Estimating the Impacts of Seasonal Variations of Streetscape on Dockless Bike Sharing Trip with Street View Images and Computer Vision

Yongqin Zhao[1], Sijia Wang[1], Difan Chen[2], Kaijie Huang[3], Siyuan Zhang[4], Waishan Qiu[5], and Wenjing Li[6](✉)

[1] Independent, Shanghai, China
[2] Independent, Missouri City, CA, USA
[3] The New School, New York City, USA
[4] Huazhong University of Science and Technology, Wuhan, China
[5] Cornell University, New York City, USA
[6] The University of Tokyo, Tokyo, Japan
liwenjing@csis.u-tokyo.ac.jp

Abstract. A significant portion of the cycling experience is influenced by the streetscape, and this impact varies throughout the year. The temporal dynamic of streetscape has been neglected in most previous studies, including urban public mobility route choices. This paper examines the correlation between dockless bike sharing and streetscape as well as spatial elements in different seasons using a large amount of GPS bike trajectory data collected by LIME. The study shows that: (1) DBS volume is significantly influenced by seasonal streetscape factors such as roads, cars, sidewalks, tree, and vegetation color; (2) How significantly these seasonal factors affect DBS volume differs in summer and autumn; (3) In both summer and autumn models, non-seasonal factors like mixed land use score, street network connectivity, etc., are significant. Some non-seasonal factors only impact the DBS volume in one season; (4) When adding subjective perception to models of both seasons, model explanatory does get improved very slightly.

Keywords: Seasonal variation · Dockless bike sharing · Street view image · Computer vision · Built environment

1 Introduction

Bikeshare promotes sustainable travel, health benefits, and economic growth (Qiu and Chang 2021). Dockless bikeshare (DBS), compared to the docked bikeshare system, is getting more popular in the last decade due to benefits like accessibility and convenience (Gu et al. 2019).

There are observed research gaps in DBS seasonal study: (1) the development of mobile applications and cashless mobile payment have make bike sharing usage even more prevalent (Guo et al. 2022). However, as a new mode of transportation, DBS has received less attention than docked bike sharing (Guo et al. 2022). (2) A majority

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of precedent studies of DBS focus mostly on where a trip starts and ends, rather than the cycling experience itself. (3) limited examination of how seasonal streetscape affects cycling. Although a small number of studies consider temporal scale, yearly comparisons (Li 2021) offer limited help in comparing seasons, and studies addressing the association between seasonal climate and bike sharing didn't examine other seasonal environmental characteristics(Li and Kamargianni 2017).

The study (1) provides a quantitative study of DBS focusing on perceived environmental elements along the journey, (2) integrates SVI and CV to estimate how seasonality of street built environment impacts DBS usage at a fine spatial scale. (3) considers previously ignored seasonal environmental features like vegetation color.

2 Data and Methodology

2.1 Study Area and Methodology

Our study area includes the Town of Ithaca and a few nearby neighborhoods (Fig. 1).

Fig. 1. Study area

Figure 2 illustrates the framework of this study: (1) Using GPS bike trajectory data from LIME, a DBS system in Ithaca USA, we computed Seasonal Weighted Rides (SWR) to capture the cycling volumes of road segments in summer and autumn. (2) We collected SVIs in summer and autumn with Google SVI API. (3) We used PSPNet to compute the view ratio indices of streetscape elements, and used Mask R-CNN to count the number of streetscape objects. We also computed CV indicators (color deviation, L, A, B values in CIELAB color space) to present the seasonal color change of these three variables: tree, plant, and grass. (4) We quantified four subjective perception scores (accessibility, ecology, enclosure, scale) of street environment in summer and autumn with ML. (5) We collected and computed non-seasonal variables (typical POI, landmark POI, infrastructure, road type, land use mixed score, street network connectivity, terrain). (6) With OLS regression models, the seasonal environment attributes are comprehensively analyzed with their impacts on DBS volumes in summer and autumn.

