

**TRCLC 15-13**  
**December 31, 2016**

# **Exploring Bicycle Route Choice Behavior with Space Syntax Analysis**

**FINAL REPORT**

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**Transportation Research Center**  
*for Livable Communities*

Western Michigan University | University of Texas at Arlington | Utah State University | Wayne State University | Tennessee State University

**Technical Report  
Documentation Page**

<b>1. Report No.</b> TRCLC 15-13	<b>2. Government Accession No.</b> N/A	<b>3. Recipient's Catalog No.</b> N/A	
<b>4. Title and Subtitle</b> Exploring Bicycle Route Choice Behavior with Space Syntax Analysis		<b>5. Report Date</b> December 31, 2016	
		<b>6. Performing Organization Code</b> N/A	
<b>7. Author(s)</b> Zhaocai Liu, Ziqi Song, Anthony Chen, Seungkyu Ryu.		<b>8. Performing Org. Report No.</b> N/A	
<b>9. Performing Organization Name and Address</b> Department of Civil and Environmental Engineering Utah State University Logan, UT 84322		<b>10. Work Unit No. (TRAIS)</b> N/A	
		<b>11. Contract No.</b> TRCLC 15-13	
<b>12. Sponsoring Agency Name and Address</b> Transportation Research Center for Livable Communities (TRCLC) 1903 W. Michigan Ave., Kalamazoo, MI 49008-5316		<b>13. Type of Report &amp; Period Covered</b> Final Report 7/1/2015 - 12/31/2016	
		<b>14. Sponsoring Agency Code</b> N/A	
<b>15. Supplementary Notes</b>			
<b>16. Abstract</b> <p>Cycling provides an environmentally friendly alternative mode of transportation. It improves urban mobility, livability, and public health, and it also helps in reducing traffic congestion and emissions. Cycling is gaining popularity both as a recreational activity and a means of transportation. Therefore, to better serve and promote bicycle transportation, there is an acute need to understand the route choice behavior of cyclists.</p> <p>This project explored the applicability of using space syntax theory to model cyclists' route choice behavior. In addition, several bicycle-related attributes were also considered as influential factors affecting cyclists' route choice. A multiple regression model was built and calibrated with real-world data. The results demonstrated that space syntax is a promising tool for modeling bicycle route choice, and cyclists' cognitive understanding of the network configuration significantly influences their route choice.</p>			
<b>17. Key Words</b> Bicycle Route Choice, Space Syntax, Local Integration, Linear Regression		<b>18. Distribution Statement</b> No restrictions.	
<b>19. Security Classification - report</b> Unclassified	<b>20. Security Classification - page</b> Unclassified	<b>21. No. of Pages</b> 27	<b>22. Price</b> N/A

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## **Acknowledgments**

This research was funded by the US Department of Transportation through the Transportation Research Center for Livable Communities (TRCLC), a Tier 1 University Transportation Center. The authors would like to thank Becka Roolf of Salt Lake City's Transportation Division for providing bicycle count data.

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## Chapter 1: Introduction

Cycling provides an environmentally friendly alternative mode of transportation. It improves urban mobility, livability, and public health, and it also helps in reducing traffic congestion and emissions. Although the mode share of bicycles accounts for only slightly more than 1% of all trips taken in the United States according to the 2009 National Households Travel Survey (NHTS) (Kuzmyak et al., 2014), cycling is gaining popularity as both a recreational activity and a means of transportation. The American Community Survey (ACS) reveals that bicycle commuting increased by 61.6% from 2008 to 2012, a larger percentage increase than in any other commuting mode (McKenzie, 2014). Therefore, to better serve and promote bicycle transportation, there is an acute need to understand the route choice behavior of cyclists.

Compared to the route choice model for private motorized vehicles, route choice behavior for bicycles is much more complex because many factors influence cyclists' route choice decisions. Empirical studies on bicycle route choice indicate that cyclists choose routes based on a number of criteria that may include distance, number of intersections, road grade, bicycle facility, and safety. In identifying the factors that affect cyclists' route choice decisions, Stinson and Bhat (2003), Hunt and Abraham (2007), and Broach et al. (2011) found that travel distance/time was significant, while Hopkinson and Wardman (1996), Akar and Clifton (1996), Dill and Carr (2009) and Winters et al. (2011) found that safety was likewise influential. Sener et al. (2009) also found that the travel distance/time and safety affected by motorized traffic volumes were important factors in cyclists' route choices. Mekuria et al. (2012) suggested that stress is an important factor in bicycle trip-making behavior. Using global positioning system (GPS) tracking data, Hood et al. (2011) developed a path-size logit (PSL) model (Ben-Akiva and Birelaire, 1999) as a cyclist route choice model and performed bicycle traffic assignment on a pre-enumerated path set generated by the doubly stochastic method (Bovy and Fiorenzo Catalano, 2007). Menghini et al. (2008) also adopted the PSL model for traffic assignment on a pre-generated path set by breadth-first search link elimination approach.

Nevertheless, the previously mentioned studies tend to be based on observable quantities associated with the street segments themselves, but overlook a fundamental issue, travelers' cognitive understanding of the network configuration (Turner and Dalton, 2005). In this study, we will tackle this problem and explore the applicability of a spatial analysis technique called space syntax for bicycle route choice estimation. The space syntax theory was originally developed by Hiller and Hanson (1984) as a tool to understand the linkages between urban spatial layout and its impact on human movement in the late 1970s.

The space syntax theory has gained popularity over the years among architects and urban planners, and it has a wide range of applications in modeling traffic flow distribution, especially for pedestrian traffic (Hiller, 1987a; Hiller, 1987b; Penn et al., 1998; Hiller, 1999; Caria et al., 2003) and vehicular movement (Peponis et al., 1997; Dawson, 2003; Karimi and Mohamed, 2003). Empirical results show that space syntax generally provides better predictions of pedestrian traffic than vehicular traffic (Paul, 2011).

