance threshold. The numbers of statutory public holidays and weekend days were likewise not significant. These patterns may reflect the fact that online tourism attention responds to multiple conditions, including event schedules, festivals, and public emergencies, and does not correspond directly to actual travel behavior [15].

Table 1. Results of the entity fixed-effects panel model for online attention to Shanghai country parks.

Variable	Estimate (95%CI)	Regression Coefficient(β) and 95% CI	*P* -Value
HOLIDAY_norm Standardized Monthly Holiday Days	0.053 (-0.395, 0.501)		0.816
WEEKEND_norm Standardized Monthly Weekend Days	-1.056 (-2.377, 0.264)		0.117
VACATION Winter & Summer Vacation	-0.430 (-0.870, 0.010)		0.056 ·
SPRING Spring (vs Winter)	1.205 (0.620, 1.790)		0.000 ***
SUMMER Summer (vs Winter)	-0.177 (-0.779, 0.425)		0.563
AUTUMN Autumn (vs Winter)	1.238 (0.700, 1.775)		0.000 ***
EVENT Event Period	0.548 (-0.040, 1.136)		0.068 ·
COVID_lockdown COVID-19 Lockdown	-1.804 (-2.514, -1.095)		0.000 ***
LOG_rain Log Precipitation	0.325 (0.053, 0.598)		0.019 *

winter is the reference category
***p<0.001,**p<0.01,P<0.05,P<0.10

Negative Effect Positive Effect

Model Information
Model:Entity Fixed Effects Model
Included Effects: Entity
Standard Errors: Robust
F(Poolability Test): *F*(5,273)=24.227,*p*=0.000

Sample Information
NO.Observations:288
Entities:6
Time Periods:48 months
Avg Obs:48.000

Model Fit
R-squared(Within):0.3736
R-squared(Between):0.4272
R-squared(Overall):0.4043

(*p*<0.05) Significant Negative (0.05 ≤ p < 0.10) Marginal Negative (p ≥ 0.10) Not Significant (0.05 ≤ p < 0.10) Marginal Positive (*p*<0.05) Significant Positive

To display seasonal variation more directly, Figure 3 presents box plots of online attention by season. Attention was generally higher in spring and autumn than in summer and winter, consistent with the time-series and fixed-effects results.

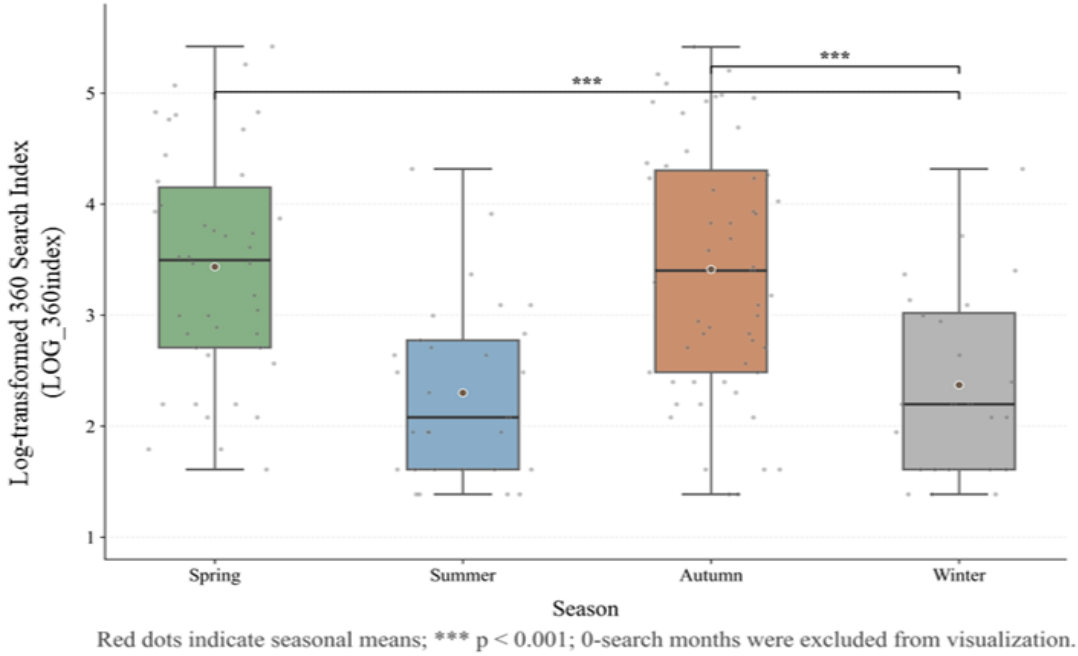


Figure 3. Seasonal distribution of online attention to Shanghai country parks based on box plots.

