Article

Cycling Greenway Planning towards Sustainable Leisure and Recreation: Assessing Network Potential in the Built Environment of Chengdu

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Abstract: In the quest to enhance urban green mobility and promote sustainable leisure activities, this study presents a comprehensive analysis of the potential for cycling greenways within the urban fabric of Chengdu, China. Leveraging the built environment and cycling routes, simulated by dockless bike-sharing (DBS) big data on weekend afternoons, the cycling flow on existing networks reflects the preference for leisure cycling in surroundings, thus indicating the potential for future enhancements to cycling greenway infrastructure. Employing Multi-Scale Geographically Weighted Regression (MGWR), this research captures the spatial heterogeneity in environmental factors influencing leisure cycling behaviors. The findings highlight the significant roles of mixed land use, network diversity, public transit accessibility, human-scale urban design, road network thresholds, and the spatially variable impacts of architectural form in determining cycling greenway potential. This study culminates with the development of an evaluation model, offering a scientific approach for cities to identify and prioritize the expansion of cycling infrastructure. Contributing to urban planning efforts for more livable and sustainable environments, this research underscores the importance of data-driven decision-making in urban green mobility enhancement by accurately identifying and efficiently upgrading infrastructure guided by public preferences.

Keywords: cycling greenways; dockless bike-sharing (DBS); leisure cycling behavior; sustainable urban mobility; greenway planning; multi-scale geographically weighted regression (MGWR)

1. Introduction

In recent decades, Chinese cities have emphasized development focused on densification, efficiency, and ecological sustainability, leading to the popularity of greenways. These multifunctional linear spaces enhance urban mobility and green infrastructure, addressing both transportation and leisure needs in dense urban areas [1]. The rise of dockless bike-sharing (DBS) systems has further supported urban cycling, appreciated for its convenience and integration with public transit, significantly contributing to congestion reduction, health improvement, and environmental stewardship [2,3].

By leveraging emerging information technologies and sophisticated data analysis, this study aims to enhance the precision, objectivity, and applicability of planning leisure-oriented cycling greenways. This research uniquely contributes to the field by bridging the gap between cycling preference analysis of DBS and urban greenway planning by potential scoring, introducing a Cycling Greenway Potential Evaluation Model. The model, informed by detailed analysis and advanced regression techniques, captures the complex relationships between urban built environment characteristics and leisure cycling activities.
It elucidates spatial nuances at multiple scales necessary for effective greenway planning and proposes a tailored master plan aligned with Chengdu’s unique urban context. This research significantly contributes to the discourse on sustainable urban mobility and infrastructure development by providing actionable insights for enhancing urban green mobility and promoting leisure cycling in Chengdu and similar urban contexts.

Specifically, this research focuses on several key items. It investigates how various built environment factors from different dimensions influence leisure cycling activities in Chengdu; it examines the spatial variations in these influences using advanced regression techniques like MGWR; it explores how insights from DBS data can be utilized to develop a comprehensive and practical Cycling Greenway Potential Evaluation Model; and it considers the implications of these findings for urban greenway planning and sustainable urban mobility in Chengdu and similar urban contexts.

1.1. Dockless Bike-Sharing (DBS) Data Analysis

In the last fifty years, bike-sharing has notably evolved, especially with dockless bike-sharing (DBS) systems introduced in 2016 [4,5]. Dockless bike-sharing (DBS) platforms in China, which leverage cashless payments and GPS tracking, enable users to locate, unlock, and pay for bikes using their smartphones [4]. Because of market competition and user experience of using on an “as-needed” bias, the shared bike industry in China has evolved to predominantly feature dockless systems, effectively eliminating the need for fixed bike stations. These systems provide extensive data from users’ interactions, accessible via open databases or directly from operators’ APIs [4,6]. Such spatial point data have fueled research into how the built environment influences DBS usage, utilizing advanced analytical methods to interpret spatial and temporal travel patterns [7,8].

However, the application of point data has limitations. To overcome these, some studies have attempted to represent DBS journeys as linear trajectories. While direct access to DBS trajectory data was available before 2017 [9,10], privacy regulations and restrictions from DBS providers have since limited data to origin–destination (OD) pairs without intermediate points. Researchers have creatively used these OD pairs, aligning them to analyze trip directions and distances [11,12] or simulating DBS routes using ArcGIS based on the actual road network [9,12]. These simulated routes facilitate further analyses, such as calculating trip distances or identifying spatial mobility patterns and hotspots, thus opening new research avenues for understanding and enhancing urban cycling infrastructure.

1.2. Association between DBS and the Built Environment

The choice of shared bicycles is influenced by the built environment, which includes factors like the destination, societal context, and the physical and experiential qualities of the environment. Pioneering work by Cervero and Kockelman [13] introduced the “3Ds” of the built environment—density, diversity, and design—later expanded to include dimensions such as land use, transportation systems, and urban design [14]. These elements encompass location types, the physical and accessible infrastructure, and the aesthetics of urban spaces, which are now more accurately assessed using advanced data-informed techniques [14–17]. Specifically, in the existing studies on the built environment and DBS, land use is one of the most frequently discussed aspects. It refers to the location, density, and mixture of different types of land or points of interest (POIs), such as work, residence, restaurants, or amenities [16,18,19]. The transportation system generally includes physical infrastructure, like roadway density, road hierarchy, or public transit stations [6,12,16], and abstract connections like accessibility via space syntax or two-step floating catchment area (2SFCA) [15]. Urban design refers to the appearance and arrangement of the streetscape, which can be evaluated on a massive scale from online streetview by image semantic segmentation techniques, and most studies have confirmed the street greenery factor as a positive influence [17,20]. Finally, architectural form refers to morphology like the floor area ratio (FAR) or building height [21,22].
Earlier research often relied on subjective assessments, but recent studies use urban big data to evaluate objectively the built environment’s effect on DBS usage patterns, though results vary by urban context and mobility culture [2]. In East Asia, the effects of urbanization and population density on DBS usage contrast with Western cities. Cities like Beijing and Tokyo show strong workplace influences on cycling, while in Chengdu, despite less infrastructure, there is notable climate suitability and preference for cycling, leading to higher bike usage [23,24]. Previous studies in Chengdu, an inland city in western China, have primarily examined service levels or usage characteristics, with few investigating the broader built environment impacts [25,26], highlighting the need for further detailed analysis.

1.3. Determinants of DBS Cycling by Trip Purposes

The purposes of DBS trips, primarily commuting and leisure, interact with the urban built environment and vary by time and day. Leisure cycling ranks second in DBS usage, peaking during rush hours and weekends [2,27]. Factors influencing commuting include proximity to transit, homes, and workplaces, which is essential for DBS-Metro connectivity [6,12]. While some studies found positive impacts of mixed land use on cycling, the anticipated benefits from bike lanes and bus stops were less evident [6,16,23].

For leisure DBS cycling, proximity to leisure facilities significantly increases engagement, as seen in Traffic Analysis Zones with increased leisure amenities [25,28]. The availability of parks, lakes, dining, and commercial areas has been shown to boost bike usage, especially during weekends when mixed land use diversifies travel purposes [2,21,29]. Additionally, the role of street greenery, particularly at eye level, enhances the appeal of cycling, evidenced by higher DBS activity around green metro stations in Shenzhen [17,20,30].

1.4. Bike Lane or Cycling Greenway Planning

Bike lane and cycling greenway planning are essential for non-motorized transport in urban renewal efforts, particularly in densely populated areas. Driven by advances in information technology, modern route planning integrates data analysis to better understand and influence non-motorized behavior and infrastructure utilization [31,32]. This approach enhances greenway or cycling infrastructure and promotes environmentally friendly lifestyles, focusing on how urban design connects non-motorized paths to parks, amenities, and services [32,33].