On the other hand, only a handful of studies has focused on employing the space syntax technique to model cyclists' route choice behavior. Raford et al. (2007) established a correlation between space syntax measures and aggregate cyclist volume in central London and found that streets with low overall angular change receive more use. However, the study was unable to identify a strong correlation between those measures and individual cyclist route choice. They argued that factors other than space syntax measures may also strongly influence the route choice of individual cyclists. McCahill and Garrick (2008) evaluated and tested various space syntax measures using data from the city of Cambridge, Massachusetts, to model the distribution of bicycle volumes in the network. A linear regression model including population density, worker density, and a space syntax measure was constructed, which can be used to predict aggregate bicycle volumes. Manum and Nordstrom (2013) carried out a survey to map route choices of individual cyclists and compared the routes with the results from space syntax analysis. Although the results match very well for most routes, they also observed some discrepancies between the two route sets. They concluded that space syntax analysis, as a purely mathematical representation of network configurations, cannot capture some features associated with road segments, such as number of intersections, road slope, and traffic volume of motorized vehicles,

all of which may influence bicycle route choice. From the literature, we can determine that space syntax analysis is a valuable tool in modeling cyclists' route choice behavior; however, the efforts to directly apply the space syntax technique to bicycle mode have some limitations. Indeed, space syntax theory was originally developed for pedestrian modeling (Hiller and Hanson, 1984) and may not be readily transferable to other modes. Therefore, it is imperative to extend the existing space syntax studies by incorporating route choice characteristics that are specific to the bicycle mode.

This research is an exploratory study with the goal of understanding cyclists' route choice decisions and evaluating the applicability of space syntax theory in the context of bicycle travel demand forecasting. It has three objectives, as follows: (1) establishing a procedure of applying space syntax theory to model cyclists' route choice decisions, (2) exploring the relationships between space syntax and other bicycle-related attributes and bicycle movement, and (3) conducting a real-world case study using the proposed methodology. The remainder of this report is organized as follows. Chapter 2 provides a brief introduction to space syntax theory. Chapter 3 presents our methodology of applying space syntax to bicycle traffic modeling. In Chapter 4, a real-world case study is conducted. Last, Chapter 5 concludes the report.

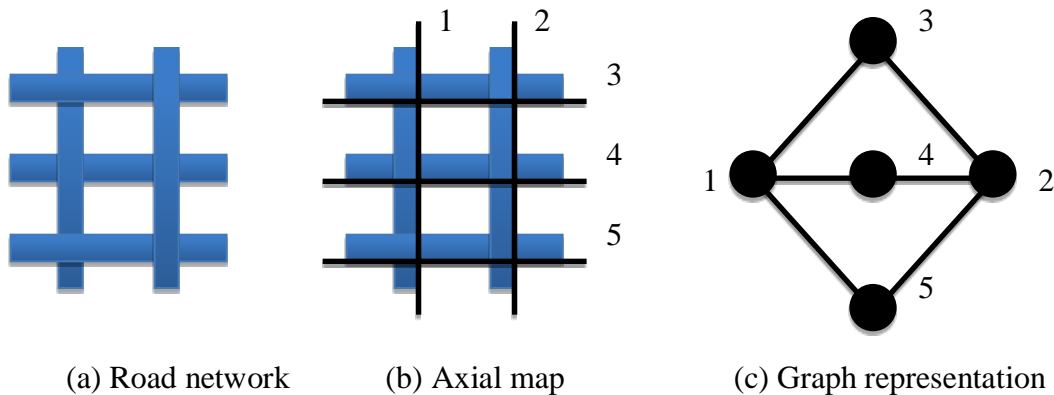
## Chapter 2: Space Syntax

Space syntax is a technique used to analyze space accessibility, and it tries to determine the complexity of the spatial arrangement in urban morphology and its effect on urban life (Paul, 2011). The concept of accessibility is based on the analysis of topological connections of unit space in the built environment. First, axial analysis is used to convert the building or urban street network into a graph. Then graph theory is used to quantify how one unit space is topologically connected to other spaces within a system. Last, a set of algorithms is used to analyze the accessibility of each unit space from all other spaces in the system. The measure “integration” (Hillier et al., 1984) is widely used in space syntax to represent the accessibility of a unit space in a system.

### 2.1 Axial analysis

The axial map is the basis of space syntax analysis. It represents the topology of the configured space. In the axial map, urban spaces such as roads and streets are modeled by straight lines, which represent views and peoples’ potential movement. Space syntax redefines people’s perception of distance and claims that people may measure travel in terms of transitions from one space to another rather than in terms of metric distance (McCahil and Garrick, 2008). Thus, the length of axial lines can be neglected, and a further simplified graph can be obtained, in which each axial line is represented as a node and the intersections between axial lines are represented as links. Figure. 2.1 shows the axial map and the graph representation of a road network.





**FIGURE 2.1 Spatial Representation of a Road Network in Space Syntax**

## 2.2 Integration

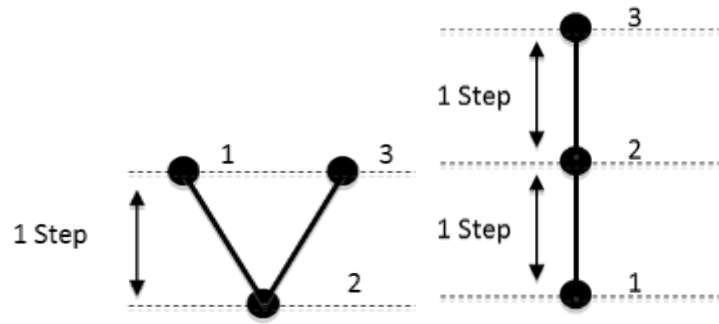
Based on the axial analysis, a set of algorithms is used to obtain the integration, which is a measure of accessibility following space syntax theory.

