

Dockless Scooter Travel: A Land Use Model with Implications for California

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A Research Report from the Pacific Southwest
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The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region*. Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

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Disclosure

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Abstract

This research builds a land use regression model to explain dockless scooter trip generations. We use publicly available scooter trip generation data for Louisville, KY and Minneapolis, MN and publicly available data on land use characteristics. The model shows that scooter trip generations are associated with higher employment densities, higher densities of entertainment land uses (bars and clubs), and in some specifications higher densities of eating establishments and university buildings. We establish that using the regression results to predict out of sample gives predictions that correspond well to observed scooter trip generations in Austin, TX. Because scooter trip data are not available for research in California, we use the Minneapolis model to predict scooter trips as a function of land use characteristics in California census tracts. The results yield a promising screening method that can highlight census tracts with land use characteristics that are potentially supportive of micromobility and non-automobile short-trip travel. We recommend that such a screening method can be a first step in more detailed analyses of planning programs or infrastructure that could support non-automobile short-trip travel.

A National Study of Dockless Transportation: Land Use and Demographic Correlates of Trip Hotspots and Mode Shift

Executive Summary

Cities throughout the State of California face a challenge of deciding how to plan for and regulate micromobility travel – most notably, dockless scooter trips. As a new mode of travel provided by private operators, data on dockless scooter trip-making is private and limited, resulting in little being known about what influences dockless scooter trip generation. Our research bridges this understanding by building a land use model of dockless scooter use from publicly available data in two cities, Louisville, KY and Minneapolis, MN and then applying our model to the State of California to identify areas with high potential for dockless scooter trip generation therein.

From the Louisville and Minneapolis data, we find that dockless scooter use is heavily concentrated in select areas, and that these areas are marked by high employment density, a high density of post-secondary education establishments, and a high density of recreational establishments – bars, pubs, night clubs, and eating places. We also find that, when these land uses are controlled for, population density has effectively no independent influence on dockless scooter trip generation.

We test our land use models in Austin, Texas, given that it is the only other U.S. city for which we have data. We find that our Minneapolis model properly predicts 61% of the census tracts that place in the highest twenty-fifth percentile of dockless scooter trip generation in Austin. Based on this validation of our model, we identify census tracts throughout the State of California with high predicted dockless scooter trip generations using the Minneapolis model. These predictions are shown for select urban counties of California in Section V and conceptually follow our general findings – high trip generation is predicted in census tracts with high employment density and/or shopping activity.

We close with a discussion of the potential for this method to be used as a screening method for locally informed planning approaches to micromobility and non-automobile short-trip planning interventions.

SECTION I: Introduction and Policy Relevance

As on-demand bicycle and scooter sharing has evolved over the past decade, planning and regulating their use has become both important and controversial. Dockless scooter use has visibly taken a dominant role in this sector, and usage appears concentrated in select areas. However, because dockless scooters only entered the mobility market in 2017, they are a relatively new travel option and little is empirically known to help explain what we observe. This lack of knowledge hinders well-informed planning and regulatory decision-making.

The planning and regulatory challenges surrounding dockless mobility are ample. Advocates of public investment in dockless mobility suggest that it can help mitigate environmental impacts of the car by converting short car trips into dockless scooter trips. Yet, while evidence shows that dockless mobility is used for short-distance trips (e.g., McKenzie, 2019; McKenzie, 2020; Younes et al., 2020; Bai and Jiao, 2020), it is not clear whether they generate new short-distance trips, convert walking or biking trips into dockless mobility trips, or indeed convert short vehicle trips into dockless mobility trips. Similarly, while there is growing concern about dockless mobility access equity, it is not clear that dockless mobility would be well utilized if it were more accessible in communities that currently lack access to them. Finally, there are also growing concerns about public safety and visual impacts surrounding scooter use and the management of where they are stored.

This research starts from a premise that these questions reflect a lack of more fundamental knowledge. What are the correlates of dockless trip-making? Where do dockless trips occur? What are the land use characteristics that are most associated with dockless trip-making. In this research, we build a land use model that can both explain and predict dockless scooter trip generation in the State of California. Due to limited data availability, our model is built from scooter trip data in the cities of Louisville, KY and Minneapolis MN. (No data on dockless trips are publicly available in California, for reasons explained later in this report.) The goal of this research is twofold: (1) To build a model of the spatial (or land use) determinants of dockless trip-making, using only data that can be easily obtained from public sources in any location, and (2) To examine how well such a model, built with data from outside of California, can inform dockless travel planning within California. We focus on building models that use only widely available data, to use data that allow the model to be ported or adapted to any location. Part of this effort, in other words, is to explore how much we can learn about the land use correlates of dockless trip-making using only widely available land use data.

Our analysis shows that dockless scooter trips are strongly correlated with employment density and entertainment land uses. We further find that our model has strong out-of-sample prediction potential and correlates with short trip data, so may be usable to explain dockless scooter potential in the State of California. On net, we find that the land use correlates of dockless scooter trip-making are stable across locations and can be understood with data available via public data sources in urban areas across the United States. We further find that our exercise of predicting dockless scooter travel in California based on models calibrated outside of the state has promise as an initial screening mechanism that can focus planning on locations where dockless travel would likely be most quickly or broadly adopted.

SECTION II: Literature Review

Dockless scooters were preceded by dockless bike-sharing programs which have, in small ways, existed for decades (DeMaio, 2009; Shaheen, Guzman, and Zhang, 2010). With the advent of geographic positioning system (GPS) and smart phone payment technology, dockless travel grew dramatically. Ofo and Mobike introduced dockless bike-sharing in China in 2015, and by March of 2017 there were an estimated 4 million dockless bikes in China, compared with 180,000 shared bikes in the country in 2012 (Shen, Xiaohu, and Zhao, 2018). Dockless scooters soon followed, and grew even more rapidly than dockless bikeshare. BIRD, the first dockless scooter company, was founded in September of 2017, and delivered 10 million dockless scooter rides in their first year (BIRD, 2018).

Research on dockless scooter use has mostly relied on data scraping of scooter availability to identify geographic locations and temporal patterns of use (e.g., McKenzie, 2019; Younes et al., 2020). Each scooter has a unique identification code, so scraping a network of scooters on a regular basis allows a researcher to impute trip start and end times and locations based on any gaps in a scooter's availability. If a scooter was available at Time Y and Point A, then went unavailable until Time Z at Point B, it can be inferred that a trip from A to B took place and lasted from Time Y to Time Z. Researchers then rely on assumptions to reason what scooter trip times, locations, and distances say about the sorts of people who use them and the environments they are used in. Among the most cited studies that use this approach is McKenzie (2019), who finds that, in Washington, DC, dockless scooter trips disproportionately occur during midday hours, about a quarter of them occur in areas he labels "Residential," and three-quarters occur in "Commercial" and "Public/Recreational" areas – the former with higher weekday share; the latter, a higher weekend share. He concludes from this that scooters "support leisure, recreation, or tourism activities, more so than commuting."

Younes et al. (2020) model dockless scooter trip data from the Washington D.C. API for approximately the first six months of 2019, modeling dockless trips as a function of weather characteristics, gas prices on the day of travel, and special events. The focus is a temporal model rather than a spatial model.

Bai and Jiao (2020) use data from Austin, Texas and Minneapolis, Minnesota to model dockless trip generations and attractions in hexagons with 500 foot sides as a function of land use. The model used regression analysis to examine how dockless scooter trip generations and attractions are associated with demographic characteristics (population density, age distribution, male/female ratio, education levels, and income levels, from Census Bureau data for the block group containing the hexagon) and land use characteristics (number of transit stops in the hexagon, distance from city center, land use diversity and mix and the dominant land use type based on broad categories of uses such as residential, commercial, mixed use, office, industrial, and the like.) Bai and Jiao (2020) find considerable variation in the correlates of dockless travel across their two study cities, with consistent results across the two cities showing more dockless travel associated with locations with higher education levels, more transit access, closer to downtown, and more land use diversity (measured by the count of land use types in a hexagon.)

The modeling literature, nascent as it is, has focused either on temporal aspects of trip-making (Younes et al., 2020) or land use correlates of trip-making (Bai et al., 2020).

Our research is most similar to Bai et al. (2020) in that we model scooter trip generations as a function of land use characteristics, as did Bai et al. (2020). We extend the literature in three ways. First, we use measures that proxy destinations, including employment densities and densities of business establishments by type of business, that give a more granular view of land use, particularly of possible destinations, compared with the analysis in Bai et al. (2020). Second, we include only variables that can be obtained for any city in the U.S. in the land use model. Our objective is, in part, to examine how land use data that are available most anywhere explain dockless scooter trip-making. While previous studies have at times focused on the particularities of a location (for example, McKenzie, 2019 notes the importance of the National Mall in Washington, D.C. for scooter trip generation), we focus on how variables that are available anywhere are associated with dockless scooter trip-making. Our reason for doing this relates to our third objective. Only a limited number of locations publicly report data on dockless scooter trip-making. Our third objective is to examine how well a scooter trip generation model, fit on data outside of California, can illuminate the potential for dockless scooter travel within California. Clearly such an exercise requires general rather than specific data. In the current environment, in which dockless scooter trip data will likely not be publicly available in many locations, understanding the potential insights from models fit out-of-sample (and hence outside of a location) will be important, and is as yet completely unstudied to our knowledge.

SECTION III: Development of a Land Use Model of Dockless Scooter Trip Generation

Our objective is to develop a land use model that can explain and predict dockless scooter trip generation, including in the State of California. This is in some ways ironic, because the City of Los Angeles was a leader in developing protocols for collecting data on dockless trip origins and destinations. The City of Los Angeles created the mobility data specification (MDS) application programming interface (API) that is broadly used for the sharing of dockless device data and is now managed by the Open Mobility Foundation. The purpose of collecting these data includes, but is not limited to, informing infrastructure planning decisions and ensuring compliance with regulations relating to location and distribution of scooter availability. As we conceptualized this research project, we anticipated that data from the City's MDS would be available to study dockless travel, but due to privacy concerns, the City has not released MDS data to any external parties as of this date. Different cities and states have approached the release of dockless scooter data differently, and ultimately we found three cities that publicly release dockless data with a level of spatial granularity that is needed for a model that explains scooter trip generations as a function of land use. Because each of those three cities are outside of California, our objective includes examining how a model of dockless scooter trip-making can inform planning outside of the location of the model's data.

We describe the data, and the development of our land use model in this section. In subsequent sections, we explain how we test our land use model in other metropolitan areas and our predictions for dockless scooter trip generation in the State of California.

Data and Methods

As of the time of our research, just three U.S. cities – Austin, TX, Louisville, KY, and Minneapolis, MN – publicly provided dockless scooter trip data. Of these, only Louisville and Minneapolis data are granular enough to support analysis at the level of census block groups. Whereas Austin scooter origin and destination trip data are assigned to census tracts, the same Louisville and Minneapolis data are rounded to the nearest third decimal geographic coordinates and nearest road segment, respectively. This allows Louisville and Minneapolis data to support block group-level analysis, while with the Austin data only census tracts can be analyzed. Given that scooter trips are short-distance, we began our analysis with a census block group land use regression model using data from scooter data portals of the cities of Louisville and Minneapolis.

Our land use data primarily come from the United States Census Bureau and OpenStreetMap. **Table 1** defines our variables and their sources.

Table 1. Variables and Sources for Model Development

Variable	Description	Data Source
<i>tripcount</i>	The number of trips per day per block group	City of Louisville, KY City of Minneapolis, MN
<i>jobdensity</i>	The density of employment (in jobs per square kilometer)	U.S. Census Bureau LODES WAC, 2017
<i>popdensity</i>	The density of residential population (in persons per square kilometer)	U.S. Census Bureau, 2010 Decennial Census
<i>density_food</i>	The combined density of establishments coded as “café,” “fast food,” “food court,” or “restaurant” (in establishments per square kilometer)	OpenStreetMap (queried on 4/15/2020)
<i>density_barclub</i>	The combined density of establishments coded as “bar,” “nightclub,” or “pub” (in establishments per square kilometer)	
<i>density_school</i>	The density of establishments coded as “school” (in establishments per square kilometer)	
<i>density_university</i>	The density of establishments coded as “university” (in establishments per square kilometer)	
<i>density_place_of_worship</i>	The density of establishments coded as “place of worship” (in establishments per square kilometer)	
<i>downtowndistance</i>	The distance from the centroid of the census tract with the highest employment density (in meters)	Authors’ calculation

The *downtowndistance* variable was derived by identifying the centroid of the census tract with the highest employment density in the respective city from the United States Census Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES) dataset, then measuring the straight-line distance from this point to the centroid of each block group in our dataset.

It is also important to note that the *density_university* variable measures density of university buildings. Thus, a university campus with a myriad of buildings – from unique schools within the campus to libraries to maintenance and operations facilities – will have each of these buildings included in the calculation of university density within a given block group.

Dockless Scooter Trip Data

In Louisville and Minneapolis, the dockless scooter trip data report the start and end times and start and end locations for each trip conducted on a commercially operated dockless scooter within city limits. Data for Louisville report times rounded to the nearest quarter hour and latitude/longitude coordinates with three decimal digits,¹ while data for Minneapolis report times rounded to the nearest half hour and locations snapped to the nearest road segment – that is, any stretch of road between two intersections. Data for Louisville contain 503,106 trips between August 9, 2018 and January 31, 2020, with no complete cessation of service during that time period. Data for Minneapolis contain 1,143,016 trips that map to a valid road segment (an additional 123,078 trips are not assigned to a road segment) between July 10, 2018 and November 26, 2019, with no trips from November 30, 2018 to May 13, 2019.

In selecting our geographic unit of analysis, our objective is to conduct that analysis at the highest spatial resolution for which both trip data and other land use variables are available. The spatial fidelity of the coordinates reported in the Louisville data would allow the use of census blocks. The road segment format of Minneapolis data on the other hand results in ambiguity for a large number of trips: If a trip occurred on a road segment that serves as a boundary between two census blocks, there is no reliable way to determine which of the two blocks to designate as the origin. To overcome this limitation, we use census block groups, as this greatly reduces the share of road segments that define a geographic boundary. We look up the census block group in which each trip originated via the street segment’s centroid (for Minneapolis) or the latitude-longitude coordinates (for Louisville) using GIS, and count the number of trips that started in any given block group on each day. For comparability across the two cities, we maintain the geography at the block group level in both cities.

Land Use Data

Our analyses rely on a number of public data sources to obtain spatial patterns of jobs, people, and various types of establishments. We obtain the number of jobs in any given area from the Census Bureau’s LODES dataset. Specifically, we take the count of all jobs from the LODES Workplace Area Characteristics (“LODES WAC”) for each census block, and aggregate these counts to the census block group level. Population for each block group is obtained from the 2010 Decennial Census.

To obtain the locations of restaurants, bars, and other establishments, we rely on OpenStreetMap (“OSM”) – a collaborative mapping project that creates and distributes free geographic data around the world. We obtain points representing individual establishments within the metropolitan statistical areas (“MSA”) that include Louisville and Minneapolis using the *osmdata* R package and *Overpass* OSM API.

¹ Reporting latitude/longitude coordinates with three decimal digits equates to a resolution of approximately 100 meters or 1/16 of a mile in between points.

Specifically, we query OSM for establishments labeled “bar,” “café,” “fast food,” “food court,” “nightclub,” “place of worship,” “pub,” “restaurant,” “school,” and “university” to receive one point feature for each building or establishment that meets the description. Since establishment labels can be somewhat arbitrary, we group together all primarily food-related businesses into one category, and all alcohol and nightlife-related businesses into another. Finally, we generate block group level counts for food businesses, nightlife businesses, schools, university buildings, and places of worship by counting the number of establishments of each type that fall within the boundaries of each block group, as defined by the Census Bureau’s TIGER Line shapefiles.

To make these land use measurements comparable across space, we convert block group-level counts of people, jobs, and amenities into densities by dividing the counts by the land area reported in the Census Bureau’s TIGER Line Shapefiles. All density measurements are in square kilometers.

Lastly, we also use the Census Bureau’s LODES data to identify the census tract with the highest employment density. We assumed this tract to be the downtown of the metropolitan area. The straight-line distance between the centroid of this tract and the centroid of each block group in our dataset represents the distance from downtown.

Model Methodology

Through initial descriptive analyses and mapping (presented later in this section), we observed that dockless scooters are heavily utilized in areas of high pedestrian activity – notably, concentrated employment centers and high-density shopping and tourism corridors. Accordingly, we hypothesize that dockless scooter use is (1) positively associated with employment density and (2) positively associated with activity zones. We use the aforementioned density variables for different establishment types – eating places, bars and clubs, schools, universities, and places of worship – to proxy activity centers.

We use ordinary least squares (OLS) models to examine the relationship between dockless scooter trip generation and these variables, all measured at the block group level, as follows:

$$\begin{aligned} \text{tripcount} = & \beta_0 + \beta_1 \text{jobdensity} + \beta_2 \text{popdensity} + \beta_3 \text{density}_{\text{food}} + \beta_4 \text{density}_{\text{barclub}} \\ & + \beta_5 \text{density}_{\text{school}} + \beta_6 \text{density}_{\text{university}} + \beta_7 \text{density}_{\text{place of worship}} \\ & + (\beta_8 \text{downtowndistance}) + \varepsilon \end{aligned}$$

We run three different models using the above regression. Our primary model regresses the trips per block group-day (*tripcount*) onto the independent variables; the number of observations is the number of block groups multiplied by the number of days. Our second variable takes the average number of trips per block group-day, and regresses this value onto the independent variable set; the number of observations is the number of block groups. Our last model follows the primary model, but adds a dummy variable for the date in order to capture any variance that can be explained by something unique on different dates – for example, local festivities or weather events; the number of observations is the number of block groups multiplied by the number of days. Hereafter, these models will be referred to as the “trips per day model,” “average trips per day model,” and “trips per day with date fixed effects model,” respectively. We run each model with and without the variable *downtowndistance*

– hence, its parenthetical inclusion in the formula – in order to examine whether controlling for downtown distance meaningfully changes the sign and significance pattern on the other variables.

