# SMART LOCATION DATABASE

# TECHNICAL DOCUMENTATION AND USER GUIDE

Version 3.0

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## **About This Report**

The Smart Location Database is a publicly available data product and service provided by the <u>U.S. EPA</u> <u>Smart Growth Program</u>. This version 3.0 documentation builds on, and updates where needed, the version 2.0 document.<sup>1</sup> Urban Design 4 Health, Inc. updated this guide for the project called *Updating the EPA GSA Smart Location Database*.

## Acknowledgements

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<sup>&</sup>lt;sup>1</sup>Smart Location Database: Version 2.0 User Guide, U.S. EPA, 2014.

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## Background

The U.S. Environmental Protection Agency's (EPA) and U.S. General Services Administration (GSA) Smart Location Database (SLD) addresses the growing demand for data products and tools that consistently compare the location efficiency of various places. The SLD summarizes several demographic, employment, and built environment variables for every Census block group (CBG) in the United States.<sup>2</sup> The database includes indicators of the commonly cited "D"<sup>3</sup> variables shown in the transportation research literature to be related to travel behavior.<sup>4</sup> The Ds include residential and employment *density*, land use *diversity*, *design* of the built environment, access to *destinations*, and *distance* to transit. SLD variables can be used as inputs to travel demand models, baseline data for scenario planning studies, and combined into composite indicators characterizing the relative location efficiency of CBG within U.S. metropolitan regions.

Previous versions of the SLD (version 1.0) were released by the EPA in early 2012 and again in 2014 (version 2.0). This guide describes a new version of the SLD (version 3.0, herein referred to as the SLD). The 2021 update features the most recent geographic boundaries (2019 CBGs) and new and expanded sources of data used to calculate variables. Entirely new variables have been added and the methods used to calculate some of the SLD variables have changed. Although the majority of SLD variables are consistent in the data source and calculation method to previous versions, it may not be appropriate to compare all variables with version 2.0 directly. Changes in data sources and methods are explained in detail in this guide.

Version 3.0 of the SLD was developed by Urban Design 4 Health for the EPA Office of Community Revitalization and the GSA Center for Urban Development. This guide contains a detailed description of the data sources and methodologies used to calculate each of the variables included in the SLD. It also reviews any known geographic or data limitations associated with variables in the SLD.

## **Accessing the Smart Location Database**

The SLD is a free resource available to the public for download, web service, or viewing online.

Download: The SLD can be downloaded as a file geodatabase from this page: <u>https://www.epa.gov/smartgrowth/smart-location-mapping#sld</u>

Web service: The SLD is available as a map service, JSON, SOAP, and KML. See the <u>SLD web</u> service<sup>5</sup> for details: <u>https://geodata.epa.gov/ArcGIS/rest/services/OA/SmartLocationDatabase/MapServer</u>

Viewing online: Visit <u>https://www.epa.gov/smartgrowth/smart-location-mapping#sld</u> to open the <u>map viewer</u>.

<sup>&</sup>lt;sup>2</sup> SLD version 3.0 uses 2018 Census TIGER/Line polygons for defining block group boundaries.

<sup>&</sup>lt;sup>3</sup> Cervero, R. & Kockelman. 1997. Travel Demand and the 3Ds: Density, Diversity, and Design. *Transportation Research Part D. 2* (3): 199-219.

<sup>&</sup>lt;sup>4</sup> Ewing, R. & Cervero, R. 2001. Travel and the Built Environment: A Synthesis. *Transportation Research Record, 1780*(1), 87-114; Ewing, R & Cervero, R. 2010. Travel and the Built Environment: A Meta-Analysis. Journal of the American Planning Association, 76(3), 265-294; Kuzmyak, J.R., Pratt, R.H., Douglas, G.B., Spielberg, F. (2003). Land Use and Site Design - Traveler Response to Transportation System Changes. Transit Cooperative Research Program (TCRP) Report 95: Chapter 15, published by Transportation Research Board, Washington.

## **Smart Location Database Measures**

Table 1 lists all of the variables available in the SLD. SLD variables are sorted by topic areas and start with administrative identifiers, geometric area characteristics and demographic and employment base data gathered from the U.S. Census. There are five main domains for calculated measures in the SLD: 1) Density (D1), 2) Diversity (D2), 3) Design (D3), 4) Transit Accessibility (D4) and 5) Destination Accessibility (D5). Identical field names from version 2.0 were retained for consistency. The few variables new to version 3.0 maintain the same naming convention. SLD variable names are identified using square brackets (e.g. [D3b]), except when referred to in formula text, tables, header titles, discussing prefix or suffix components, or field name prefixes are used to relate to multiple variables. The sections that follow describe the data sources and the technical approach used to calculate the measures in further detail.

	······································		
Field Name	Description	Data Source	Geographic
Administrativo			Coverage*
GEOID10	Census block group 12-digit EIPS code (2010)	2010 Census TIGER/Line	50 States PR OT
GEOID10	Census block group 12-digit FIPS code (2010)	2010 Census TIGER/Line	50 States PR OT
STATEFP	State FIPS code	2019 Census TIGER/Line	50 States PR OT
COUNTVEP	County FIPS code	2019 Census TIGER/Line	50 States PR OT
	Census tract EIPS code in which CBG resides	2019 Census TIGER/Line	50 States PR OT
BLKGRPCE	Census block group FIPS code in which CBG resides	2019 Census TIGER/Line	50 States PR OT
CSA	Combined Statistical Area (CSA) Code	US Census	50 States PR OT
CSA Name	Name of CSA in which CBG resides	US Census	50 States PR OT
	FIPS for Core-Based Statistical Area (CBSA) in which	US Census	50 States PR OT
CD5A	CBG resides	05 Celisus	50 States, 1 K, 01
CBSA Name	Name of CBSA in which CBG resides	US Census	50 States PR OT
Core-Based Statis	stical Area Measures	00 001545	20 54405, 110, 01
CBSA Pop	Total population in CBSA	2018 US Census ACS (5-Year	50 States, PR
obori_i op		Estimate)	00 2000,110
CBSA Emp	Total employment in CBSA	2017 Census LEHD.	50 States, PR
CBSA Wrk	Total number of workers that live in CBSA	2017 Census LEHD.	50 States, PR
Area		,	1
Ac Total	Total geometric area (acres) of the CBG	2019 Census TIGER/Line	50 States, PR, OT
Ac Water	Total water area (acres)	Census, 2018 HERE Maps	50 States, PR, OT
_		NAVTREETS, HERE Maps	
		Water & Oceans, 2018 USGS	
		PAD-US, USGS National	
		Hydrography Data Plus	
Ac_Land	Total land area (acres)	Census, 2018 HERE Maps	50 States, PR, OT
		NAVTREETS, HERE Maps	
		Water & Oceans, 2018 USGS	
		PAD-US, USGS National	
		Hydrography Data Plus	
Ac_Unpr	Total land area (acres) that is not protected from	Census, 2018 HERE Maps	50 States, PR, OT
	development (i.e., not a park, natural area or conservation	NAVTREETS, HERE Maps	
	area)	Parks, 2018 USGS PAD-US,	
		USGS National Hydrography	
Domographies		Data Plus	
TotPor	Domulation 2018	2018 Congue ACS (5 Veer	50 States DR OT
Totrop	Population, 2018	Estimate) 2010 Decennial	JU States, FK, UI
		Census (OT only)	
CountHU	Housing units 2018	2018 Census ACS (5-Vear	50 States PR OT
Countilo	Trousing units, 2018	Estimate) 2010 Decennial	50 States, 1 K, 01
		Census (OT only)	
нн	Households (occupied housing units) 2018	2018 Census ACS (5-Year	50 States PR OT
	reasenous (occupies nousing units), 2010	Estimate), 2010 Decennial	20 54400, 110, 01
		Census (OT only)	
P WrkAge	Percent of population that is working aged 18 to 64 years.	2018 Census ACS (5-Year	50 States, PR

