**Full Title:** Exploring the relationship between built environment and public sharing bike flow in Suzhou, China using geographically weighted regression model

**Abstract:** In recent years, many countries have implemented public bike sharing programs (PBSP) to improve travel efficiency of short trips. Early studies have analyzed how built environment factors affect public sharing bike usage. However, these studies mainly used global regression model which cannot demonstrate the spatial variation relationship between built environment and bike flow. Therefore, this study employs a global regression model and a geographically weighted regression (GWR) model to examine the global and local influences of built environment on bike flow. This research takes Suzhou, China as a case study area and uses one-year sharing bike trip data and online points of interest (POI). The global results show that bike stations nearby public transit, restaurants, shopping malls, educational and financial places have high bike trips on both working days and non-working days; however, bike stations proximate to workplaces are positively associated with bike trips on working days while not on non-working days. The results of GWR are consistent with the global results partially. They show the local effects of built environment on bike flow in different parts of Suzhou. In addition, the goodness of fit in the GWR is better than the global regression. The findings of this study provide strategic guidance to improve service quality of public sharing bike systems as there is a pressing need to design PBSP policies to encourage more diverse modal change and incentivize more commuting.

**Manuscript Classifications:** Economics; Public Transportation Planning and Development AP025; Accessibility; Transportation and Land Development ADD30; Accessibility

**Manuscript Number:**

**Article Type:** Publication & Presentation

**Order of Authors:** Chunliang Wu

Inhi Kim, Ph.D.

Hyungchul Chung, Ph.D.
Exploring the relationship between built environment and public sharing bike flow in Suzhou, China using geographically weighted regression model

Chunliang Wu
Ph.D candidate
Monash Institute of Transport Studies
Department of Civil Engineering
Monash University, Clayton
Victoria 3800, Australia
Tel: (+86) 188 5170 9307; Email: chunliang.wu@monash.edu

Inhi Kim
Dr. Lecturer
Monash Institute of Transport Studies
Department of Civil Engineering
Monash University, Clayton
Victoria 3800, Australia
Tel: (+613) 9905 4240; Email: inhi.kim@monash.edu

Hyungchul Chung, Corresponding Author
Dr. Lecturer
Urban Planning and Design
Xi’an Jiaotong-Liverpool University
Tel: (+86) 183 5110 8471; Email: hyungchul.chung@xjtlu.edu.cn

Word count: 5,881 words text + 6 tables/figures x 250 words (each) = 7,381 words

Submission Date: August 1st, 2018
ABSTRACT

In recent years, many countries have implemented public bike sharing programs (PBSP) to improve travel efficiency of short trips. Early studies have analyzed how built environment factors affect public sharing bike usage. However, these studies mainly used global regression model which cannot demonstrate the spatial variation relationship between built environment and bike flow. Therefore, this study employs a global regression model and a geographically weighted regression (GWR) model to examine the global and local influences of built environment on bike flow. This research takes Suzhou, China as a case study area and uses one-year sharing bike trip data and online points of interest (POI). The global results show that bike stations nearby public transit, restaurants, shopping malls, educational and financial places have high bike trips on both working days and non-working days; however, bike stations proximate to workplaces are positively associated with bike trips on working days while not on non-working days. The results of GWR are consistent with the global results partially. They show the local effects of built environment on bike flow in different parts of Suzhou. In addition, the goodness of fit in the GWR is better than the global regression. The findings of this study provide strategic guidance to improve service quality of public sharing bike systems as there is a pressing need to design PBSP policies to encourage more diverse modal change and incentivize more commuting.

Keywords: PBSP, Built Environment, Spatial Variation, GWR
INTRODUCTION

Public bike sharing programs (PBSP) are popularized by governmental entities across the globe as they become a centerpiece of sustainable transportation policies. Over the last decade, the number of cities adopting and implementing a PBSP has been increased from 13 in 2004 to 855 as of 2014 (1). In China, over 50 cities have implemented PBSP and it is expected to increase more cities planning to adopt the PBSP (2). This dramatic growth of PBSP is attributed to the fact that it is viewed as an effective way for solving problems such as air pollution and traffic congestion (3).