Finally, due to many “0” observations in our dataset (block groups with zero dockless scooter trip generations, either on a day or for the entire data set), we also run Tobit models that are left-censored at 0.

Findings

Our descriptive statistics and model results support much of our observations and are consistent with expectations about dockless scooter travel. Specifically, we find that dockless scooter trips are heavily concentrated in select areas, and that these areas are characterized by heightened employment and activity center establishment densities.

Descriptive Statistics

Table 2 summarizes the descriptive statistics of our dataset.

Table 2: Descriptive Statistics

Variable	Louisville, KY				Minneapolis, MN			
	Min	Mean	Max	Standard Dev	Min	Mean	Max	Standard Dev
<i>Tripcount (trips per day per block group)</i>	0	1.63	2,085	22.7	0	8.16	1209	43.02
<i>jobdensity</i>	0.92	661.37	27,272.1	1860.57	3.08	1954.9	89,026.02	6,389.68
<i>popdensity</i>	0	927.01	5,153.47	725.65	0	2,143.13	44,608.3	3,089.63
<i>density_food</i>	0	0.89	12.09	1.77	0	2.91	23.02	4.41
<i>density_barclub</i>	0	0.15	7.8	0.69	0	0.66	21.31	2.08
<i>density_school</i>	0	0.48	10.12	1	0	0.64	8.59	1.44
<i>density_university</i>	0	0.05	3.45	0.32	0	0.11	7.76	0.75
<i>density_place_of_worship</i>	0	0.88	10.12	1.29	0	1.18	8.21	1.94
<i>downtowndistance (in meters)</i>	334.62	11,792.67	29,152.7	6,125.54	166.46	5,120.69	11,242.94	2,354.13
Date Range	August 9, 2018 to January 31, 2020				July 10, 2018 to November 30, 2018, May 13, 2019 to November 26, 2019			
Total Trips Taken	503,106				1,143,016			

A few noteworthy details are that the *tripcount* variable is heavily left-skewed – which is consistent with a vast number “0” observations in this variable. In addition, there is no block group whose *downtowndistance* variable is “0.” The reason for this is that no block group’s centroid is also the centroid of the census tract with the highest employment density that is the reference point for deriving this measurement. Lastly, Minneapolis has much higher scooter trip generation than Louisville, despite fewer days in our study period – 1.1 million trips across 323 total days versus 0.5 million trips across 540 consecutive days.

Figures 1 and 2 map where trips are concentrated in Louisville and Minneapolis, respectively – primarily in the downtowns and around the major university of both cities. As well, **Figure 3** graphically represents the distribution of dockless scooter trips across block groups in both cities. In Louisville, 98% of block groups generate no more than fifteen (15) dockless scooter trips per day, on average, while 2.5% of block groups are responsible for 80% of the dockless scooter trips made in the city. In Minneapolis, 93% of block groups generate no more than twenty-one (21) dockless scooter trips, while 10% of the city’s block groups account for 80% of the city’s dockless scooter trip generation.

Figure 1: Map of Trip Starts by Block Group (Louisville, KY)

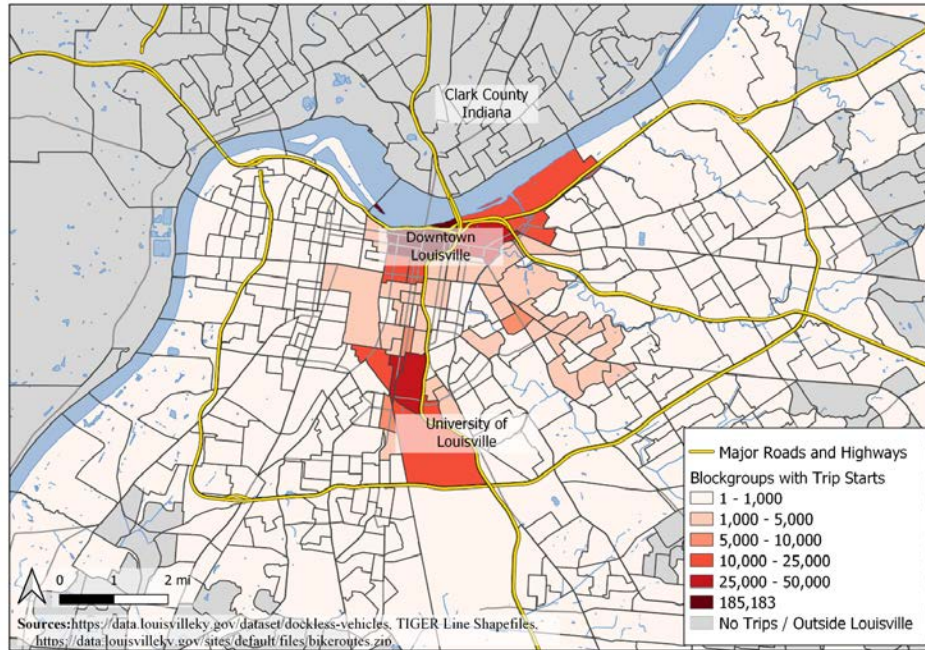


Figure 2: Map of Trip Starts by Block Group (Minneapolis, MN)

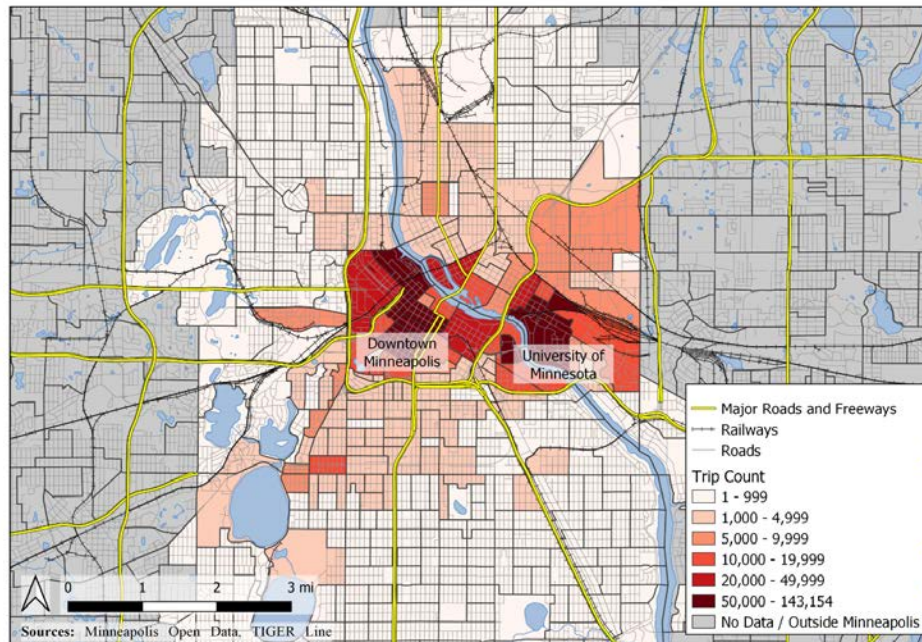
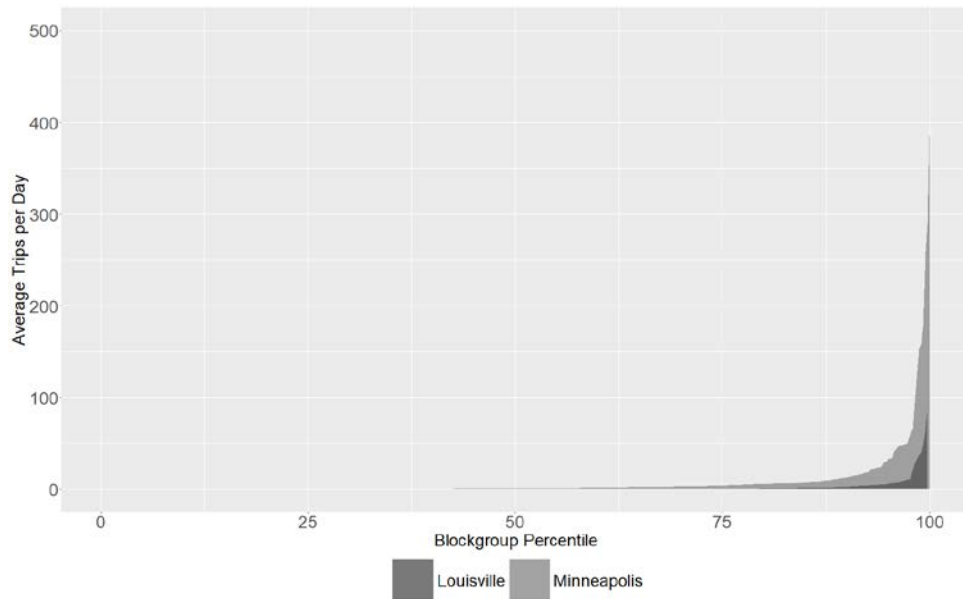


Figure 3: Distribution of Trip Starts across Block Group Percentiles



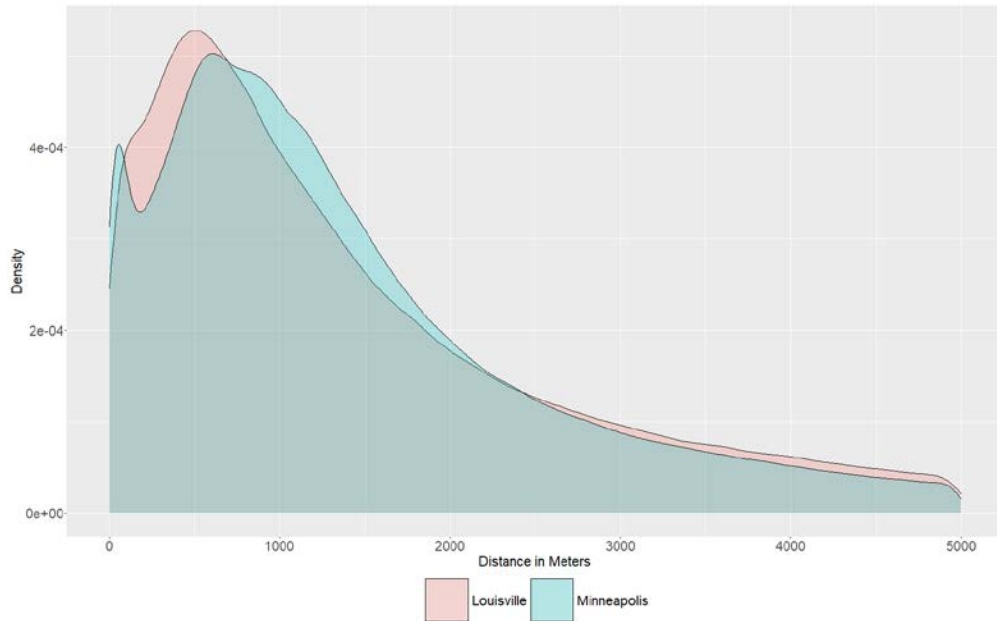
Together, these underscore that dockless scooter use is heavily concentrated in select areas.

In addition to where trips are generated, there is the question of trip lengths. **Table 3 and Figure 4** show that the vast majority of trips are relatively short in length. The median trip length in both cities is around 0.75 miles (1,200 meters), while 75% of trips are equal to or less than 1.6 miles (2,575 meters) in Louisville and 1.4 miles (2,260 meters) in Minneapolis.

Table 3: Distribution of Trip Length

	Mean	Minimum	25 th Percentile	Median	75 th Percentile	99.5 th Percentile	Maximum
Louisville	2,053 meters	1 meter	579 meters	1,207 meters	2,575 meters	13,065 meters	160,934 meters
Minneapolis	1,853 meters	1 meter	624 meters	1,206 meters	2,260 meters	12,317 meters	38,583 meters

Figure 4: Density Plot of Scooter Trip Lengths for Trips under 5000 meters (3.1 miles)



Finally, our data also shows time of use. **Figures 5 through 8** show the distribution of dockless scooter trip starts in sixty-minute increments throughout average weekdays and weekends in Louisville and Minneapolis with corresponding sunrise and sunset times. Because Louisville usage is not suspended at any time, we contrast winter and summer scooter trip patterns – the former being shown in blue, and the latter in yellow, in **Figures 5 and 6**.

Figure 5: Weekday Trips with Sunlight Hours (Louisville, KY)

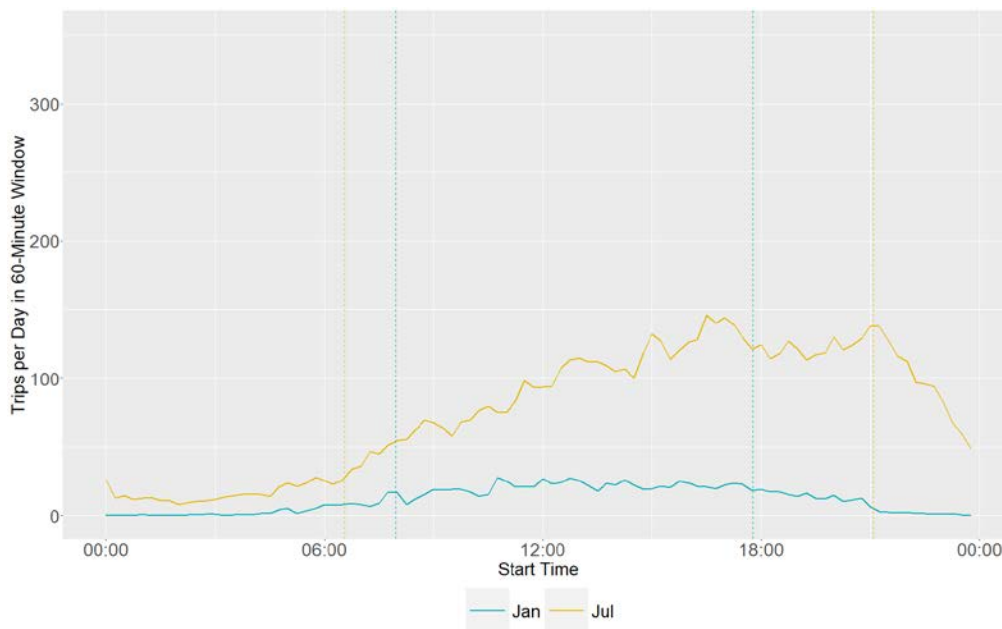


Figure 6: Weekend Trips with Sunlight Hours (Louisville, KY)

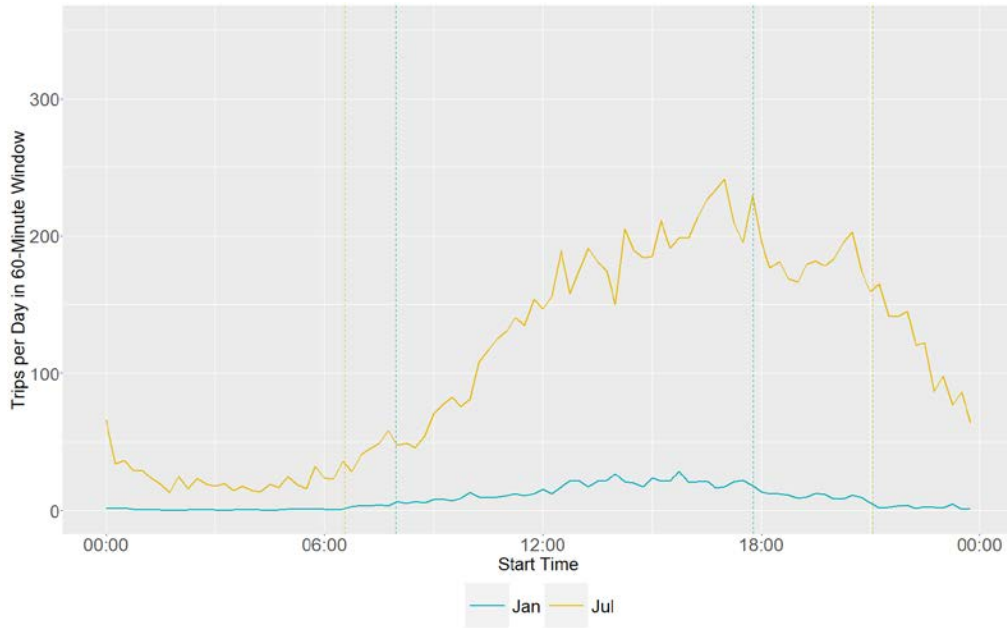


Figure 7: Weekday Trips with Sunlight Hours (Minneapolis, MN)

