Deciphering Urban Bike-Sharing Patterns: An In-depth Analysis of Natural Environment and Visual Quality in New York's Citi Bike System

Abstract:

Bike-sharing offers a convenient and sustainable mode of transportation. Numerous studies have investigated the influence of temporal variations in the natural environment on cycling, as well as the impact of physical street characteristics like networks and infrastructures. However, few studies integrated and compared the effects of natural environment and street visual quality on cycling in the spatial dimension. As a case study, we focused on the impact of these two factors on the Citi Bike system on weekdays and weekends in New York City, while accounting for sociodemographic and functional factors. This study employed machine learning and multiscale geographically weighted regression (MGWR) models at both station and neighborhood scales for a comprehensive analysis of their relationships. The results reveal that the natural environment factors, particularly visibility, are more important factors associated with bike-sharing use. Among the visual quality factors, motorized traffic has a negative impact on both weekday and weekend cycling. When considering geographical location, sky openness exhibits an unfavorable influence on weekday cycling in specific areas. By combining natural environment and visual quality factors, our study promotes optimal resource allocation and the development of bike-friendly cities.

Keywords: Bike-sharing usage, Weather conditions, Air quality, Visual quality, Machine learning, Multiscale geographically weighted regression

1. Introduction

Cycling is vital in urban transportation, sustainability, and public health (Pucher and Buehler, 2017; Neves and Brand, 2019; Oja et al., 2011). It has drawn considerable interest from researchers and policymakers due to its potential to ease road congestion, lower carbon emissions, and encourage active lives (Buehler, 2012; Chau et al., 2015; Götschi et al., 2016). In recent years, the factors affecting bike-sharing have been extensively investigated, such as weather conditions, air quality, built environment, and sociodemographic attributes (Wu et al., 2021; An et al., 2019; He et al., 2023).

Natural environment factors such as weather conditions and air quality have been widely investigated in terms of their influence on bike-sharing demand (Noland, 2021; Morton, 2020). Nevertheless, these studies have mainly focused on the temporal scales and large spatial units, ignoring the variation in the spatial dimension across different areas within the city, especially weather conditions. It has been recognized that some weather conditions such as temperature and wind speed can exhibit local variations within a city due to factors like urban form and landscape (Elnahas, 2003; Gago et al., 2013). Furthermore, given that riding behavior takes place within a spatial area, it is reasonable to infer that the connection between natural environment factors and cycling could exhibit localized variations within that particular region. This has been exemplified in previous literature on public transit ridership, revealing that the influence of weather within a city is defined by spatial location, rather than being a constant global factor (Wei, 2022).

The visual quality of streets affects people's perception, which is an important part of the cycling experience. Limited by constraints in measuring and assessing the impact of visual quality, there exists an insufficient understanding of how fine-scale design factors specifically influence cycling (Wang et al., 2023). Street view images (SVIs) and Computer Vision (CV) have yielded opportunities for the research of cycling, enabling the capture of detailed visual data on urban streetscapes (Ito and Biljecki, 2021). Existing research, however, has mainly examined how the element of greenery in SVIs affects cycling (Chen et al., 2020; R. Wang et al., 2020), with relatively little attention paid to the effects of other visual quality features.

Many previous studies have analyzed the factors influencing cycling at the bike-sharing station level, focusing either on built environment factors or natural environment factors (Wang et al., 2018; El-Assi et al., 2017). Collectively, these studies suggest that cycling is not determined by a sole factor but rather by a complex interplay of various forces (Cervero et al., 2019). In addition, these studies generally rely on traditional linear models, and overlook the consideration of neighboring stations and the effects of spatial heterogeneity. However, the relationship between these factors and active travel tends to be non-linear (Xiao and Wei, 2023; Nosal and Miranda-Moreno, 2014). Daily travel and mobility patterns also vary spatially and defy the stationarity hypothesis (Chen et al., 2019). Therefore, it is essential to integrate and compare the impact of built environment factors, particularly visual quality, which have received less exploration, with natural environment factors on bike-sharing use in the spatial dimension and it is crucial to address non-linear relationships and spatial autocorrelation as key considerations when evaluating the relationship between bike-sharing use and influencing factors.

