

Evaluating the spatial-temporal impact of urban nature on urban vitality in Vancouver: A social media and GPS data approach

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ABSTRACT

Natural elements in urban environments enhance livability and health, strengthening urban vitality. However, existing research has primarily focused on physical indicators, with limited attention paid to the joint influence of behavioral and perceptual dimensions on urban vitality. To address this gap, this study integrates a spatio-temporal analytical framework encompassing three dimensions: natural elements, human perception, and activity diversity. Focusing on Vancouver, we utilized smartphone-GPS and social media data from 2018 to 2023 to explore temporal (weekdays vs. weekends) and spatial dimensions. Using machine learning techniques (Google vision, K-means and Sentiment analysis) on multivariate social media data, and we also analyzed changes in activity diversity over time. We assessed the multidimensional influences on urban vitality using the Geographically and Temporally Weighted Regression (GTWR) model. Our results show that during the pandemic, attention to nature and outdoor activities increased significantly, while cultural and social activities and transportation initially decreased but quickly recovered. Sentiment scores, natural elements, and human activity preferences significantly influenced urban vitality during COVID-19, with notable spatiotemporal heterogeneity. The pandemic intensified residents' reliance on natural spaces and green transportation, altering the spatial distribution of urban vitality. These findings provide a basis for optimizing natural spaces and sustainable transportation planning in future urban development.

1. Introduction

Urban vitality originates from people and their activities within cities (Gehl, 1971; Jacobs, 1961). Interactions between individuals and their activity spaces continuously impact urban vitality (Li et al., 2018; Li et al., 2022a,b; Lu et al., 2019; Scepanovic et al., 2021). Vibrant cities attract investment and talent, promote development, enhance competitiveness, improve residents' well-being, increase social cohesion, and are essential for societal development and health (Chen et al., 2024; Zhang et al., 2021). Successful urban places are characterized by diverse activities that keep the city dynamic and maintain activity diversity (Gehl, 1971; Jacobs, 1961; Scepanovic et al., 2021). This underscores

the crucial role of human activities in inducing urban vitality and assessing environmental quality (Li et al., 2022a,b).

Urban nature (such as parks, street trees, and water bodies) plays a pivotal role in shaping urban vitality by enhancing spatial environments and providing broad benefits for human health, society, and ecosystems (Chen et al., 2024; Council of Europe, 2020; Zhang et al., 2023a,b). It improves urban environmental quality and promotes individuals' activities, behaviors, and psychological well-being (Chen et al., 2024; Zhang et al., 2021). However, existing studies typically investigate individual natural elements in isolation, lacking a thorough exploration of how diverse urban natural features collectively shape urban vitality. Given the significance of urban vitality, a comprehensive assessment is

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crucial for deepening our understanding and informing strategies to enhance it.

However, external shocks like COVID-19 have further complicated the interaction between urban nature and human activities. While access to natural environments and social interaction is widely recognized as beneficial to public health and urban vitality (Kleinschroth and Kowarik, 2020; Xie et al., 2020), the pandemic severely disrupted this equilibrium. Governmental restrictions on mobility and social distancing (Nguyen et al., 2020; Zhu and Tan, 2022) led to significant declines in vitality and changes in activity patterns (Wu et al., 2023; Xie et al., 2020). Even post pandemic, these shifts persisted in some regions (Li et al., 2024), highlighting the need to reconsider how nature and activity interact under rapidly changing urban conditions. (Wu et al., 2023).

Despite growing interest, most existing studies focus on isolated dimensions, such as natural elements, human perception, or visitation patterns (Chen et al., 2025), and often neglecting their interconnected effects and contextual variability (Li et al., 2022a,b; Liu et al., 2020; Xia et al., 2020; Zhang et al., 2023a,b). Perception-based studies may overlook spatial heterogeneity and environmental quality (Li et al., 2022a,b; Zhang et al., 2021), while research on physical elements might fail to reflect actual vitality. Similarly, although analyzing activity diversity is useful for identifying areas of social interaction, it alone is insufficient for comprehensive vitality assessment (Chen et al., 2024)., while research on physical elements might fail to reflect actual vitality. Similarly, although analyzing activity diversity is useful for identifying areas of social interaction, it alone is insufficient for comprehensive vitality assessment. (Chen et al., 2024; Li et al., 2022a,b; Zhang et al., 2023a,b).

To address these challenges, this study aims to examine how diverse forms of urban nature influence urban vitality. We develop a comprehensive analytical framework that integrates multi-functional urban nature, human perception, activity diversity, and intensity—particularly during dynamic periods such as the COVID-19 pandemic—to better understand the mechanisms behind urban vitality and support evidence-based urban development.

Moreover, urban vitality exhibits pronounced spatial and temporal heterogeneity (Park and Lee, 2024). According to Chen (2023), vitality levels often follow clustered, polycentric patterns, decreasing from city centers to suburban areas, with substantial differences between weekdays and weekends as well as between daytime and nighttime. These patterns suggest that the determinants of urban vitality vary across space and time, necessitating modeling techniques that can capture these local variations. Therefore, we adopt the GTWR model to investigate the spatiotemporal drivers of urban vitality, extending traditional GWR by incorporating temporal dynamics (Zhao et al., 2023).

To this end, we develop a new research framework that integrates human emotions, activity diversity, and urban nature to comprehensively assess their spatial and temporal impacts on urban vitality. The proposed research questions are as follows:

- 1) What diverse types of human activity can be extracted from social media data? What specific changes in these activity types are exhibited as the epidemic progresses?
- 2) What factors are significantly correlate with urban vitality regarding human activities, perceived ratings and natural element variables in urban nature?
- 3) How do these key elements affect the spatial and temporal heterogeneity of urban vitality, and what changes in the mechanisms of this influence have been brought about by the external shocks of COVID-19?

2. Literature review

2.1. Urban vitality and urban nature

Jacobs (1961) introduced urban vitality as a measure of a city's sustainability and attractiveness, reflecting residents' activity preferences within dynamic environments. Vibrant cities enhance quality of

life by being economically productive, socially cohesive, culturally diverse, and rich in public spaces (Huai et al., 2022; Song et al., 2020). Both Jacobs (1961) and Gehl (1971) stressed that vitality stems from daily activities and interactions, with spatial design shaping behavior and social cohesion.

Studies show urban structures and socio-economic contexts influence vitality. For instance, Chen et al. (2022) found innovation flourishes in high-density areas. While Liu et al. (2023) highlighted the role of social cooperation and public participation, aligning assessments with policy needs.

Recognizing urban nature's essential role, researchers note it enriches urban spaces and offers various societal benefits (Conzen, 1960; Keshtkaran, 2019; Whitehand, 2006; A. Zhang et al., 2019; Zhang et al., 2023a,b). Natural elements improve mental and physical health, promote social interaction, and strengthen community cohesion (Huai et al., 2022; Kaplan and Kaplan, 1989; Ulrich, 1984). And urban green spaces boost well-being and foster a sense of "wildness," positively impacting residents' psychological and social experiences (Samus et al., 2022). However, the accessibility of these benefits may vary, pointing to the need for inclusive policies (Juntti and Ozsezer-Kurnuc, 2023).

Urban nature also facilitates community cohesion by enhancing social bonds and reducing stress (Dobson et al., 2021). They also benefit children's cognitive development by enhancing executive functioning and attention (Schutte et al., 2017). Conversely, certain vegetation may negatively affect allergy sufferers, underscoring the need for careful, inclusive environmental design (Cariñanos et al., 2017).

As a crucial link between people and the urban environment (Lynch, 1964), urban nature influences activities, behaviors, and psychology, thus affecting vitality (Cai et al., 2022; Keshtkaran, 2019; Zhang et al., 2021). However, existing research has mainly focused on elements like parks, with less attention to everyday features such as street greenery and their impact on vitality.

The mechanisms by which diverse urban nature influences vitality is not fully explored, particularly regarding natural elements like the type and density of street greenery. This gap limits our comprehensive understanding of urban nature's overall role. As urbanization and technology evolve, so do urban spaces and behavioral patterns, necessitating further research on the relationship between urban nature and urban vitality using new theories and methods.

2.2. The impact of COVID-19 on urban vitality

The global COVID-19 pandemic profoundly disrupted urban life and inhabitants' behaviors due to unprecedented government measures such as canceling public events, restricting travel, and limiting access to public spaces (Kleinschroth and Kowarik, 2020; Li et al., 2024). These restrictions hindered residents from traveling and socializing in outdoor areas (Nguyen et al., 2020; Zhu and Tan, 2022), adversely affecting their physical and mental health (Xie et al., 2020).

In this context, significant changes occurred in access patterns to public spaces. Kleinschroth and Kowarik (2020) observed that while many European parks initially remained open, challenges in maintaining social distancing eventually led to restricted access. This situation underscored the need for sustainable urban planning that emphasizes the importance of green spaces in enhancing quality of life. Similarly, Song et al. (2023) found substantial declines in campus visits, especially to dining venues and recreational sites, indicating a reduced reliance on on-campus facilities during the pandemic. Then, the pandemic also altered work and lifestyle patterns, with many individuals adopting remote work as their primary mode, thereby shifting preferences for urban outdoor environments (Belzunegui-Eraso and Erro-Garcés, 2020). The negative impact on mental health and social interactions highlighted the crucial role of urban parks in enhancing overall well-being and fulfilling social needs (Xie et al., 2020).

Regarding urban vitality, Li et al. (2024) reported that Shenzhen's overall vitality recovered to only 86 % of its 2019 level post-lockdown,

with some districts continuing to decline even after the outbreak abated. This impact displayed significant spatial heterogeneity influenced by factors such as population density, traffic flow, and urban form. However, the reliance on social media data in this study may introduce sample bias, necessitating verification in other cities.

In some cities, declines in urban vitality persisted even after the epidemic subsided (Li et al., 2024). Researching how to restore urban vitality based on residents' shifting spatial preferences has become crucial in the post-pandemic period (Wu et al., 2023). These findings offer new perspectives on the interplay between urban spatial planning, public health, and sustainable development. Existing studies mainly focus on specific urban spaces like parks and campuses, lacking comprehensive analyses of access patterns and recovery across diverse urban areas, as well as the combined effects of environmental factors, human perceptions, and emotions (Li et al., 2024). Addressing this gap is essential for developing adaptive urban planning strategies that improve residents' quality of life and advance sustainable development.