Overall, online attention to Shanghai country parks displayed clear seasonality and was associated with multiple temporal conditions, including public emergencies, activity schedules, and weather.

5. Spatial Patterns and Associated Factors

Online attention differed substantially among the six parks. Based on the mean log-transformed 360 Search Index across the panel, Changxing Island (approximately 2.454) and Pujiang (approximately 2.223) received relatively high attention; Qingxi (approximately 2.095) and Jiabei (approximately 1.693) occupied intermediate positions; and Guangfulin (approximately 0.533) and Langxia (approximately 0.493) received comparatively low attention (Figure 4).

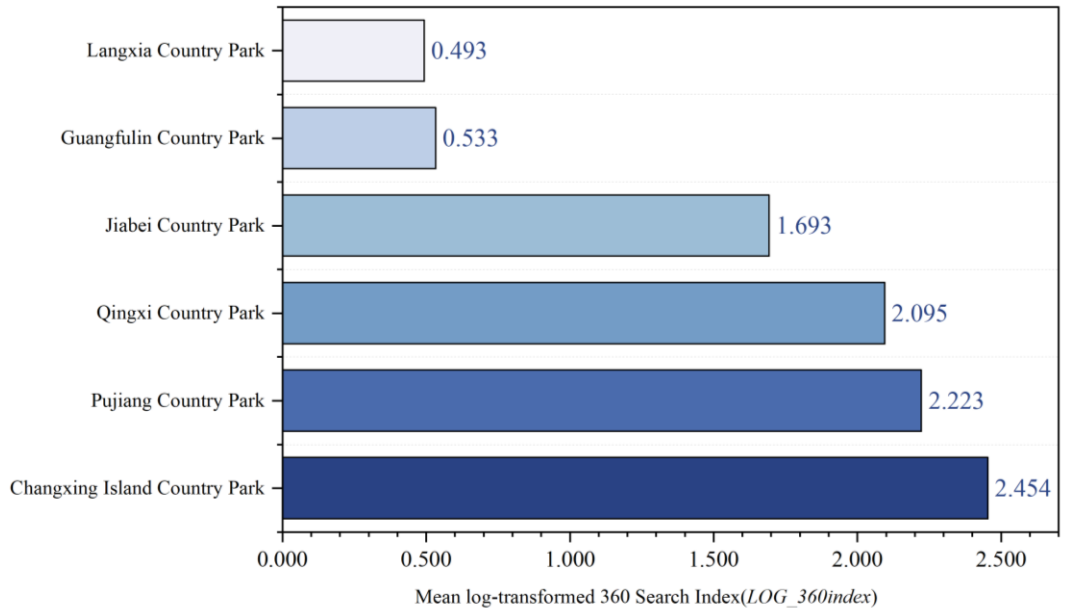


Figure 4. Mean online attention to the six Shanghai country parks.

The ArcGIS thematic maps (Figure 5) show the locations of the six parks and the kernel densities of metro stations, bus stops, residential areas, and road networks across Shanghai. The radar chart (Figure 6) compares normalized online attention, metro-station density, bus-stop density, residential-area density, road-network density, and distance from the city center. The parks differed markedly in these spatial characteristics, but online attention did not correspond consistently to any single indicator. Pujiang had relatively high values on several spatial indicators and also received high online attention. Changxing Island, by contrast, ranked first in online attention despite relatively low values on most spatial indicators. Guangfulin had intermediate values on some spatial indicators but received comparatively low attention. These comparisons suggest that differences in online attention cannot be explained solely by transportation facilities, residential development, or location [23].