In this study, we aim to address the following research questions: (1) How do spatial differences in visual quality and natural environment factors including weather and air quality affect bike-sharing usage at the station level within a city? (2) Specifically, which attribute group of these two categories, and which specific features, are more strongly associated with bike-sharing usage? In the temporal dimension, how do their impacts differ on weekdays and weekends? Taking Citi Bike in New York City (NYC) as a case study, we focused on the impact of the natural environment and visual quality factors on the Citi Bike system on weekdays and weekends, while considering functional factors that influence the visual appeal of streets and sociodemographic characteristics. This study provides a more detailed understanding by setting up a series of experiments to compare the effects of these factors, using machine learning (ML) models to explore non-linear association at the bike-sharing station scale and multiscale geographically weighted regression (MGWR) models to explore spatial variation relationships at the neighborhood scale. The utilization of two spatial analysis units stemmed from the necessity to account for potential demand disparities between two distinct groups. Bike-sharing companies benefit from precise machine learning models for each station, enabling accurate predictions and efficient resource scheduling. Conversely, transportation and urban planners, along with policymakers, may find it more advantageous to adopt a macro perspective. This broader viewpoint aids in understanding the utilization of bike-sharing in various neighborhoods while accounting for geographical factors. It facilitates planning and regulation on a larger scale, thereby promoting a bike-friendly city and transportation system.

The following sections of this study are organized as follows. Section 2 reviews the literature on the relationship between various factors and cycling. Section 3 introduces the data and methodologies. Section 4 summarizes the key research results. In Section 5, we make discussions and possible implications. Finally, conclusions and limitations are presented in Section 6.

(Below are the tables and figures.)

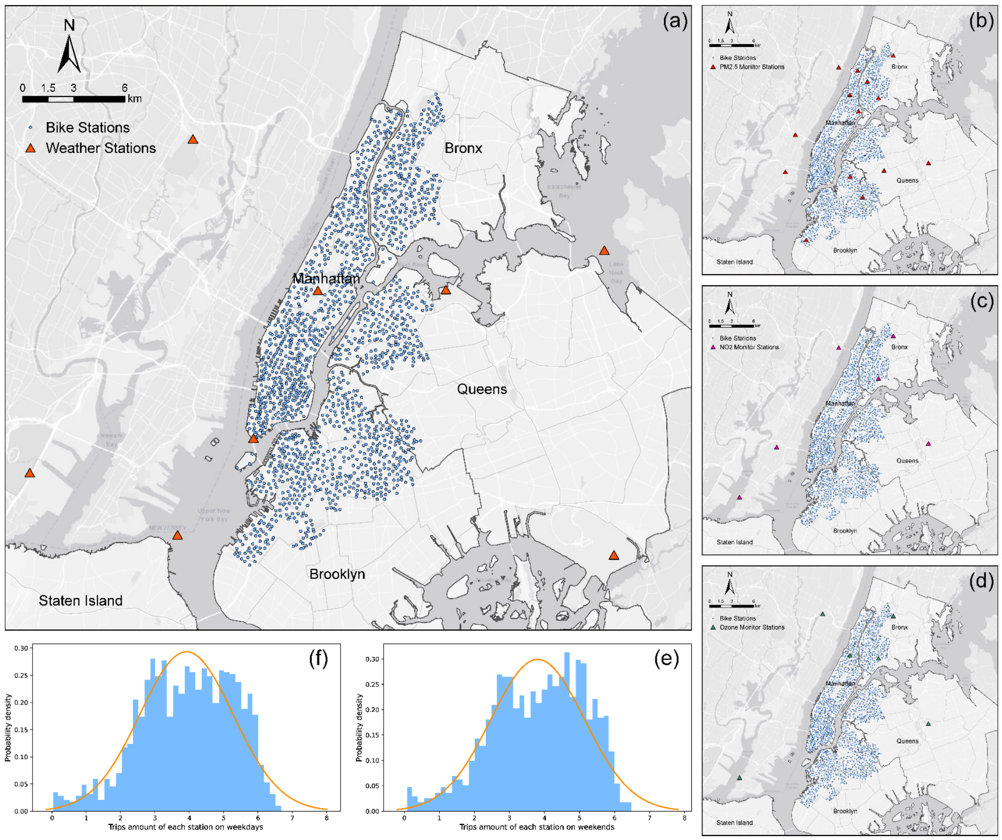

Figure 1. (a-d) Spatial distribution of Citi Bike stations and weather stations or air quality monitor stations. (e-f) Histogram plots of the trip amount of each bike station after natural logarithm conversion.