2.3. Integrated study of environmental elements, human perception and activities

Human perception, shaped by psychological feelings and sense of place, influences emotional attachment and belonging (Huang et al., 2023). Public spaces like parks, gardens, and streets foster social interaction, encourage exercise, and enhance mental well-being (Zhang et al., 2023a,b). Environmental characteristics (such as aesthetics, spatial layout, and comfort) play a critical role in shaping human perception and behavior (Rapoport, 1977), with studies showing that green spaces and water bodies positively impact well-being, as factors like landscape diversity enhance perceptions of cultural ecosystem services (Bi, 2024; Costanza et al., 2017; Riechers et al., 2016).

Most research, however, tends to focus on either environmental elements or human activities, limiting a holistic understanding of their combined effects on urban vitality. Behavior-focused studies may overlook environmental impacts, while those centered on physical elements may miss the dynamic aspects of urban vitality (Li et al., 2022a,b; Zhang et al., 2023a,b).

Therefore, integrating human activity preferences, activity diversity, and environmental elements is essential for a comprehensive understanding of urban vitality (Li et al., 2022a,b). Using GIS technology alongside social media data and spatial statistics enables capturing both environmental features and behavioral patterns. For example, Ma et al. (2023) used social media, eye-tracking, and sentiment analysis to assess satisfaction with urban spaces. Similarly, (Yang et al., 2022a,b) analyzed urban space usage intensity and distribution using big data, offering new perspectives. (Yang et al., 2022a,b) integrated environmental and activity data to explore complex vitality drivers. (Zhang et al., 2023a,b) used spatial syntax and social media data to analyze interactions between urban green spaces and human activities, finding that green space layout and accessibility significantly influence residents' usage frequency and duration.

Studies like these, which merge subjective and objective data, more accurately describe and predict urban vitality changes, informing urban planning to enhance sustainability and quality of life (Ardic et al., 2020). Challenges remain in acquiring and processing large-scale, multidimensional data and effectively combining subjective and objective data. Future research should focus on methodological innovations and efficient analytical tools to advance integrated studies of environmental elements and human activities.

2.4. Big data-based data processing and analysis technology

The advent of urban big data has transformed the measurement of urban vitality by providing extensive insights into environmental elements and human activities. Unlike traditional methods, which are qualitative, time-consuming, and lack scalability (Chen et al., 2020; Li

et al., 2022a,b; Sung and Lee, 2015), big data enables precise quantification of human behavior, detailed mapping of urban environments, and complex data analysis (Ardic et al., 2020; Yang et al., 2022a,b; Zhang et al., 2023a,b).

Various big data sources, including street view images, GPS tracking, mobile phone data, UAVs, webcams, IoT, Points of Interest, and social media support analyses of spatial layouts, movement patterns, pedestrian distributions, and resident evaluations of urban spaces (Chen et al., 2020; Fareh and Alkama, 2022; Parra-Ovalle et al., 2023; Petrasova et al., 2019). To interpret these variables, scholars increasingly use advanced statistical and machine learning techniques. Traditional methods like correlation analysis and OLS are common (Yang et al., 2022a,b), yet often insufficient to capture complex interactions. Consequently, newer methods such as geo-detectors, machine learning, and deep learning are now employed to identify multilevel interactions and process large-scale, multidimensional data (Li et al., 2024; Zhang et al., 2023a,b). For example, geo-detectors identify the impact intensity of environmental factors (Han et al., 2023), while machine learning algorithms build predictive models to simulate potential impacts of policies and environmental changes (Cao and Tao, 2023).

These advanced techniques enhance precision, efficiency, and explanatory power in urban vitality research. By integrating multiple data sources, researchers can comprehensively analyze dynamic changes and intricate mechanisms, providing essential insights for urban planning and decision-making (Biljecki and Ito, 2021). However, challenges remain in data acquisition, integration, technological demands, and privacy concerns.

Future research should pursue methodological innovation, developing robust analytical tools and fostering interdisciplinary collaboration. As cities are complex and evolving systems, analyzing urban vitality demands a focus on spatial and temporal heterogeneity and a careful selection of relevant variables for in-depth, quantitative analysis.

3. Methods

3.1. Study area

North American urban planning increasingly promotes "sustainability as density," encouraging walkable, high-density neighborhoods near transit and amenities (Quastel et al., 2012). Vancouver exemplifies this approach through the Greater Vancouver Livable Region Strategic Plan, balancing economic growth with natural landscape preservation (Smith and Haid, 2024).

As a highly urbanized city with a globally renowned downtown (Luo et al., 2020), Vancouver has a population of approximately 662,000 and covers a land area of about 115 square kilometers, making it the most populous city in British Columbia (Vancouver, 2025). Its central areas exhibit strong urban vitality and abundant social media activity. Therefore, we selected Vancouver's downtown and Central Business District (CBD) as our study area. The study utilized the Canada Dissemination Area (DA) Boundaries—2021 dataset obtained from ArcGIS Hub (<https://hub.arcgis.com/>), which includes attributes such as land area, population, and housing characteristics (Fig. 1).

3.2. Research flow

We developed a research framework (Fig. 2), collecting visitation data from the Canadian Neighborhood Patterns dataset on the Dewey platform as urban vitality data for Canada's central districts. To represent human activity preferences, we used Flickr images and Google Reviews, and gathered natural element data from the City of Vancouver and 52 other sources.

For implicit information extraction, Google Vision was used to label and classify images by activity type, while EasyNMT and NLTK processed text-based reviews for sentiment analysis, yielding spatial evaluations. Average sentiment scores per block were calculated to indicate

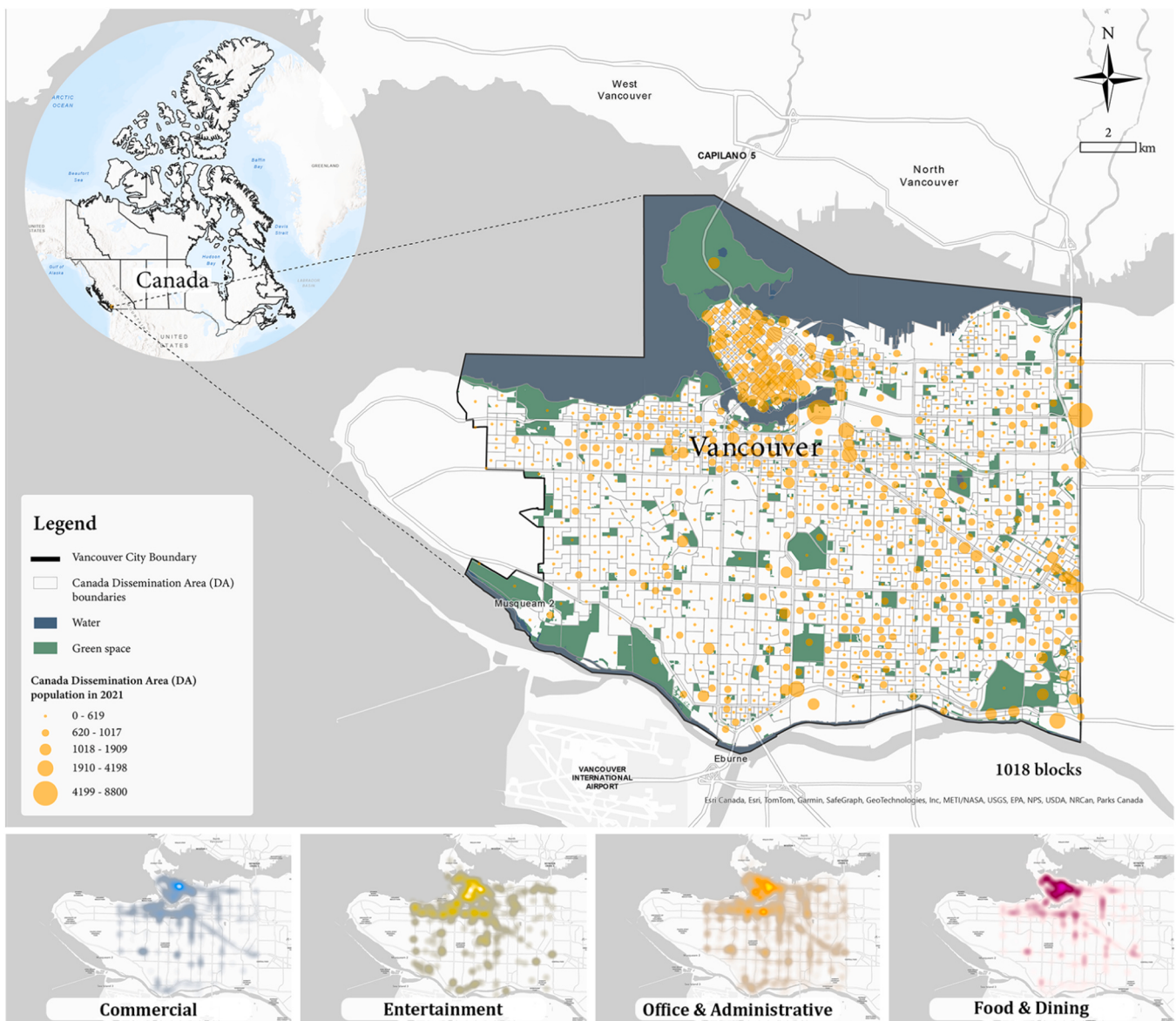


Fig. 1. Study area: City of Vancouver.

subjective spatial evaluations, combined with image-based activity types to track changes in human activities. Urban natural elements were quantified by assessing park areas, tree counts, dominant species, tree heights, roughness, and food tree distribution.