Despite the benefits of PBSP, the success of PBSP operation depends on sound connection of users and built environment. Recent studies found that the built environment is an important factor which affects the usage of public sharing bikes as it is associated with locations in urban settings. For instance, public sharing bike stations located in higher density areas tend to have more bike users than lower density areas since there are more potential users. Moreover, if the public sharing bike docks are located nearby host community, people tend to use them as high accessibility to public transport facilities saves time and cost for urban trip (4). Particularly, the relationship between public sharing bike flow and built environment is more evident than any other transport mode because of its unique characteristics. These include that (a) trips are generally short less than 30 min/trip (1), (b) transportation cost is relatively inexpensive, of which pricing structures encourage short-term rental (5), (c) it incentivizes modal shift from public transit particularly in high density environments while encouraging more shift towards public transit in lower density areas (6), and (d) younger and active people prefer to use PBSP (1,6).

However, the implementation and operation of PBSP occasionally may not support demand of PBSP users. For instance, the proximity to bike docking stations could not be desirable for local residents. Modal shift may not be expected to happen due to long distance to transit system from bike docking system. Additionally, population density may be too low to get PBSP fully functioned in an area. This mismatch between built environment and PBSP should be addressed. Therefore, it is essential to evaluate the effectiveness of the PBSP to understand conditions of success and failure of the PBSP policies with regard to built environmental factors. Indeed, a vast number of earlier studies emphasized that built environment significantly affects transportation system and some of the latest studies analyzed how built environment affects the usage of PBSP (7-11). However, little is known about the spatial variation relationship between built environment and the public sharing bike demand.

The objective of this research is to provide empirical evidence on the relationship between built environment and public sharing bike travel flow in Suzhou, China. To this end, two questions will be addressed: (1) What is the impact of built environment on public sharing bike flow? (2) What is the spatial variation of those built environment effects? To answer the questions in a comprehensive way, multiple quantitative methods including a global regression model, a local spatial regression model, and other relevant methods are utilized and developed.

Based on the literature review, this study contributes to existing literature in three aspects: (1) more comprehensive definition on built environment and its operationalization, (2) methodological improvement through a geographically weighted regression model, and (3) first attempt to examine the relationship built environment and public sharing bike flow in a city like Suzhou, China where a significant size of shared bike system (about 2,000 shared bike stations) is currently operated. The results of the analyses provide some evidence on the impact of built environment on bike flow.
LITERATURE REVIEW
Recent years have witnessed an increasing number of studies on exploring how built environmental factors influence the usage of PBSP. These studies attempted to address the most suitable locations and routes by identifying gap between current locations of stations and shared bike usage. However, the effects of built environment on the bike usage are still on a debate. In general, early studies utilized various types of built environmental factors. These include socio-economic and demographics (12,13), land use type (8,14), the proximity to public transit stations (15,16), bike stations attributes such as bike racks and bike lanes (17), the accessibility of bike stations (18) and street density (19). On the one hand, these studies show that there is a positive relationship between built environment and bike flows. They found that population and employment density, the capacity of stations, the proximity of stations to public transit and bike lanes, street density and the number of POIs such as restaurants and residences surrounding each bike stations are positively correlated with public bike ridership (12,18,20-25). On the other hand, few studies analyzing the relationship between built environmental factors and bike ridership in developing countries have made different conclusions. For example, Zhao (13) revealed that residential density has no significant relationship with bike usage. This is because high service quality of public transit such as bus and metro could attract users to choose public transit rather than public sharing bikes in Beijing, China. Cervero et al. (19) also pointed out that land use mixtures and public transport accessibility have no relation with bike ridership in Bogota. Thus, it is necessary to analyze how built environmental factors affect the usage of PBSP in some developing countries and promote PBSP can be operated successfully in these countries.

Existing studies have used various data and quantitative methods to investigate the effects of built environment on bike flow depending on the different contexts. Early studies mainly used survey data to obtain bike user characteristics, their travel behavior, and built environment factors that may influence their travel choice (12,13). In recent development, scholars in Europe and North America collected and released online bike sharing data to expedite the PBSP research. This large amount of data enables a growing number of research to get conducted. In contrast, China has a data-poor environment. The government has a culture of secrecy, and companies tend to withhold data to maintain demand for information as a commodity. PBSP data in China has a strong research value. In addition, most of previous research applies traditional regression model to examine how built environmental factors influence bike ridership. However, these quantitative analysis models cannot demonstrate spatial correlation of nearby station-pairs. Only few research have attempted to address this autocorrelation problem over the last two years. For instance, Faghih-Imani and Eluru (17) applied two spatial regression models including spatial error and spatial lag models to consider impacts of spatial and temporal variables on bike flow. Zhang et al. (8) used spatial multiple regression model to examine the spatial relationship between neighboring stations. It is worthwhile to note that existing studies mainly use global spatial regression models where the coefficient of each variable is the same in all areas while this study address this localized spatial autocorrelation issue using a spatial model.

