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What are the environmental preferences of runners? Evidence from Guangzhou

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ABSTRACT

The impact of the built environment on running behavior is a subject of interest in existing theories. However, empirical evidence is limited due to data acquisition challenges. This paper addresses this gap by utilizing 3271 valid running routes sourced from the Chinese fitness app Keep to construct a running intensity index based on 10664 road segments in Guangzhou, China, with intensity values ranging from 0.000013 to 17.645459 m/m^2. It analyzes the spatial characteristics of running intensity. Using global and local regression methods, the study explores runners' environmental preferences concerning natural exposure, street environment, and neighborhood. The results indicate that streets with higher running intensity, exceeding 10.082 m/m^2, are closer to water bodies and green spaces, while lower-intensity areas, below 2.049 m/m^2, are often associated with busy traffic, noisy commercial activities, and sparsely populated regions. Global regression results demonstrate that positive environmental attributes, such as street greenery (OLS coefficient: 2.658**), promote running behavior, while negative attributes like street density (OLS coefficient: −18.681**), hinder it. However, several local regression results contradict these global findings. Our results offer valuable insights for planners and policymakers to develop targeted intervention strategies that enhance vibrant running streets, fostering the integration and symbiosis of urban public spaces.

1. Introduction

Public health and well-being are closely intertwined, with physical exercise playing a pivotal role in enhancing both (Althoff et al., 2017). As the quality of life improves, an increasing number of individuals are prioritizing their physical well-being, turning to fitness activities as a preferred option (Scheerder, Breedveld, & Borgers, 2015). In 2014, the State Council of China issued the "Opinions on Accelerating the Development of the Sports Industry and Promoting Sports Consumption", marking a pivotal moment where nationwide fitness has been elevated to a national strategy (Li, An, & Wei, 2023). Outdoor running is one of the most basic and primary forms of exercise for urban residents. Its advantages include low cost, flexible timing, and minimal environmental impact (Gan, Yang, Zeng, & Timmermans, 2021; Hong, Philip McArthur, & Stewart, 2020; Vich, Marquet, & Miralles-Guasch, 2019). Furthermore, long-term engagement in outdoor running offers numerous benefits, such as stress relief, physical and mental rejuvenation, improved bodily functions, and prevention of chronic diseases (Lee et al., 2017). Therefore, promoting outdoor running among citizens holds significant implications for enhancing public health and fostering urban vitality.

The rapid urbanization in China, driven by the real estate market and industrialization (Ma, Jiang, Zhang, Li, & Jiang, 2018), has often overlooked residents' running activities in urban planning (Azizi Mohammad, 2020). Despite the emphasis on nationwide fitness and the need for designated running spaces, the quality of running environments struggles to improve significantly amidst the dominance of motorized transportation (Sohrabi, Khreis, & Lord, 2020). Various factors within the built environment, including facilities, greenery, and street quality, exert significant influence on running behavior, constraining the choice

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of suitable running paths (Dong et al., 2023; Huang, Kyttä, Kajosaari, Xie, & Zhang, 2023). Individual running behavior and its collective regularity also reflect the demand for pleasant running environments, providing important evidence for authorities to improve these spaces and enhance their appeal (Huang, Tian, & Yuan, 2023).

Current research pays insufficient attention to running behavior, with most studies analyzing the influence of urban form on walking and cycling at various scales, from neighborhood to street levels (Aultman-Hall, Hall, & Baetz, 1997; Salazar Miranda, Fan, Duarte, & Ratti, 2021). However, running differs from these activities, and environments conducive to pedestrians and cyclists may not necessarily have an equal effect on runners. Some studies have begun to focus on running behavior, predominantly relying on field surveys to collect questionnaire and GPS trajectory data (Deelen et al., 2017, 2019; McCormack & Shiell, 2011; Yang, Yu, Liang, Tang, & Li, 2022). The former method yields limited data with significant collection challenges, while the latter struggles with accurately identifying running behavior. Although a few studies have utilized programming techniques to gather running trajectory data from platforms like Strava, the limited number of Chinese users on Strava hinders its effectiveness in reflecting running behavior in Chinese regions (Dong et al., 2023; Huang, Kyttä, et al., 2023; Huang, Tian, & Yuan, 2023). In contrast, the Keep app, with over 200 million users and more than 1.1 billion kilometers of recorded running distance in 2019, offers an extensive dataset of running behaviors. Due to its large user base and comprehensive running records, Keep serves as an ideal platform for analyzing the running behavior of Chinese users in this study. While Strava provides raster data to analyze the popularity of running routes, Keep directly offers vector data of individual running tracks. In this study, we define running intensity as the total length of running routes per unit area within street buffers, based on Keep's detailed route data. This concept is similar to the raster heat map used in Strava, which reflects the popularity of routes. In terms of research focus, most studies concentrate on the physiological and psychological benefits of running, such as immunity enhancement and anxiety relief, with insufficient attention given to running behavior itself (Chakravarty, Hubert, Lingala, & Fries, 2008). Methodologically, studies investigating the relationship between running behavior and the built environment typically employ global regression methods such as ordinary least squares regression, logistic regression, and two-level multilevel regression, treating running behavior as a holistic concept and overlooking its spatial patterns, thus failing to analyze spatial heterogeneity (Deelen et al., 2019; Ettema, 2015).

This paper addresses existing gaps by utilizing Python scripts to acquire running trajectory data from the Keep app in Guangzhou's core area, calculating running intensity based on road segments, and employing spatial analysis and geographically weighted regression to analyze the spatial characteristics of running intensity and its influencing factors. The study aims to address the following questions: (1) Does running intensity exhibit spatial distribution patterns, such as proximity to green vegetation and water bodies? (2) How do natural exposures and urban artificial environments influence running intensity, and do these effects display heterogeneity? The research results contribute significantly in several aspects: Firstly, they shed light on the impact of the built environment on running, a novel focus in urban geography. By capturing residents' outdoor running characteristics and the variations in running behaviors due to different built environments, the study enhances the understanding of the intrinsic relationship between the built environment and running, providing new theoretical support for the development of urban geography. Secondly, amidst a shift in urban development focus from vehicles to residents, analyzing the spatial distribution of running intensity and its influencing factors provides better guidance for urban residents in choosing running environments, thereby improving their health and quality of life. Thirdly, this study inspires planners to view urban public spaces from a bottom-up perspective and address fairness issues related to supporting facilities along running routes. By integrating green spaces, parks, squares, and streets into running behaviors, urban spaces can become more integrated and symbiotic, improving the urban internal structure and promoting functional integration.

2. Literature review

2.1. Research subjects related to running behavior

Current research subjects on running behavior mainly involve three aspects: the health effects of running, the characteristics of running, and the assessment of the runnability of built environments. Among these, the health effects of running received the most attention, with further categorization into psychological and physical health effects. Regarding psychological health, the relationship between green running environments and psychological recovery was primarily examined. Specifically, the optimal dosage of this effect and its differences across age and gender were explored (Barton & Pretty, 2010; Hansmann, Hug, & Seeland, 2007; Huang, Jiang, & Yuan, 2022). The experience of running and satisfaction with the running environment are another important focus. Runners often prefer routes offering a complete running experience, typically characterized by independence, safety, and tranquility (such as within parks or along riverbanks) (Edensor, Kärrholm, & Wirdelöv, 2018; Hockey & Collinson, 2006). The quality and convenience of built environments, such as road greenery, traffic conditions, road density, road surface quality, and street lighting (Dong et al., 2023; Krenichyn, 2006; Schuurman, Rosenkrantz, & Lear, 2021; Shashank, Schuurman, Copley, & Lear, 2021; Zhang, Liu, Ma, & Yan, 2023), significantly impact running comfort, perceived resilience, and satisfaction. Furthermore, the physical health benefits of running are well-documented. Regular running contributes to strengthening bones, weight control, immunity enhancement, and a reduced risk of cardiovascular diseases (Lavie et al., 2015; Oja et al., 2016). However, some studies emphasize the exploration of negative aspects related to running addiction (Williams & Thompson, 2014).

Research on running behavior is currently limited to micro-level qualitative approaches such as field surveys, questionnaires, interviews, and observations, severely constraining our focus on running itself (Rinne et al., 2022). Key aspects of running behavior include frequency, amount, duration, and intensity of running. For instance, field surveys and interviews can provide data on residents' running times and frequencies within specific areas, with the number of runs per unit time (week or month) serving as the running frequency (Ettema, 2015). By extracting grid values of each sample point from the open-source platform Strava, the running amount can be quantified (Dong et al., 2023). Alternatively, GPS routes from Strava can be used to calculate the running length per unit area of each street (Huang, Tian, & Yuan, 2023; Jiang, Dong, & Qiu, 2022). The underlying logic of theories in environmental psychology, such as environmental determinism, environmental-behavior interactionism, intrinsic motivation theory, field theory, social-ecological theory, and the hierarchy of walking, provides a basis for studying the influencing factors of running behaviors (Alfonzo, 2005; Bronfenbrenner, 1977; Lewin, 1951; Locke & Latham, 1991; McLeroy, Bibeau, Steckler, & Glanz, 1988; Watson, 1913; Wendel-Vos, Droomers, Kremers, Brug, & Lenthe, 2007). Overall, there remains a need to strengthen the focus on running itself. Although platforms like Strava offer insights into general patterns, there is limited research utilizing this data, and the number of users in China is restricted, potentially not fully reflecting Chinese individuals' running behaviors. Compared to other research subjects on running, running intensity of street snippets not only concerns the physical training of individual runners but also reflects the aggregated patterns of running, providing profound insights into urban sports environments (Hockey & Collinson, 2006; Luo, Yu, Li, & Liang, 2022). By examining the running intensity of street snippets, researchers can explore the fairness of sports spaces, assess whether sports resources are evenly distributed across different communities, and evaluate the contribution of urban planning to promoting residents' health activities, among other aspects.