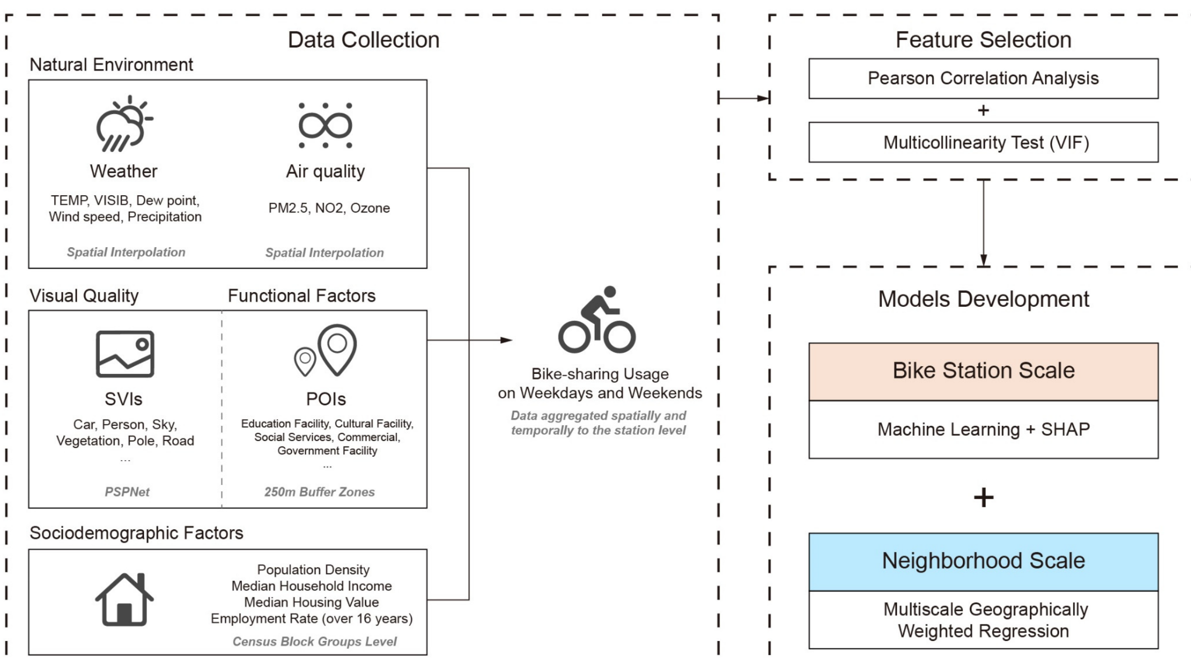

Figure 2. Analytical framework.

Table 1. Summary statistics of all variables included in the models.

Category		Variables		Description	Mean	S.D.	Min	Max
Sociodemographic factors		Population Density (person/km²)		The related sociodemographic data of the census block group level where a bike station is located	24953.833	20765.960	0.000	176260.000
		Median Household Income ($)			77384.270	66152.905	0.000	250000.000
		Median Housing Value ($)			552302.550	665319.243	0.000	2000000.000
		Employment Rate (over 16 years) (%)			0.629	0.232	0.000	1.000
Built environment factors	Visual Quality factors	Car (%)		Average of each feature in SVIs of four directions for a bike station calculated by PSPNet semantic segmentation	0.065	0.052	0.000	0.554
		Person (%)			0.013	0.028	0.000	0.417
		Sky (%)			0.125	0.091	0.000	0.617
		Vegetation (%)			0.151	0.119	0.000	0.742
		Pole (%)			0.002	0.002	0.000	0.032
		Road (%)			0.297	0.076	0.002	0.520
	Functional factors	Education Facility (number)		Number of each category POIs within a 250m search radius of a bike station	2.668	3.702	0.000	45.000
		Cultural Facility (number)			0.613	1.572	0.000	23.000
		Social Services (number)			0.985	1.224	0.000	8.000
		Commercial (number)			0.965	2.340	0.000	19.000
		Government Facility (number)			0.880	4.329	0.000	76.000
Natural environment factors		TEMP (°F)	Weekdays	Daily mean temperature of a bike station on weekdays/weekends after spatial interpolation	56.377	0.174	56.010	57.067
			Weekends		55.203	0.188	54.770	55.941
		VISIB (miles)	Weekdays	Daily mean visibility of a bike station on weekdays/weekends after spatial interpolation	9.226	0.046	9.126	9.336
			Weekends		9.375	0.015	9.352	9.428
		PM2.5 (ug/m3)	Weekdays	Daily mean PM2.5 concentration of a bike station on weekdays/weekends after spatial interpolation	7.229	0.411	6.175	8.268
			Weekends		6.783	0.338	5.739	7.681
		NO2 (ppb)	Weekdays	Daily max 1-hour NO2 concentration of a bike station on weekdays/weekends after spatial interpolation	30.458	0.658	26.843	31.338
			Weekends		24.213	0.423	22.481	25.494
		Ozone (ppm)	Weekdays	Daily max 8-hour ozone concentration of a bike station on weekdays/weekends after spatial interpolation	0.035	0.001	0.033	0.036
			Weekends		0.037	0.001	0.035	0.038
Dependent variables		Bike-sharing usage (number)	Weekdays	Daily mean trip amount of a bike station on weekdays/weekends	99.703	116.819	0.019	762.200
			Weekends		36.396	41.403	0.027	264.538