Efficient greenway planning requires identifying key environmental factors and assessing the potential of network segments. Traditional methods often rely on subjective assessments like expert scoring or questionnaire-based analysis to determine the weights of various factors, which can limit the quantification of data [32]. However, the popularity of DBS in China offers a unique dataset for research, enabling innovative planning approaches like using bike trajectory data for bike lane construction [9] and developing optimization models based on cyclists’ usage [31]. For built environment-related studies, regression models play a crucial role in quantitative research by helping identify potential weights and patterns based on multiple built environment factors. However, in the existing studies on the built environment and DBS, researchers often focus on exploring the advantages and differences among various regression models (to be detailed in the next section). Comprehensive studies that integrate DBS data with environmental analysis to enhance bike lane and greenway planning are still limited [34].

1.5. Regression Models for Quantitative Research

Using regression analysis to derive factor weights is an effective, quantitative method for urban planning, as demonstrated by studies like the Urban Quality Index [35]. This approach clearly defines the impact of various built environment factors on urban outcomes by using model coefficients as interpretable weights, thus advancing data-driven planning for enhancing urban cycling infrastructure.
In quantitative research, DBS data are used as the dependent variable in regression models to measure the impact of built environment factors. Common regression models include Ordinary Least Squares (OLS), negative binomial [6], and logistic regression [17]. There are also enhanced learning algorithms such as XGBoost [36], but they assume spatially invariant relationships, which can be a limitation in urban studies where spatial heterogeneity is significant. Recent advancements have incorporated Spatial Lag Models (SLMs) [12] and Geographically Weighted Regression (GWR) [20,22] to address spatial autocorrelation and heterogeneity, improving the interpretability of these studies. A few scholars have started using Multiscale Geographically Weighted Regression (MGWR), an extension of GWR that models spatially varying relationships with enhanced precision in capturing spatial relationships within DBS research [37]. This method enables the analysis of complex urban systems by identifying significant differences across regions at different scales, thus providing a deeper understanding of the diverse impacts of built environment characteristics on non-motorized traffic patterns.

1.6. Our Contributions

In recent years, the integration of cycling greenways into urban planning has gained significant attention, driven by the need for sustainable mobility and enhanced urban livability. However, existing studies often fall short in several key areas, as highlighted in the preceding literature review (Sections 1.1–1.5).

Firstly, many studies focus on one or two aspects of the built environment, lacking a comprehensive approach that considers multiple dimensions simultaneously. This study addresses this gap by employing MGWR, which allows coefficients to vary spatially and scale proportions to adapt across different explanatory variables while minimizing the impact of multicollinearity. By considering land use, transportation systems, urban design, and architectural form together, this research provides a holistic understanding of the built environment’s impact on leisure cycling.

Secondly, previous MGWR analyses often overlook spatial heterogeneity in the significance of built environmental factors. By incorporating a 95% confidence interval in the MGWR analysis, this study identifies significant spatial variations, providing deeper insights into cycling behaviors and avoiding the inclusion of non-significant influences. This spatially nuanced approach reveals localized impacts that global models might miss, thus offering more tailored urban planning recommendations.

Lastly, this research bridges cycling routes with greenways using a data-driven method that directly reflects public cycling behavior without subjective bias. The approach is based on the linear nature of both cycling routes and greenways, ensuring that greenway planning is fully grounded in empirical data. This method not only aligns with public preferences but also provides a scalable model that other cities with dockless bike-sharing services can adapt to suit their unique contexts, promoting widespread applicability and transferability of the findings.

These contributions not only advance the methodological framework for studying urban cycling but also offer practical guidelines for the development of cycling infrastructure that is closely aligned with public preferences. By addressing the gaps identified in the literature review, this study underscores its necessity and provides a robust foundation for future research and urban planning practices.

2. Methodology

2.1. Research Design and Objectives

This study aims to enhance urban cycling infrastructure based on the existing urban fabric by integrating various regression models to analyze DBS data and built environment factors. The research framework, depicted in Figure 1, involves the application of OLS, GWR, and MGWR models to capture the spatial heterogeneity in and varying scales of the influence of environmental factors on cycling behavior. It introduces an evaluation model for assessing cycling greenway potential and proposes a tailored master plan for Chengdu.
This study conceptualizes an urban cycling greenway as an expansive, linear area designed primarily for cycling, facilitating seamless connections while integrating regional or inter-city greenways with urban green spaces. It addresses a wide range of communal needs, from facilitating transportation—including links to metro and bus networks—to supporting neighborhood commutes, public amenities, and spaces for leisure and recreation. Primarily catering to leisure and entertainment, urban cycling greenways are distinct from bike highways or cycleways, which are optimized mainly for commuting.

2.2. Regression Models

In this study, we utilize a hierarchical approach to regression analysis to capture the complexities and spatial heterogeneity in urban environments. The selected regression models—OLS, GWR, and MGWR—are applied in a sequential manner to refine our understanding of the relationships between built environment factors and DBS usage. This approach allows us to first establish baseline relationships using OLS, account for spati-
tial non-stationarity with GWR, and finally address varying spatial scales with MGWR. Although GWR and MGWR are both used to understand spatial relationships, MGWR provides a more nuanced understanding and is ultimately preferred for further analysis because of its superior performance metrics such as higher R-squared values.

The sequential application of these regression models is guided by the following specific objectives and the inherent characteristics of urban data:

- **OLS**: As the foundational regression model, OLS is utilized to establish baseline relationships between built environment factors and DBS usage. It provides a straightforward method to evaluate these relationships but does not account for spatial heterogeneity.
- **GWR**: To address the spatial non-stationarity present in urban environments, GWR is employed. GWR allows for local variations in regression coefficients, thereby providing a more accurate depiction of how built environment factors influence DBS usage across different locations.
- **MGWR**: Building on the insights gained from GWR, MGWR is used to further refine the analysis by considering varying spatial scales for different explanatory variables. MGWR’s ability to model spatially varying relationships at multiple scales offers a more detailed understanding of the spatial dynamics at play, leading to more precise and reliable results.

### 2.2.1. Ordinary Least Squares (OLS) Regression Model

OLS serves as a foundational tool for spatial regression analysis and is applied to evaluate relationships between dependent and independent variables in our study. The model formula is represented as:

\[
Y = \beta_0 + \sum_{j=1}^{m} \beta_j x_j + \varepsilon
\]

where \(Y\) represents the number of times shared bikes are used in the walking catchment area, \(x_j\) represents the \(j\)th built environment factor, \(\beta_j\) represents the corresponding estimated coefficient, and \(\varepsilon\) represents the random error term.

Moreover, while conventional statistical practices typically consider \(p\)-values below 0.05 as significant, this study adopts a more nuanced approach that is especially relevant in urban research contexts. Following the recommendations of Pritschet et al. [38], indicators with \(p\)-values ranging from 0.05 to 0.07 are regarded as marginally significant and are thus included for further investigation because of the inherent variability of urban settings.

### 2.2.2. Geographically Weighted Regression Model (GWR)

In contrast to the OLS model, which assumes spatially invariant relationships, GWR recognizes that geographical proximity among data points affects variable values, reflecting the spatial heterogeneity within a city. GWR allows for local variations in regression coefficients, accommodating the non-stationarity of built environment variables across different locations. The formula for GWR is:

\[
y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{m} \beta_j(u_i, v_i) x_{ji} + \varepsilon_i
\]

where \(i\) represents the \(i\)th catchment area, \(y_i\) represents the cycling flow (line density) of DBS, \(x_{ji}\) represents the \(j\)th built environment indicator of catchment area \(i\), \(m\) represents the total number of grids, \(\varepsilon_i\) represents the random error term of grid \(i\), \((u_i, v_i)\) represents the location of grid \(i\), \(\beta_0(u_i, v_i)\) represents the intercept at location \(i\), \(\beta_j(u_i, v_i)\) represents the local coefficient of the built environment variable \(x_{ji}\), and \(\varepsilon_i\) is the error term.
2.2.3. Multi-Bandwidth Geographically Weighted Regression Model (MGWR)

Expanding upon this framework, Multi-Scale Geographically Weighted Regression (MGWR), which was proposed by Fotheringham in 2017 [39], extends GWR by modeling spatially varying relationships in a more nuanced manner. MGWR permits variations in neighborhoods around each spatial element for every explanatory variable. This method not only allows coefficients to vary spatially but also accommodates varying scales across different explanatory variables. By employing distinct neighborhoods for each explanatory variable, MGWR elucidates the unique spatial proportions of relationships between each explanatory variable and the dependent variable. This approach effectively integrates explanatory variables operating at both larger and smaller spatial scales.

