MAXIMIZING BICYCLE SHARING:
AN EMPIRICAL ANALYSIS OF CAPITAL BIKESHARE USAGE

by

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Approved by:

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NOREEN MCDONALD, ADVISOR

Image courtesy of Alta Bicycle Share

Image courtesy of Eric Gilliland

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Executive Summary

As one of three large North American systems, Capital Bikeshare represents a wealth of empirical data not only for the Washington Metropolitan area as it looks to expand its bicycle sharing system, but for other cities planning their own systems. In the past, North American cities relied on international practices to inform feasibility analyses and planning processes for nascent bicycle share systems. With actual usage, membership, and revenue figures in hand, researchers are just beginning to understand the operational dynamics of the technology in the context of American culture and urban spatial structure.

To date, the public has committed more than $13 million in funding to the regional Capital Bikeshare system (mostly by way of federal grants). This study seeks to synthesize Capital Bikeshare data in order to help planners assess and improve it as a viable transportation investment. In doings so, this report helps to inform a larger policy dialogue about bicycle sharing locally and nationally.

The methodology presented here adds to the small but growing body of bicycle share feasibility work; helping fill the empirical void in the North American literature and expand the suite of analytic approaches available to practitioners and academics. Specifically, this study seeks to answer the research question:

<u>What are the determinants of Capital Bikeshare usage?</u>

Through a spatial analysis of October 2011 trips taken across Capital Bikeshare stations in the District of Columbia (n=97), this study:

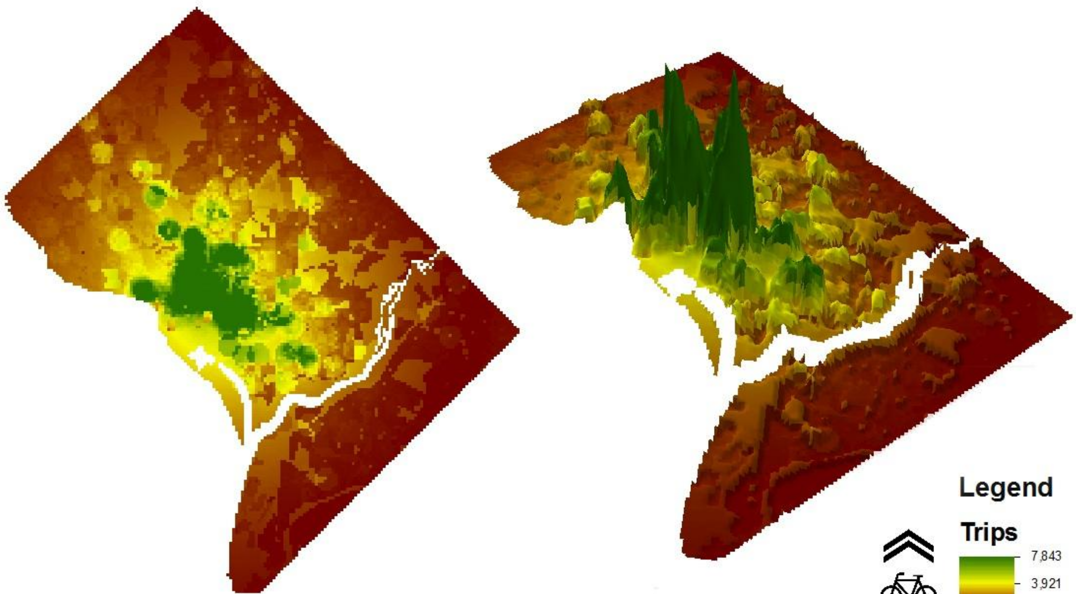
- Determines the association between bicycle sharing ridership and a number of built environment and socioeconomic factors through a regression
- Provides policy recommendations for Capital Bikeshare expansion and station reallocation based on a suitability map
- Develops a replicable framework for assessing and utilizing bicycle sharing data in the Washington region and beyond

Independent variables in the regression analysis include trip generation, trip attraction, and transportation network factors within 400 walking meters of each station. An initial unadjusted regression indicates that 12 of the 14 independent variables are statistically significant (without controlling for the effects of other variables). A multivariate regression points to five statistically significant determinants of Capital Bikeshare use:

- Population (Aged 20-39)
- Non-white population
- Retail density (using alcohol licenses as a proxy)
- Metrorail stations
- Distance from the center of the bicycle sharing system

These significant variables informed a suitability map which provides a framework for transportation planners and policymakers to assess the system's current configuration and inform future expansions and station reallocations (see Figure A).

Figure A: Empirically-Based Bicycle Share Suitability Analysis for Washington, DC

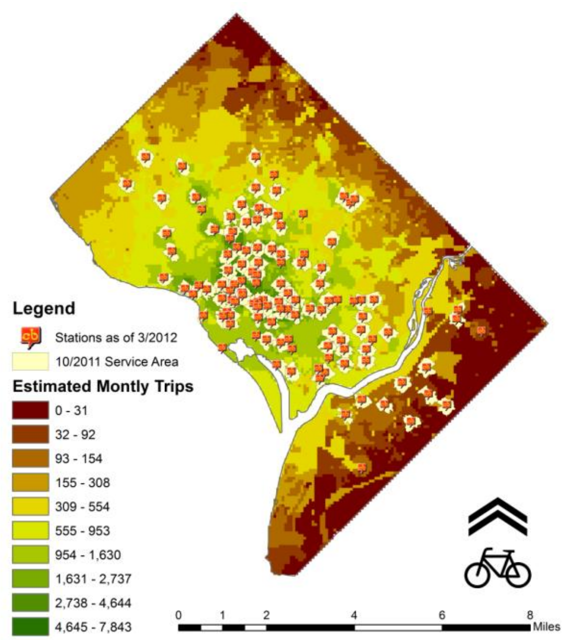


The analysis reveals that approximately 13% of Capital Bikeshare stations as of March 2012 are located in areas expected to experience fewer than 18 trips a day. Actual usage data shows substantially worse performance for a significant share of stations. While such stations meet equity goals of the program, there are multiple areas around the city that are both under-served by and highly suitable for bicycle sharing. Planners and policymakers should consider as they build out and tweak the system in the coming years (see Figure B).

Overall, this study points to the following policy-sensitive conclusions for bicycle share planning and implementation in the Washington region and beyond:

- Bicycle share planning should be highly customized to a specific geography
- Cross-sectional regression analysis of bicycle sharing systems is a difficult, data hungry process
- Distance from the center of the system carries particular explanatory power in this empirical model
- Planners should use performance measures and indicators to carefully weigh goals of equity and coverage against ridership
- Suburbanization of bicycle sharing carries both opportunities and pitfalls
- Open bicycle sharing data promotes transparency, scholarship, and innovation

Figure B: Capital Bikeshare Stations and Service Areas Overlaid on Suitability Analysis



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Any undertaking of this nature depends on the support of a larger community of institutions, scholars, practitioners, and friends.

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The views expressed in this document are those of the author and do not necessarily reflect the views of the individuals or organizations listed herein.

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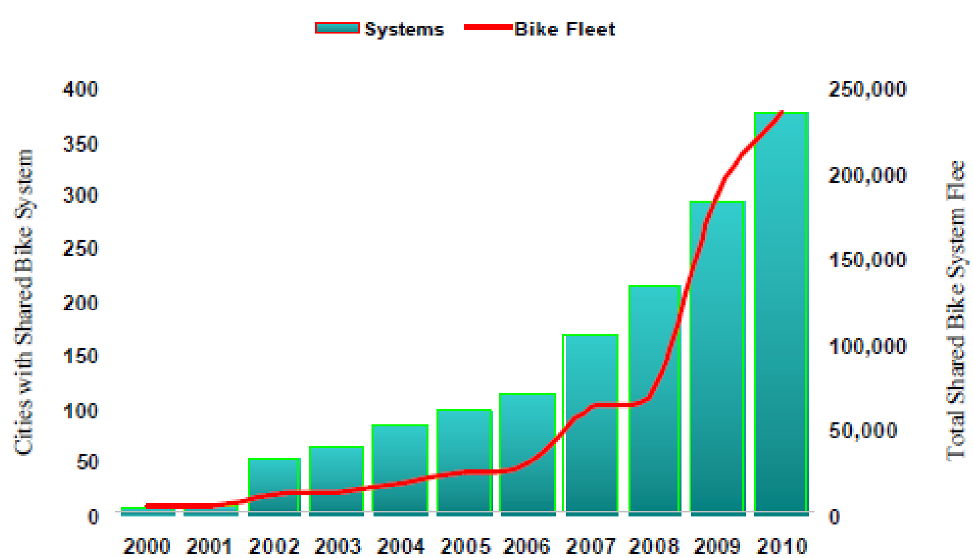
Introduction and Background

With an increasingly diverse set of goals and dramatically decreased financial capacity to carry out projects, the transportation planning field stands at a crossroads. On one hand, governments promote often competing priorities of economic development, environmental sustainability, and social justice. On the other, they increasingly look to the private sector to finance, operate, and maintain transportation systems of all types. Amid these prevailing forces, two trends have emerged: 1) the proliferation of cheaper, more policy-oriented transportation initiatives like the promotion of walking and bicycling and 2) private sector involvement in public infrastructure. The rapid emergence of bicycle sharing in U.S. cities represents a fusion of these two trends.

A Bike Sharing Moment

The Capital Bikeshare system represents the fourth generation of a concept that originated in Amsterdam in the 1960s and took hold in Lyon, France in 2005 as technology rapidly evolved. The 2007 launch of Vélib' in Paris gave bicycle sharing an international stage from which it quickly took hold in hundreds of western European and Chinese cities by 2010. Montreal's Bixi system launched in 2009, while Minneapolis-St. Paul unveiled NiceRide Minnesota in June 2010 (Midgley 2011; Shaheen 2010) (See Figure 1).

Figure 1: Cumulative Increase in Bicycle Sharing Systems Worldwide, 2000-2010



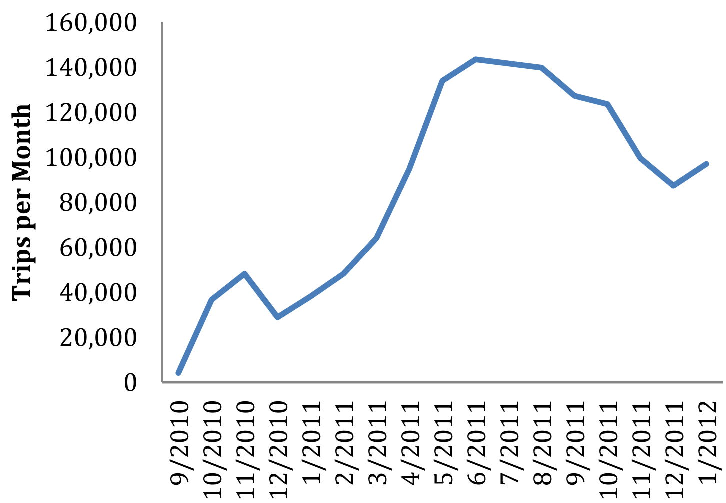
Source: Midgley (2011), based on detailed research as of October 12, 2010

Bicycle sharing arrived to the United States in force with the launch of Capital Bikeshare in September 2010.[1] Since then, the system has registered some 20,000 annual memberships and

[1] Capital Bikeshare replaced a nascent 10 station, 120 bicycle system launched in August 2008 in the District called SmartBike DC.

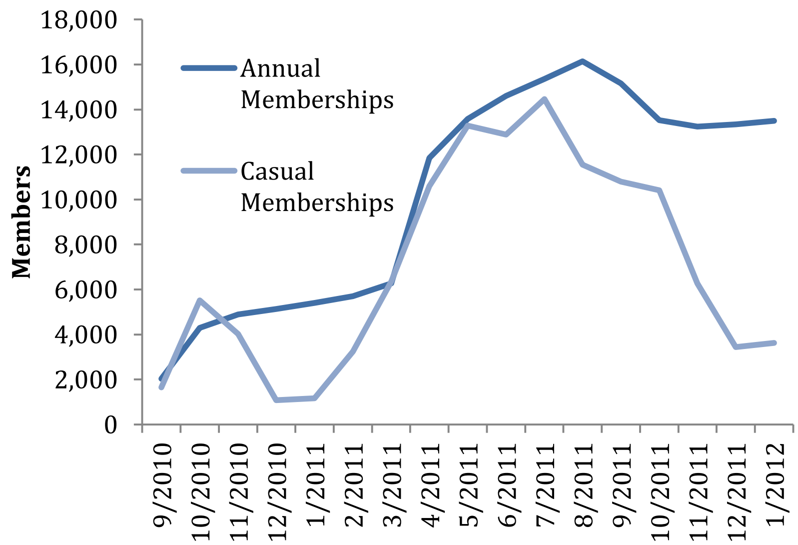
well over 100,000 casual, short term users. The system recorded over 1 million total trips in its first year and the rate and number of signups continues to grow rapidly despite dips in the winter months (See Figure 2 and Figure 3). Approximately 70 stations are part of an ongoing expansion plan both within the District and in nearby Maryland and Virginia suburbs.