The assessment of the runnability of built environments is a niche area within the scope of running behavior. Its primary significance lies in providing a vital perspective on running for "residents-oriented" urban planning by evaluating the running suitability (or unsuitability) of streets or spaces. Currently, only a few scholars have conducted assessments of runnability. For instance, Shashank roughly constructed a runnability index for the built environment of Surrey by analyzing quantified architectural features (Shashank et al., 2021). Li combined questionnaire surveys with multi-source big data to establish an evaluation system for the tunability of Guangzhou's built environment using the analytic hierarchy process (Li et al., 2023). Hodgson studied outdoor runners' perceptions of air pollution during running in London, assessing running unsuitability from the perspective of air quality (Hodgson & Hitchings, 2018).

2.2. Relationship between the built environment and running behavior

The built environment refers to human-made surroundings formed through alterations to the natural environment, including transportation, land use, landscaping, and more (Walford, Samarasundera, Phillips, Hockey, & Foreman, 2011). It is a significant spatial factor influencing physical activities among populations and a crucial entry point for urban planning to interventions aimed at enhancing public health (Koohsari, Badland, & Giles-Corti, 2013). While runners typically move at slower speeds compared to vehicles, they often exhibit heightened perception and sensitivity to their surroundings. From a behavioral standpoint, running habits may be influenced by factors such as navigation tools, geographical landmarks, optimal routes, and environmental conditions (Cools, Moons, Creemers, & Wets, 2010; Helbing, 1991; Streeter, Vitello, & Wonsiewicz, 1985). However, the impacts of these factors are manifested through the built environment. For runners, the choice of running locations is closely related to the recreational value of the built environment along the route, which can partly offset the additional costs of long-distance running. Certain attractive features, such as pedestrian-friendly facilities and diverse urban landscapes, may provide motivational factors for walking activities in certain areas (Zhang, Song, & Zhang, 2022). Studies on running preference also suggest that runners consider various built environment factors when selecting optimal running routes (Barnfield, 2016). Overall, the built environment profoundly influences running behavior, and their relationship warrants further attention. Drawing on existing research, this paper categorizes the built environment into three aspects: natural environment, street environment, and neighborhood environment, to analyze their impacts on running (Dong et al., 2023; Huang et al., 2022; Huang, Kyttä, et al., 2023; Huang, Tian, & Yuan, 2023).

Natural exposure factors typically have a significant impact on running. Contact with green and blue spaces during running can provide a tranquil and relaxing experience for runners, enhancing their enjoyment and encouraging exploration along the way (Qviström, 2016). Physically, green and blue spaces often offer fresher air and higher oxygen levels, while the presence of microclimates may create more comfortable ambient temperatures. This explains why areas abundant in greenery and large water bodies tend to become hotspots for running (Daniel, Lemonsu, & Viguié, 2018). However, areas with significant terrain variations are generally considered less suitable for running due to the increased energy expenditure required to overcome gravity and the challenge of maintaining speed compared to flat terrain (Campbell, Dennison, Butler, & Page, 2019). The impact of sky openness on running remains not fully understood. While it may promote running due to its open and airy nature, it could also pose challenges such as increased exposure to direct sunlight and a sense of insecurity from fewer obstructions (Dong et al., 2023). Street environment factors, including elements such as traffic-related infrastructure (e.g., traffic lights and road intersections), are often negatively correlated with running as they imply potential traffic safety risks (Nixon, 2012). Generally, higher densities of public transport stations have similar negative effects as the former two factors, but their higher accessibility to running locations may mitigate these effects (Huang, Kyttä, et al., 2023). The broader street environment, including factors like street density, the mix of amenities, and street architecture, has uncertain effects on running. This aligns with previous research findings (Dong et al., 2023; Huang, Kyttä, et al., 2023; Huang, Tian, & Yuan, 2023), as these factors may either promote running by increasing route options, service convenience, and environmental safety or restrict it by creating a fragmented experience. The impact of strong community cohesion and neighborhood experiences on outdoor running is evident. Research indicates that residents in poorer neighborhoods may have weaker access to green spaces and fewer opportunities for outdoor activities, thereby reducing running participation (Heynen, Perkins, & Roy, 2006). There are significant differences in the influence of different grades of neighborhood environments on recreational running activities (Abercrombie et al., 2008).

3. Materials and methods

3.1. Research area

This study selects Guangzhou as the research area for empirical analysis for the following reasons: Firstly, Guangzhou enjoys a maritime subtropical monsoon climate, with an average annual temperature ranging from 20 to 23 °C. The majority of the year sees clear weather, which is ideal for outdoor running. Secondly, Guangzhou boasts a vibrant running culture, with strong government support for running events. The "Guangzhou Marathon" has become a prominent symbol of the city's identity. Thirdly, as one of China's most densely populated cities, Guangzhou had approximately 18.677 million permanent residents in 2019, with around 38 million mobile internet users, providing a solid foundation for analyzing outdoor running using mobile device data.

Geographically, the central districts of Guangzhou, including Yuexiu, Tianhe, Haizhu, Liwan, and Baiyun, form the core area of the city. These districts showcase typical urban landscapes of Guangzhou and are often referred to as the "true Guangzhou". It boasts a diverse and well-developed urban landscape, typical of one of China's largest metropolitan areas. It is densely populated with a mix of residential, commercial, and public spaces. The core's extensive road network not only accommodates vehicular and pedestrian traffic but also facilitates outdoor running. In addition, its numerous natural spaces, including parks and the Pearl River's water systems, provide natural settings that encourage physical activity. While its topography is mostly flat, occasional gentle slopes add variation to running conditions. The availability of street amenities—ranging from public transportation and convenience stores to a blend of traditional and modern architecture—further enhances the area's accessibility and aesthetic appeal. As a result, the built environment of Guangzhou's core fosters a wide range of outdoor activities, making the study's findings relevant to other cities with similarly dense, well-developed urban cores. Building upon this, instead of relying solely on administrative boundaries, this study defines the research area based on morphology: the area where the Guangzhou Ring Expressway intersects with the administrative boundaries of the aforementioned five districts. This densely populated area covers approximately 214.57 km^2 and includes several popular running spots and routes in Guangzhou, along with various amenities. Using the OSM road network, the central lines of roads were extracted through a series of steps, including buffer construction, employment of Arcscan tools, and topological checks. The result is a simplified road network, as depicted in Fig. 1.

3.2. Research design

This research comprises four steps (Fig. 2): The initial step entails computing the running intensity. Firstly, a 20-m buffer is created

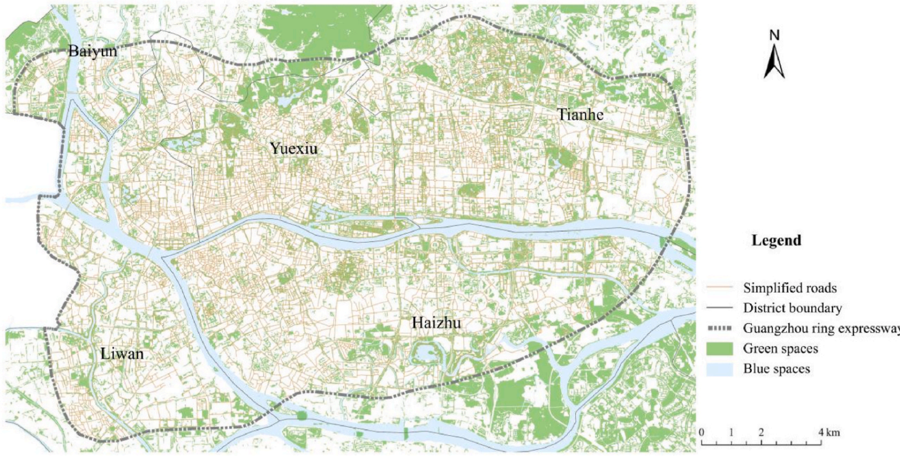

Fig. 1. Research area.

utilizing the simplified road network from OSM, simultaneously intersecting the preprocessed Guangzhou Keep running routes within the vector data of our study area. The 20-m buffer was selected to account for potential inaccuracies in GPS data, ensuring a more accurate measurement of running intensity. The "Summarize Within" tool in ArcGIS Pro 2.8 is then employed to determine the subtotal length of running routes within the buffer zone of each road segment. After excluding buffer units with zero total running route length, the running intensity for each remaining unit is derived by dividing the total length by the area of each buffer zone. The second step involves spatial analysis. Natural break points and Moran's I statistics in ArcGIS Pro 2.8 are applied to analyze the spatial hierarchy and clustering characteristics of running intensity. The third step entails collecting variables affecting running intensity. Through a literature review, variables are categorized into three types: natural exposure factors, street environment factors, and neighborhood factors. Fourteen indicators under these categories are determined using street view images, remote sensing data, building vector data, various types of POIs, and housing transaction data. The fourth step is determining the optimal buffer zone for regression analysis. Buffers of 50, 100, 150, and 200 m were constructed for each street unit to account for the varying spatial influences of the running environment. This range is supported by existing literature and reflects the distance within which runners are most likely to perceive and be affected by their surroundings, allowing for accurate calculation of the 14 indicators within each buffer zone (Huang, Kyttä, et al., 2023). Subsequently, a global regression using the OLS model is employed to determine the buffer zone with the best model fit for global analysis, and local regressions are conducted using the GWR and MGWR models, with the optimal cases across four buffer zones and eight scenarios compared, serving as a reference for the local regression analysis.