After compiling a dataset comprising 53 explanatory variables and baseline vitality data, we first conducted a correlation analysis and evaluated the spatial autocorrelation of each variable using Moran's I statistic, aiming to identify spatial dependency patterns and inform subsequent modeling. The GTWR model was employed as the core analytical tool, with only those variables that passed multicollinearity diagnostics included in the modeling process. Compared to traditional OLS or stepwise regression methods, GTWR enables the simultaneous selection of variables and local estimation of regression coefficients during model construction. Specifically, during the automatic bandwidth optimization process, variables with limited explanatory power or lacking statistical significance across most locations are automatically excluded, thereby mitigating the risks of overfitting and multicollinearity. This approach ensures that only key variables with consistent explanatory strength across spatial and temporal dimensions are retained, enhancing the robustness and interpretability of the model. All retained variables were subsequently incorporated into the GTWR

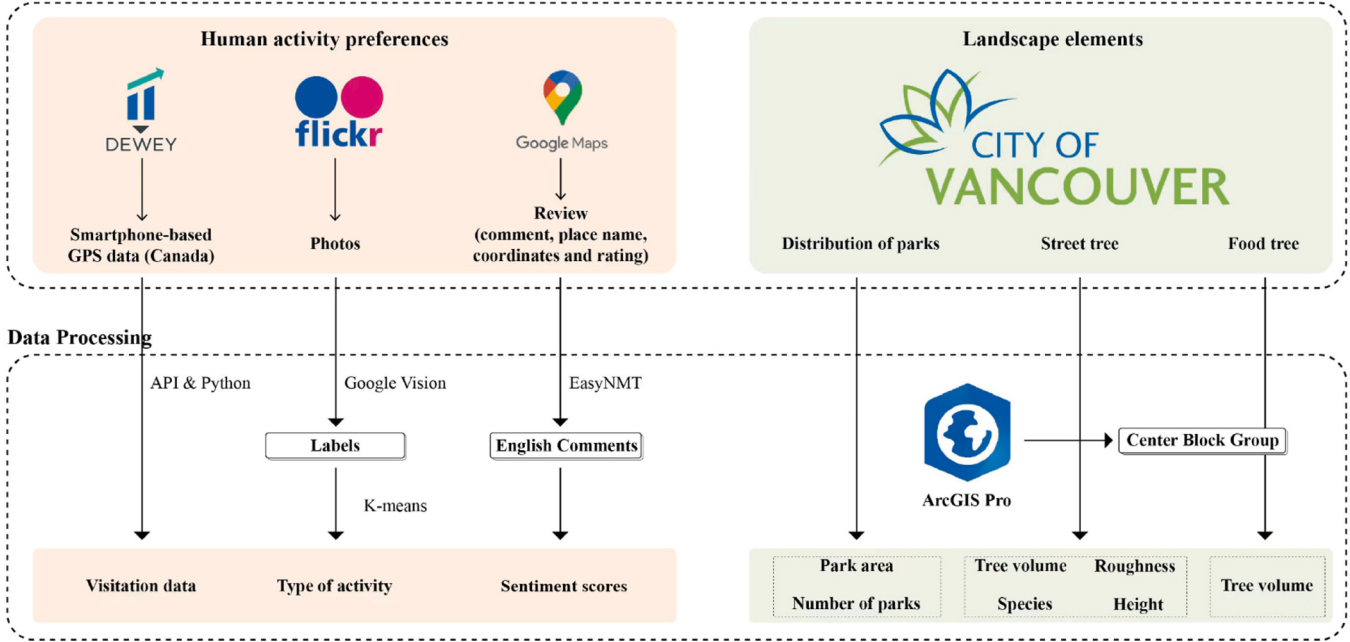
model for spatiotemporal analysis.

3.3. Dependent variable: weekday and weekend visitation

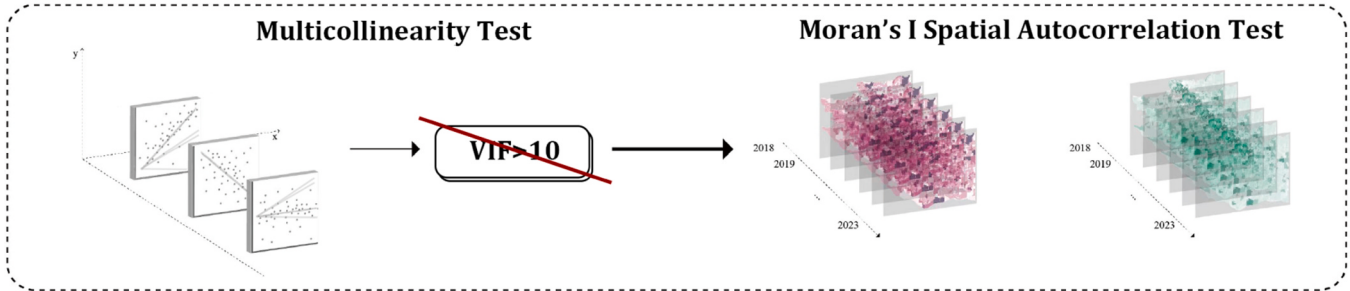
We used the "Canadian Neighborhood Patterns" dataset from the Dewey API (<https://app.deweydata.io/home>). This dataset, based on anonymized smartphone location data, reveals population movements across different areas (Dewey, 2024). It has been shown to be demographically and spatially representative and reliable when aggregating large geographic units (Song et al., 2020).

From this dataset, we extracted weekend and weekday visitation. We extracted and summarized visitation numbers from 7:00 am to 6:00 pm on weekends and from 7:30 am to 5:30 pm on weekdays. Summing the values for each block across all months of the year, we calculated the total annual unique visits per block as the base vitality data based on human activities (Appendix A).

Data Preparation, Mean and Types



Data Checking



Spatial Data Statistics

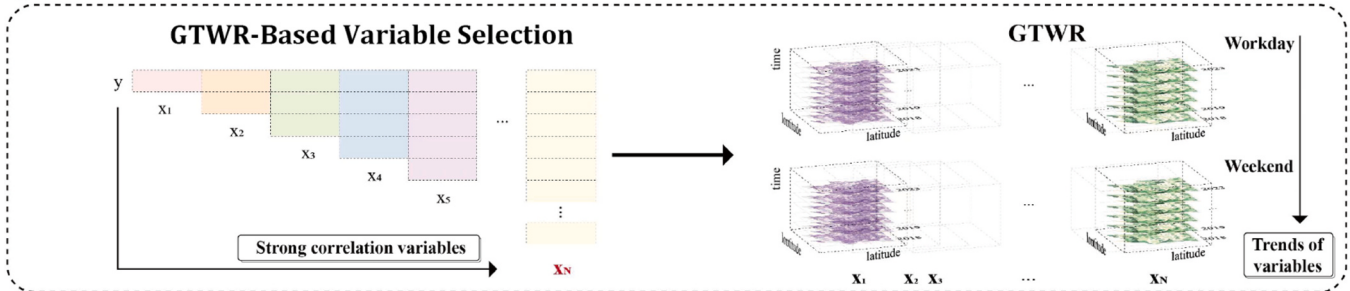


Fig. 2. Research framework.

3.4. Independent variable: activity diversity, sentiment scores and natural elements

3.4.1. Activity diversity: image-based social media

Urban vitality is influenced not only by physical design but also by human interactions and the diversity of activities occurring within spaces (Jacobs, 1961). To capture the multidimensionality of activity as an independent variable, we utilized Flickr images, which provide spatiotemporal data and semantic labels reflecting users' activity interests (Chen et al., 2024; Yang et al., 2022a,b; Zhang et al., 2023a,b).

We collected 23,035 Flickr images from 2018 to 2023 via the Flickr API. The Google Vision API, a machine learning-based tool for image recognition and labeling, was then employed to label image elements

and classify activity themes, effectively representing public interactions (Chen et al., 2024; Ghermandi et al., 2022). Subsequently, we applied K-means clustering (Ding and He, 2004; Krishna and Narasimha Murty, 1999) to the TF-IDF numerical labels (Ghermandi et al., 2022), determining the optimal number of clusters using the elbow method and silhouette coefficient. To ensure the validity of the clusters, we examined the top-weighted label groups and manually reviewed images, assigning a distinct activity theme to each identified cluster.

3.4.2. Sentiment scores: text-based data from google review

Text-based location reviews reflect perceived spatial quality (Song et al., 2020). We collected Google Maps reviews centered on Vancouver using 14 outdoor-related keywords (beach, bus stop, ground, lake,

natural area, outdoor area, outdoor space, park, playground, public square, river, sea, square, walking). By dividing the area into smaller zones (0.03 longitude, 0.015 latitude), we retrieved 1691 locations and downloaded 392,451 reviews containing text, ratings, place names, coordinates, and dates. After removing entries without reviews and filtering for dates between 2018–2023, we obtained 174,113 reviews.

For sentiment analysis, we translated all reviews into English using EasyNMT and preprocessed the text with NLTK, including tokenization, lemmatization, and part-of-speech tagging. We extracted sentiment scores (positive, neutral, negative, composite) for each word based on a sentiment lexicon and aggregated them to rate each review (Fig. 3), providing an assessment of perceived spatial quality. Finally, we averaged the sentiment scores of reviews within each block using ArcGIS Pro to represent area ratings.

3.4.3. Urban nature distribution

Natural elements like parks, gardens, and tree-lined streets are crucial for enhancing urban life quality and significantly impact urban vitality (Chen et al., 2024).

We collected data on park distribution, area, and street trees (distribution, species, height, and roughness) from Vancouver's open data website, along with edible tree data from over 50 additional sources (Appendix B). Using ArcGIS Pro, we linked these data points to block IDs, extracting variables such as total park area, number of parks, street tree counts, proportions of top 10 tree species, and counts of trees by height and diameter categories.

To ensure data quality, we addressed outliers statistically and used neighborhood-based interpolation to fill gaps. Categorizing tree heights and diameters allowed a detailed yet manageable analysis of natural elements' effects on urban vitality in Vancouver.

3.5. Data analysis

3.5.1. The result of correlation and spatial diagnostic

We first explored the pair-wise correlations among the variables to identify potential interrelationships. To mitigate multicollinearity among the predictor variables, we then examined their Variance Inflation Factor (VIF) values and excluded five variables with VIFs exceeding 10. Spatial autocorrelation was assessed using Moran's I statistic to

determine whether the variables exhibited spatial dependence, thereby providing justification for the subsequent use of the GTWR method. Descriptive statistics (mean, standard deviation, minimum, and maximum) for all variables used in the analysis are reported in Appendix C.