Figure 2: System-Wide Capital Bikeshare Usage



Source: Alta Bicycle Share – Capital Bikeshare Trip History Data

Figure 3: Annual vs. Causal Capital Bikeshare Users



Source: Alta Bicycle Share – Capital Bikeshare Trip History Data

While 3rd generation bicycle share systems brought smart cards and key fobs, electronic locking docks, telecommunications systems, and kiosks with screens, 4th generation systems like Capital Bikeshare are characterized by GPS tracking technology, improved distribution, and mobile, solar powered stations (DeMaio 2009).

Although expensive to implement, these systems are increasingly self-supporting, technologically sophisticated, and popular. Bicycle sharing technology is now in various stages of planning and deployment in several large and small American cities, from New York, Chicago, and San Francisco to Baltimore, Nashville, and Philadelphia.[2]

Financing Capital Bikeshare

The federal government funded the original 1,100 bike, 115-station Capital Bikeshare system which spans the Potomac River and includes the District of Columbia as well as the Crystal City and the Rosslyn-Ballston corridor in Arlington. A $7.2 million grant from the Congestion Mitigation and Air Quality Improvement (CMAQ) Program funded the initial capital and operations costs of the program. Alta Bicycle Share, the Portland-based contracted operator of the system, plans, deploys, and manages the system in partnership with the participating jurisdictions.

Subsequent federal funding allocations and state grant programs support ongoing expansion of the system across the District, Arlington County and Alexandria (Virginia), as well as Montgomery and Prince George's counties (Maryland). In all, the public has committed just over $13 million to date for the capital costs of the system, primarily in federal funds. By the end of 2012, there will be approximately 1,800 bikes and 220 stations deployed regionally (see Table 1). Meanwhile, the District is exploring corporate sponsorship of the system to cover operations costs and different jurisdictions are looking to community benefit agreements to provide for new, developer-financed stations in high growth areas.

Table 1: Funding Sources for Capital Bikeshare

Location	Date of Installation	Bikes	Stations	Costs	Funding Source
Original System					
Arlington – Crystal City	Sept. 2010	100	14	$800,000	CMAQ/ Crystal City BID
DC	Sept. 2010 – Feb 2011	1000	100	$6.4 million	CMAQ/ local match
Expansions					
DC	Fall 2011-Spring 2012	265	50, Expand 18	~$2.5 million	CMAQ/ local match
Arlington	Spring 2012	192	30	$1.243 million	CMAQ/ local match
Rockville and Shady Grove (MD)	2012	200	20	$1.288 million/ $488,000/ $200,000	Job Access and Reverse Commute (JARC) / Montgomery County/ City of Rockville
Alexandria (VA)	2012	54	6	$400,000	CMAQ/ local match
			Total Committed:	**~$13,319,000**	

[2] Toronto's BIXI system launched with 80 stations and 1,000 bikes in summer 2011. Boston launched its Hubway System in summer 2011 with 61 stations and 600 bikes. Denver has 51 stations and 510 bikes. New York recently announced its intention to launch a 600 station, 10,000-bike system in Manhattan and Brooklyn in the summer 2012 and Chicago is looking at a 3,000-bike, 300 station system over the same time frame. Baltimore, Nashville, Philadelphia, Sacramento, San Francisco, and Seattle are all in various states of planning and deployment.

Stations have an operating life of approximately 6 years and cost roughly $50,000 depending on size, while bikes cost $1,200 each. Although there are economies of scale, each station is associated with approximately $20,000 in operations and maintenance costs.

Bicycle Share Planning in the Washington Region and Beyond

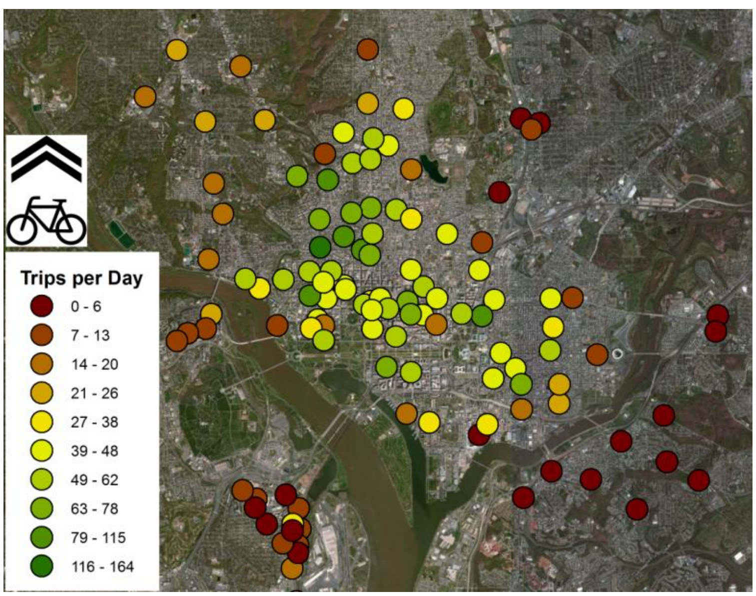
Bike share system planning generally follows three steps between program concept and implementation:

1) Defining the service area
2) Forecasting financial feasibility
3) Determining station locations

Steps 1 and 3 are usually driven by some combination of political decision-making and technical analysis. In the case of the Washington Metropolitan Area, stakeholder meetings, online crowdsourcing, professional judgment, and political logrolling are all used to capture public sentiment and determine the system layout. This combination of a planning and political process, for instance, led to the installation of stations in each of the District's 8 Wards, despite varying demand potential in different parts of the city.

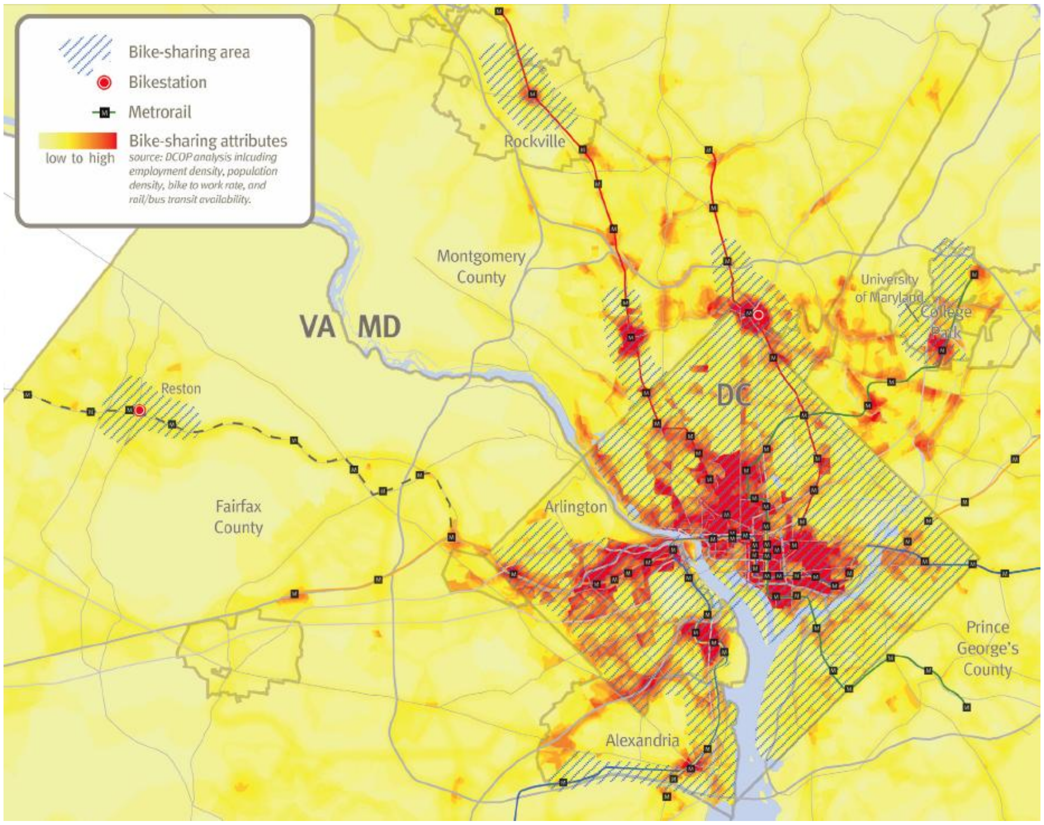
Figure 4 depicts how system planning decisions translate into widely varying station utilization across the Capital Bikeshare system.

Figure 4: Capital Bikeshare Trips by Station per Day in October 2011



In each jurisdiction in the Washington region, the original technical analysis that informed station location was based on models developed by Alta Bicycle Share as well as the planning and transportation departments in the District and Arlington. These theory-based studies point to built environment factors like population density, employment density, proximity to transit and bike infrastructure, and bike to work rates as all key contributors to successful station location. These characteristics were used to create a series of "heat maps" based on weighted sum raster analyses in GIS and served to inform the original system layout. After a year and a half of operation, much of the public sector modeling taking place for Capital Bikeshare grant proposals and expansion planning is grounded in rudimentary, theory-based models focusing on built environment factors (see Figure 5).

Figure 5: Heat Map Showing Bike Share Suitability Region-Wide



This theory-based analysis was part of a failed August 2010 federal TIGER grant to dramatically expand the Capital Bikeshare system. Image produced by the DC Office of Planning.

Conversations with Atla Bicycle Share indicate that, while they do analyze the robust public data on system usage, there has not been a regression analysis of Capital Bikeshare in some time and that an updated assessment of the data is in order. The lack of analysis of ridership data in part signals the political forces at play in station placement. Perhaps more importantly, as a profit-motivated firm on a fixed operations and maintenance contract, Alta's primary interest is operating the DC system efficiently and expanding into other markets, not refining station placement or engaging politically sensitive matters.

Literature Review

In order to assess the prospect of new bike share systems, researchers and consultants have produced and made publicly available feasibility studies for New York, Ottawa, Philadelphia, Sacramento, Seattle, and Vancouver since 2008. While presumably many other studies exist, they remain proprietary.

Feasibility studies are generally concerned with defining a system service area and extrapolating demand to determine the financial solvency of a proposal, this study instead will deal with the central tradeoff between expanding Capital Bikeshare's core service versus its reach (see methodology section below). This was accomplished through a refined suitability and demand estimation analysis, using available Capital Bikeshare data. As such, this literature review focuses on quantitative approaches to assessing bike share station suitability and placement while referencing applicable theory and practice.

Modeling Bike Share Suitability

Of six feasibility studies evaluated, analyses from Philadelphia, Sacramento, and Seattle, were the most thorough, data-rich, and fine-grained. Each employed GIS weighted sum raster analysis to define a service area based on a number of indicators designed to maximize bike usage. This was accomplished through a weighting of variables like job and housing density and proximity to transit, parks, and bike infrastructure. While the Philadelphia and Seattle studies offer comprehensive theory-based frameworks for defining a service area, due to lack of data availability at the time, they fall short of applying empirical models. Neither takes into account confounding demographic and socioeconomic variables (such as age, median income, racial composition, and household vehicle availability) that have a significant but largely unexplored influence on bike share usage. In Sacramento; however, Maurer (2011) combined socioeconomic variables with empirical data through the following three-step analytic framework:

1) Development of a regression model that explained bike share rentals in the Minneapolis Nice Ride system
2) Application of suitability values derived from the Minneapolis analysis to create a GIS "heat map" of Sacramento to delineate a proposed primary service area
3) Estimation of potential rental demand in Sacramento through the application of coefficients from the regression model to a series of hypothetical stations in the proposed service area

While methodologically sound, a drawback of a regression approach is the fundamental underlying spatial and cultural differences between cities, which can ultimately cause significant bias in both the suitability and demand estimation analyses. Such was the case when Maurer (2011) applied a regression model of Nice Ride Minnesota and predicted relatively low suitability for Downtown Sacramento, which the author attributed to a different distribution of transit service, jobs, and socioeconomic characteristics in the two cities. However, this drawback is avoidable if data analysis and application are kept within the same jurisdiction.

The New York, Vancouver, and Ottawa studies attempt to define suitability parameters, but the methods in each are not as satisfactory or comprehensive as the three studies discussed above. Although the New York study acknowledged a series of variables important to station success, the authors fail to combine the variables in a fine-grained analysis that offers a set of discrete recommendations. Instead, the authors of the New York study offer a simplistic phasing plan that radiates out from lower Manhattan and downtown Brooklyn and state the system should “focus on the city’s medium- and high-density areas.” They cite 28 stations per square mile in the Paris and (the then-proposed) London systems as a good benchmark, despite widely different population densities and system scales in both cities.

Similarly, the authors of the Vancouver feasibility study develop a series of five indicators — population density, other demographics, employment density, cycling mode split, and transit mode split — and associated measures and apply them to the metropolitan region. While the authors offer a detailed analysis, like New York, they fail to quantify and synthesize the indicators in a meaningful way. A qualitative analysis of the indicators ultimately leads the authors to conclude that all six neighborhoods in Vancouver’s metro core are suitable for a bicycle sharing system.