3.3. Data collection

Data collection involved crawling Keep running trajectories in Guangzhou in August 2019 using "Guangzhou" as a keyword. The collected data were then trimmed according to the research area, with various invalid trajectories such as duplicates, excessively short trips, and mismatched locations removed. This resulted in 3271 valid running trajectories. Subsequently, the road network was divided into multiple segments based on the rules of interruption at intersections, and 20-m buffers were constructed. The lengths of all running routes that partially overlapped or were completely within each road segment buffer were then tallied. Finally, the total length of running routes was divided by the area of their respective buffers to calculate running intensity. After excluding street units without running routes, the study encompassed 10664 units with running intensities ranging from 0.000013 to 17.645459 m/m^2.

Based on the literature, exposure to natural environments significantly impacts the frequency, satisfaction, and recovery of running exercises. This study investigates five variables related to natural exposure that may influence running intensity: Normalized Difference Vegetation Index (NDVI), terrain slope, distance to the nearest blue space, Green View Index (GVI), and Sky Openness Index (SOI). NDVI, acquired from Landsat 8 OLI and TIRS with a 30-m spatial resolution from the USGS Earth Explorer website, is utilized. The formula for calculating NDVI is NDVI = (NIR-R)/(NIR + R), where NIR represents the near-infrared band and R represents the red band. Negative NDVI values are excluded, resulting in values ranging from 0 to 1, with higher values indicating denser and healthier vegetation. Terrain slope is calculated using the "Slope" tool in ArcGIS Pro 2.8 based on DEM data obtained from the NASA Earth Science Data Platform. The average slope within each buffer zone is then determined. Distance to the nearest blue space is the distance from the location of running activity to the nearest water body. Water body raster images from Sentinel-2 are converted into vector polygons using the Google Earth Engine platform. The "Near" tool in ArcGIS Pro 2.8 is used to calculate this distance variable. The terms GVI (Green View Index) and SOI (Sky Openness Index) represent the perceived greenery and sky openness observed by runners. These indices are computed using deep learning methodologies, involving the following steps: Firstly, 11904 sampling points are generated along the simplified road network at uniform intervals of 100 m. Python code is then employed to retrieve panoramic street images at these sampling point coordinates. Using the deep learning model PSPNet, the collected images are semantically segmented to quantify GVI and SOI values at each sampling point. The specific formulas for calculating GVI and SOI are as follows: GVI = (Number of Green Vegetation Pixels)/(Total Number of Pixels) and SOI = (Number of Sky Pixels)/(Total Number of Pixels). Finally, statistical analysis is conducted to determine the average GVI and SOI values within the buffer zone of each road segment.

Street environments encompass a variety of factors that influence the route choices of runners, including traffic-related and other broader environmental aspects. This study examines several variables related to traffic, including road intersection density, traffic signal density, and density of public transportation stops. Road intersection density is calculated as the ratio of the total number of road intersections to the area of the road buffer. Similarly, traffic signal density and public transportation station density are computed using analogous processes, with data sourced from POI data from Amap. As for broader street environment factors, while variables such as street density, POI density, building density, and building height are believed to significantly influence running exercise, the magnitude and direction of these effects remain uncertain and can vary depending on specific contexts. Street

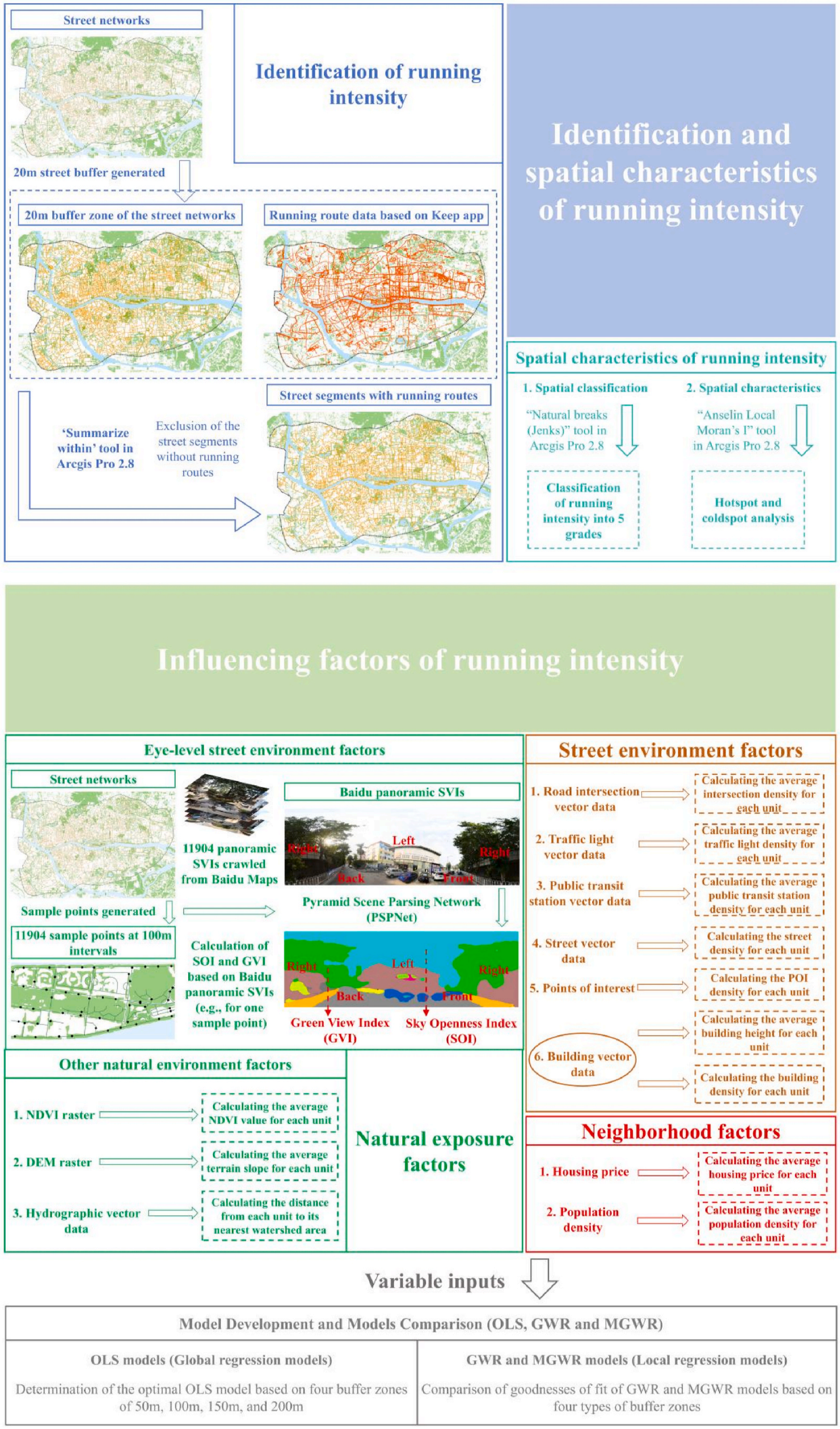

Fig. 2. Technical roadmap.

density is determined by calculating the ratio of the total road length within a specific buffer zone to its area. POI density is calculated as the ratio of the total number of different types of POIs within the buffer zone to the area. These POIs are categorized into 15 types according to the Amap, including food services, shopping services, lifestyle services, sports and leisure services, healthcare services, accommodation services, business residences, government institutions and social groups, science and education cultural services, financial insurance services, companies, road facilities, transportation service, public facilities, and passage facilities. Original data for building density and building height are sourced from building vector data retrieved from Zenodo database. Building density represents the total building area within each road segment's buffer zone relative to the buffer area while building height refers to the height attribute value of the vector data.

Neighborhood conditions often mirror the socioeconomic development status of local areas, with running being more prevalent in well-developed neighborhoods. In this study, two variables, housing price and population density, are utilized to gauge the socioeconomic status at the neighborhood level. The housing price variable is derived by collecting housing price data with coordinates from the Lianjia and Beike property websites. Subsequently, the average housing price within each buffer zone is computed. Population density represents the average population density within the buffer zone.

3.4. Methods

3.4.1. Spatial analysis

Spatial analysis encompasses two primary components: analyzing the spatial hierarchy of running intensity employing the natural breaks method, and exploring the spatial agglomeration of running intensity using Moran's Index (Anselin & Li, 2019; Moran, 1950). To examine the spatial hierarchy, this study utilizes ArcGIS Pro 2.8's natural breaks tool to categorize the running intensity into five levels. For the analysis of spatial agglomeration, a two-stage approach was adopted. Initially, the global Moran's I statistic is computed using inverse Euclidean distance. This provides parameters, including z-values, p-values, and Moran's I index ranging from −1 to 1, to reflect the overall distribution of running intensity. Positive values indicate clustering patterns, negative values indicate dispersion patterns. Subsequently, while global spatial autocorrelation captured the overall clustering characteristics, it could not discern specific locations of clustering. To address this, local Moran's I statistics are employed to identify local spatial clusters around each location, offering z-values, p-values, and confidence intervals. The results are classified into 4 spatial correlation types: High-High (H-H), High-Low (H-L), Low-High (L-H), and Low-Low (L-L).