### (1) Mean depth

Space syntax typically describes the topological connections of unit space through the notion of depth analysis. As shown in Figure 2.2, when moving from one space to its connected space, there is a transition of space. In space syntax, the transition of space, which is also called step or turn, is the unit of measurement of “distance”. The distance from one space to another is called depth. The mean depth (MD) from one space to all other space can represent the connectivity of the spaces in the system. It is calculated as follows

$$MD_k = \frac{\sum_{i \neq k} d(i, k)}{n - 1}$$

where  $d(i, k)$  is the steps between unit space  $i$  and  $k$ , and  $n$  is the total number of unit spaces.



**FIGURE 2.2 Three Connected Spaces**

As shown in Fig. 2.2, the topological distance between spaces 2 and 1 is  $d(2,1) = d(1,2) = 1$ , the distance between 2 and 3 is  $d(2,3) = 1$ , and the distance between 1 and 3 is  $d(1,3) = 2$ . Thus, the mean depth of unit space 2 is  $MD_2 = \frac{1+1}{2} = 1$ , and the mean depth of unit space 1 is  $MD_1 = \frac{1+2}{2} = 1.5$ .

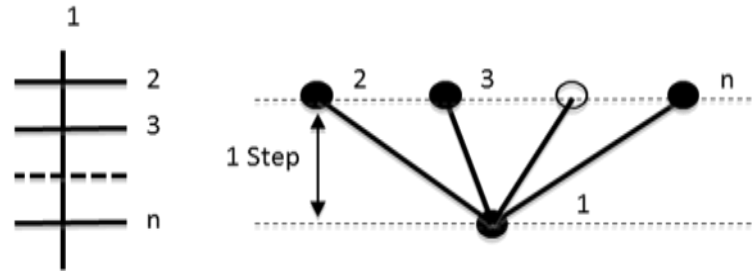
## (2) Relative asymmetry

As shown in Fig. 2.3, when a space is directly connected to all other spaces, it has the lowest mean depth  $MD(\text{lowest}) = \frac{1(n-1)}{n-1} = 1$ , where  $n$  is the total number of spaces in the system. As

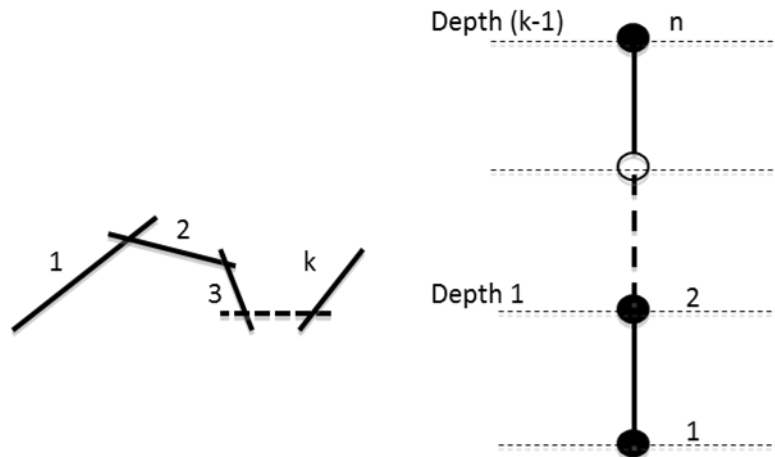
shown in Fig. 2.4, when a space needs to travel the longest topological distance to reach all other spaces, it has the highest mean depth  $MD(\text{highest}) = \frac{1(1) + 2(1) + \dots + (n-1)(1)}{n-1} = \frac{n}{2}$ . In space

syntax, the concept of symmetricity is used to describe the MD of a space. Space 1 in Figure 2.3 is thought to have the highest symmetricity, and space 1 in Figure 2.4 is thought to have the lowest. It is clear that the MD is relative in terms of how the unit space is located in the system; thus, the MD of a unit space cannot be compared with the others in the system unless they are all measured on a common scale. The concept of relative asymmetry (RA) is introduced as a common scale to make the measurement of connectivity comparable between different unit spaces in a system. RA is defined by the following equation:

$$RA_k = \frac{MD_k - MD(\text{lowest})}{MD(\text{highest}) - MD(\text{lowest})} = \frac{MD_k - 1}{\frac{n}{2} - 1} = \frac{2(MD_k - 1)}{n - 2}$$



**FIGURE. 2.3 Lowest Mean Depth**



**FIGURE 2.4 Highest Mean Depth**

(3) Real relative asymmetry

The measurement RA makes it possible to compare the accessibility of different unit spaces in a system. However, different systems may have different sizes (i.e., different number of unit spaces), and this will also influence the accessibility measures of unit spaces. The measurement RA of two unit spaces from two different systems cannot be compared on the same scale unless they have the same number of unit spaces. Thus, the real relative asymmetry (RRA) is introduced as a generalized measurement of accessibility. The real relative asymmetry is calculated as follows:

$$RRA_k = \frac{RA_k}{D_n}$$

where  $D_n = \frac{2(n(\log_2(\frac{n+2}{3})-1)+1)}{(n-1)(n-2)}$  is the RA of root space in the “diamond-shaped” graph with the same number of unit spaces. For details about “diamond-shaped” graph, refer to [Hiller and Hanson \(1984\)](#).