In Ottawa, researchers approached bike share suitability through a more qualitative but fine-grained approach than New York and Vancouver. Working with the Canadian equivalent of Transportation Analysis Zones (TAZs), the authors selected candidate zones with higher than average trip origins and destinations as well as population and employment for the downtown area. Within each zone, they looked for “concentrations of employment, housing, hotel, shopping, bus stations served by several bus numbers to determine the viability of station locations.” From there, the TAZs and candidate sites within each were field researched and ranked based on a qualitative assessment that incorporated location, visibility, size, proximity to pathways/bicycle lanes, security, and proximity to heritage/national symbols.

Ottawa’s approach in part reflects the perceived difficulty of siting stations there, as compared to other cities, due to a more pronounced concern over station security and a desire to locate them near hard services and maintenance infrastructure. This approach synthesizes a much wider array of information in a more comprehensive framework than either the New York or Vancouver studies, seamlessly meshing quantitative and qualitative attributes. It represents one compelling alternative/complement to the weighted sum raster approach. By using TAZs as the basic unit of analysis, the researchers in effect narrowed the socio-demographic scope of the high-level analysis, but to some degree make up for this shortfall through field research and siting decisions which most planning efforts leave for future study.

In conclusion, the review of publicly available feasibility studies indicates the importance of seeking out a comprehensive set of suitability indicators and applying them in a spatially-based, quantitative framework. Although empirical data for North American systems has only recently come on the scene, such data can be a valuable resource to determine bicycle share suitability, especially when applied across similarly situated cities or within the context of the same city. This approach represents the best available science and will be applied to the Capital Bikeshare system in this project.

Estimating Bicycle Share Demand

Of the six feasibility studies evaluated, all attempted to quantify bicycle share demand. Maurer (2011) applied regression coefficients to hypothetical stations superimposed on a suitability analysis in order to calculate rentals per station. With the exception of Ottawa, all of the studies calculate demand based on uptake of the system by the general population or diversion rates from other transportation modes. These rates were usually derived from user surveys of existing European systems.

New York: Developed an uptake rate of 3%-9% of the population who live and work within the service area based on the experience in Paris and surveys conducted in London.

Ottawa: Used intercept surveys to determine uptake rates among different user types. Employees, residents, tourists in the service area were estimated to use the service at 20%, 13%, and 1% respectively.

Philadelphia: Determined high, medium, and low demand scenarios across two different proposed implementation phases. Lyon, Paris, and Barcelona diversion rates were applied.

Seattle: Determined high, medium, and low demand scenarios across three different proposed implementation phases based on Paris, Lyon, and Barcelona

Vancouver: Determined high, medium, and low demand projections based on Lyon, Oslo, Barcelona, and Berlin

Krykewycz et al. (2010) note that such a methodology implicitly assumes that the proposed system is "comparable in scale and scope with those of the peer European cities from which diversion rates were derived." Yet, for Paris, Barcelona, and Lyon, the basis for demand estimation in three of the six studies review, have 20,000, 3,000, and 1,000 bike systems respectively. While multiple demand scenarios are method to account for differences in scaling, other programmatic issues like pricing and supportive policies and infrastructure raise serious questions for this overall approach. Beyond programmatic issues, there are also considerable geographic, climatic, and cultural differences not only between North American and European cities, but also among the European cities themselves.

The review of demand estimation approaches reveal a common set of tools across the majority of publicly available feasibility studies despite the serious methodological drawbacks involved. To address uncertainty, multiple demand scenarios applied at different system implementation scales should be carried forward in future studies, but the recent availability of data from North American cities makes empirical research possible.

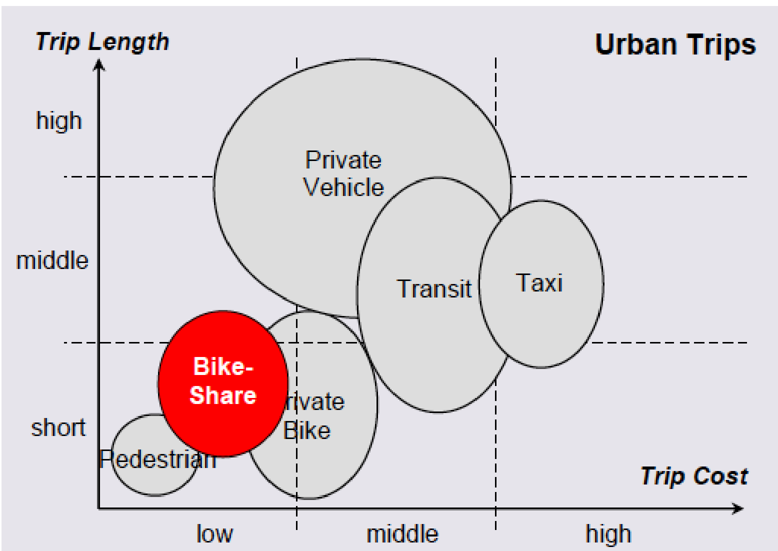
While Maurer's reliance on regression model coefficients is also subject to error, the confidence interval constructed around each estimate more adequately accounts for the uncertainty involved. More importantly, Maurer's technique is grounded in the actual determinants of station success, rather than arbitrary uptake/diversion rate approaches from European systems.

Station Spacing and Implementation

Bicycle sharing systems are generally designed for short distance trips with the average intended trip length between 15 - 25 minutes or about 3 miles. While some smaller rental systems are designed more for recreational users and longer hauls, the pricing structure for Capital Bikeshare and similarly deployed urban systems favor trip lengths under 30 minutes.

Bicycle share programs are designed to fill a gap in the urban transportation network between walking and transit/automobile travel, where the distance is too far to walk but at the same time too close to justify waiting for transit or incurring the cost of a car trip (see Figure 6). People will walk up to 10 minutes for most trips or slightly over a mile to access work. Average cycling distances range between 0.5 and 3 miles. Transit use becomes prevalent at trip distances in excess of 2.5 miles (Witte 2009).

Figure 6: The Bicycle Share Niche in the Urban Transportation System



Quay Communications 2008

Major redistribution is needed in systems across the world due to the problem of over- and under-subscription of stations; a problem not escaped by the District of Columbia. These issues are particularly acute during early adoption of programs where decision makers, like those in the District of Columbia, choose to expand the reach of the program at the expense of providing a properly dense network of stations. 300 meter station spacing has become the gold standard of sorts for bike share industry, which is a distance equivalent to roughly a 5 minute walk from anywhere within the station coverage area and a ¼ mile walking distance along streets (Quay Communication 2008).

Redundancy in station location combined with a high ratio of total station spaces to bikes, are key concerns of bike share system planners. A contiguous network designed to minimize the distance between stations is critical to ensure that users can find a bicycle when they need one and return it easily when they reach a destination (Gregerson et al. 2010).

Other Relevant Built Environment Research

The effect of the built environment on transportation mode choice is perhaps the most exhaustively studied topic in transportation literature (Ewing and Cervero 2010). Although there are many gaps in such research, especially with regards to non-motorized transportation, the paramount roles of “the 4 Ds” – density, diversity, design, and destination accessibility – are generally accepted. Through a meta-analysis, Ewing and Cervero (2010) found that the built environment attributes of diversity (land use mix) and design (intersection density) are approximately 2 and 3 times more influential than density in their respective effects on transportation choice.

Although the methodological basis for the meta-analysis are sound, the drawbacks of such approaches along with the authors’ admitted weaknesses of the studies that comprise the analysis, make it not as clean and easily to generalize as many practitioners would like. This is particularly true given the ongoing debate on how to properly measure diversity and what represents a “good” land use mix. McConville et al. (2011), for instance, found that certain retail mixes were more supportive of walking than others. These caveats aside, built environment variables are just one piece of the overall picture. As already noted, Maurer (2011) shows that the success of bike sharing, is at least as dependent on demographic and socioeconomic factors; particularly income, age, and race.

Research Question

This study seeks to quantify the determinants of Capital Bikeshare usage and make policy recommendations for the system as it grows and matures. Specifically, through an evaluation of recently released ridership data, this study answers the question:

<u>What are the determinants of Capital Bikeshare usage?</u>

In answering this research question, this study also fulfills the following objectives:

- Determine the association between bicycle sharing ridership and a number of trip generation, trip attraction, and transportation network factors
- Provide policy recommendations for Capital Bikeshare expansion and station reallocation based on a suitability map
- Develop a replicable framework for assessing and utilizing bicycle sharing data in the Washington region and beyond

Methodology

This study fits squarely within a growing, albeit mostly propriety, body of bicycle share planning practice. The methodology builds primarily on empirical demand estimation methodology developed by Maurer (2011) for Sacramento and bicycle share suitability analysis developed by Krykewycz et al. (2010) for Philadelphia, but also draws from additional research in accomplishing each of the three main objectives proposed above.

The nature of the business behind bike sharing largely explains the dearth of scholarly literature on the topic. Several publicly available studies assess the feasibility and configuration options of bicycle sharing systems before implementation based on theory and the experience of European cities (see Literature Review above). Instead, through an empirical and data-driven analysis, this study informs potential system expansions and redeployments *after* initial system implementation and *within* the same city.

Since expansion of the system is ongoing and fourth generation bike share stations are mobile, an analysis of Capital Bikeshare is not simply an academic exercise; it could inform planned system expansion and potential redeployment of the existing stations to more suitable locations. The two main analytical tasks are as follows:

1) **OLS Regression/Demand Estimation**: With empirical data from the on-the-ground Capital Bikeshare system, a regression analysis is employed to explain station demand based on the demographic, socioeconomic, and built environment characteristics around each existing station.
2) **Raster Analysis**: The variables from the regression contributes to an overall "heat map" using a raster analyses in GIS, which visually convey the most suitable station locations in Washington, DC.

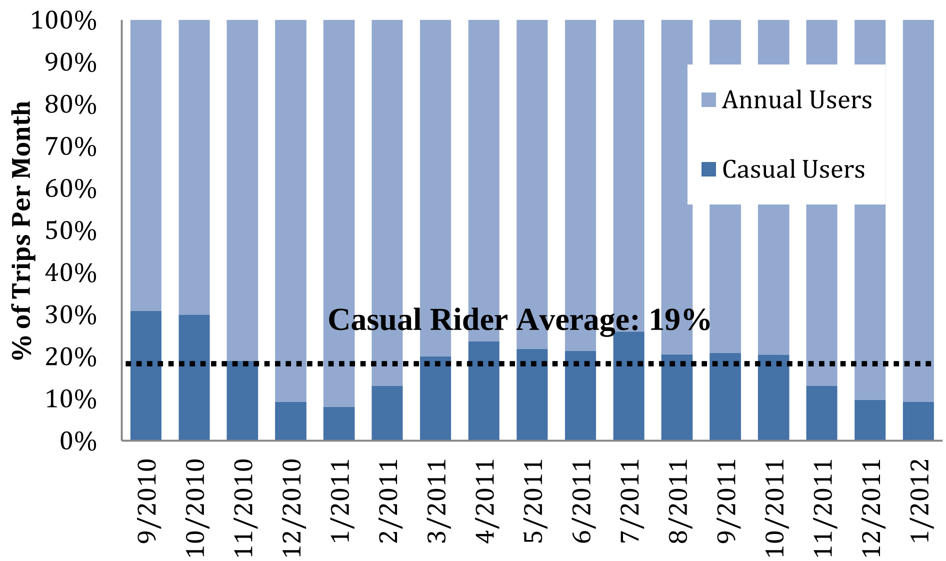
A regression of rentals for October 2011 and theoretically important independent variables reveals the statistical significance of different station area attributes holding all other variables constant. The District is then divided into a grid of 10-meter-by-10 meter cells and GIS shapefiles for significant variables are rasterized into the grid, summed, and reclassified to produce a heat map of the most suitable bike share areas.

The heat map is then used to assess and ongoing expansion of the system. Taking into account the operational aspects of the multi-jurisdictional system, the results of the regression and the demand analysis will help inform different expansion and redeployment scenarios for Capital Bikeshare. Furthermore, the analysis will allow planners and policymakers to more accurately assess the program's equity goals in light of a refined understanding of key socioeconomic attributes that contribute to bicycle share station use and success. This will further inform education and outreach efforts to culturally and economically diverse parts of the city that are already underway.

Dependent Variable

The dependent (outcome) variable in this study was trip departures per station (n=97) in October 2011. Capital Bikeshare is primarily used by annual members for utilitarian trip making purposes; however, overall usage fluctuates with tourism and seasonal climate (see Figure 2 and Figure 7). October 2011 was chosen as the subject month because it represents the most recent data available before the onset of winter. Conveniently, October predates a major system expansion in November and the system extent remained relatively constant leading to that point.

