Delineating the Dichotomy and Synergistic Dynamics of Environmental Determinants on Temporally Responsive Park Vitality

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Abstract: Promoting park vitality is fundamental for advancing both residents’ well-being and sustainable urban development. Current research often sidesteps the temporal fluctuations and combined effects of environmental factors on park vitality. Drawing on real-time user density data from Tencent, this investigation analyzed park vitality across 64 urban parks in Fuzhou, China, divided into five specific temporal periods on weekdays and weekends. Through the application of geographic detector models, this study examined the impact and interplay of both intrinsic and extrinsic environmental characteristics on park vitality over these different times. Our primary findings include: (1) environmental attributes affecting park vitality vary temporally, with aspects like commercial density, leisure facility density, and park size consistently influencing vitality; (2) on weekdays, external attributes linked to convenience are predominant, while on weekends, internal attributes connected to recreation take precedence; and (3) there is a synergetic interaction between environmental determinants, often leading to either additive or more intricate effects on park vitality. Based on these insights, we propose recommendations for spatial planning and time-based policies to enhance the alignment between urban settings and park quality. This research provides actionable strategies for enhancing park vitality, both within China and internationally.

Keywords: park vitality; intrinsic/extrinsic environmental attributes; geographic detector model; interactive effect; time periods

1. Introduction

Urban parks constitute integral components of city green infrastructure and public spaces that afford invaluable ecological services, including air purification and heat island mitigation [1,2], while also serving cultural roles [3], such as the facilitation of social interactions and physical exercise. However, the functionality of these parks and the consequent realization of their potential benefits are not guaranteed. Amidst urbanization, numerous parks have emerged; nevertheless, many suffer from underutilization and insufficient vitality, eventually devolving into unused “green deserts” [4]. As urban development matures, the investigation of determinants influencing urban park vitality and the invigoration of existing park resources becomes critical, thus enhancing residents’ well-being and promoting sustainable urban growth [5].

Urban park vitality is a type of user activity affected by the environmental attributes of the park [6]. Activity intensity is its external representation, while environmental attributes, which are divided into intrinsic and extrinsic, are its internal driving force [7]. Intrinsic environmental attributes, such as park size, water proportion, vegetation cover, services and facilities, and park boundary, have been found to have significant ties to...
park vitality [8,9]. Furthermore, better extrinsic environmental attributes, which refer to a favorable urban built environment surrounding the park—characterized by diverse land use, developed commercial and leisure facilities, easy accessibility, and a substantial, high-income populace—are pivotal for nurturing urban park vitality [10–12]. The tangible demonstration of activity intensity of park users, that is, the value of park vitality, often materializes at the urban scale as clusters of individuals, thus indicating high spatial and temporal regularity in daily mobility and gatherings of city dwellers [13]. In recent years, many scholars have used big data to capture this law, perceive the temporal dynamics and spatial changes of park vitality, and explore the reasons affecting the differences in the vitality of various parks on the urban spatial scale [14–16]. However, compared with the dynamic research on the measurement of park vitality, the current mechanism of vitality is from a static perspective. Scholars often take the average value of one moment or all moments of a day as the value of park vitality (a dependent variable) of that day to build models to explain the vitality mechanism, which provides limited insights into how park environmental attributes affect different times of the day [13,17]. Therefore, building a dynamic mechanism model affecting park vitality, deciphering the differential impact of environmental determinants behind these changes, and understanding their distinct patterns during various periods can foster a comprehensive understanding of park vitality formation mechanisms, thereby informing more targeted vitality revitalization planning strategies.

The environmental factors within and surrounding a park comprise a complex system of interconnected elements whose interactions, due to spatial relationships, either enhance or mitigate the influences of individual determinants on park vitality [18]. For instance, a high service level within the park, in conjunction with abundant commercial and leisure facilities outside the park, catalyzes population aggregation, thereby fostering park vitality [19]. Moreover, the relationships between environmental determinants and park vitality are not always linear, with some presenting nonlinear dynamics [20]. Unfortunately, current research tends to adopt linear regression methods, presuming a linear interplay between two environmental determinants [13,21]. This approach fails to account for potential nonlinear relationships and interactions between determinants, thus leading to flawed conclusions. The geographical detector model is a novel spatial statistical method that does not assume linear relationships and is capable of detecting spatial hierarchical heterogeneity in the dependent variable. This methodology identifies the relative significance of driving determinants and deciphers the interactions between these determinants [22], thus offering solutions to the aforementioned problems and revealing deeper insights into the synergistic effects of internal and external urban park environments on park vitality.