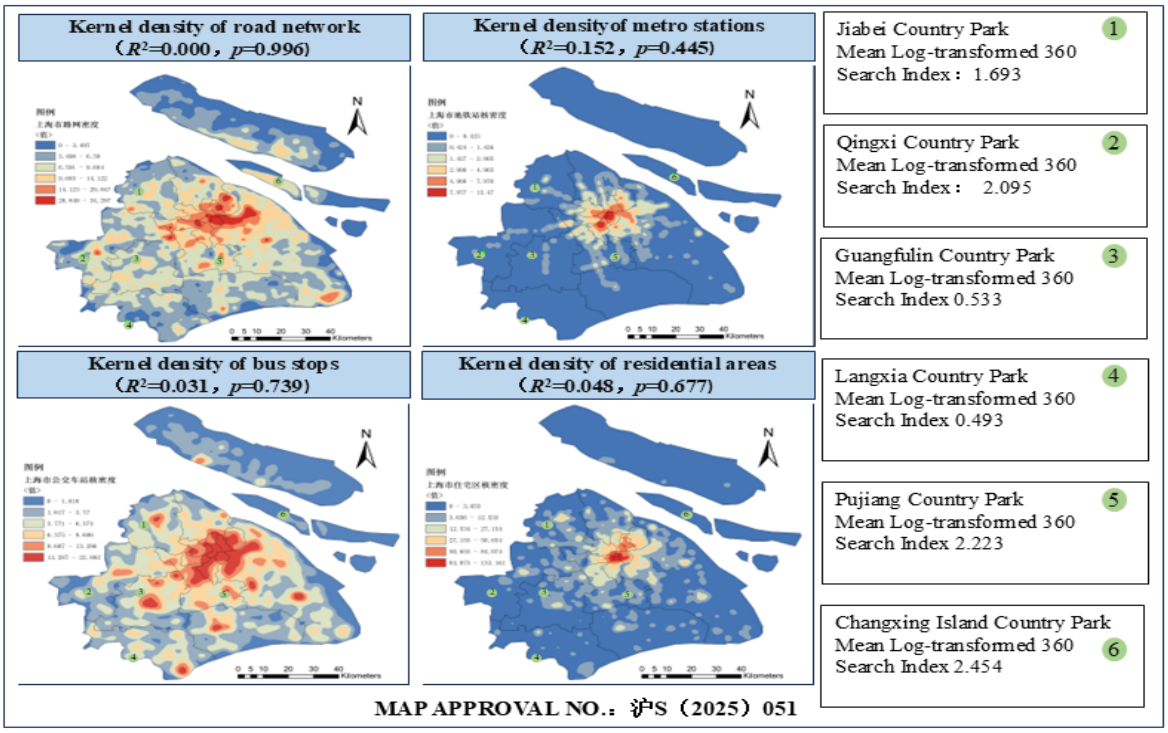


Figure 5. Thematic maps of metro-station, bus-stop, residential-area, and road-network kernel densities in Shanghai.

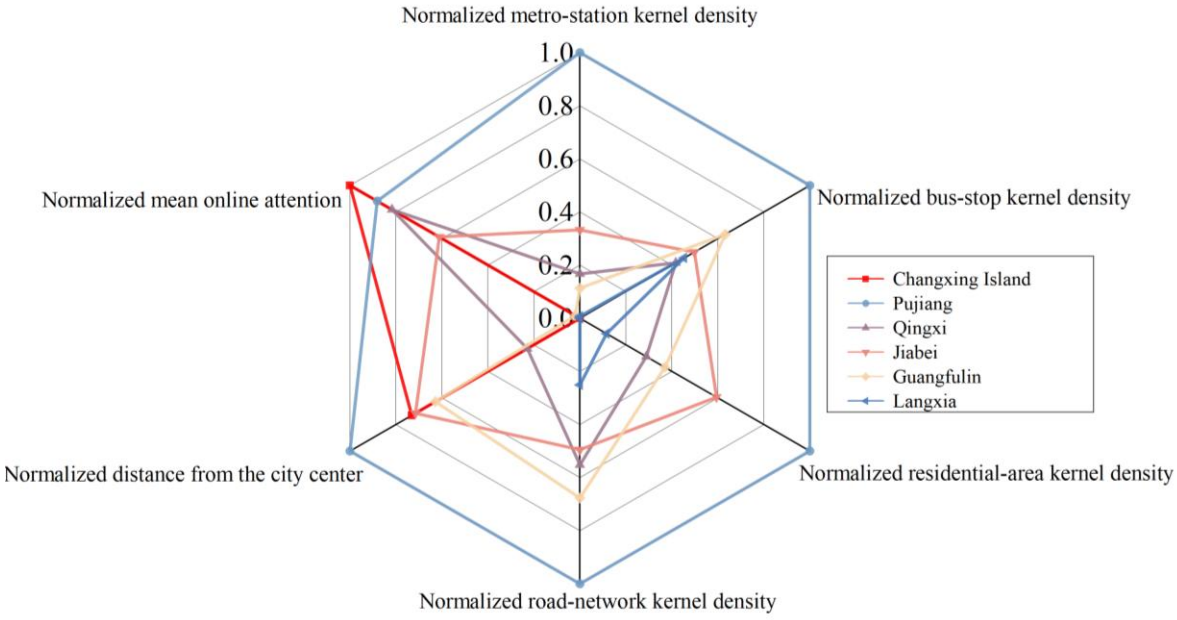


Figure 6. Radar chart of normalized spatial indicators for the six Shanghai country parks.