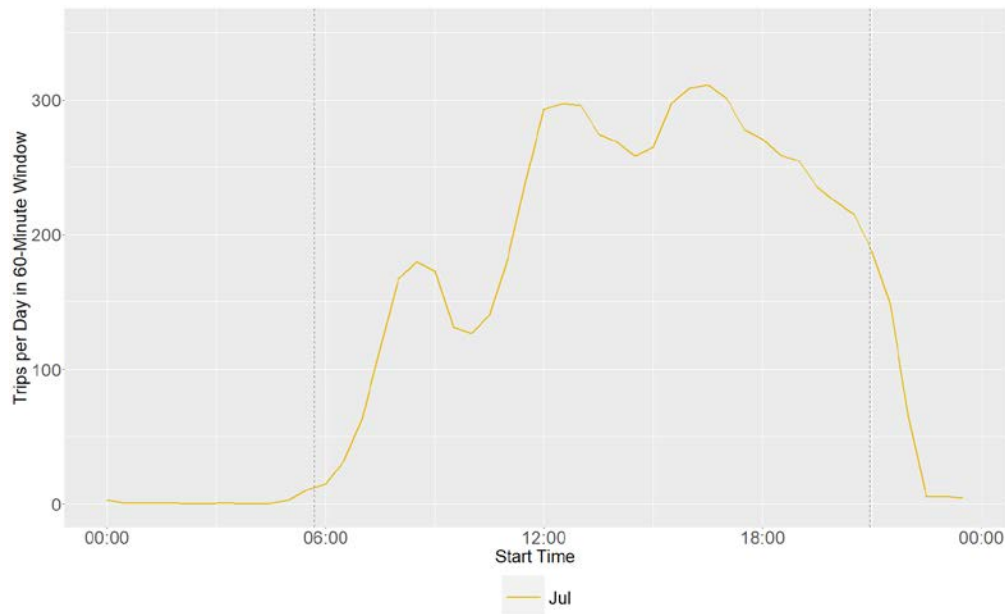
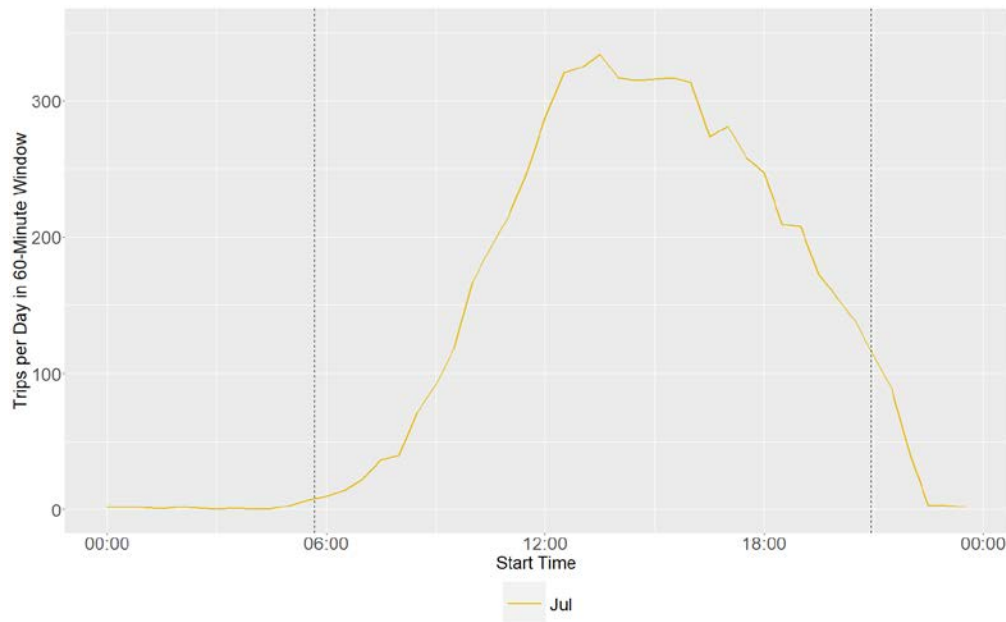


Figure 8: Weekend Trips with Sunlight Hours (Minneapolis, MN)

Our time-of-use findings are consistent with past studies (e.g., MacKenzie, 2019) that found dockless scooter use to be unassociated with commute travel and primarily associated with midday activity.

Model Results

Tables 4 and 5 show our land use model results for the Cities of Louisville and Minneapolis, respectively. Across all models and in both cities, employment density has a statistically significant and positive relationship with dockless scooter trip generation. In both the trips per day model and trips per day model with date fixed effects model, there are around five additional dockless scooter trips taken per day in Louisville for every 1,000 jobs per square kilometer. In Minneapolis, the corresponding value is approximately four. However, in the average daily trips model, the influence of employment density is about one-tenth the magnitude as in the other models. Our findings are similar for the relationship between bar/nightclub/pub density and trip generation, which is positive and statistically significant in both the trips per day model and the trips per day model with date fixed effects.

The relationship between the density of university facilities and trip generation on the other hand is not as directionally consistent in both cities. Whereas the density of university facilities has a positive association with trip generation across all three models in Minneapolis, it has a statistically significant negative association with trip generation in Louisville in both the trips per day model and the trips per day model with fixed effects. This is counter to our maps' suggestion that major universities in both cities are hot spots of dockless scooter use. However, when a Tobit Model is used, the effect of university facilities in Louisville becomes positive and significant in most models.

All of our trips per day and trips per day models with fixed effects models indicate that proximity to either city's central business district is positively associated with commercial dockless scooter trips. For every ten thousand meters (ten kilometers, 6.2 miles) from the CBD, there is a corresponding decrease

Table 4: Model Results (Louisville, KY)

Model	Trips Per Day Model				Average Daily Trips Model				Trips Per Day With Date Fixed Effects Model			
	w.o. <i>downtowndistance</i>		w. <i>downtowndistance</i>		w.o. <i>downtowndistance</i>		w. <i>downtowndistance</i>		w.o. <i>downtowndistance</i>		w. <i>downtowndistance</i>	
Specification	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit
Independent Variables												
<i>jobdensity</i>	0.005***	0.0096***	0.0049***	0.0058***	0.0005***	0.0016***	0.0005***	0.0009**	0.005***	0.0098***	0.0049***	0.006***
<i>popdensity</i>	-0.0014***	0.003***	-0.0015***	0.0012***	-0.0001	-0.0013	-0.0002	-0.0015	-0.0014***	0.003***	-0.0015***	0.0011***
<i>density_food</i>	-0.2249***	5.3692***	-0.2738***	4.1472***	0.0134	0.5584	0.0062	0.5153	-0.2249***	5.412***	-0.2738***	4.2517***
<i>density_barclub</i>	2.1084***	13.6013***	2.003***	8.3804***	0.0641	1.9887*	0.0486	1.3548	2.1084***	13.8094***	2.003***	8.6802***
<i>density_school</i>	-0.4584***	-0.3376*	-0.5292***	-3.3764***	-0.0457	-1.2744	-0.0561	-2.6466*	-0.4584***	-0.4272*	-0.5292***	-3.6287***
<i>density_university</i>	-2.6242***	5.7905***	-2.7197***	-0.9126*	0.5631	4.544*	0.5491*	3.3618*	-2.6242***	6.0371***	-2.7197***	-0.6027
<i>density_place_of_worship</i>	0.2292***	9.0899***	-0.0468	-2.6851***	0.0184	1.8897*	-0.0223	-0.2168	0.2292***	9.0534***	-0.0468	-2.7267***
<i>downtowndistance</i>	-	-	-0.0002***	-0.0133***	-	-	0.00002	-0.0021***	-	-	-0.0002***	-0.0136***
<i>constant</i>	-0.3019***	-124.5582***	1.9572***	0.4846***	0.0235	-24.0218***	0.3099	-3.3331	-1.4206	-157.9974***	0.8385	-37.3802***
N (uncensored)	307,800	33,132	307,800	33,132	570	23	570	23	307,800	33,132	307,800	33,132
R ² / Psuedo-R ²	0.1599	0.087	0.1611	0.158	0.2769	0.1856	0.2803	0.2699	0.1635	0.1052	0.1647	0.1778

Statistical Significance: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.1

Table 5: Model Results (Minneapolis, MN)

Model	Trips Per Day Model				Average Daily Trips Model				Trips Per Day With Date Fixed Effects Model			
	w.o. <i>downtowndistance</i>		w. <i>downtowndistance</i>		w.o. <i>downtowndistance</i>		w. <i>downtowndistance</i>		w.o. <i>downtowndistance</i>		w. <i>downtowndistance</i>	
Specification	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit	OLS	Tobit
Independent Variables												
<i>jobdensity</i>	0.004***	0.0047***	0.0038***	0.0038***	0.0001***	0.0002***	0.0001***	0.0002*	0.0039***	0.0047***	0.0038***	0.0038***
<i>popdensity</i>	-0.0007***	0.0009***	-0.0009***	-0.0013***	-0.00003	-0.00002	-0.00004	-0.0006	-0.0007***	0.001***	-0.0009***	-0.0013***
<i>density_food</i>	-0.1554***	1.1388***	-0.2264***	0.3302***	-0.0059	0.195	-0.0083	0.1405	-0.1554***	1.1981***	-0.2264***	0.3681***
<i>density_barclub</i>	1.8584***	2.6143***	1.8418***	2.5551***	0.0768	0.5848*	0.0762	0.4649	1.8584***	2.6978***	1.8418***	2.6618***
<i>density_school</i>	0.0273	-0.0724	-0.0083	-0.4436***	0.0229	-0.2679	0.0216	-0.2437	0.0273	-0.1505	-0.0083	-0.5403***
<i>density_university</i>	4.5739***	6.9566***	4.4718***	5.7751***	0.4804***	1.4617*	0.4768***	1.3784*	4.5739***	7.3345***	4.4718***	6.1833***
<i>density_place_of_worship</i>	0.1276**	1.4416***	0.036	0.6341***	0.0148	0.1503	0.1158	0.1314	0.1276**	1.3483***	0.036	0.5249***
<i>downtowndistance</i>	-	-	-0.0008***	-0.0114***	-	-	-0.00003	-0.0023***	-	-	-0.0008***	-0.012***
<i>constant</i>	0.5159***	-45.4994***	5.7478***	18.1382***	0.0482	-12.9684***	0.233	-1.1711	-6.4917***	-90.9416***	-1.2598	-28.6268***
N (uncensored)	139,944	58,105	139,944	58,105	408	33	408	33	139,944	58,105	139,944	58,105
R ² / Psuedo-R ²	0.3861	0.0626	0.3876	0.082	0.2219	0.1499	0.2364	0.2105	0.4037	0.0853	0.4052	0.1071

Statistical Significance: *** p ≤ 0.001, ** p ≤ 0.01, * p ≤ 0.1

of two and eight commercial daily dockless scooter trips per block group in Louisville and Minneapolis, respectively.

Further, we find that, after controlling for all other land use variables studied, residential population density has a slight negative association with dockless scooter use in the OLS models in Louisville and only a slight positive association in the Tobit models in Louisville. The pattern in Minneapolis also shows that population density changes signs and significance, although not consistently across the OLS and Tobit specifications in that city. While our maps suggest that there may be more scooter usage in higher density neighborhoods, these associations may be the result of the co-location of dense residential areas with other amenities such as bars or pubs that have a positive relationship with trip generation.

SECTION IV: Out-of-Sample Predictions

To make our model applicable to the State of California, we test our model results against data in cities for which data are already available. As discussed in Section III, only the Cities of Austin, Louisville, and Minneapolis provide public data on dockless scooter trips. Thus, our testing of the generalizability of our findings is constrained to these cities. We then use these results to predict locations with high potential for dockless scooter use in the State of California – details for which are described in Section V.

Data and Methods

Similar to the data used for developing our land use model, we rely on data from the cities of Austin, Louisville, and Minneapolis, as well as Census LODES and OSM data, to predict dockless scooter trip generations based on the regression results. We repeat the variables, which now will be used to generate predicted trips from the regression results, in **Table 6**, below.

The content and nature of our trip data for Louisville and Minneapolis, as well as our land use data, are summarized in Section III.

With regards to Austin scooter trip data, the city assigns all scooter trip origins and destinations to census tracts. The trip data for Austin report a total of 8,328,788 dockless trips for both bicycles (5% of trips) and scooters (95% of trips) between April 3, 2018 and December 31, 2019², and continuous data from 5/23/2018 onwards³. For each trip, the data record a vehicle identifier, the respective census tracts and council districts in which the trip started and ended, as well as the times at which the trip started or ended, each rounded to the nearest quarter hour. For the purpose of this analysis, we transform this data into a table containing the average number of trips starting in any given census tract across all days in the data.

² We exclude data for the year 2020.

³ There are three gaps in the data, all close to the beginning of dockless operations in Austin: the seven days starting 4/29/2018, the nine days starting 5/6/2018, and the nine days starting 5/15/2018.

Table 6: Variables and Sources for Out-of-Sample Model Predictions

Variable	Description	Data Source
<i>tripcount</i>	The number of trips per day per block group / census tract	City of Austin, TX City of Louisville, KY City of Minneapolis, MN
<i>jobdensity</i>	The density of employment (in jobs per square kilometer)	U.S. Census Bureau LODES WAC, 2017
<i>popdensity</i>	The density of residential population (in persons per square kilometer)	U.S. Census Bureau, 2010 Decennial Census
<i>density_food</i>	The combined density of establishments coded as “café,” “fast food,” “food court,” or “restaurant” (in establishments per square kilometer)	
<i>density_barclub</i>	The combined density of establishments coded as “bar,” “nightclub,” or “pub” (in establishments per square kilometer)	
<i>density_school</i>	The density of establishments coded as “school” (in establishments per square kilometer)	OpenStreetMap (queried on 4/15/2020)
<i>density_university</i>	The density of establishments coded as “university” (in establishments per square kilometer)	
<i>density_place_of_worship</i>	The density of establishments coded as “place of worship” (in establishments per square kilometer)	

Methodology

We perform a series of out-of-sample prediction tests to test whether the relationships between land uses and scooter trip generation learned from the regression model for Louisville and Minneapolis can predict observed trips in Austin. The Austin scooter trip data are only available at the census tract level, requiring that predicted trip generations from the Louisville and Minneapolis models be aggregated from block groups to census tracts for those cities. That allowed us to also compare predicted scooter trip generations in Louisville and Minneapolis to actual trip generations at the census tract level in both those cities, in addition to the comparison in Austin. Importantly, the Austin comparison is a true out-of-sample analysis, comparing census tract predicted trip generations in Austin from models fit on Louisville and Minneapolis data to actual (observed) census tract dockless scooter trip generations in Austin.

We take two approaches to aggregate block group level predictions to the census tract: summing block group level predicted scooter trip generations, and summing block group level predictions after replacing all negative predictions with zero. The latter approach is indicated by “Yes” in the “zeroing” row in **Table 7**.

Findings

Table 7: Tract-level Prediction Accuracy of Models for Louisville, Minneapolis, and Austin

Predicted Based on:	Louisville				Minneapolis				Austin			
	Louisville		Minneapolis		Louisville		Minneapolis		Louisville		Minneapolis	
Zeroing:	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Root Mean Square Error:												
Trips per Day (Count)	18.71	18.50	19.93	19.94	43.75	41.55	39.23	39.10	376.23	374.90	375.07	374.97
Percentile Rank	0.31	0.30	0.30	0.29	0.29	0.25	0.25	0.23	0.34	0.27	0.28	0.26
Spearman Rank Order Correlation:	0.414	0.465	0.494	0.499	0.505	0.636	0.628	0.685	0.29	0.54	0.54	0.59
Correctly predicts ≥ 75% percentile:	0.542	0.563	0.563	0.563	0.588	0.647	0.618	0.647	0.50	0.50	0.61	0.61

Bold numbers indicates this being the best model for each city and each indicator.

Table 7 shows, in turn, the following: In the left two columns, actual census tract scooter trip generations in Louisville are compared to predicted scooter trip generations from first the Louisville regression model (left-most column) and from the Minneapolis regression model (second column from left.) Then the actual tract trip generations in Minneapolis are compared to predicted trip generations from the Louisville and Minneapolis regressions in the middle two columns. The last block shows how actual trip generations in Austin compare to predicted trip generations from, in turn, the Louisville and Minneapolis models.

The first row shows the root mean square error (RMSE) for the difference between the actual and model-predicted trip generations. The RMSE is larger in Austin than in Louisville or in Minneapolis if measured in terms of trips per day, indicating that the absolute number of trips is not the same. This is consistent with the observation that the Austin data contain more than seven times as many trips as the Minneapolis data. However, the root mean square error for tracts' percentile ranks - that is, comparing how tracts rank in terms of predicted trips versus in terms of actual trips - suggests that the Minneapolis and Louisville models perform similarly well at ordinal ranking tracts within Austin as they do in the other two cities. The next row shows the Spearman rank order correlation between actual and predicted census tract scooter trip generations in each city, for each model. The correlation between actual in Austin and predicted Austin values from the Minneapolis model (an out-of-sample prediction compared to actual values), at 0.59, is comparable to the correlation between actual and predictions from the Minneapolis model in Minneapolis (an in-sample prediction compared to actual values.) The high-trip generation census blocks are particularly important, given the spatial concentration of scooter trip generation that we documented earlier in the report. The model from Minneapolis predicts the census tracts with scooter trip generations in the 75th percentile or higher almost as well as it does in Minneapolis. The correlation of actual scooter trip generations above the 75th percentile with predicted scooter trip generations above the 75th percent is 0.61 comparing Minneapolis prediction to Austin actual and 0.647 comparing Minneapolis prediction to Minneapolis actual. This gives confidence that the Minneapolis model, in particular, can provide insights outside of Minneapolis. Going forward, we used the zeroed Minneapolis model to predict dockless trip generations in California census tracts.

SECTION V: Short Trips and Dockless Mobility in California

Short Trips in the 2017 National Household Travel Survey

The 2017 National Household Travel Survey’s California add-on reports information on trips conducted by a representative sample of the population collected through one-day travel diaries. Across California, 55,819 respondents were asked to record all trips taken on an assigned travel day.⁴ Using these data, we are able to evaluate where in California trips occur that of similar length to a typical dockless scooter trip.⁵ Further, we can test whether the generation of such short trips appears to be associated with the same land uses as dockless trips.