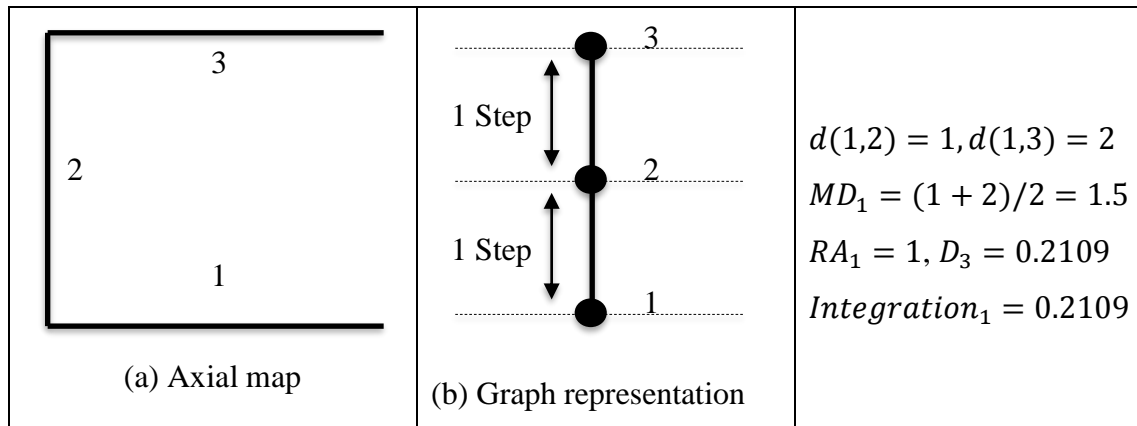
(4) Integration

In the above discussion, we have shown that the MD of a unit space represents its accessibility from all other spaces. A high value of MD means the unit space is distantly accessible, while a low value makes it closely accessible. Through introducing the measurements RA and RRA, we can compare the accessibility of two unit spaces from two different systems.

The integration of a unit space is the reciprocal of its RRA, and it represents the topological accessibility of a unit space from all other spaces within a given system considering its symmetricity and size. Integration is calculated as follows:

$$Integration_k = \frac{1}{RRA_k}$$

To summarize, Figure 2.5 shows an example calculation of integration. For simplicity, there are only three axial lines in the map.



**FIGURE 2.5 Representation of a Simple Network and Parameter Calculations**

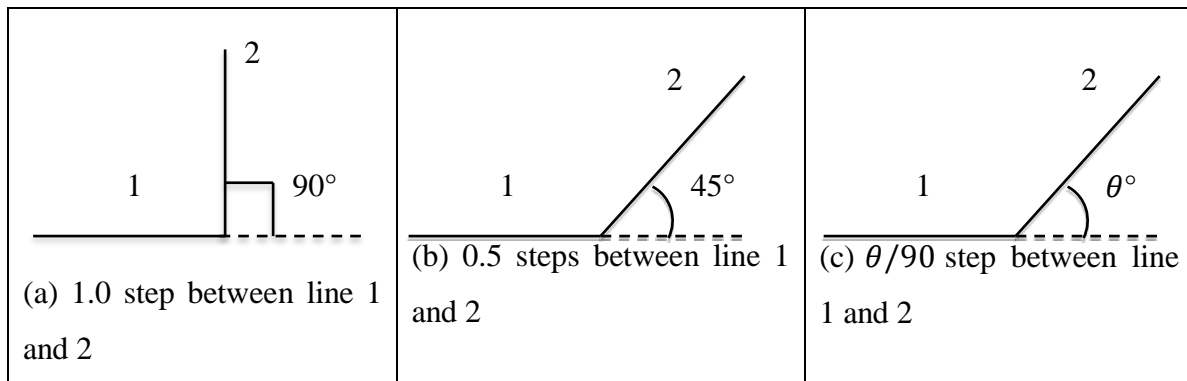
(5) Global and local integration

The integration can be defined based on the whole system as well as at a local level. The global integration, as discussed above, measures how closely or distantly each unit space is accessible

from all other spaces of a system. If we restrict the unit spaces that are used to determine the mean depth of a unit space at a lower depth of connectivity (e.g., three steps), then we develop a new measurement of local integration. The local integration represents the accessibility of the unit space at a local or neighboring level. For instance, in an integration radius-3 analysis, only the spaces that are three depths away are considered.

### 2.3 Angular segment analysis

Traditional axial line analysis has shown the problem of inconsistency. First, the generation of axial lines is highly subjective and can vary because of different personal preferences. Second, [Ratti \(2004\)](#) demonstrated that, when a single axial line is broken into many axial lines due to minor changes in urban configuration, the predicted pattern of movement will change significantly, which is unreasonable. [Turner \(2001\)](#) introduced angular segment analysis to obtain a new representation of urban space. In essence, axial lines are broken into segments, and the step between two connected segments is weighted based on the angle between them. [Figure 2.6](#) shows the corresponding steps of different turning angles. We can observe that a turn of  $90^\circ$  corresponds to one full step while a turn of  $45^\circ$  represents only 0.5 steps.



**FIGURE 2.6** Corresponding Steps of Different Turning Angles

Based on angular segment analysis, [Dalton et al. \(2003\)](#) and [Turner \(2005\)](#) demonstrated that the road centerline maps from a geographic information system (GIS) can be used to represent the

corresponding axial maps. With GIS maps, even for metropolitan areas, the space syntax models can be easily obtained.

## 2.4 Travel demand estimation

Many statistical studies have been conducted to investigate the applicability of space syntax in predicting traffic volumes in transportation networks. Some only adopted one space syntax measurement, integration, in building the predication models (Hillier et al, 1987, Peponis et al, 1997). These works tried to demonstrate a positive correlation between space syntax measurements and actual traffic flow data, and the reported results indeed showed high correlation. Also, the vehicular traffic flow is highly correlated to the global integration, whereas the pedestrian traffic flow has higher correlation with local integration. Table 2.1 shows some of these statistical studies. As mentioned earlier, only limited works have been conducted to apply space syntax theory to bicycle traffic (i.e., Raford et al., 2007; McCahill and Garrick, 2008; Manum and Nordstrom, 2013), and their results are not as ideal as expected. Bicycle traffic is a transportation mode that falls somewhere between vehicular traffic and pedestrian traffic. Thus, to model bicycle traffic with space syntax theory, we need to choose proper space syntax measurements and determine a specific modeling procedure.