3.4.2. Global regression model

This article employs the classic Ordinary Least Squares (OLS) regression to examine the relationship between running intensity and various variables (Hodgson & Hitchings, 2018; Huang, Kyttä, et al., 2023). In the model, the dependent variable is running intensity, while the independent variables consist of three categories of factors that may significantly affect running exercise (Table 1). The expression of the OLS model is as follows:

$$y_i = \beta_0 + \sum_{k=1}^{m} \beta_k x_{ik} + \varepsilon_i \tag{1}$$

In this equation, i(where $i = 1, \ldots,$n) represents the street buffer zone containing running routes, where y_i is the dependent variable, x_{ik} is the value of the kth predictor variable, β_k is the regression coefficient of the kth predictor variable, m is the number of predictor variables, β_0 is the intercept parameter, and ε_i is the random error term for observation i. To address multicollinearity issues, the variance inflation factor (VIF) is used for collinearity diagnosis, and only predictor variables with VIF values less than 7.5 are included in subsequent model analysis.

To ensure robust regression results and determine the most suitable buffer zone, buffer zones of 50, 100, 150, and 200 m are constructed around road units. The parameter values of each variable within these buffer zones are statistically measured. By comparing the regression results of the four buffer zones, the optimal size is determined.

3.4.3. Local regression model

The results of the OLS model reflect the overall characteristics of the region but overlook the complexity of local variations caused by spatial autocorrelation and heterogeneity. Geographically Weighted Regression (GWR) models can effectively address this issue by calculating local linear regression coefficients for each unit based on the attributes and proximity of neighboring units (Brunsdon, Fotheringham, & Charlton, 1996). The GWR model can be represented as:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{m} \beta_k(u_i, v_i) x_{ik} + \varepsilon_i \tag{2}$$

In this context, $(u_{i,} v_i)$ represents the coordinates of research unit i, $\beta_k(u_{i,} v_i)$ and $\beta_0(u_{i,} v_i)$ are the local regression coefficients of the kth predictor variable and intercept parameter at research unit i, respectively, with the remaining parameters being the same as in Equation (1).

The GWR model employs a uniform bandwidth during regression and does not account for variations in the spatial scale of each feature among different explanatory variables. Building upon the GWR model,

Table 1
Variable description and data sources.

Variable type	Variable name	Variable calculation	Abbreviation	Data source	Data Year
Dependent variable	Running intensity	Total length of running routes/Area of the buffer zone	R	Keep app	2019
Natural exposure factors	NDVI	Average value of NDVI	NA1	United States Geological Survey	2019
	Terrain slope	Average value of terrain slope	NA2	NASA Earth Science Data Platform	2020
	Blue space distance	Distance to the nearest blue space	NA3	Google Earth Engine platform—Sentinel-2 imagery	2019
	GVI	Average value of GVI	NA4	Baidu Street View Maps	2019
	SOI	Average value of SOI	NA5	Baidu Street View Maps	2019
Street environment factors	Road intersection density	Number of road intersections/buffer area	B1	Open Street Map	2019
	Traffic signal density	Number of traffic signals/buffer area	B2	Amap	2019
	Public transportation station density	Number of public transportation stations/ buffer area	B3	Amap	2019
	Street density	Total street length/buffer area	B4	Open Street Map	2019
	POI density	Number of POIs/buffer area	B5	Amap	2019
	Building density	Built area/buffer area	B6	Zenodo	2020
	Building height	Average building height	B7	Zenodo	2020
Neighborhood factors	Housing price	Average housing price	NE1	Lianjia and Beike property websites	2019
	Population density	Average population density	NE2	WorldPop platform	2019

this paper incorporates such bias by adopting the MGWR model, which assigns a separate bandwidth to each predictor to capture the non-stationary nature of spatial data (Fotheringham, Yang, & Kang, 2017). The expression of the MGWR model is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{m} \beta_{bwk}(u_i, v_i)x_{ik} + \varepsilon_i \tag{3}$$

In β_{bwk}, "bwk" represents the bandwidth used to calibrate the kth conditional relationship, while the remaining parameters are the same as those in Equation (2).

4. Results

4.1. Descriptive statistics

Table 2 presents descriptive statistics for variables across different radius buffer zones. Among the natural exposure factors, the mean values of each variable remain relatively stable, showing slight variations as the buffer zone radius increases. Specifically, the average slope value tends to increase, while the average NDVI and GVI values continuously decrease. The average SOI value initially decreases and then increases. The "blue space distance" refers to the distance from the nearest water body to the centerline of a specific road, with an average of 207.108 m across all buffer zones. As for street environment factors, the average road intersection density decreases with increasing buffer zone radius. Conversely, the average traffic signal density and public transportation station density first increase and then stabilize. The average values of street density, POI density, and building density decrease as the buffer zone radius increases. In contrast, the average building height initially increases and then decreases. In terms of neighborhood factors, the average housing price continuously increases with a buffer zone radius, while the average population density continuously decreases. From the perspective of variable correlations (Fig. 3), the absolute values of correlations for most variables increase with buffer zone radius. However, some correlations change directions. For example, the correlation between building height and slope changes from positive to negative. Similarly, the correlations between street density and blue space distance, as well as road intersection density and blue space distance, shift from not significant positive to significantly negative. The correlations between building height and road intersection density, and between street density and building height, change from not significant negative to significantly positive. Additionally, the correlation between building density and building height shifts from significantly positive to not significantly negative. Overall, although the average values of most variables decrease as the buffer zone radius increases, the correlations between variables significantly strengthen.

4.2. Spatial characteristics of running intensity

The natural breakpoint was chosen to classify running intensity because it effectively identifies natural groupings within the data, minimizing within-group variance and maximizing between-group variance. Despite the group size differences, this classification approach provides an accurate and meaningful representation of the spatial patterns observed in the data. The running intensity of road segments is divided into five levels: low (0–0.615 m/m^2), relatively low (0.616–2.049 m/m^2), moderate (2.050–4.628 m/m^2), relatively high (4.629–10.082 m/m^2), and high (10.083–17.645 m/m^2) (Fig. 4). Overall, higher running intensity roads are mainly distributed along water bodies and green spaces, offering quality natural landscapes, fresh air, and tranquil environments, which provide pleasant experiences for runners and facilitate a sense of community atmosphere and social connections. Moderate running intensity roads are mainly distributed near secondary schools and universities, where students, due to schedule constraints, often run in their surrounding environments. Roads with relatively low intensity are mainly distributed near government institutions, dense commercial areas, and sparsely populated areas. These regions are usually busy with traffic and noise, making them less suitable for running. Sparsely populated areas may lack running paths or facilities, further limiting running activities.

The global Moran's I for running intensity is 0.847, with a significance test p-value of 0.001 ($p < 0.01$). This indicates that the spatial distribution of running behavior is not random, as roads with similar running intensities are spatially clustered. To further investigate spatial heterogeneity, the local Moran's I index is used to obtain LISA maps (Fig. 5). The figure implies a significant local spatial autocorrelation, predominantly characterized by high-high and low-low clusters.

The distribution of high-high and low-high clusters is consistent, primarily found along both sides of the Pearl River, Huangpu Avenue, Flower City Square, and Dongfeng Road. These areas are popular urban landmarks, including riverside greenway corridors and university campuses. The parks and tree-lined avenues along the Pearl River and Flower City Square provide rare cool spots in Guangzhou's high-density urban areas, offering a refreshing microclimate that supports outdoor activities and urban cooling. Large residential areas on both sides of the river attract numerous runners with easy access to running streets. The well-connected running routes and robust support facilities minimize urban traffic interference, resulting in concentrated running activity overall. However, around Flower City Square, high-density commercial amenities often lack suitability for running, coexisting with some roads of low-high agglomeration types. Also, Huangpu Avenue and Dongfeng Road feature many primary and secondary schools, as well as university campuses, making students the primary contributors to running. Nevertheless, the running paths in this area intersect with numerous vehicular lanes, leading to a mixed layout of high-high and low-high clusters.

Table 2
Descriptive statistics.