For the purposes of this analysis, we define “short trips” as all trips covering a distance of 0.75 miles or less⁶ – approximately equal to the median distance of scooter trips observed in the Minneapolis, Louisville, and Austin scooter trip data. Performing an OLS regression analysis modeling the number of short trips originating in each census block group as a function of the same variables included in our regressions detailed in **Section III**, we find that many of the same associations hold: Short trips are more common in places with greater job density, more food establishments, and more bars, pubs, and night clubs (see, **Table 8**). Our analysis suggests that scooter trips (as recorded in Louisville and in Minneapolis) appear to have similar associations with land use as short trips overall (as recorded in California).

Table 8: OLS Regression Results for Scooter Trips and California Short Trips per Day⁷

Dependent Variable Distance Measurement Geographic Location	(1) Scooter Trips — Louisville	(2) Scooter Trips — Minn-eapolis	(3) Short-Trip Origins Straight Line California	(4) Short-Trip Destinations Straight Line California	(5) Short-Trip Origins Vehicle-Miles California	(6) Short-Trip Destinations Vehicle-Miles California
<i>jobdensity</i>	0.00498*** (2.19e-05)	0.00390*** (1.47e-05)	0.000241 *** (8.73e-06)	0.000239*** (8.72e-06)	0.000217*** (6.49e-06)	0.000214*** (6.49e-06)
<i>popdensity</i>	-0.00142*** (5.71e-05)	-0.000674*** (3.24e-05)	-0.000266*** (1.05e-05)	-0.000262*** (1.05e-05)	-0.000177*** (7.84e-06)	-0.000174*** (7.83e-06)
<i>density_food</i>	-0.225*** (0.0247)	-0.155*** (0.0235)	0.108*** (0.0123)	0.109*** (0.0123)	0.0746*** (0.00917)	0.0756*** (0.00916)
<i>density_barclub</i>	2.108*** (0.0598)	1.858*** (0.0508)	0.0720*** (0.0228)	0.0705*** (0.0228)	0.0577*** (0.0170)	0.0568*** (0.0170)
<i>density_place_of_worship</i>	0.229*** (0.0319)	0.128*** (0.0478)	0.0241 (0.0211)	0.0252 (0.0210)	0.0304* (0.0157)	0.0289* (0.0157)

⁴ Note that this amounts to approximately 4.5 respondents per census tract in California. Sampling of households for the NHTS was not uniform across all of California; as such, visual comparisons between different metropolitan areas may be misleading.

⁵ See Figures 10, 12, 14, 16, 18, 20, 22, 24, and 26 for maps of where such trips are recorded in the 2017 NHTS.

⁶ Measured in straight-line / “Euclidean” distance. For robustness, we also perform regression analysis using a second definition of “short trip”, defined as trips recorded in the NHTS as having incurred 0.75 or fewer “vehicle miles”.

⁷ The NHTS includes a “vehicle miles” distance based on queries to a mapping service. For this analysis, we use two different dependent variables: the number of trips that are no more than 0.75 miles long based on a straight line between their origin and destination, and this “vehicle miles” distance recorded in the NHTS. Since the “vehicle miles” distance is along a road network, the number of trips under 0.75 miles long is smaller by this definition than if measured using a straight line.

<i>density_school</i>	-0.458*** (0.0408)	0.0273 (0.0639)	-0.0605** (0.0240)	-0.0646*** (0.0240)	-0.0324* (0.0178)	-0.0383** (0.0178)
<i>density_university</i>	-2.624*** (0.125)	4.574*** (0.130)	0.403*** (0.0908)	0.393*** (0.0907)	0.336*** (0.0676)	0.317*** (0.0675)
<i>constant</i>	-0.302*** (0.0627)	0.516*** (0.131)	2.562*** (0.0483)	2.552*** (0.0482)	1.621*** (0.0359)	1.617*** (0.0359)
Observations	307,800	139,944	23,188	23,188	23,188	23,188
R-squared	0.160	0.386	0.066	0.065	0.078	0.076

Standard errors in parenthesis

Statistical Significance: *** $p \leq 0.001$, ** $p \leq 0.01$, * $p \leq 0.1$

Applying Model Coefficients to California

Having validated that our models are capable of performing out-of-sample prediction for the approximate ranks of census block groups or tracts in terms of trip generation, we apply the coefficients of our Minneapolis models to all census block groups in California, aggregating predictions to the census tract level with zeroing.⁸ We then create maps displaying what our model coefficients tell us about potential for dockless trips (as would be suggested by Minneapolis’ coefficients), and juxtapose these prediction maps with maps of short trips⁹ recorded in the 2017 NHTS. As such, the maps below do nothing other than multiply coefficients estimated by our Minneapolis OLS trips per day regression model (Table 5, column 1) with data on the same land use variables included as regressors on our model, collected for each block group in California.

While our models were estimated using data from the medium-to high-density areas that comprise Minneapolis and Louisville, many of the areas we generate predictions for are rural or low-density exurbs – areas where scooter operators are unlikely to ever operate. Our predictions for such areas tend to be around zero, with predictions of ten or more trips per day per census block group only appearing in more densely populated urban and suburban areas. This suggests to us that applying our models’ coefficients to block groups across the entire state of California does not pose issues for interpreting results.

Since only approximately the top four thirtieths of census tracts¹⁰ are predicted to have ten or more trip originations per day, we narrow our focus to presenting and interpreting variation in predicted scooter trips within that top four thirtieths of census tracts in California. In other words, we divide predicted scooter trips into 30 centiles (equal sized groups) in the state and then analyze predicted scooter trips for census tracts that comprise the top four of those 30 centiles, i.e. the top 4/30th of the distribution of predicted trips.

Predicted Trip Generation within California Metro Areas

The maps on the following pages visualize what our Minneapolis Model with Zeroing tells us about which parts of Californian urban areas have land uses that could support scooter trips, presented at the census tract level. We juxtapose our model’s predictions with short trips observed in the 2017 NHTS for

⁸ That is, we replace all block group level predictions smaller than zero with zero before summing up predicted trip counts across all block groups within a tract.

⁹ Here, we define “short trips” as trips covering a straight-line distance of no more than 0.75 miles, regardless of mode by which they were taken.

¹⁰ If all census tracts are sorted by predicted trip originations and divided into thirty groups, only the tracts in the top four of those 30 groups are predicted to have ten or more trips originate in them.

visual comparison.¹¹ We note that locations with a high value of predicted scooter trips, as shown in the maps that follow, are locations that have relatively high values for the key independent variables that are associated with scooter trips in the regression model. In particular, those variables include employment density and activity densities. Hence the locations with high predicted scooter trips are places with land uses that correlate with scooter trips (technically in Minneapolis, but noting that the evidence suggests that out-of-sample prediction may have validity.) These are not locations where dockless scooter mobility will necessarily be high, and while the maps below are informative we caution that those maps should be used as a first pass to filter locations with land uses that could support dockless mobility. We discuss this interpretation more in the concluding section.

¹¹ Given the NHTS' relatively small sample size and non-uniform sampling strategy, short trip maps are intended for gaining a cross-sectional sense of where short trips occur within metropolitan areas.

Figure 9: Predicted Daily Scooter Trips for Fresno, Minneapolis Model¹²

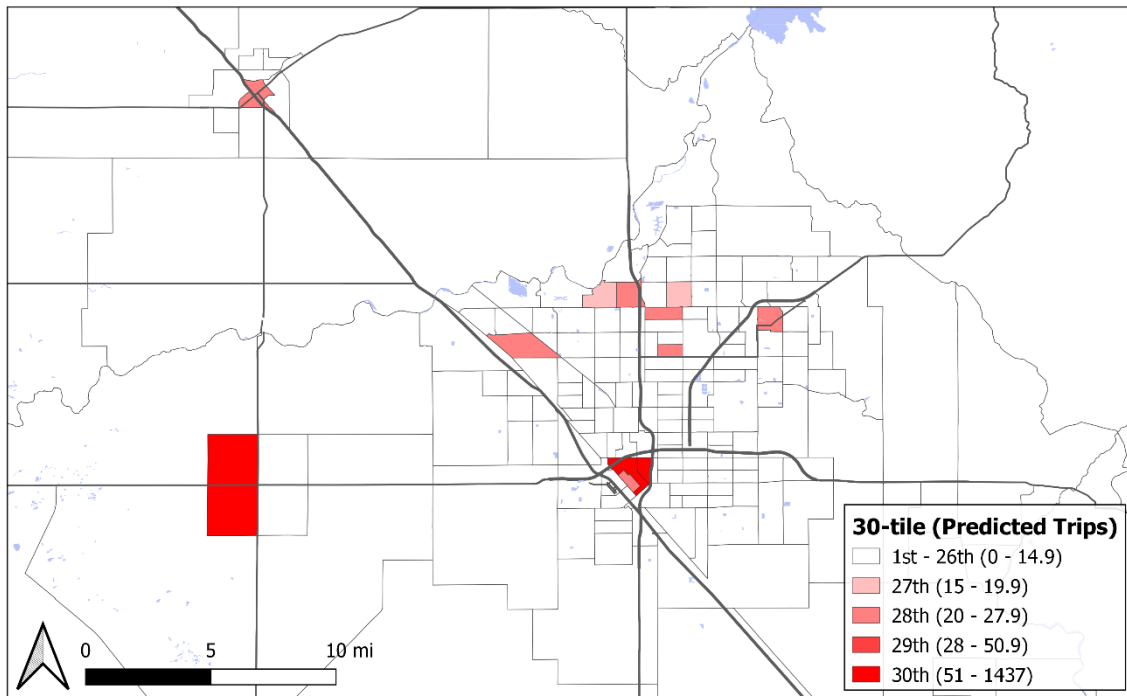
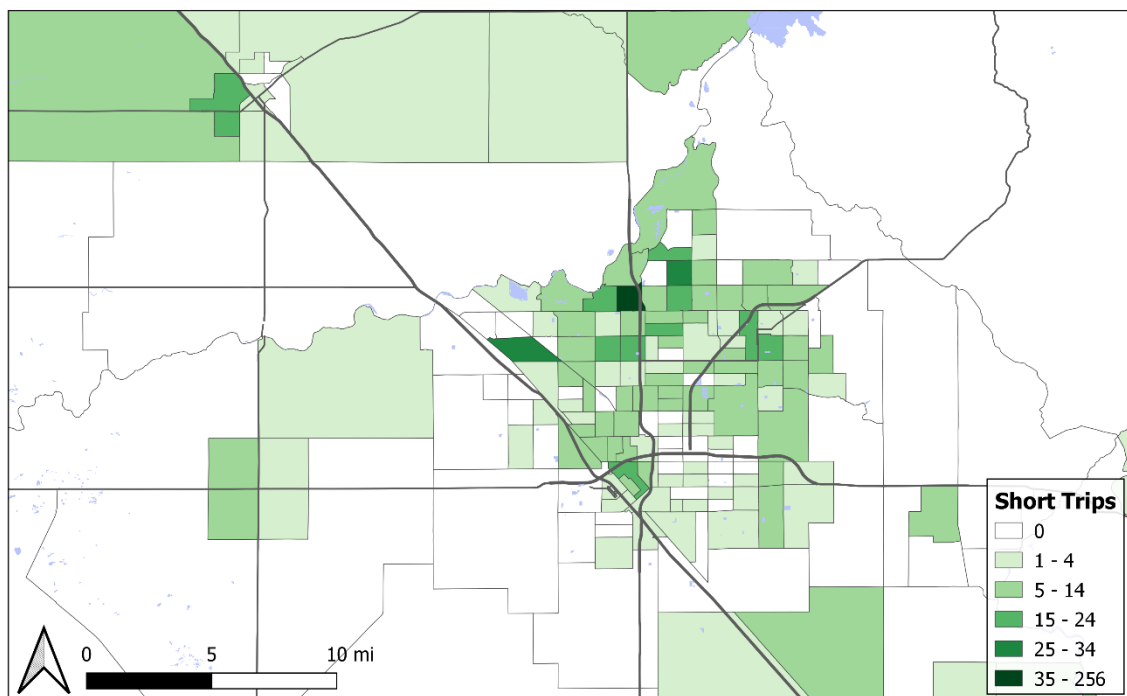


Figure 10: Trip Originations of Trips (< 0.75 Miles Straight Line) in Fresno in 2017 NHTS



¹² In **Figure 9** and all subsequent figures displaying predicted daily scooter trips, we use the Minneapolis Model with Zeroing described in **Section IV**.

Figure 11: Predicted Daily Scooter Trips for Long Beach & Orange County, Minneapolis Model

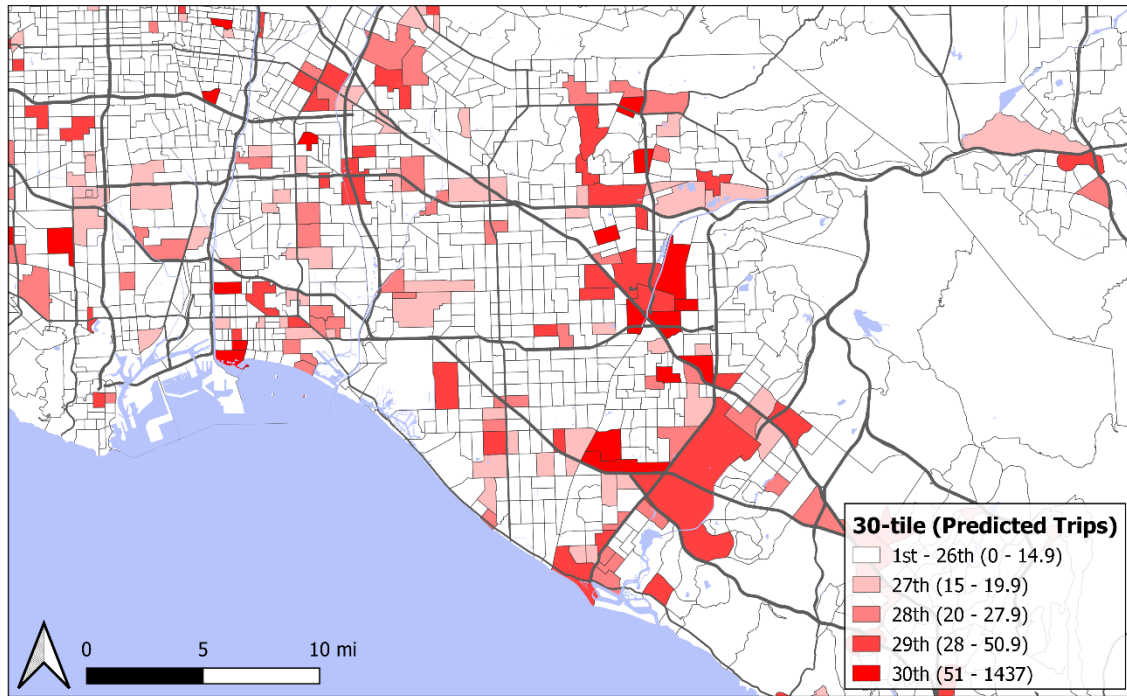


Figure 12: Trip Originations of Trips < 0.75 Miles in Long Beach & Orange County, 2017 NHTS

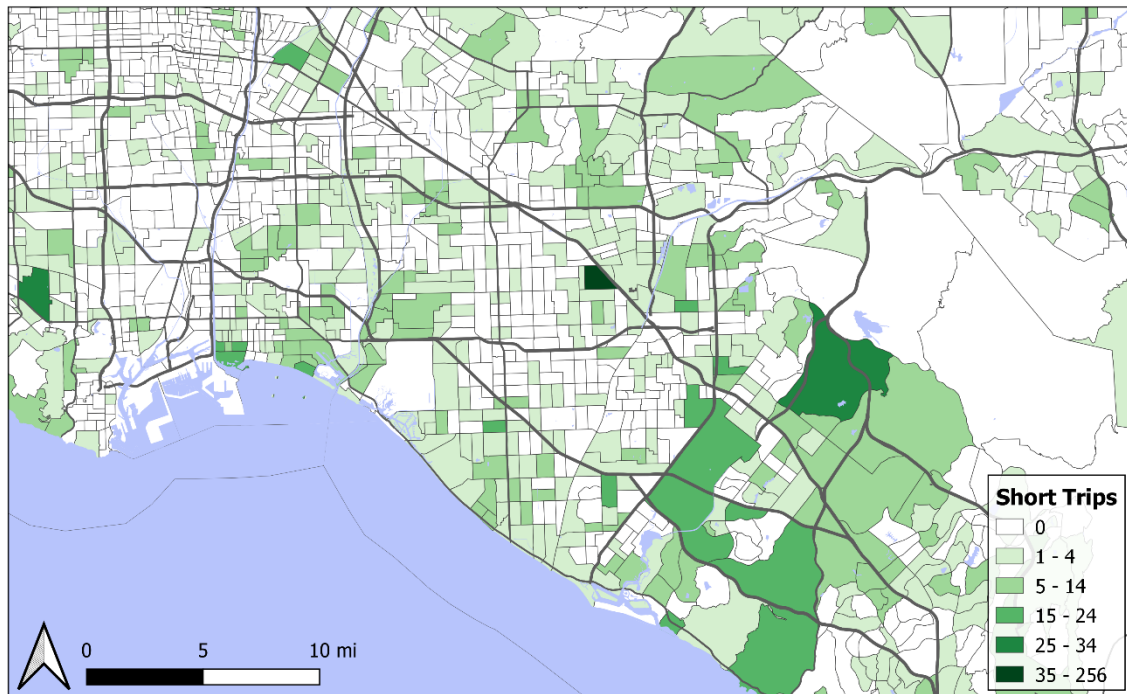


Figure 13: Predicted Daily Scooter Trips for Los Angeles, Minneapolis Model

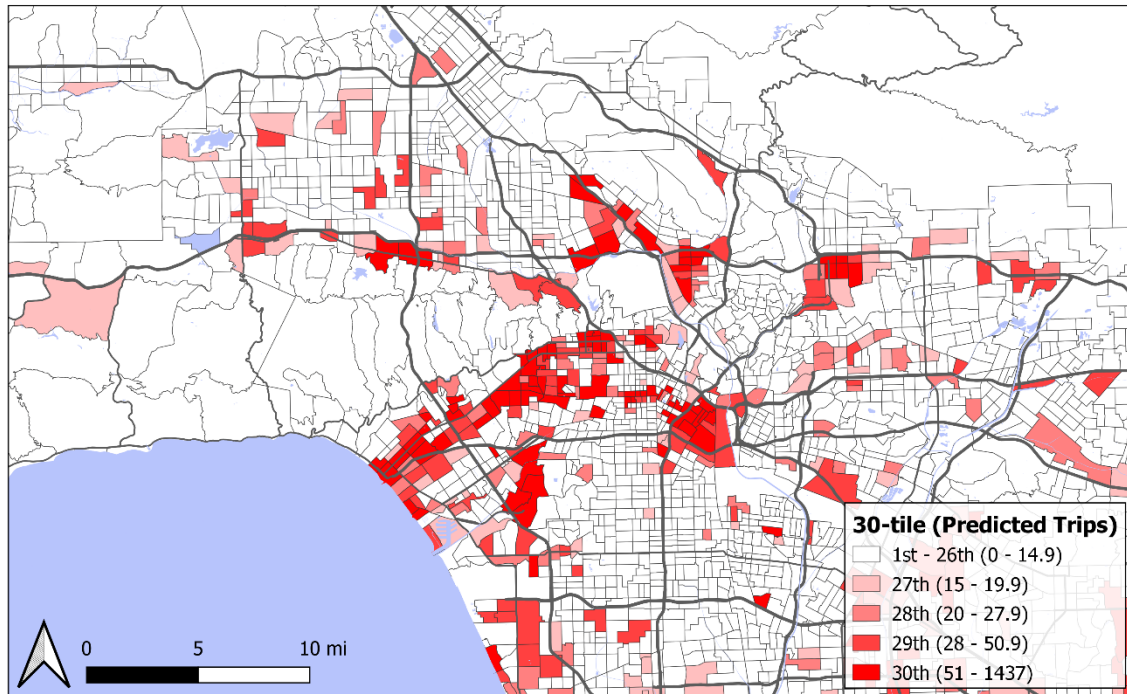


Figure 14: Trip Originations of Trips (< 0.75 Miles Straight Line) in Los Angeles in 2017 NHTS