**TABLE 2.1 Correlation Studies between Integration and Traffic Volumes**

No.	Source	Study area	R-squared	Remarks
1	Hillier, 1998	Baltic House area	0.773	Pedestrian
2	Hillier et al., 1987	Bransbury	0.641	Pedestrian
3	Hillier, 1998	Santiago	0.54	Pedestrian
4	Hillier et al., 1987	Islington	0.536	Pedestrian

<b>5</b>	Eisenberg, 2005	Waterfront, Hamburg	0.523	Pedestrian
<b>6</b>	Peponis et al., 1997	Six Greek towns	0.49	Pedestrian
<b>7</b>	Karimi et al., 2003	City Isfahan	0.607	Vehicular
<b>8</b>	Peponis et al., 1997	Buckhead, Atlanta	0.292	Vehicular
<b>9</b>	Paul, 2009	City of Lubbock, Texas	0.18	Vehicular

## Chapter 3: Methodology

Many factors influence cyclists' route choice. Using space syntax theory, cyclists' cognitive understanding of the network configuration can be modeled and analyzed. However, previous studies employing the space syntax technique to model cyclists' route choice have found that space syntax measures cannot fully explain bicycle movement (Raford et al., 2007; McCahill and Garrick, 2008; Manum and Nordstrom, 2013). In this research, we tried to combine the space syntax measure with several other bicycle-related attributes, including safety, pollution exposure, bicycle facility, and terrain slope, and propose a model that may provide better explanatory power for modeling cyclists' route choice decisions.

### 3.1 An Overview of Bicycle-related Attributes

This section provides an overview of bicycle-related attributes, including (1) link cognition, (2) segment bicycle level of service (BLOS), (3) motorized vehicle volume on a link, (4) link pollution exposure, (5) presence of a bicycle facility on a link, and (6) average slope of terrain on a segment.

#### (1) Link cognition

For link cognition, we adopt the *Integration* measurement computed by the space syntax model. In a road network, each link has one *Integration* value that represents the accessibility of the link within the network. Global integration and local integration should be tested, respectively, to determine which one has higher correlation with bicycle traffic flow. Let  $I_a$  denote the integration of link  $a$ .

#### (2) Segment bicycle level of service

Numerous measures are used to assess the safety aspect of bicycle facilities or the suitability for bicycle travel. In this study, we adopt the BLOS measure developed by the HCM (2010) as a surrogate measure to account for different attributes contributing to the safety of bicycle routes.



The segment bicycle score ( $B_{seg_a}$ ) provided is calibrated based on the volume and speed of motorized vehicles, width configuration of bicycle facilities, and pavement conditions, among other factors. The details of the BLOS development can be found in NCHRP Report 616 (Dowling et al., 2008).

$$B_{seg_a} = 0.507 \ln \left( \frac{V_a}{4 \times PHF_a \times La_a} \right) + 0.199 F_{s_a} \left( 1 + 10.38 \times HV_a \right)^2 + 7.066 \left( \frac{1}{PC_a} \right)^2 - 0.005 (We_a)^2 + 0.057$$

where

$PHF_a$  : peak hour factor of link  $a$

$HV_a$  : proportion of heavy vehicles of link  $a$   
(in motorized vehicle volume)

$We_a$  : average effective width on outside  
through lane of link  $a$  (ft)

$F_{s_a}$  : effective speed factor on link  $a$

$La_a$  : total number of directional through  
lanes on link  $a$

$V_a$  : directional motorized vehicle volume  
on link  $a$  (vph)

$PC_a$  : FHWA's five point pavement surface  
condition rating on link  $a$

### (3) Motorized vehicle volume on a link

The motorized vehicle volume on a link is another measure for assessing the safety aspect of bicycle facilities. Stinson and Bhat (2003) found that the motorized vehicle volume on a link is an important determinant for commuter cyclists in choosing a route.

### (4) Link pollution

For simplicity, we consider carbon monoxide (CO) as an important indicator for the level of atmospheric pollution. Other pollutants can be modeled in a similar manner. Let  $PSeg_a$  denote

the amount of CO pollution in grams per hour (g/h) on link (segment)  $a$ . To estimate the amount of CO pollution, we adopt the nonlinear macroscopic model of Wallace et al. (1998):

$$PSeg_a(\bar{v}_a) = 0.2038 \cdot t_a(\bar{v}_a) \cdot \exp\left(\frac{0.7962 \cdot l_a}{t_a(\bar{v}_a)}\right)$$

where  $\bar{v}_a$  is the motorized vehicle volume on link  $a$ ;  $t_a(\bar{v}_a)$  is the link travel time measured in minutes; and  $l_a$  is the link length measured in kilometers.

#### (5) Presence of a bicycle facility on a link

A number of studies has suggested that the presence of a bicycle facility on a link has a significant effect on cyclists' route choice (e.g., Stinson and Bhat, 2003; Griswold et al., 2011). For simplicity, we only consider whether a bicycle lane exists on a link and do not differentiate various bicycle facilities (e.g., bike lanes with physical separation, bike lanes with painted buffer, shared bike lanes).

#### (6) Average slope of terrain on a segment

Because bicycles are human-powered, terrain roughness is an important factor considered by cyclists in their route choice. In this project, we use the average slope on a segment to represent its terrain roughness. Previous studies have found that a steep slope on a road discourages cyclists from choosing the road (e.g., Aultman-Hall et al., 1997; Dill and Gliebe, 2008; Griswold et al., 2011).