To sum up, there are an increasing number of studies exploring the relationship between built environment and bike ridership. However, only few studies analyzed PBSP of developing countries and examine local spatial relationship between built environment and bike flow. Thus, the main purpose of this research is to fill these two research gaps.

STUDY AREA
The study area of this research focuses on Suzhou located in the southeast Jiangsu Province of East China and east about 100 km to Shanghai (Figure I(a)). It is the second largest city of
Wu, Kim, Chung

Jiangsu Province and an important part of Yangtze economic zone. This city consists of urban areas including five districts and five satellite cities (Figure 1(b)). Suzhou has high population and a well-developed public transit system. The urban center of Suzhou is Gusu district called the “Old Town”. The public transit stations in other four districts are radiated from this area. Because the urban form of Old Town is relatively unstructured, the street density of this district is high and the roads are narrow. In the east, there is Suzhou Industrial Park (SIP) which is newly developed area. The urban form of this new town is well structured in that the roads are wide and the buffer zone is placed to separate bikes and vehicles. The land use of this area is mixed. Many prestigious universities and advanced technology companies are located in the south and big shopping malls and financial buildings are located in the northern part of this area. In the west, Huqiu district is another high and new technology development zone. Other two districts are mainly planned as tourism and agricultural development zone.

In 2010, Suzhou government began to implement PBSP to solve the last-mile problem. At present, PBSP is mainly launched in urban area of Suzhou. People with age between 16 years old and 70 years old can use public sharing bikes by swiping smartcards or scanning QR codes on the bike racks. Moreover, when users choose to use smartcards, the first hour is free and 1 RMB per hour will be charged after the rent. When users prefer to use mobile phones to scan QR codes, the cost is free within first 30 minutes, and they have to pay 0.5 RMB per hour. Statistics show that there are around 1,750 bike stations and 40,000 public sharing bikes put into use in Suzhou (26). Figure 1(c) presents the spatial distribution of bike stations and metro stations in urban area of Suzhou. It shows that most of bike stations are clustered around the urban center of Suzhou. In addition, there are three metro lines operating in Suzhou which enables the Old Town to get linked with four surrounding districts.
FIGURE 1 Study area. (A) Location of Suzhou in China; (B) Administrative division of Suzhou; and (C) the spatial distribution of bike stations, metro stations and population density in urban area of Suzhou.

DATA

Data Sources
This research utilizes four different dataset: (1) Shared bike usage and bike racks data were obtained from Suzhou Environment & Municipal Administration Bureau. These data include public sharing bike records such as bike station ID, type of users, QR code, smartcard ID, pick-up/drop-off time, the latitude and longitude of each station. The temporal scope of this study ranges from January to December 2017. There are 14,562,120 trips recorded with smartcards and 25,955,319 trips generated from QR scanning. (2) Metro station and trip data were obtained from Suzhou rail transit Group. There are more than 32,000,000 trip records per month. Each dataset consists of trip start and end time, start and end station ID, and the location of each station. Since data in November 2017 were only provided by Suzhou rail transit Group, this research mainly uses metro usage data in the particular month. (3) Demographic data were obtained from Suzhou Statistics Bureau. This data describes population of each Suzhou subdistrict in 2016. (4) POI data were extracted by using Amap application programming interface (API) (see https://lbs.amap.com/). These data include the latitude and longitude of each POI. This Amap
API divides the data into 14 categories. Based on the existing literature, this paper selects 9 categories which are restaurants, public transit stations, shopping malls, local financial services, dwellings, public leisure and religion places, public parks, workplaces and educational places (see Table 1).