Compared with GWR, the MGWR model can obtain a more reliable result by providing an optimal bandwidth for each independent variable that can estimate more precise local coefficients while encountering fewer issues related to multicollinearity [40]. Additionally, MGWR is particularly adept at handling large datasets containing hundreds of features, especially when the dependent variable exhibits spatial heterogeneity.

The model is expressed as:

\[ y_i = \sum_{j=1}^{m} \beta_{bwj}(u_i, v_i) x_{ji} + \epsilon_i \] (3)

where \( \beta_{wj} \) represents the bandwidth used for the regression coefficient of the \( j \)th independent variable, \( x_{ji} \) represents the independent variable, and \( \epsilon_i \) is the error term.

2.3. Study Area

Chengdu, located in Southwest China, serves as a major inland city and transport hub, with a population of 21.92 million and covering 14,270 square kilometers, primarily plains. The city’s development is focused on a north–south axis, with the southern district becoming a prominent high-tech zone, reflecting its status as an IT hub. Urban expansion, as shown in NDVI (Normalized Difference Vegetation Index) imagery (Figure 2, middle), displays concentric growth from the city center, with a clear contrast between green spaces and urban areas based on multispectral remote sensing.

Endorsing President Xi Jinping’s “Park City” initiative of 2018, Chengdu aims to be a leader in urban green mobility. However, it confronts weekend traffic congestion and a lack of non-motorized transport infrastructure, a challenge noted in the pending Cycleway Network Plan 2018 [41]. This study focuses on the urban core within the third ring road with a 500 m buffer, in addition to the Wuhou to Gaoxin South Districts for the developed area of the high-tech zone. This 256.56 square kilometer area, divided into 4038 grid units.
of 300 × 300 m each for detailed analysis, is illustrated in Figure 2 (left and right). This grid system forms the basis for studying Chengdu’s unique urban environment and its impact on sustainable transport planning.

2.4. DBS Data

This study utilizes DBS data as a proxy for cycling activities, focusing on leisure cycling within the developed urban fabric of Chengdu, particularly during non-commuter hours on weekend afternoons, a period noted for high DBS usage. This choice helps isolate leisure behaviors from weekday commuting patterns. Further discussions on the spatial and temporal conditions of the built environment relevant to this study are presented in subsequent sections.

2.4.1. DBS Data Collection

Data collection was conducted using the API of the WeChat “Mobike” application, capturing over a million real-time parking points between 13:00 and 17:00 on 20 and 21 October 2018. These dates fall on Saturday and Sunday, which research has identified as peak periods for leisure cycling [27]. This substantial dataset includes detailed timestamps, geographic coordinates, and unique identifiers for bikes, as shown in the example provided in Table 1. Weather records for these dates in Chengdu indicate favorable conditions, ensuring the data reflect typical local cycling behavior.

<table>
<thead>
<tr>
<th>Point #</th>
<th>Time</th>
<th>Bike ID</th>
<th>Longitude</th>
<th>Latitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>245449</td>
<td>10/21 14:01:44</td>
<td>8642537806#</td>
<td>104.108740</td>
<td>30.686553</td>
</tr>
<tr>
<td>1758056</td>
<td>10/21 14:20:59</td>
<td>8642537806#</td>
<td>104.109295</td>
<td>30.673153</td>
</tr>
<tr>
<td>3535177</td>
<td>10/21 14:45:30</td>
<td>8642537806#</td>
<td>104.087047</td>
<td>30.673014</td>
</tr>
<tr>
<td>4449558</td>
<td>10/21 14:58:04</td>
<td>8642537806#</td>
<td>104.088442</td>
<td>30.682501</td>
</tr>
</tbody>
</table>

To ensure the representativeness of leisure cycling and to filter out non-commuter cycling behavior, we conducted preliminary data exploration. We performed a simple linear regression analysis between the collected DBS data and commonly recognized work-related points of interest (POIs), such as company and enterprise locations. The $p$-value from this regression was 0.823014, indicating no significant correlation between the two and thus confirming that the data primarily represent leisure cycling rather than commuter cycling.

2.4.2. DBS Data Preprocessing

The preprocessing of DBS data entailed several comprehensive steps to ensure the integrity of the analysis. Initially, the data were aggregated and cleaned with a focus on creating an hourly breakdown to extract precise parking information. This involved sorting the data by bike ID to identify and remove duplicates or anomalies, such as instances where bikes were reported more than 15 km apart within the same hour, likely because of maintenance or relocation.

Subsequently, DBS bike routes were simulated to represent them as linear movements using ArcGIS Pro’s “Route” with “Stops” function. This process organized the data based on unique IDs and parking timestamps, facilitating detailed simulations of real-world cycling routes and patterns (refer to Table 1 and Figure 3). The analysis extended to calculating line densities from these routes, providing insights into cycling flows and distribution across different urban and recreational areas. The results of these analyses are presented in Figure 4a, b.
Post-cleansing, the analysis revealed an average of 26,437 DBS uses per hour, predominantly concentrated in the old city center and the southern high-tech district, areas noted for significant commercial and recreational activities. These patterns align with expected leisure cycling behavior during weekends. In the final step of the analysis, all hourly line density data were equally weighted and integrated into this study’s grid matrix, illustrating spatial cycling flows within Chengdu, as depicted in Figure 4c,d.
Figure 4. The process of DBS cycling indicator and built environment indicators.
2.5. Built Environment Data

2.5.1. Land Use

This research utilized block land use data from Chengdu, obtained from Tsinghua University’s 2018 EULUC-China project, and the Basic Urban Land Use Category Map of China, which uses remote sensing for classifying land use [42]. These data helped assess the city’s Mix Use Rate, an important indicator of land use diversity, which was evaluated using the entropy weight method to measure the complexity of the built environment.

Additionally, for detailed urban analysis, point of interest (POI) data were essential. Extracted via Python 3.10 from the Amap API, this dataset included 247,467 categorized POIs that map critical urban functions necessary for this study, including residential, entertainment and fitness, restaurants, shops, parks, and educational facilities. The Average Kernel Density of these categories was key in analyzing the spatial distribution of urban amenities, as illustrated in Figure 4e, which aided in understanding Chengdu’s urban structure and its impact on cycling greenway potential.

Refer to Table 2 for a detailed explanation of the factors, formulas, and methods used in this study.

### Table 2. Factors of land use.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Abbr.</th>
<th>Formula</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mix Use Rate</td>
<td>MUR</td>
<td>( X_{MUR} = - \sum_{i=1}^{n} P_i \times \ln P_i )</td>
<td>( P_i ) represents the area ratio of the ( i )th land use type in each block; ( n ) is the count of land use categories.</td>
</tr>
</tbody>
</table>

### Kernel Density of various land use POIs

- PRD
- PEF
- PRT
- PSP
- PPT
- PCG

\( X = \frac{1}{(\text{radius})^2} \sum_{i=1}^{n} \left[ \frac{3}{\pi} \text{pop}_i \left(1 - \left( \frac{\text{dist}_i}{\text{radius}} \right)^2 \right)^2 \right] \)

\( i \) (1 to \( n \)) denotes each input point including points within the radius of position \((x, y)\).
\( \text{pop}_i \) and \( \text{dist}_i \) are the optional population and distance from point \( i \) to \((x, y)\), respectively.

2.5.2. Transportation System

This research conducted a comprehensive analysis of Chengdu’s cyclable network using polyline data from Open Street Map, which were carefully validated against satellite imagery to ensure accuracy in identifying cyclable versus non-cyclable routes. The visualization differentiates standard roads from wider avenues with two-way bike lanes, marked distinctly to show varying access levels.