This study investigates the relative impacts of intrinsic and extrinsic environmental park attributes on park vitality and the interactive dynamics of these attributes during distinct time periods in the city of Fuzhou, China. An analytical framework is proposed to address the limitations of preceding studies. Specifically, fine-scale geotagged data, denoted as real-time Tencent user density (RTUD), were employed to gauge the urban park vitality, representing peak population periods during weekdays and weekends in 64 Fuzhou parks. Multisource big data were used to determine the values of various influencing determinants within and surrounding the parks. A suite of models, constructed using geographical detectors, highlights the relative importance of environmental attributes and illuminates the nonlinear and interactive effects of these attributes on urban park vitality across different periods. Through these models, this study aims to (1) delineate the differential effects of intrinsic and extrinsic environmental attributes on urban park vitality during various periods, (2) pinpoint the nonlinear and interactive impacts of environmental attributes on park vitality, and (3) offer refined planning and management strategies to foster urban park vitality.
2. Materials and Methods

2.1. Analytical Framework and Selection of Study Area

A robust analytical approach was employed in this study, as illustrated in Figure 1. It incorporated four primary steps: (1) utilize RTUD data to gauge park vitality at peak times on weekdays and weekends, followed by an application of Moran’s $I$ index to evaluate spatial associations of vitality values; (2) identify and characterize intrinsic and extrinsic environmental features within and surrounding the parks; (3) apply factor and interaction detectors from the geographical detection method to evaluate the relative importance and interaction effects of intrinsic and extrinsic environmental attributes on park vitality across various timeframes; and (4) propose a park vitality optimization strategy.

Fuzhou, the capital city of Fujian Province in China and a prominent socio-economic hub on the southeast coast, was chosen for this study. Characterized by its lush parks and colloquially known as “The City of Thousands of Gardens” or “The City that Grows in Parks,” Fuzhou provides an ideal backdrop for the study. This investigation targeted the bustling core area of Fuzhou, focusing on 64 large urban parks noted for heavy pedestrian traffic (Figure 2).

2.2. Calculation of Variable Values and Data Source

2.2.1. Determination of Park Vitality as a Dependent Variable

The term “vitality” traces its roots back to the realm of biology. Pioneers in urban studies adopted this terminology to depict urban vibrancy and assess levels of urban development [23]. Esteemed researchers, such as Lynch [24], Gehl [25], and Montgomery [26], married the concepts of urban vitality and urban space, evaluating urban vitality via spatial...
clustering of human activities. Subsequent scholars operationalized the spatial vitality of diverse cities by quantifying population intensity during particular periods [27].

Similarly, urban park vitality is measured by population intensity. Social media, mobile signaling, and RTUD data have been harnessed for these measurements [9,28–30]. Social media data, such as Flickr, Instagram, Twitter, and Weibo, require users to actively upload real-time location information, which is highly dependent on user tagging, leading to active reporting that sometimes deviates from the objective behavior of users [17], which limits our access to objective and real-time fine-grained temporal dynamic vitality data. Mobile phones can be programmed to automatically send the users’ location to the base station every half an hour to overcome this limitation [21]. However, the weakness of the 100–300 m spatial resolution of mobile signaling data would exclude urban parks under 10 hm² from the study [31,32]. RTUD data fills this gap by providing population data for every hour of every day, with a spatial resolution of 25 m, that can meet the accuracy standards for all park sizes except mini parks smaller than 1600 m² [33]. In our study, the minimum park area was 10,050 m². These data were collected when individuals use Tencent mobile applications, such as QQ, WeChat, and Tencent Maps [17]. The location information of users was recorded in shapefile format on the online geographic information system platform of Tencent. The data points were then aggregated to derive the total population and aggregation density for each park. Given that WeChat accommodates 1.26 billion active accounts monthly, constituting a significant majority of the Chinese population (1.44 billion) [34], RTUD data emerged as the most trustworthy source of urban population geographic information in China [31]. Hence, these data aptly serve the purpose of accurately monitoring the dynamic vitality of urban parks on an hourly and daily basis.

In this study, RTUD data were harnessed from 05:00 to 22:00 for the 64 parks under consideration on three sequential Wednesdays (typical of weekdays) and three sequential Saturdays (typical of weekends) in November 2021. The selected experimental days featured sunny and breezy weather conditions, with temperatures between 15 and 25 °C, deemed...
suitable for outdoor activities. No special events or festivals were held in the parks during
this period. The mean value derived from the three repeated experiments performed for
each park on the weekdays (i.e., the three Wednesdays) was then divided by the park area
to determine the dynamic park vitality value for a day. This process was replicated for
the weekend group (comprising the three consecutive Saturdays) (Figure S1). Spearman’s
coefficient was employed to investigate the potential correlation between the change in
park vitality and the time period from 05:00 to 22:00, revealing a significant correlation for
both the weekday and weekend groups (Table S1).