Table 2. MLR models comparison for different combinations of attribute groups.

		SD	SD+BE		SD+NE	All Factors
			SD+VQ	SD+VQ+FP		
Weekdays	R^2	0.12	0.31	0.38	0.51	0.59
	MSE	1.54	1.21	1.08	0.73	0.71
Weekends	R^2	0.12	0.27	0.33	0.44	0.48
	MSE	1.47	1.22	1.12	0.92	0.87

Notes: SD: Sociodemographic factors; BE: Built environment factors, including VQ: Visual quality factors and FP: Functional factors (POIs); NE: Natural environment factors

Table 3. Performance comparison of different ML models on weekdays and weekends.

ML models		Weekdays		Weekends	
		R^2	MSE	R^2	MSE
Ensemble Method	GBR	0.75	0.42	0.73	0.43
	RFR	0.78	0.37	0.77	0.37
	XGB	0.77	0.38	0.73	0.43
Artificial Neural Network	MLP	0.62	0.63	0.56	0.70

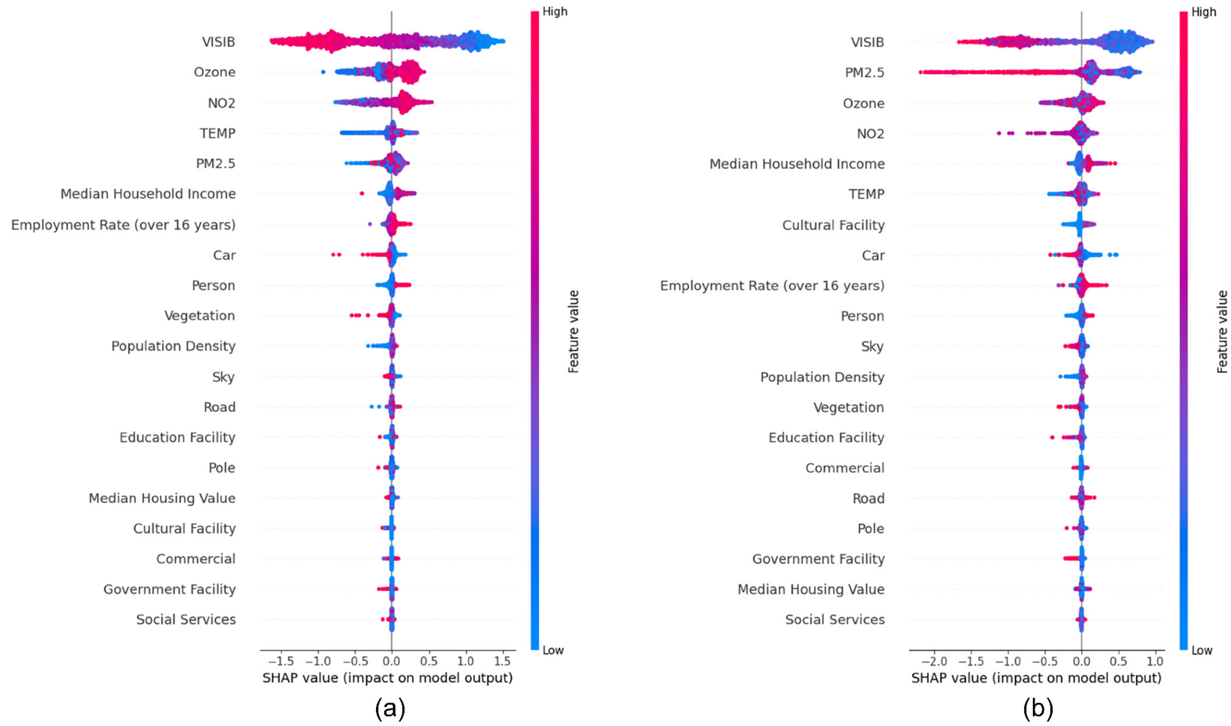

Figure 3. SHAP summary plots on (a) weekdays and (b) weekends.

