To: SCDOT

From: Alta Planning + Design

Date: November 15, 2024

Re: SCDOT Regional Bike/Ped Demand Analysis: CMCOG and LSCOG

Estimating Demand

Overview

Several datasets were used to assess both existing and suppressed demand for (non-motorized) active transportation. The evaluation of suppressed demand, known as *latent demand,* comprises trips that are not or cannot be taken because a key factor—like safe, comfortable, and connected infrastructure—is missing. Measuring suppressed demand is incredibly important to understanding the overall potential for active transportation to meet daily travel needs.

By creating a composite heat map that considers both the location of (a) trip *producers*, such as where people live, and (b) trip *attractors*, such as work, schools and retail establishments where people learn and play, it is possible to develop a generalized picture of existing and latent demand across area region. Our team also utilized SCDOT provided StreetLight Data's estimates of modal volumes to create a blended index of where location-based services data indicate existing bicycle and pedestrian activity. The resulting, generalized picture of active travel demand can be used on its own or combined with other existing conditions data to identify critically important network gaps along existing transportation desire lines.

Methodology

The team estimated the latent travel demand for both walking and biking within the regional study areas using five (5) variables (shown in **Table 1**) that collectively describe current behavior and suitable conditions for walking or biking trips. The variables chosen can be used to estimate demand for both modes: walking and bicycling at once. The variables are grouped into the following categories:

- **StreetLight 2021 estimates of existing modal volumes,** used to show relative importance of corridors based on existing trips from mobile trace data.
- **Proximity to trip attractors and generators**, like schools, parks, and denser residential areas.
- **Household characteristics,** like those with limited access to vehicles.

Data for these variables was provided by SCDOT (as in the case of StreetLight data) or pulled from national standardized databases, see **Table 1**.

Figure 1 illustrates the overall scoring process, from assembling the study area unit of analysis and data to computing final walk and bike scores. Details on variable sources, notes and assumptions are found in **Table 1**.

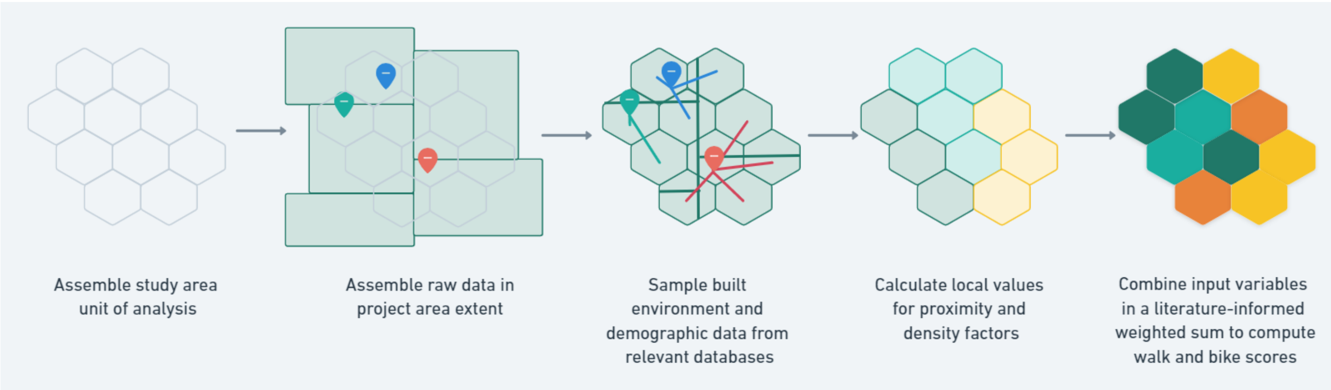

Figure 1. Scoring Process

Each indicator is associated with the H3 size 9 hexagonal grid using one of the ArcGIS geospatial techniques described below:

- **Proportional average**: Data is aggregated based on the average value of the underlying data within each hex grid cell, weighted by percent coverage.
- **Proximity**: Data is aggregated based on the Euclidean (straight-line) distance from the centroid of the hex grid to the nearest feature.

After the score for each indicator has been associated with the hex grid, scores are percentile ranked and normalized so all scores range from 0–1. Proximity measures are scored based on the distance in miles according to the classifications in **Table 2**, shown at the end of this memo**.**

A local, composited demand index score for each hex grid cell is calculated through the application of equal weights to variables shown in **Table 1**. Higher values indicate more demand for walking or biking, and lower scores indicate less demand for walking and biking. Since five variables are used, each with a maximum point value of 1, the highest Demand Index value within the region could be a score of five (5). As mentioned previously, the results of the analysis are unique to each region, meaning analysis results from two independent geographies may not be directly comparable. Comparisons of scores should be made within each region, not between them.