*Table 1: Description, data source and geographic coverage of all SLD measures.* 

Field Name	Description	Data Source	Geographic	
	2018	Estimate)	Coverage*	
AutoOwn0	Number of households in CBG that own zero automobiles, 2018	2018 Census ACS (5-Year Estimate)	50 States, PR	
Pct_AO0	Percent of zero-car households in CBG, 2018	2018 Census ACS (5-Year Estimate)	50 States, PR	
AutoOwn1	Number of households in CBG that own one automobile, 2018	2018 Census ACS (5-Year Estimate)	50 States, PR	
Pct_AO1	Percent of one-car households in CBG, 2018	2018 Census ACS (5-Year Estimate)	50 States, PR	
AutoOwn2p	Number of households in CBG that own two or more automobiles, 2018	2018 Census ACS (5-Year Estimate)	50 States, PR	
Pct_AO2p	Percent of two-plus-car households in CBG, 2018	2018 Census ACS (5-Year Estimate)	50 States, PR	
Workers	Count of workers in CBG (home location), 2017	2017 Census LEHD RAC	50 States	
R_LowWageWk	Count of workers earning \$1250/month or less (home location), 2017	2017 Census LEHD RAC	50 States	
R_MedWageWk	Count of workers earning more than \$1250/month but less than \$3333/month (home location), 2017	2017 Census LEHD RAC	50 States	
R_HiWageWk	Count of workers earning \$3333/month or more (home location), 2017	2017 Census LEHD RAC	50 States	
R_PctLowWage	Percent of low wage workers in a CBG (home location), 2017	50 States		
Employment				
TotEmp	Total employment, 2017	2017 Census LEHD WAC	50 States	
E5_Ret	Retail jobs within a 5-tier employment classification scheme (LEHD: CNS07), 2017	2017 Census LEHD WAC	50 States	
E5_Off	Office jobs within a 5-tier employment classification scheme (LEHD: CNS09 + CNS10 + CNS11 + CNS13 + CNS20), 2017	2017 Census LEHD WAC	50 States	
E5_Ind	Industrial jobs within a 5-tier employment classification scheme (LEHD: CNS01 + CNS02 + CNS03 + CNS04 + CNS05 + CNS06 + CNS08), 2017	2017 Census LEHD WAC	50 States	
E5_Svc	Service jobs within a 5-tier employment classification scheme (LEHD: CNS12 + CNS14 + CNS15 + CNS16 + CNS19), 2017	2017 Census LEHD WAC	50 States	
E5_Ent	Entertainment jobs within a 5-tier employment classification scheme (LEHD: CNS17 + CNS18), 2017	2017 Census LEHD WAC	50 States	
E8_Ret	Retail jobs within an 8-tier employment classification scheme (LEHD: CNS07), 2017	2017 Census LEHD WAC	50 States	
E8_Off	Office jobs within an 8-tier employment classification scheme (LEHD: CNS09 + CNS10 + CNS11 + CNS13), 2017	2017 Census LEHD WAC	50 States	
E8_Ind	Industrial jobs within an 8-tier employment classification scheme (LEHD: CNS01 + CNS02 + CNS03 + CNS04 + CNS05 + CNS06 + CNS08), 2017	2017 Census LEHD WAC	50 States	
E8_Svc	Service jobs within an 8-tier employment classification scheme (LEHD: CNS12 + CNS14 + CNS19), 2017	2017 Census LEHD WAC	50 States	
E8_Ent	Entertainment jobs within an 8-tier employment classification scheme (LEHD: CNS17 + CNS18), 2017	2017 Census LEHD WAC	50 States	
E8_Ed	Education jobs within an 8-tier employment classification scheme (LEHD: CNS15), 2017	2017 Census LEHD WAC	50 States	
E8_Hlth	Health care jobs within an 8-tier employment     2017 Census LEHD WAC     50 Stat       classification scheme (LEHD: CNS16) 2017     2017     2017 Census LEHD WAC			
E8_Pub	Public administration jobs within an 8-tier employment classification scheme (LEHD: CNS20), 2017	2017 Census LEHD WAC	50 States	
E_LowWageWk	# of workers earning \$1250/month or less (work location), 2017	2017 Census LEHD WAC	50 States	
E_MedWageWk	# of workers earning more than \$1250/month but less than \$3333/month (work location), 2017	2017 Census LEHD WAC	50 States	
E HiWageWk	# of workers earning \$3333/month or more (work	2017 Census LEHD WAC	50 States	

Field Name	Description	Data Source	Geographic
	location) 2017		Coverage*
E_PctLowWage	% LowWageWk of total #workers in a CBG (work	2017 Census LEHD WAC	50 States
Density (D1)	location), 2017		
Dla	Gross residential density (HU/acre) on unprotected land	Derived from other SLD	50 States, PR, OT
D1b	Gross population density (people/acre) on unprotected	Derived from other SLD variables	50 States, PR, OT
D1c	Gross employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c5_Ret	Gross retail (5-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c5_Off	Gross office (5-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c5_Ind	Gross industrial (5-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c5_Svc	Gross service (5-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c5_Ent	Gross entertainment (5-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Ret	Gross retail (8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Off	Gross office (8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Ind	Gross industrial (8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Svc	Gross service (8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Ent	Gross entertainment (8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Ed	Gross education(8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Hlth	Gross health care (8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1c8_Pub	Gross retail (8-tier) employment density (jobs/acre) on unprotected land	Derived from other SLD variables	50 States
D1d	Gross activity density (employment + HUs) on unprotected land	Derived from other SLD variables	50 States (employment and housing), PR (housing only), OT (housing only)
D1_Flag	Flag indicating that density metrics are based on total CBG land acreage rather than unprotected acreage	Derived from other SLD variables	50 States, PR, OT
Diversity (D2)			<b>5</b> 0 <b>2</b>
D2a_JpHH	Jobs per household	Derived from other SLD variables	50 States
D2b_E5Mix	5-tier employment entropy (denominator set to observed employment types in the CBG)	Derived from other SLD variables	50 States
D2b_E5MixA	5-tier employment entropy (denominator set to the static 5 employment types in the CBG)	Derived from other SLD variables	50 States
D2b_E8Mix	8-tier employment entropy (denominator set to observed employment types in the CBG)	Derived from other SLD variables	50 States
D2b_E8MixA	8-tier employment entropy (denominator set to the static 8 employment types in the CBG)	Derived from other SLD variables	50 States
D2a_EpHHm	Employment and household entropy	Derived from other SLD variables	50 States, PR (housing only), OT (housing only)
D2c_TrpMx1	Employment and Household entropy (based on vehicle trip production and trip attractions including all 5 employment categories)	Derived from other SLD variables	50 States, PR (housing only), OT (housing only)

Field Name	Description	Data Source	Geographic Coverage*
D2c_TrpMx2	Employment and Household Entropy calculations, based on trips production and trip attractions including 4 of the 5 employment categories (excluding industrial)	Derived from other SLD variables	50 States, PR (housing only), OT (housing only)
D2c_TripEq	Trip productions and trip attractions equilibrium index; the closer to one, the more balanced the trip making	Derived from other SLD variables	50 States
D2r_JobPop	Regional Diversity. Standard calculation based on population and total employment: Deviation of CBG ratio of jobs/pop from the regional average ratio of jobs/pop	Derived from other SLD variables	50 States, PR (housing only)
D2r_WrkEmp	Household Workers per Job, as compared to the region: Deviation of CBG ratio of household workers/job from regional average ratio of household workers/job	Derived from other SLD variables	50 States
D2a_WrkEmp	Household Workers per Job, by CBG	Derived from other SLD variables	50 States
D2c_WrEmIx	Household Workers per Job Equilibrium Index; the closer to one the more balanced the resident workers and jobs in the CBG.	Derived from other SLD variables	50 States
Design (D3)			
D3a	Total road network density	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3aao	Network density in terms of facility miles of auto-oriented links per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3amm	Network density in terms of facility miles of multi-modal links per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3apo	Network density in terms of facility miles of pedestrian- oriented links per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3b	Street intersection density (weighted, auto-oriented intersections eliminated)	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3bao	Intersection density in terms of auto-oriented intersections per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3bmm3	Intersection density in terms of multi-modal intersections having three legs per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3bmm4	Intersection density in terms of multi-modal intersections having four or more legs per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3bpo3	Intersection density in terms of pedestrian-oriented intersections having three legs per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
D3bpo4	Intersection density in terms of pedestrian-oriented intersections having four or more less per square mile	2018 HERE Maps NAVSTREETS	50 States, PR, VI
Transit Access (D	4)		
D4a	Distance from the population-weighted centroid to nearest transit stop (meters)	2020 GTFS, 2020 CTOD	50 States (participating GTFS transit service areas) PR
D4b025	Proportion of CBG employment within <sup>1</sup> / <sub>4</sub> mile of fixed- guideway transit stop	2020 GTFS, 2020 CTOD, 2018 USGS PAD-US, SLD unprotected area polygons	50 States, PR
D4b050	Proportion of CBG employment within <sup>1</sup> / <sub>2</sub> mile of fixed- guideway transit stop	2020 GTFS, 2020 CTOD, 2018 USGS PAD-US	50 States, PR
D4c	Aggregate frequency of transit service within 0.25 miles of CBG boundary per hour during evening peak period	2020 GTFS	50 States (participating GTFS transit service areas)
D4d	Aggregate frequency of transit service [D4c] per square mile	Derived from other SLD variables	50 States (participating GTFS transit service areas)
D4e	Aggregate frequency of transit service [D4c] per capita	Derived from other SLD variables	50 States (participating GTFS transit service areas)
Destination Acces	sibility (D5)	L	