Figure S1 shows that the vitality values of the parks in the weekday group peaked dur-
during three periods: 06:00–07:00, 10:00–11:00, and 15:00–17:00. Conversely, for the weekend
group, the vitality trend was more level, with peaks in only two periods: 08:00–09:00 and
16:00–18:00. The average vitality value for each peak hour in each park was established as
the peak vitality value. A Kruskal–Wallis nonparametric test was conducted to ascertain
whether there were differences in park vitality during the five peak hours, yielding a signif-
icient difference (Table S2). Consequently, the peaks Weekday Peak I (AM 6–7), Weekday
Peak II (AM 10–11), Weekday Peak III (PM 15–17), Weekend Peak I (AM 8–9), and Weekend
Peak II (PM 16–18), abbreviated as WDI, WDII, WDIII, WKDI, and WKDII, were chosen as
dependent variables and incorporated into five models (Table 1).

2.2.2. Calculation of Influence Factors and Data Source

Park vitality is driven by both intrinsic and extrinsic environmental factors. Extrinsic
environments encompass urban facilities, such as public and commercial services, resi-
dential areas, and office spaces. The varied composition ratios and densities of these
facilities translate into diverse urban spaces that indirectly influence vitality within associ-
ated parks [13]. Intrinsic factors, however, are dictated by the array of landscape elements,
service amenities, and user satisfaction levels, all of which contribute to overall park quality
and vitality. Consequently, based on summarizing previous research [6,8,13], this study con-
siders three evaluative factors pertaining to extrinsic park vitality characteristics: land use,
regional accessibility, and socio-economic population indicators. Moreover, two aspects,
namely self-spatial attributes and visitor perception, were assessed for intrinsic park vitality
characteristics (Table 1). Specific indicators aligned with previous research [6,13,32,35] were
introduced for each dimension as independent variables (Table 1). It should be pointed out
that in terms of the selection of internal attribute indicators, we chose general indicators
and gave up some micro-spatial indicators to cope with the macro-urban spatial scale
perspective of this paper. Details of the variable calculation and data collection for each
factor are as follows.

The extrinsic environment area incorporated in the calculation involved a buffer zone
extending 500 m from the park boundary, traditionally recognized as the park service
radius [21]. The point-of-interest data for Fuzhou in 2021, obtained via Amap [36], the
premier map application of China, were categorized to calculate four variables: leisure
facility density (LFD), commercial facility density (CFD), enterprise density (ED), and
bus and railway station density (BRSD). LFD encapsulated essential services such as post
offices and express and beauty salons, while CFD primarily accounted for dining and
shopping facilities.

The land use mix (LUM), a measure of relative percentages of land use types within
a specified area, was evaluated via land use entropy [37], where a higher entropy value
indicated a superior LUM. Here,

\[ \text{Entropy} = - \left( \sum_{j=1}^{k} P_j \ln(P_j) \right) / \ln(k), \]

where \( P_j \) is the percentage of each land use type \( j \) in the area around the considered urban
park, and \( k \) is the number of incidences of land use type \( j \).
### Table 1. Environmental attributes influencing urban park vitality.

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Sub-Dimensions</th>
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<th>Abb.</th>
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<td>Park vitality (Dependent variables)</td>
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<td>Weekday peak I (AM 6–7)</td>
<td>WDI</td>
<td>Average active Tencent users (Collected from RTUD) per hour per unit area during peak hours</td>
<td>population/hm²·h</td>
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<td>Weekday peak II (AM 10–11)</td>
<td>WDII</td>
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<td>Weekday peak III (PM 15–17)</td>
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<td>Weekends’ park vitality</td>
<td>Weekend peak I (AM 8–9)</td>
<td>WKDI</td>
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<td>Weekend peak II (PM 16–18)</td>
<td>WKDII</td>
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#### Land use

- **Extrinsic environmental attributes**
  - **Land use mix** (LUM): The relative percentage of two or more types of land use within the 500 m park service radius. (1)
  - **Leisure facilities density** (LFD): Density of leisure facilities within the 500 m park service radius. (n/hm²)
  - **Commercial facilities density** (CFD): Density of commercial facilities within the 500 m park service radius.
  - **Enterprises density** (ED): Density of enterprises within the 500 m park service radius.

#### Regional accessibility

- **Distance to the city center** (DTC): Straight-line distance from the city center (m).
- **Bus and railway station density** (BRSD): Density of bus and railway station within the 500 m park service radius (n/hm²).
- **Walking in an isochronous circle (15 min)** (W15): Area accessibility from walking for 15 min in non-peak hours on weekdays from the park (hm²).
- **Driving in an isochronous circle (30 min)** (D30): Area accessibility from driving for 30 min in non-peak hours on weekdays from the park.