Table 4. Model comparison between the OLS, GWR, and MGWR models.

	OLS		GWR		MGWR	
	Weekdays	Weekends	Weekdays	Weekends	Weekdays	Weekends
RSS	489.33	639.62	183.65	178.76	130.56	137.14
R^2	0.61	0.47	0.86	0.85	0.90	0.89
Adjusted R^2	0.60	0.45	0.82	0.81	0.87	0.86
AICc	1850.70	2051.05	1461.70	1469.76	1186.63	1179.23

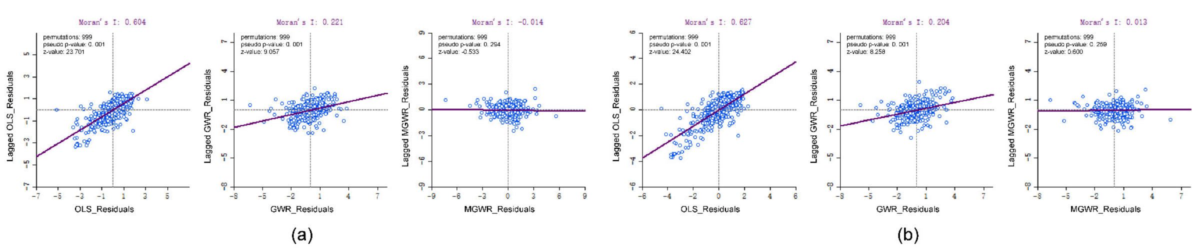

Figure 4. Moran's I residuals test of the OLS, GWR, and MGWR models on (a) weekdays and (b) weekends.

Table 5. Summary statistics of the local coefficients of the MGWR model on weekdays and weekends.

Variables	Usage on weekdays			Usage on weekends		
	P≤0.05 (%)	+(%)	-(%)	P≤0.05 (%)	+(%)	-(%)
Intercept	93.32	100.00	0.00	100.00	100.00	0.00
Population Density	33.69	100.00	0.00	18.18	100.00	0.00
Median Household Income	0.00	0.00	0.00	31.95	100.00	0.00
Median Housing Value	49.87	0.00	100.00	23.80	0.00	100.00
Employment Rate (over 16 years)	0.13	100.00	0.00	5.48	100.00	0.00
Car	0.00	0.00	0.00	17.78	0.00	100.00
Person	0.00	0.00	0.00	0.00	0.00	0.00
Sky	20.86	0.00	100.00	0.00	0.00	0.00
Vegetation	0.80	0.00	100.00	0.00	0.00	0.00
Pole	0.00	0.00	0.00	0.00	0.00	0.00
Road	0.00	0.00	0.00	0.00	0.00	0.00
Education Facility	6.28	0.13	99.87	0.00	0.00	0.00
Cultural Facility	6.68	100.00	0.00	0.00	0.00	0.00
Social Services	0.27	100.00	0.00	0.00	0.00	0.00
Commercial	100.00	100.00	0.00	0.00	0.00	0.00
Government Facility	0.00	0.00	0.00	0.00	0.00	0.00
TEMP	40.24	100.00	0.00	16.98	0.00	100.00
VISIB	95.32	0.00	100.00	82.49	37.60	62.40
PM2.5	0.00	0.00	0.00	26.74	39.00	61.00
NO2	16.18	0.00	100.00	18.58	35.97	64.03
Ozone	42.51	96.54	3.46	29.01	0.00	100.00