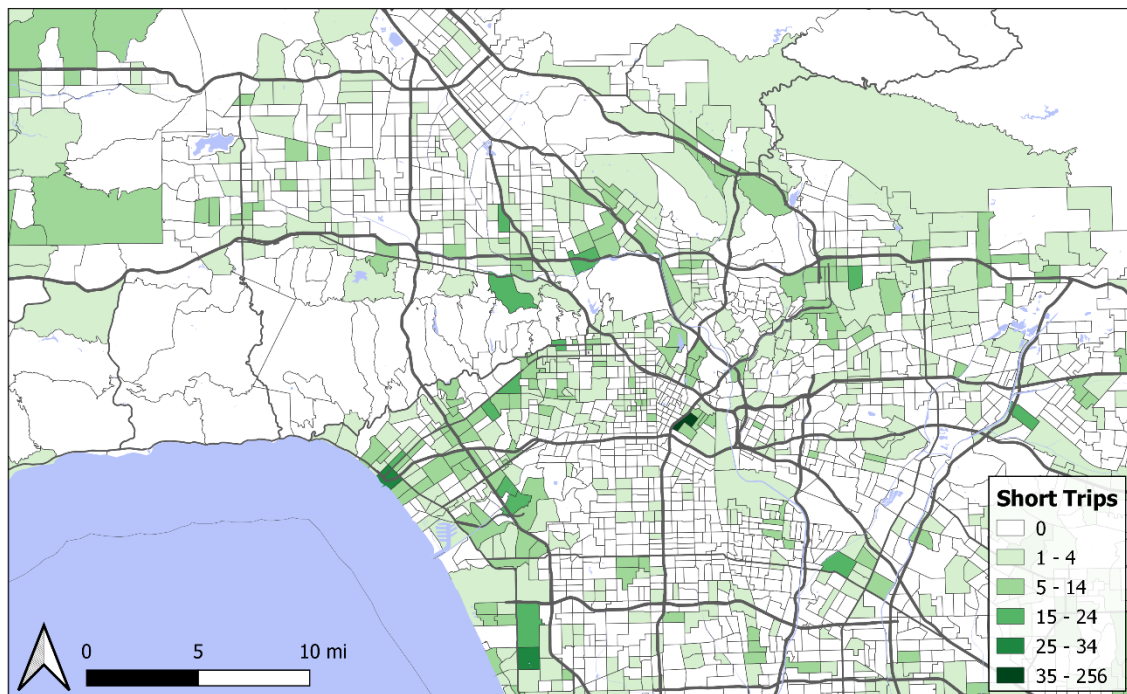


Figure 15: Predicted Daily Scooter Trips for Sacramento, Minneapolis Model

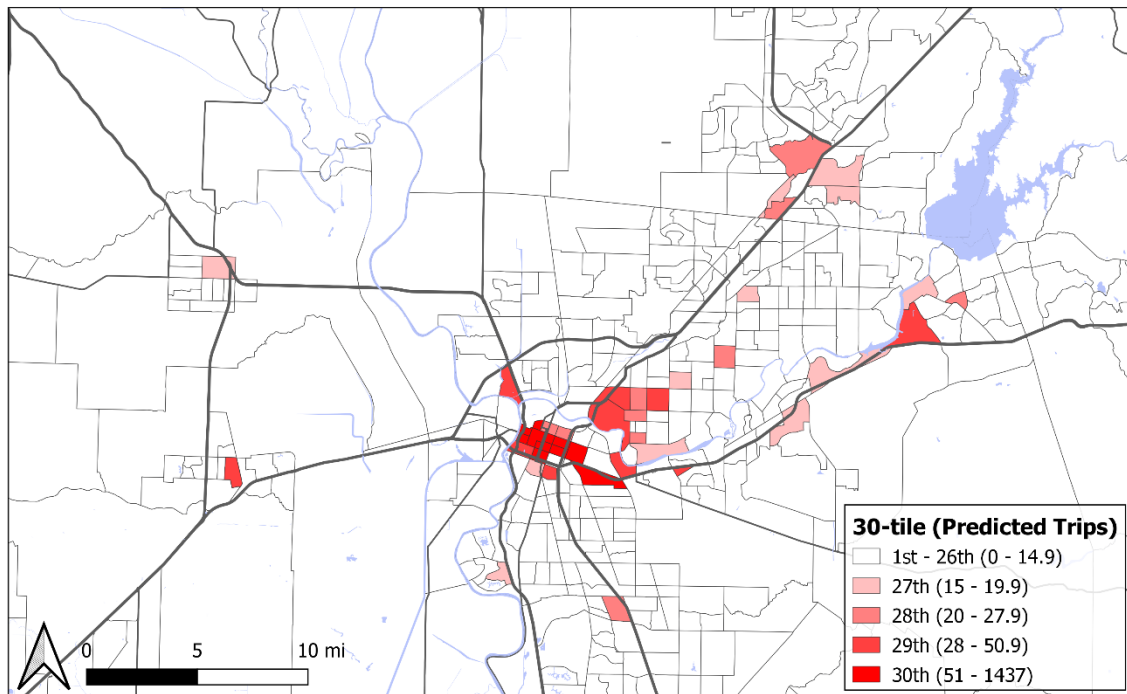


Figure 16: Trip Originations of Trips (< 0.75 Miles Straight Line) in Sacramento in 2017 NHTS

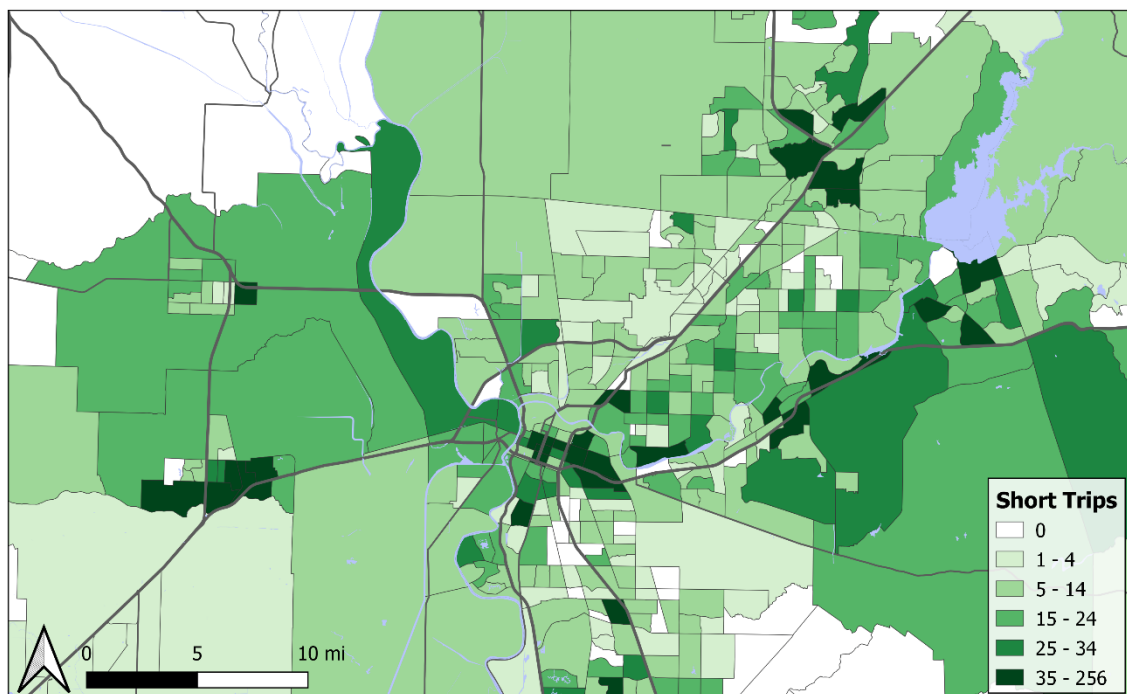


Figure 17: Predicted Daily Scooter Trips for San Diego, Minneapolis Model

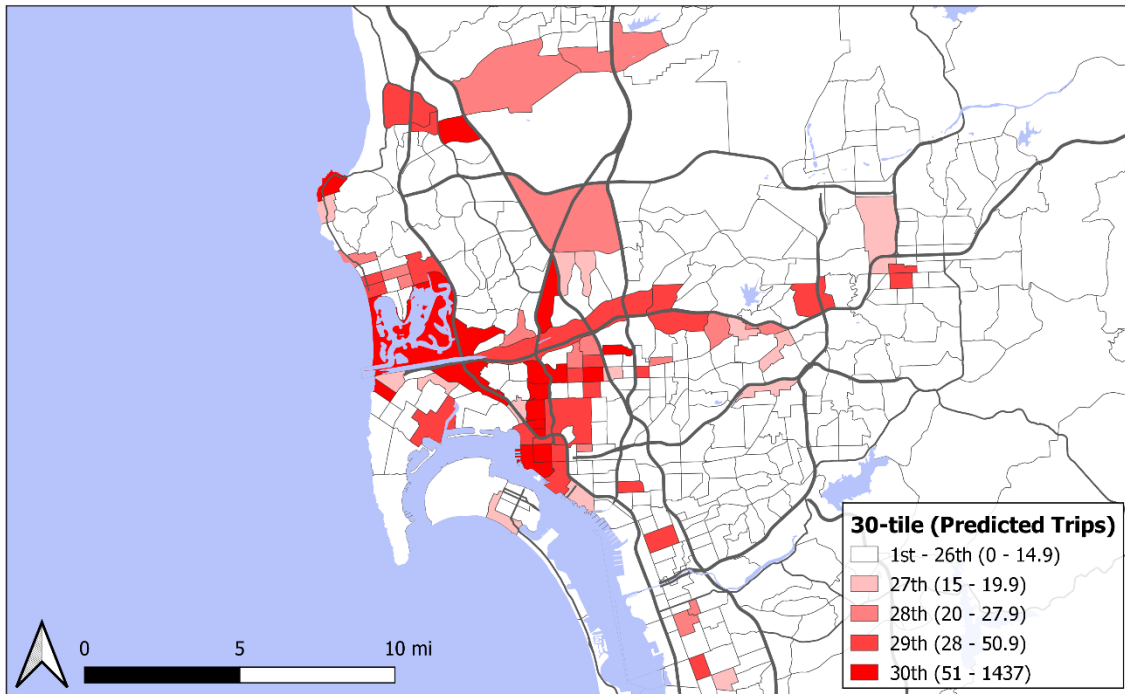


Figure 18: Trip Originations of Trips (< 0.75 Miles Straight Line) in San Diego in 2017 NHTS

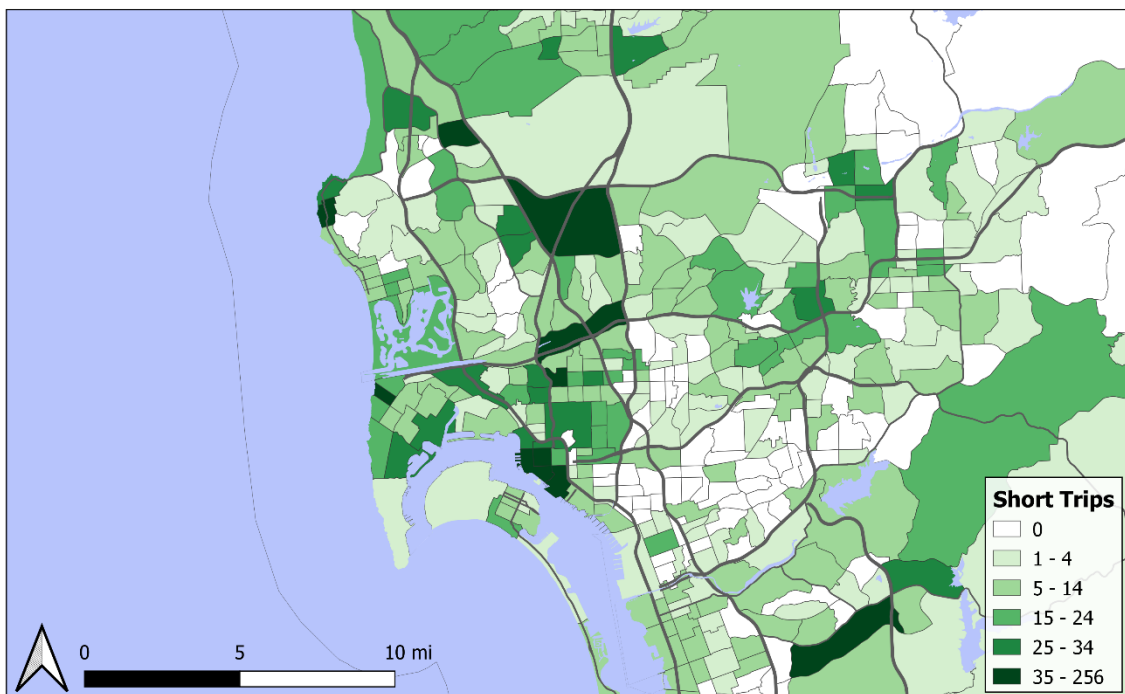


Figure 19: Predicted Daily Scooter Trips for San Francisco & Oakland, Minneapolis Model

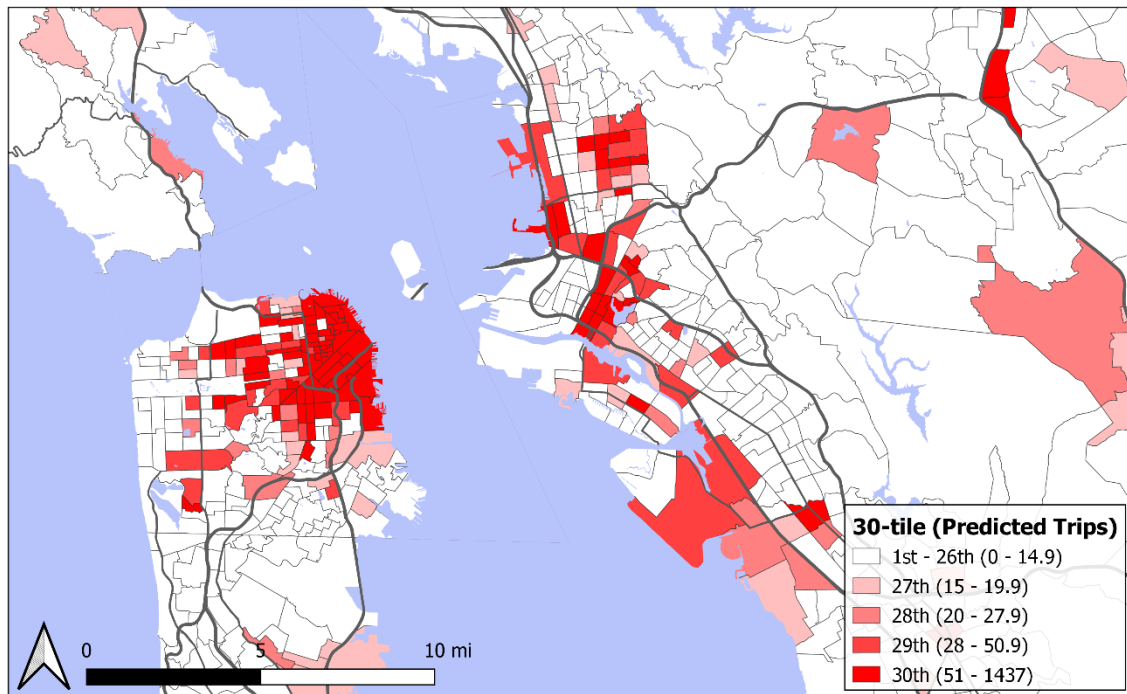


Figure 20: Trip Originations of Trips < 0.75 Miles in San Francisco & Oakland, 2017 NHTS