#### Socioeconomic and population

- **Residential population density** (RPD): Density of residential population within the 500 m park service radius (population/hm²).
- **Working population density** (WPD): Density of working population within the 500 m park service radius (population/hm²).
- **Housing price** (HP): Average house price within the 500 m park service radius (yuan/m²).
- **Park size** (PS): Park area (hm²).

#### Intrinsic environmental attributes

- **Self-spatial features**
  - **Landscape shape index** (LSI): The zigzag degree of the park boundary shape.
  - **Normalized digital vegetation index** (NDVI): Measure the vegetation coverage in parks (1).
- **Percentage water area** (PWA): Ratio of water area to the total park area (%).
- **Park facilities density** (PFD): Density of facilities in the park (n/hm²).
- **Perception of visitors**
  - **Comprehensive score** (CS): Visitors’ ratings of the park (score).

The land use data used in this study were extracted from Essential Urban Land Use Categories in China [38], as studied by Gong et al. [39]. These data were further optimized.
via visual interpretation based on Google Earth high-definition images and Amap area-of-interest data [40]. A measure of regional accessibility was calculated using the Amap real-time path planning tool to approximate accessibility via 15 min of walking (W15) and 30 min of driving (D30) during off-peak hours on weekdays [36] (Figure S2). In lieu of detailed population data from the census, cellphone signal data were used to identify residential and working population densities (RPD and WPD, respectively).

To assess the park’s intrinsic attributes, park size (PS) and percentage water area (PWA) were computed using park and water polygons in ArcGIS10.6. To determine the shape of the park boundary, the landscape shape index (LSI) [20] was used. Here,

\[
LSI = 2\sqrt{\frac{\pi \cdot Si}{Ci}}
\]

where \( Si \) represents the area of the urban park \( i \) in hectares, and \( Ci \) signifies the circumference of the park \( i \) in meters. A larger LSI value indicates a more tortuous park boundary.

The landscape shape index (LSI) was employed to analyze the park boundary’s shape. In addition, the normalized digital vegetation index (NDVI) was used to measure vegetation coverage. The density of park facilities (PFD), including playgrounds, themed squares, lounge corridors, restaurants, shops, toilets, and car parks, was determined through field studies. Finally, the park’s comprehensive score (CS) based on ratings by park visitors on Dianping [41], China’s leading social media platform for local lifestyle information, was considered.

2.3. Modeling Approach

2.3.1. Moran’s I Index

Moran’s I index is an important statistical index for measuring spatial relationships and has been separated into the global and local Moran’s I indexes (\( I_{global} \) and \( I_{local} \), respectively). The former is used to measure the global spatial autocorrelations of items, whereas the latter reflects the spatial local heterogeneity [42]. In this study, Moran’s I index was used to evaluate the global spatial autocorrelation and local heterogeneity of the vitality of each park for the five peak periods “WDI, WDII, WDIII, WKDI, and WKDII” discussed in Section 2.2.1. Here,

\[
I_{global} = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (y_i - y) (y_j - y)}{\left( \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \right) \sum_{i=1}^{n} (y_i - y)^2},
\]

\[
I_{local} = \frac{n (\bar{y} - y) \sum_{i=1}^{n} w_{ij} (y_i - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2},
\]

where \( n \) represents the total number of parks; \( y_i \) and \( y_j \) are the vitality values of parks \( i \) and \( j \), respectively; \( \bar{y} \) represents the average vitality of all parks; and \( w_{ij} \) is the spatial weight matrix between parks \( i \) and \( j \) (generally the spatial distance matrix). The value of \( I_{global} \) is \([-1, 1]\). Furthermore, \( I_{global} > 0 \) indicates that the data present a global spatial positive correlation; the larger the value is, the more pronounced the spatial correlation will be. Conversely, \( I_{global} < 0 \) indicates that the data present a global spatial negative correlation; the smaller the value is, the greater the spatial difference will be. Finally, \( I_{global} = 0 \) indicates that the data are distributed randomly [42]. The result of \( I_{local} \) can be visualized using a local indicator of spatial association (LISA) cluster diagram.

2.3.2. Geographic Detector Model

Based on the analysis of the urban park-vitality spatial distribution differentiation discussed in Section 2.3.1, geographic detector models were established to analyze the nonlinear influence, interactive influence, and comparative temporal difference of the intrinsic and extrinsic environments on park vitality. Based on the spatial differentiation theory, the geographic detector model determines the correlation between independent and dependent variables. The core concept is based on the assumption that, if an independent variable
has an important impact on a dependent variable, the spatial distributions of the independent and dependent variables should be similar [43]. The concrete calculation consists of four modules; this study primarily implemented two: the factor and interaction detectors.