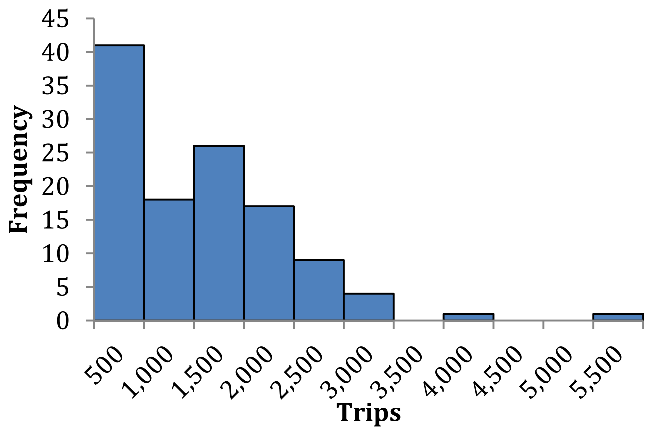
Figure 7: Annual vs. Causal Capital Bikeshare Users per Month



Source: Alta Bicycle Share – Capital Bikeshare Trip History Data

The variable is continuous, with the number of trips departing from a station ranging from 8 to 5,077. The mean rental value for the system was 1,210. However, the frequency distribution of October trips (displayed in Figure 8) reveals that the variable is not normally distributed. Nearly half the stations experienced fewer than 500 trips a month, while many others exhibit well above 1,500 rentals a month. Given this distribution, the dependent variable was transformed to the square root of October 2011 trips for the regression. According to a statistical analysis, this transformation gives the distribution the smallest chi-square of any transformation, thus making the trip data as normally distributed as possible.

Figure 8: Frequency Distribution of October 2011 Capital Bikeshare Trips (Untransformed)



Independent Variables

The independent variables in this study account for a number of trip generation, trip attraction, and transportation network factors. With the exception of median household income and variables measuring proximity, all independent variables are measured within at 400-meter (1/4 mile) walk distance of each station using the Network Analyst Tool in ArcGIS. This distance represents a transit industry accepted service "catchment" area within which most people can walk comfortably in 5-10 minutes and are far more likely to use transit.[3] Using network distance helps account for intersection density, which is a key determinant of transit ridership in the literature.

For trip generation variables, a non-overlapping service area was determined, so as not to double count trip generators. For trip attraction and transportation network variables, overlapping service area were used, since the presence of these variables is not mutually exclusive between stations (see Figure 9). Definitions, sources, and the predicted effect for each independent variable are provided in Table 2. Summary statistics for the analysis are included in Appendix A.

[3] Relationship Between Transit and Urban Form Handbook, Transit Cooperative Research Program TCRP H-1, November 1995, page 29.

Figure 9: Overlapping vs. Non-Overlapping ¼ Mile Service Areas

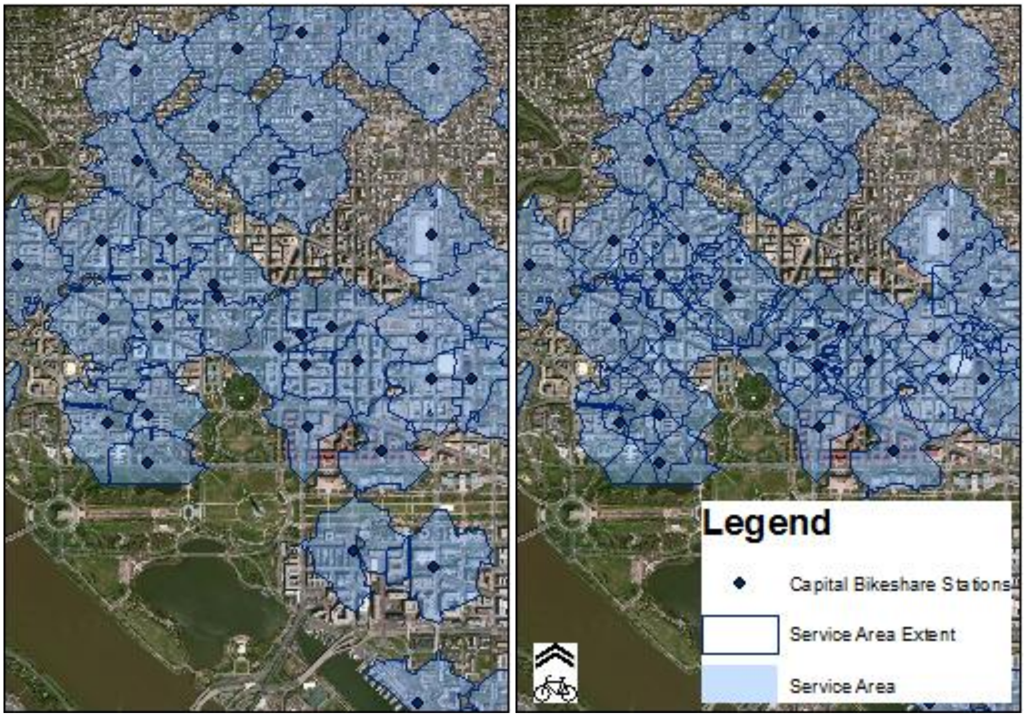


Table 2: Independent Variables with Definitions, Predicted Effects, and Sources

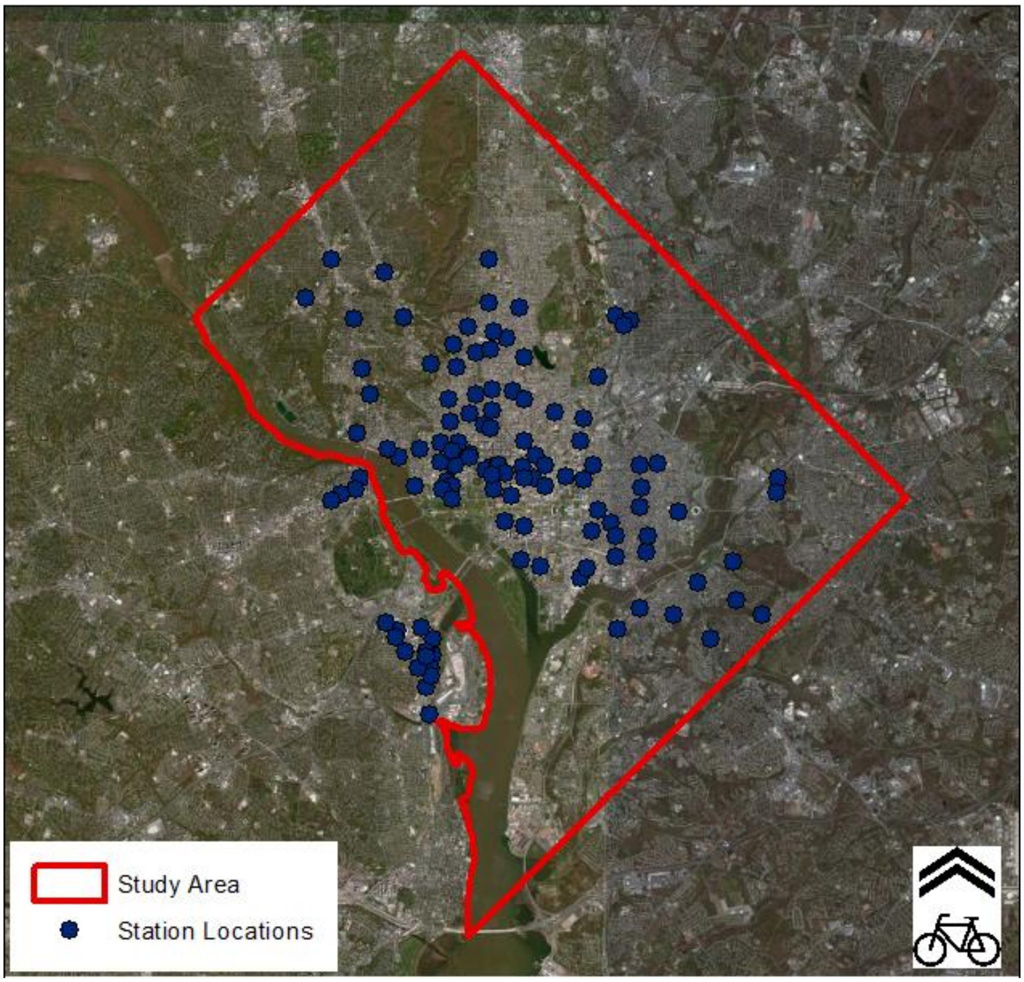
Variable	Definition (Units as applicable)	Predicted Effect	Scale	Data Source	Date
Dependent					
Trips	Number of trips during October 2011 (in 10s of trips)	N/A	Station	Alta Bicycle Share	10/2011
Sqrt (Trips)	Square root of the number of trips during October 2011	N/A	Station	Alta Bicycle Share	10/2011
Independent					
Trip Generation					
Age 20-39	Population between the ages of 20 and 39	Positive	Census Block	Census*	2010
Non-White Population	Proportion of population that is of a race other than "white alone"	Negative	Census Block	Census*	2010
Low-Vehicle Household Prevalence	Proportion of households that have one or zero vehicles available	Unknown	Census Tract	American Community Survey*	2006-2010
Income	Median household income (in 1000s of dollars)	Unknown	Census Tract	American Community Survey*	2006-2010
Hotel Rooms	Number of hotel rooms (in 10s of rooms)	Positive	Study Area	DC Office of the Chief Technology Officer (OCTO)***	8/2011
Alternative Commuters	Proportion of workers who commuted by bicycle, walking, or public transportation	Positive	Census Tract	American Community Survey*	2006-2010
Trip Attraction					
Attractors	Number of "attractors" (shopping centers, cultural/historic/civic sites, sports complexes, entertainment centers, museums, etc.)	Positive	Study Area	Geographic Names Information System (GNIS)**	12/2011
Retail (Alcohol Licenses)	Retail establishments selling alcohol	Positive	Study Area	DC Alcoholic Beverage Regulation Administration (ABRA)***	9/2011
Colleges	Area of university campus (in 1000s of square meters)	Positive	Study Area	DC Emergency Management Agency (EMA)***	5/2011
Parks	Area of park and recreation sites (in 1000s of square meters)	Unknown	Study Area	DC Office of the Chief Technology Officer (OCTO)***, DC Department of Parks and Recreation (DPR)***	6/2002, 5/2010
Transportation Network					
Bus Stops	Number of bus stops (WMATA and Circulator)	Positive	Study Area	WMATA***, DDOT***	8/2011, 20/2011
Metrorail	Number of metro stations	Positive	Study Area	WMATA***	10/2011
Bike Infrastructure	Length of existing bike lanes and paths (in 100s of meters)	Positive	Study Area	DDOT***	7/2010
Distance From System Center	Distance from weighted mean (ridership) center of full DC and CA Capital Bikeshare system (in 1000s of meters)	Negative	Study Area	DDOT ***	8/2011

** U.S. Census Bureau* *** U.S. Geological Survey* **** DC Data Catalog*

Study Area

The study area for this analysis is limited to the District of Columbia (see Figure 10). While 18 of the 115 Capital Bikeshare stations in operation during October 2011 were located in Arlington, Virginia, the differences in data availability and quality across the two jurisdictions for the independent variables are considerable and ultimately precluded an analysis of the whole system. Out of over 123,000 trips taken during the study period, Virginia accounted for just over 15% of the stations in the overall system, but just less than 5% of total trip origins.

Figure 10: Study Area



Results

This study uses GIS analysis to assess Capital Bikeshare data and build a suitability heat map used to provide recommendations for future system expansions and redistributions. Determinants of bicycle share trips are identified through a regression of October 2011 rentals across Capital Bikeshare stations in the District of Columbia (n=97). The square root of monthly origin trips is used as the dependent variable. Independent variables in the analysis include trip generation, trip attraction, and transportation network factors (see Table 2) within 400 walking meters of each station. First, determinants of bicycle share trips are modeled. Then a suitability map is constructed. Next, the suitability analysis is applied to stations both in place as of October 2011 and installed through March 2012. Finally, the nature and sources of error in this analysis are examined through comparison of predicted and actual station usage.

Modeling the Determinants of Capital Bicycle Usage

An initial unadjusted regression indicates that 12 of the 14 independent variables are statistically significant without controlling for other variables (see Table 3). The full regression results are provided in Appendix A.

Table 3: Unadjusted Regression Model of October 2011 Capital Bikeshare Trips (n=97)

Variable	Coefficient	Standard Error	p-value	Adjusted R-Square
Population (Aged 20 to 39)	0.010	0.002	0.000***	0.233
Non-White Population Prevalence	-0.273	0.040	0.000***	0.320
Low-Vehicle Household Prevalence	0.652	0.140	0.000***	0.177
Median Household Income	0.073	0.037	0.053*	0.029
Hotel Rooms	0.151	0.037	0.000***	0.142
Alternative Commuter Prevalence	1.118	0.297	0.000***	0.120
Attractors	0.275	0.060	0.000***	0.172
Retail (Alcohol Licenses)	0.659	0.102	0.000***	0.299
University Area	0.001	0.001	0.294	0.001
Park Area	0.001	0.001	0.208	0.006
Bus Stops	0.533	0.195	0.007***	0.063
Metrorail	5.384	2.236	0.018**	0.048
Bike Infrastructure	0.414	0.093	0.000***	0.164
Distance from Capital Bikeshare System Center	-5.295	0.448	0.000***	0.591

****=p<0.01;*
***=p<0.05;*
**=p<0.10.*

Interestingly, these results suggest that any individual station's distance from the system center explains nearly 60% of the variation in usage among all stations. This is consistent with the gravity model: an oft-used model in transportation planning which posits that interactions between two locations decline with increasing distance, time, and costs between them. This is expected given that Capital Bikeshare (and bicycle sharing more generally) is designed for short trips. The majority of the District's origins and destinations are tightly clustered in the city's northwest quadrant, while other trip generators and attractors are located much further afield.