Field Name	Description	Data Source	Geographic Coverage*
D5ar	Jobs within 45 minutes auto travel time, time- decay (network travel time) weighted	2020 TravelTime API, 2017 Census LEHD	50 States
D5ae	Working age population within 45 minutes auto travel time, time-decay (network travel time) weighted	2020 TravelTime API, 2018 Census ACS	50 States
D5br	Jobs within 45-minute transit commute, distance decay (walk network travel time, GTFS schedules) weighted	2020 TravelTime API, 2017 Census LEHD, 2020 GTFS	50 States (participating GTFS transit service areas)
D5be	Working age population within 45-minute transit commute, time decay (walk network travel time, GTFS schedules) weighted	2020 TravelTime API, 2018 Census ACS, 2020 GTFS	50 States (participating GTFS transit service areas)
D5cr	Proportional Accessibility to Regional Destinations - Auto: Employment accessibility expressed as a ratio of total CBSA accessibility	Derived from other SLD variables	50 States
D5cri	Regional Centrality Index – Auto: CBG [D5cr] score relative to max CBSA [D5cr] score	Derived from other SLD variables	50 States
D5ce	Proportional Accessibility to Regional Destinations - Auto: Working age population accessibility expressed as a ratio of total CBSA accessibility	Derived from other SLD variables	50 States
D5cei	Regional Centrality Index – Auto: CBG [D5ce] score relative to max CBSA [D5ce] score	Derived from other SLD variables	50 States
D5dr	Proportional Accessibility of Regional Destinations - Transit: Employment accessibility expressed as a ratio of total MSA accessibility	Derived from other SLD variables	50 States
D5dri	Regional Centrality Index – Transit: CBG [D5dr] score relative to max CBSA [D5dr] score	Derived from other SLD variables	50 States (participating GTFS transit service areas)
D5de	Proportional Accessibility of Regional Destinations - Transit: Working age population accessibility expressed as a ratio of total MSA accessibility	Derived from other SLD variables	50 States (participating GTFS transit service areas)
D5dei	Regional Centrality Index – Transit: CBG [D5de] score relative to max CBSA [D5de] score	Derived from other SLD variables	50 States (participating GTFS transit service areas)
Walkability Index	ζ	1	
D2A_Ranked	Quantile ranked order (1-20) of [D2a_EpHHm] from lowest to highest	Derived from other SLD variables	50 States (participating GTFS transit service areas)
D2B_Ranked	Quantile ranked order (1-20) of [D2b_E8MixA] from lowest to highest	Derived from other SLD variables	50 States (participating GTFS transit service areas)
D3B_Ranked	Quantile ranked order (1-20) of [D3b] from lowest to highest	Derived from other SLD variables	50 States (participating GTFS transit service areas)
D4A_Ranked	Quantile ranked order (1,13-20) <sup>6</sup> of [D4a] from lowest to highest	Derived from other SLD variables	50 States (participating GTFS transit service areas)
NatWalkInd	Walkability index comprised of weighted sum of the ranked values of [D2a_EpHHm] (D2A_Ranked),	Derived from other SLD variables	50 States (participating

<sup>&</sup>lt;sup>6</sup> All CBGs with no transit access were assigned a rank of 1. The remaining CBGs were assigned a rank from 13-20 (n=8 classes) following the same methodology used in the previous version except adding two additional ranks due to an increase in the number of CBGs that now have access to transit.

Field Name	Description	Data Source	Geographic
			Coverage*
	[D2b_E8MixA] (D2B_Ranked), [D3b] (D3B_Ranked) and [D4a] (D4A_Ranked)		GTFS transit

\* Comprises, where stated, the 50 U.S. states including the District of Columbia, Puerto Rico (PR) and the U.S. overseas territories (OT), which include Guam (GU), American Samoa (AS), the Commonwealth of the Northern Mariana Islands (MP) and the U.S. Virgin Islands (VI) (unless otherwise mentioned).

\*\* Two sets of FIPS CBG identifiers are provided for the SLD database. The first is the original 2010 FIPS CBG identifier [GEOID10] and the second is an updated 2019 FIPS CBG identifier [GEOID20]. A total of 74 (0.3%) of FIPS CBG identifiers were changed. Both are required for the database because many base data sources continue to use the 2010 FIPS CBG identifier.

## **Data Sources**

This section summarizes each of the data sources used to develop the SLD. These include:

- Census datasets (TIGER/Line, 2010 Summary File 1, American Community Survey, and Longitudinal Employer-Household Dynamics),
- HERE Maps NAVSTREETS highway/streets, parks and water data,
- U.S. Geological Survey Protected Areas Database of the United States,
- U.S. Geological Survey National Hydrography Data Plus,
- fixed-guideway transit station locations from the Center for Transit-Oriented Development Transit-Oriented Development Database, and
- transit service route and schedule data from various inventories, including TransitFeeds, TransitLand and directly from individual transit authorities shared in the General Transit Feed Specification format.

## **Block Group Boundaries**

CBG polygon geography was acquired from 2019 Census TIGER/Line databases<sup>7</sup> and combined them into a single national ArcGIS (ESRI, Redlands, CA) feature class.<sup>8</sup> *EPA\_SLD\_Database\_V3\_2021* is the core geographic dataset to which all SLD variables were appended. It represents the 2019 geographic boundaries of all CBGs in the contiguous United States, District of Columbia, Alaska, Hawaii, Puerto Rico, the U.S. Virgin Islands, Guam, American Samoa and the Commonwealth of the Northern Mariana Islands.<sup>9</sup> The most recent, publicly available CBG "centers of population"<sup>10</sup> are the same as what was used for version 2.0 of the SLD. These 2010 points were used in geoprocessing routines developed for spatially derived variables, notably the distance to the nearest transit stop and regional accessibility measures.<sup>11</sup> Lastly, tables containing county, Core-Based Statistical Areas and Combined Statistical Areas information were also acquired from the U.S. Census Bureau. These tables were used to associate CBGs with their respective metropolitan areas and micropolitan areas based on county location and were also used to develop some regional diversity measures.

## **Census American Community Survey**

American Community Survey (ACS) Five-Year Estimates (2014-2018) data furnished by the Census Bureau were used for all population, demographic and housing information for the SLD for the 50 States and Puerto Rico.<sup>12</sup> Due to the extended time since the release of version 2.0 of the SLD, ACS

<sup>8</sup> EPA\_SLD\_Database\_GDB\_V3\_UD4H\_Jan\_2021\_Final.gdb: EPA\_SLD\_Database\_V3\_UD4H\_Jan\_2021\_Final.

<sup>9</sup> Not all SLD variables are available for Puerto Rico and other overseas territories of the U.S. due to a lack of base data to calculate the measures.

<sup>&</sup>lt;sup>7</sup> These boundaries closely mirror the 2010 Decennial CBG boundaries used for version 1.0 and 2.0, however, there are some minor changes in geography and CBG FIPS identifiers.

<sup>&</sup>lt;sup>10</sup> <u>Centers of Population</u>, U.S. Census Bureau, 2010.

<sup>&</sup>lt;sup>11</sup> No updated population centers were available in 2020, so the same data used for version 2.0 of the SLD was used for version 3.0 of the SLD. This allows for improved comparability between the different versions of the SLD metrics.

<sup>&</sup>lt;sup>12</sup> ACS block group-level data is not currently acquired for the U.S. overseas territories, thus 2010 Decennial Census information was used, where available for these areas.

data provided more recent socio-demographic estimates compared to the legacy 2010 Decennial Census<sup>13</sup> information used before.

#### Longitudinal Employer-Household Dynamics

Employment information was acquired from the US Census' Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES)<sup>14</sup> database at the CBG level for all 50 states, the District of Columbia and Puerto Rico.<sup>15</sup> LODES version 7 block-level data from 2017<sup>16</sup> were then aggregated to the CBG geography. LODES data is separated by Work Area Characteristics (WAC) tables for employment tabulations and Residence Area Characteristics (RAC), which identifies the home location of workers. LODES data categorizes a range of employment types using the North American Industry Classification System (NAICS).<sup>17</sup> The structures and field definitions of the RAC and WAC datasets are identical and displayed for reference in Table 2.

Position	Variable Name	Туре	Length	Explanation
1	h_geocode	Character	15	Residence/Workplace Census Block Code
2	C000	Numeric	8	Total Number of Jobs
6	CE01	Numeric	8	Number of jobs with earnings \$1250/month or less
7	CE02	Numeric	8	Number of jobs with earnings \$1251/month to \$3333/month
8	CE03	Numeric	8	Number of jobs with earnings greater than \$3333/month
9	CNS01	Numeric	8	Number of jobs in NAICS sector 11 (Agriculture, Forestry, Fishing and
				Hunting)
10	CNS02	Numeric	8	Number of jobs in NAICS sector 21 (Mining, Quarrying, and Oil and Gas
				Extraction)
11	CNS03	Numeric	8	Number of jobs in NAICS sector 22 (Utilities)
12	CNS04	Numeric	8	Number of jobs in NAICS sector 23 (Construction)
13	CNS05	Numeric	8	Number of jobs in NAICS sector 31-33 (Manufacturing)
14	CNS06	Numeric	8	Number of jobs in NAICS sector 42 (Wholesale Trade)
15	CNS07	Numeric	8	Number of jobs in NAICS sector 44-45 (Retail Trade)
16	CNS08	Numeric	8	Number of jobs in NAICS sector 48-49 (Transportation and
				Warehousing)
17	CNS09	Numeric	8	Number of jobs in NAICS sector 51 (Information)
18	CNS10	Numeric	8	Number of jobs in NAICS sector 52 (Finance and Insurance)
19	CNS11	Numeric	8	Number of jobs in NAICS sector 53 (Real Estate and Rental and Leasing)
20	CNS12	Numeric	8	Number of jobs in NAICS sector 54 (Professional, Scientific, and
				Technical Services)
21	CNS13	Numeric	8	Number of jobs in NAICS sector 55 (Management of Companies and
				Enterprises)
				Number of jobs in NAICS sector 56 (Administrative and Support and
22	CNS14	Num	8	Waste Management and Remediation Services)
23	CNS15	Num	8	Number of jobs in NAICS sector 61 (Educational Services)
24	CNS16	Num	8	Number of jobs in NAICS sector 62 (Health Care and Social Assistance)
				Number of jobs in NAICS sector 71 (Arts, Entertainment, and Recreation)
25	CNS17	Num	8	
				Number of jobs in NAICS sector 72 (Accommodation and Food Services)
26	CNS18	Num	8	
				Number of jobs in NAICS sector 81 (Other Services [except Public

Table 2: Summary of LEHD LODES WAC and RAC variables.