Transportation system indicators include metrics derived from space syntax theory, such as integration and choice. Space syntax theory is a method for analyzing spatial configurations, commonly used to assess the accessibility and integration of urban street networks. Integration measures how well-connected a street segment is within the network, while choice measures the likelihood of a street segment being used as part of a route. These metrics help quantify the connectivity and accessibility of different parts of the city, which is crucial for understanding non-motorized transport patterns. In this study, integration and choice values were calculated and used as part of the built environment indicators in the regression analysis to evaluate their influence on DBS usage.

Additionally, Cyclable Network Density was calculated to promote densely connected streets and compact urban blocks, enhancing the public realm’s accessibility for cyclists. This measure highlights the significance of a cohesive street network for active transportation.

Public transit access points, including bus stops and metro stations, were mapped using POI data from Amap’s API. Kernel density analysis was used to quantify the Average Kernel Density of these transit nodes, shedding light on public transportation’s role in supporting cycling by improving connectivity and accessibility throughout the urban area.

Refer to Table 3 for a detailed explanation of the factors, formulas, and methods used in this study.
Table 3. Factors of the transportation system.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Abbr.</th>
<th>Formula</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Integration</td>
<td>SSI</td>
<td>( X_{SSI} = \frac{2}{(n-1)(n-2)} \sum_{j=1}^{n} D_{ij} )</td>
<td>( n ) is the total number of system elements. ( D_{ij} ) is the shortest distance between element ( i ) and ( j ). The formula calculates global integration; for local integration, it considers only elements within a specified radius.</td>
</tr>
<tr>
<td>Choice</td>
<td>SSC</td>
<td>( X_{SSC} = \frac{\sum_{i=1}^{n} p_i}{(n-1)} )</td>
<td>( n ) represents the system’s total elements. ( P_{ij} ) counts how often element ( i ) is on the shortest path from ( j ) to others. The formula measures global choice; for local choice, it is limited to a specified radius.</td>
</tr>
<tr>
<td>Cyclable Network Density</td>
<td>CND</td>
<td>( X_{CND} = \left( \sum_{i=1}^{n} Len_i \right) / A )</td>
<td>( Len_i ) is the length of the ( i )th bike lane segment in a grid cell, ( n ) is the count of segments in the cell, and ( A ) is the grid space’s total area.</td>
</tr>
<tr>
<td>Kernel Density of bus stop/metro Station POIs</td>
<td>PBS, PMS</td>
<td>( X = \frac{1}{(\text{radius})^2} \sum_{i=1}^{n} \left[ \frac{3}{\pi} \text{pop}_i \left(1 - \left(\frac{\text{dist}_i}{\text{radius}}\right)\right)^2 \right] )</td>
<td>( i ) (1 to ( n )) denotes each input point including points within the radius of position ((x, y)). ( \text{pop}_i ) and ( \text{dist}_i ) are the optional population and distance from point ( i ) to ((x, y)), respectively.</td>
</tr>
</tbody>
</table>

2.5.3. Urban Design

While street view imagery used for urban design analysis is typically captured from the perspective of cars, it provides valuable insights into the built environment that are relevant for non-motorized transport studies [17,20,30]. Street view imagery transforms traditional top-down urban studies by allowing comprehensive quantitative research on street quality at an urban scale. Although the car perspective differs from the cycling perspective, street view imagery primarily captures elements such as the sky, trees, and built structures, which contribute to the overall environment rather than focusing solely on the visual or psychological experiences of cyclists.

This study utilized 109,048 streetview images to assess street quality, retrieved in batches using Python from the Baidu Map API at intervals of 50 m along network medians. Advanced machine learning techniques, specifically image semantic segmentation using a Fully Convolutional Neural Network (FCN), were employed to analyze these images [43]. This approach allowed for the quantification of human-scale environmental experiences by calculating the proportion of pixels corresponding to plant elements (Street Greenery Factor), sky (Street Sky-view Factor), and built structures (Street Enclosure Factor), as shown in Figures 4g and 5.

Refer to Table 4 for a detailed explanation of the factors, formulas, and methods used in this study.
2.5.4. Architectural Form

Building-based polygon data, including details on building heights and floor counts, were sourced from Baidu and Amap APIs and processed in ArcGIS Pro for precision. Drawing from the Form Syntax theory [44], this study examined how the intensity of development and urban morphology affect urban vitality. As shown in Figure 4h, the key metrics analyzed included the Floor Area Rate (FAR), which measures the density and utility of urban space, and Average Floors, indicating building height. These metrics are crucial for assessing the spatial characteristics and vibrancy of urban environments, helping to understand the impacts on non-motorized transportation modes.

Refer to Table 5 for a detailed explanation of the factors, formulas, and methods used in this study.

**Table 5. Factors of architectural form.**

<table>
<thead>
<tr>
<th>Factor</th>
<th>Abbr.</th>
<th>Formula</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floor Area Rate</td>
<td>FAR</td>
<td>$X_{FAR} = \frac{\sum_{i=1}^{n}(FA_i \times L_i)}{A}$</td>
<td>$FA_i$ represents the floor area of the $i$th building in a grid cell, $L_i$ is the average number of floors per building in the cell, $n$ is the count of buildings in the cell, and $A$ is the total area of the grid.</td>
</tr>
<tr>
<td>Average Floors</td>
<td>AGF</td>
<td>$X_{AGF} = \frac{\sum_{i=1}^{n}(FA_i \times F_i)}{\sum_{i=1}^{n} FA_i}$</td>
<td>$FA_i$ is the floor area of the $i$th building in a grid cell, $F_i$ is the average number of floors per building in the cell, and $n$ is the count of buildings in the grid.</td>
</tr>
</tbody>
</table>

2.6. Preparation

2.6.1. Dependent Variables

Prior to analysis, DBS cycling flow (line density) data required initial preparation and preprocessing to serve as dependent variables in the regression models. To refine the dataset and reduce potential biases, research units without cycling flow (zero values) were excluded, reducing the original 4038 grids to 3782 grids suitable for analysis. Furthermore, to comply
with the assumptions of classical linear regression and to enhance statistical robustness, cycling flow values were log-transformed. This transformation helped normalize the data distribution and minimize outlier effects, with the transformed values detailed in Figure 6.

2.6.2. Independent Variables

The review of the existing research in Section 1.2 helped identify preliminary indicators from three key dimensions of the built environment—land use, transportation system, and architectural form—that could influence DBS leisure cycling. Additionally, three main indicators derived from human-scale perspectives were selected using image semantic segmentation technology applied to streetview images.

To ensure robust regression analysis, this study first checked for multicollinearity among the indicators using the Variance Inflation Factor (VIF). Indicators with a VIF above 7.5, indicating high multicollinearity, were excluded, refining the list to 17 valid indicators (shown in Table 6). Data normalization was conducted using the Min–Max method to scale

Figure 6. Matrix grids based on valid dependent variables.
all indicators to a uniform range of 0 to 1, ensuring no dimensional or unit discrepancies affected the analysis.