A multivariate regression suggests that, when controlling for the influence of each of the 14 variables, 5 emerge as statistically significant (see Table 4).

Table 4: Adjusted Regression Model (Full and Reduced) of October 2011 Capital Bikeshare Trips (n=97)

Variable	Full Model	Reduced Model
	Coef. (p-value)	Coef. (p-value)
Population (Aged 20 to 39)	0.007 (0.000)***	0.006 (0.000)***
Non-White Population Prevalence	-0.118 (0.000)***	-0.120 (0.000)***
Low-Vehicle Household Prevalence	-0.099 (0.412)	--
Median Household Income	0.009 (0.730)	--
Hotel Rooms	-0.010 (0.678)	--
Alternative Commuter Prevalence	-0.156 (0.497)	--
Attractors	-0.006 (0.894)	--
Retail (Alcohol Licenses)	0.217 (0.004)***	0.217 (0.001)***
University Area	-0.000 (0.866)	--
Park Area	0.001 (0.126)	--
Bus Stops	0.144 (0.233)	--
Metrorail	2.857 (0.047)**	2.732 (0.029)**
Bike Infrastructure	0.028 (0.660)	--
Distance from Capital Bikeshare System Center	-3.481 (0.000)***	-3.362 (0.000)***
Constant	46.4 (0.000)	46.6 (0.000)
R-Square	0.816	0.798
Adjusted R-Square	0.784	0.787
F (Prob > F)	25.93 (0.000)	72.08 (0.000)

****=p<0.01;*
***=p<0.05;*
**=p<0.10.*

It is important to remember regression measures association or correlation between Capital Bikeshare trips and the respective independent variables, *not causation*. Given that the dependent variable is square-root transformed, the relationship is not constant. Coefficients represent the marginal effect of independent variable (X) on the square root of monthly trips (Y).

Suitability Mapping

As outlined in the methodology section, GIS allows us to visually represent these inputs in a suitability map. Given the 5 variables identified in the reduced demand model, significant variables were rasterized into a District-wide 10-meter-by-10 meter grid (see rasterization methods in Appendix B), weighted by their respective coefficients and associated directional effects (see Table 4 and Table 5), summed to estimate monthly station demand (see Figure 11), and reclassified produce a heat map that depicts the most suitable areas for bicycle sharing (see Figure 12). While Figure 11 provides a precise number of trips for nearly 16,000 discrete 100 square meter geographic units across the District, the data points represent estimates subject to several caveats (described below). Figure 12 takes these estimates and reclassifies them into 10 discrete bins in order to assign suitability scores. This helps to both smooth out false precision and convey the results more succinctly.

Table 5: Suitability Model Inputs – Significant Variables and Directional Effects

Variable	Directional Effect
Population (Aged 20 and 39)	Positive
Non-White Population Prevalence	Negative
Retail (Alcohol Licenses)	Positive
Metrorail	Positive
Distance from Capital Bikeshare System Center	Negative

Figure 11: Empirically-Based Bicycle Share Demand Analysis for Washington, DC

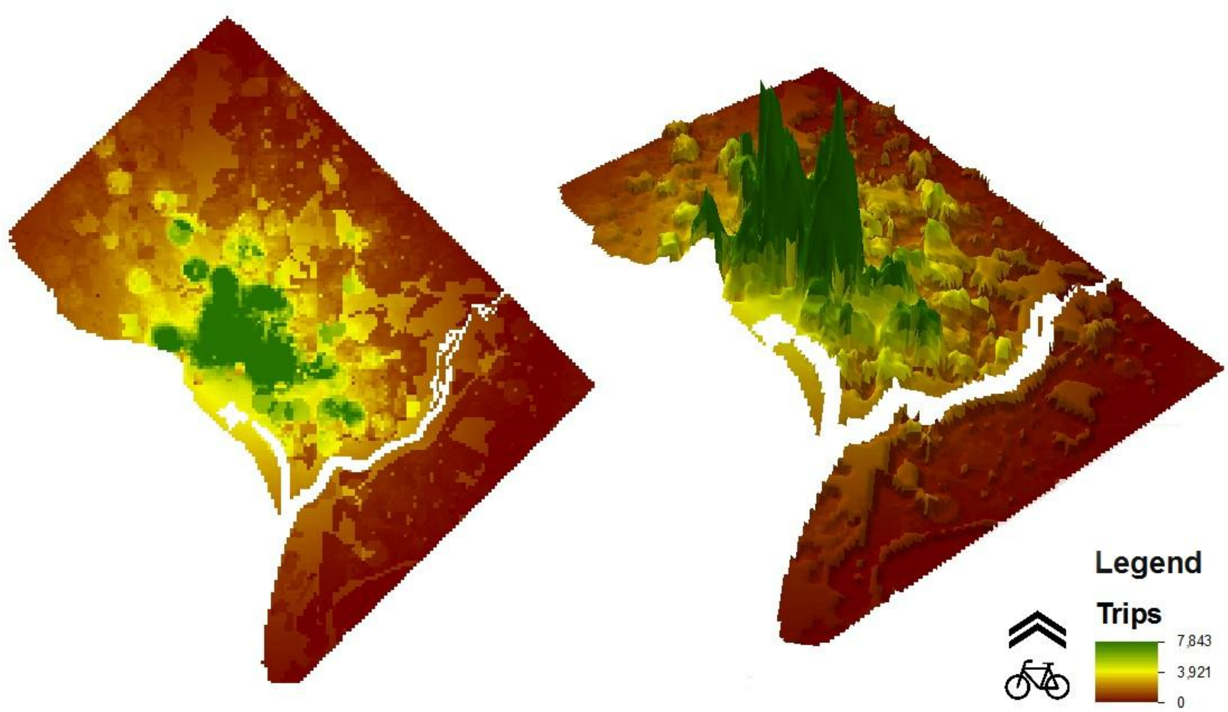
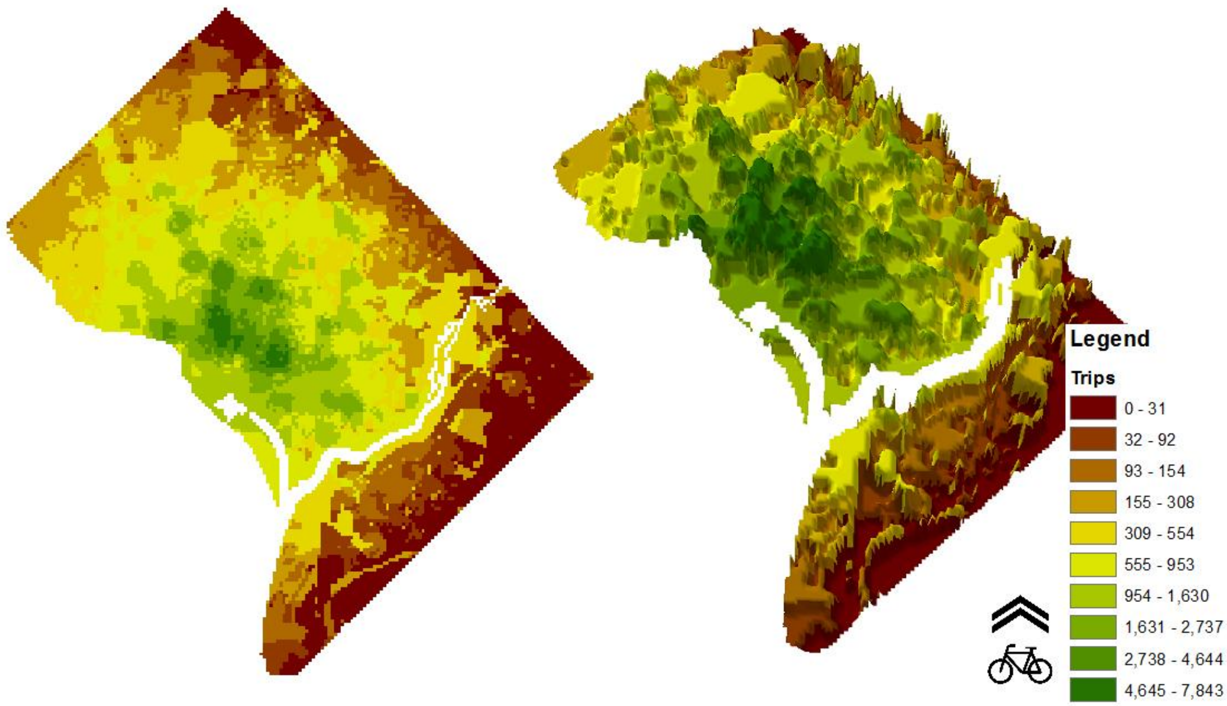


Figure 12: Empirically-Based Bicycle Share Suitability Heat Map for Washington, DC (Geometric Interval)



The geometric interval classification method employed here is designed for continuous data, like in this suitability analysis, where the data are heavily skewed by a preponderance of duplicate values. The classification scheme creates discrete bins by minimizing the square sum of elements per class. This ensures that each class range has approximately the same number of values and that the change between intervals is fairly consistent (see Figure 13).

Figure 13: Frequency Distribution of Raster Values across Washington, DC (Depicting Geometrical Intervals)

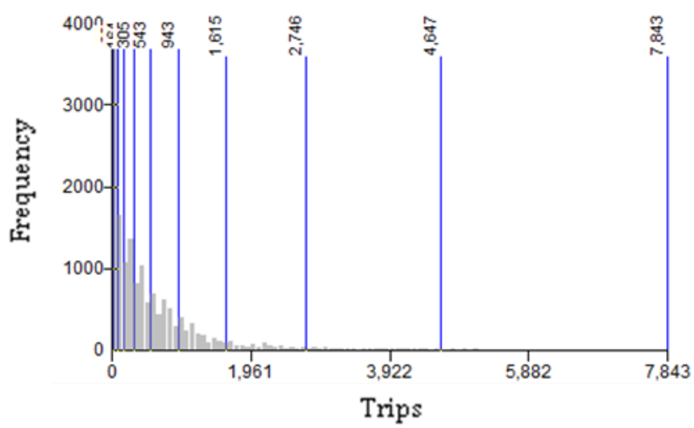
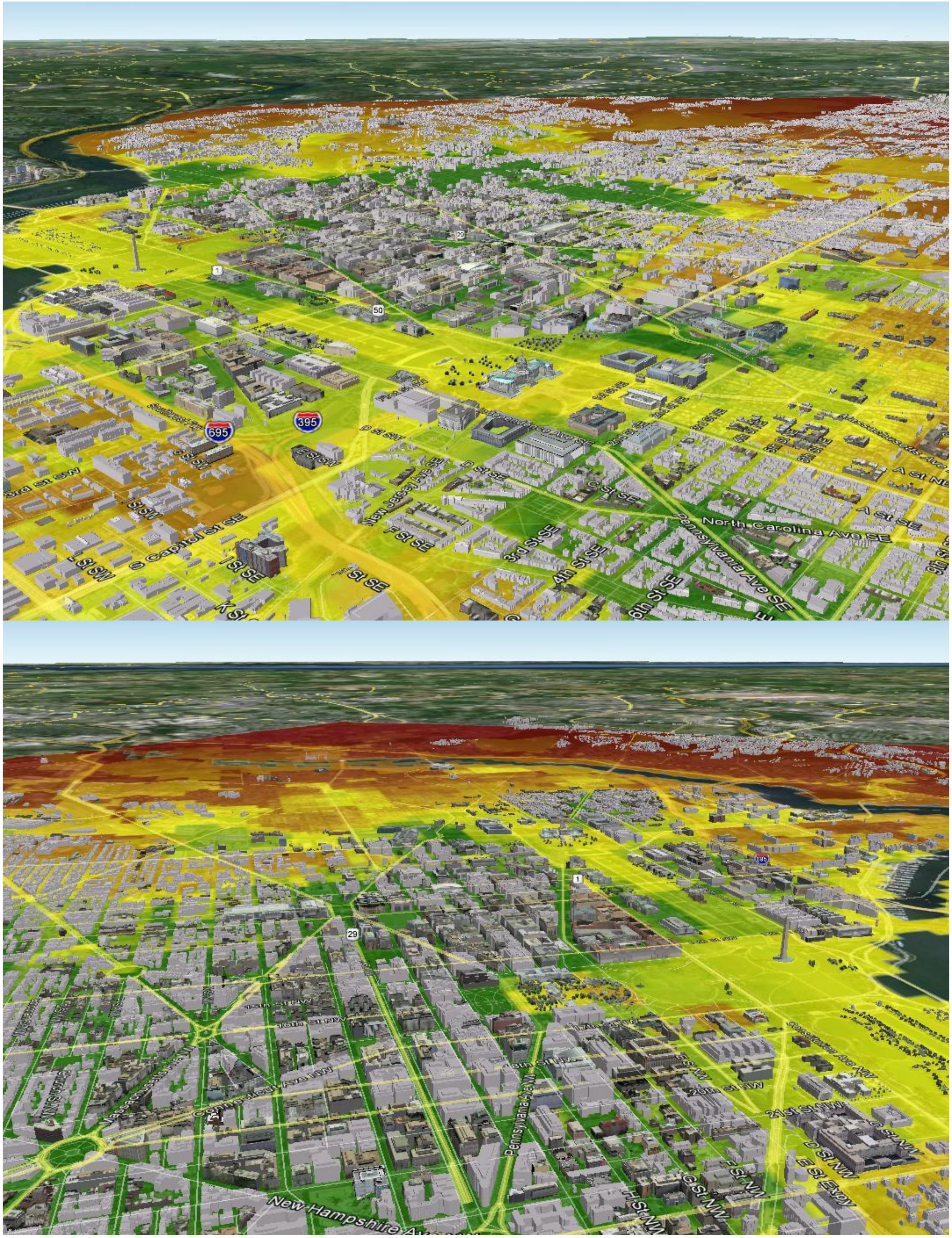


Figure 14: Suitability Analysis Overlaid on 3D Model in Google Earth



Station Placement Analysis

Capital Bikeshare expansion was ongoing during the writing of this report. Although many planned station were installed from November 2011 into the spring, the full scope of the effort remained somewhat in flux as of this writing.