<sup>13</sup> <u>2010 Decennial Census</u>, U.S. Census Bureau, 2010.

<sup>14</sup> LEHD LODES, U.S. Census Bureau, 2020.

<sup>15</sup> Unlike for previous versions of the SLD, complete employment information is available for the Commonwealth of Massachusetts, thus no additional data sources from InfoUSA on employment information were required. Employment information used in SLD variables was comprehensively applied to all block groups, which was not the case in previous version of the SLD.

<sup>16</sup> LEHD LODES typically releases block-level employment information on an annual basis and is typically at least one year behind the ACS data releases.

<sup>17</sup> Introduction to the NAICS, North American Industry Classification System, U.S. Census Bureau, 2020.

Position	Variable Name	Туре	Length	Explanation
27	CNS19	Num	8	Administration])
28	CNS20	Num	8	Number of jobs in NAICS sector 92 (Public Administration)

Source: LODES: WAC/RAC, LEHD, U.S. Census Bureau, 2018.

## HERE

EPA maintains a license for the use of the HERE Maps (formerly NAVTEQ) NAVSTREETS<sup>18</sup> road networking data layers. The most recent available version (release date 2018 Q4) of the NAVSTREETS database was utilized to develop network and intersection density measures as part of the Design (D3) SLD metrics. NAVSTREETS is a detailed nationwide street network and road network node database with comprehensive network attribute information. These attributes include network functional class and speed categories, direction of travel restrictions, vehicular and pedestrian restrictions, tags for highway ramps and other variables of interest for developing a multimodal travel network and characterizing network design.

In addition to the NAVSTREETS layer, other HERE Maps North American databases were used to support SLD data development. These supplementary databases include polygon features for water bodies and a park layer, and both are used in area calculations. The HERE water bodies layer was compared with the USGS National Hydrography Dataset and the Census TIGER/Line land and water area measures. The parks layer was compared with the Protected Areas Database for use calculating developable area measures.

## **TravelTime API**

Auto and transit accessibility metrics were generated from a commercial application programming interface (API) data source<sup>19</sup> that maintains road and transit transportation networks for all 50 U.S. states. This data, accessed through the API, provides time-of-day specific travel speeds and travel times, and travel distances by mode or across modes. This data source was used extensively in the development of the destination accessibility (D5) SLD measures, as well as with some of the transit accessibility (D4) variables. This API was used to generate:

- walking travel times between CBG population centers and
- driving travel times between CBGs during the AM peak period
- transit travel times between CBGs during the PM peak period

#### **Protected Areas Database**

The Protected Areas Database (PAD)<sup>20</sup> developed by the U.S. Geological Survey (USGS) is an inventory of public lands' protection status and voluntarily provided private conservation lands in the U.S. The PAD version 2.0, with a public release date of 2018, was used. PAD coverage extends to the 50 states, as well as Puerto Rico and all overseas territories. This database was used to develop the unprotected land area measure which is used as the denominator for many SLD measures, including many Density (D1) variables and some Transit Accessibility (D4measures.

## National Hydrography Data

The National Hydrography Dataset Plus Version  $2^{21}$  is a joint database developed by the USGS and EPA to support geospatial analysis of water resources and catchment areas in the US. Among the various data layers is a polygon dataset of surface water and coastal boundaries. This dataset was used in conjunction with the PAD data and CBG data to determine the acreage of surface water and the unprotected land area.

<sup>&</sup>lt;sup>18</sup> HERE NAVSTREETS, Chicago, IL, 2019.

<sup>&</sup>lt;sup>19</sup> <u>TravelTime API</u>, 2020

<sup>&</sup>lt;sup>20</sup> Gap Analysis Project: Protected Areas Database, USGS, 2018.

<sup>&</sup>lt;sup>21</sup> National Hydrology Data, USGS, 2019.

## **General Transit Feed Specification**

Local transit agencies use a General Transit Feed Specification (GTFS)<sup>22</sup> to share transit schedules and associated geographic information about transit services in a common standardized format. GTFS files contain stop locations, stop times, routes, route types and trips, and other transit network attributes. Since its release in the mid-2000s, GTFS has become the most recognizable and common format for transit service data in the U.S. and internationally. GTFS data were acquired for use in metrics summarizing transit service availability, frequency, and accessibility to destinations via transit. These data were gathered between July and September 2020. Data were downloaded with a targeted release date of early 2020.<sup>23</sup> Not all transit agencies in the U.S. develop GTFS data for their systems, other agencies do but do not share it with the public, and others make it available only upon individual request. However, the large majority of large and medium-sized transit agencies regularly update their GTFS data. GTFS data obtained for this version of SLD represents a substantial increase from version 2.0. Version 3.0 has over double the number of transit agencies, increasing from 228 in 2014 to 573 agencies in 2020.<sup>24</sup> Data were acquired from a series of different sources, including TransitFeeds<sup>25</sup>, TransitLand<sup>26</sup> and individual transit agency websites. Table 9 in Appendix B provides an overview of the transit agencies included in the inventory used to develop the SLD metrics.

## **Transit-Oriented Development Database**

The Center for Transit Oriented Development (CTOD) developed an inventory of existing, planned, and proposed fixed-guideway transit station locations in the United States.<sup>27</sup> This transit oriented development (TOD) database relies on information about existing and planned federal grants for the development of future transit systems from the U.S. Federal Transit Authority (FTA). The status of planned and proposed stations was updated to bring them to the most current status as of mid-2020.<sup>28</sup> The database includes fixed-guideway transit systems such as metro (heavy rail, subway, light metro), commuter rail, light rail, streetcars (trams, interurbans),<sup>29</sup> bus rapid transit (BRT)<sup>30</sup>, cable cars, funiculars and aerial trams, as well as ferry and water taxis.<sup>31</sup> The database also includes a selected set of intercity Amtrak stations that serve commuters. These systems include portions of the Acela, Northeast Regional and Keystone Service among others in the Northeast and the Cascades and Capital Corridor on the West Coast. Table 8 in Appendix A summarizes the metropolitan areas served by fixed-guideway transit used to develop transit accessibility measures in the SLD.

#### National Transit Database

Public transit ridership information was gathered from the National Transit Database (NTD) developed by

<sup>&</sup>lt;sup>22</sup> Overview of General Transit Feed Speciation (GTFS), 2020.

<sup>&</sup>lt;sup>23</sup> Transit service data were targeted for February, 2020 when possible before the onset of the COVID-19 pandemic. When possible, release dates in late 2019 were preferred over those after March 2020. Some transit agencies only offer the most recent GTFS data for download, so in some cases obtaining GTFS data from early 2020 was not possible. Some transit operators have stopped updating their GTFS data, so only legacy versions of the data are available, some being several years old. See Table 9 in Appendix A for more information.
<sup>24</sup> Not all GTFS data contained sufficient information to identify schedule details required for some SLD measures. See the methods used to develop the transit accessibility (D4) and destination accessibility (D5) measures in the section that follows.

<sup>&</sup>lt;sup>25</sup> <u>TransitFeeds</u>, OpenMobilityData, 2020.

<sup>&</sup>lt;sup>26</sup> <u>TransitLand</u>, Interline Technologies, 2020.

<sup>&</sup>lt;sup>27</sup> <u>Transit-Oriented Development Database</u>, Center for Transit-Oriented Development, 2012.

<sup>&</sup>lt;sup>28</sup> Planned and proposed stations were reviewed to see which were now in operation as of mid-2020. The methods used to do this are further explained in the transit accessibility (D4) section of this document.
<sup>29</sup> Streetcar systems do not require a dedicated right-of-way (ROW) and may operate in mixed traffic.

<sup>&</sup>lt;sup>30</sup> Transit agencies have varying definitions and stylization for bus rapid transit (BRT) service. To meet the requirement for the fixed-guideway inventory, bus service must have a dedicated ROW.

<sup>&</sup>lt;sup>31</sup> Ferry system comprise mainly coastal urban ferry systems and long-distance ferry routes and do not include smaller in-land ferry systems.

the FTA.<sup>32</sup> Ridership information is calculated as total annual (FY 2019) unlinked passenger trips by transit agency by transit mode. These data were then summarized for all transit agencies within Census urbanized areas (UZAs) in the country. Although not directly used as an input for SLD variables, ridership information was compared with GTFS data coverage to provide a relative percentage of transit service coverage by region. Over 95% of total transit ridership in the U.S. was covered by the GTFS used in the SLD, increasing from 88% coverage for version 2.0 of the SLD in 2014. See Table 10 in Appendix C for more information on the urbanized areas covered by the available GTFS data.

<sup>&</sup>lt;sup>32</sup> National Transit Database, U.S. FTA, 2020.