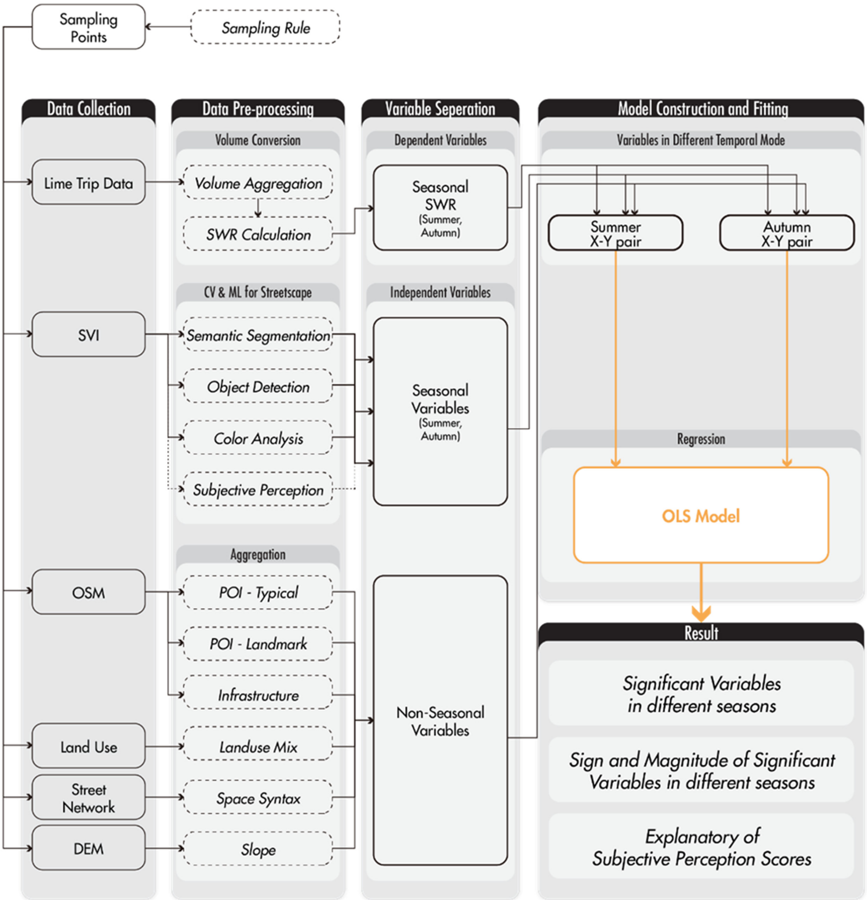

Fig. 2. Research framework

2.2 Data and Processing

2.2.1 Dependent Variable: DBS Data and Seasonal Weighted Rides (SWR)

LIME provided us with the DBS trips data for this study, accessible through an API. LIME's app was used to collect the data. After the users agreed to LIME's terms and conditions for using the services, LIME recorded and analyzed their journeys. The dataset does not include identifiable individual information. To clean the data, trips that started or ended outside the Greater Ithaca area (Qiu and Chang 2021), trips with distances shorter than 0.05 miles or 264 feet (Qiu and Chang 2021), and trips with durations less than 3 min or more than 120 min were removed. The validated dataset has 102,178 trip records.

To make cyclists' choice and preference of routes comparable across different seasons, we have to capture the popularity of road segments in each season with Seasonal

Weighted Rides (SWR). This conversion can be found in Eq. (1).

$$SWR_j = SR_j / (\sum_{j=1}^{n} r_j) \tag{1}$$

For segment j, SR_j represents the volume of rides on it in this particular season, n represents the number of segments with rides on them in this particular season, and $\sum_{j=1}^{n} r_j$ represents the total number of rides on all segments in Ithaca during this particular season. The SWR_j that is aggregated to the sampling points i is the dependent variable of this study, and has the precision of street segments, so sampling points on the same segment would have the same value for one season.

To reduce the bias caused by data sparsity, we removed segments with a total annual volume of less than 500 riders (approximately 1.5 riders a day) from the aggregated data. Then we sampled points every 25 m in segments with lengths more than 50 m (which is too short). Therefore, 671 out of 10508 road segments were selected, and 2,082 sampling points were obtained from them.