Table 6. Statistics of independent variables.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Name of Variables</th>
<th>Abbr.</th>
<th>Unit</th>
<th>Mean</th>
<th>Max</th>
<th>Median</th>
<th>Min</th>
<th>Std.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land use</td>
<td>Mix Use Rate</td>
<td>MUR</td>
<td>%</td>
<td>0.51</td>
<td>1.0</td>
<td>0.57</td>
<td>0</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>Resident</td>
<td>PRD</td>
<td>Count per KM²</td>
<td>26.1</td>
<td>307.3</td>
<td>13.2</td>
<td>0</td>
<td>35.1</td>
</tr>
<tr>
<td></td>
<td>Entertainment and fitness</td>
<td>PEF</td>
<td>Count per KM²</td>
<td>20.8</td>
<td>793.2</td>
<td>9.6</td>
<td>0</td>
<td>36.7</td>
</tr>
<tr>
<td></td>
<td>Restaurant</td>
<td>FRT</td>
<td>Count per KM²</td>
<td>74.2</td>
<td>1375.2</td>
<td>35.1</td>
<td>0</td>
<td>96.7</td>
</tr>
<tr>
<td></td>
<td>Shop (store)</td>
<td>PSP</td>
<td>Count per KM²</td>
<td>5.6</td>
<td>175.2</td>
<td>2.54</td>
<td>0</td>
<td>175.2</td>
</tr>
<tr>
<td></td>
<td>Park and tour</td>
<td>PPT</td>
<td>Count per KM²</td>
<td>2.1</td>
<td>245.9</td>
<td>0</td>
<td>0</td>
<td>11.0</td>
</tr>
<tr>
<td></td>
<td>College gate</td>
<td>PCG</td>
<td>Count per KM²</td>
<td>0.058</td>
<td>0.9</td>
<td>0</td>
<td>0</td>
<td>0.197</td>
</tr>
<tr>
<td>Transportation system</td>
<td>Integration</td>
<td>SSI</td>
<td>-</td>
<td>4.5</td>
<td>8.8</td>
<td>4.8</td>
<td>0</td>
<td>2.0</td>
</tr>
<tr>
<td></td>
<td>Choice</td>
<td>SSC</td>
<td>-</td>
<td>27.5</td>
<td>99.7</td>
<td>26.4</td>
<td>0</td>
<td>18.4</td>
</tr>
<tr>
<td></td>
<td>Cyclable Network Density</td>
<td>CND</td>
<td>Meter per KM²</td>
<td>464.7</td>
<td>1384.5</td>
<td>490.1</td>
<td>0</td>
<td>259.0</td>
</tr>
<tr>
<td></td>
<td>Bus stop</td>
<td>PBS</td>
<td>Count per KM²</td>
<td>7.5</td>
<td>41.8</td>
<td>6.6</td>
<td>0</td>
<td>6.4</td>
</tr>
<tr>
<td></td>
<td>Metro station</td>
<td>PMS</td>
<td>Count per KM²</td>
<td>0.23</td>
<td>7.7</td>
<td>0</td>
<td>0</td>
<td>0.96</td>
</tr>
<tr>
<td>Urban design</td>
<td>Street Enclosure Factor</td>
<td>SEF</td>
<td>%</td>
<td>0.183</td>
<td>0.5</td>
<td>0.18</td>
<td>0</td>
<td>0.089</td>
</tr>
<tr>
<td></td>
<td>Street Sky-view Factor</td>
<td>SVF</td>
<td>%</td>
<td>0.203</td>
<td>0.54</td>
<td>0.21</td>
<td>0</td>
<td>0.095</td>
</tr>
<tr>
<td></td>
<td>Street Greenery Factor</td>
<td>SGF</td>
<td>%</td>
<td>0.173</td>
<td>0.48</td>
<td>0.175</td>
<td>0</td>
<td>0.083</td>
</tr>
<tr>
<td>Architectural form</td>
<td>Floor Area Rate</td>
<td>FAR</td>
<td>%</td>
<td>2.1</td>
<td>22.7</td>
<td>1.83</td>
<td>0</td>
<td>1.84</td>
</tr>
<tr>
<td></td>
<td>Average Floors</td>
<td>AGF</td>
<td>Floors</td>
<td>11.9</td>
<td>100</td>
<td>10</td>
<td>0</td>
<td>8.8</td>
</tr>
</tbody>
</table>

2.7. Evaluation Model of Cycling Greenway Potential

Based on the regression outcomes, this model identifies key environmental factors influencing leisure cycling and quantifies their impacts. To enhance practical applicability, the model integrates coefficients from MGWR into a global regression framework to assign weights to significant environmental factors. Depending on the distribution of coefficients, either the mean or median from the MGWR results is chosen as the basis for calculation to improve interpretability. This structured Evaluation Model serves as a tool to assess the general potential of cycling greenways within the existing urban network, assuming that public cycling preferences remain unchanged.

This approach simplifies the calculation process while enhancing interpretability. It is summarized by the equation:

\[
\text{Cycling Greenway Potential} = \sum_{i=1}^{n} \alpha_i x_i + \epsilon
\]

where \( n \) is the number of indicator types (17 in total), \( i \) represents the index of a specific independent variable, \( x_i \) is the variable of each built environmental factor, \( \alpha_i \) is the specific weight corresponding to each indicator, and \( \epsilon \) represents the error term.

3. Results

3.1. OLS Regression Model

The OLS regression model evaluated the effects of 17 built environment indicators on DBS usage, achieving an adjusted R-squared of approximately 0.61, which indicates strong explanatory power. The normal distribution of standardized residuals and a significant Koenker (BP) statistic suggest spatial heterogeneity, pointing to the need for further localized analyses, corroborated by a significant global Moran’s index.

The analysis showed varied impacts of the indicators on DBS usage, as detailed in Table 7. Notably, the AGF indicator had a negative correlation with DBS cycling, while indicators like PRT, PPT, SSI, SSC, CND, and SEF had significant positive impacts, highlighted by their Beta coefficients after normalization. PRD showed marginal significance, with a Robust_Pr value just above 0.05.
Table 7. Regression results of Ordinary Least Squares regression.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Beta Coefficient</th>
<th>StdError</th>
<th>t-Statistic</th>
<th>Pr</th>
<th>Robust_Pr</th>
<th>VIF</th>
</tr>
</thead>
<tbody>
<tr>
<td>MUR</td>
<td>0.684220</td>
<td>0.060276</td>
<td>11.3514</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>1.525971</td>
</tr>
<tr>
<td>PRD</td>
<td>0.283464</td>
<td>0.183869</td>
<td>1.5417</td>
<td>0.123254</td>
<td>0.066606 *</td>
<td>2.590164</td>
</tr>
<tr>
<td>PEF</td>
<td>0.952129</td>
<td>0.405371</td>
<td>2.353623</td>
<td>0.018627 **</td>
<td>0.024453 **</td>
<td>1.541121</td>
</tr>
<tr>
<td>PRT</td>
<td>1.100874</td>
<td>0.341852</td>
<td>3.220324</td>
<td>0.001307 ***</td>
<td>0.000019 ***</td>
<td>2.509164</td>
</tr>
<tr>
<td>PSP</td>
<td>0.736264</td>
<td>0.431048</td>
<td>1.708078</td>
<td>0.087714 ***</td>
<td>0.009053 ***</td>
<td>1.669444</td>
</tr>
<tr>
<td>PPT</td>
<td>1.219866</td>
<td>0.361821</td>
<td>3.371465</td>
<td>0.000772 ***</td>
<td>0.028350 **</td>
<td>1.027895</td>
</tr>
<tr>
<td>PCG</td>
<td>0.435710</td>
<td>0.071151</td>
<td>6.123752</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>1.070703</td>
</tr>
<tr>
<td>SSI</td>
<td>1.704831</td>
<td>0.095449</td>
<td>17.8612</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>1.434708</td>
</tr>
<tr>
<td>SSC</td>
<td>1.470030</td>
<td>0.137695</td>
<td>10.6759</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>1.862042</td>
</tr>
<tr>
<td>CND</td>
<td>1.773577</td>
<td>0.113871</td>
<td>15.5753</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>1.705265</td>
</tr>
<tr>
<td>PBS</td>
<td>0.726410</td>
<td>0.115635</td>
<td>6.281914</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>1.300038</td>
</tr>
<tr>
<td>PMS</td>
<td>0.302653</td>
<td>0.054921</td>
<td>5.510673</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>1.13847</td>
</tr>
<tr>
<td>SEF</td>
<td>1.767075</td>
<td>0.123378</td>
<td>13.3487</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>2.0903</td>
</tr>
<tr>
<td>SVF</td>
<td>0.894438</td>
<td>0.152063</td>
<td>5.882023</td>
<td>0.000000 ***</td>
<td>0.000167 ***</td>
<td>2.686267</td>
</tr>
<tr>
<td>SGF</td>
<td>0.395494</td>
<td>0.140042</td>
<td>2.824099</td>
<td>0.004770 ***</td>
<td>0.035573 **</td>
<td>2.429821</td>
</tr>
<tr>
<td>FAR</td>
<td>0.045394</td>
<td>0.011530</td>
<td>3.937105</td>
<td>0.000930 ***</td>
<td>0.000024 ***</td>
<td>3.043379</td>
</tr>
<tr>
<td>AGF</td>
<td>−1.187154</td>
<td>0.256429</td>
<td>−4.629554</td>
<td>0.000000 ***</td>
<td>0.000001 ***</td>
<td>2.141385</td>
</tr>
<tr>
<td>Constant</td>
<td>7.815048</td>
<td>0.265704</td>
<td>29.4126</td>
<td>0.000000 ***</td>
<td>0.000000 ***</td>
<td>-</td>
</tr>
</tbody>
</table>

R²: 0.611547
Adjusted R²: 0.609793
AICc: 10,341.35
Koenker (BP) Statistic: 374.162
Pr(>chi-square), (12) degrees of freedom: 0.000000 *

For the significance of the regression coefficient, *** represents the 0.01 level; ** represents the 0.05 level; and * represents marginal significance at the 0.07 level.