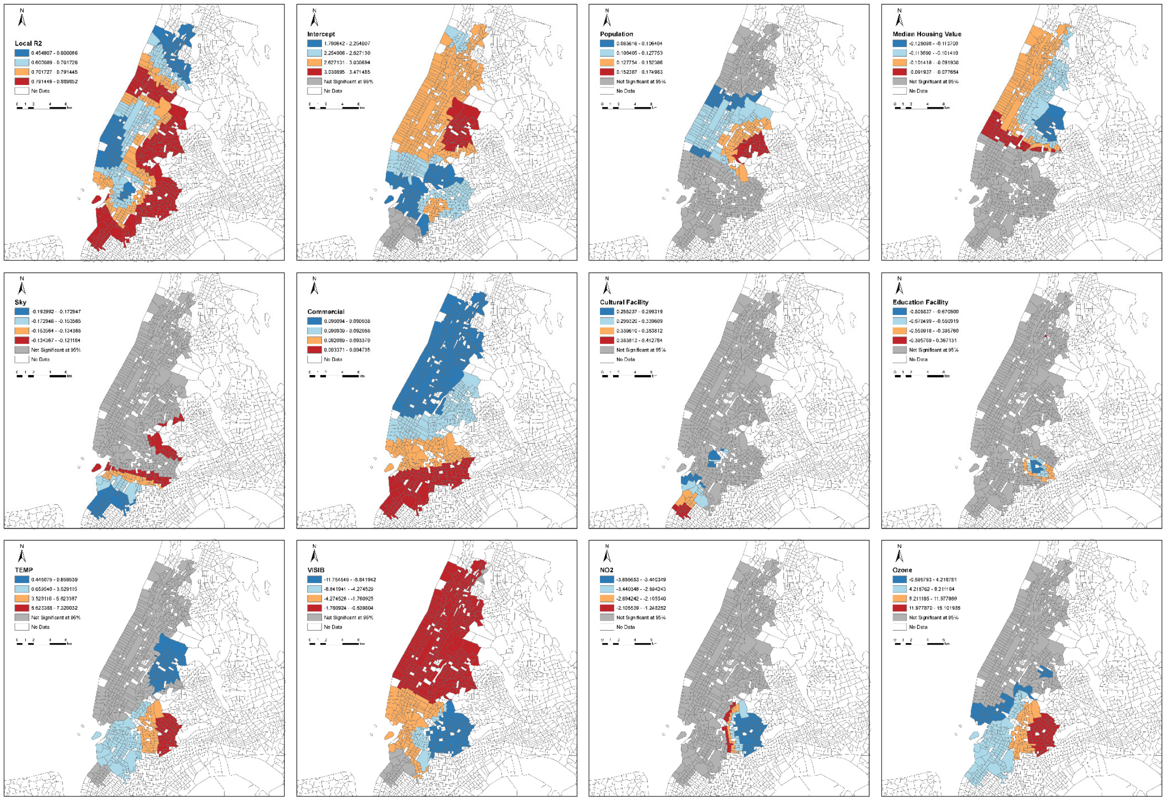

Figure 5. Spatial distribution of local R^2 and coefficients of influencing factors of the MGWR model on weekdays.