2.2.2 Independent Variable: Street View Measuring

Google Street View (GSV) is only available in summer (Jun, July, Aug) and fall (Sept, Oct, Nov) in our study area, and out of 2,082 sampling points, there are only 1,170 points having GSV in both seasons. With GSV panorama ID and Street View Download 360 software (Street View Download 360, n.d.) we download the panorama in both summer and fall of each point. To extract the count of elements in a panorama SVI, we use a Mask-RCNN pre-trained on COCO dataset with ResNet-50 backbone. Then we use Pyramid Scene Parsing Network (PspNet) with pre-trained model psp_resnet101_ade to conduct image segmentation.

Undesired segmentation distortions might occur near the top and button of a panorama image, so we unwarp the panorama into images in 6 directions (Forward, Back, Left, Right, Up, and Down) with py360convert package and extracted the four directions at eye-level: forward(F), back(B), left(L), and right(R) (Fig. 3).

From percentage that the pixels of the specific visual element take-up of the total pixels of an SVI we calculated the visual ratio of an element in the image. Not all objective view indices will be input to the regression model after the Variance Inflation Factor (VIF) test, only 20 out of 28 visual ratio are kept, including: tree, road, grass, car, streetlight, wall, building, sidewalk, earth, water, plant, awning, van, person, bridge, railing, bicycle, minibike, ceiling, chair.

To study color and change of street greenness from urban cyclists' perspective, we used the CIELAB colorspace and extracted PSPNet pixels for three types of greenness. Converted from RGB to CIELAB using the Python-colormath library, we calculated average A and B values for each pixel and the standard deviation from actual values. To eliminate potential interference, we eliminated the L value (brightness) as SVIs are taken in different conditions.

We evaluate street perceptions using a 300-point pre-labeled dataset and an ML framework developed by related research (Qiu et al. 2023; Su et al. 2023) to evaluate the subjective perceptions score of the streetscape: Accessibility (accessibility to

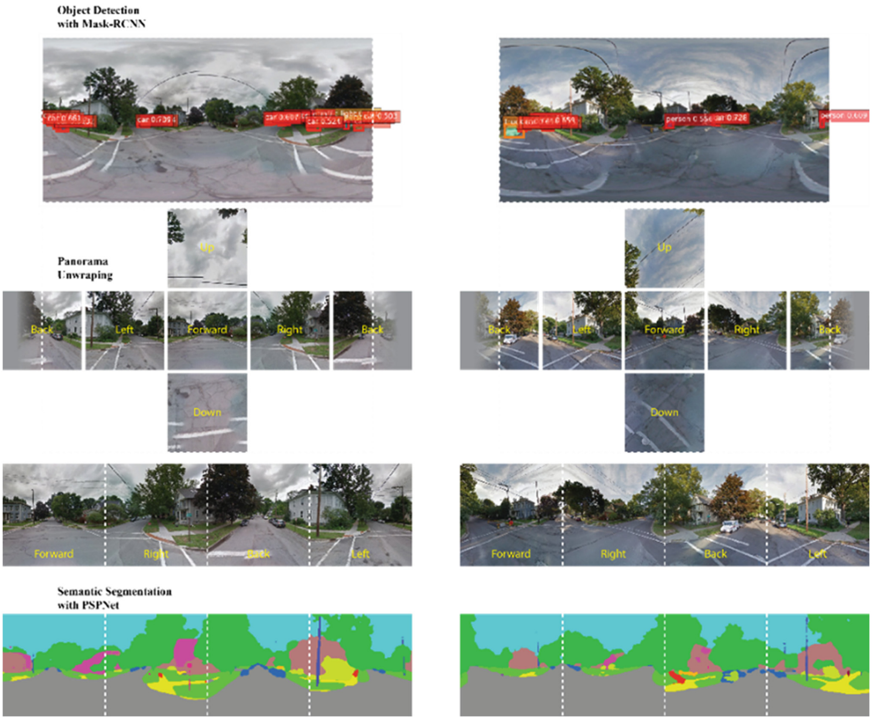

Fig. 3. Panorama object detection with Mask_RCNN, unwarping(in 4 directions: F, R, B, L), and semantic segmentation with PSPNet. Left: Summer SVI. Right: Autumn SVI