### TABLE 1 The Category of POI Data

<table>
<thead>
<tr>
<th>POI Category</th>
<th>POI Types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Restaurants</td>
<td>Coffee house, Snack bar, Cold-drink bar, Dessert, Chinese restaurant, Foreign restaurant</td>
</tr>
<tr>
<td>Public transit stations</td>
<td>Metro station, Bus station</td>
</tr>
<tr>
<td>Shopping malls</td>
<td>Shopping center, Convenience store, Supermarket, Electronics store, Business street, Exclusive shop</td>
</tr>
<tr>
<td>Local financial services</td>
<td>Local Bank, ATM</td>
</tr>
<tr>
<td>Dwellings</td>
<td>Apartment, House, Dormitory</td>
</tr>
<tr>
<td>Public leisure and religion places</td>
<td>Zoo, Scenic spot, Temple, Aquarium, Church, Memorial</td>
</tr>
<tr>
<td>Public Parks</td>
<td>Park, Botanical garden</td>
</tr>
<tr>
<td>Educational places</td>
<td>University, Library</td>
</tr>
<tr>
<td>Workplaces</td>
<td>Office Building, Industrial Park</td>
</tr>
</tbody>
</table>

### Operationalization of Variables

The purpose of this research is to analyze the relationship between bike flow and built environment. The dependent variable is bike flow of each station. To operationalize this variable, the bike usage data from smartcards and QR codes in 2017 are combined. The combined data are divided into two parts based on workdays and non-workdays. Then, total bike trips of each station including pick up and return on workdays and non-workdays are calculated. Finally, the average bike trips on every workday and non-workday of each bike station are operationalized as dependent variables.

The explanatory variables are largely divided into two sets of vector variables: public bike systems and built environment (see Table 2). In this study, the bike system refers to juxtaposition of capacity and proximity of bike stations. The capacity of each station is measured through summing total number of bike racks at each station. For the proximity between bike stations, Manhattan distance is applied to calculate the distance between two different locations as the urban form of Suzhou is mostly consisted of large urban blocks. According to data statistics, trip distance of most bike trips is found to be less than 5 km which is used for the maximum distance threshold of station-pairs. The following equation is used to compute the accessibility to other bike stations of each bike station.

\[
B_i = \sum_{j=1}^{k} \frac{C_j}{d_{ij}^{k}}
\]

where \(B_i\) is the accessibility of bike station \(i\) to other bike stations, \(C_j\) means the capacity of bike station \(j\), \(d_{ij}\) is the distance from bike station \(j\) to a given station \(i\), and \(k\) is the distance decay factor. To reflect non-linear distance decay, \(k\) is set to 2 in this research.
TABLE 2 Summary Statistics of Dependent Variables and Independent Variables

<table>
<thead>
<tr>
<th>Dependent variables</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average bike trips on working days</td>
<td>113.198</td>
<td>102.801</td>
</tr>
<tr>
<td>Average bike trips on non-working days</td>
<td>109.349</td>
<td>103.008</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent variables-Attributes of public bike system</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capacity of bike station</td>
<td>28.459</td>
<td>6.795</td>
</tr>
<tr>
<td>Accessibility to bike station</td>
<td>1.511</td>
<td>0.959</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent variables-Built environment</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population density (people/km²)</td>
<td>5530.920</td>
<td>0.006</td>
</tr>
<tr>
<td>Accessibility to metro station</td>
<td>0.347</td>
<td>2.364</td>
</tr>
<tr>
<td>Accessibility to shopping mall</td>
<td>0.803</td>
<td>1.255</td>
</tr>
<tr>
<td>Accessibility to bus station</td>
<td>1.154</td>
<td>0.944</td>
</tr>
<tr>
<td>Accessibility to restaurant</td>
<td>9.670</td>
<td>14.941</td>
</tr>
<tr>
<td>Accessibility to dwelling</td>
<td>1.678</td>
<td>1.966</td>
</tr>
<tr>
<td>Accessibility to local financial services</td>
<td>0.760</td>
<td>1.366</td>
</tr>
<tr>
<td>Accessibility to public leisure and religion place</td>
<td>0.419</td>
<td>1.412</td>
</tr>
<tr>
<td>Accessibility to public park</td>
<td>0.086</td>
<td>0.316</td>
</tr>
<tr>
<td>Accessibility to educational place</td>
<td>0.177</td>
<td>1.017</td>
</tr>
<tr>
<td>Accessibility to workplace</td>
<td>0.747</td>
<td>1.503</td>
</tr>
</tbody>
</table>