3.2. GWR and MGWR Models

To better address spatial heterogeneity overlooked by the OLS model, this study employed GWR and MGWR. These models, optimized via the Golden Search’s Number of Neighbors method, offered deeper insights into DBS usage and trip distances. Comparative analysis of these models showed that MGWR, with its adaptive bandwidth, provided a better fit than both OLS and GWR, as indicated by higher R-squared values and lower Akaike Information Criterion corrected (AICc) scores, detailed in Table 8.

Table 8. Models comparison of OLS, GWR, and the MGWR model.

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>GWR</th>
<th>MGWR</th>
</tr>
</thead>
<tbody>
<tr>
<td>R²</td>
<td>0.611547</td>
<td>0.740838</td>
<td>0.8924</td>
</tr>
<tr>
<td>Adjust R²</td>
<td>0.609793</td>
<td>0.739668</td>
<td>0.8598</td>
</tr>
<tr>
<td>AICc</td>
<td>10,341.35</td>
<td>9217.42</td>
<td>4597.69</td>
</tr>
</tbody>
</table>

In this study, we employed MGWR to capture the varying impacts of built environment factors on leisure cycling across different areas. Table 9 presents the MGWR coefficient results and the weights for the evaluation model. The coefficients indicate the strength and direction of the relationship between each built environment factor and leisure cycling. This approach revealed the substantial influence of several built environment indicators such as MUR, SSI, SSC, CND, and SEF, all demonstrating average scaled coefficients greater than 0.1. These results highlight the significant impact these factors have on urban cycling behaviors.

Several variables exhibit relatively consistent influences across the study area. For example, the Mix Use Rate (MUR) has a mean coefficient of 0.1085 with a relatively small standard deviation of 0.0242, suggesting a generally consistent positive influence across the study area. Resident (PRD) has a mean coefficient of 0.0399 with a very small standard deviation of 0.0004, indicating a generally uniform positive impact. Similarly, entertainment and fitness (PEF) and shop (store) (PSP) also show consistent positive influences, with mean
coefficients of 0.0165 and 0.0206, respectively, and small standard deviations. However, the variable Average Floors (AGF) demonstrates a relatively consistent negative impact, with a mean coefficient of −0.0213 and a small standard deviation of 0.0028, suggesting that taller buildings are generally associated with reduced leisure cycling.

Table 9. MGWR scaled coefficient result and weights for the evaluation model.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Name of Variables</th>
<th>Abbr.</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
<th>Weights for the Evaluation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land use</td>
<td>Mix Use Rate</td>
<td>MUR</td>
<td>0.1085</td>
<td>0.0242</td>
<td>0.0520</td>
<td>0.1086</td>
<td>0.1665</td>
<td>8.96%</td>
</tr>
<tr>
<td></td>
<td>Resident</td>
<td>PRD</td>
<td>0.0399</td>
<td>0.0004</td>
<td>0.0387</td>
<td>0.0399</td>
<td>0.0406</td>
<td>3.29%</td>
</tr>
<tr>
<td></td>
<td>Entertainment and fitness</td>
<td>PEF</td>
<td>0.0165</td>
<td>0.0008</td>
<td>0.0150</td>
<td>0.0166</td>
<td>0.0178</td>
<td>1.37%</td>
</tr>
<tr>
<td></td>
<td>Restaurant</td>
<td>PRT</td>
<td>0.0316</td>
<td>0.0011</td>
<td>0.0299</td>
<td>0.0313</td>
<td>0.0343</td>
<td>2.58%</td>
</tr>
<tr>
<td></td>
<td>Shop (store)</td>
<td>PSP</td>
<td>0.0206</td>
<td>0.0011</td>
<td>0.0183</td>
<td>0.0205</td>
<td>0.0229</td>
<td>1.69%</td>
</tr>
<tr>
<td></td>
<td>Park and tour</td>
<td>PPT</td>
<td>0.0195</td>
<td>0.0104</td>
<td>-0.0034</td>
<td>0.0222</td>
<td>0.0408</td>
<td>1.83%</td>
</tr>
<tr>
<td></td>
<td>College gate</td>
<td>PCG</td>
<td>0.0397</td>
<td>0.0014</td>
<td>0.0370</td>
<td>0.0396</td>
<td>0.0428</td>
<td>3.27%</td>
</tr>
<tr>
<td>Transportation system</td>
<td>Integration</td>
<td>SSI</td>
<td>0.2235</td>
<td>0.1750</td>
<td>-0.2438</td>
<td>0.2050</td>
<td>1.1373</td>
<td>18.45%</td>
</tr>
<tr>
<td></td>
<td>Choice</td>
<td>SSC</td>
<td>0.1538</td>
<td>0.0211</td>
<td>0.1243</td>
<td>0.1513</td>
<td>0.2209</td>
<td>12.49%</td>
</tr>
<tr>
<td></td>
<td>Cyclable Network Density</td>
<td>CND</td>
<td>0.2058</td>
<td>0.0971</td>
<td>-0.0124</td>
<td>0.1867</td>
<td>0.7678</td>
<td>15.41%</td>
</tr>
<tr>
<td></td>
<td>Bus stop</td>
<td>PBS</td>
<td>0.0476</td>
<td>0.0114</td>
<td>0.0296</td>
<td>0.0466</td>
<td>0.0670</td>
<td>3.85%</td>
</tr>
<tr>
<td></td>
<td>Metro station</td>
<td>PMS</td>
<td>0.0532</td>
<td>0.0013</td>
<td>0.0500</td>
<td>0.0534</td>
<td>0.0553</td>
<td>4.41%</td>
</tr>
<tr>
<td>Urban design</td>
<td>Street Enclosure Factor</td>
<td>SEF</td>
<td>0.1289</td>
<td>0.0016</td>
<td>0.1249</td>
<td>0.1292</td>
<td>0.1312</td>
<td>10.66%</td>
</tr>
<tr>
<td></td>
<td>Street Sky-view Factor</td>
<td>SFV</td>
<td>0.0533</td>
<td>0.1325</td>
<td>-0.6365</td>
<td>0.0595</td>
<td>0.7187</td>
<td>4.40%</td>
</tr>
<tr>
<td></td>
<td>Street Greenery Factor</td>
<td>SGF</td>
<td>0.0386</td>
<td>0.0112</td>
<td>0.0209</td>
<td>0.0369</td>
<td>0.0591</td>
<td>3.05%</td>
</tr>
<tr>
<td>Architectural form</td>
<td>Floor Area Rate</td>
<td>FAR</td>
<td>0.0297</td>
<td>0.0028</td>
<td>0.0240</td>
<td>0.0303</td>
<td>0.0336</td>
<td>2.50%</td>
</tr>
<tr>
<td></td>
<td>Average Floors</td>
<td>AGF</td>
<td>-0.0213</td>
<td>0.0028</td>
<td>-0.0276</td>
<td>-0.0217</td>
<td>-0.0155</td>
<td>(-)1.79%</td>
</tr>
</tbody>
</table>

In contrast, some variables exhibit significant spatial heterogeneity. The Street Sky-view Factor (SVF) has a mean coefficient of 0.0533 but with a large standard deviation of 0.1325, and its values range from −0.6365 to 0.7187. This indicates that SVF’s impact on leisure cycling can vary greatly depending on the location, having both positive and negative effects. Integration (SSI) also shows considerable spatial variability with a mean coefficient of 0.2235 and a standard deviation of 0.1750, ranging from −0.2438 to 1.1373.