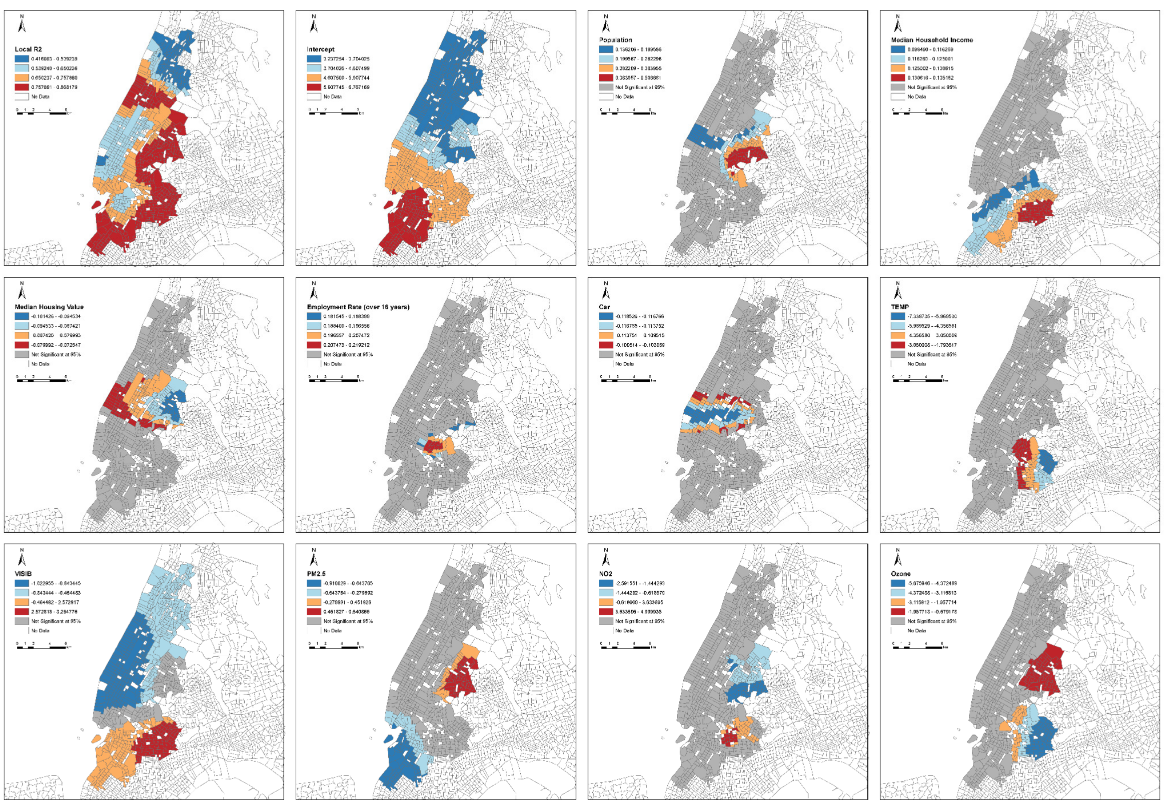

Figure 6. Spatial distribution of local R^2 and coefficients of influencing factors of the MGWR model on weekends.

Appendix A:

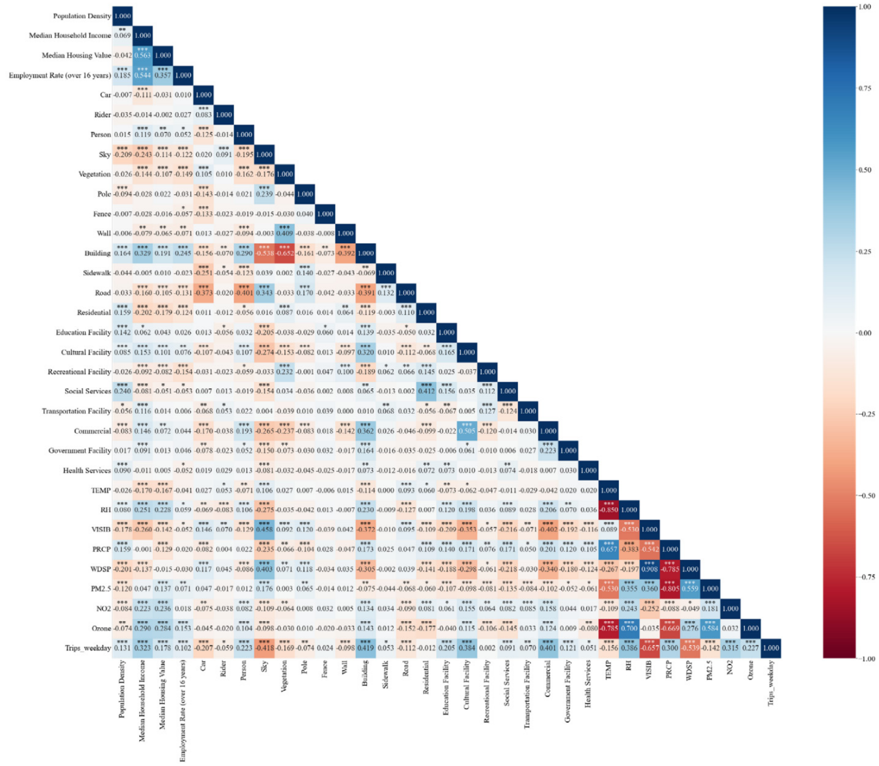

Figure A1. Pearson correlation analysis of potential variables on weekdays.