This research considers two types of built environment which include population density and accessibility to points of interest (POI). The population density is calculated by dividing total number of populations by area size of each subdistrict in Suzhou. Regarding accessibility to POI, there are two basic approaches being adopted in this research: gravity-based accessibility and catchment area based accessibility. For gravity-based accessibility, metro station is the only POI to be considered. This is because the spatial distribution of metro station is different from other POIs as they mainly pass through primarily in the high density areas in the city. Since the distance to metro stations is more likely to affect bike flow (8), the metro station accessibility of each station is calculated as follows:

\[ M_i = \sum_{j=1}^{k} \frac{R_j}{d_{ij}^k} \]  (2)

where \( M_i \) is the bike station \( i \) accessibility to metro stations, \( R_j \) is ridership of metro station \( j \), \( d_{ij} \) is the Manhattan distance from metro station \( j \) to bike station \( i \), and \( k \) is the distance decay factor and set it to 2 in this paper. It should be noted that since metro ridership is quite constant on a daily basis in Suzhou, the average daily ridership of each metro station in November 2017 is considered as the numerator of Equation (2) in this research. Furthermore, in order to ensure the reliability of the result, the metro stations located more than 1 km away from each bike station are removed since these metro stations are less likely to have an impact on bike flow.

With regard to catchment area accessibility, the following steps are taken. The average walking distance from origins to public sharing bike stations in Suzhou is about 300m which is considered as service area distance of each bike station. Because the distance between some station-pairs is less than 600m, there are some overlaps in some service areas of bike stations. It is assumed that bike users prefer to select the closest bike stations. The thissen polygons which consist of a set of vertical bisector line connecting two adjacent points are used to divide these overlapping areas. Figure 2 presents the service area of each station used in this research. Finally, the catchment area accessibility can be measured by counting total number of POIs falling in...
bike station service area. These POIs include bus stations, restaurants, dwellings, local financial services, public leisure and religion places, public parks, workplaces and educational places. Table 2 presents summary statistics of dependent variables and independent variables.

FIGURE 2 Service Area of each bike station in Suzhou.

METHODOLOGY

Global Regression

A global regression examines the effects of built environment on bike flow in global term. This model does not consider the spatial variation of residuals and independent variables. The model is defined as:

$$y_i = \beta_0 + \sum_{k=0}^{j} \beta_k x_{ik} + \epsilon_i$$  \hspace{1cm} (3)$$

where $y_i$ represents average bike usage per workday or non-workday of bike station $i$, $\beta_0$ is the intercept, $x_{ik}$ is the $k$th independent variable at location $i$, $j$ is the number of regression terms, $\beta_k$ is the coefficient of explanatory variable $k$ and $\epsilon_i$ is the random error term at location $i$. 

[Diagram 1: Service Area of each bike station in Suzhou.]

[Diagram 2: Bike Stations.]

[Diagram 3: Water.]

[Diagram 4: Urban Area of Suzhou.]
Geographically Weighted Regression (GWR)

A Geographically Weighted Regression (GWR) model is a local spatial regression model, which considers spatial autocorrelation and heterogeneity. In general, the residual of the global regression model has spatial autocorrelation issue and the GWR can eliminate this problem by setting up weight in each local area. In addition, if the spatial distribution of variables is uneven, the GWR can solve this spatial non-stationary problem by putting varying estimated parameters in each location. This model can be expressed as:

\[ y_i = \beta_0 (u_i, v_i) + \sum_{k=0}^{j} \beta_k (u_i, v_i) x_{ik} + \epsilon_i \] (4)

where \( y_i \), \( x_{ik} \), \( j \) and \( \epsilon_i \) are the same meaning as the Equation (3), \( (u_i, v_i) \) is the coordinate of the \( i \)th location and \( \beta_k (u_i, v_i) \) is the varying conditional of the \( i \)th location. The major difference between this model and global regression model is that the regression coefficients at each location are varying in this model (27).

In order to express more convenience in matrix form, this model is normally simplified as:

\[ y_i = X_i \beta_i + \epsilon_i \] (5)

where \( X_i \) is the 1-by-\( n \) vector of dependent variables of the \( i \)th location, \( \beta_i \) is the \( n \)-by-1 vector of regression coefficients and \( \epsilon_i \) is random error at location \( i \) (28). The regression coefficients \( \beta_i = (\beta_{i0}, \beta_{i1}, ..., \beta_{ik})^T \) are estimated as follows:

\[ \hat{\beta}_i = \left[ X_i^T W_i X_i \right]^{-1} X_i^T W_i Y \] (6)

where \( X = \left[ X_1^T, X_2^T, ..., X_n^T \right]^T \) is a matrix of independent variables and \( X_i = [1, x_{i1}, x_{i2}, ..., x_{in}] \). \( W_i = \text{diag}[W_{i1}, W_{i2}, ..., W_{im}] \) is a \( n \)-by-\( n \) diagonal weight matrix, and \( Y = \left[ y_1, y_2, ..., y_n \right]^T \) is a column vector of dependent variables (29).