Exploratory univariate regression results were reported on the ArcGIS thematic maps. None of the associations was statistically significant: bus-stop kernel density (R^2=0.031, p=0.739), metro-station kernel density (R^2=0.152, p=0.445), residential-area kernel density (R^2=0.048, p=0.677), road-network kernel density (R^2=0.000, p=0.996), and distance from the city center (R^2=0.265, p=0.296). Distance from the city center had a somewhat larger R^2 than the other indicators, but its explanatory value remained limited. Given the sample of only six parks, these nonsignificant results should not be interpreted as evidence that spatial relationships are absent.

Taken together, the radar chart, thematic maps, and regression results show that the spatial indicators distinguish parks in terms of transportation facilities, residential development, road networks, and location, but do not individually account for the observed spatial variation in online attention. Online attention may instead reflect the combined influence of spatial context, temporal conditions, park-specific resources, and promotional exposure [24].

6. Conclusions and Discussion

Using monthly panel data for six Shanghai country parks from 2022 to 2025, this study represented online attention with the 360 Search Index and combined an entity fixed-effects panel model with ArcGIS-based spatial analysis. The principal findings are as follows.

(1) Online attention to Shanghai country parks fluctuated over time and followed a clear seasonal pattern. Attention was generally higher in spring and autumn and lower in winter. In the fixed-effects model, spring and autumn were significantly positively associated with online attention relative to winter.

(2) The temporal variables differed in their associations with online attention. Public-health-emergency lockdowns were significantly negatively associated with attention, whereas precipitation was significantly positively associated with it. School vacations and special events showed marginal negative and positive associations, respectively, but neither was significant at the 5% level. The monthly numbers of statutory public holidays and weekend days were also not significant. Overall, season and public-health emergencies displayed the clearest relationships with online attention.

(3) The spatial indicators captured differences among parks in the concentration of transportation facilities, residential development, road networks, and location, but none showed a statistically significant linear association with online attention. No single spatial indicator therefore accounted for much of the observed variation in this sample. Because the spatial analysis included only six parks, these findings are exploratory and do not rule out potentially meaningful spatial relationships. Differences in online attention may reflect a combination of spatial context, park-specific resources, promotional exposure, and temporal conditions.

Taken together, the temporal and spatial analyses suggest that online attention to Shanghai country parks may be related to both temporal conditions and spatial context, although the strength of evidence differs. Attention followed a seasonal pattern of higher levels in spring and autumn and lower levels in summer and winter. Lockdowns showed a significant negative association and precipitation a significant positive association, whereas school vacations and special events showed only marginal associations. By contrast, the kernel densities of metro stations, bus stops, residential areas, and road networks, together with distance from the city center, showed no statistically significant linear association with online attention. Changxing Island illustrates this mismatch: it ranked relatively low on most spatial indicators but consistently received high online attention. This pattern suggests that park-specific resources, public recognition, and promotion may also be relevant to online attention.

Online attention captures public information seeking and digital interest rather than actual recreational use. It should therefore be treated as a complement to, rather than a substitute for, visitor counts and user surveys. In planning and managing country parks, seasonal patterns in online attention can inform the timing of public communication and activity programming, while decisions about transport and facilities should continue to be based on observed visitor needs and site conditions.

This study has several limitations. First, the 360 Search Index represents behavior on a single search platform and cannot fully capture public attention or actual recreational demand. Second, the spatial regressions included only six parks and consequently had limited statistical power. Third, potentially relevant variables, including park resources, activity quality, promotional expenditure, service provision, and observed visitor numbers, were not available. Future research should expand the park sample and observation period, combine visitor counts and surveys with social-media and multi-platform search data, and apply methods that account for spatial heterogeneity to examine the relationship between online attention and actual park use more rigorously.

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