The factor detector detected the degree of influence of determinants (Xn) on park vitality (Y) based on the q-statistic [22]:

$$q = 1 - \frac{-\sum_{h=1}^{L} N_h \sigma^2}{N \sigma^2} = 1 - \frac{SSW}{SST},$$

where \(q\) represents the explanatory ability of Xn on Y, \(h = (1, 2, 3, \ldots L)\) is the variable classification or stratification, \(N\) and \(N_h\) are the numbers of units in layer \(h\) and the entire region, respectively, \(\sigma^2\) and \(\sigma^2_h\) denote the variance of units in \(h\) and the global variance of \(Y\) over the entire region, respectively, SSW represents the sum-of-squares, and SST represents the total SSW. The greater the value of \(q\), the stronger the effect of the independent variable \(X\) on \(Y\) will be. The \(q\) range is 0–1.

The interactive detector detected determinants (X1, X2, …, Xs) and determined whether their interactions affected the urban park’s vitality; this principle is shown in Figure 3. For X1 and X2, representing two environmental attributes, Figure 3a shows the vitality pattern of the park. Figure 3b shows four regions divided by X1 and X2, respectively. When one figure is superimposed on the other, a new partition of park vitality, \(X_1 \cap X_2\) (Figure 3c) is formed, in which the two attributes interact. From Equation (5), the influence of \(X_1 \cap X_2\) on \(Y\) is calculated as \(q(X_1 \cap X_2)\).

Figure 3. Example of interaction detection principle: (a) pattern of park vitality, (b) subareas divided by factor X1 and X2, and (c) subareas divided by \(X_1 \cap X_2\).

If \(q(X_1 \cap X_2) < \min (q(X_1), q(X_2))\), the interaction has a weakened nonlinear effect; if \(\min (q(X_1), q(X_2)) < q(X_1 \cap X_2) < \max (q(X_1), q(X_2))\), the interaction has a unique weakened effect. If \(q(X_1 \cap X_2) > \max (q(X_1), q(X_2))\), the interaction has an enhanced bilinear effect; if \(q(X_1 \cap X_2) > q(X_1) + q(X_2)\), the interaction has a nonlinear-enhanced effect; and, if \(q(X_1 \cap X_2) = q(X_1) + q(X_2)\), determinants X1 and X2 are independent.

These calculations were performed using the GD program package in R 3.6.3, which was developed by Wang et al. [22] and is freely available online [44]. Note that there is no linearity assumption for geographic detector models; therefore, no collinearity test for independent variables is required. In addition, the geographical detector model requires that each independent variable be a discrete variable. The GD package provides six discretization methods (the “equal” interval classification method divides attribute values into equal size ranges; “natural” is based on the Jenks Natural Breaks algorithm to group similar values and maximize differences between classes; “quantile” assigns the same number of data values to each class; “geometric” creates geometric intervals by minimizing the SSW of the number of elements in each class; “sd” creates a classification interval using an equivalent range proportional to the standard deviation; “manual” uses manual intervals to set the range of classes that fit the data.): equal, natural, quantile, geometric, standard
deviation (sd), and manual. We calculated the optimal method and classification automatically using the “optidisc” function and then discretized the 17 continuous independent variables considered in this study. The specific treatment methods and results for each variable are provided in Table S3.

3. Results and Analysis

3.1. Temporospatial Distribution of Park Vitality

A detailed examination of the vitality values in Fuzhou’s 64 urban parks during five distinct periods highlights a marked temporal variation (Table S4). The period WKDII yielded the maximum average vitality and the minimum standard deviation coefficient, underscoring the superior and well-balanced vitality of the period compared with others. Conversely, WKDI showed the least average vitality. A relatively consistent vitality profile was observed during WDII and WDIII, with a slight dip during WDI.

Iglobal metrics, used to examine the spatial autocorrelations of park vitality across these periods, yielded results greater than zero for all periods barring WKDI, clearing the 0.05% significance level threshold (Table S5). This result implies significant positive global spatial correlations during the periods of WDI, WDII, WDIII, and WKDII.

The color-graded spatial distribution of urban park vitality, depicted in Figure 4, showed an ever-changing profile across the five periods. Notably, smaller parks situated in the city center and along the waterfront consistently maintained high-value zones throughout all periods.