A total of 121 stations were in place in the District by March 2012, representing an increase of 27 stations from October 2011. 75 stations remained in the same location as before, while 19 were expanded in place. Overlaying the current extent of the system on the suitability analysis reveals an interesting breakdown of station placements over time (see Table 6).

Table 6: Capital Bikeshare Existing/Expanded/New Stations Overlaid on Suitability Analysis

Suitability Score (Expected Trips Per Month)	Existing (Unchanged)	Expanded	New	Total
1 (0-31)	1	-		1
2 (32-92)	-	-	1	1
3 (93-154)	2	-	1	3
4 (155-308)	2	-	1	3
5 (309-554)	6	-	2	8
6 (555-953)	13	2	5	20
7 (954-1,630)	22	3	5	30
8 (1,631-2,737)	14	6	4	24
9 (2,738-4,644)	12	8	5	25
10 (4,645-7,843)	6	-	-	6
Total	78	19	24	121

On the whole, nearly 90% of stations as of March 2012 were located in an area with a suitability score of least 6, according to the regression model developed for this report. All told, 11 stations in the District scored lower than a 6 in October 2011. Since then, 5 more stations were added to low suitability areas; meaning that about 13% of DC stations as of March 2012 were in areas expected to experience fewer than 18 trips a day.

A closer look at predicted versus actual usage for stations existing in October 2011 reveals some estimation error at work, particularly in very high and low suitability areas (see Table 7). For instance, while the model predicts 11% of stations will experience fewer than 18 trips per day (just over 550 trips per month); usage data indicates that nearly 27% of stations experienced this relatively low usage. Similarly, the model predicts that 47% of stations should experience over 52 trips per day (just over 1,631 trips per month), but only about 30% of stations actual had that level of usage. Some of this estimation error is attributable to a combination of empirical error and the relatively arbitrary process of classifying the raster values into bins. Other explanations of this error are explored below.

Table 7: Comparison of Predicted and Actual Capital Bikeshare Usage for October 2011

Suitability Score (Expected Trips Per Month)	Predicted (# of Stations)	Actual (# of Stations)	*Difference*
1 (0-31)	1	6	5
2 (32-92)	-	4	4
3 (93-154)	2	2	0
4 (155-308)	2	6	4
5 (309-554)	6	8	2
6 (555-953)	15	13	2
7 (954-1,630)	25	29	4
8 (1,631-2,737)	20	24	4
9 (2,738-4,644)	20	4	16
10 (4,645-7,843)	6	1	5

It is important to point out several caveats of this analysis. First and foremost, rasterization in spatial analysis has some inherent drawbacks. Most significant is the difficulty of constructing the variables the same way for both the regression model and the suitability analysis. This analysis, for instance, does not take into account the network effects used to construct the two socioeconomic variables in the original regression.

These results should be interpreted with extreme caution given the extrapolation employed. They are based on October 2011 data, which represents as close of a baseline to annual bicycle share usage for Washington, DC as available for study. October is both conducive to bicycling and helps minimize the confounding effects of casual short-term usage, which spikes in the summer months. At the same time, of course, it is not representative of ridership patterns of annual members which also peak during the summer and plummet in the winter.

Furthermore, it is important to remember the complex ways bicycle share stations interact with each other and the immediate surroundings. Stations too close to one another can poach each other's riders, while station too far away may not benefit from the network effects of proximity to other stations. This observation is particularly important in light of the fact that the Capital Bikeshare system has grown immensely since October 2011. An updated regression analysis would likely reveal different ridership patterns.

Perhaps most significantly, this analysis does not reflect fine-grained, highly disaggregate factors like low station visibility, pedestrian network barriers, and large institutional uses. These all are expected to have deadening effects on station usage.

Lastly, the analysis also does not take into account site level characteristics that may preclude station placement. Sites have to be in the public right of way (unless otherwise negotiated) and must meet minimum space, surface type, and solar access requirements.

Discussion

While ridership maximization should not be the ultimate goal of any transportation investment (bicycle sharing included), it is essential to assess usage in light of various economic, social, and environmental goals. Such an analysis helps planners assess the opportunity costs of one investment over another and may reveal chances to redeploy stations to more cost-effectively achieve multiple public goals.

At an approximate cost of $50,000, Capital Bikeshare stations last 6 years and are associated with approximately $20,000 in operations and maintenance costs per year. Excluding marketing, operations and maintenance expenses are covered by user fees in the District. Still, the Capital Bikeshare station and bicycle fleet represents a substantial depreciating capital asset whose costs are almost entirely bourn by the federal government. Although local governments may not feel the brunt of these costs, given the current national fiscal situation and political pushback on pedestrian and bicycle program, the scrutiny of publicly-funded bicycle sharing systems, including Capital Bikeshare, is likely to increase in the comings years.

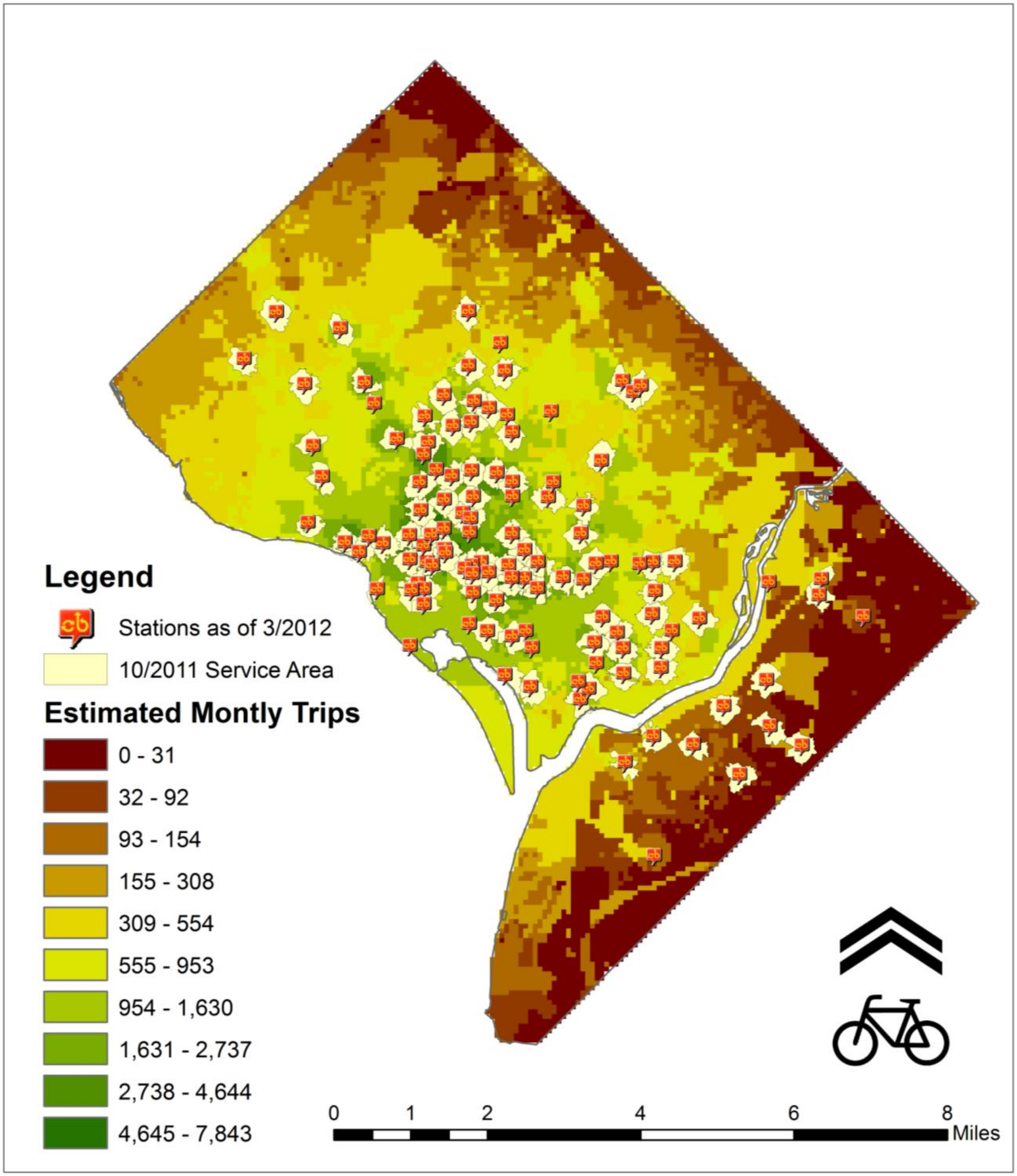
Anecdotally, in October 2011, nearly half of the stations in the District had fewer than 500 trips a month (16 trips a day), while many others have well above 1,500 rentals a month (48 trips a day). During the same month, twenty-one of 97 stations experienced 13 or fewer trips per day. Ten of those stations are located in the impoverished Anacostia neighborhood (see Figure 8). All told, these 13 underperforming stations represent a fixed investment of over $1 million and account for approximately $400,000 of the annual Capital Bikeshare operations and maintenance budget in the District. Ridership at several of these stations can probably be attributed to a handful of citizens.

Based on the regression model in this report, low ridership at these stations is primarily explained by socioeconomic factors (namely age and race), low retail amenities and Metrorail stations, and substantial distance from the center of the bicycle sharing system. Although the District continues to reach out to underprivileged communities through marketing and expanded membership access,[4] these results point to larger structural forces and spatial constraints to increasing Capital Bikeshare usage among marginalized groups. Most significant among these forces is extreme gentrification over the last 20 years that price low income, primarily African American communities, out of the central city.

The station placement analysis reveals considerable investment (both past and ongoing) in low suitability areas. This is not surprising given the initial and ongoing political commitment to install Capital Bikeshare stations across the District's 8 Wards. In announcing the system expansion in Fall 2011, Terry Bellamy, director of DDOT, noted that while the system as a whole would expand 38% overall beginning in November 2011, capacity would increase 22% downtown and 80% in Anacostia. While peripheral, poorly performing stations tend to also serve the city's low income and minority populations, this analysis reveals that there are multiple areas in the central city that planners and policymakers should consider as they build out and tweak the system in the coming years (see Figure 15).

[4] Capital Bikeshare works with Bank on DC to make the program accessible to individuals without bank accounts. A recently announced partnership with Back on My Feed DC makes the bicycle share available to homeless individuals.

Figure 15: Capital Bikeshare Stations Overlaid on Suitability Analysis



Conclusions and Recommendations

Through an array of analytic, and in some cases novel techniques, this study answered its primary research question, while providing planners a replicable methodology for assessing existing and planned bicycle share systems. Building upon empirical demand estimation methodology developed by Maurer (2011) and bicycle suitability analysis developed by Krykewycz et al. (2010), this project informs and sheds light on a growing, albeit mostly propriety, body of bicycle share planning practice. Through the course of this study, the following conclusions were reached:

Bicycle share planning should be highly customized to a specific geography. While this analysis provides a methodology for assessing bicycle share suitability, it does not take the place of geographically-specific analyses. Cities vary greatly in terms of their respective urban spatial structure, bicycling culture, topography, and weather. Systems have different objectives, scales, scopes, and program designs. Three of the statistically significant variables could be applied nationally, but such an analysis would introduce multiple transferability issues.