3.5.2. GTWR-based variable selection and modeling under spatial autocorrelation

Given the significant spatial autocorrelation inherent in the mechanisms underlying urban vitality, preliminary results from Moran's I tests indicated a clear presence of spatial autocorrelation in the residuals (Dogan and Lee, 2024; Yang and Chen, 2025). Moreover, the initial model incorporated up to 53 environmental explanatory variables; thus, further variable selection was necessary to avoid excessive model complexity and mitigate the adverse effects of multicollinearity on interpretability and model stability. In this study, GTWR was employed to facilitate automatic variable selection, eliminating factors exhibiting limited or insignificant spatial explanatory power while retaining key variables (Huang et al., 2010). This approach effectively reduced potential model bias arising from spatial dependence (Liao et al., 2023).

The spatial weight matrix used in the GTWR analysis was constructed based on an adaptive Gaussian kernel function, utilizing the geographic coordinates of each spatial unit (Huang et al., 2010). The optimal spatial bandwidth was determined via a cross-validation procedure aimed at minimizing the corrected Akaike Information Criterion (AICc). Temporally, the model was structured using discrete integer years from 2018 to 2023, and the temporal dimension was incorporated into the spatiotemporal kernel, jointly calibrated alongside the spatial bandwidth through cross-validation.

To effectively assess and visualize spatial heterogeneity, the weighted average of each variable's regression coefficients was calculated for every spatial block over the six-year period. These averaged coefficients were subsequently visualized using ArcGIS to intuitively illustrate spatial variations. Finally, to evaluate whether spatial dependence remained after model fitting, Moran's I tests were also conducted on the residuals of the GTWR model as a post-model diagnostic. The weighted average formula applied is as follows:

$$\bar{x}_w = \frac{\sum_{i=1}^n \omega_i x_i}{\sum_{i=1}^n \omega_i} \quad (1)$$

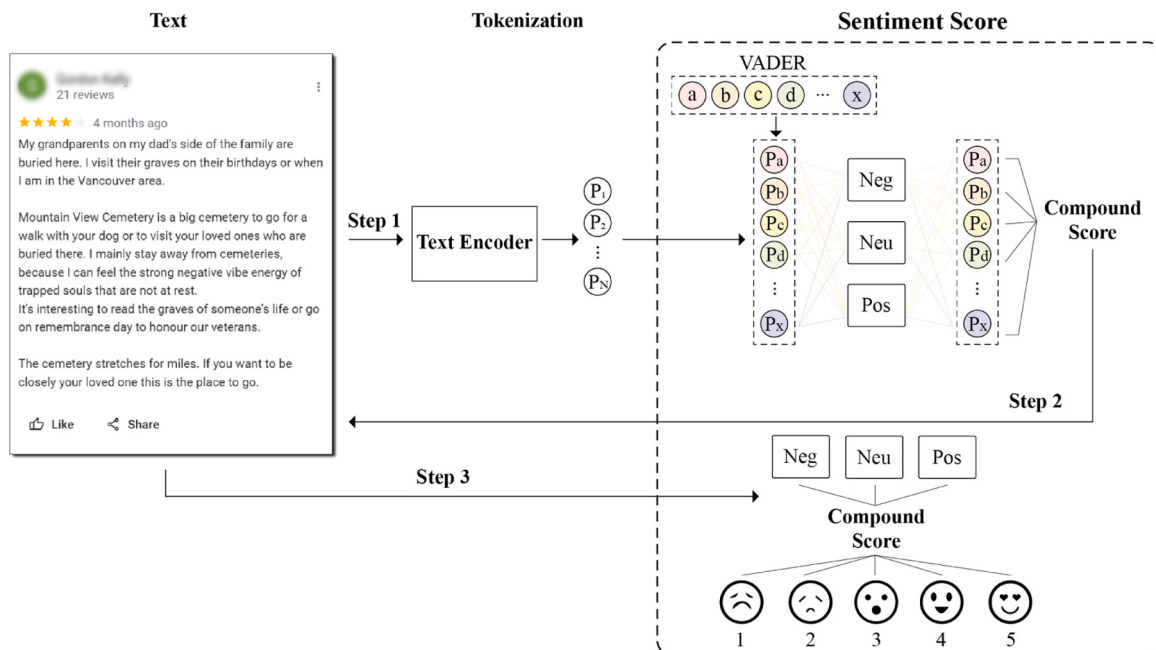


Fig. 3. Sentiment analysis process.

$\bar{x}_w$: represents the weighted average regression coefficient of the variable over the six-year period.

x_i : denotes the GTWR-estimated regression coefficient of the variable in year i .

ω_i : denotes the weight for year i , typically defined as the number of valid spatial units in that year.

n : represents the total number of years; in this study, $n = 6$ (from 2018 to 2023).

4. Results

4.1. Activity diversity results

4.1.1. Activity themes identification

We identified ten distinct urban activity themes by applying K-means clustering to semantic labels extracted from Flickr images using the Google Vision API (Fig. 4). The optimal number of clusters ($K=10$) was determined by employing the elbow method and silhouette coefficient, ensuring robust clustering validity (Figs. 4a, b). Fig. 4c summarizes representative semantic labels characterizing each cluster, and Fig. 4d provides an example of the automatic labeling process. Each resulting cluster clearly represents a specific type of urban activity (Fig. 4e), including Natural Landscape & Greening, Life & Cultural Events, Green Transportation, Food & Markets, Streetscapes & Living Scenes, Flowers & Plants, Urban Elements & Artistic Expressions, Urban Architecture, Traffic, and Waterfront & Outdoor Recreation (Appendix D). These activity categories provide a foundation for subsequent analyses of spatial-temporal urban vitality dynamics.

4.1.2. Changes in the activity's diversity affected by COVID-19

An analysis of ten activity categories from 2018 to 2023 shows that COVID-19 significantly reshaped activity patterns (Fig. 5). During the pandemic, there was a clear shift toward nature, outdoor, and daily life-related activities, reflecting a preference for open spaces. Cultural and social activities initially declined but rebounded as restrictions eased, eventually surpassing pre-pandemic levels (see Appendix E for details).

We also find that transportation patterns also shifted, with increased reliance on green transportation modes as traditional options declined due to lockdowns. Engagement with the urban built environment grew, as residents focused more on local neighborhoods and community spaces when long-distance travel decreased.

These trends underscore COVID-19's multifaceted impact on activity diversity, driving preferences toward nature, transforming social engagement, and reshaping transportation and urban space usage.

4.2. Screening of key factors influencing urban vitality

First, we examined Moran's I values and conducted multicollinearity diagnostics for all variables (Table 1). The results indicated that most variables exhibited significant spatial autocorrelation, confirming the appropriateness of employing geographically weighted regression methods. Subsequently, variables demonstrating high multicollinearity were excluded to enhance the stability of parameter estimation.

Specifically, the presence of Red Maple trees and higher sentiment scores were positively associated with increased visitation, suggesting that both the aesthetic appeal of certain tree species and positive emotional experiences enhance urban vitality (Fig. 6). Additionally, factors such as cultural activities, accessible transportation, and high-quality urban architecture contributed significantly to increased visitation, underscoring the importance of cultural richness, transportation accessibility, and well-designed spaces in fostering urban vitality (see Appendix F). Furthermore, sentiment scores correlated positively with the number of parks and specific natural features, highlighting nature's critical role in shaping emotional experiences and engagement within urban spaces.

These findings emphasize the multifaceted nature of urban vitality,

illustrating the complex interplay between environmental elements and human perceptions. Identifying these key factors offers valuable insights for urban planners aiming to enhance vitality within urban areas (see Appendix G for details).

4.3. Explore the spatio-temporal distribution of key variables

Using GTWR analysis over a six-year period, we first conducted variable selection through stepwise elimination, then examined the spatial and temporal impacts of 19 key variables on urban vitality (see Appendix H). The analysis focused on natural elements, activity types, and sentiment scores across regions, as well as differences between weekdays and weekends (see Appendix I for details).

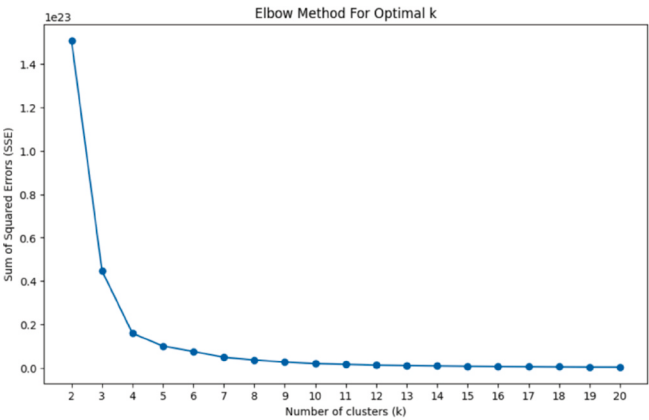
Initially, we generated a GTWR model report, which demonstrated a reasonable level of explanatory power. Additionally, we provided GWR and OLS model reports for benchmark comparison to assess the stability and suitability of the chosen modeling approach (Appendix J). To further examine the residuals, we applied Moran's I tests after model fitting. For the results showed that Moran's I was -0.000164 with a z -score close to 0.00, indicating that the observed value did not deviate from the random expectation, and a p -value of 1.00, which is far above the 0.05 threshold. These results indicate that the spatial autocorrelation test on the GTWR residuals was entirely insignificant, suggesting that the model adequately explained the spatial structure and achieved a satisfactory fit (Fig. 7). Moreover, all estimated coefficients from the GTWR model were statistically significant ($p < 0.05$). To provide a concise overview of the localized estimations, we report descriptive statistics for each explanatory variable in Appendix K.