The spatial distribution of these effects is visualized in Figure 7, which uses color coding to map the regression results across the study grid. This visualization helps articulate the varying impacts of urban design elements on cycling preferences across Chengdu, providing an intuitive understanding of environmental influences on cycling activity.

3.3. Weights in the Evaluation Model of Cycling Greenway Potential

Following the regression analysis that identified critical environmental determinants affecting DBS cycling, we applied the regression coefficients as weights to formulate an equation for evaluating cycling greenway potential. This approach transforms the theoretical findings into a tool with practical applications.

As described in Section 2.7, we calculated global weights for each environmental factor based on the distribution of coefficients from the MGWR results. For factors with skewed distributions (factors except SSI and SVF), median values from the MGWR analysis were used, and for those with normal distributions (SSI and SVF), mean values were applied. The selected values for each factor are within Table 9. These global coefficients were then proportionally used as weights for the indicators, detailed in the final column of Table 9. The results were synthesized into the formula from Section 2.7 to create the evaluation model.
4. Discussion

4.1. Cycling Greenway Planning Based on Linear DBS Data

DBS data, widely accepted in China [2], represent a rapid and comprehensive means to understand citizens’ real cycling behaviors. Through scientific processing and analysis, these data can be transformed into an important reference for guiding urban bicycle greenway planning and construction. This study simulated linear cycling routes in the urban network based on shared bicycle point data, using extensive data overlays to reflect the cycling travel frequency (cycling flow) on each road. Such linear traveling patterns
coincide with the linear characteristics of cycling greenways, inspiring the use of this feature to discuss the impact of the urban built environment and thereby support cycling greenway planning. This method distinguishes itself from prior research that focused on the density or extent of DBS’s OD pairs [11] or bike lane planning from direct trajectory pattern [9], thus avoiding subjective biases and limitations of non-quantitative greenway planning research [32] and presenting a novel way to integrate DBS behaviors with greenway development, even within the bounds of data accessibility.

This study enhances its analysis by employing local regression models that consider spatial autocorrelation alongside traditional global models. By utilizing MGWR for its enhanced explanatory power, this research explores how various built environment factors influence cycling at different urban scales. This methodological approach enables a detailed evaluation of cycling greenway potential across diverse areas, providing data-driven insights for urban planning to improve green mobility and leisure activities through efficient resource allocation.

4.2. Environmental Determinants and Spatial Difference

Using MGWR, this study highlights the variable impact of environmental determinants on cycling behavior across Chengdu, as detailed in Figure 7. This analysis enhances the Cycling Greenway Potential Evaluation Model, informing targeted strategies for urban cycling infrastructure that meet specific local needs.

The following key findings emphasize the importance of spatially tailored planning for cycling greenways, accounting for the diverse needs of different urban sectors:

1. Within the land use dimension, MUR exerts the strongest influence on leisure cycling, which is significantly greater than single land use POI densities. This indicates the importance of mixed-use areas in promoting cycling activities.
2. SSC shows that cyclists prefer routes that offer freedom of movement and diverse path choices. However, SSI indicates considerable spatial heterogeneity, with both positive and negative impacts. High integration in central urban areas may deter cycling because of congestion, whereas increased integration in peripheral areas promotes cycling.
3. Positive factors SSI and CND display widespread insignificance. The influence of road network accessibility and density stabilizes once a certain threshold is reached.
4. Public transit POIs, particularly subway stations, positively influence leisure cycling more than any single type of leisure and entertainment venue (e.g., PEF, PRT, PSP, PPT, PCG), highlighting the critical role of public transit accessibility.
5. Urban design factors significantly affect leisure cycling, with the Street Sky-view Factor (SVF) showing the most spatial variability. The SVF’s impact varies widely, indicating different regional preferences for sky visibility, light conditions, and open views.
6. Differences between old and new urban areas are notable. In the southern new city, FAR, SGF, and PSP show insignificant effects, while AGF in the old city displays widespread insignificance, reflecting the impact of distinct planning and spatial layouts from different eras on leisure cycling.

4.2.1. Land Use

This research confirmed the significant influence of land use indicators on leisure cycling, with the cumulative impact quantified at 22.99%. The MGWR results indicate that within the land use dimension, MUR has the most substantial impact on leisure cycling, with a mean coefficient of 0.1085 and a relatively small standard deviation. This underscores a preference for cycling in mixed-use areas, corroborating previous studies [2]. However, this study found that the influence of MUR is significantly greater than the density of any single land use POIs, which differs from previous research [45].

Additionally, the densities of residential POIs (PRD) and college gates (PCGs) were significant, indicating a strong consistent influence of residential areas on cycling patterns citywide, with little spatial variation. The MGWR results also highlighted the significant
positive effect of leisure and entertainment-related POI density, particularly the exceptional influence of PRT on leisure cycling, surpassing other land use types across Chengdu. This distinct preference for leisure cycling locations differs from other regions, indicating unique local cycling behaviors.

These insights should inform greenway planning and urban development strategies, focusing on accommodating local preferences and understanding the diverse impacts of various land use types on cycling behavior.

4.2.2. Transportation System

The analysis highlighted the transportation system as a critical determinant for cycling greenway potential, attributing the highest cumulative weight of 54.61%. This finding reinforces the importance of non-motorized transportation spaces, as significant weights were assigned to indicators such as Spatial Syntax Integration (SSI), Spatial Syntax Choice (SSC), and Cyclable Network Density (CND). These components are supported by spatial syntax and network density studies like those by Kamel and Sayed and Soltani et al. [46,47], which confirm their positive influence on cycling behavior.

Notably, while both SSI and SSC generally enhance cycling preferences, cyclists tend to favor diverse routing options over direct, straightforward main-road cycling. This preference highlights a nuanced relationship between road network configuration and the appeal of leisure cycling. Furthermore, it was observed that SSI exhibited considerable spatial heterogeneity, with both positive and negative impacts. High integration in central urban areas may deter cycling because of congestion somewhere, whereas increased integration in peripheral areas always promotes cycling. On the other hand, SSC consistently showed a positive influence across all regions, indicating a universal preference for routes that offer freedom of movement and diverse path choices.

Additionally, public transit POIs, particularly subway stations, were found to positively influence leisure cycling more than any single type of leisure and entertainment venues (e.g., PRD, PEF, PRT, PSP, PPT, PCG), highlighting the critical role of public transit accessibility. This significant influence, which previous studies have not explicitly confirmed [6,12], suggests that well-integrated transit options can greatly enhance the attractiveness of cycling routes.

Once certain areas achieve adequate accessibility and road density, the influence of SSI and CND stabilizes. This conclusion is based on the MGWR results, particularly the 95% confidence interval significance comparison, as visualized in Figure 7, which shows large areas of insignificance. It suggests a threshold effect where further improvements in these metrics do not significantly enhance cycling potential. This insight should guide future greenway planning and urban development strategies. Further improvements in these metrics do not significantly enhance cycling potential, suggesting that resources should be strategically allocated to other factors to maximize their impact on cycling infrastructure.

4.2.3. Urban Design

In this study, urban design elements such as plants, sky visibility, and structural forms, analyzed through streetview images, collectively contributed 18.11% to the overall impact on leisure cycling. This study also noted a stronger impact of SEF on leisure cycling in Chengdu compared with previous studies [34,46], while the influence of SGF was less significant than reported elsewhere [17,20,30]. The varying influence of SVF further highlighted significant regional differences, diverging from uniformly positive correlations seen in other studies [46].

SEF was particularly influential, enhancing feelings of security and fostering engaging street environments, as supported by Ma et al. and Ewing and Handy [47,48]. SEF’s positive effect was consistently observed across Chengdu, indicating its broad appeal in urban cycling design.
Meanwhile, SGF displayed a universally positive impact on leisure cycling, although its influence was less pronounced in the southern high-tech zones, suggesting that different urban areas have varying functional demands that affect leisure cycling preferences.