activities, attractions, and amenities), Ecology (detecting living organisms, animals, plants, humans, and their physical environment), Enclosure (the degree to which buildings, walls, trees, and other vertical elements define streets and public spaces visually), and Scale (human-sized and proportional elements). The dataset was collected from a crowdsourced visual survey of an expert panel and includes SVI input variables and 4 perceptual scores as output labels. 75% (225) of the dataset is used for training and 25% (75) for testing. Multiple ML algorithms are used, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), Gaussian Process (GP), Gradient Boosting Regression (GB), ADA boost, and Bagging Regression. GP is chosen as the optimal model for predicting the target perceptions (Table 1).

2.2.3 Independent Variable: Non-seasonal Variables

We use Open Street Map (OSM) to get typical POI, infrastructure (transit facility), road types, and landmarks POI. The buffer zone radius is 500m for typical POIs, 100 m for infrastructure, and 1000 m (typical 5 min bike rides) and 3000 m (typical 15 min bike rides) for landmark POIs.

We use land use data collected from Tompkins County Open Data Portal (Land Use and Land Cover 2015; Tompkins County Open Data Portal, n.d.), and use a method

Table 1. Performance of GaussianProcessRegressor (GP) predictions

Perceptions score	R2	RMSE	MAE
Accessibility	0.4	0.18	0.15
Ecology	0.43	0.17	0.13
Enclosure	0.53	0.16	0.13
Scale	0.39	0.18	0.15

originally developed to calculate the evenness of distribution of the area of different use types (Frank et al. 2005). The calculation is shown in Eq. (2).

$$LanduseMix = (-1) * \left(\sum_{i=1}^{n} p_i \ln(p_i) \right) / \ln(n) \tag{2}$$

With p_i, the proportion of land use i within the 500m buffer is divided by the total area within the 500 m buffer, while n represents the number of exclusive land use types within the 500 m buffer. This formula would calculate the mixed land use level within range 0–1, a higher value means a higher level of mixed land use.

We use Depthmap X to run the space syntax calculation. However, we finally choose Connectivity and Angular Integration (with segment length weighted, or SLW) after removing space syntax score with high multicollinearity (VIF $>$ 10). Angular Integration (SLW) has two metric radius parameters: 250 and 1000 m. For a particular segment, Connectivity describes quantity of other segments it connects with, and Angular Integration (SLW) captures accessibility and how close(integration level) of this segment is to all others in terms of the sum of angular change(Angular Integration Space Syntax—Online Training Platform, n.d.).

We use high resolution(1 m) Digital Elevation Model (DEM) from United States Geological Survey (USGS) collected in May 2020. The medium value of slope within 5 m of sampling point along the road is chosen as the slope value.

2.3 Model Architecture

We start with a simple OLS model Eq. (3).

$$Y_i = \alpha + \sum_m X_{(i,m)} \beta_m + \epsilon_i \tag{3}$$

Y_i is the dependent variables of the sampling point. X is the independent variables that explains SWR. β is the coefficient of variable m that reveals how and to what extent variable m is related to SWR. Constant term α refers to the average SWR when all other variables are zero. Error term ϵ_i captures elements that influence the Y but are not included in X.

A baseline model (M1_Summer, M1_Autumn) with significant variables was constructed using all variables except subjective perception. VIF was calculated in the whole process and only variables with VIF less than 10 are kept. Then all 4 perception scores are added (M2_Summer and M2_Autumn) (Table 2).