Table 1. Data Inputs and Assumptions

Variable	Source	Spatial Treatment	Notes and Assumptions
Daily Total Trips (Bicycle + Pedestrian)	StreetLight data, 2021	Assigned to SCDOT LRS road network	Low volumes overall, especially for bicycle mode. Used with caution to provide relative importance of different corridors. Assigned a points value based on highest volume in the hexagon or near the hexagon in a grouping of high, medium-high, medium-low, low or none. This is the only variable in the analysis evaluating a mobile trace derived proxy of existing behavior. Final variable: MAX_stL2atla_adtPB, MAX_stLatla_adtPB_PCT_SCR, StL_Score
Population Density	Smart Location Database, (EPA, 2021), D1b Gross population density on unprotected land	Proportional average	Persons per acre: higher density relates with higher potential for walking or biking. The current vintage Smart Location Database metric for population density on unprotected land is based on ACS five-year summary estimates (2013-2018). The project team does not expect land use patterns to have changed overly drastically since this time, and the value of having protected lands removed is important in this analysis. Relevant GIS variables: Mean_d1_b, Mean_d1_b_PCT_SCR
Percent Zero Vehicle Households	U.S. Census ACS five year summary estimates (2018-2022) at block group level.	Proportional average	Percent of zero-car households in the census block group. Households without vehicles available are more likely to walk or bike for their primary trip mode. Relevant GIS variables: Mean_acs22_per_zero_veh_hh; Mean_acs22_per_zero_veh_hh_PCT_SCR
Proximity to Parks	Overture Data, downloaded November 2024	Proximity from demand surface centroid to nearest feature	Locations listed as parks or exercise facilities in Overture land use. These serve as trip generators and may increase trip-making activity in the vicinity. Calculated distance in miles, relevant GIS variables: Park_NEAR_DIST, PARK_NEAR_DIST_W_SCR
Proximity to Schools	Homeland Infrastructure Foundation-Level Data (HIFLD) (2023)	Proximity from demand surface edge to nearest feature (Geoprocessing Near)	Centroid points of public and private elementary and secondary school campuses for the 2022-2023 school year. These serve as trip generators and may increase trip-making activity in the vicinity. Calculated distance in miles, relevant GIS variables: School_NEAR_DIST, School_NEAR_DIST_W_SCR

The proximity bands outlined in **Table 2** are informed by typical walking and biking trip distances, as observed in the 2017 National Household Travel Survey (ORNL, n.d.). In general, both walking and biking mode shares decline with increasing trip distances, but the shapes and thresholds are different for each form of active transportation. For this analysis, only walking proximity bands were used to determine a distance point value, as walking provides a more focused estimate of demand.

Table 2. Walking and Biking Proximity Bands

Walking Proximity Bands	Points
< 1/8th mile (0.125)	1
1/8th – 1/4th mile	0.9
1/4th – 1/2 mile	0.6
1/2 – 3/4th mile	0.3
3/4th – 1 mile	0.1
> 1 mile	0

Biking Proximity Bands	Points
< 1/4th mile	0.85
1/4th – 1 mile	1
1 – 2 miles	0.75
2 – 3 miles	0.5
3 – 6 miles	0.25
> 6 miles	0

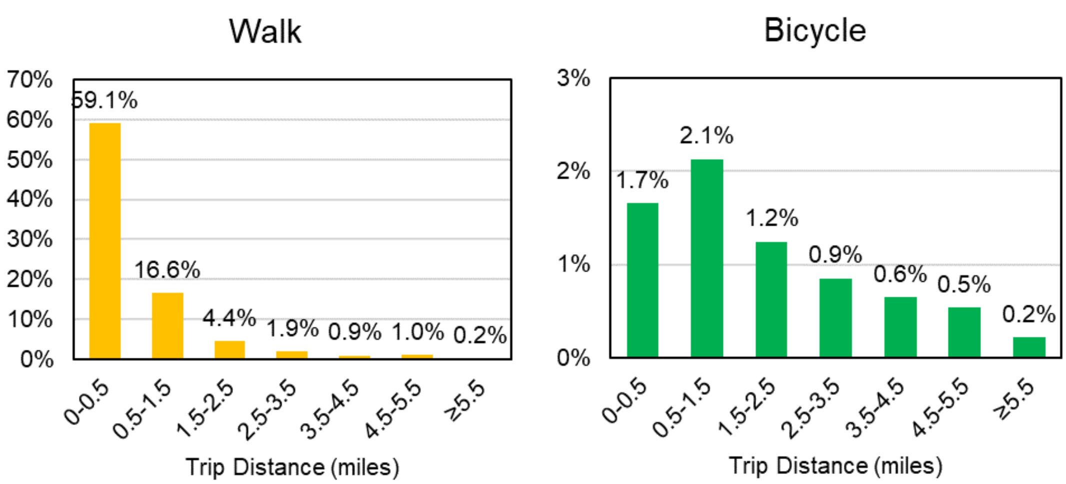

Figure 1. US Mode Shares for Walking (left) and Bicycling (right) by Trip Distance, 2017 National Household Travel Survey Estimated Person Trips (ORNL, n.d.)

To allow for a better generalization of the volumes, the percentile ranked scores were then grouped into none, low, medium-low, medium-high, and high. For CMCOG these groupings equated to percentiles of 0, more than 0 but less than 0.235; 0.235 – 0.5; 0.5 to 0.75; and greater than or equal to 0.75. For LSCOG, percentiles of 0, more than 0 but less than 0.25; 0.25 – 0.5; 0.5 to 0.75; and greater than or equal to 0.75. Each grouping received 0, 0.25, 0.5, 0.75 or 1 points respectively.

Overture points of interest were narrowed to parks using the following key words: sanctuary, landmark, field, park, camp, gym, stadium, lake, campground, martial, sports, river, cabin, beach, rink, equestrian, track. Then reviewed, and further narrowed when something like “sports bar” was still in the dataset. This data has been downloaded for all of South Carolina, so that a similar process could be replicated for other regions.

Limitations

This methodology is informed by key pieces of literature across the US and internationally to inform the considerations for this analysis, but it does have the following limitations:

- The results are a relative index rather than an absolute estimate of trips that can be unlocked.
- The index does not consider all potentially relevant factors to existing and latent travel demand, such as weather, slopes, and barriers to bicycle and pedestrian activity.
- The analysis is subject to edge effects from the sampling of census geographies and vintage of the different datasets.
- This index is combining StreetLight Data’s measure of existing trip taking behavior by pedestrians and cyclists with other latent measures to provide a comprehensive view of possible bicycle and pedestrian activity. These existing trips are possibly subject to error due to low sample sizes in mobile trace data used to derive them. Additionally, the existing demand data are influenced by existing barriers to active travel and should be considered alongside the latent travel demand measures.

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