To estimate the regression coefficients of this model, the local weight matrix \( W_i \) should be computed. It is generally assumed that the observed data point closer to the regression point \( i \) might have greater influence on the parameter estimation of regression point than the data point far away from point \( i \). There are two types of kernel functions including Gaussian fixed and adaptive bi-square kernels that are normally adopted to calculate the local weight matrix as follows:

\[ W_{ij} = \exp \left[ - \left( \frac{d_{ij}}{b} \right)^2 \right] \] (7)

\[ W_{ij} = \begin{cases} 1 - \left( \frac{d_{ij}}{b_{IN}} \right)^2 & \text{if } d_{ij} < b_{IN} \\ 0 & \text{otherwise} \end{cases} \] (8)

where \( d_{ij} \) is the distance between point \( i \) and \( j \), \( b \) is a fixed bandwidth and \( b_{IN} \) is an adaptive bandwidth defined as the distance from point \( i \) to the \( N \)th nearest neighbor. In this
research, the adaptive bi-square kernel function is selected since the spatial distribution of bike
stations is uneven and this function can adjust local extents for modeling fitting. It can be
observed that in the kernel functions mentioned above, appropriate bandwidth needs to be
selected. In this research, the Akaike Information Criterion (AIC) is applied to obtain the optimal
bandwidth locally because this criterion can tradeoff the local degree of freedom and the
goodness of fit (29).

7 RESULTS AND DISCUSSIONS

8 Global Regression
9 Prior to global regression, correlation analysis between independent variables and multicollinearity
test were conducted by using the Pearson correlation coefficient and the variance inflation factor
(VIF) respectively. The result shows that the absolute values of correlation coefficients between
all independent variables are less than 6. This means that there is no strong correlation between
independent variables (30). In addition, the VIF of all variables is less than 3, which indicate
that there is no multicollinearity problem among all explanatory variables (11).

Then, the global regression model is built to explore the effect of built environment on
bike flow on working days and non-working days. Table 3 presents the result of this model. It
shows that the capacity and proximity of bike stations are positively related with bike ridership
on working days and non-working days. These findings are consistent with previous studies
(8,15). In addition, apart from accessibility to dwellings and public parks of bike stations, most
of built environment variables have significant impacts on bike flow on both working days and
non-working days. For example, the accessibility to public transit stations of bike stations has a
positive impact on bike flow. This indicates that users prefer to choose bike stations which near
public transit stations and public sharing bikes are considered as transfer hubs which promote
different travel mode transformation in Suzhou. These results are consistent with existing studies
which analyzed PBSP in Paris and New York (16,23). However, a study exploring PBSP in
Zhongshan, China found that bike stations nearby public bus stops has no statistically significant
impact on bike usage (8). The reason might be that bike station density or connectivity of public
transit is different in different cities. The results also demonstrate that the bike stations
surrounding shopping malls, restaurants, local financial and educational places have a positive
impact on bike trips, which are similar to the findings from a study conducted by Faghig-Imani
et al. (22).

Moreover, it should be noted that population density have a negative impact on bike flow.
Intuitively, it is normally reckoned that bike stations located in the area with high population
density attract more users. Indeed, the area with high population density is less likely to have
enough space for users to ride bikes. The connectivity of other public transit such as bus and
metro in these areas is also higher than areas with low population density. Thus, people might be
more willing to choose other travel modes in high population density area. This might be also
related with urban form. Although the new town has relatively low population density, the urban
form of this area could be nicely structured. Bike operating efficiency of this area is relatively
high and people tend to use shared bikes in this area. In addition, there are some notable
differences between working days and non-working days. The accessibility to public leisure
places and public parks on working days has far less than ones on non-working days. This
indicates that people tend to use more bikes for leisure on non-working days. Also, the bike
stations nearby workplaces are positively associated with bike flow on working days while the
coefficient is negative on non-working days. This suggests that there are more bike users for
work trip on working days.
TABLE 3 The results of Global Regression and GWR