![Figure 4. Spatial distribution of park vitality in five time periods.](image)

Local indicators of spatial association (LISA) were employed to ascertain the agglomeration of park vitality during these five periods (Figure 5). Clusters of high-density (“high–high”), low-density (“low–low”), and dissimilar vitality (“high–low” and “low–high”) parks were observed.
Local indicators of spatial association (LISA) were employed to ascertain the agglomeration of park vitality during these five periods (Figure 5). Clusters of high-density (“high–high”), low-density (“low–low”), and dissimilar vitality (“high–low” and “low–high”) parks were observed.

During WDI, a broad “high–high” cluster was identified in the center of the study area. As time progressed into WDII and WDIII, the cluster range contracted and shifted toward the Minjiang River waterfront. In contrast, “low–low” clusters were predominantly located in areas distant from the city center. While weekends showed a similar high–high clustering as weekdays, the range was smaller and less pronounced during WKDI. Interestingly, “low–high” outliers were often found along the Minjiang River during different periods. Despite similar riverside environments, the vitality of these parks varied, reflecting the park competition previously noted by scholars [33].

3.2. Impact of Environmental Attributes on Park Vitality across Timeframes

The geographic detector model’s factor detector elucidated the degree of influence of various determinants on park vitality, gauged using the q-value. These findings, compiled at a 0.05 significance level, are depicted in Figure 6. The q-values, which ranged from 0.244 to 0.646, revealed differential impacts of these determinants on park vitality across temporal periods.

Determinants such as LFD, CFD, and PS were consistently significant across all periods, whereas LUM, HP, LSI, NDVI, PWA, and CS showed no substantial effect during any period. WPD displayed significant effects during WDI, WDII, WDIII, and WKDII; D30 was influential during WDII, WDIII, and WKDII; W15 mattered in WDI, WDII, and WKDII; PFD was significant during WDII and WKDII; and ED, DTC, BRSD, and RPD demonstrated importance solely during WDI.

The factor explanatory power rankings diverged across periods. In brief, the rankings across the five periods were as follows: WDI prioritized land use, followed by socioeconomic and population factors, regional accessibility, and intrinsic environmental attributes. WDII and WDIII ranked socioeconomic and population factors highest, followed by land use, intrinsic environmental attributes, and regional accessibility. WKDI and WKDII both placed intrinsic environmental attributes first, followed by land use, socioeconomic and population factors, and regional accessibility.
Figure 6. Relative importance of environmental features during five different time periods.

Focusing on specific variable determinants, the paramount influencers during WDI were LFD (0.646), CFD (0.571), WPD (0.481), and RPD (0.424). This is attributable to the predilection for morning exercise among residents, leading to higher park use in areas with ample leisure and commercial facilities, which typically have denser populations. Parks near city centers with abundant enterprises, a larger working populace, and superior access to walking and public transportation options recorded higher WDI vitality. Thus, determinants such as ED, DTC, W15, and BRSD also demonstrated significance in WDI. As weekdays advanced into WDII and WDIII, the importance of RPD, DTC, and BRSD dwindled, whereas D30 rose to prominence and WPD emerged as the chief factor. This shift aligns with urban work and rest schedules, indicating that park vitality increases during morning rush hour in WDII due to commuters traversing parks. Determinants CFD, LFD, and PS held consistent importance during WDII and WDIII, ranking among the top four influencers.

Weekend periods (WKDI and WKDII) showed different determinant dynamics compared with weekdays, with PS ranking first in both periods, attributed to park size influencing functional zoning and spatial layout, essential factors affecting park choice, especially on weekends. WPD was the second most important determinant during WKDII for reasons similar to those in WDI: parks in central business districts with dense working populations tend to have superior environments and support facilities. Meanwhile, WKDII showed the least significant determinants among the five periods, with no regional accessibility influencing functional zoning and spatial layout. WKDI and WKDII focused on intrinsic environmental attributes, and regional accessibility. WKDI showed a slight decline compared with the single-factor explanatory power of WPD, indicating an isolated diminished effect. Conversely, the remaining 90 pairings of factors manifested either bilinear or nonlinear enhancement, suggesting that the interplay between two determinants yielded a more pronounced influence on park vitality than a single constituent determinant. The interaction q value’s magnitude was directly proportional to the interaction’s impact on park vitality.