## **Technical Approach**

This section summarizes the methods used to calculate all variables in the SLD, including geoprocessing components and tabular calculations. The discussion is organized by variable category (see Table 1 for category headings and a full list of variables).

## **Geographic Coordinate System & Projection**

All spatial analysis techniques and geoprocessing required establishing a Geographic Coordinate System (GCS) and a Projected Coordinate System (PCS) for all spatial layers used in the SLD. The GCS used was the North American 1983 (NAD 83).<sup>33</sup> Several different PCSs were used for analysis to distinguish between the lower continuous 48 states and Alaska, Hawaii and some U.S. overseas territories. The U.S. Geological Survey (USGS) USA Contiguous Albers Equal Area Conic<sup>34</sup> PCS was used for the contiguous 48 states, as well as Puerto Rico and the U.S. Virgin Islands. In contrast, the Alaska Albers Equal Area Conic<sup>35</sup> was used for Alaska, and the Hawaii Albers Equal Area Conic<sup>36</sup> was used for analysis in Hawaii. The World Geodetic System (WGS) 1984<sup>37</sup> GCS and Asia South Albers Equal Area Conic<sup>38</sup> projection were used for U.S. overseas territories to the west of the International Dateline including Guam, American Samoa and the Northern Mariana Islands.<sup>39</sup> The GCSs and PCSs used for version 3.0 of the SLD are consistent with those used for version 2.0. All CBGs were eventually merged together and the SLD is provided in the NAD 83 GCS and the USGS USA Contiguous Albers Equal Area Conic PCS. Some base data sources provide geographic references in WGS 1984 for latitude and longitude coordinates (e.g., GTFS data), which were eventually converted into NAD 83 for geoprocessing.

## Administrative

Administrative variables provide classification system information for each CBG using the Federal Information Processing Standard (FIPS) system.<sup>40</sup> Administrative variables were from the 2019 CBG data. FIPS codes are provided for the state, county, tract and CBG for all database records.<sup>41</sup> In addition, information regarding metropolitan areas including Core-Based Statistical Areas (CBSA) and Combined Statistical Areas (CSA) was acquired from the U.S. Census Bureau.<sup>42</sup> Also, text descriptions of the CBSAs and CSAs were added to the SLD database. CBSA information was utilized in the development of some employment entropy variables.

## **Demographics**

Demographic variables are from the most recent ACS five-year estimate (2014-2018) data at the block group-level furnished by the U.S. Census. These include population and residential activity (dwelling units and households). Variables related to worker earnings feature the prefix "R\_" to reflect that they summarize workers by residential location using LEHD RAC tables rather than a work location (LEHD WAC tables). The methods outlined below were the same used in the development of version 2.0 of the SLD for consistency.

• Total population of all ages [TotPop] and housing units [CountHU] were tabulated. The

<sup>&</sup>lt;sup>33</sup> Lower 48-state geographic coordinate system: GCS\_North\_American\_1983.

<sup>&</sup>lt;sup>34</sup> Lower 48-state projected coordinate system: USA\_Contiguous\_Albers\_Equal\_Area\_Conic\_USGS.

<sup>&</sup>lt;sup>35</sup> Alaska projected coordinate system: NAD\_1983\_Alaska\_Albers.

<sup>&</sup>lt;sup>36</sup> Hawaii projected coordinate system: *Hawaii\_Albers\_Equal\_Area\_Conic.* 

<sup>&</sup>lt;sup>37</sup> Pacific Ocean U.S. overseas territories geographic coordinate system: GCS\_WGS\_1984.

<sup>&</sup>lt;sup>38</sup> Pacific Ocean U.S. overseas territories projected coordinate system: *Asia\_South\_Albers\_Equal\_Area\_Conic.* 

<sup>&</sup>lt;sup>39</sup> This projection was limitedly used due to the lack of data availability for these areas.

<sup>&</sup>lt;sup>40</sup> <u>Federal Information Processing Standard</u>, U.S. Census Bureau, 2020.

<sup>&</sup>lt;sup>41</sup> Two sets of FIPS block group identifiers are provided for the SLD database. The first is the original 2010 FIPS block group identifier [GEOID10] and the second is an updated 2019 FIPS block group identifier [GEOID20]. A total of 74 (0.3%) of FIPS block group identifiers were changed. Both are required for the database because many base data sources continue to use the 2010 FIPS block group identifier.

<sup>&</sup>lt;sup>42</sup> Note that these CBSA and CSA identifiers are only applied to block groups in metropolitan areas.

percentage of working age [P\_WrkAge] population (between 18 years and 64 years of age) was identified.<sup>43</sup>

- Auto ownership fields were derived from the ACS table B08201 and were calculated using a two-step process. First, percent auto ownership fields were calculated as the share of all households having zero cars [Pct\_AO0], one car [Pct\_AO1], or two or more cars [Pct\_AO2p], with respect to total households reported in the ACS table. These percent auto ownership rates were then applied to the housing unit count [CountHU] field of the Demographics table to ascertain the number of households estimated to own zero cars [AutoOwn0], one car [AutoOwn1], or two or more cars [AutoOwn2p]. The process was conducted in this order because isolated discrepancies were observed between the total number of households reported in the ACS table and the corresponding figure in the Demographics table. The Demographics table was given precedence, and only the auto ownership rates were taken directly from the ACS table.
- The number of workers [WORKERS] was summarized from LEHD RAC tables, which report employment based on worker residence.
- The LEHD RAC tables were also referenced to produce wage stratification variables based on worker residence. High wage workers [R\_HighWageWk] earn more than \$3,333 per month, while low wage workers [R\_LowWageWk] earn \$1,250 or less per month. Medium wage workers [R\_MedWageWk] earned between \$1,251 and \$3,333 a month. The share of total workers consisting of low wage workers [R\_PctLowWage] was also computed.

## Employment

Employment information is based on LEHD LODES data for all 50 states.<sup>44</sup> These employment variables report job activity and worker information for each CBG. Variables summarizing worker earnings feature the prefix "E\_" to reflect that they summarize workers by employment location rather than home location. All other employment data are from LEHD. LEHD WAC and RAC tables at the census block-level were consolidated state-by-state into a nationwide dataset and then summarized by CBG.

A summary of employment variables from LEHD data is provided below.

- Total employment [TotEmp] was summarized for each CBG from the LEHD WAC tables, using the C000 field (total number of jobs).
- Two employment classification systems were developed: five-tier employment and eight-tier employment. The five-tier classification summarizes jobs into the five employment sectors: 1) retail, 2) office, 3) service, 4) industrial, and 5) entertainment. Five-tier employment classifications were denoted by "E5\_" prefix for each employment variable. The distribution of individual employment sectors into the five-tier employment categories from the LEHD WAC data are shown in Table 3.
- The eight-tier classification summarizes jobs into the five employment sectors: 1) retail, 2) office, 3) service, 4) industrial, 5) entertainment, 6) education, 7) healthcare and 8) public administration. Eight-tier employment classifications were denoted by "E8\_" prefix for each employment variable. The distribution of individual employment sectors into the eight-tier employment categories from the LEHD WAC data are shown in Table 4.
- Lastly, wage stratification variables based on workplace location were developed for each CBG.

<sup>&</sup>lt;sup>43</sup> Version 2.0 of the SLD characterized this variable as the proportion of the population greater than 17 years of age. The definition of this variable was changed for SLD version 3.0.

<sup>&</sup>lt;sup>44</sup> No employment information is currently available at the block or CBG-level for Puerto Rico or the U.S. overseas territories. Although, where available, some employment-based variables that also utilize demographics information were used to calculate SLD variables for these areas.

High wage workers [E\_HiWageWk] earned more than \$3,333 per month, while low wage workers [E\_LowWageWk] earned \$1,250 or less per month. Medium wage workers [E\_MedWageWk] earned between \$1,251 and \$3,333 a month. The total number of workers comprised by each wage group was tabulated for each CBG. The share of total workers comprised by low wage workers [E\_PctLowWage] was also computed.

Position	Variable Name	Туре	Length	Explanation	
1	h geocode	Character	15	Residence/Workplace Census Block Code	
Office Job	s	•	•		
17	CNS09	Numeric	8	Number of jobs in NAICS sector 51 (Information)	
18	CNS10	Numeric	8	Number of jobs in NAICS sector 52 (Finance and Insurance)	
19	CNS11	Numeric	8	Number of jobs in NAICS sector 53 (Real Estate and Rental and Leasing)	
21	CNS13	Numeric	8	Number of jobs in NAICS sector 55 (Management of Companies and Enterprises)	
28	CNS20	Numeric	8	Number of jobs in NAICS sector 92 (Public Administration)	
Retail Jobs	3				
15	CNS07	Numeric	8	Number of jobs in NAICS sector 44-45 (Retail Trade)	
Industrial 3	Jobs				
9	CNS01	Numeric	8	Number of jobs in NAICS sector 11 (Agriculture, Forestry, Fishing and Hunting)	
10	CNS02	Numeric	8	Number of jobs in NAICS sector 21 (Mining, Quarrying, and Oil and Gas Extraction)	
11	CNS03	Numeric	8	Number of jobs in NAICS sector 22 (Utilities)	
12	CNS04	Numeric	8	Number of jobs in NAICS sector 23 (Construction)	
13	CNS05	Numeric	8	Number of jobs in NAICS sector 31-33 (Manufacturing)	
14	CNS06	Numeric	8	Number of jobs in NAICS sector 42 (Wholesale Trade)	
16	CNS08	Numeric	8	Number of jobs in NAICS sector 48-49 (Transportation and Warehousing)	
Service Jol	bs				
20	CNS12	Numeric	8	Number of jobs in NAICS sector 54 (Professional, Scientific, and Technical Services)	
22	CNS14	Numeric	8	Number of jobs in NAICS sector 56 (Administrative and Support and Waste Management and Remediation Services)	
23	CNS15	Numeric	8	Number of jobs in NAICS sector 61 (Educational Services)	
24	CNS16	Numeric	8	Number of jobs in NAICS sector 62 (Health Care and Social Assistance)	
27	CNS19	Numeric	8	Number of jobs in NAICS sector 81 (Other Services [except Public Administration])	
Entertainm	ent, Accommodation	on, Food Servic	es Jobs		
25	CNS17	Numeric	8	Number of jobs in NAICS sector 71 (Arts, Entertainment, and	

Table 3: Groups of LODES WAC characteristics to support five-tier employment entropy.