Variable name	Buffer = 50m		Buffer = 100m		Buffer = 150m		Buffer = 200m	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
NDVI	0.413	0.128	0.404	0.115	0.401	0.106	0.399	0.100
Terrain slope (°)	14.674	10.333	14.793	9.792	14.861	9.535	14.865	9.358
Blue space distance (m)	207.108	16.621	207.108	16.621	207.108	16.621	207.108	16.621
GVI (%)	21.108	10.474	21.091	10.219	21.073	9.915	21.052	9.580
SOI (%)	37.391	9.561	37.389	9.314	37.396	9.024	37.406	8.718
Road intersection density (no./km^2)	1.920	10.144	1.266	7.522	1.084	6.325	0.994	5.699
Traffic signal density (no./km^2)	0.367	0.404	0.467	0.440	0.467	0.402	0.466	0.401
Public transportation station density (no./km^2)	0.142	0.544	0.148	0.543	0.157	0.542	0.156	0.541
Street density (km/km^2)	1989.317	483.866	1512.006	465.651	1358.313	439.625	1276.052	417.601
POI density (no./km^2)	276.087	213.407	275.711	211.459	275.163	208.720	274.474	205.350
Building density (%)	41.523	35.009	33.827	19.436	30.956	14.805	29.468	12.737
Building height (m)	21.626	21.312	22.833	20.500	22.854	17.601	22.819	16.250
Housing price (yuan/m^2)	41648.177	10889.595	41652.170	10855.822	41655.862	10815.853	41657.781	10766.992
Population density (pp/km^2)	338.589	288.971	338.333	284.592	338.122	279.390	337.867	273.712

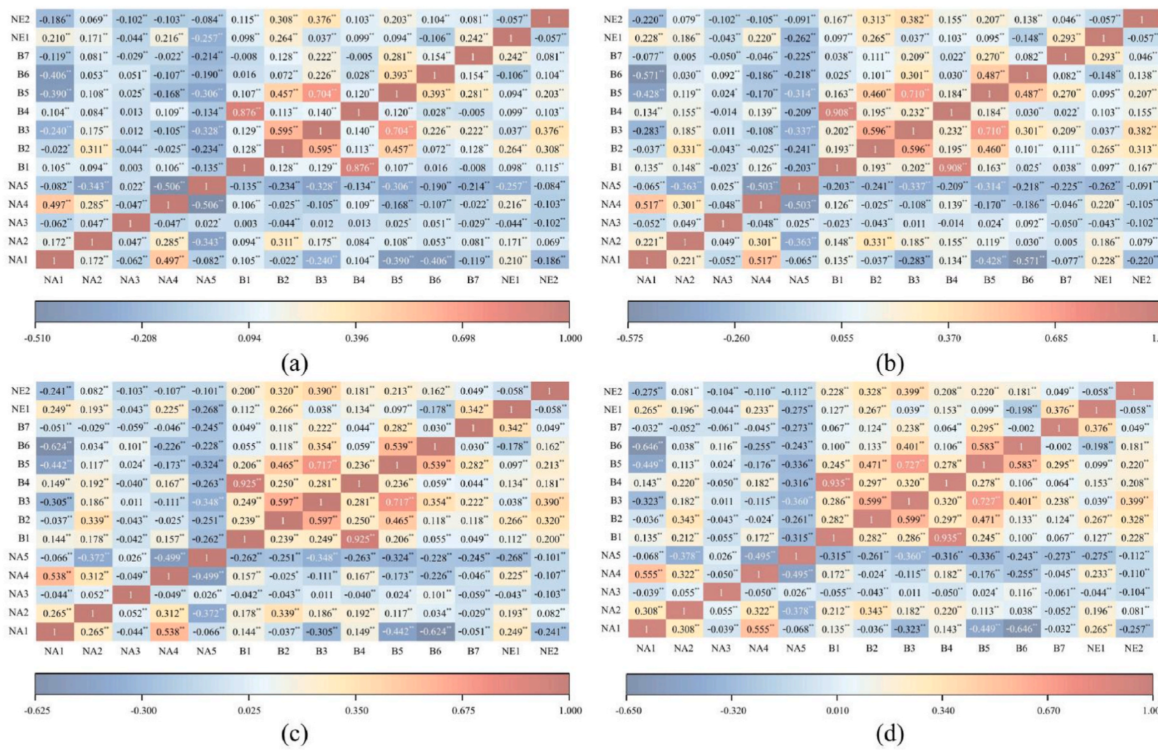

Fig. 3. Pearson correlation coefficients of explanatory variables (a) buffer = 50m; (b) buffer = 100m; (c) buffer = 150m; (d) buffer = 200m; **p < 0.01; *p < 0.05.

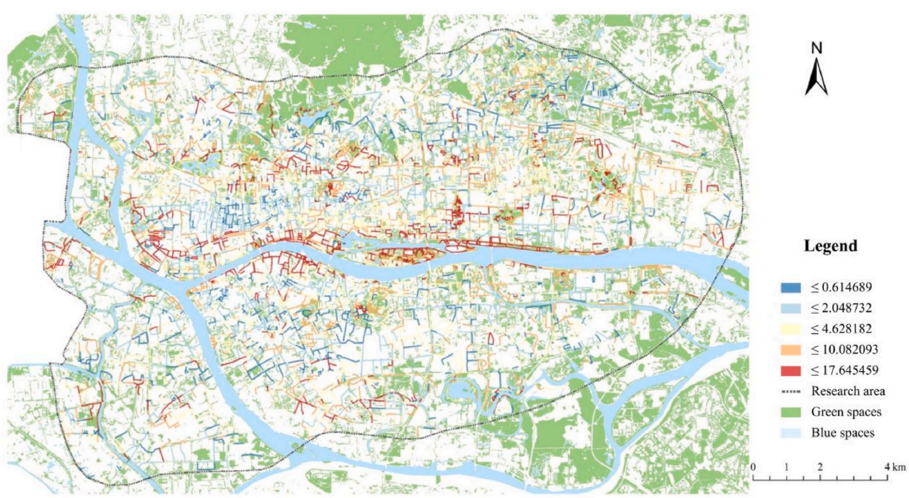

Fig. 4. Running intensity of road segments in the core area of Guangzhou.

The distribution of low-low and high-low clusters is consistent, forming a pattern of fragmented zones. These areas include the western part of Haizhu District, the southwestern and northern parts of Yuexiu District, and the northern part of Tianhe District. Although Haizhu District and Yuexiu District represent "classic Guangzhou", their overall running intensity is low, mainly due to the presence of numerous commercial and government facilities and busy roads, which are not conducive to running activities. However, there are also a few high-low clusters, indicating a distribution of high value units nearby. These units are often adjacent to parks, historic cultural districts, schools, and sports stadiums, such as Guangzhou Cultural Park, the Tenth Fu Historic Cultural District, Guangzhou University of Chinese Medicine, and Baogang Stadium. These locations provide conditions for local high-intensity running. In the northern parts of Tianhe and Yuexiu District, where the population density is low, the overall running intensity is similarly low but surrounded by numerous high-value units. The reasons for this pattern are similar to those mentioned previously: the presence of sporadic parks and schools contributes to pockets of higher running intensity within these otherwise low-activity areas.

4.3. Comparison and selection of regression results

As shown in Table 3, the comparison of OLS results reveals that the p-values of the Koenker (BP) statistics for all four buffer zones are less than 0.01, indicating a lack of consistency in both geographical and data space. Subsequently, the significance of the OLS models is determined using the Joint Wald statistics, with all model p-values being less than 0.01, confirming the overall statistical significance of the OLS models. When the buffer zone is 50m, the coefficient of the variable B1 (road intersection density) is negatively significant. However, for the other