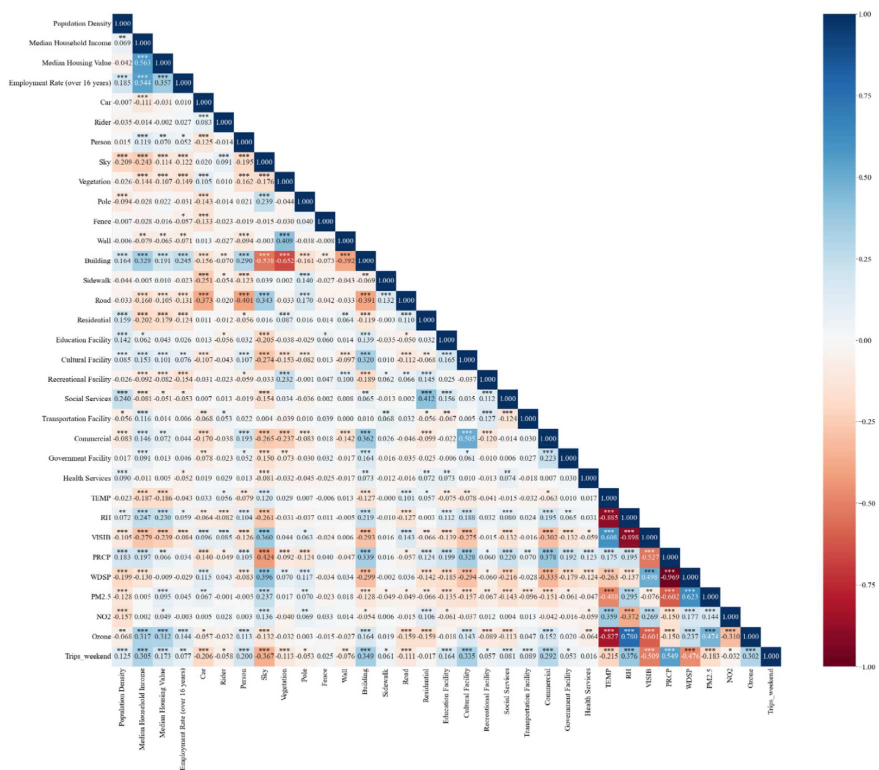

Figure A2. Pearson correlation analysis of potential variables on weekends.

Table A1. Influencing factors' correlation and VIF values with dependent variables in the final models

Category		Variables	Pearson Correlation Coefficients		VIF	
			Weekdays	Weekends	Weekdays	Weekends
Sociodemographic factors		Population Density	0.131***	0.125***	1.256	1.262
		Median Household Income	0.323***	0.305***	2.132	2.082
		Median Housing Value	0.178***	0.173***	1.581	1.575
		Employment Rate (over 16 years)	0.102***	0.077**	1.575	1.552
Built environment factors	Visual Quality factors	Car	-0.207***	-0.206***	1.419	1.416
		Person	0.223***	0.200***	1.408	1.408
		Sky	-0.418***	-0.367***	1.788	1.782
		Vegetation	-0.169***	-0.113***	1.256	1.258
		Pole	-0.074**	-0.053*	1.108	1.108
		Road	-0.112***	-0.111***	1.817	1.820
	Functional factors	Education Facility	0.205***	0.164***	1.153	1.151
		Cultural Facility	0.384***	0.335***	1.505	1.504
		Social Services	0.091***	0.081***	1.185	1.181
		Commercial	0.401***	0.292***	1.763	1.725
		Government Facility	0.121***	0.053*	1.092	1.089
Natural environment factors		TEMP	-0.156***	-0.215***	3.119	4.409
		VISIB	-0.657***	-0.509***	2.078	2.285
		PM2.5	-0.142***	-0.183***	2.416	2.119
		NO2	0.315***	-0.032*	1.401	1.502
		Ozone	0.227***	0.302***	3.895	4.475

Notes: *** indicates a significant correlation at level 0.001. ** indicates a significant correlation at level 0.01. * indicates a significant correlation at level 0.05.

Appendix B:

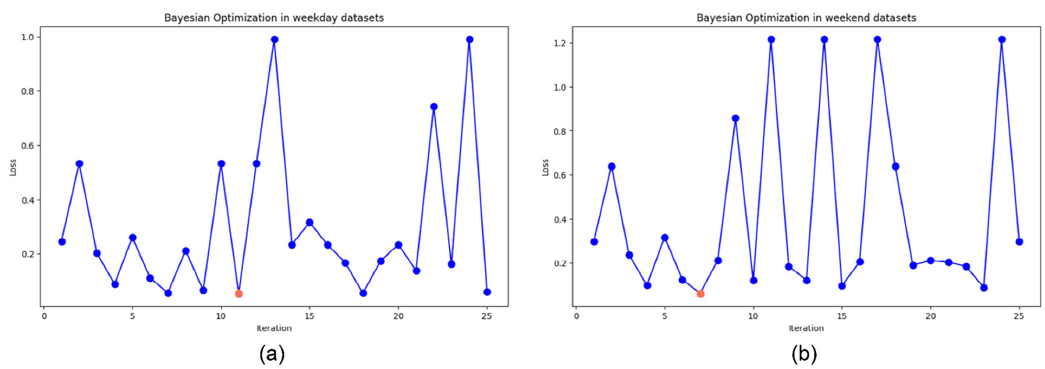

Figure B1. Interactive process of Bayesian optimization on (a) weekdays and (b) weekends.

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