Source: LODES: WAC, LEHD, U.S. Census Bureau, 2018.

Table 4: Groups of LODES WAC characteristics to support eight-tier employment entropy.

Position	Variable Name	Туре	Length	Explanation
1	h_geocode	Character	15	Residence/Workplace Census Block Code
Office Job	S			
17	CNS09	Numeric	8	Number of jobs in NAICS sector 51 (Information)
18	CNS10	Numeric	8	Number of jobs in NAICS sector 52 (Finance and Insurance)
19	CNS11	Numeric	8	Number of jobs in NAICS sector 53 (Real Estate and Rental and Leasing)
21	CNS13	Numeric	8	Number of jobs in NAICS sector 55 (Management of Companies and Enterprises)
Retail Jobs	5			
15	CNS07	Numeric	8	Number of jobs in NAICS sector 44-45 (Retail Trade)
Industrial .	lobs			

Position	Variable	Туре	Length	Explanation
9	CNS01	Numeric	8	Number of jobs in NAICS sector 11 (Agriculture, Forestry, Fishing and Hunting)
10	CNS02	Numeric	8	Number of jobs in NAICS sector 21 (Mining, Quarrying, and Oil and Gas Extraction)
11	CNS03	Numeric	8	Number of jobs in NAICS sector 22 (Utilities)
12	CNS04	Numeric	8	Number of jobs in NAICS sector 23 (Construction)
13	CNS05	Numeric	8	Number of jobs in NAICS sector 31-33 (Manufacturing)
14	CNS06	Numeric	8	Number of jobs in NAICS sector 42 (Wholesale Trade)
16	CNS08	Numeric	8	Number of jobs in NAICS sector 48-49 (Transportation and Warehousing)
Service Jo	bs	-		
20	CNS12	Numeric	8	Number of jobs in NAICS sector 54 (Professional, Scientific, and Technical Services)
22	CNS14	Numeric	8	Number of jobs in NAICS sector 56 (Administrative and Support and Waste Management and Remediation Services)
27	CNS19	Numeric	8	Number of jobs in NAICS sector 81 (Other Services [except Public Administration])
Entertainm	ent, Accommodatio	n, Food Service	e Jobs	
25	CNS17	Numeric	8	Number of jobs in NAICS sector 71 (Arts, Entertainment, and Recreation)
26	CNS18	Numeric	8	Number of jobs in NAICS sector 72 (Accommodation and Food Services)
Education	Jobs	•		• • •
23	CNS15	Numeric	8	Number of jobs in NAICS sector 61 (Educational Services)
Healthcare	Jobs			
				Number of jobs in NAICS sector 62 (Health Care and Social
24	CNS16	Numeric	8	Assistance)
Public Adı	ninistration Jobs		T -	
28	CNS20	Numeric	8	1 Number of jobs in NAICS sector 92 (Public Administration)

Source: LODES: WAC, LEHD, U.S. Census Bureau, 2018.

## Area

The total geometric area of each CBG [Ac\_Total], the unprotected area [Ac\_Unpr], and land area [Ac\_Land] values were calculated. [Ac\_Unpr] represents the total land area in the CBG that is not protected from development activity. The area not protected from development activity was identified using the USGS PAD-US database and is referred to as "unprotected" area in this guide. The unprotected area represents a portion or all of the land area of a CBG but may never be more than the CBG land area and does not consider protected areas in water bodies. Unprotected area was used in the calculation of all density metrics (D1), proportional area metrics for fixed-guideway transit accessibility (D4b), and informed intrazonal travel times used in calculating the destination accessibility metrics (D5).

Calculating the area of unprotected land for each CBG required identifying CBG areas of protected land and surface water. A polygon GIS database was created that is the intersection between the CBGs, the USGS Protected Area Database (PAD)<sup>45</sup>, and the USGS surface water database.<sup>46</sup> The resulting polygon database includes protected land polygons with CBG identifiers from which total acreage is calculated. Unprotected land area is simply the CBG land area minus the CBG protected land area.

The PAD (version 2.0) database was prepared before simple protected area polygons were established. PAD contains many layers of information that overlap, not all of which are relevant for establishing protected area. A Federal Geographic Data Committee (FGDC) guidance document<sup>47</sup> provided an

<sup>&</sup>lt;sup>45</sup> Protected Areas Database, USGS, 2019.

<sup>&</sup>lt;sup>46</sup> <u>National Hydrology Data</u>, USGS, 2019.

<sup>&</sup>lt;sup>47</sup> <u>How to Use Protected Areas Data in Base Maps</u>, USGS, 2019.

overview and clarification of various PAD data layers for establishing protected area base maps. Within this document, the following guidance was identified and followed:

- Exclude "Proclamation" areas as these do not represent ownership of legal control
- Exclude "Easements" area overlap private land and has a status that is unreliable

Additionally, Federal, State, and Local "Resource Management Areas" are locations where active development may occur with some restrictions related to mining, forestry, or other commercial harvesting. These areas were also excluded.

The PAD database documentation also clearly states that many state and local parks are missing. For this reason, park areas were included from the 2017 NAVTEQ database. The additional NAVTEQ features included beaches, wildlife refuges, parks, and national forest. The polygons representing these areas were merged and dissolved with the PAD polygons to generate the final protected land polygons used in the analysis.

## Density (D1)

All density variables summarize population, housing, or employment within a CBG per unprotected CBG acreage [Ac\_Unpr]. The primary density variables examine residential (housing units [D1a], population [D1], employment (jobs) [D1c] and activity (housing units and jobs) [D1d] characteristics. Employment density is also disaggregated by employment categories for both five-tier and eight-tier job classifications. The definitions of employment categories parallel those specified in the Employment table. Variables with the "D1c5..." prefix summarize employment based on the 5-tier ("E5...") employment classification scheme. Variables with the "D1c8..." prefix summarize employment based on the 8-tier ("E8...") employment classification scheme.

In a few cases, unexpectedly high densities were observed in known low density areas. This occurred in CBGs in which nearly all the land area was classified as protected area. In such cases, it was clear that population, housing, and/or employment were present in otherwise protected areas. To correct this overestimation of protected areas, all CBGs in which the unprotected area represented less than one half of one percent of its total area were identified. For only these CBGs, all density metrics were recalculated to be based on total land area, rather than unprotected area. CBGs to which this adjustment applied were identified using a flag [D1\_Flag] and were given a value of 1.

## **Employment & Housing Diversity (D2)**

Employment and housing diversity refer to the relative mix of employment and residential development within an analysis zone. These measures act as proxies for land use diversity by quantifying the relative blend of the number of jobs in different employment sectors and residential housing types. Since there is no uniformly measured, publicly available national land use parcel database that can be allocated to the CBG, assumptions were made about the mixture of land uses based on counts of job by employment sector and housing unit counts. Using these employment and housing characteristics, the SLD includes a variety of alternative metrics to measure entropy. Base data used to derive the employment and housing diversity variables are listed in Table 2.

Table 3 and Table 4 describe the five-tier and eight-tier employment categorization used to develop the diversity measures. Detailed descriptions and methods used to calculate the diversity variables are provided in Table 5.

The most simplistic of the measures characterize the jobs to household balance [D2a\_JpHH] and the

workers' residential location to the employment location balance [D2a\_WrkEmp] by CBG. Three trip generation measures were also developed to quantify the average number of trips produced and attracted by job type and household. Trip generation rates by location type were derived from the same Institute of Transportation Engineer (ITE) Trip Generation manual used for version 2.0 of the SLD. Lastly, two regional diversity measures were developed to quantify population, jobs and workers within each CBG relative to the regional average. The jobs to population balance [D2r\_JobPop] and worker home residence to job location balance [D2r\_WrkEmp] were calculated by comparing CBG-level values to average values for the CBSA.