## 3.2 Statistical Modeling

Linear regression was used to analyze the relationship between bicycle volume and various segment attributes including space syntax measurements and other bicycle-related attributes. The linear regression model has the following general form:

$$Y_a = \beta_0 + \beta_1 X_{1a} + \beta_2 X_{2a} + \dots + \beta_m X_{ma}$$

where

$Y_a$  = bicycle volume on link  $a$

$X_{ma}$  = explanatory variable  $m$  on link  $a$ .

$\beta_m$  = model coefficient for variable  $m$ .

As discussed above, space syntax measurements and five other bicycle-related attributes were investigated in this project. For space syntax measurements, global integration and local integration will be separately tested to determine which one has better correlation with observed bicycle volume. Then space syntax measurements will be combined with other bicycle-related attributes to further improve the explanatory power of the model. Table 3.1 describes the explanatory variables that were considered in the modeling process. In total, seven explanatory variables were studied.

**TABLE 3.1 Description of Explanatory Variables Considered in Modeling Process**

<b>Variables</b>	<b>Description</b>
$IntG_a$	Global integration of link $a$
$IntL_a$	Local integration of link $a$
$BSeg_a$	Bicycle level of service score on link $a$
$Motv_a$	Motorized vehicle volume on link $a$
$PSeg_a$	Hourly pollution exposure on link $a$
$BikeL_a$	Presence of a bicycle lane on link $a$
$Slope_a$	Average slope on link $a$

## Chapter 4: Case Study

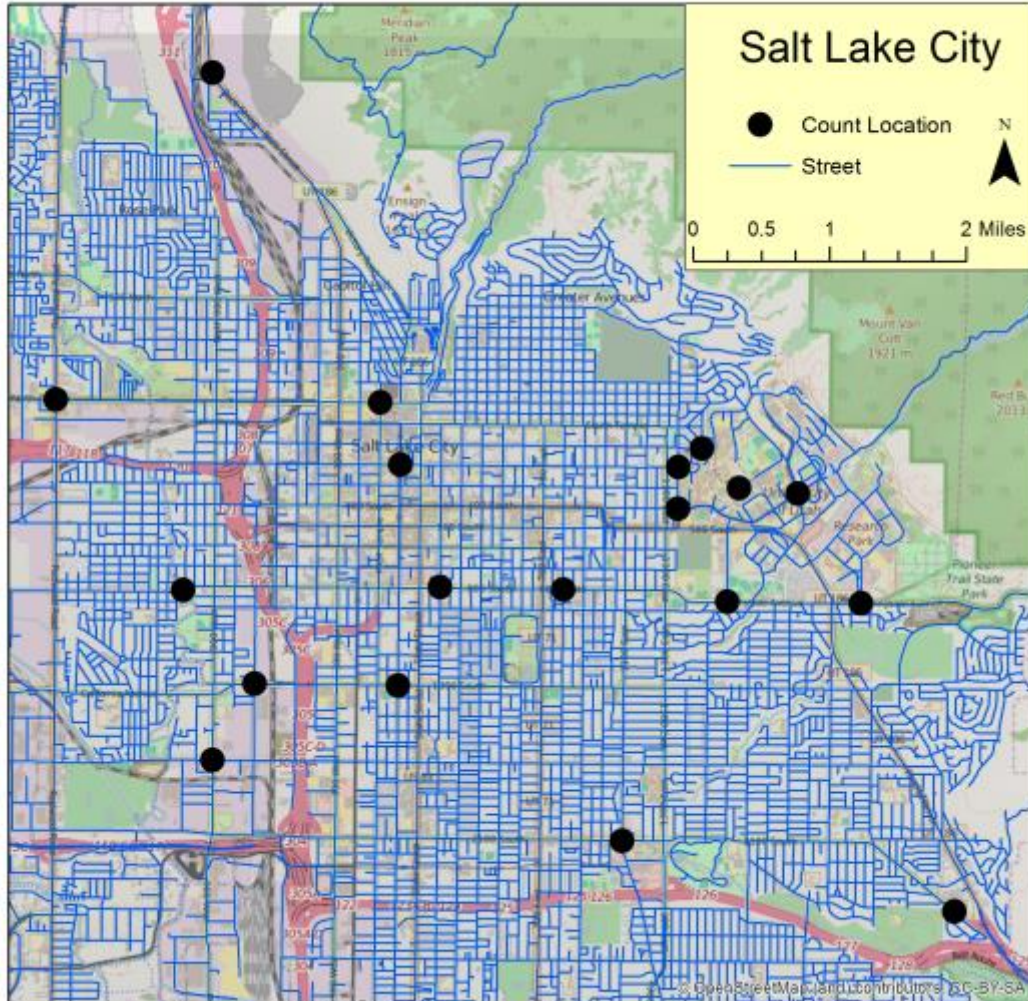
In this section, a real-world case study in Salt Lake City, Utah, is conducted to demonstrate the proposed methodology.

### 4.1 Bicycle Counts

The bicycle count data in this project are obtained from Salt Lake City's Transportation Division. In 2010, Salt Lake City joined the National Bicycle/Pedestrian Documentation Project. Since then, the city has recruited volunteers every year to record the number of bicyclists at key intersection locations throughout the city. In this project, we used the latest bicycle count data, which were collected in September 2015. The data collection process was conducted on September 15, 16, 17, 19, and 20, which were a Tuesday, a Wednesday, a Thursday, a Saturday, and a Sunday, respectively. In total, 19 intersections were involved. The counting duration at each intersection was two hours each day. The time of day for the counts was 5-7 p.m. on weekdays, and 12-2 p.m. on weekends. Table 4.1 shows the statistics summary for the bicycle count data. Because we cannot identify the specific location of one intersection in the University of Utah campus, we removed it from our analysis. Figure 4.1 presents a map of the bicycle counts locations.