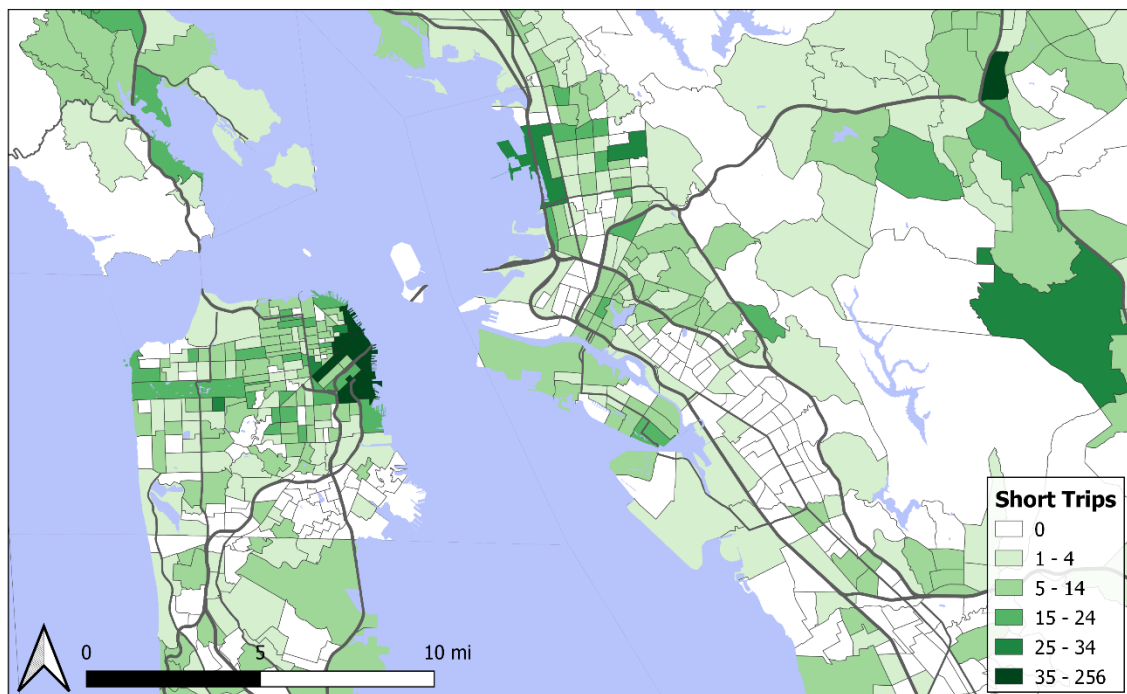


Figure 21: Predicted Daily Scooter Trips for San Jose, Minneapolis Model

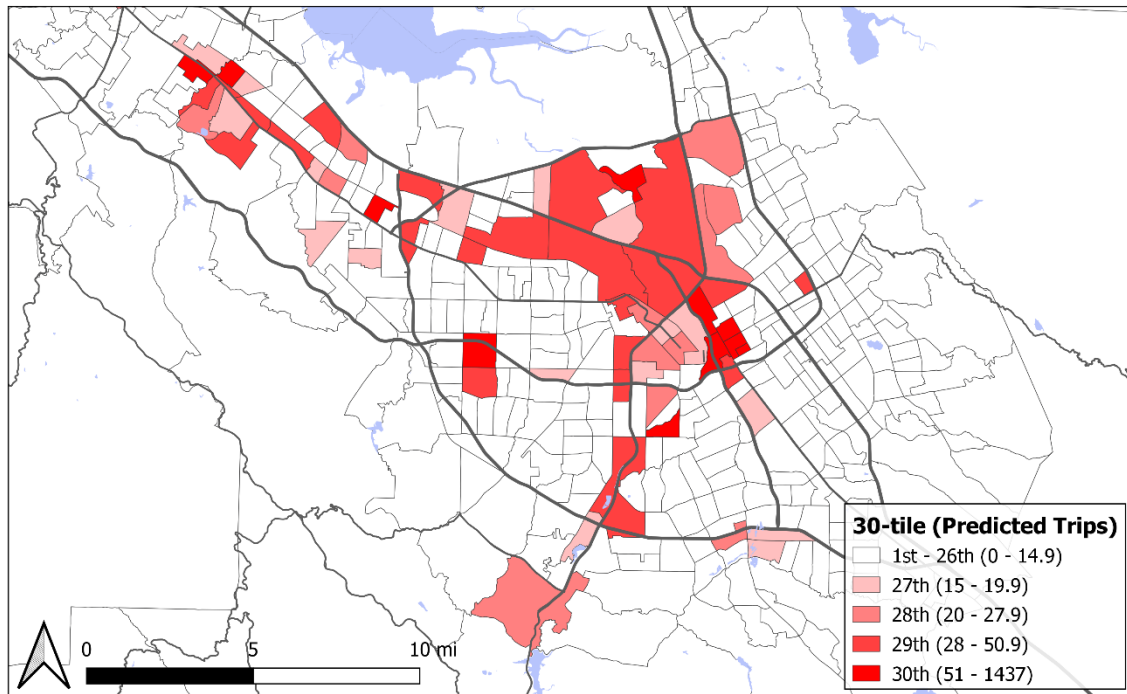


Figure 22: Trip Originations of Trips (< 0.75 Miles Straight Line) in San Jose in 2017 NHTS

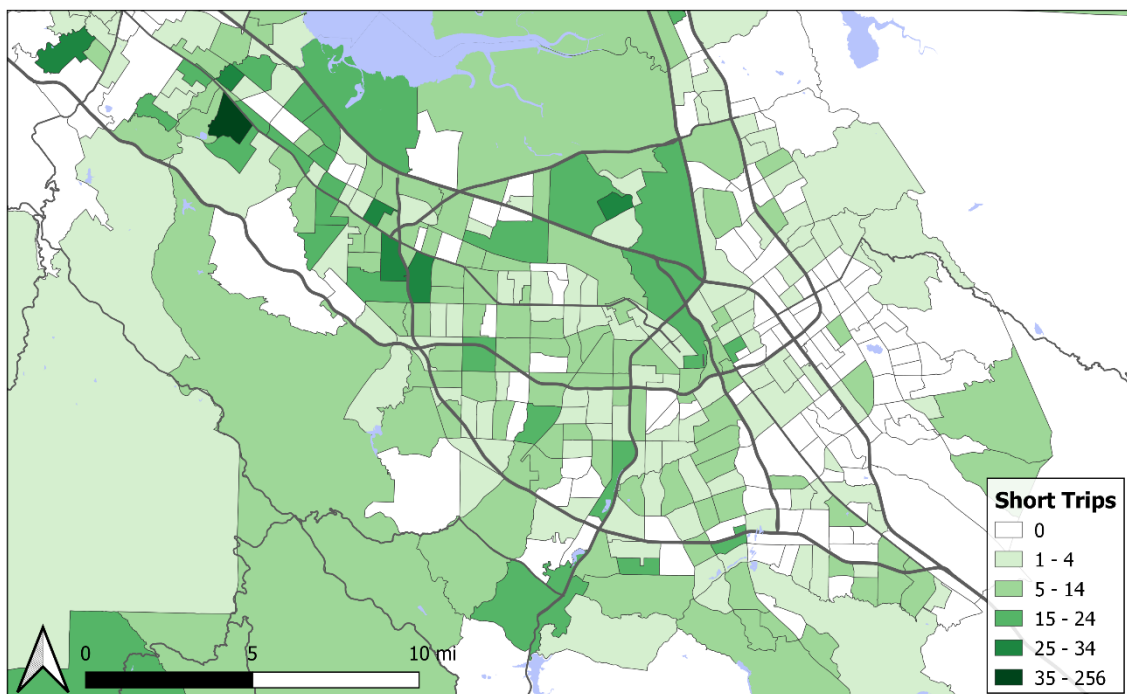


Figure 23: Predicted Daily Scooter Trips for San Mateo County, Minneapolis Model

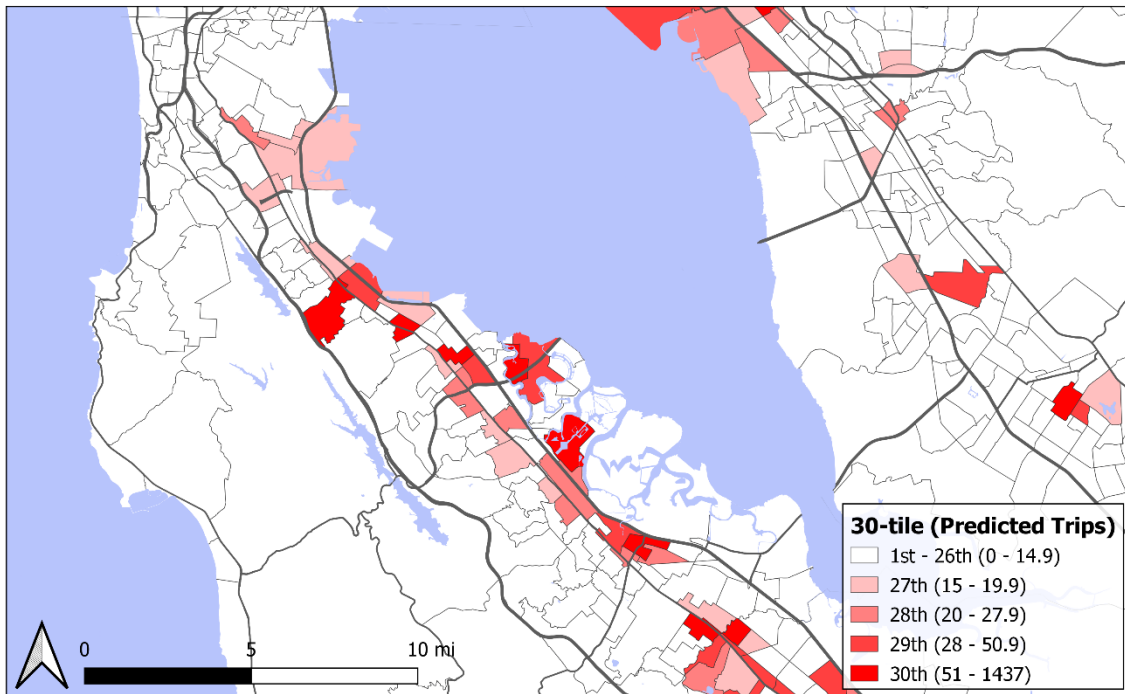


Figure 24: Trip Originations of Trips < 0.75 Miles in San Mateo County, 2017 NHTS

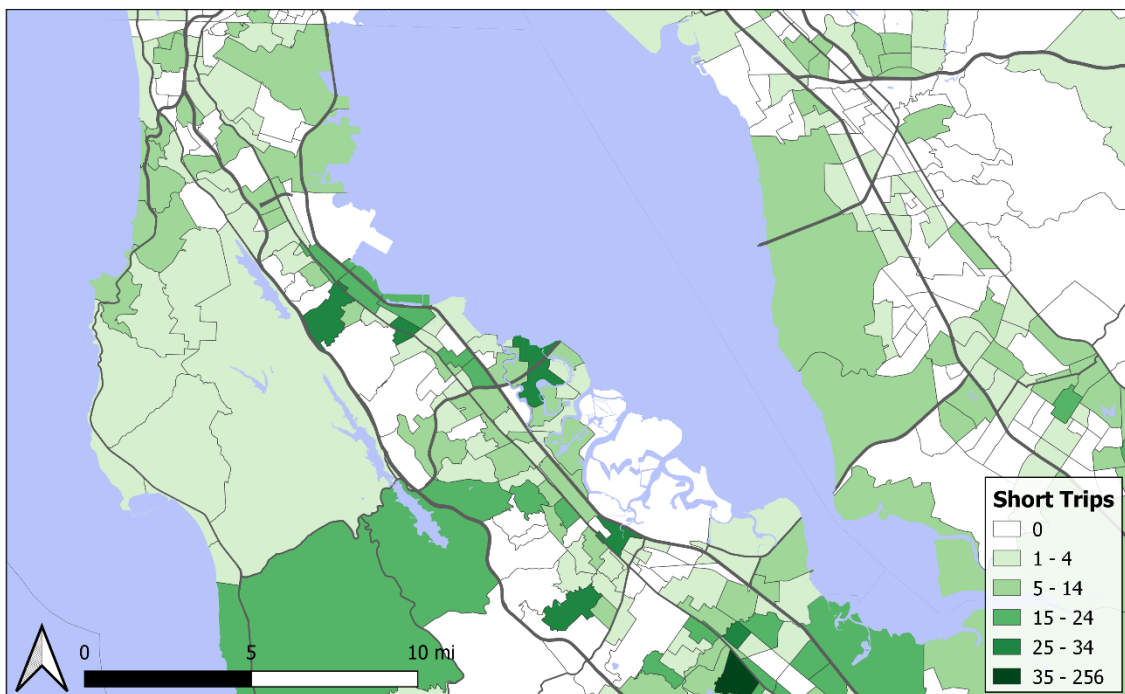


Figure 25: Predicted Daily Scooter Trips for Santa Barbara, Minneapolis Model

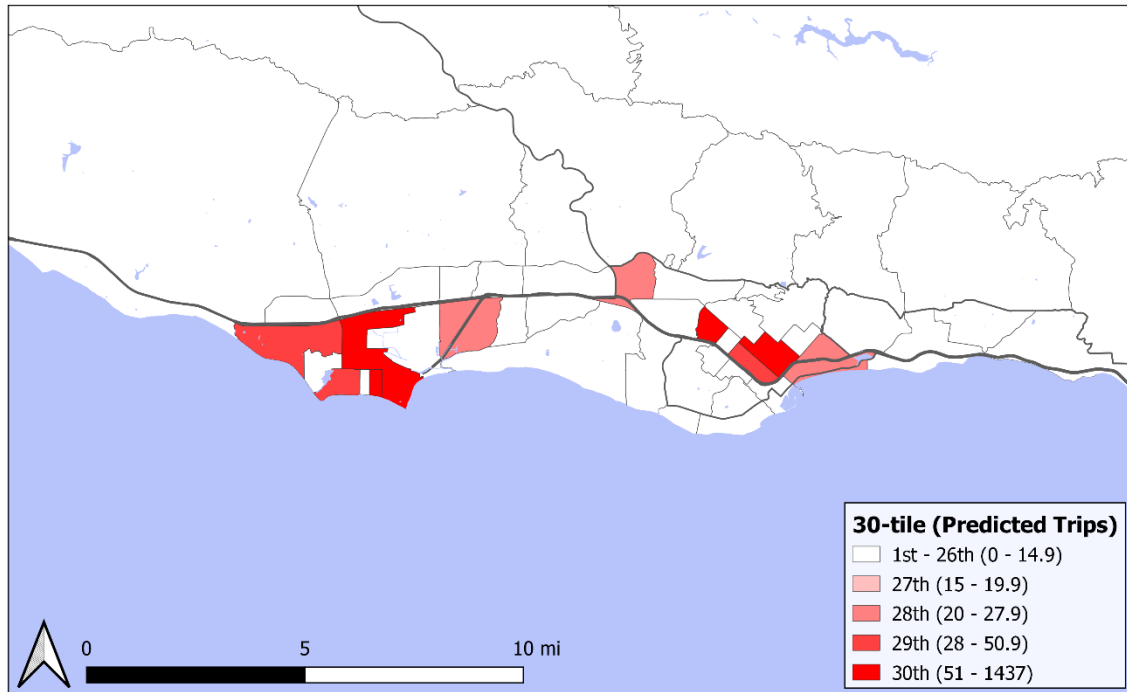
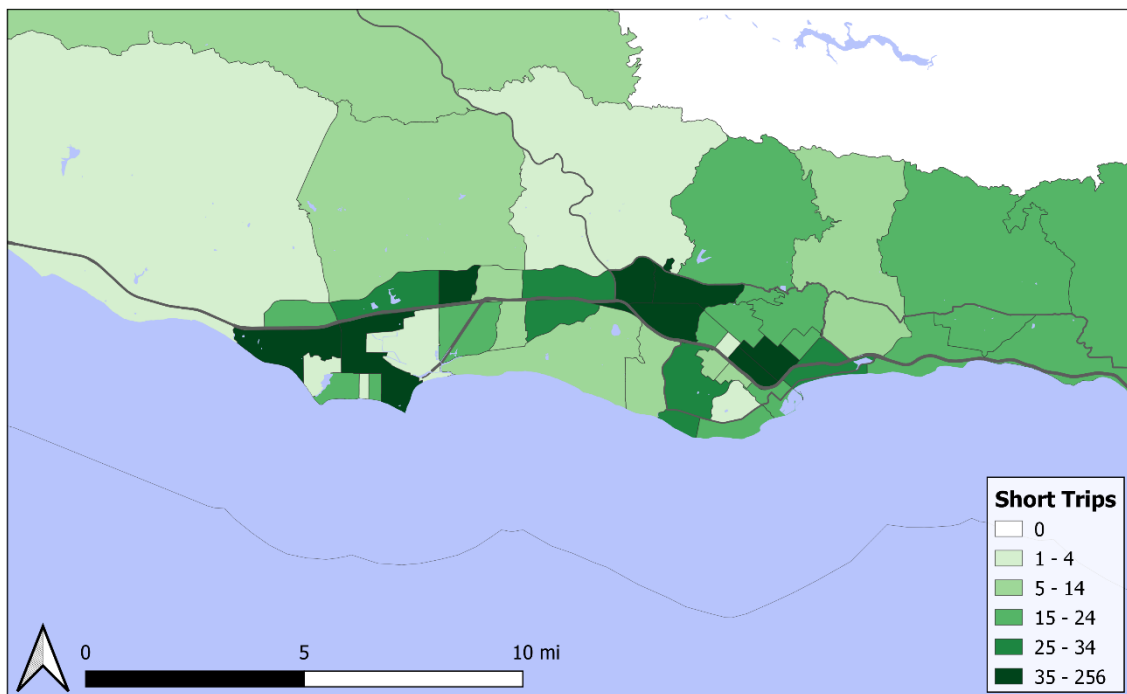


Figure 26: Trip Originations of Trips (< 0.75 Miles Straight Line) in Santa Barbara in 2017 NHTS



The maps point toward one potential caveat for our predictions: Our models from Minneapolis and Louisville explain how cross-sectional variation in land uses explain cross-sectional variation in trip origination for generally short trips made using scooters within urban areas. While scooter trips are almost by definition short trips,¹³ short trips are not necessarily scooter trips. To what extent scooter trips are representative of all short trips may not be the same across space, as urban short trips may differ from non-urban short trips.