3.3. Interaction Dynamics of Environmental Attributes across Time Periods

The results for the interactive detection of significant determinants across the five periods are detailed in Figure 7 and Table S6. PFD ∩ WPD in WDII uniquely demonstrated a slight decline compared with the single-factor explanatory power of WPD, indicating an isolated diminished effect. Conversely, the remaining 90 pairings of factors manifested either bilinear or nonlinear enhancement, suggesting that the interplay between two determinants yielded a more pronounced influence on park vitality than a single constituent determinant. The interaction q value’s magnitude was directly proportional to the interaction’s impact on park vitality.
For the weekend periods, the highest q values were PS ∩ CFD (0.614), PS ∩ LFD (0.581) for WKDI, and PS ∩ WPD (0.813), CFD ∩ PFD (0.757), and PS ∩ PFD (0.749) for WKDII. The highest interaction values over the weekend were attributed to interactions between intrinsic environmental attributes and either extrinsic or intrinsic attributes. WKDI's first minor peak indicated that ample facilities and park size were crucial for attracting park visitors. During WKDII, besides PS, PFD also showed high interaction values with CFD and PS, with the most significant interaction being PS and WPD, indicative of the importance of the urban and park environments. These results suggest that weekend park visitors prioritize intrinsic park quality, along with integrated facilities and environments within and around their chosen park. Additionally, W15, LFD, and CFD demonstrated robust interactions with PS.

4. Discussion
4.1. Traits of Environmental Influences on Park Vitality Dynamics

The promotion of urban park vitality can bolster human activity and interactions, augment the appeal of public urban spaces, and provide inhabitants with enhanced living conditions [45]. However, planners aiming to revitalize park resources must reconsider urban environment optimization within and around these parks. From this study, four salient insights emerge.

Initially, the park’s vitality in Fuzhou was marked by noticeable spatial-temporal variability. Previous studies align with the observed temporal differences [6,32], with park
vitality noticeably higher on weekends than on weekdays. Diverging patterns between weekdays and weekends are likely a result of different travel habits: corporate schedules dominate weekdays, while weekends allow for more flexibility. Consequently, weekend afternoons tend to be more vibrant than mornings [40], mirroring the vitality distribution patterns observed in other metropolitan areas such as Shanghai [16].

Second, environmental attributes demonstrated varying impacts on park vitality. CFD, LFD, and PS consistently exhibited significant effects across the five periods, emphasizing their enduring influence on park vitality. The abundance of commercial and leisure amenities aligns with Jacob’s prediction that these facilities bolster park vitality at any time of day [4]. However, this study also identified several determinants, such as NDVI, PWA, CS, LSI, HP, and LUM, that previously have been considered essential [13,21,33,46], yet showed insignificant effects on park vitality within this specific context. This discrepancy may be attributed to the timing of the study (autumn) [47], recent improvements to park quantity and quality in Fuzhou [48], and the increased connectivity of parks within the urban space [49]. It is crucial to understand the built environment and park vitality through the lens of the impact of facilities within the park buffer zone, which had a considerable impact.

Third, the impact ranking of environmental features showed significant differences between the different time periods. Socioeconomic and population factors, along with land use, emerged as critical during the weekdays, whereas intrinsic environmental attributes were more influential on weekends. This dichotomy underlines how weekday and weekend park vitality rely on extrinsic and intrinsic determinants, respectively. This suggests that park visitors value convenient park access during the weekdays and a comfortable recreational experience during the weekends.

Lastly, the interaction between environmental determinants predominantly showed bilinear or nonlinear enhancement, signaling that urban planners can target multiple dimensions simultaneously to elevate park vitality. Though accessibility determinants did not rank highly as single factors [17,47,50], they interacted with the intrinsic and extrinsic environment of the park significantly during the weekdays. However, the interactions of accessibility determinants with other environmental factors were less significant during weekends, when park visitors were more purpose-driven [47]. These findings highlight the relative importance of accessibility factors on weekdays and suggest adjusting park accessibility according to the time period.

4.2. Implications for Urban Park Planning and Management

Firstly, research findings underscore the need to bolster the symbiotic relationship between urban parks and their surrounding environs, emphasizing an enhancement of park vitality within urban design frameworks. This substantiates the “park city” concept advocated by Chinese policymakers, which promotes the seamless integration of parks into urban and consumer spaces, thereby fostering a “human-garden-city” community [51]. This comprehensive, top-down approach to urban planning considers factors such as land, traffic, social, economic, and population dynamics. It encourages the permeation of park boundaries, enabling a structured spatial synergy with the city.

Secondly, cities echoing Fuzhou’s urban blueprint could benefit from improved land use policies by considering external determinants that influence park vitality [52]. This research accentuates the continual impact of commercial and leisure facilities on park vitality and their high-explanatory power for the intrinsic park environment, thereby making the proximity to recreational business districts an important factor in new park location selection. While city center land area is inherently limited, constructing smaller, interconnected parks can boost vitality, as indicated by the high-vitality cluster of small parks identified in the city center by the LISA map (Figure 5).