**TABLE 4.1 Summary Statistics for Two-hour Bicycle Counts**

<b>Statistic</b>	<b>All Counts</b>	<b>Weekday</b>	<b>Weekend</b>
<b>Number of counts</b>	95	57	38
<b>Minimum</b>	2	7	2
<b>Maximum</b>	161	129	161
<b>Median</b>	47.0	47	42
<b>Mean</b>	54.8	54.1	55.9
<b>Standard deviation</b>	35.7	31.3	41.8



**FIGURE 4.1** Map of Locations of Bicycle Counts

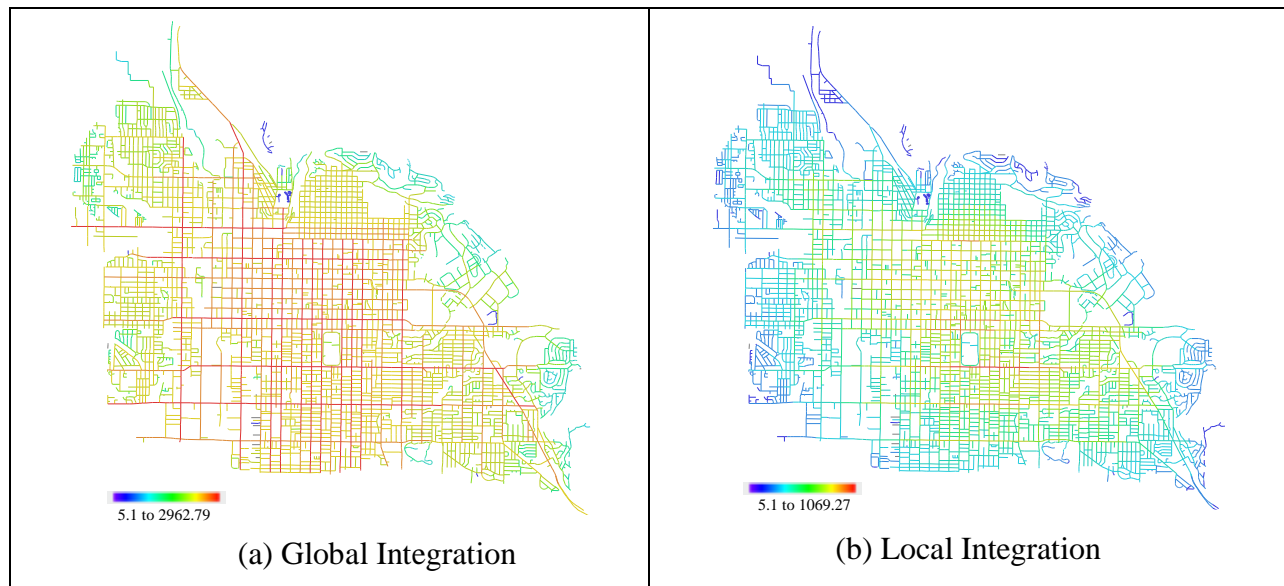
## 4.2 Space Syntax Analysis

The bicycle counts were conducted east of Interstate 215, therefore, in this study, we only considered the eastern part of the transportation network in Salt Lake City (Figure 4.2), covering the downtown area of the city. To compute the space syntax measurements, [DepthMapX](http://varoudis.github.io/depthmapX/) software (<http://varoudis.github.io/depthmapX/>) was used. Global integration and local

integration with a metric radius of three kilometers were calculated separately using angular segment analysis. Note that here we assume that the comfortable travel distance of a cyclist is within three kilometers. Figure 4.3 (a) and (b) provide a visual representation of the global integration and local integration, respectively. The integration value for a link can be extracted from the analysis results.



**FIGURE 4.2 Transportation Network**



**FIGURE 4.3 Space Syntax Analysis**

### 4.3 Supplementary Data

To consider bicycle-related attributes excluding link cognition and compute the values of their corresponding explanatory variables, relevant data were collected. The motor vehicle volume on a link was estimated based on the annual average daily traffic (AADT) data, which were obtained from the Utah Department of Transportation (UDOT). The speed limit information was also provided by UDOT. The data regarding the number of lanes on a link were manually collected in Google Maps (<https://www.google.com/maps/>). The bicycle lane information was provided by the Salt Lake Transportation Division (<http://bikeslc.com/Wheretoride/SLCBikeMap.html>). To measure the slope of a link, we downloaded the digital elevation model (DEM) data from the Utah Automated Geographic Reference Center (AGRC) (<http://gis.utah.gov/>) and computed the slope of a link in ArcGIS. For unavailable data, including the peak hour factor of a link, the proportion of heavy vehicles, average effective width on outside through lane of a link, and FHWA's 5-point pavement surface condition rating, we used the default values recommended in the HCM (2010).

#### 4.4 Regression Analysis

The bike count data we obtained are bicycle volume counts at intersections. Because our methodology, as introduced in the last chapter, is a link-based analysis, gate counts of bicycle volumes along segments would be preferable. To have our methodology accommodate the collected data, we considered the sum of space syntax measurements for all entering legs at an intersection as the measurement of cyclists' cognition at the intersection. Other bicycle-related attributes were summed and averaged at each intersection based on values for all entering legs. For each intersection, we calculated the average hourly bicycle volume according to all five days' recorded bicycle trips at the intersection.

The relationship between space syntax measurements and bicycle volumes was first investigated. Table 4.2 shows the coefficients and statistics for the regression models with global integration and local integration as the sole explanatory variables. Global integration is not statistically significant and can hardly explain the actual bicycle volumes. Local integration, however, is statistically significant and exhibits a good R-squared value. Moreover, the regression results indicate that local integration is positively related to bicycle volumes, which is as expected. This finding suggests that local integration provides stronger explanatory power than global integration in modeling bicycle movement. The bicycle is extremely convenient for short-range trips, however, it is not suitable for a long-distance travel because it is human-powered. Therefore, local integration, which only considers the accessibility of a road segment within a limited travel distance, is more appropriate in modeling bicycle traffic.