It is important to keep in mind a few things when interpreting these metrics. First, the D2 variables say nothing about how different uses or activities are spatially distributed within a CBG. A large CBG in an area of low density development may include a variety of different activities. But those activities may be spatially separated within the CBG area. As a result, any given part of the CBG might have little diversity when examined in detail. Second, in some higher density urban areas CBGs may be quite small in area. So, a uniformly residential CBG might be located next to a CBG with a greater diversity of land uses. These metrics will assess the residential CBG to be low in diversity even though the diverse land uses are just a short walk away. In other words, the analysis contributing to these metrics did not consider activities that may be in just outside of CBG boundaries. Third, the entropy formulas assess the evenness of the distribution across the types of employment and households without consideration of the aggregate quantity of jobs or households. For example, a CBG may have a small number of jobs (relative to another CBG), but if the mixture of these jobs is present in the same ratio as in a CBG with more jobs, they will have the same mix score.

Field name	Description	Method of calculation
D2a_JpHH	Jobs to Household Balance per CBG	TotEmp/HH
D2b_E5Mix	This employment mix (or entropy) variable uses	$D2b_E5Mix = -E/(ln(N))$
	the five-tier employment categories (Error!	
	Reference source not found.) to calculate	Where: E=(E5_Ret/TotEmp)*ln(E5_Ret/TotEmp) +
	employment mix. The entropy denominator is	(E5_Off/TotEmp)*ln(E5_Off/TotEmp) +
	set to observed existing employment types	(E5_Ind/TotEmp)*ln(E5_Ind/TotEmp) +
	within each CBG. <sup>48</sup>	(E5_Svc/TotEmp)*ln(E5_Svc/TotEmp) +
		(E5_Ent/TotEmp)*In(E5_Ent/TotEmp)
		N= number of employment types with employment $> 0$
D2h E5MixA	This entrony variable uses the five-tier	D2h E5MixA = $-F/(\ln(5))$
D20_L5MiA1	employment categories to calculate employment	
	mix. The entropy denominator is set to all five	Where: E=(E5_Ret/TotEmp)*ln(E5_Ret/TotEmp) +
	employment types within each CBG.	$(E5 \text{ Off/TotEmp})*\ln(E5 \text{ Off/TotEmp}) +$
	1 5 51	(E5 <sup>Ind</sup> /TotEmp)*ln(E5 <sup>Ind</sup> /TotEmp) +
		(E5 Svc/TotEmp)*ln(E5 Svc/TotEmp) +
		(E5_Ent/TotEmp)*ln(E5_Ent/TotEmp)
D2b_E8Mix	This entropy variable uses the eight-tier	$D2b_E8Mix = -E/(ln(N))$
	employment categories (Error! Reference	
	source not found.) to calculate employment	Where: E=(E8_Ret/TotEmp)*ln(E8_Ret/TotEmp) +
	mix. The entropy denominator is set to observed	(E8_Off/TotEmp)*ln(E8_Off/TotEmp) +
	existing employment types within each CBG.	(E8_Ind/TotEmp)*ln(E8_Ind/TotEmp) +
		(E8_Svc/TotEmp)*ln(E8_Svc/TotEmp)+
		$(E8\_Ent/TotEmp)*In(E8\_Ent/TotEmp) +$
		$(E8\_Ed/IotEmp)*ln(E8\_Ed/IotEmp) +$
		$(E\delta_{HIII}/IOEmp)^{*}In(E\delta_{HIII}/IOEmp) +$ (E8_Dub/TotEmm)*In(E9_Dub/TotEmm)
		$(Eo_ruo/10Emp)^{*III}(Eo_ruo/10Emp)$

Table 5: Detailed description of employment and housing diversity (D2) variables.

<sup>&</sup>lt;sup>48</sup> This entropy equation was originally applied by Robert Cervero and has been used since then in different land use entropy formulations. [Cervero, R. (1989). Land-Use Mixing and Suburban Mobility. UC Berkeley: University of California Transportation Center. Retrieved from <u>https://escholarship.org/uc/item/4nf7k1v9</u>]

Field name	Description	Method of calculation
		N= number of the employment types with employment $> 0$ .
D2b_E8MixA	This entropy variable uses the eight-tier employment categories to calculate employment mix. The entropy denominator is set to all eight employment types within each CBG.	D2b_E8MixA = -E/(ln(8)) Where: E=(E8_Ret/TotEmp)*ln(E8_Ret/TotEmp) + (E8_Off/TotEmp)*ln(E8_Off/TotEmp) + (E8_Ind/TotEmp)*ln(E8_Ind/TotEmp) + (E8_Svc/TotEmp)*ln(E8_Svc/TotEmp) + (E8_Ed/TotEmp)*ln(E8_Ed/TotEmp) + (E8_Hlth/TotEmp)*ln(E8_Hlth/TotEmp) + (E8_Pub/TotEmp)*ln(E8_Pub/TotEmp) +
D2a_EpHHm <sup>49</sup>	Employment and household entropy calculations, where employment and occupied housing are both included in the entropy calculations. This measure uses the five-tier employment categories.	D2a_EpHHm = -A/(ln(N)) Where: A = (HH/TotAct)*ln(HH/TotAct) + (E5_Ret/TotAct)*ln(E5_Ret/TotAct) + (E5_Off/TotAct)*ln(E5_Off/TotAct) + (E5_Ind/TotAct)*ln(E5_Ind/TotAct) + (E5_Svc/TotAct)*ln(E5_Svc/TotAct) + (E5_Ent/TotAct)*ln(E5_Ent/TotAct) TotAct = TotEmp + HH N= number of activity categories (employment or households)
		with count > 0.
D2c_TrpMx1 <sup>50</sup>	Employment and household entropy calculations, based on trip production and trip attractions, including five-tier employment categories. The vehicle trip productions and attractions are derived by multiplying the average Institute of Transportation Engineers (ITE) vehicle trip generation rates by employment types and households. The trip generation rates were used as a proxy for trip activity.	$D2c_TrpMx1 = - [H(VT) +E(VT)]/(ln(6))$ Where: H(VT) + E(VT) = (HH*11/ TotVT)*ln(HH*11/ TotVT) + (E5_Ret*22/ TotVT)*ln(E5_Ret*22/ TotVT) + (E5_Off*3/ TotVT)*ln(E5_Off*3/ TotVT) + (E5_Ind*2/ TotVT)*ln(E5_Ind*2/ TotVT) + (E5_Svc*31/ TotVT)*ln(E5_Svc*31/ TotVT) + (E5_Ent*43/ TotVT)*ln(E5_Ent*43/ TotVT)
		TotVT = Total trips generated (production and attraction) for all activity categories in the CBG based on <u>ITE Trip</u> <u>Generation Rates (rates shown in equation above).<sup>51</sup></u>
D2c_TrpMx2 <sup>52</sup>	Employment and household entropy calculations, based on trip productions and trip attractions, including 4 of the 5 employment categories (excluding industrial). The vehicle trip productions and attractions are derived by multiplying the average Institute of ITE vehicle trip generation rates by employment types and households. The trip generation rates were used as a proxy for trip activity.	Employment and Household Trips Mix = - [H(VT) +E(VT)]/(ln(5)) Where: H(VT) + E(VT) = (HH*11/VT)*ln(HH*11/VT) + (E5_Ret*22/TotVT)*ln(E5_Ret*22/TotVT) + (E5_Off*3/ TotVT)*ln(E5_Off*3/TotVT) + (E5_Svc*31/ TotVT)*ln(E5_Svc*31/TotVT) + (E5_Ent*43/ TotVT)*ln(E5_Ent*43/TotVT) TotVT = Total trips generated (production and attraction) for
		all activity categories (excluding industrial jobs) in the CBG based on ITE Trip Generation Rates.

<sup>&</sup>lt;sup>49</sup> Only accounts for households in Puerto Rico and the U.S. overseas territories due to a lack of employment data in these regions.

<sup>&</sup>lt;sup>50</sup> Only accounts for households in Puerto Rico and the U.S. overseas territories due to a lack of employment data in these regions.

 <sup>&</sup>lt;sup>51</sup> Trip generation rates used previously for version 2.0 of the SLD were used again for version 3.0.
 <sup>52</sup> Only accounts for households in Puerto Rico and the U.S. overseas territories due to a lack of employment data in these regions.