Natural elements, such as street-tree volume, positively influenced urban vitality, exhibiting variations depending on time and location (Fig. 8). On weekdays, the influence of these elements was strongest in central and southern areas, while during weekends their effect shifted towards western and northern regions, reflecting changes in residents' activity patterns. Similarly, park availability significantly enhanced weekday vitality, particularly in the city center, whereas its influence became more dispersed during weekends. These patterns underscore the dynamic role of the natural environment in shaping resident activities across varying temporal and spatial contexts. Notably, the impact of specific tree species on urban vitality did not exhibit uniform spatial shifts; rather, it displayed high spatial concentration during weekdays and a more dispersed yet comparatively weaker influence during weekends.

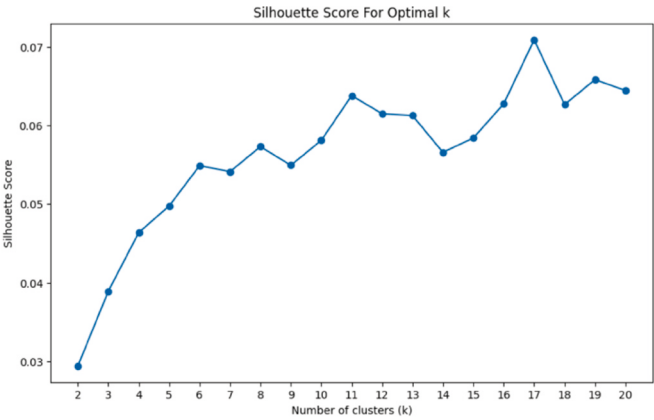
Different activity types influenced urban vitality in distinct ways. On weekdays, "Natural Landscapes & Greening" and "Flowers & Plants" were more influential in western and northern areas, indicating their integration into daily routines and commuting patterns (Fig. 9). On weekends, their impact concentrated in the west, suggesting a preference for leisure spaces rich in natural features. "Life & Cultural Events" and "Waterfront & Outdoor Recreation Activities" showed the strongest impact during weekends, particularly in areas with frequent cultural activities. In contrast, "Traffic" had reduced influence during weekends, indicating a shift toward non-motorized or environmentally friendly travel modes and reflecting changing behavioral patterns.

Sentiment scores also exhibited temporal and spatial variability. Positive impacts were more concentrated in commercial and office areas on weekdays, extending to major recreational areas during weekends, demonstrating enhanced positive emotions associated with leisure activities.

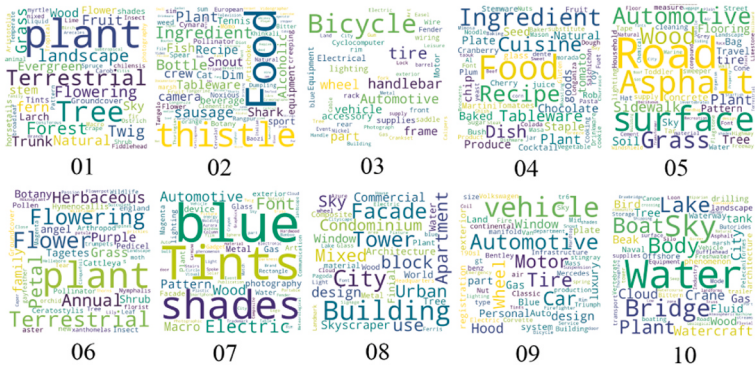
Examining weighted coefficients over the six-year period (see Appendix L), we observed notable shifts in three key areas (Fig. 10). Sentiment scores sharply declined during the 2020 pandemic but gradually recovered afterward, with weekday activities resuming faster than weekend social interactions. Traffic significantly decreased from 2020 and remained low, particularly on weekdays, largely due to increased telecommuting and reduced travel demand. Conversely, the role of parks in weekday vitality markedly increased post-pandemic,



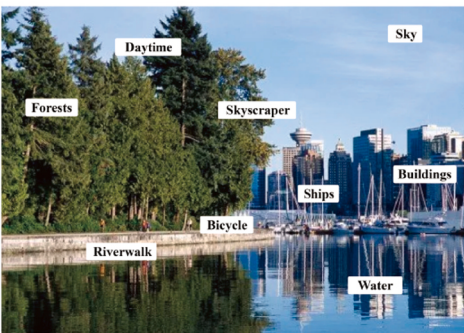
(a)



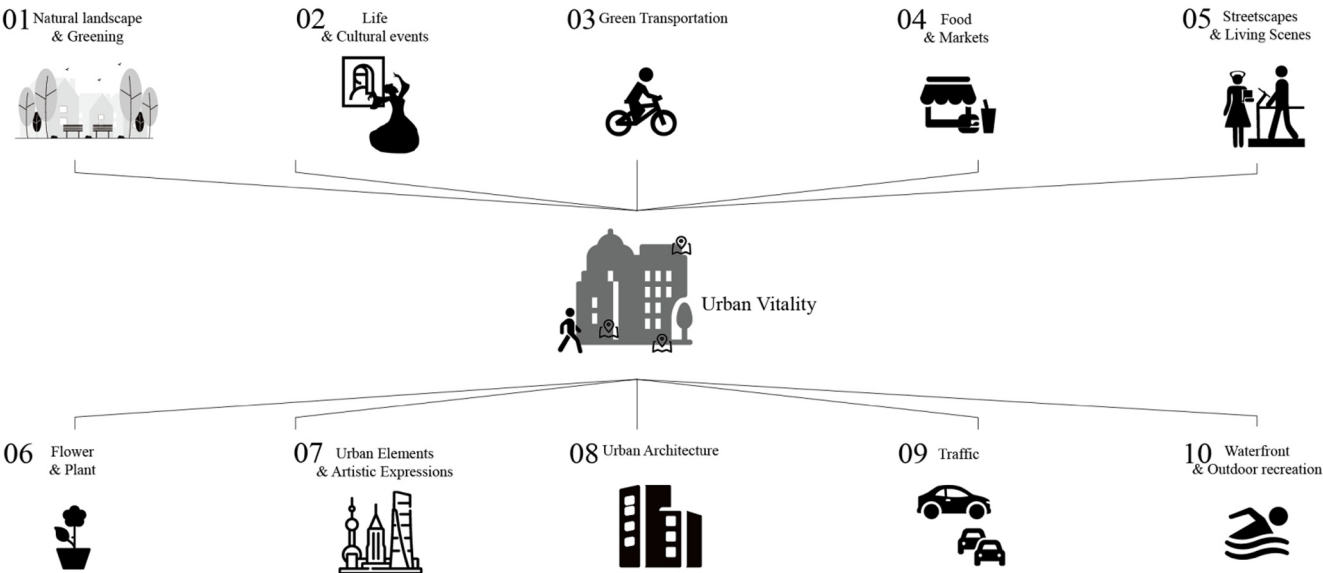
(b)



(c)



(d)



(e)

Fig. 4. Clustering results: (a) Elbow method. (b) Profile coefficients. (c) Label cloud image. (d) Tagged by google vision. (e) 10 labels clustering.

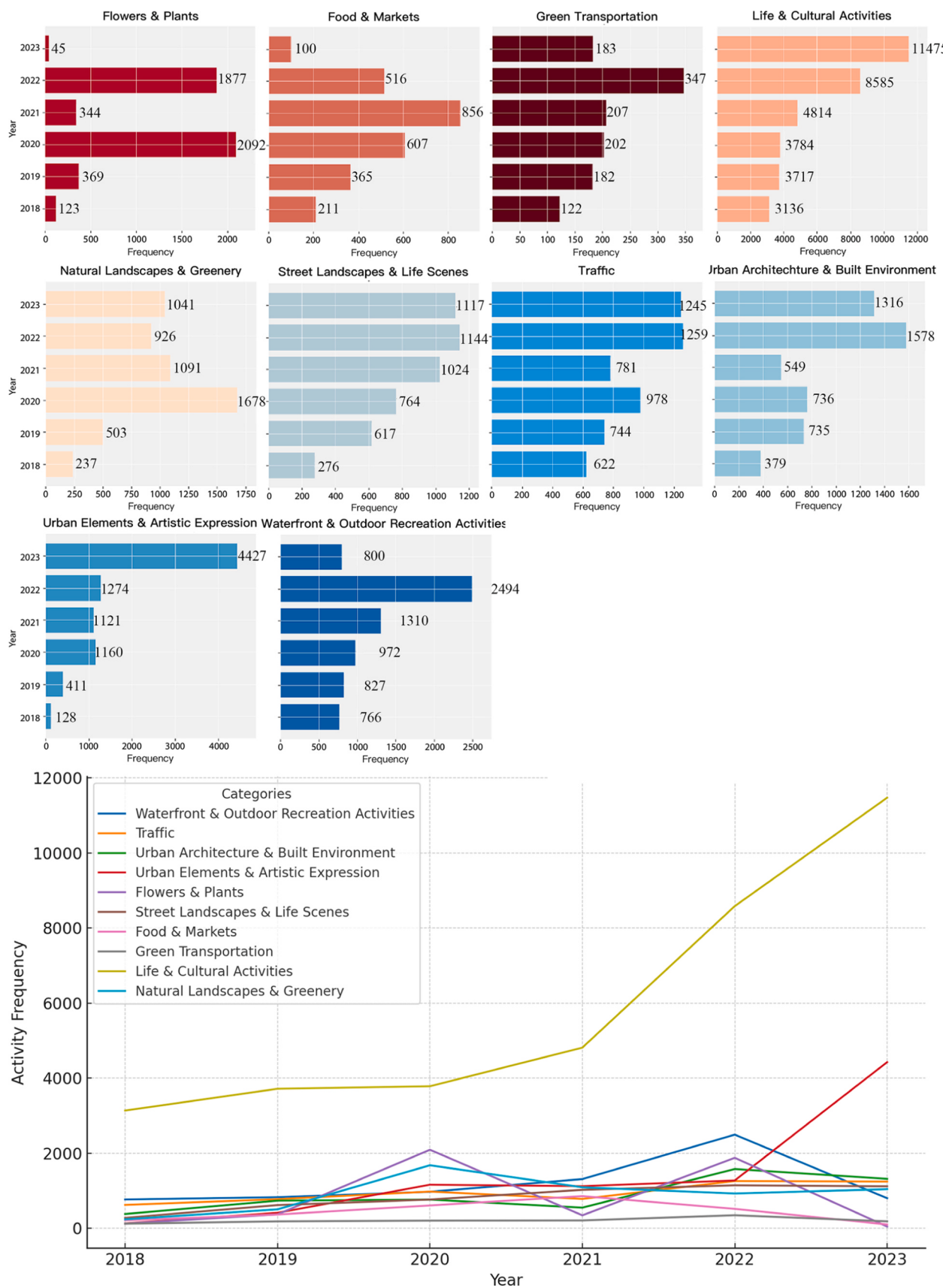


Fig. 5. Annual changes in 10 types of activities.