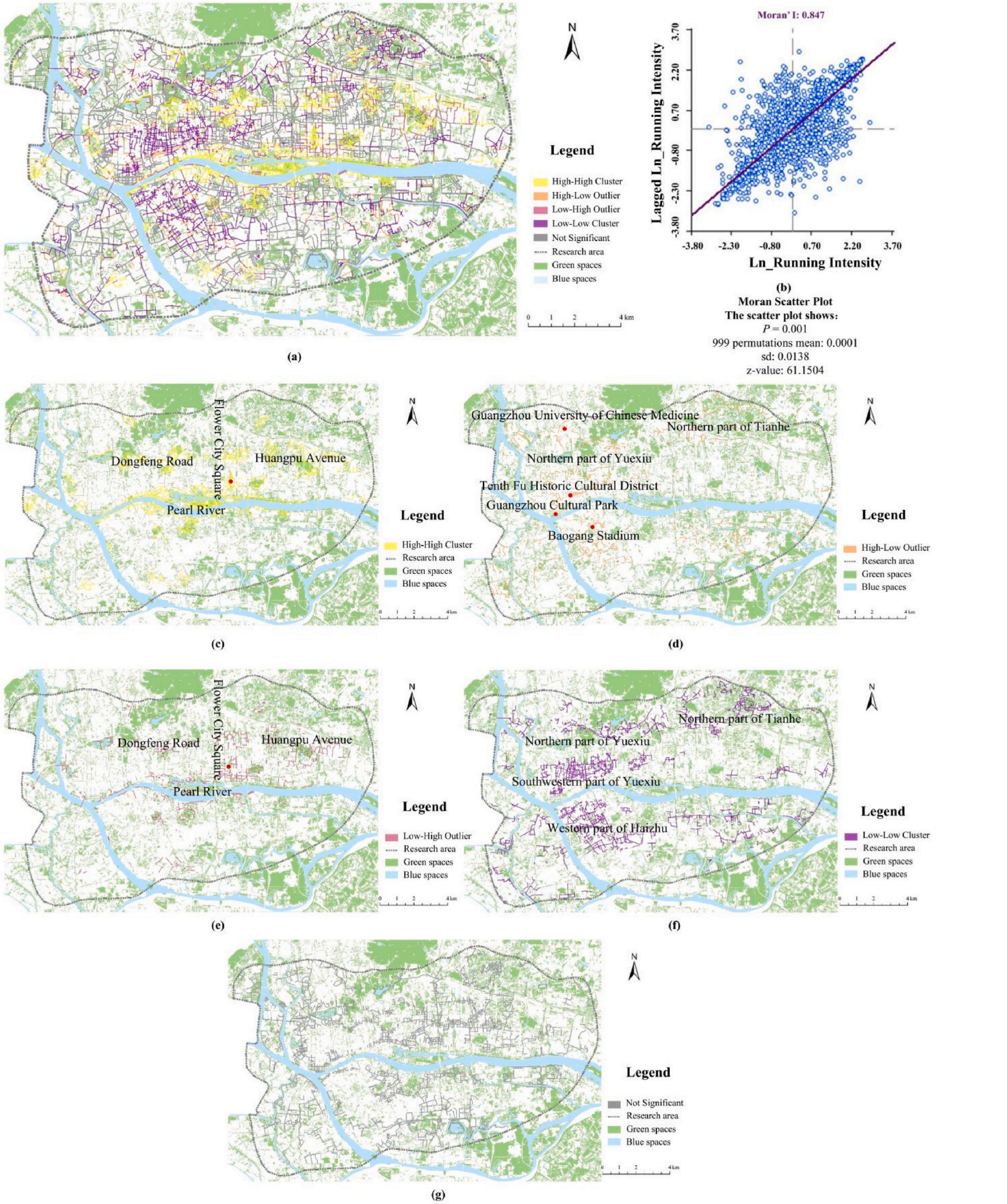

Fig. 5. LISA map of running intensity.

three buffer zones, its coefficient becomes positively insignificant. The signs and significance levels of the coefficients of the other variables across the four buffer zones remain largely unchanged. The results of the 200m buffer zone, which retains the maximum adjusted R^2 and the minimum AICc, are used for further analysis (the adjusted R^2 for the four models of buffer zones ranging from 50m to 200m are 0.207, 0.255, 0.312, and 0.354, respectively; the AICc values are 27811.483, 27135.801, 26289.319, and 25613.588, respectively). Linear regression, represented by OLS regression, provides good interpretability and is commonly used to examine the association between behavioral activities and environmental characteristics. However, it assumes spatial stationarity, meaning the association between running intensity and influencing factors is static. Nevertheless, running behavior often exhibits spatial heterogeneity, and the association between running intensity and influencing factors may vary spatially (Huang, Kyttä, et al., 2023). Therefore, further consideration is given to

Table 3
OLS results with four buffer radius options.

Abbreviation	Buffer = 50m			Buffer = 100m			Buffer = 150m			Buffer = 200m		
	β	p	VIF	β	p	VIF	β	p	VIF	β	p	VIF
NA1	2.29576	0.000	1.837	1.97404	0.000	2.359	1.42886	0.000	2.783	1.10894	0.000	3.135
NA2	−0.03126	0.000	1.282	−0.03442	0.000	1.355	−0.03370	0.000	1.443	−0.03283	0.000	1.547
NA3	−0.00060	0.000	1.033	−0.00044	0.000	1.039	−0.00040	0.000	1.043	−0.00034	0.000	1.049
NA4	1.57934	0.000	2.032	2.02033	0.000	2.124	2.38358	0.000	2.205	2.65778	0.000	2.302
NA5	−0.32380	0.080	1.947	−0.84879	0.000	2.074	−1.13478	0.000	2.180	−1.34639	0.000	2.328
B1	−0.00183	0.000	4.335	0.00011	0.779	5.803	0.00014	0.768	7.104	0.00068	0.185	8.219
B2	−0.00003	0.000	1.919	−0.00003	0.000	1.948	−0.00003	0.000	1.983	−0.00004	0.000	2.029
B3	0.00004	0.000	2.816	0.00005	0.000	2.894	0.00005	0.000	2.965	0.00006	0.000	3.067
B4	−11.47712	0.035	4.346	−29.05073	0.000	5.878	−17.87591	0.008	6.261	−18.68153	0.009	7.468
B5	−0.00007	0.000	2.609	−0.00006	0.000	2.778	−0.00006	0.000	2.984	−0.00005	0.000	3.236
B6	−0.64398	0.000	1.380	−1.81354	0.000	1.835	−3.07776	0.000	2.215	−3.87939	0.000	2.627
B7	0.00243	0.000	1.189	0.00566	0.000	1.244	0.00874	0.000	1.352	0.01106	0.000	1.496
NE1	0.00001	0.000	1.329	0.00001	0.000	1.384	0.00001	0.000	1.457	0.00010	0.000	1.521
NE2	0.00030	0.000	1.267	0.00041	0.000	1.302	0.00049	0.000	1.339	0.00057	0.000	1.380
Intercept	6.45743	0.000		7.76528	0.000		8.72604	0.000		9.44491	0.000	
Koenker (BP) Statistic	411.451	0.000		388.124	0.000		371.651	0.000		406.601	0.000	
Joint Wald Statistic	2347.490	0.000		3320.839	0.000		4713.799	0.000		5938.819	0.000	
AICc	27811.483			27135.801			26289.319			25613.588		
Adjusted R^2	0.207			0.255			0.312			0.354		

spatial non-stationarity effects using GWR and MGWR. In the OLS results of the 200m buffer zone, the p-value of B1 did not pass the test, and the VIF exceeded 5, indicating potential multicollinearity. Thus, the B1 variable is not included in subsequent GWR and MGWR models. The remaining variables are separately regressed using GWR and MGWR, yielding the model-fitting results in Table 4. The comparison reveals that, compared to OLS and GWR, the MGWR results exhibit higher overall model fit. Specifically, the MGWR result based on the 200m buffer zone shows the best performance. Therefore, this model is selected for further analysis.

5. Discussion

5.1. Relationship between built environments and running intensity

According to Table 3, both NDVI (NA1) and GVI (NA4) significantly influence running intensity. NA1 reflects the degree of greenness from a top-down perspective, while NA4 measures greenness from a runner's eye-level. The principles of environmental-behavior interactionism can be used to help explain their positive impacts (Smith, Foley, & Panter, 2019; Wali, 2023): The degree of greenness effectively represents a runner's longing for nature and their perception of the surroundings. Contact with green landscapes can increase the likelihood and frequency of running, as natural environments offer better air quality, relaxing scenery, and relative quietness. Exercising in such environments is more conducive to physical recovery and mental well-being compared to concrete-dominated settings (Boakye, Amram, Schuna, Duncan, & Hystad, 2021). This also aligns with intrinsic motivation theory, which suggests that natural environments enhance intrinsic motivation through enjoyable experiences, promoting regular running habits (Astell-Burt, Navakatikyan, White, & Feng, 2024; Vitale et al., 2022). Terrain slope (NA2), blue space distance (NA3), and SOI (NA5) are negatively correlated with running intensity. NA2 affects the comfort and perceived difficulty of running. Running is easier on flat terrain where runners can control their speed more effectively and minimize the risk of injury (Campbell et al., 2019). Running behavior is also more frequent near blue spaces, as the cooling effect of water bodies makes it more comfortable for runners and can reduce the risk of heatstroke (Nutsford, Pearson, Kingham, & Reitsma, 2016). NA5 is negatively correlated with running intensity, meaning that the more open the street, the lower the running intensity. This may be because Guangzhou, located in a subtropical region, has many sunny days throughout the year. A higher SOI implies more direct sunlight, leading to discomfort due to the rise in environmental temperature for runners. Moreover, runners may feel less secure and intimate in open areas, which could deter them from running (Liu, Li, Yang, & Hu, 2023). This relates to field theory, where the perception of safety and comfort in one's environment significantly influences behavior (Lewin, 1951).

In terms of street environment factors, the relationship between road intersection density (B1) and running intensity is not significant. On the one hand, more road intersections provide more path choices; on the other hand, they also imply more vehicles and increased running risks (Yang, Li, Liu, Fan, & Yue, 2024). Traffic signal density (B2) shows a significant negative correlation with running intensity. In areas with dense traffic signals, runners need to stop frequently for red lights, resulting in a fragmented exercise experience and weaker continuity. Additionally, runners must constantly monitor traffic conditions, leading to a sense of pressure and insecurity (Titze, Stronegger, & Owen, 2005). The social-ecological theory from the perspective of perceived environmental risk supports our explanation well (Stokols, 1996; Zhang & Zhou, 2024). Public transportation station density (B3) shows a significant positive correlation with running intensity, consistent with findings by Huang (Huang, Kyttä, et al., 2023). High-density public transportation stations enable runners to easily reach numerous outdoor activity locations. The convenience and reduced reliance on private transportation encourage more active participation in running activities.

Table 4
Model fitting of OLS, GWR, and MGWR models for four types of buffer zones.