Table 2. Dependent variable, independent variable, and method of different models

Identifier	*Y* (dependent variable)	*X* (Independent variables)	Method
M1_Summer	ln(*SWR*)	All variables except subjective perception	OLS
M1_Autumn	ln(*SWR*)	All variables except subjective perception	OLS
M2_Summer	ln(*SWR*)	With subjective perception	OLS
M2_Autumn	ln(*SWR*)	With subjective perception	OLS

3 Result and Discussion

3.1 Models Performance and Diagnosis Results

Because DBS volume is not statistically significant with all variables, we remove unrelated variables from models. The remaining significant variables are used to build models after removing variables with high correlations and multicollinearity with a VIF test. The Regression diagnosis results show that: (1) All Autumn models have higher R2 than Summer models. (2) M1 model and M2 model have very close R2 with or without subjective perception. (3) There is high correlation and multicollinearity between the new perception scores and other segmentation results.

M1_summer and M1_autumn results show consistent significance for some variables in both seasons, such as visual ratios for roads, cars, sidewalks, grass color deviation, land use mix scores, and road network angular integration. Some variables are only significant in summer, like building and wall ratios and number of education POIs, while others like color deviation and lab_A values of tree, lab_A and lab_B values of grass only show significance in autumn. For variables significant in both seasons, the positive or negative effects are consistent across seasons (Table 3).

3.2 The Seasonal Variations of the Streetscape

Cycling volume is positively impacted by the presence of roads and sidewalks, with dedicated bike lanes potentially available on a larger network. Studies of the built environment often examine both walking and cycling behaviors together (Mertens et al. 2016), so sidewalks play an important role as well. A pedestrian-friendly neighborhood promotes sustainable mobility and slows down traffic. Trees positively impact cycling in both seasons. Street greenery offers ecological benefits to neighborhoods, including providing shade for microclimate control, and creating an enjoyable environment for cyclists (Li et al. 2018). Waterfront areas provide a desirable setting for cycling, which aligns with previous research findings (Ding 2016; Lee et al. 2021; Song et al. 2021).

3.3 Other Non-seasonal Variables

Land use mix score is positively related to DBS volume in both season, aligning with prior evidence that the mix ratio of land use affects travel behavior (Van Dyck et al.

Table 3. Coefficients between bikeshare volume and selected variables

	M1_summer		M1_autumn		M2_summer		M2_autumn	
Model performance (R2)	0.369 (0.323)		0.415 (0.373)		0.370 (0.323)		0.417 (0.373)	
Seasonal independent variables								
Semantic segmentation	Coef	P > |t|	Coef	P > |t|	Coef	P > |t|	Coef	P > |t|
SVI_tree	0.3527	*	0.2787		2.1593		5.1894	
SVI_building	−0.8333	*	0.0054		−2.6513		10.3405	
SVI_grass	0.775		0.7243		0.9535		6.0026	
SVI_road	1.8981	***	1.3642	**	0.1751		1.5192	
SVI_car	6.1842	***	3.1505	***	6.1603	***	3.3088	***
SVI_streetlight	2.3391		2.2767		0.0644		−0.0829	
SVI_wall	3.4627	*	−0.5201		−3.284		9.5372	
SVI_sidewalk	2.7117	***	3.3953	***	0.3213		6.5315	
SVI_earth	1.6018	*	0.8198		1.4124		4.66	
SVI_water	7.0456		12.2701	**	8.0279		13.933	**
SVI_plant	1.8375	*	0.5223		5.094	**	2.096	
SVI_awning	−9.5765		−39.0994	*	−10.4363		−37.991	*
SVI_van	8.7069	**	−3.704		8.6148	**	−3.5039	
SVI_person	−29.8536	*	20.2838		−28.1134	*	19.3872	
SVI_bridge	15.9634		20.4284	*	11.7645		33.2558	*
SVI_railing	−11.1146		−3.9123		−14.2389		14.0118	
SVI_bicycle	61.4131	*	32.6207		61.1798	*	31.84	
SVI_minibike	−8.4968		−70.7002		−6.8219		−65.8006	
SVI_ceiling	−3.5628	*	−1.7442	*	−2.8515		−0.5603	
SVI_chair	−7.1647		87.7615		−9.1576		91.5884	