Table 1
Data verification results.

Variable	Moran_I	p. sig	VIF	Variable	Moran_I	p. sig	VIF
Sentiment Score	0.775	***	1.544	Red Maple	0.659	***	1.589
Tree Height_50_60	0.771	***	4.848	Tree Height_90_100	0.654	***	1.259
Norwegian Maple	0.77	***	2.904	TrunkDiameter_61_122	0.648	***	> 10
Pissard Plum	0.76	***	3.035	Park Area	0.638	***	1.386
Number of Trees	0.722	***	> 10	Acer rubrum	0.634	***	1.412
TrunkDiameter_0_61	0.722	***	> 10	TrunkDiameter_183_244	0.625	***	> 10
Tree Height_60_70	0.715	***	4.419	TrunkDiameter_244_305	0.624	***	> 10
Tree Height_30_40	0.71	***	8.612	Food Tree	0.623	***	1.151
Tree Height_70_80	0.707	***	3.399	TrunkDiameter_122_183	0.622	***	> 10
Tree Height_20_30	0.703	***	> 10	Life & Cultural Events	0.169	***	1.334
Nigra	0.7	***	2.557	Urban Elements & Artistic Expressions	0.141	***	1.789
Tilia euchlora	0.696	***	1.425	Urban Architecture	0.109	***	2.276
Tree Height_80_90	0.695	***	2.025	Traffic	0.104	***	1.446
Kwanzan Flower Cherry	0.682	***	2.29	Waterfront & Outdoor Recreation Activities	0.104	***	2.104
Number of Parks	0.673	***	2.037	Food & Markets	0.1	***	1.103
Pyramidal European Hornbeam	0.673	***	1.414	Flower & Plant	0.084	***	1.423
Akebono Flowering Cherry	0.672	***	1.628	Natural Landscape & Greening	0.074	***	1.711
Tree Height_40_50	0.67	***	6.061	Street Landscapes & Life Scenes	0.07	***	1.41
Tree Height_0_10	0.666	***	1.065	Green Transportation	0.021	***	1.271
Kobus Magnolia	0.666	***	1.369				

*: $p < 0.05$. **: $p < 0.01$. ***: $p < 0.001$.

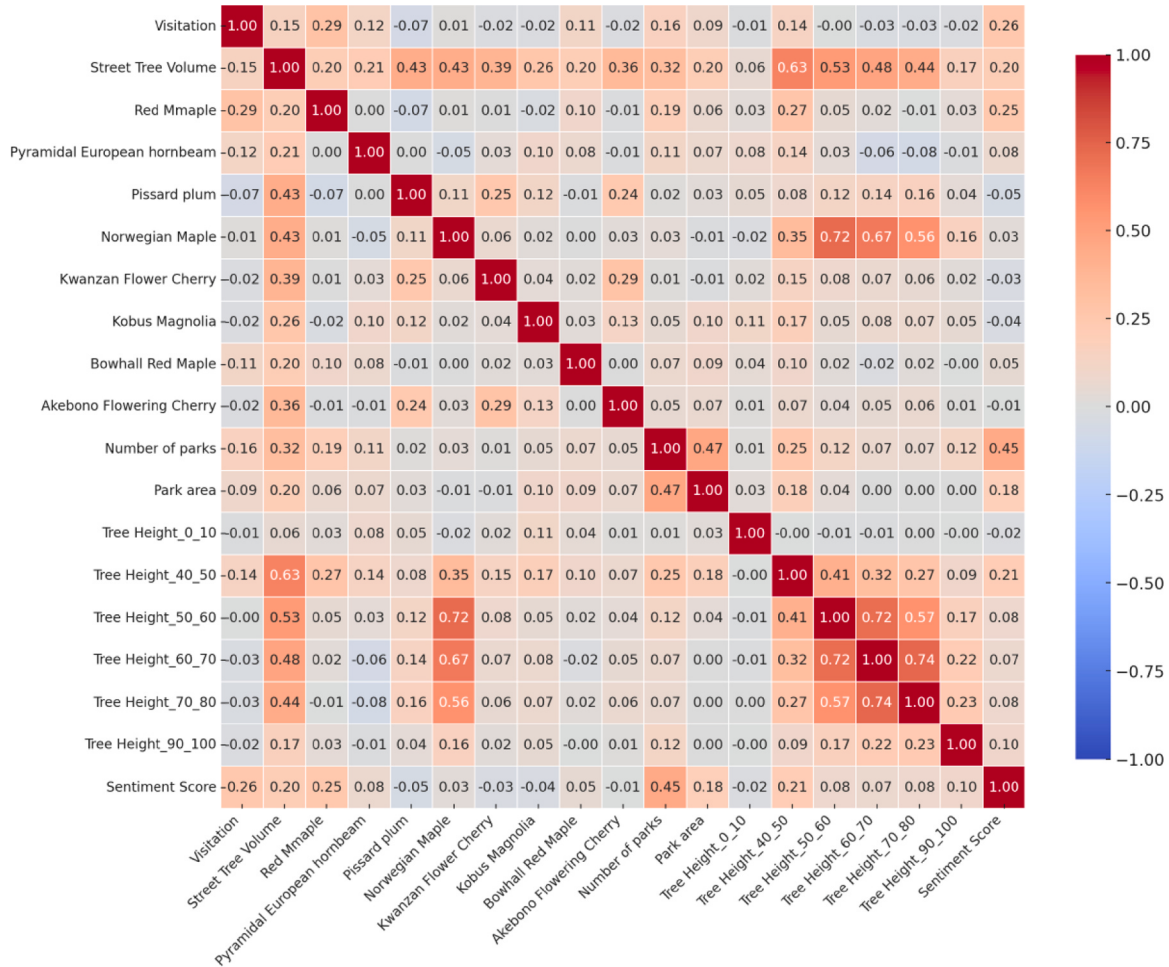


Fig. 6. Correlation results for green variable and sentiment.

reflecting heightened reliance on open spaces, while weekend park usage saw only modest growth, likely due to more varied recreational activities. These trends highlight evolving urban living patterns and underscore the need for urban planners to optimize public space utilization and adapt to changing travel behaviors driven by telecommuting

(see [Appendix M](#) for details).

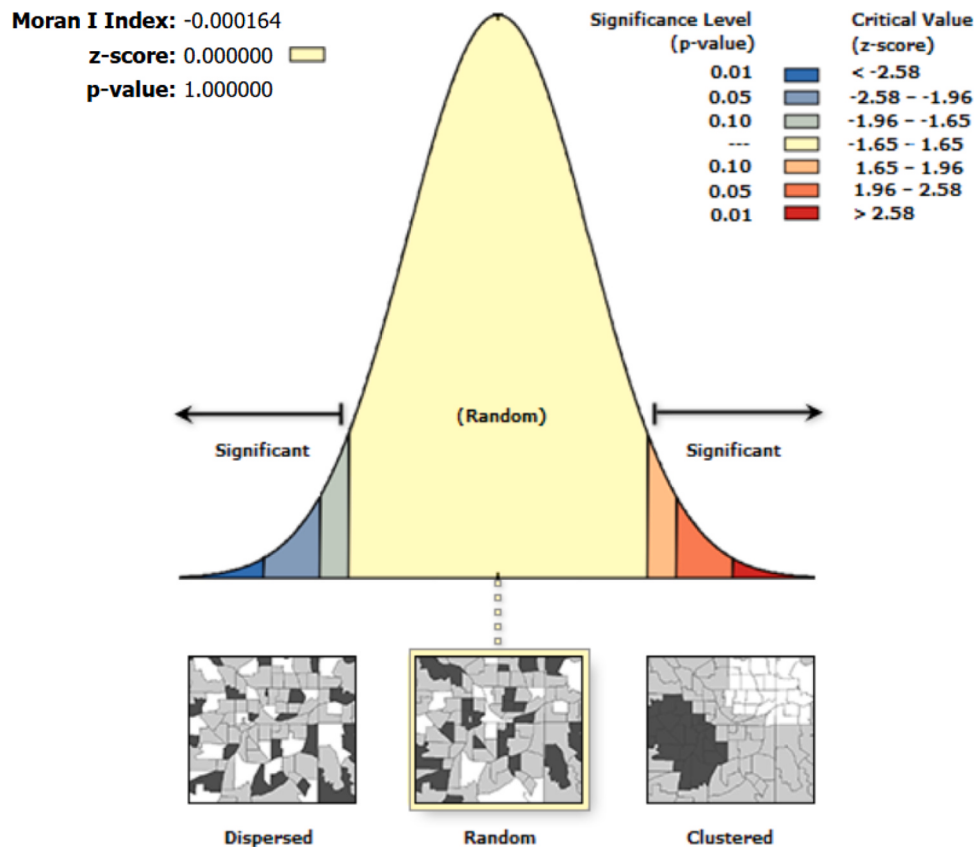


Fig. 7. Global Moran's I spatial autocorrelation significance diagram.

5. Discussion

5.1. Answers to the research questions and summary of findings

By integrating activity diversity and urban nature data using big data and machine learning, we assessed urban vitality. Our main findings are:

1) Attention to nature and outdoor activities increased significantly during the pandemic, while cultural, social, and transportation activities initially decreased but rapidly recovered by the after.

2) Sentiment scores, natural elements (tree species, number of parks), and human activity preferences (natural landscapes, cultural activities, transportation) are strongly associated with urban vitality. These effects became more pronounced during COVID-19, highlighting the moderating role of natural spaces.

3) The impacts of key elements on urban vitality differ across time and regions. The pandemic led residents to rely more on natural spaces and green transportation, altering the spatial distribution of urban vitality. This suggests that future urban planning should prioritize natural spaces and sustainable transportation.