	Parameter	OLS	GWR	MGWR		Parameter	OLS	GWR	MGWR
Buffer = 50m	R^2	0.208	0.931	0.944	Buffer = 150m	R^2	0.313	0.933	0.96
	Adjusted R^2	0.207	0.896	0.916		Adjusted R^2	0.312	0.907	0.94
	AICc	27811.483	12726.711	10163.227		AICc	26289.319	9814.147	6442.628
Buffer = 100m	R^2	0.256	0.944	0.961	Buffer = 200m	R^2	0.355	0.878	0.966
	Adjusted R^2	0.255	0.919	0.94		Adjusted R^2	0.354	0.836	0.949
	AICc	27135.801	9081.795	6910.908		AICc	25613.588	15153.888	4892.169

Furthermore, choosing public transportation contributes to energy conservation and emission reduction, promoting environmental awareness, which aligns with the health-conscious views of many runners. Street density (B4), POI density (B5), and building density (B6) are all significantly negatively correlated with running intensity. These factors typically imply more vehicles, pedestrians, other obstacles, and busier and noisier commercial spaces. Such environments lead to more frequent interruptions and passive interactions between runners and other road users, increasing safety risks for runners (Dong et al., 2023). Conversely, building height (B7) shows a significant positive correlation with running intensity. Taller buildings can create a sense of enclosure and security, which is important for running (Dong et al., 2023). These findings also align with environmental determinism, suggesting that the physical environment's characteristics, influence runners' perceptions of safety and comfort (Harden, 2012; Nielsen & Sejersen, 2012).

Neighborhood factors, including housing prices (NE1) and population density (NE2), are both significantly positively correlated with running intensity. Communities with higher housing prices are associated with aesthetically pleasing community environments. Higher housing prices often indicate aesthetically pleasing environments, which may include more parks, green spaces, and running trails, providing enjoyable emotional experiences for runners. These areas also tend to have higher socioeconomic status, implying that residents may have a greater health consciousness and be more willing to engage in outdoor running (Staats & Swain, 2020). Areas with high population density are typically residential neighborhoods where a culture of health consciousness and healthy lifestyles may be more easily formed. Like street environment factors, these two factors are also grounded in environmental determinism and social-ecological theory, as densely populated areas tend to foster social interactions that promote physical activity (Harden, 2012; Nielsen & Sejersen, 2012; Stokols, 1996; Zhang & Zhou, 2024). Individuals in such areas are more likely to be influenced by their neighbors and more exposed to information about health and physical exercise, thereby increasing the likelihood of running (Rosenkrantz, Schuurman, & Lear, 2024).

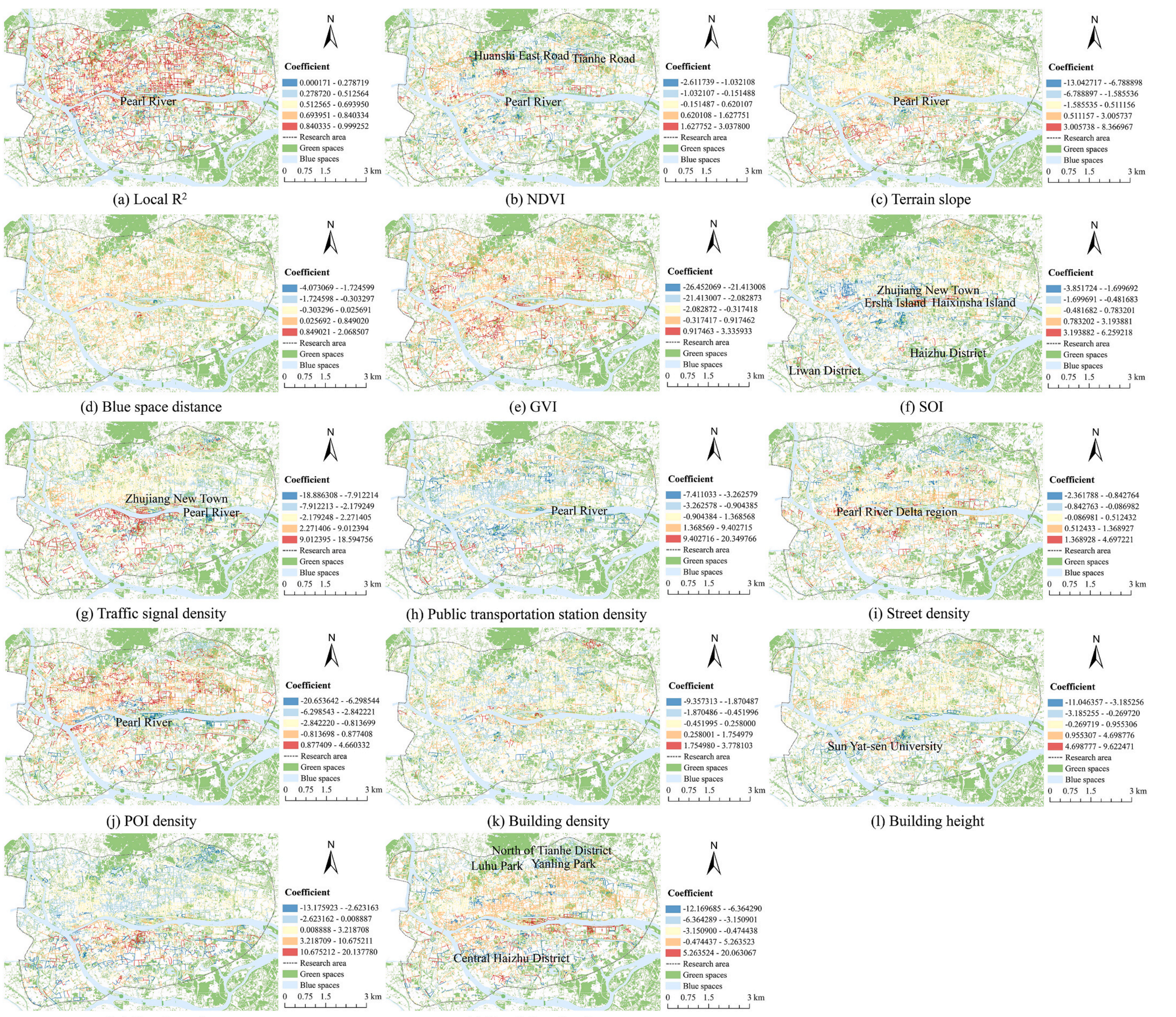

Fig. 6. Spatial distribution of MGWR coefficients for the influencing factors of running intensity.

5.2. Spatial patterns of the associations between built environments and running intensity

Fig. 6 illustrates the local R^2 of the MGWR model using natural breakpoints, ranging from 0.000171 to 0.999252. Notably, areas with higher R^2 values are predominantly located in the northern region of the Pearl River and along its southern coast, which may correlate with varying levels of running intensity. Additionally, the coefficients of other influencing factors, visualized using natural breakpoints, show significant regional variations in both direction and magnitude. Further analysis is required to understand the non-stationarity effects of each indicator in relation to specific locations.

There are significant regional differences in the correlations between NDVI and running intensity. Specifically, in the north of the Pearl River and south of "Huanshi East Road-Tianhe Road", these correlations tend to be positive, which is consistent with our previous findings. However, in the north of "Huanshi East Road-Tianhe Road" and south of the Pearl River, they tend to be negative. One possible explanation is that in areas with higher population density, where communities tend to be disconnected from nature, the positive correlation holds true. In contrast, in the north of "Huanshi East Road-Tianhe Road", where there is high greenery but low population density, running is less frequent. Moreover, compared to green vegetation in densely populated areas, vegetation in areas with sparse population is not particularly rare, hence NDVI may not have a significant impact on running (Huang, Tian, & Yuan, 2023). Meanwhile, the positive relationship between GVI and running intensity is consistent across almost every local area, further suggesting that using GVI to reflect the perceived greenness is more accurate than NDVI (Huang, Tian, & Yuan, 2023). The coefficient of terrain slope and running intensity gradually decreases from south to north. In the north of the Pearl River, the correlation is weakly negative, while in the south of the Pearl River, the relationship is positive. Although most areas in the south of the Pearl River are flat and suitable for running, running intensity might not be high due to the presence of densely populated residential and commercial areas, which limit running. Thus, while flatter terrain generally supports more running, this effect is reduced in high-density areas where other factors limit running opportunities (Huang, Tian, & Yuan, 2023). In the study area, there is a weak negative correlation between the distance to blue spaces and running intensity. This suggests that running locations closer to blue spaces tend to exhibit higher running intensity, potentially due to the increased probability and perceived satisfaction, as well as enhanced recovery effects associated with blue spaces (Harden, Schuurman, Keller, & Lear, 2022). In older urban areas like Liwan and Haizhu District, where buildings are relatively low and the visible sky area of streets is large, runners' perception of streets weakens, lacking a sense of security and intimacy. Conversely, in Zhujiang New Town, Ersha Island, and Haixinsha Island, although the sky openness is high, running intensity is also high due to the presence of numerous popular landmarks and comprehensive running infrastructure, attracting many runners. This indicates that while high sky openness usually restrict running behavior, well-designed urban features can mitigate this effect (Yang et al., 2024).