**TABLE 4.2 Estimation Coefficients and Model Statistics**

Model Variable	Coefficients	
	Global Integration Model	Local Integration Model
Constant	18.877 (0.325)	7.056 (0.332)
<i>IntG<sub>a</sub></i>	0.001 (0.617)	-



<i>IntL<sub>a</sub></i>	-	0.010 (0.005)
<b>R-squared</b>	0.016	0.396
<b>F-statistic</b>	0.261 (0.617)	10.502 (0.005)

Beta-coefficient is shown in each cell. Level of significance is shown in parentheses.

To further improve the explanatory power of the model, we tried to incorporate additional explanatory variables into the model. We considered five bicycle-related variables, as discussed in the last chapter. We estimated a series of regression models with various combinations of independent variables. The results of three representative models are shown in Table 4.3. Model 1 includes local integration and all five bicycle-related variables. The model has a fairly high R-squared value, however the coefficients for the bicycle level of service score, motor vehicle volume and presence of bike lanes are not statistically significant (at the 90% confidence level). Thus, Model 1 needs to be further improved. Note that the coefficient of slope is positive in Model 1, which is contrary to expectation. This may be explained by the fact that a major bicycle trip attraction/production zone in this area, i.e., the University of Utah campus, is located on the east bench of the Salt Lake Valley, which is substantially higher than the downtown Salt Lake City. In Model 2, we remove the slope variable and the presence of bike lane variable, both of which have coefficients with low level of significance. All coefficients in Model 2 have reasonable signs, but only the coefficient for local integration is statistically significant. Model 3 only involves two explanatory variables, which are local integration and motor vehicle volume. The F-statistic value of Model 3 is 9.055 with a significance level of 95%, meaning that the overall model is statistically significant. The coefficients of both variables in Model 3 are reasonable and significant (at the 95% level of significance). Thus, Model 3 is a relatively good model. Furthermore, compared with the regression model that only includes local integration, Model 3 improves the R-squared value from 0.396 to 0.547; therefore, Model 3 has more explanatory power.

**TABLE 4.3 Results of Regression Models**

	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
<b>Constant</b>	264.884 (0.075)	137.917 (0.333)	18.200 (0.039)
<i>IntL<sub>a</sub></i>	0.014 (0.002)	0.012 (0.002)	0.013 (0.001)
<i>BSeg<sub>a</sub></i>	-20.242 (0.242)	-8.295 (0.648)	
<i>Motv<sub>a</sub></i>	-0.001 (0.497)	-0.001 (0.191)	-0.001 (0.041)
<i>PSeg<sub>a</sub></i>	-4526.53 (0.068)	-2107.57 (0.352)	
<i>BikeL<sub>a</sub></i>	0.298 (0.970)	-	
<i>Slope<sub>a</sub></i>	4.978 (0.034)	-	
<b>R-squared</b>	0.731	0.588	0.547
<b>F-statistic</b>	4.986 (0.011)	4.635 (0.015)	9.055 (0.003)

Beta-coefficient is shown in each cell. Level of significance is shown in parentheses.

## 4.5 Discussion of Results

In this project, the available data set only contains 18 valid bicycle count locations. The regression model still performed reasonably well. It would be interesting to further validate the results with other large-scale datasets so that the proposed methodology can be more useful in transportation planning practices.

The integration measurement in space syntax theory represents the accessibility of a link within a network. Global integration represents the global accessibility, whereas local integration

describes the accessibility at a neighboring level. Because the bicycle is more suitable for short-range trips than for long-distance travel, local integration should be more useful than global integration in modeling bicycle traffic volume. According to the results of the regression analysis, the local integration indeed worked better than global integration in describing bicycle movement in the Salt Lake City network. Moreover, among various explanatory variables, local integration itself explained a large proportion of bicycle volumes. Thus, space syntax is demonstrated as a very promising tool for modeling bicycle traffic.

Except for local integration, only one bicycle-related explanatory variable (i.e., motor vehicle volume) was included in the final specification of the model. Nevertheless, because our data points are limited, we should be cautious in concluding that other excluded factors do not have a significant correlation with bicycle volumes. In future studies, more extensive datasets should be used to further investigate the relationship between bicycle volumes and these bicycle-related attributes. In addition, space syntax analysis is purely based on the topology of transportation networks, and does not consider the heterogeneity of trip production/attraction and trip distribution among traffic zones in a region, therefore, it cannot fully explain the traffic flow distribution within a network. Future studies can adopt additional variables, such as population densities and job densities to represent travel demands and combine them with space syntax measurement to improve the explanatory power of the model.

## Chapter 5: Concluding Remarks

This report proposes a methodology to apply space syntax theory to modeling bicycle traffic. Travelers' cognitive understanding of the network configuration, which plays an important role in their route choices, is explicitly analyzed and modeled using space syntax theory. Linear regression is used to analyze the correlation between bicycle volumes and space syntax measurements. To improve the explanatory power of the model, a number of bicycle-related attributes are considered through multiple regression analysis. A real-world case study is conducted in Salt Lake City, Utah, to demonstrate the proposed methodology. The results show that a space syntax measurement (i.e., local integration) can explain the bicycle volume distribution fairly well. By incorporating another bicycle-related attribute (i.e., motor vehicle volume), the model improves significantly in describing bicycle movement. Therefore, the combination of the space syntax measurement and other bicycle-related attributes can provide better explanatory power in modeling bicycle traffic.

The findings in this project have importation implications in bicycle facility assessment. Space syntax theory is demonstrated to be a useful tool in modeling cyclist route choice and can be used to guide the design of networks to accommodate bicycle travel more efficiently.

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