The core findings outlined above provide the foundation for the in-depth discussions in Sections 5.2–5.4. In the following sections, we situate our results within existing research frameworks, analyze the underlying mechanisms, and offer practical implications for post-pandemic urban planning.

5.2. Types of human activities extracted from social media data and their changes during the epidemic

COVID-19 significantly altered activity patterns, revealing complex social, economic, and psychological dynamics. The surge in Nature & Outdoor Activities (such as Natural Landscapes & Greenery, Waterfront Recreation, and Flowers & Plants) reflects a renewed reliance on nature for physical health and psychological relief during the epidemic (Huai

et al., 2022; Kaplan and Kaplan, 1989; Ulrich, 1984). With social venues closed, residents found comfort and aesthetic satisfaction in nature-based activities, highlighting natural landscapes' role in alleviating stress and anxiety (Chen et al., 2024; Rapoport, 1977).

Conversely, Life & Cultural Activities initially declined but rebounded quickly as restrictions eased, underscoring the strong demand for social interactions and cultural engagement, which are crucial for mental health and community cohesion (Dobson et al., 2021; Gehl, 1971; Jacobs, 1961).

In transportation, the rise in Green Transportation modes like walking and cycling and the decline in vehicle use indicate a shift toward healthier, safer travel options during the pandemic (Belzunegui-Eraso and Erro-Garcés, 2020; Li et al., 2024). This suggests not only a change in travel habits but also a potential shift in urban planning towards sustainable transportation.

Furthermore, increased use of Urban Architecture & Built Environment and Street Landscapes also reflects a deeper reliance on local community spaces as long-distance travel decreased. Familiar neighborhoods became focal points for daily life, reinforcing residents' sense of security and belonging (Keshtkaran, 2019; Lynch, 1964).

In conclusion, COVID-19 reshaped daily activities, revealing interactions between social, economic, and psychological factors. These shifts reflect a reassessment of natural spaces, social interactions, transportation, and community reliance, offering insights for future urban planning. Prioritizing residents' psychological needs, creating spaces for social interaction, and promoting green transportation can enhance city sustainability and quality of life.

5.3. Impact of key elements on spatial and temporal heterogeneity of urban vitality

Our analysis reveals that natural elements, activity types, and residents' perception scores influence urban vitality differently across times

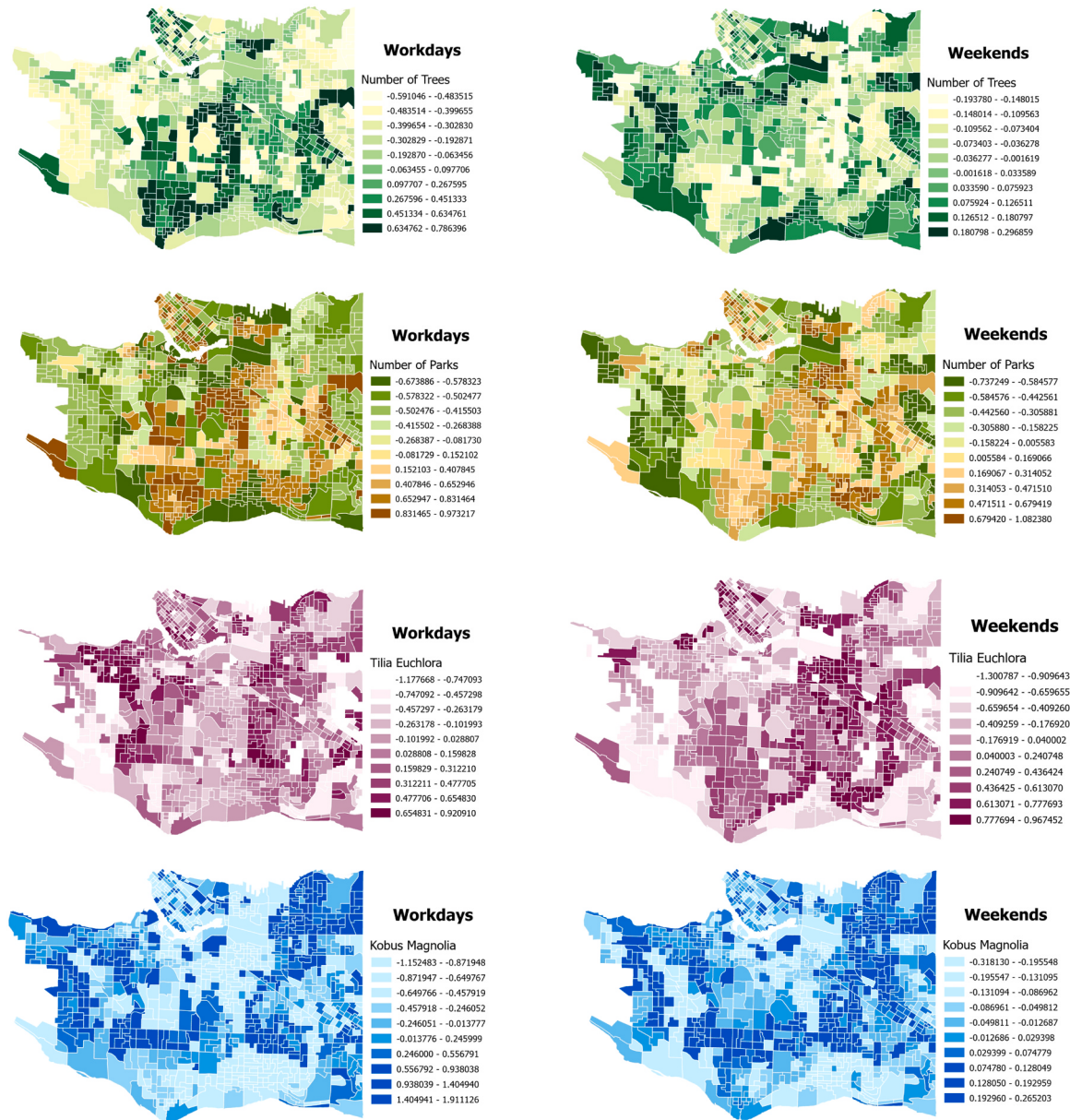


Fig. 8. The GTWR result of natural elements.

and regions, reflecting both urban physical structures and the combined effects of social, economic, and psychological factors.

Natural elements such as street trees and parks exhibit significant regional and temporal variations in their impact on urban vitality. On weekdays, street trees enhance vitality in central and southern high-density areas by providing psychological support and meeting diverse preferences through species variation, as demonstrated by the prominence of Akebono Flowering Cherry in city centers and Red Maple in peripheral regions (Wang et al., 2024a,b). On weekends, their influence shifts toward western and northern areas near natural hills, aligning with residents' recreational habits and offering psychological relief (Ulrich, 1984). Notably, the spatial influence of tree species on urban vitality varied temporally rather than remaining constant; however, a consistent pattern emerged, wherein their impact tended to be more spatially concentrated on weekdays and comparatively dispersed on weekends. Similarly, parks boost vitality in city centers on weekdays by serving as resting places and improving visual quality (Keshkaran, 2019). Their influence becomes dispersed on weekends, however, as residents prefer alternative outdoor venues. These findings underscore

the need for equitable park distribution to mitigate socioeconomic disparities (Liu et al., 2023).

Secondly, activity types also exhibit heterogeneity in their influence on urban vitality, shaped by sociocultural contexts. On weekdays, activities like Natural Landscapes & Greening and Flowers & Plants enhance vitality in center areas, improving commuting and living environments (Kaplan and Kaplan, 1989). Conversely, on weekends, residents favor relaxing natural areas and coastal area, while Life & Cultural Events and Waterfront & Outdoor Recreation Activities significantly boost weekend vitality in areas with concentrated cultural activities, supporting Gehl (1971) assertion that cultural activities in public spaces promote social cohesion and community vitality.

Finally, sentiment scores further vary spatially and temporally, illustrating the interplay between residents' psychological states and urban vitality. Positive sentiments are concentrated in commercial and office areas on weekdays and spread to major recreational areas on weekends, reflecting enhanced emotional experiences during leisure activities (Lynch, 1964). These variations highlight the importance of enhancing the visual environment to meet residents' psychological