Thirdly, acknowledging the differential impact of environmental attributes on park vitality across varying time periods can facilitate targeted zoning and time-sharing policies. For instance, parks in densely populated residential zones could be designated as morning exercise parks, optimizing surrounding amenities and expanding accessibility through
early bus routes and elevated walkways. Similarly, parks in high-occupancy work areas can be crafted into business commuter parks, enhancing walkability for the working population and fostering aesthetic landscapes that contribute to the overall commuting experience. Moreover, the mid-evening peak hours (WDII, WDIII, and WKDII) can be targeted to improve space utilization by introducing mobile vendors and optimizing commercial spaces, thereby promoting park vitality.

Lastly, there is an imperative to amplify the intrinsic environmental allure of parks. The explanatory power of intrinsic environmental attributes (PS and PFD) emphasizes the potential for optimizing park spaces, routes, and facilities to cater to human needs. Moreover, introducing city landscapes such as Gushan Mountain and Minjiang River into parks can enhance spatial quality. The implementation of greenways to connect multiple city center parks, alongside the construction of large parks on Fuzhou’s mountains, can extend leisure time in parks and enhance vitality during weekends.

4.3. Limitations

This study acknowledges limitations due to seasonal variations [46], potentially influencing the significance of NDVI and PWA variables, which could be mitigated by considering different seasons in future research. The large-scale approach (using RTUD big data for park vitality measurements) excludes demographic information (age, gender, and origin), necessitating further research using traditional methods to gain an in-depth understanding of the vitality formation mechanism. The exclusive use of aggregation density as a vitality measurement index presents a singular evaluation perspective, suggesting the need for further research to measure park vitality in multiple dimensions by adopting indicators such as diversity of age group, space using intensity, and richness of activity types [6] from the micropark spatial scale. Meanwhile, more intrinsic environmental attributes such as space combination, plant composition, and pavement type should be included on the microscale to study the mechanism of park vitality [53]. The study also suggests future research should extend to parks surrounding the focal park, exploring the mutual promotional or competitive relationships between parks. Lastly, the current applicability of RTUD data to China only might limit the global application of findings, although it is expected that similar data will be obtainable from other nations in the near future.

5. Conclusions

The study delved into the relative importance of intrinsic and extrinsic environmental attributes on park vitality, investigating their dynamics over different time frames within Fuzhou’s urban milieu. Using geographic detector models, park vitality was assessed based on RTUD data within specific periods, and both intrinsic and extrinsic environmental traits of these parks were meticulously categorized.

Temporal variances emerged as a central theme, highlighting the fluctuating influence of various environmental attributes on park vitality. While attributes like CFD, LFD, and PS consistently showcased substantial influence, others, such as NDVI, PWA, CS, LSI, HP, and LUM, did not significantly impact vitality. On weekdays, extrinsic factors held sway, particularly during the periods WDI, WDII, and WDIII. In contrast, weekend segments WKDI and WKDII were predominantly influenced by intrinsic factors. The intricate interactions among environmental determinants manifested mainly as bilinear or nonlinear enhancements throughout, with notable attributes like CFD and LFD showing high interplay values within the park’s intrinsic environment.

The findings from this research provide valuable insights for urban planning and landscape design to enhance park vitality, emphasizing the need to harmonize parks with their surrounding environs. Strategic recommendations are made to strengthen the balance between intrinsic and extrinsic factors. This investigation provides a solid theoretical foundation for probing deeper into the effects of environmental variables on park vitality. Implementing this model and methodology in similar urban environments will reinforce the conclusions and shed light on ideal strategies for maximizing park vitality and overall
benefits. By emphasizing future directions, it’s recommended that subsequent studies:
(1) execute multi-season and multi-city evaluations to validate certain variables. (2) On
weekends, delve deeper into intrinsic environmental traits at a micro-park spatial scale.
(3) Incorporate data from neighboring parks to understand the competitive temporal
dynamics influencing park vitality.

Supplementary Materials: The following supporting information can be downloaded at: https://

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alization; Roles/Writing—original draft. C.L.: Conceptualization; Funding acquisition; Investigation;
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tion; Formal analysis; Methodology; Investigation; Writing—review and editing. C.Z.: Data curation;
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Abbreviations

RTUD real-time Tencent user density
WDI Weekday Peak I (AM 6–7)
WDII Weekday Peak II (AM 10–11)
WDIII Weekday Peak III (PM 15–17)
WKDI Weekend Peak I (AM 8–9)
WKDII Weekend Peak II (PM 16–18)
LFD leisure facility density
CFD commercial facility density
ED enterprise density
BRSD bus and railway station density
LUM land use mix
W15 walking in an isochronous circle in 15 min
D30 driving in an isochronous circle in 30 min
RPD residential population density
WPD working population density
HP housing price
PS park size
PWA percentage water area
LSI landscape shape index
NDVI normalized digital vegetation index
PFD park facilities density
CS comprehensive score
GD geographic detector

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