(continued)

Table 3. (*continued*)

	M1_summer		M1_autumn		M2_summer		M2_autumn	
Model performance (R2)	0.369 (0.323)		0.415 (0.373)		0.370 (0.323)		0.417 (0.373)	
Seasonal independent variables								
Object detection								
SVI_ct_car	−0.0028		−0.0006		0.0077		−0.0196	
SVI_ct_truck	0.016		0.003		−0.0211		0.0669	
SVI_ct_person	0.011	*	−0.0016		−0.0147		−0.0085	
SVI_ct_bus	0.0021		−0.0012		−0.0626		−0.2846	
SVI_ct_traffic_light	0.0068		−0.0003		0.0444		0.0531	
SVI_ct_bicycle	−0.0075		0.0151		−0.0135		−0.0093	
SVI_ct_motorcycle	−0.032		−0.0387		−0.2219		0.7779	
SVI_ct_boat	0.0414		−0.0272		−0.0474		0.0289	
SVI_ct_dining_table	0.0066		−0.1617		0.2525		−0.6193	
SVI_ct_dog	0.3405		−0.5107	*	0.3239		−0.5042	*
Color analysis								
tree_deviation	0.0015		0.0206	**	0.0031		0.0225	***
tree_lab_a	0.0305		0.0561	***	0.0274		0.0537	***
tree_lab_b	0.0298		0.0142		0.0264		0.0126	
grass_deviation	−0.0292	***	−0.0096	**	−0.0291	***	−0.0099	**
grass_lab_a	−0.0184		−0.0346	*	−0.018		−0.0341	*
grass_lab_b	−0.0026		−0.0132	*	−0.0023		−0.0137	*
plant_deviation	0.0111	*	−0.0014		0.0111	*	−0.0011	
plant_lab_a	0.0118		−0.0109		0.0113		−0.011	
plant_lab_b	−0.0022		0.0011		−0.0028		0.0012	

(*continued*)

Table 3. (*continued*)

	M1_summer		M1_autumn		M2_summer		M2_autumn	
Model performance (R2)	0.369 (0.323)		0.415 (0.373)		0.370 (0.323)		0.417 (0.373)	
Seasonal independent variables								
Subjective perception								
Accessibility	\	\	\	\	−0.1563		−1.061	
Ecology	\	\	\	\	−2.7427		−0.3405	
Enclosure	\	\	\	\	2.4852		−11.0069	
Scale	\	\	\	\	−4.0534		9.9033	
Non-seasonal independent variables								
POI-typical								
Normalized no. of commercial	0.1618		0.1492		0.168		0.1369	
Normalized no. of office	0.0926		0.0766		0.102		0.0881	
Normalized no. of education	0.2519	*	−0.0219		0.2578	*	−0.0197	
Infrastructure								
Normalized no. of transit facility	0.122		−0.2733	*	0.1408		−0.2648	*
Road type								
Normalized type of road	0.0074		−0.0514		0.0039		−0.049	
Land use mixed								
Normalized landuse_score	0.8173	***	0.7867	***	0.7873	***	0.7734	***
POI-landmark								
1000 m_Actual_North_campus	0.2264	*	0.4216	***	0.2345	*	0.4265	***
1000 m_College_at_Dtyden	−0.141	*	−0.1594	*	−0.1453	*	−0.1683	*
1000 m_Engineering_Quad	0.1396	*	0.3845	***	0.1414	*	0.3927	***
1000 m_Green_St_Station_TC_Library	0.0579		0.1079		0.0676		0.1122	
1000 m_South_Meadow_Strip_Malls	0.1342		−0.1968	*	0.1416		−0.1905	*
1000 m_West_Campus_Residences	−0.0084		0.0048		−0.0192		0.0005	

(*continued*)

Table 3. (*continued*)