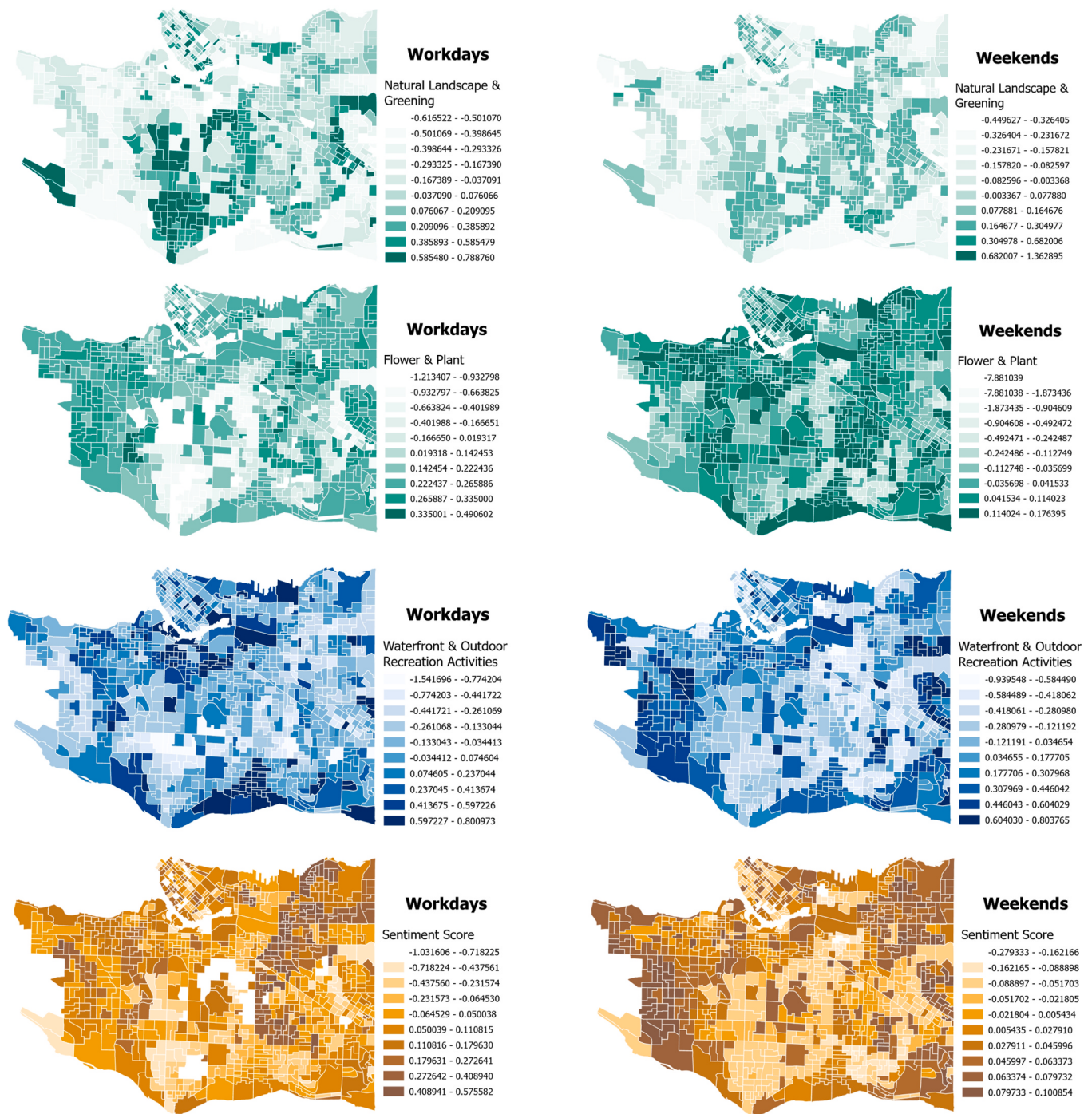


Fig. 9. The GTWR results for nature activities and sentiment score.

needs and boost overall urban vitality (Keshtkaran, 2019).

5.4. External shocks and changes in the mechanisms of COVID-19's impact on urban vitality

COVID-19 profoundly altered urban life, reducing human activities and interactions in public spaces vital to urban vitality (Gehl, 1971; Jacobs, 1961). Social isolation and the shift to telecommuting decreased public space usage, diminishing vitality. While closure policies helped control virus spread, they suppressed economic activity, underscoring the need for city managers to balance public health with economic vitality during crises (Li et al., 2024).

The drop in sentiment scores reflects the mental health toll of social

isolation. Natural spaces helped alleviate psychological stress (Ulrich, 1984), as seen in the increased focus on nature-based activities during the pandemic. Sentiment scores rebounded as lockdowns eased, especially on weekdays, indicating that resuming daily routines improved mental health (Kaplan and Kaplan, 1989). However, weekend recovery was slower, likely due to altered social interaction habits (Maslow, 1943).

Changes in transportation patterns reveal telecommuting's lasting impact. Reduced daily travel significantly decreased transportation dynamics in 2020–2021 (Belzunegui-Eraso and Erro-Garcés, 2020). Over time, residents increasingly opted for green transportation like walking and biking on weekends, signaling a shift toward healthier travel modes that may persist (Thaler and Sunstein, 2009). GTWR analysis showed

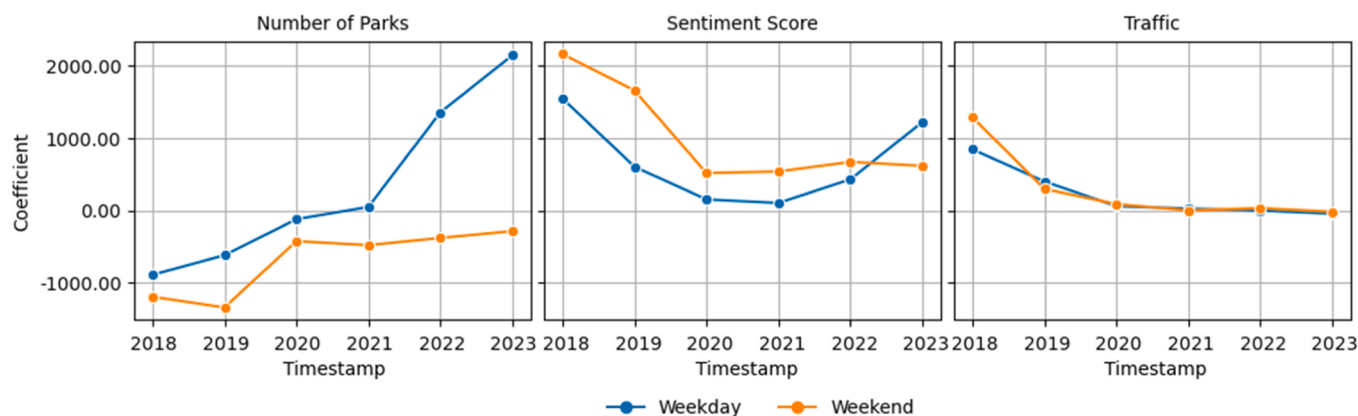


Fig. 10. Coefficients of each independent variable generated based on GTWR.

weekend increases in green transportation, suggesting that urban planning should prioritize sustainable travel options.

The pandemic highlighted the importance of public spaces, especially parks. With indoor activities limited, parks became primary recreational areas, enhancing urban vitality by providing psychological recovery and social support (Cai et al., 2022; Keshtkaran, 2019). The parallel rise in sentiment scores and park usage indicates that natural spaces contribute to well-being and community resilience, aiding vitality recovery (Putnam, 2001).

The lag in traditional transportation recovery, in contrast, reflects reduced dependence on commuting, pointing to the need for urban planners to reorient infrastructure priorities toward green transportation. The pandemic's lasting effects on social and lifestyle habits have shifted travel and activity patterns toward sustainable modes that are likely to persist. Urban design should embrace these changes, emphasizing green spaces and sustainable transportation to foster resilience and enhance quality of life.

5.5. Research implications and limitations

This study provides a comprehensive assessment of urban vitality by integrating multiple factors, but some limitations remain. Urban vitality is influenced by a broader set of factors, such as biodiversity, ecological composition, economic activity, and commercial density, which were not fully accounted for here. Additionally, natural landscape elements vary due to seasonal changes and human interventions, impacting their characteristics over time (Wang et al., 2022). Future studies could incorporate more multidimensional data and examine these temporal variations for a deeper analysis.

While we used big data, some blocks had null values in GPS-based vitality data, highlighting that data accuracy and sample size affect results. Moreover, as this study focuses solely on Vancouver, the findings may not fully apply to other cities. Field validation in culturally diverse regions is needed to ensure broader relevance (Hu et al., 2025).

6. Conclusions

This study developed a multidimensional urban vitality assessment framework that integrates behavioral, perceptual, and ecological factors. By combining machine learning techniques with GTWR, it systematically reveals the dynamic nature of urban vitality as an adaptive process. The findings suggest that urban vitality is not shaped by static structures or isolated factors but emerges instead as a comprehensive outcome of ongoing interactions among residents, the natural environment, psychological perceptions, and activity preferences—particularly in response to external shocks such as the COVID-19 pandemic.

In the aftermath of the pandemic, natural landscapes and green mobility emerged as critical mechanisms supporting urban resilience.

These elements not only significantly reshaped activity patterns and travel preferences but also played a crucial role in alleviating emotional stress and mitigating the effects of social isolation caused by lockdown measures. This shift highlights a fundamental transformation in the role of urban natural environments—from peripheral supplements to infrastructure to integral components of residents' everyday lives. Natural spaces have evolved into essential assets for sustaining urban functionality, enhancing resilience, and facilitating psychological recovery, thereby underscoring their emotional significance and restorative potential.

Theoretically, this study advances the understanding of urban vitality by introducing an interactional framework linking natural spatial structures, human perceptual experiences, and social behaviors. It moves beyond conventional planning paradigms, which predominantly emphasize spatial attributes, population density, or infrastructure alone, and instead highlights the central roles of perceptual dimensions, emotional states, and specific natural elements in assessing urban vitality. Methodologically, the study demonstrates substantial advantages in integrating multimodal big data with interpretable machine learning approaches. This integration effectively uncovers dynamic mechanisms and spatiotemporal variations within urban systems, providing robust empirical support for the adaptive transformation of urban governance.

Finally, based on the above findings, this study advocates for a fundamental shift in urban governance at the practical level. Urban environmental development should transition from an infrastructure-centered model toward a more perception-oriented approach that prioritizes residents' sense of fairness and emotional well-being. This shift also calls for a departure from static, centralized planning toward data-driven, adaptive decision-making practices grounded in empirical evidence. The century-long evolution of the urban landscape from Shinjuku Gyoen to Omotesandō in Tokyo exemplifies this governance philosophy. Rather than adhering to fixed planning schemes, this area has adopted dynamic landscape adjustment mechanisms sustained over decades. Natural elements have consistently served as initiators guiding pedestrian flows and stimulating local vitality, evolving alongside changing urban functions and societal needs. This adaptive approach has fostered a co-evolutionary relationship between people and the environment.

This nonlinear, adaptive landscape governance strategy embodies the core concepts proposed by this study—namely, the "dynamic mechanism of urban vitality" and "perception-driven urban governance." In the face of compound challenges such as climate change, public emergencies, and social fragmentation, cities must prioritize developing public spaces that are resilient, inclusive, psychologically restorative, and ecologically valuable. The sustainability and well-being of future urban vitality will ultimately depend upon cities' capacities to foster deep connections between people and nature, cultivate community resilience, and implement adaptive governance.

CRediT authorship contribution statement

Yuxuan Lin: Writing – review & editing, Validation. **Shaopo Huang:** Writing – review & editing, Writing – original draft, Visualization. **Jiani Du:** Writing – original draft, Visualization, Software. **Mingze Chen:** Writing – review & editing, Supervision, Project administration. **Yuxuan Cai:** Writing – review & editing. **Yongming Huang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.landusepol.2025.107824](https://doi.org/10.1016/j.landusepol.2025.107824).

Data availability

Data will be made available on request.

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