In terms of street environment factors, the correlations between traffic signal density and running intensity exhibit distinct zonal characteristics. North of the Pearl River and west of the Pearl River New Town, there is a weak positive correlation. In most areas south of the Pearl River, the correlation is significantly positive, possibly because areas with fewer traffic signals have higher traffic risks, while in areas with more traffic signals, runners may experience fragmented running experiences but feel safer. The differing effects of traffic signal density in local versus global regressions suggest that running behavior is influenced by the interaction of runner's experience and safety considerations (Huang et al., 2022; Yang et al., 2022). In both the northern and southern regions of the Pearl River, there are areas where the density of public transportation stations is negatively associated with running intensity, contradicting our previous findings. This may be due to these areas often being densely populated, suffering from traffic congestion, or having poor air quality, thereby affecting residents' willingness to engage in outdoor running. The negative association between public transportation density and running intensity in both northern and southern Pearl River areas, often due to high population density, traffic congestion, or poor air quality, highlights a relevant challenge for other metropolitan areas balancing transportation accessibility with public health (Huang, Kyttä, et al., 2023). In the Pearl River Delta region, higher street density correlates with increased running intensity. This is due to the popularity of running in the high-fitness area along the Pearl River waterfront, attracting a large number of runners. The presence of numerous streets increases the availability of diverse running routes, thereby decreasing the likelihood of encountering pedestrians and other obstacles (Huang, Tian, & Yuan, 2023). Similarly, the relationship between street density and running intensity holds true in other areas. The link between street density and running intensity highlights the need to foster a running-friendly atmosphere and culture in urban areas. In some commercial-intensive areas north of the Pearl River, POI density is positively correlated with running intensity. It means that high-density facilities are already an expected part of the urban runner's experience. Additionally, diverse land use usually means abundant amenities, attracting residents to run (Ettema, 2015). However, in other areas, the correlation is negative, indirectly indicating that running behavior usually requires the support of green and blue spaces (Huang, Tian, & Yuan, 2023). The relationship between building density and running intensity suggests that in most areas, higher building density corresponds to a lower probability of running occurring. This is because in high-density building areas, green and outdoor spaces are relatively scarce, often accompanied by more traffic and noise pollution (Shashank et al., 2021). Generally, the higher the building floors, the more likely running behavior occurs, which aligns with the sense of security and enclosure mentioned earlier. However, around the Sun Yat-sen University campus, this correlation does not hold true, which may be attributed to students and young individuals longing for spacious public spaces (Dong et al., 2023).

The relationship between housing prices and running intensity does not exhibit distinct zonal characteristics in the research area. Streets display an interlaced distribution, reflecting both positive and negative relationships. Areas with higher housing prices typically have more prominent urban landscapes and better facilities. However, they also face safety hazards such as busy traffic and high vehicle volume (Yang et al., 2024). Except for some areas in the north of Tianhe District and the central Haizhu District, the observed relationship conforms to our expectations. In these two blocks, the former has a lower population density, closer to the boundary of the research area, but features large green parks, such as Yanling Park and Luhu Park. Compared to areas with similar population densities, it is easier to engage in running activities. The latter is concentrated in commercial areas with higher population density, which are more suitable for indoor activities rather than outdoor running (Ettema, 2015). This indicates that parks and green spaces can alleviate the negative impact of low population density on running behavior, while areas with excessively high population density tend to limit it.

The identified relationships between environmental features and running intensity underscore the need for a localized approach to promoting running activities, considering the unique characteristics of different urban areas. This pattern can offer insights for other rapidly urbanizing cities with complex street environments, high population density, and similar climates, such as Shenzhen, Bangkok, Singapore, Mexico City, São Paulo, or Jakarta.

5.3. Comparison of case studies and recommendations for urban planning

In comparison to other case studies, the findings from Guangzhou align with similar conclusions drawn from Boston, Beijing, Helsinki, Chengdu, Surrey, and Inner London, all of which demonstrate the significant role of built environment factors in shaping running behavior (Dong et al., 2023; Huang, Tian, & Yuan, 2023; Jiang et al., 2022; Luo et al., 2022; Shashank et al., 2021; Yang et al., 2024). For instance, like Guangzhou, studies from Boston and Helsinki highlight the positive influence of proximity to green and blue spaces on running intensity, with natural elements such as street greenery and water bodies acting as strong motivators for physical activity. Meanwhile, previous research in Beijing has highlighted the complex relationship between environmental factors and running behavior, something we also observe in our study. For instance, our local regression results sometimes differ from the global findings, underscoring the nuanced nature of these relationships. Additionally, the Helsinki case similarly observes that higher street density and urban density negatively impact running behavior, which corresponds to our finding that densely populated areas tend to restrict running activities. In contrast, Surrey and Inner London focus more on micro-level street features, noting that wider streets, greater accessibility, and street amenities contribute to a more running-friendly environment. These comparative insights suggest that while Guangzhou's built environment fosters outdoor running activities, the findings from this study could be adapted to other cities with similar dense, well-developed urban cores. The results offer valuable guidance for city planners and policymakers aiming to design more attractive and functional running-friendly streetscapes, integrating both natural and built elements to enhance public space utilization across various urban settings.

Urban planning should focus on enhancing green spaces at the street level, as both NDVI and GVI positively influence running intensity. Expanding access to parks and tree-lined streets encourages outdoor activity. In areas where NDVI negatively affects running, improving the quality of greenery or offering alternative outdoor amenities is recommended. Additionally, blue spaces' cooling effect boosts running, so developing waterfront routes and increasing access to these areas, particularly in hotter regions, can improve running comfort. Planners should also balance flat terrain with population density to prevent overcrowding or disruptions. For street environments, minimizing traffic signal disruptions while ensuring safety is crucial. Smart traffic management and expanded public transport can improve access to green spaces and running trails, but congestion and air quality must be managed in high-density areas. The positive link between street density and running highlights the need for interconnected networks, possibly repurposing streets for pedestrians and runners. Taller buildings may provide a sense of security, and integrating green corridors or rooftop parks can mitigate the negative effects of dense urban environments. Mixed results on neighborhood factors like housing prices and population density suggest tailored planning strategies. In affluent areas, reducing safety hazards from traffic is essential, while in lower-density neighborhoods, creating appealing outdoor spaces can promote a running culture. Given the local variations in running behavior, flexible and neighborhood-specific policies are necessary to maximize the benefits of urban planning interventions.

5.4. Strengths and limitations

Our study has certain strengths. First, it leverages large-scale running trajectory data from the Keep app to analyze the spatial differentiation of running behavior and its underlying mechanisms. Unlike small-scale surveys that rely on questionnaire data, our use of big data allows us to capture a broader range of actual running activities, reducing the randomness and incompleteness often associated with survey-based research. Second, our analysis introduces both NDVI and GVI to assess the impact of greenery on running behavior. The results demonstrate that GVI offers stronger explanatory power than NDVI, as GVI is derived from actual street-level images processed through semantic segmentation, providing a more accurate representation of road greening compared to satellite-derived NDVI data. Third, by employing OLS, GWR, and MGWR models, our study thoroughly investigates runners' environmental preferences. GWR and MGWR models, in particular, account for spatial heterogeneity in influencing factors, and the results suggest that these models are more suitable for interpreting the complexity of running behavior. As research on running behavior is still in its early stages, our findings contribute to a deeper understanding of the mechanisms behind runners' environmental preferences and provide a useful reference for future studies in this field.

Our study also has limitations. First, due to data availability constraints, we were unable to obtain comprehensive road traffic monitoring data or datasets reflecting road safety, which limits our ability to fully explore the mechanisms behind runners' environmental preferences. Second, the data provided by the Keep app underwent anonymization, preventing us from accessing socio-demographic information such as age, gender, education level, and income. As a result, this study does not analyze the running behavior characteristics of different groups. Third, limited access to long-term historical data also restricted our ability to analyze the temporal variation of running behavior, as we could not obtain an extended time series dataset. Finally, the mechanisms behind runners' environmental preferences require further exploration. As running behavior research is still in its early stages, this study focused on linear relationships between environmental factors and running behavior, overlooking potential non-linear associations. Future research could incorporate machine learning techniques to quantify these non-linear relationships. Additionally, this study only considered the relationship between environmental factors and running behavior, without addressing how the interaction between these factors influences behavior. Future work could explore mediating variables, such as perceived environmental factors, to gain new insights into the mechanisms driving runners' environmental preferences.

6. Conclusion

This paper utilizes multi-source data to analyze the spatial characteristics of running intensity in Guangzhou's core area and explores runners' preferences from aspects such as natural exposure, street environment, and neighborhood. In terms of natural exposure, running behavior tends to occur in areas with rich blue-green spaces, flat terrain, and limited sunlight exposure. In terms of the street environment, running behavior is less likely to occur in areas with too many traffic signals, but more likely in areas with convenient public transportation, the former being related to fragmented running experiences and the latter being related to the convenient accessibility of running locations. Noisy and crowded streets deter running opportunities. Neighborhoods with better environments and higher population density are associated with increased running behaviors. Additionally, the superior performance of GVI over NDVI in the regression results suggests that relying on observable greenness perceived by runners is more effective in capturing the influence of green exposure on running behavior. Moreover, the local regression results are more ideal than global ones, providing a basis for optimizing the runnability of local areas. These methods uncover valuable insights for urban planning and public health from the perspective of running, including optimizing green space layouts, enhancing street connectivity and safety, and improving streetscape quality to promote running activities. The results provide quantitative literature supplements for running-related studies and validate the relationship between urban landscapes and public health. They also inspire planners to view running as a guiding principle for urban planning, urging authorities to enhance running-related facilities to promote the integration and symbiosis of public spaces.

CRediT authorship contribution statement

Mingke Xie: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Zhangxian Feng:** Validation, Supervision, Resources, Project administration, Funding acquisition, Formal analysis. **Wang Long:**

Visualization, Software, Methodology, Data curation. **Shijun Wang:** Supervision, Project administration, Funding acquisition. **Xiajing Liu:** Visualization, Software, Data curation. **Gufeng Ji:** Validation, Software, Data curation. **Xiaoxuan Guo:** Resources, Investigation, Data curation.

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.

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