The Role of Urban Form

Along with a place having job and amenity densities to support a sufficient volume of short trips, the urban form – that is, for example, the lengths of blocks and widths of roads – may be a factor in determining the viability of scooters and other non-automobile modes for conducting short trips: If an area’s roads do not feel safe enough or are not inviting to pedestrians, cyclists, and scooters, job and amenity density alone may not suffice to foster non-automotive modes of travel. Therefore, when attempting to predict where scooters or other micromobility modes have the most potential, it is critical to evaluate areas not only based on their potential for trip generation, but also based on their suitability for the mode.

Fortunately, proxy measurements for urban form are available through OpenStreetMap. We collect information on average block lengths and average speed limits for each census tract in California.¹⁴ All else held equal, shorter blocks and lower speed limits are likely more conducive to using scooters or other non-automotive modes for short trips (Adkins et al., 2012, Frank et al., 2005 and 2006). The maps on the following pages present which census tracts are above the 50th, 70th, 85th, 90th, and 95th statewide percentiles on all three of the following indicators:¹⁵ 1) The predicted trip generation as per our Minneapolis model with zeroing, 2) short average block lengths, and 3) low speed limits.¹⁶

¹³ See descriptive statistics of scooter trip lengths observed in Minneapolis and Louisville in **Section III**. All observed scooter trips in this study are urban since we are not aware of any scooter providers operating outside of urban or suburban areas, let alone non-urban municipalities reporting data on scooter trips.

¹⁴ Block lengths and average speed limits are collected from OpenStreetMap using OSMnx, and apply default speed limits where OpenStreetMap does not report that information (Boeing, 2017).

¹⁵ That is, their minimum percentile across the three indicators is at least the 50th, 70th, 85th, 90th, or 95th percentile.

¹⁶ Block length and speed limits are calculated as distance-weighted averages across all streets within a census tract. For the calculation of speed limits, we exclude all sections of road labeled *motorway*, *motorway_link*, *trunk*, or *trunk_link* as not to include freeways, since they would be off-limits to micromobility modes.

Figure 27: Three-Indicator Approach to Micromobility Viability for Fresno¹⁷

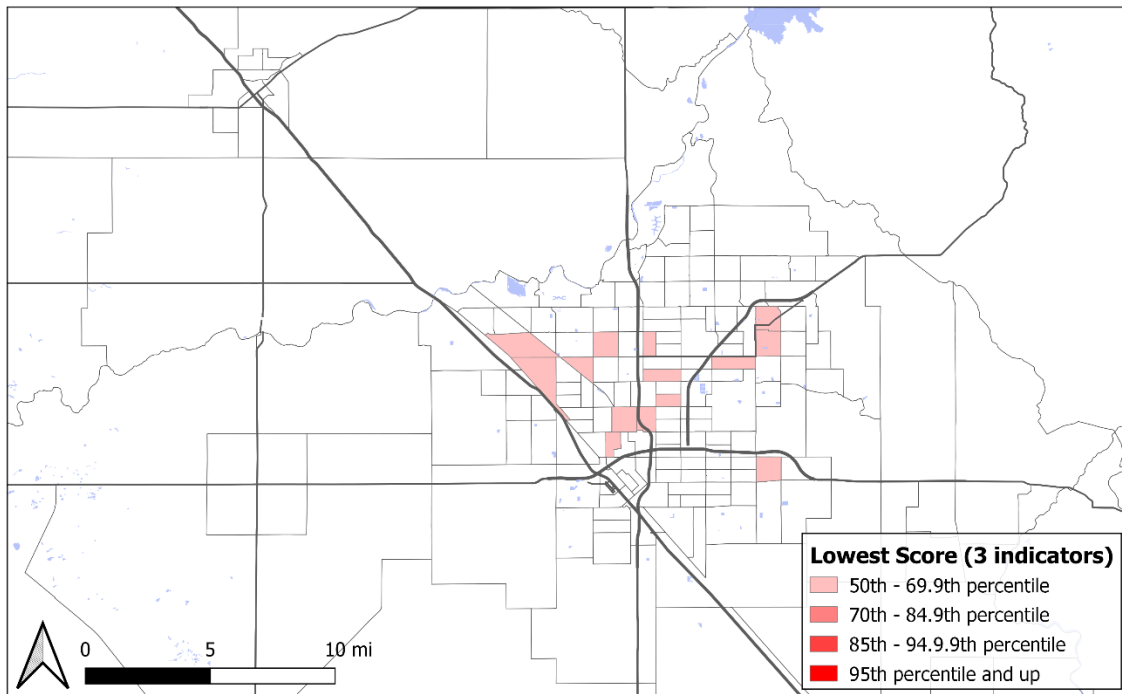
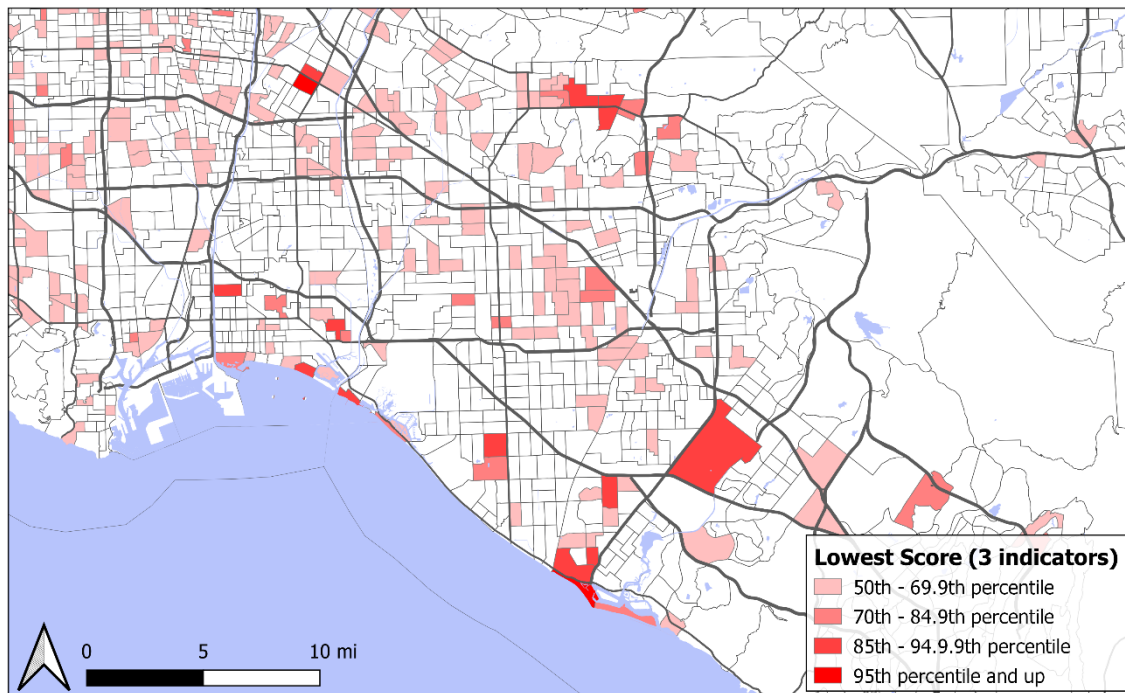


Figure 28: Three-Indicator Approach to Micromobility Viability, Long Beach & Orange County



¹⁷ The three indicators employed in **Figures 27 - 35** are: predicted trips: higher is better; average speeds: lower is better; and block lengths: shorter is better. We rank census tracts by each factor, and then shade them by the minimum percentile across all three factors.

Figure 29: Three-Indicator Approach to Micromobility Viability for Los Angeles

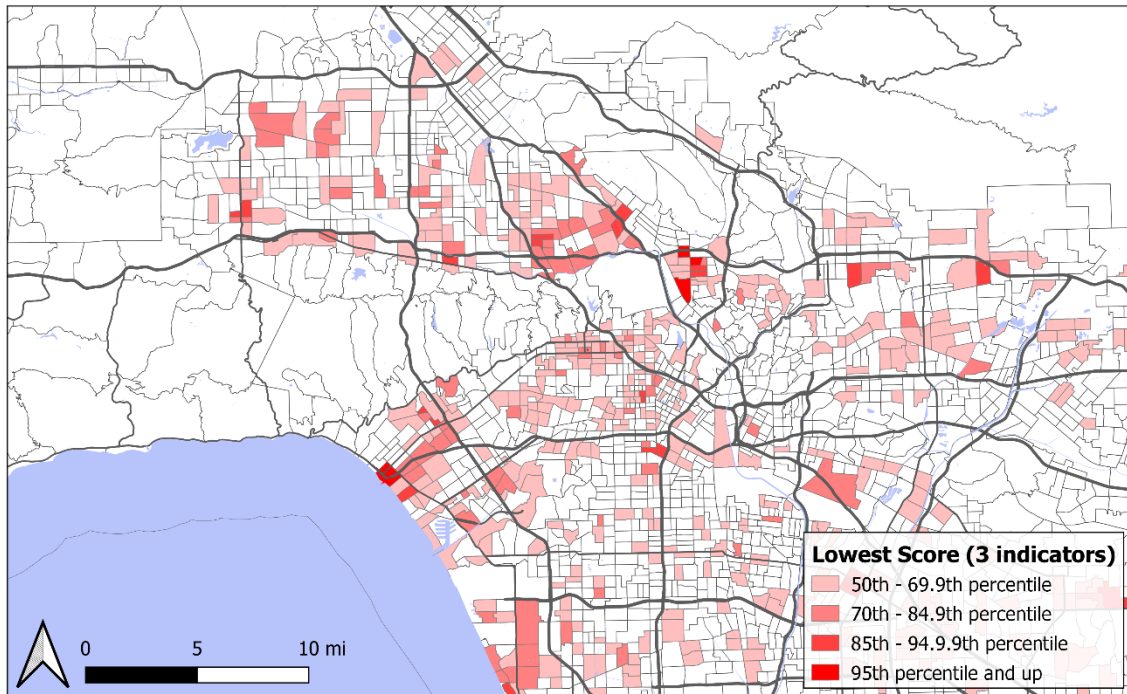


Figure 30: Three-Indicator Approach to Micromobility Viability for Sacramento

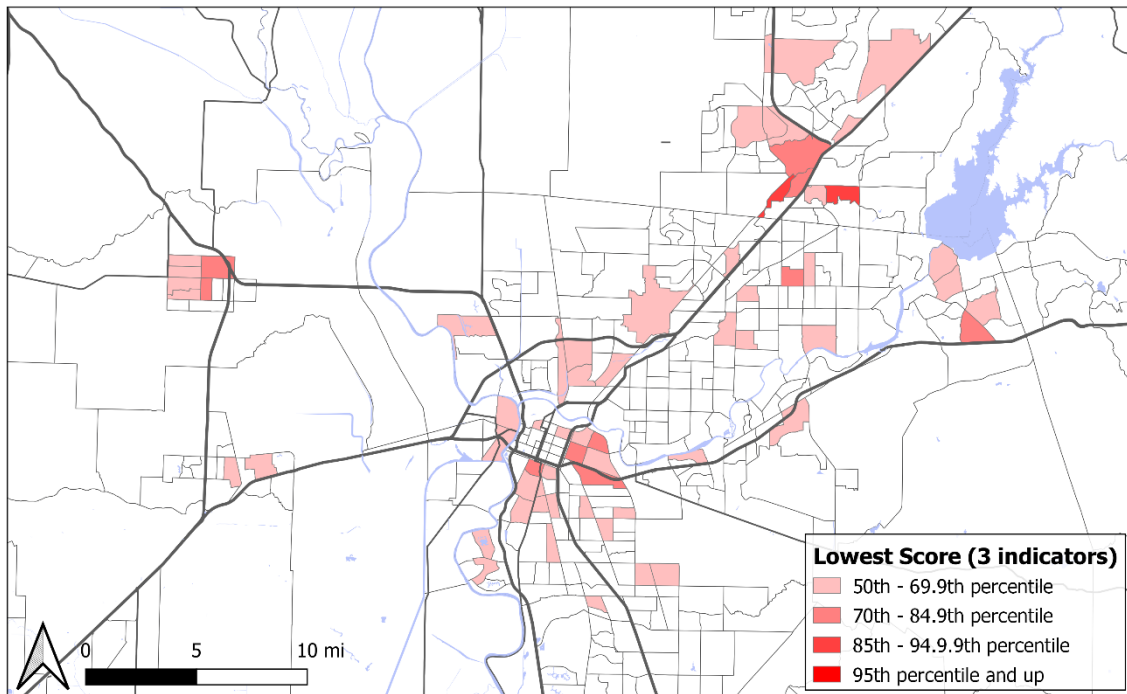


Figure 31: Three-Indicator Approach to Micromobility Viability for San Diego

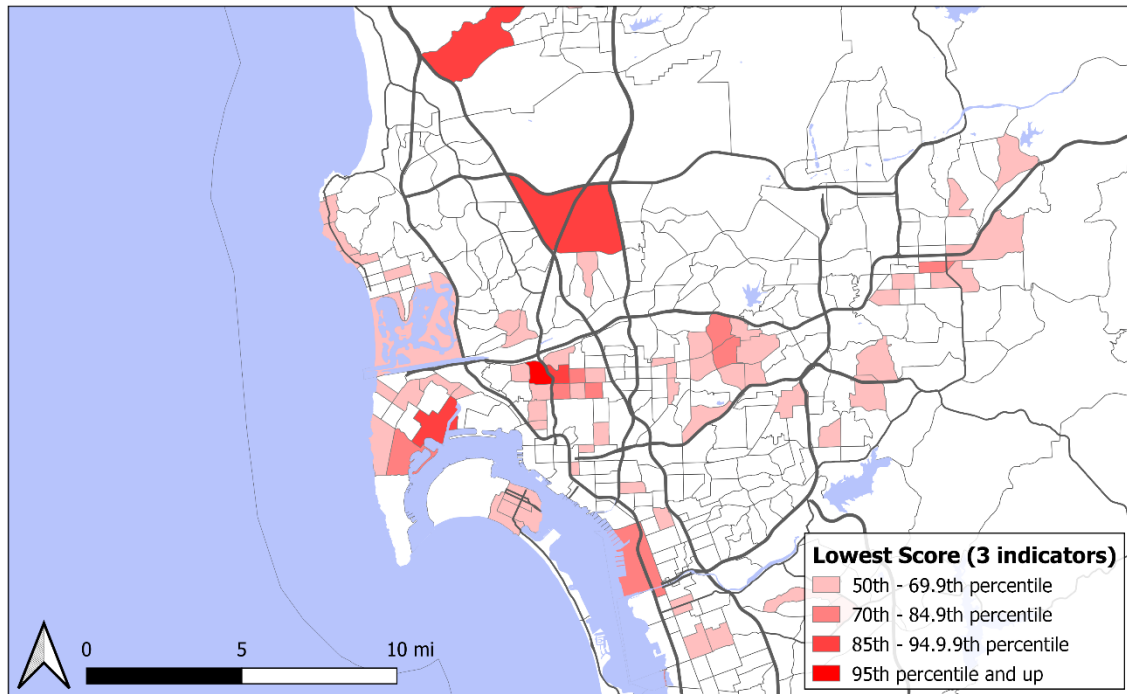


Figure 32: Three-Indicator Approach to Micromobility Viability, San Francisco & Oakland