SVF, reflecting openness, showed mixed impacts on cycling preferences, with significant effects in specific areas where openness greatly influences cycling experiences. SVF’s impact exhibited considerable spatial variability, with both positive and negative effects, indicating different regional preferences for sky visibility and openness in urban design. For example, in some central urban areas, a higher SVF was associated with increased cycling, while in peripheral areas, complete sky obstruction was not preferred by cyclists, as reflected in Figure 7. This finding highlights the regional variations in the preference for sky visibility and openness, suggesting that entirely obstructed skies are not favored by cyclists in peripheral areas.

4.2.4. Architectural Form

Architectural form factors accounted for 4.29% of the overall evaluation of cycling greenway potential, aligning with observed trends [21,45]. FAR, which measures building density and the active population, is positively associated with urban vitality and cycling engagement in various cities [21]. In Chengdu, this positive correlation persists except in the southern high-tech district, where dense office environments offer limited recreational cycling opportunities. Differences between old and new urban areas were notable. In the southern new city, FAR showed insignificant effects, similar to SGF and PSP, indicating that these factors are less influential in newly developed areas.

In contrast, AGF, indicating building height, negatively correlated with leisure cycling, particularly in the city’s western peripheral areas and southern new districts. Conversely, AGF in the old city displayed widespread insignificance, reflecting the impact of distinct planning and spatial layouts from different eras on leisure cycling. This suggests that high-rise environments might discourage outdoor leisure activities. However, thoughtful urban planning and cultural inclusivity may mitigate the negative impacts of high-rise structures on leisure cycling, particularly in areas like the eastern central city.

4.3. Instantiation Application on Latest Built Environment

The evaluation model created in this study serves as a robust tool for assessing and planning cycling greenways across urban landscapes, as illustrated in Figure 8. It supports the scientific distribution of resources to enhance bicycle infrastructure on the most promising roads. Despite challenges in collecting dockless bike-sharing data, the stability of public cycling preferences ensures that even historical data remain valuable for urban planning and research. This model allows for dynamic adjustments to cycling infrastructure plans to align with ongoing urban development and leisure cycling needs.

The methodology used in this study is universally applicable across different urban contexts and calculates potential scores for cycling greenways by integrating spatial data on environmental factors, each weighted by its impact. This results in a detailed scoring system that identifies the potential for greenway development in each urban segment.

A case study utilizing 2023 data from Chengdu demonstrates the practical application of the general model, aligning with the overarching government strategy for greenway development. The model aids in formulating a master plan that categorizes network segments into primary and secondary networks and identifies opportunities to enhance connectivity. This includes strategies such as creating non-motorized bridges to link disjointed but high-potential areas, thereby improving the functionality and reach of Chengdu’s cycling network.

It is essential to emphasize that this master plan is based on a comprehensive global perspective. In its specific implementation, it is crucial to integrate discussions from earlier sections, tailoring unique strategies for enhancing cycling greenways across different areas of the city. This entails focusing on specific actions to improve the built environment and determining the priority sequence for facility upgrades.
Figure 8. Proposed cycling greenway planning master plan.
4.4. Implications

This research advances our understanding of the interaction between the urban built environment and leisure cycling behavior using advanced spatial analysis techniques such as MGWR. The development of a nuanced evaluation model for general cycling greenway potential based on DBS data, along with a discussion of how coefficients of built environmental factors vary across space and scale using MGWR, represents a significant methodological advancement. This model highlights the importance of considering spatial differences in planning, potentially leading to more tailored and effective urban interventions.

Practically, this study offers a data-driven tool for urban planners and policymakers, aiding the identification and prioritization of cycling infrastructure investments. It underscores the value of mixed land use, accessibility, and human-scale design, advocating for an integrated approach to urban development that promotes sustainable mobility. Municipalities can use the evaluation model to expand or retrofit cycling greenways strategically, optimizing resource allocation to areas with the greatest potential to enhance cycling. This includes not only the construction of new cycling paths but also the integration of supporting facilities such as repairing stations and rest areas along principal routes. Additionally, this study provides actionable insights for improving urban livability and sustainability, supporting broader goals like traffic reduction, air quality improvement, and public health promotion. Furthermore, the scalable and transferable nature of this evaluation model allows other cities to adapt it to their specific built environment characteristics and cycling preferences.

4.5. Limitations and Further Study

While this study has advanced greenway planning quantitatively and scientifically, it faces several limitations that warrant further research including the following:

(1) Data Limitations: The coverage of DBS data excludes certain age groups like children and the elderly. Dockless bike-sharing systems often restrict registration to those over 18 years old, and the use of smartphone apps for accessing these services may not be user-friendly for older adults. Additionally, the physical design of the bikes, such as saddle height adjustments, may not accommodate all users. This exclusion limits the generalizability of the findings and might lead to planning and design biases in public spaces. Meanwhile, obtaining real-time data or actual riding trajectories is challenging because of DBS providers’ operations and privacy policies. Future research should include targeted studies on green mobility services for children and the elderly, such as non-motorized greenways around schools and senior centers, using methods like field surveys or image semantic segmentation based on panoramic photo records to gather relevant data and understand their cycling preferences.

(2) Built Environment Data Limitations: The indicators derived from online mapping services and other data sources are constrained by their collection and classification processes, which cannot be customized for experimental needs. Additionally, the evaluation of streetview images may lack the natural human perception required for comprehensive analysis. Future research could explore the use of advanced AI technologies, such as large visual models, to improve the classification of urban features and assess the spatial quality of street views in a manner akin to human understanding.

(3) Temporal Dimension: This study focuses on spatial variations but lacks discussion on temporal changes. The static nature of the data used limits the understanding of how cycling patterns may vary over different times of the day, weeks, or seasons. Future studies could integrate temporal analyses using models like GTWR (Geographically and Temporally Weighted Regression) to explore green transportation in both temporal and spatial dimensions, providing a more dynamic understanding of urban mobility. Additionally, advanced methods like Recurrent Neural Networks (RNNs) could be employed to perform time-series analysis.

(4) Behavioral Factors: This study primarily uses quantitative data to analyze cycling patterns but does not fully account for qualitative behavioral factors such as personal
preferences, perceptions of safety, or cultural attitudes towards cycling. Incorporating qualitative research methods in future studies could provide a deeper understanding of the motivations and barriers to cycling. Methods such as interviews, focus groups, and participatory observations could be used to gather insights into user experiences and preferences, leading to more comprehensive and effective urban planning strategies.

5. Conclusions

This research synthesizes cycling route simulations from DBS data with the planning of linear, non-motorized transportation spaces—cycling greenways—providing a robust framework for urban cycling infrastructure development. This novel perspective for identifying and assessing cycling greenway potential bridges the prior gap of treating DBS systems and greenway planning as separate entities. Through advanced urban big data collection and analysis, including regression analyses like MGWR, this study meticulously evaluates the multifaceted impacts of the built environment on leisure cycling. It introduces a nuanced evaluation model for identifying potential cycling greenways, facilitating a strategic approach to enhancing urban cycling networks.

This study’s key findings highlight the necessity of context-specific strategies for greenway planning, emphasizing the importance of mixed-use areas (MUR) in promoting cycling activities, the preference for diverse path choices over highly integrated routes (SSI and SSC), the threshold effect of road network accessibility and density (CND), the critical role of public transit accessibility (especially subway stations) over individual leisure and entertainment venues, the significant but spatially variable impact of urban design factors like the Street Sky-view Factor (SVF), and the notable differences in the effects of architectural form between old and new urban areas.

These conclusions not only encapsulate this research’s comprehensive approach to analyzing and planning cycling greenways but also emphasize the necessity of adopting spatially informed strategies to bolster urban cycling infrastructure. This study acknowledges several limitations, including data constraints and the need for more localized studies, and suggests avenues for future research to address these gaps. By doing so, it contributes valuable insights to the fields of urban planning and sustainable transportation, advocating for the development of more livable, accessible, and green urban spaces.

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