	M1_summer		M1_autumn		M2_summer		M2_autumn	
Model performance (R2)	0.369 (0.323)		0.415 (0.373)		0.370 (0.323)		0.417 (0.373)	
Seasonal independent variables								
1000 m_Stewart_Park	0.9009	***	0.1026		0.8831	***	0.0977	
1000 m_Senece_St_Station	0.3211	***	0.2583	***	0.326	***	0.2644	***
1000 m_Wegmans	0.4781	***	0.4009	***	0.4848	***	0.3937	***
1000 m_Hotel_School	−0.2996	***	−0.1687	*	−0.2914	**	−0.177	*
1000 m_Actual_Maplewood_Area	0.2831	**	0.0511		0.2948	**	0.0592	
1000 m_Ag_Quad	−0.1864	*	−0.0213		−0.1962	**	−0.0377	
1000 m_Ithaca_Farmers_Market	0.4079	***	0.1134		0.389	***	0.1049	
1000 m_Gimme_On_State	−0.2582	***	−0.4277	***	−0.267	***	−0.434	***
1000 m_Inlet_Island	−0.179	*	−0.3197	***	−0.1763	*	−0.316	*
3000 m_Actual_North_campus	0.2742	***	0.4235	***	0.2746		0.4336	
3000 m_College_at_Dtyden	0.448	***	0.5729	***	0.4338		0.5656	
3000 m_Engineering_Quad	−0.417	***	−0.252	*	−0.3994		−0.2409	*
3000 m_Green_St_Station_TC_Library	0.0397		−0.1586	*	0.0491		−0.15	
3000 m_South_Meadow_Strip_Malls	0.0201		−0.0011		0.0183		−0.0049	
3000 m_West_Campus_Residences	−0.0637		−0.4505	***	−0.0788		−0.4653	***
3000 m_Stewart_Park	0.2871	***	0.1739	**	0.294	***	0.1734	**
3000 m_Senece_St_Station	−0.0327		0.4586	***	−0.0256		0.4727	***
3000 m_Wegmans	0.032		0.1183		0.0255		0.1272	
3000 m_Hotel_School	−0.1316		−0.0943		−0.1234		−0.0945	
3000 m_Ag_Quad	0.1831	*	0.1337	*	0.1812	*	0.1321	*
3000 m_Ithaca_Farmers_Market	−0.1989	**	−0.1442	*	−0.192	**	−0.1397	*

(*continued*)

Table 3. (*continued*)

	M1_summer		M1_autumn		M2_summer		M2_autumn	
Model performance (R2)	0.369 (0.323)		0.415 (0.373)		0.370 (0.323)		0.417 (0.373)	
Seasonal independent variables								
3000 m_Gimme_On_State	0.0272		0.1219		0.0246		0.1295	*
3000 m_Inlet_Island	0.01		−0.238	**	0.0148		−0.2634	**
Terrain								
Normalized slope	0.0454		0.1073		0.0179		0.0464	
Street network								
Normalized connectivity	−0.1685	*	−0.1123		−0.1706	*	−0.1106	
Normalized T1024_Integration_SLW_R1000_metric	1.274	***	1.4537	***	1.2718	***	1.4641	***
Normalized T1024_Integration_SLW_R250_metric	0.421	*	0.2711		0.4226	*	0.2802	
Constant	−9.2286	***	−9.5608	***	−6.7409		−11.2574	***

p values are shown in parentheses; ***, **, and * indicate a significance level of 0.01, 0.05, and 0.1, respectively

2012; Kerr et al. 2016). Angular integration at 1000 m radius positively contributes to DBS volume in both seasons, in line with previous research suggesting that road network accessibility influences cycling behavior (Saghapour et al. 2017; Tucker and Manaugh 2018). However, angular integration at 250 m radius and connectivity are only significant in summer, which may be because autumn rides are more commuter-related. More research is needed to understand how space syntax impacts DBS at various scales and times. The number of points of interest (POI) is found to have a positive impact on DBS volume in both seasons. However, only educational POI has a significant positive impact in summer. This difference would need further research with more POI data.