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Global Regression</th>
<th>GWR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trips on working day</td>
<td>Trips on non-work day</td>
</tr>
<tr>
<td>Intercept</td>
<td>-75.388 (-8.27)</td>
<td>-67.948 (-7.25)</td>
</tr>
<tr>
<td><strong>Attributes of public bike systems</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capacity of bike station</td>
<td>3.508 (11.88)</td>
<td>3.372 (11.11)</td>
</tr>
<tr>
<td>Accessibility to bike stations</td>
<td>33.441 (14.66)</td>
<td>27.991 (11.93)</td>
</tr>
<tr>
<td><strong>Built environment</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Population density</td>
<td>-2.2E-04 (-2.13)</td>
<td>-2.2E-04 (-2.00)</td>
</tr>
<tr>
<td>Accessibility to metro station</td>
<td>4.852 (5.83)</td>
<td>3.803 (4.44)</td>
</tr>
<tr>
<td>Accessibility to shopping mall</td>
<td>8.254 (4.23)</td>
<td>10.003 (4.99)</td>
</tr>
<tr>
<td>Accessibility to bus station</td>
<td>6.719 (3.23)</td>
<td>6.054 (2.83)</td>
</tr>
<tr>
<td>Accessibility to restaurant</td>
<td>1.075 (5.82)</td>
<td>1.491 (7.84)</td>
</tr>
<tr>
<td>Accessibility to dwelling</td>
<td>0.544 (0.49)</td>
<td>0.411 (0.36)</td>
</tr>
<tr>
<td>Accessibility to local financial services</td>
<td>11.608 (6.84)</td>
<td>11.494 (6.59)</td>
</tr>
<tr>
<td>Accessibility to public leisure and religion place</td>
<td>-3.258 (-2.22)</td>
<td>-0.906 (-0.60)</td>
</tr>
<tr>
<td>Accessibility to public park</td>
<td>-7.613 (-1.22)</td>
<td>-1.131 (-0.18)</td>
</tr>
<tr>
<td>Accessibility to educational place</td>
<td>7.276 (3.83)</td>
<td>9.130 (4.68)</td>
</tr>
<tr>
<td>Accessibility to workplace</td>
<td>5.190 (3.78)</td>
<td>-1.610 (-1.14)</td>
</tr>
<tr>
<td>R²</td>
<td>0.392</td>
<td>0.360</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.387</td>
<td>0.355</td>
</tr>
<tr>
<td>AICc/AIC</td>
<td>20387.892</td>
<td>20490.475</td>
</tr>
<tr>
<td>Number of observations:</td>
<td>1755</td>
<td></td>
</tr>
</tbody>
</table>
GWR
The GWR is built using adaptive bi-square kernel function with the AIC. The model diagnostic results report that the adjusted R-square and AIC of the GWR are clearly less than that of the global regression model (see Table 3). This indicates that the goodness of fit of the GWR is better than that of the global regression model in this study. Moreover, the results of ANOVA also show that the sum of squares of GWR residuals is almost half of that of the global regression model. This confirms the statistical performance of GWR is better than the global regression model.

GWR can examine the spatial variation of influencing factors. Table 3 shows that the range of estimated coefficient of local independent variables varies from negative to positive value. Because the GWR results are almost identical on working days and non-working days, this study mainly focuses on nine explanatory variables on working days and the spatial distributions of these local estimated coefficients and t-value with significance less than 90% are visualized in Figure 3. In terms of accessibility to bike stations, this independent variable has a positive impact on bike usage near the urban center of Suzhou. It should be noted that in the center of Suzhou (Old Town), bike trips has no significant relationship between the accessibility to bike stations (see Figure 3 (a)). This indicates that establishing many bike stations in the center of a city is not an efficient way to increase utilization of public sharing bikes.

![Accessibility to Bike Station](image1)
![Accessibility to Metro Station](image2)
FIGURE 3 Spatial distributions of local coefficients on working day and t-value with significance less than 90%.

In addition, the spatial effect of public transit on bike usage is similar. Figure 3 (b) and (c) illustrate that in the urban center of Suzhou, public transit has almost no significant influence on bike usage. In some areas surrounding urban center, the accessibility to public transit is positively correlated with bike flow. This may be because bike stations proximate to these public transit stops are served as transfer modes which allow local users to easily move to other parts of a city. This indicates that building bike stations nearby public transit stops encourages the bike and ride travel mode particularly in the periphery of a city center.