Cross-sectional regression analysis of bicycle sharing systems is a difficult, data hungry process. The model presented in this report required a tremendous amount of data collection, time consuming complex spatial operations, and expensive statistical software. Without tools that make the information more easily accessible, this type of analysis is limited to academic settings or specialized consulting firms.

Distance from the center of the system carries particular explanatory power in this empirical model. This is consistent with the gravity model in transportation planning which posits that interactions between two locations decline with increasing distance, time, and costs between them. This sharp falloff in trips makes intuitive sense given Capital Bikeshare's program design, which favors relatively short utilitarian trips under 30 minutes.

Image courtesy of BeyondDC.com

Planners should use performance measures and indicators to carefully weigh goals of equity and coverage against ridership. This study in no way discounts the importance of providing active, multi-modal transportation options to low-income and minority communities. That being said, it is important to carefully assess the tradeoffs in achieving various objectives; especially in light of the opportunity costs of providing other mobility options.

Performance measures and indicators can help jurisdictions allocate scarce resources and recognize the opportunity costs of policy decisions, while being transparent to the public. The transit industry serves as an excellent model for such measures.

Suburbanization of bicycle sharing carries both opportunities and pitfalls. The prospect of a region-wide bicycle sharing system in the nation's capital is an alluring one to advocates. It is easy to imagine a robust polycentric system built around development nodes like Alexandria, Arlington, Bethesda, College Park, and Silver Spring. This enthusiasm should be tempered by the fact that even some relatively close-in stations in District experience very low usage. Nearly forty of the 97 stations in operation during October 2011 experienced 15 or fewer trips a day. Similarly, the densest parts of Arlington, with 18 stations during the same period, had 15% of stations system-wide but just 5% of trips. Successful expansion into the suburbs requires careful consideration of station location and substantial investment to develop a critical mass of stations early on. Rushing implementation of inadequate suburban expansions may act to blunt public support for the program and preclude a more economically sustainable system later on.

System flexibility makes data analysis relevant. So-called "4th generation" bicycle sharing systems like Capital Bikeshare have mobile, solar powered stations. Within a matter of hours, stations can be loaded on a truck and redistributed to more suitable locations. While Capital Bikeshare operates year round, stations in colder cities like Montreal and Boston are taken in each winter. Planners use the spring launch of the system to refine station placement based on careful assessment of station performance. Capital Bikeshare should consider annual station redistributions.

Image courtesy of Flickr user ianseanlivingston

Open bicycle sharing data promotes transparency, scholarship, and innovation. The recent proliferation of bicycle sharing systems is encouraging to nonmotorized transportation advocates everywhere; however, the proprietary nature of data for some systems is a growing concern of open government advocates. Despite $4.5 million in grants from public sources ($3 million from the Federal Transit Administration), data from Boston's Hubway remains proprietary because of a private sponsorship agreement with New Balance. New York may well follow suite, given the City's intention to fully fund the system's operations and capital costs with private dollars. This would be a huge blow to future research.

Future Research

Future regression analyses of bicycle sharing usage could benefit from these considerations:

- **Station Service Area Size** – The station service area used in this analysis is based on the notion that the incidence of walking to transit drops dramatically beyond 400 meters (1/4 mile). While widely used, this estimate has little empirical basis. Future studies could benefit from an analysis of multiple service area sizes and a more nuanced understanding of the relationship between built environment and willingness to walk.

- **Data Limitations for Job Density** – Other similar studies have found job density and high income job density as highly influential determinants of bicycle ridership. While this study used the best available data, it is important to acknowledge that the 2010 Census Transportation Planning Products (CTPP) were not available for use in this analysis. Similarly, the District of Columbia was not a partner in the most recent release of the U.S. Census Bureau's Local Employment Dynamics data (LED OnTheMap). Future studies will benefit from these robust data products.

- **Finer-grain Demographic Data** – For demographic data, this study uses spatially-derived Census data aggregated at different geographies. Station service areas helped determine the proportion of various Census geographies within 400 walking meters of each station. Where the margin of error is low, future studies could benefit from using Census Block Groups rather than Census Tracts for some variables.

Potential future areas of empirical bicycle share research identified through the course of this project include:

- **Understanding User Types** – Given increasing fiscal pressure and the trend towards self-supporting bicycle sharing systems, there is considerable interest in understanding different trip and user types; particularly recreation trips and non-annual members. A further understanding of these aspects of bicycle sharing helps system operators tweak fees and redistribute stations to ensure programs are financially sustainable in the long term.

- **Modeling Usage in Non-traditional Station Locations** – Amid ongoing concerns about whether Capital Bikeshare fits within the historic areas, iconic view, and monuments under National Park Service management, 5 stations were installed on the National Mall in spring 2012. Minneapolis Nice Ride stations are approved for installation at the Mississippi National River and Recreation Area. Bicycle sharing is now being considered for Jackson Hole and Grand Tetons National Park, while there are preliminary discussions about a system at Grand Canyon National Park. Such programs offer opportunities to study and model bicycle sharing usage in a variety of non-traditional settings.

Image courtesy of Flickr user ep_jhu

- **Applying Regression Models to Other Cities** – While it may be tempting apply the model produced in this study to other cities considering bicycle sharing, past attempts show the difficulty of such endeavors. However, much like in transit planning, regression models represent one of the best tools at our disposal to assess the feasibility of proposed bicycle sharing systems. With publicly available and universal socioeconomic data provided by the Census, researchers could produce a simple tool for assessing bicycle share potential nationally. Such work, of course, should not preclude a more detailed local analysis.

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Appendix A: Supplementary Regression Materials

Table A1: Summary Statistics for Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
TrpCnt	97	120.9804	88.57019	.8	507.7
SqrtTrpCnt	97	31.80367	14.15614	2.828427	71.25307
Pop20to39	97	703.4124	709.9733	0	2640
PropNonWht	97	46.24908	29.59709	0	100
PropLowVeh	97	85.04923	9.355826	59.07347	99.19103
MedianHHI	97	67.96875	38.20696	0	213.889
HotelRms	97	17.67423	36.40526	0	160.1
PropAltCom	97	6.171767	4.557068	.422833	17.24409
Attractors	97	25.89691	21.91864	2	101
ABRALic	97	10.65979	11.89002	0	58
UniArea	97	614.2431	1827.99	0	10116.68
ParkArea	97	1008.61	2027.651	0	7576.217
BusStops	97	14.64948	7.172054	1	37
Mtrorail	97	.5257732	.6306872	0	2
BikeInfra	97	13.02078	14.20829	0	59.86234
DistFrmCtr	97	3.324167	2.062155	.4916306	8.558303

Table A2: Full Regression Model

Source	SS	df	MS
Model	15693.2489	14	1120.94635
Residual	3544.80537	82	43.2293338
Total	19238.0543	96	200.396399

Number of obs =	97
F(14, 82) =	25.93
Prob > F =	0.0000
R-squared =	0.8157
Adj R-squared =	0.7843
Root MSE =	6.5749

SqrtTrpCnt	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Pop20to39	.0067841	.0013372	5.07	0.000	.004124	.0094443
PropNonWht	-.1175792	.0284628	-4.13	0.000	-.1742007	-.0609576
PropLowVeh	-.0994546	.1205597	-0.82	0.412	-.3392862	.140377
MedianHHI	.0086566	.0249655	0.35	0.730	-.0410077	.0583209
HotelRms	-.0096926	.0232674	-0.42	0.678	-.0559789	.0365938
PropAltCom	-.155982	.2287432	-0.68	0.497	-.6110251	.2990611
Attractors	-.0062455	.0467567	-0.13	0.894	-.0992595	.0867684
ABRALic	.2166203	.0732354	2.96	0.004	.0709318	.3623088
UniArea	-.0000755	.0004447	-0.17	0.866	-.0009601	.0008091
ParkArea	.0006127	.0003964	1.55	0.126	-.0001759	.0014014
BusStops	.1436591	.1194964	1.20	0.233	-.0940572	.3813755
Mtrorail	2.857218	1.418112	2.01	0.047	.0361417	5.678294
BikeInfra	.0275333	.0622645	0.44	0.660	-.0963307	.1513972
DistFrmCtr	-3.481079	.552955	-6.30	0.000	-4.581083	-2.381076
_cons	46.3611	11.54663	4.02	0.000	23.39118	69.33102

Table A3: Variance Inflation Factors (VIFs) Demonstrating Minimal Collinearity among Variables

Variable	VIF	1/VIF
DistFrmCtr	2.89	0.346326
PropLowVeh	2.83	0.353948
PropAltCom	2.41	0.414419
Attractors	2.33	0.428739
MedianHHI	2.02	0.494929
Pop20to39	2.00	0.499610
Mtrorail	1.78	0.562935
BikeInfra	1.74	0.575364
ABRALic	1.68	0.593882
BusStops	1.63	0.613071
HotelRms	1.59	0.627598
PropNonWht	1.58	0.634533
UniArea	1.47	0.681466
ParkArea	1.43	0.696878
Mean VIF	1.96	

Table A4 Reduced Regression Model with Standardized Coefficients

Source	SS	df	MS
Model	15359.8147	5	3071.96294
Residual	3878.23959	91	42.6180174
Total	19238.0543	96	200.396399

Number of obs	97
F(5, 91)	72.08
Prob > F	0.0000
R-squared	0.7984
Adj R-squared	0.7873
Root MSE	6.5282

SqrtTrpCnt	Coef.	Std. Err.	t	P>|t|	Beta
Pop20to39	.0059566	.001115	5.34	0.000	.2987415
PropNonWht	-.1204386	.0253341	-4.75	0.000	-.2518081
ABRALic	.217029	.0651759	3.33	0.001	.1822869
Mtrorail	2.731602	1.228292	2.22	0.029	.1216988
DistFrmCtr	-3.362043	.3953056	-8.50	0.000	-.4897558
_cons	40.6102	2.271999	17.87	0.000	.

Appendix B: Supplementary Suitability Analysis Materials

Table B1: Suitability Model Inputs - Rasterization Methods, Direction, and Weights

Variable	Rasterization Method	Grouping	Directional Effect
Population (Age 20 and 39)	Polygon to Raster Conversion	Natural Breaks	Positive
Non-White Population Prevalence	Polygon to Raster Conversion	Natural Breaks	Negative
Retail Density (Alcohol Licenses)	Point Density (400 meter buffer)	Natural Breaks	Positive
Metrorail	Point Density (400 meter buffer)	Natural Breaks	Positive
Distance from Capital Bikeshare System Center	Euclidean Distance	Natural Breaks	Negative

Figure B1: Full Suitability Model, Trip Generation, Trip Attraction, and Transportation Network Factors

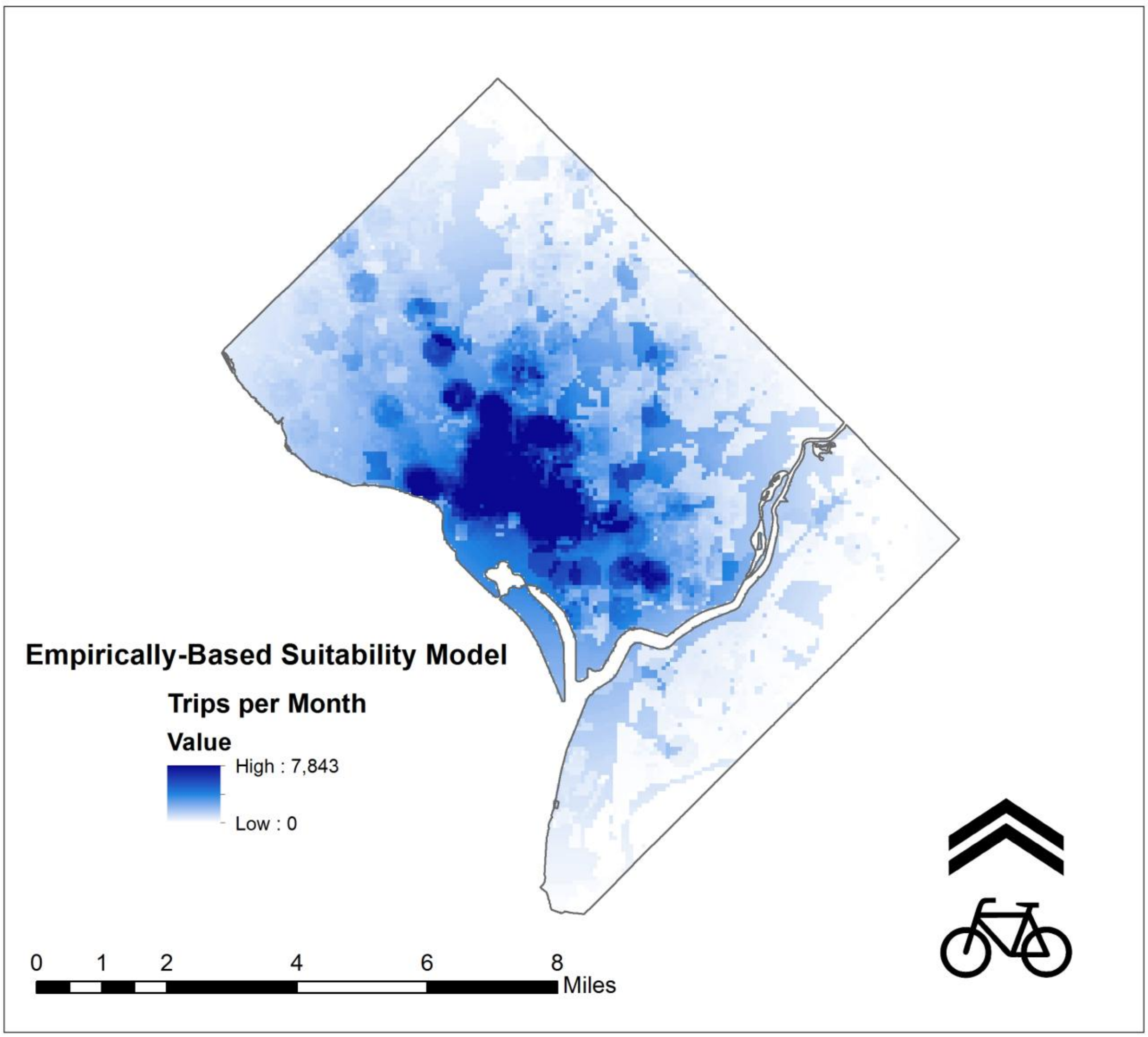

Figure B2: Rasterized Suitability Analysis Inputs, Trip Generation Factors – Population (Age 20-39) and Non-White Population