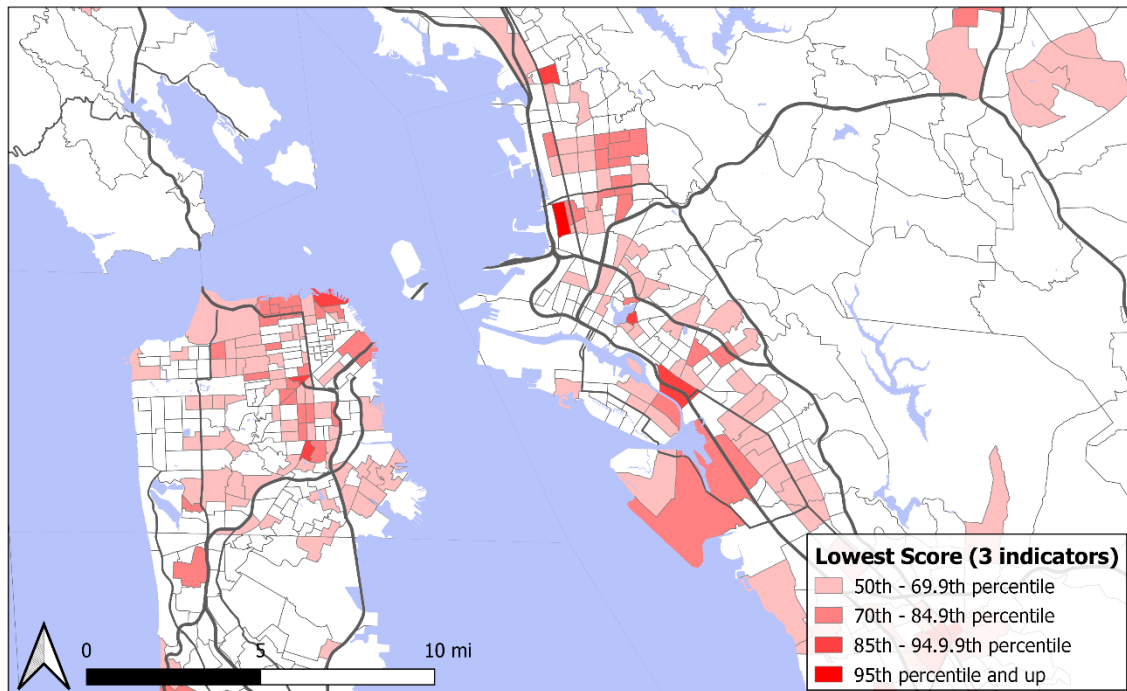


Figure 33: Three-Indicator Approach to Micromobility Viability for San Jose

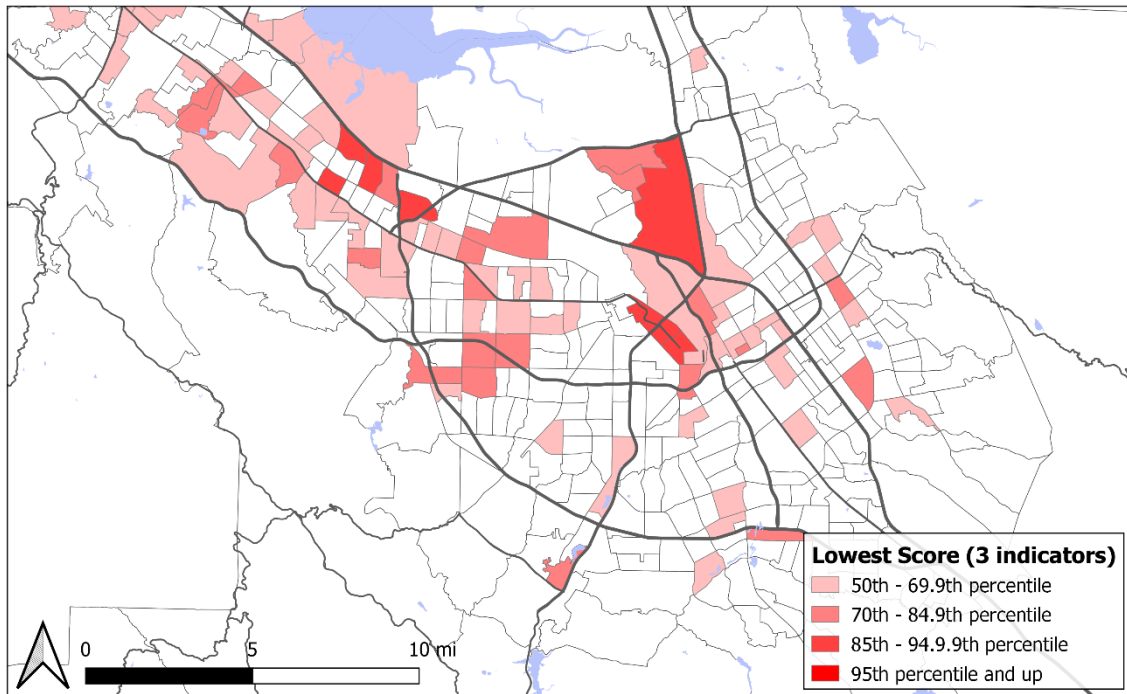


Figure 34: Three-Indicator Approach to Micromobility Viability for San Mateo County

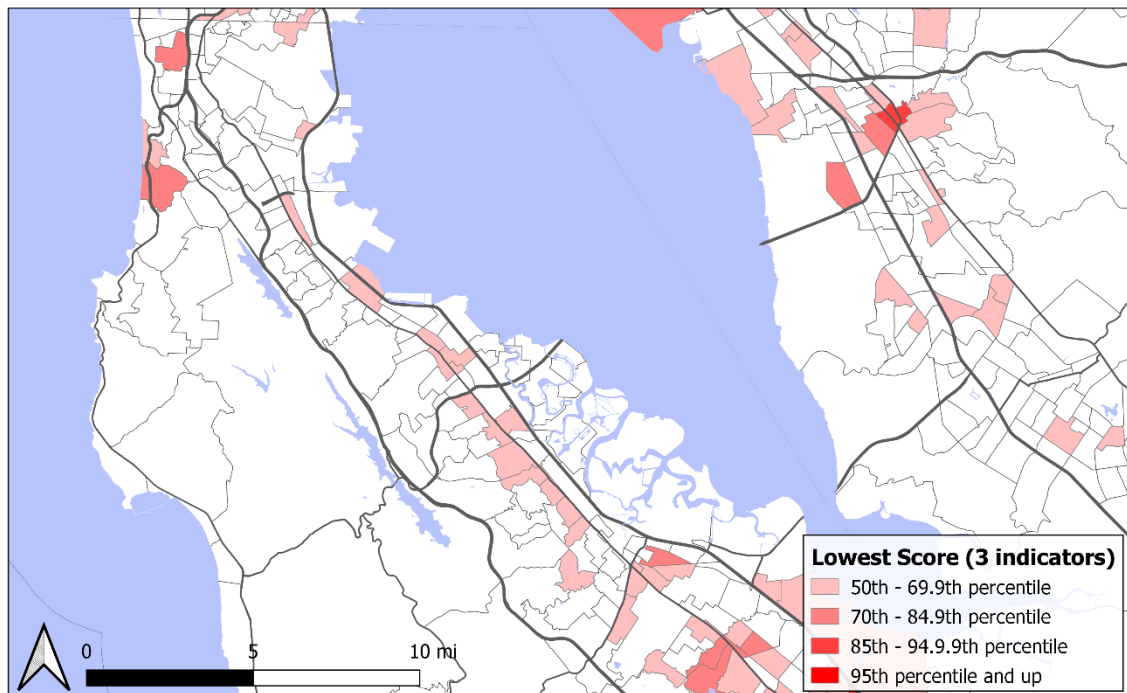
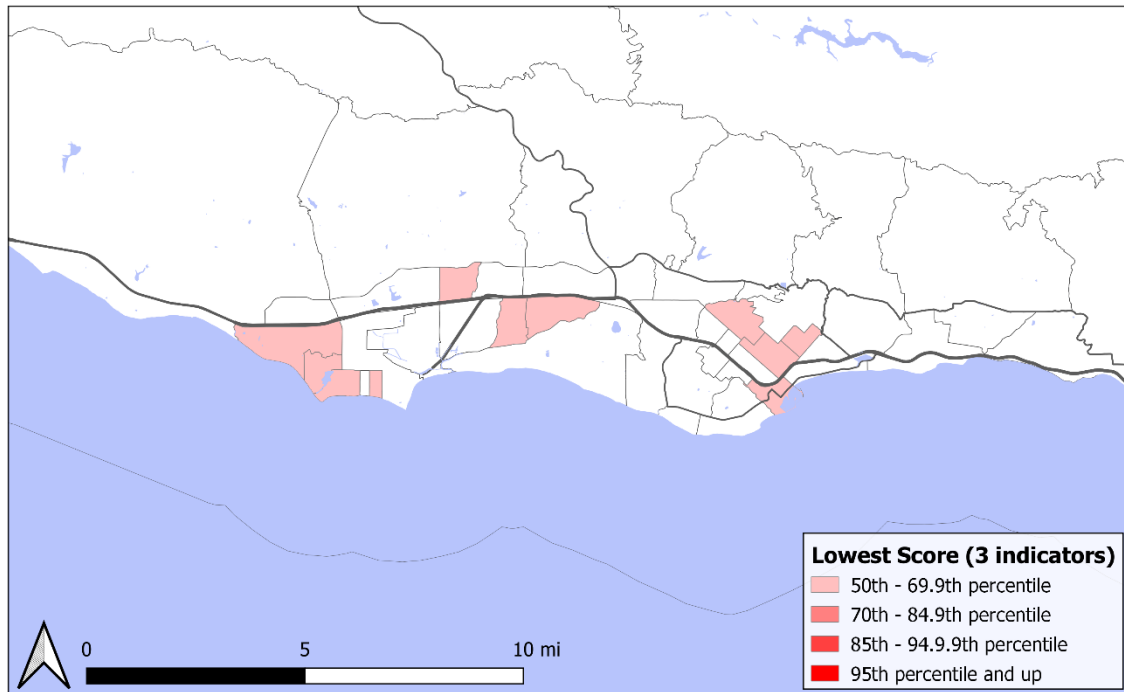


Figure 35: Three-Indicator Approach to Micromobility Viability for Santa Barbara

The above maps are developed solely using variables that are available for any location in California or elsewhere in the United States. We note that this is an advantage. The maps of predicted dockless scooter trip generation (Figures 9, 11, 13, 15, 17, 19, 21, 23, and 25) and of the three indicator approach (Figures 27-35) can be constructed from publicly available data for any location, without requiring data on unique local circumstances. As such, the advantage of the approach shown above is that it can be applied anywhere, with public data. Yet we note that because the maps highlight locations with land uses that are correlated with scooter trip generation (predicted scooter trips) or those land uses combined with small blocks and low speed limits (the three indicator approach) without local knowledge, some of the highlighted areas will be places that do not have much actual dockless scooter travel and that may not be good locations for such travel. The maps above should be used as a filtering approach, highlighting locations that might warrant further examination based on local knowledge either as locations for micromobility or more generally for non-automobile travel initiatives and infrastructure. Such a screening approach should be combined with local knowledge, on, e.g., elevation or street surface quality that might influence would-be micromobility users' mode decisions, or a broad variety of other factors. A knowledgeable planner would likely possess additional information on where short trips happen, as opposed to merely knowing where there are land uses *associated* with short trip and scooter trip generation – information that at the local scale is likely more valuable than our prediction exercise in determining the extent to which scooters may be able to provide mobility within that place.

The Importance of Local Knowledge

In thinking about the maps as a screening tool, we note that the locations with high predicted scooter trip generations include locations that might be ripe for micromobility or other short-distance non-

automobile travel and other locations that are less ripe for such interventions. We discuss two maps to illustrate both patterns.

In Figure 21, San Jose and nearby locations in Santa Clara County, the map indicates high frequencies of predicted dockless scooter trips along much of the SR-17/I-880 corridor, including in Los Gatos, Campbell, near Valley Fair Mall, Downtown San Jose, and areas of North San Jose. Downtown Los Gatos and Downtown Campbell each have strip mall or promenade style developments that include work, shopping, and dining opportunities in close proximity with street-facing entrances, which may well lend these environments to high scooter use potential. As well, Downtown San Jose has job density, ground-floor retail and dining, various bars and nightclubs, low-speed streets with wide sidewalks, and a major university – all of which facilitate both short trip generation and scooter trip generation. Our three-indicator predictor map for the area, Figure 33, also reflects this.

By comparison, the Pruneyard and Valley Fair Mall areas of Campbell and San Jose, also indicated as areas of high predicted scooter trip generations in Figure 21, are car-oriented shopping centers. Our predictions likely suggest a high propensity for scooter trips in these areas due to a high concentration of recreation and eating establishments in each. However, the car-oriented streetscape and plaza and enclosed mall nature of dining and shopping opportunities make these less conducive to scooter travel.

Finally, the Golden Triangle of North San Jose and the area surrounding San Jose International Airport show high values for predicted scooter trips in Figures 21 and 33, likely due to the high employment density in these areas. However, the limited amount of mixed-use development in these areas; related fragmentation between commercial, recreation, and dining establishments; and campus-style commercial developments make these environments less likely to be conducive for short trips made via scooter. Similarly, the Whisman Station and Middlefield Road corridor areas of Mountain View are shown to have high potential for dockless scooter use in Figure 33, though these results are most certainly due to the high employment density in the area and the streetscape and single-use nature of development is unlikely to facilitate high dockless scooter use. By comparison, in Figure 21, Downtown Mountain View is shown to have heightened potential of dockless use, whereas the adjacent business districts are not – a prediction that is more aligned with what we'd anticipate.

In short, the approach we use to identify predicted scooter trip generations is sensitive to employment and activity densities. In some cases, those locations are the locations where short-distance, non-car travel may be possible. In other locations – campus-oriented suburban employment centers or indoor shopping malls – those locations are not necessarily conducive to micromobility but, possibly with careful planning and retrofitting, might over time be transformed into more mixed-use, amenity rich locations that might be suitable for non-car short-trip travel.

Figure 11, Orange County, illustrates the same patterns. The Irvine Business Complex, which is the census block group abutting and to the south of Interstate 55, has a high value for predicted scooter trip generation. That area is home to John Wayne Airport, and is mostly a commercial office park with some older industrial and manufacturing land uses. The arterial streets are wide (often six-lanes or more) and the area is not inviting for scooter or micromobility travel. That area has high predicted dockless trips likely in large part due to the high employment densities in that area. The Irvine Business Complex is the heart of the second largest employment sub-center in Southern California. The predicted scooter trip approach will pick up large suburban office parks that might not, at this time, be conducive to short-trip, non-car mobility. Yet we note that the City of Irvine has for years had a goal to foster new multi-family

housing in the Irvine Business Complex, as part of a strategy to transform that job-rich area into a more mixed-use locale. The predicted scooter trip approach might in part highlight locations which, while not conducive to micromobility today, could be targets for long-term micromobility planning in the future. Additionally, Figure 11 (predicted scooter trips in Orange County) and Figure 28 (the three-indicator approach for Orange County) both show high values for the University of California, Irvine campus and for activity-rich beach locations in Newport Beach, Huntington Beach, and Seal Beach – all of which are locations conducive to micromobility travel.

We note that the maps highlight many locations where micromobility is popular or could be popular. For example, Figure 13, predicted scooter trips in Los Angeles County, highlights downtown, large parts of the Wilshire corridor, and beach communities from Santa Monica south. All of those locations are either current areas where micromobility is popular (based on anecdotal and press accounts) or locations where micromobility is likely to be successful. On net, we emphasize that the maps for both the predicted scooter trip generation and the three-indicator approach have promise as an initial screening technique, to be used in conjunction with more detailed local knowledge.

SECTION VI: Conclusions and Planning and Policy Considerations

In this research, we examined how land use variables are related to dockless scooter trip generation. There are a few studies which have built similar regression models, but this research is the first to our knowledge to use only data that can be easily obtained from public data sources for any city in the U.S. The advantage of such an approach is that it allows quick learning from the few locations that currently report dockless trip generations publicly.

We downloaded publicly available dockless scooter trip generation data for the cities of Austin, TX, Louisville, KY, and Minneapolis, MN, and built regression models of block group scooter trip generations for Louisville and Minneapolis. The regression models showed that scooter trip generations are positively associated with employment density, the density of bars and clubs, and negatively related to distance from downtown. The association between scooter trip generations and the density of eating establishments was only positive in Tobit regressions, and the association between scooter trip generations and the density of university buildings was positive in Minneapolis but not in Louisville.

We compared predicted scooter trip generations, out of sample, to actual scooter trip generations, using data at the census tract level for Austin. We found that the Minneapolis model correctly identified over 60 percent of tracts in the top 75th percentile of scooter trip generation or above as tracts with high trip generation.

The Minneapolis model was used to predict scooter trip generations at the census tract level throughout California, and we present maps for major cities throughout the state. Those maps show predicted scooter trips (which are areas with high values for land use correlates of scooter trip generations) and a three-indicator approach that shows tracts that score highly on all three of predicted scooter trips, small block sizes, and low street speed limits. We suggest that method has promise as an initial screening approach to identify possible locations where non-car short-trip modes might have potential. We note that such a screening approach should be combined with deep local knowledge of a location. The predicted scooter trip generation and three-indicator approaches highlight locations that include both

places that are likely attractive locations for micromobility and places with high employment densities that are auto-oriented, such as office parks or indoor malls.

Overall, we find that the land use determinants of dockless scooter trip generation conform well to intuition and theory and are largely stable across regression specifications. Going forward, we suggest that combining results of this research with local knowledge about specific locations can help identify places where supportive infrastructure and policy can encourage shifts of short trips from automobile to non-automobile and micromobility modes.

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Data Management Plan

Products of Research

Our research relied on the use of data on dockless scooter trips, population, employment, commercial establishments, travel surveys, and land area (for density measurements). These data came from municipalities that collect and publicly share commercial dockless scooter trip data, OpenStreetMap, various United States Census Bureau products, and the National Household Travel Survey of 2017. See Sections III and IV of our report for more information.

Data Format and Content

The raw data that were collected are provided in Excel compatible comma separated (CSV) format.

Data Access and Sharing

The data have been deposited into the Dataverse repository. Files include:

Variable names and variable descriptions, in file “2020.12.21 Data Description v.1a.”

Files with data for the Louisville regression, the Minneapolis regression, the Austin analysis, the California predictions, the urban form variables used for the 3-indicator method in California. The short trip data, aggregated to census tracts for California, is based on geographic detail that is not publicly available, and hence those data are not shared as part of the DMP. All remaining data in the DMP are aggregated to a geography that ensures anonymity and confidentiality of individual users and single trips.

Link to data on Dataverse: <https://doi.org/10.7910/DVN/B2LJSB>

Reuse and Redistribution

Data provided as part of this DMP are from data sources that were publicly available at the time of this report.

Data Sources

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