With regard to accessibility to certain POI categories such as shopping malls and workplaces and educational places, these explanatory variables have a significantly positive impact on bike usage (see Figure 3 (d), (e) and (f)). Especially, shopping centers, industrial park and universities from POI categories appear the most significantly influenced factors to bike usage. Moreover, the accessibility to restaurants and local financial places in some areas are highly positive related with bike usage (see Figure 3 (g) and (h)). Interestingly, Table 2 reports that there is no statistically relationship between bike stations nearby dwellings and bike usage. In Figure 3 (i), the local coefficient of this independent variable is locally significant in the periphery of SIP. As mentioned before, these areas are residential districts. This suggests that it is necessary to consider the spatial property of each area before establishing bike stations.

CONCLUSION

This research examines the relationship between built environment and bike flow and how the local effects of these variables on bike flow using a global regression model and a GWR. The global results indicate that the attributes of public bike systems including the capacity and proximity of bike stations are positively correlated with bike usage. In addition, gravity-based accessibility to metro stations of bike stations may increase bike flow. The bike stations nearby shopping malls, bus stations, restaurants, financial and educational places are also positively correlated with bike usage on both working days and non-working days. However, population density has a statistically negative impact on bike usage.

The GWR visualizes how built environment affects bike flow in each location. The findings broadly confirm that the built environment has significant effects on the shared bike...
flow, which is consistent with other studies (15,19,22,23). Increased activation in the
accessibility measures in this study corroborates these earlier findings. However, these effects
are divergent across the Suzhou region. Most of the coefficient appears to have zero or negative
value in the central areas of Suzhou (Old Town) while surrounding areas have modest built
evironment effect on bike flows. This suggests that carefully designed planning strategies can
improve the accessibility to bike stations nearby the center of a city by increasing the capacity of
bike station or establishing more bike stations around existing bike stations, and these bike
stations can improve the travel efficiency of users.

These findings also help us to understand that urban form of Suzhou has distinctive
difference between old town area and new towns (SIP, Xiangcheng and Huqiu district). SIP has
relatively strong accessibility to bus stations, shopping malls, and dwellings. On the other hand,
southern part of Xiangcheng district presents highly positive coefficients in accessibility to
workplaces and restaurants. A possible explanation for this spatial variation might be that new
district developments including SIP, Huqiu and Xiangcheng districts happened in different stages
of urbanization in Suzhou of which planning framework and strategies are not consistent. These
different spatial planning could lead to disconnected typology of urban configuration. Another
possible explanation for this is that location of bike stations are not matched with existing
demand of bike use. For instance, SIP is the area of financial and IT service companies where
young professionals work. However, accessibility to workplaces may not support the demand of
bike use. In addition, the goodness of fit in the GWR is better than the global regression model.
This proves that the local effects should be examined in urban form and bike research. If the
spatial property of variables does not consider during the planning and operating public sharing
bike systems, resources will not be allocated reasonably and the operating efficiency of public
sharing bike systems cannot be improved. Moreover, this model is easy to use in practice and
many studies proved that the prediction performance of this model is better than the global
regression model (11).

However, there are some limitations of this research. For example, this research did not
consider explanatory variables such as weather and temporal variables. In some specific areas,
the reason why bike stations nearby restaurants and local financial places are highly correlated
with bike flow did not explore in this study. In addition, this research only focuses on the public
sharing bike system in Suzhou and PBSP in other countries did not analyze. In the future, the
above issues can be further studied.

ACKNOWLEDGMENTS
This work was supported by Jiangsu Industrial Technology Research Institute and Research
Institute of Future Cities at Xi’an Jiaotong-Liverpool University.

AUTHOR CONTRIBUTION STATEMENT
The authors confirm contribution to the paper as follows: study conception and design:
Chunliang Wu, Inhi Kim and Hyungchul Chung; data collection: Chunliang Wu and Inhi Kim;
analysis and interpretation of results: Chunliang Wu, Inhi Kim and Hyungchul Chung; draft
manuscript preparation: Chunliang Wu and Hyungchul Chung. All authors reviewed the results
and approved the final version of the manuscript.

REFERENCES
1. Fishman, E. Bikeshare: A review of recent literature. Transport Reviews, Vol. 36, No. 1,