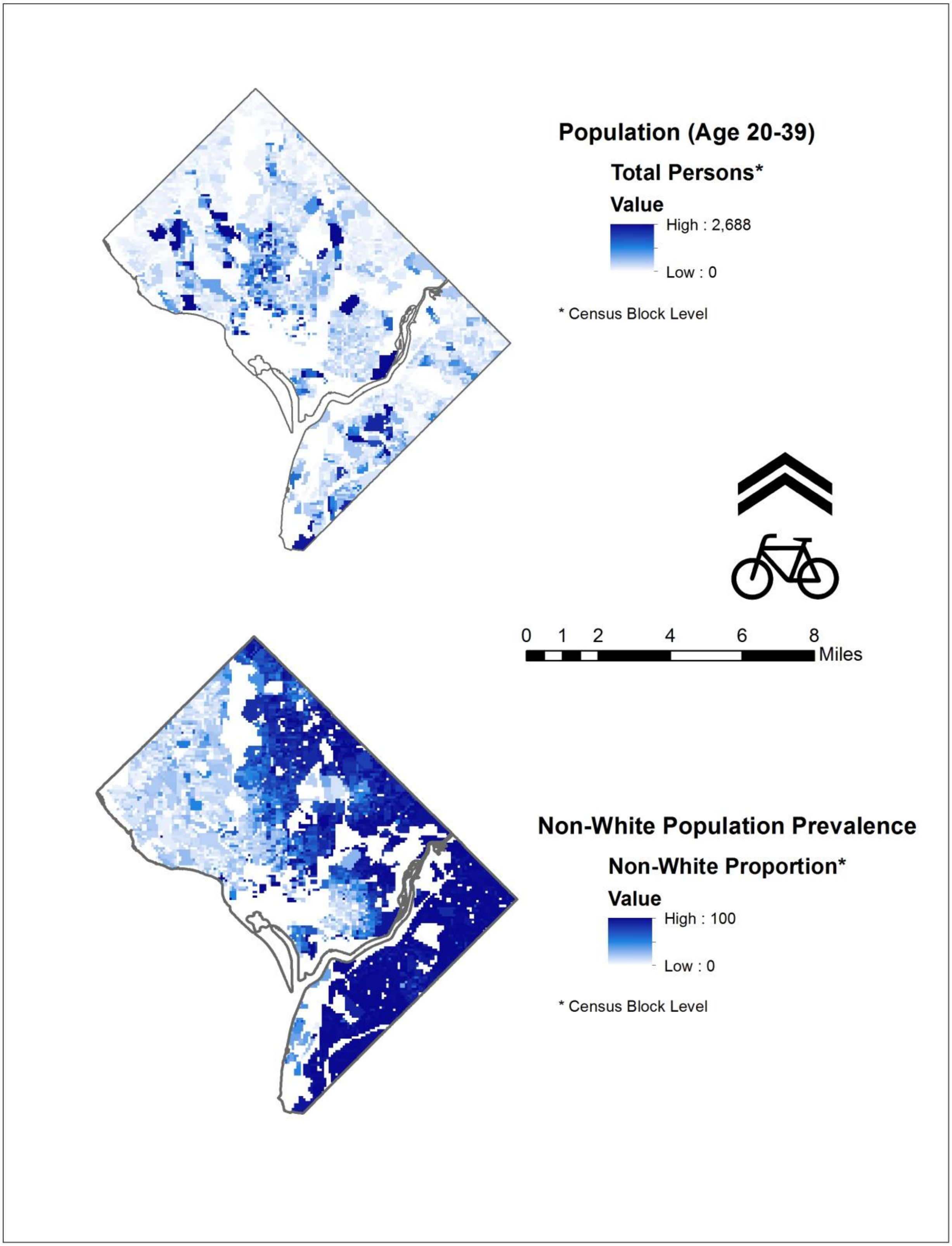

Figure B3: Rasterized Suitability Analysis Inputs, Trip Attraction Factors – Retail Density

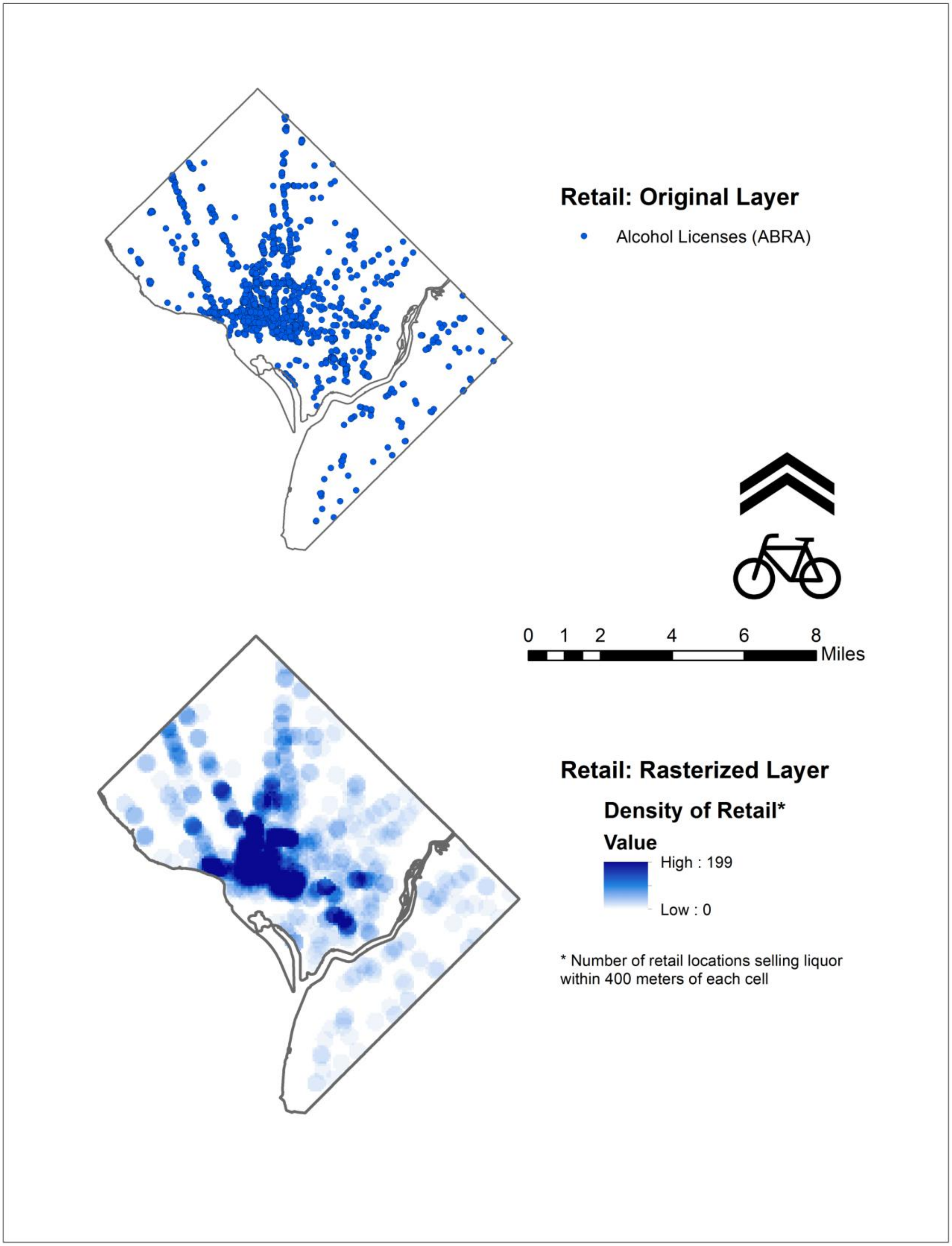

Figure B4: Rasterized Suitability Analysis Inputs, Transportation Network Factors – Metrorail Stations

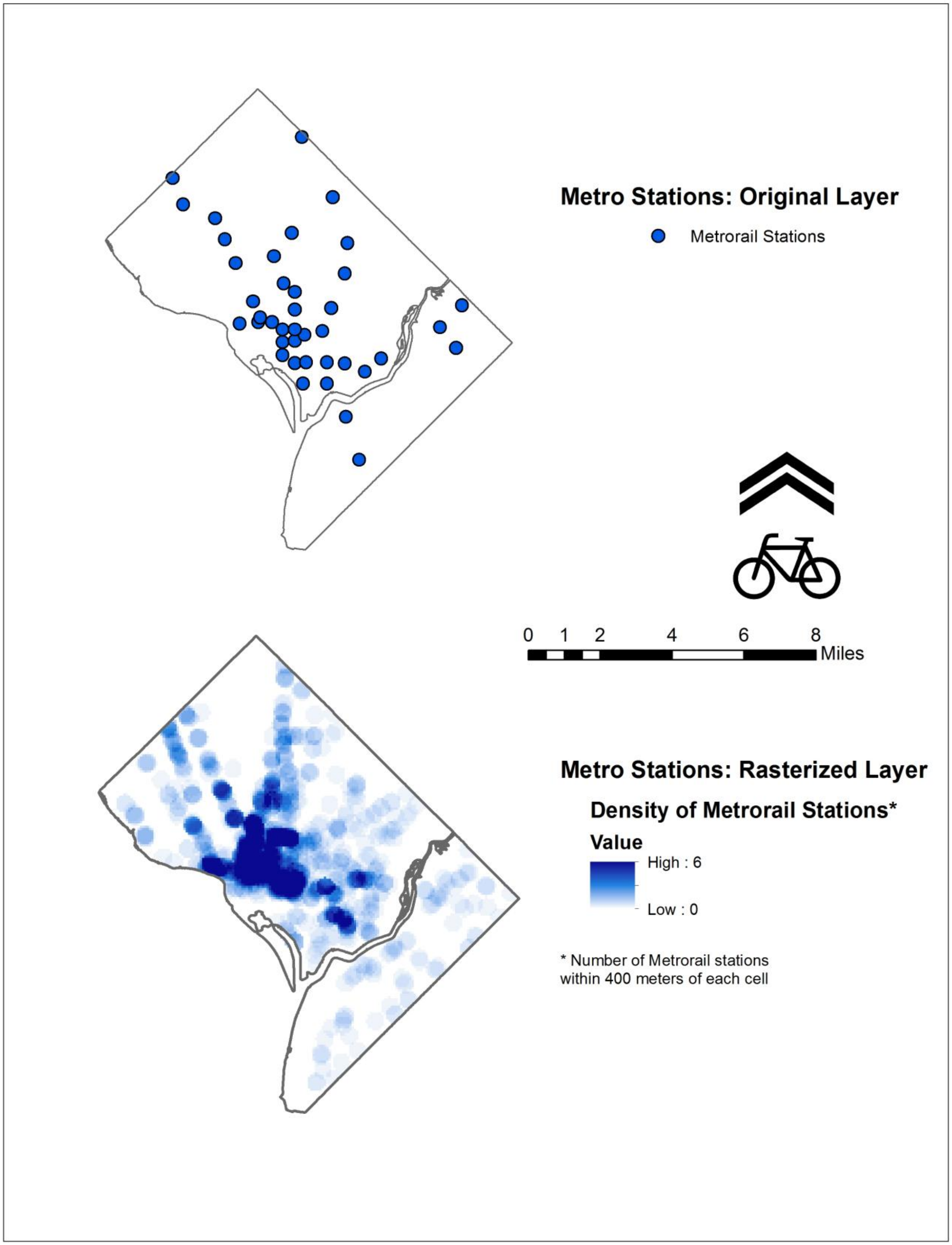

Figure B5: Rasterized Suitability Analysis Inputs, Transportation Network Factors – Distance from Capital Bikeshare System Center