4 Conclusion

Using GPS trajectory data, this study examines the correlation between DBS, streetscape, and spatial elements in different seasons. The study finds that: (1) seasonal streetscape factors such as roads, cars, sidewalks, tree, and vegetation color significantly influence DBS volume; (2) the significance varies in summer and autumn; (3) non-seasonal factors like mixed land use score, street network connectivity, etc., are significant in both seasons, some only show significance in one season; (4) adding subjective perception to both seasons improves explanatory slightly.

There are several limitations in this study that can be improved in future studies. Firstly, due to the data source limitation, only summer and autumn SVIs are collected in Ithaca. Finer temporal resolution can also be taken into consideration when SVI from more seasons or even months is available. Secondly, more advanced spatial model can be introduced to examine the spatial effect. Thirdly, microclimate-related data like temperature would better explain the seasonal variation.

References

Frank, L.D., et al.: Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ. Am. J. Prev. Med. **28**(2), 117–125 (2005)

Gu, T., Kim, I., Currie, G.: To be or not to be dockless: empirical analysis of dockless bikeshare development in China. Transp. Res. Part A: Policy Pract. **119**, 122–147 (2019). https://doi.org/10.1016/j.tra.2018.11.007

Guo, Y., Yang, L., Chen, Y.: Bike share usage and the built environment: a review. Front. Publ. Health **10** (2022)

Kerr, J., et al.: Perceived neighborhood environmental attributes associated with walking and cycling for transport among adult residents of 17 cities in 12 countries: the IPEN study. Environ. Health Perspect. **124**(3), 290–298 (2016). https://doi.org/10.1289/ehp.1409466

Lee, M., et al.: Factors affecting bike-sharing system demand by inferred trip purpose: integration of clustering of travel patterns and geospatial data analysis. Int. J. Sustain. Transp. 1–14 (2021)

Li, W., Kamargianni, M.: A seasonal analysis on factors affecting bike-sharing choice: with a focus on air pollution's impact. In: 96th Transportation Research Board Annual Meeting. Transportation Research Board, pp. 17–04281 (2017)

Li, X.: Examining the spatial distribution and temporal change of the green view index in New York City using Google Street View images and deep learning. Environ. Plan. B: Urban Anal. City Sci. **48**(7), 2039–2054 (2021)

Li, X., Ratti, C., Seiferling, I.: Quantifying the shade provision of street trees in urban landscape: a case study in Boston, USA, using google street view. Landsc. Urban Plan. **169**, 81–91 (2018). https://doi.org/10.1016/j.landurbplan.2017.08.011

Mertens, L., et al.: Perceived environmental correlates of cycling for transport among adults in five regions of Europe. Obes. Rev. **17**, 53–61 (2016)

Qiu, W., et al.: Subjective and objective measures of streetscape perceptions: relationships with property value in Shanghai. Cities **132**, 104037 (2023)

Qiu, W., Chang, H.: The interplay between dockless bikeshare and bus for small-size cities in the US: a case study of Ithaca. J. Transp. Geogr. **96**, 103175 (2021)

Saghapour, T., Moridpour, S., Thompson, R.G.: Measuring cycling accessibility in metropolitan areas. Int. J. Sustain. Transp. **11**(5), 381–394 (2017)

Song, J., et al.: Where are public bikes? The decline of dockless bike-sharing supply in Singapore and its resulting impact on ridership activities. Transp. Res. Part A: Policy Pract. **146**, 72–90 (2021)

Su, N., Li, W., Qiu, W.: Measuring the associations between eye-level urban design quality and on-street crime density around New York subway entrances. Habitat Int. **131**, 102728 (2023)

Tucker, B., Manaugh, K.: Bicycle equity in Brazil: access to safe cycling routes across neighborhoods in Rio de Janeiro and Curitiba. Int. J. Sustain. Transp. **12**(1), 29–38 (2018)

Van Dyck, D., et al.: Perceived neighborhood environmental attributes associated with adults' transport-related walking and cycling: findings from the USA, Australia and Belgium. Int. J. Behav. Nutr. Phys. Act. **9**(1), 70. https://doi.org/10.1186/1479-5868-9-70