Field name	Description	Method of calculation
D2c_TripEq <sup>53</sup>	Trip Equilibrium Index. It is derived by	$D2c_TripEq = exp(- [H(VT)/E(VT)]-1 )$
	calculating trip productions and trip attractions	
	by CBG; the closer to one, the more balanced	Where:
	the trip making at the CBG level. The vehicle	HH(VT) = Productions: total occupied household units
	trip productions and attractions were derived by	in CBG * ITE Vehicle Trip (VT) Generation Rates.
	multiplying average ITE vehicle trip generation	
	rates by employment types and households. The	J(VT) = Total trip attractions for the five-tier employment
	trip generation rates were used as a proxy for	(job) categories based on ITE Trip Generation Rates.
	trip activity.	and the exponential function (a formation take 2 719291929]
		exp – the exponential function (e [approximately 2./18281828]
D2n JohDon 54	Designal diversity of smaleyment to	D2n Jah Dan = 1 //k*/Tat Dan
D2r_JobPop**	Regional diversity of employment to	$D2I_JODPOP = 1 -  (0^{\circ}(10POP) - 1 - 10^{\circ}(10POP)) $
	and total amployment by CPC. It quantifies the	$101Emp)/(6^{-1}(101Pop+101Emp)) $
	deviation of the CBC ratio of jobs/non from the	Where h=CBSA Don/CBSA Emp
	regional average ratio of jobs/pop.	where o-ebsA_i op/ebsA_ehip
D2r WrkEmp <sup>55</sup>	Regional diversity of household workers to	D2r WrkEmp = $1 -  (b^*(Workers -$
	employment. Household Workers per Job, as	TotEmp))/(b*(Workers +TotEmp))
	compared to the region. It quantifies the	
	deviation of CBG ratio of household	Where b=CBSA_Wrk/CBSA_Emp
	workers/job from regional average ratio of	
	household workers/job.	
D2a_WrkEmp	Household Workers per Job, by CBG.	D2a_WrkEmp = Workers/TotEmp
D2c_WrEmIx	Working population and actual jobs equilibrium	$D2c_WrEmIx = exp(- (Workers/TotEmp) - 1 )$
	index. The closer to one, the more balanced the	
	resident workers and jobs are in a CBG.	Where <i>exp</i> = the exponential function (e [approximately
		2.718281828] raised to the power of the number in parenthesis)

## **Urban Design (D3)**

Urban design variables measure connectivity or the ability to traverse distances in many directions along a street network. Areas with higher connectivity typically have a gridded street network with shorter block lengths than more disconnected areas with fewer intersections and longer block lengths. The urban design (D3) variables measure connectivity in terms of street network density and street intersection density by facility orientation. The street network is categorized into three distinct facility orientation types: 1) automobile, 2) multi-modal and 3) pedestrian. The denominator used in street network density [D3a] and street intersection density [D3b] calculations was total land area [Ac Land]. Additionally, street intersection density [D3b] also summarizes total intersection density weighted to emphasize pedestrian and bicycle travel connectivity. While intersection density is often used as an indicator of more walkable urban design and the source network database includes pedestrian or nonmotorized pathways only in addition to streets which vehicles can traverse. However, it is important to note that the source data provides no information regarding the presence or quality of sidewalks. The urban design variables required substantial preparation of the HERE Maps NAVSTREETS databases<sup>56</sup> to assign each network feature's facility orientation. The *Streets* layer displayed network links and includes a link-level attributes such as functional class, speed category, direction of travel (one-way or two-way), auto or pedestrian restrictions, and identifiers for ramps, tunnels, and bridges. The Zlevels layer displayed all points of articulation on the network (node junctions) and included node-level attributes such as intersections, node identifiers, link identifiers, and relative elevation fields to govern connectivity at coincident grade separated nodes.

<sup>&</sup>lt;sup>53</sup> Only accounts for households in Puerto Rico and the U.S. overseas territories due to a lack of employment data in these regions.

<sup>&</sup>lt;sup>54</sup> This measure is not calculated for block groups in rural areas or small towns that are not part of CBSA.

<sup>&</sup>lt;sup>55</sup> This measure is not calculated for block groups in rural areas or small towns that are not part of CBSA.

<sup>&</sup>lt;sup>56</sup> Mainly the *Streets* (polyline network) and *Zlevels* (network node junctions) datasets.

Node features were stacked with each feature representing an endpoint of a particular link in the Streets layer. Thus, where three or more coincident node features were found, at least three associated links and their descriptive attributes could be related to that point, which would (in most cases) represent a three-way or more intersection. This relationship between the Streets and Zlevels layers allowed street network and intersections to be summarized by type.

Preparing the network base data to process the SLD design metrics required several steps. First, street centerlines were grouped into three facility categories: 1) auto-oriented links, 2) multi-modal links, and 3) pedestrian-oriented links. Then the link length by facility category was summed to obtain total facility miles by type for each CBG. Next, link-level facility groups were joined to the Zlevels layer based on link identifier. Finally, intersections were counted in each CBG based on the types of facilities found at the intersection and the number of legs at the intersection (for multi-modal and pedestrian-oriented intersection sonly). The summary figures of facility miles by type and intersection total by type and number of legs were divided by the total land area for each CBG to obtain network density (facility miles per square mile) and intersection density (intersections per square mile) for each CBG.

Links were grouped into facility categories as follows:

- Auto-Oriented Facilities:
  - Any controlled access highway, tollway, highway ramp, or other facility on which automobiles are allowed but pedestrians are restricted
  - Any link having a speed category value of 3 or lower (speeds are 55 mph or higher)
  - Any link having a speed category value of 4 (between 41 and 54 mph) where car travel is restricted to one-way traffic
  - Any link having four or more lanes of travel in a single direction (implied eight lanes bi-directional turn lanes and other auxiliary lanes are not counted)
  - For all of the above, ferries and parking lot roads were excluded.
  - Multi-Modal Facilities:
    - Any link having a speed category of 4 (between 41 and 54 mph) where car travel is permitted in both directions
    - Any link having a speed category of 5 (between 31 and 40 mph)
    - Any link having a speed category of 6 (between 21 and 30 mph) where car travel is restricted to one-way traffic
    - For all of the above, autos and pedestrians must be permitted on the link
    - For all of the above, controlled access highways, tollways, highway ramps, ferries, parking lot roads, tunnels, and facilities having four or more lanes of travel in a single direction (implied eight lanes bi-directional) are excluded
  - Pedestrian-Oriented Facilities:
    - Any link having a speed category of 6 (between 21 and 30 mph) where car travel is permitted in both directions
    - Any link having a speed category of 7 or higher (less than 21 mph).
    - Any link having a speed category of 6 (between 21 and 30 mph)
    - $\circ$  Any pathway or trail<sup>57</sup> on which automobile travel is not permitted (speed category 8).
    - For all of the above, pedestrians must be permitted on the link
    - For all of the above, controlled access highways, tollways, highway ramps, ferries, parking lot roads, tunnels, and facilities having four or more lanes of travel in a single direction (implied eight lanes bi-directional) are excluded

<sup>&</sup>lt;sup>57</sup> While NAVTEQ data does include some pedestrian pathways and bicycle trails, coverage is far less comprehensive than it is for automobile facilities. When these bike/ped facilities do exist in the NAVTEQ database, they are considered in SLD metrics.

Street network density measures were calculated by summing links from all three categories described above and dividing by land area in square miles. Four network density measures were created: 1) total network density (all facility types) [D3a], 2) auto-orientated network density [D3aao], 3) multi-modal network density [D3amm], and 4) pedestrian-orientated network density [D3apo].

To identify intersections by facility type, the network links were first joined to the Zlevels layer. Link nodes at intersections were queried out of the Zlevels layer and then spatially dissolved into discrete intersections based on the node identifier and Zlevel attributes (the latter ensuring that duplicate grade-separated nodes were not counted as one intersection). Intersection nodes at roundabouts were maintained, <sup>58</sup> while nodes identified on "manoeuvre"<sup>59</sup> links were removed as invalid intersections.

For each intersection, the total number of intersecting links (legs) were summarized to and any nodes with fewer than three legs were discarded. Intersections were then summarized by type for each CBG, which are also summarized in Table 6:

- Intersections at which auto-oriented facilities met or at which auto-oriented facilities intersected multi-modal facilities were described as auto-oriented intersections and summed for each CBG regardless of the total number of legs.
- Intersections at which multi-modal facilities met or at which multi-modal facilities intersected pedestrian oriented facilities were described as multi-modal intersections and summed for each CBG where the number of legs was equal to three and where the number of legs was greater than 3.
- Intersections at which pedestrian-oriented facilities met were described as pedestrianoriented intersections and summed for each CBG where the number of legs was equal to three and where the number of legs was greater than 3.

Intersection Type	Legs	Intersecting Facilities		Variable Name	
Auto	N/A	Auto	Auto	D2haa	
Auto		Auto	Multi-Modal	DSbao	
Multi Madalı 2 lag	3	Multi-Modal	Multi-Modal	D21	
Multi-Modal: 5-leg		Multi-Modal	Pedestrian-Oriented	DSomms	
Multi Model: 4 log	≥4	Multi-Modal	Multi-Modal	D2hmm4	
Multi-Modal. 4-leg		Multi-Modal	Pedestrian-Oriented	D30IIIIII4	
Pedestrian-Oriented: 3-leg	3	Pedestrian-Oriented	Pedestrian-Oriented	D3bpo3	
Pedestrian-Oriented: 4-leg	≥4	Pedestrian-Oriented	Pedestrian-Oriented	D3bpo4	

Table 6: Summary of intersection density measures by type groupings and corresponding urban design variables.

Finally, the total number of intersections was systematically discounted in some cases to account for an overestimation due to divided highways portrayed as individual one-way links. Thus, when an undivided street intersected a divided highway, it intersected it in two places, at the "from-bound" link and at the "to-bound" link causing duplication. These locations should be interpreted as a single intersection, but they would be tabulated as two intersections in the processes described above. This effect was further compounded when two divided highways intersect each other.

To account for this condition, individual intersections were discounted based on the number of one-way links found at the intersection. Where a one-way link intersected a two-way link, the intersection was counted as half an intersection; and where two one-way links intersected, the intersection was counted as a quarter of an intersection. This prevented intersection counts in areas with a high density of auto-oriented facilities (such as in the vicinity of a freeway interchange) from being overestimated. Since most of these types of intersections were found among auto-oriented facilities, this discount weight primarily

<sup>&</sup>lt;sup>58</sup> May result in some minor duplication of multiple link nodes representing one intersection.

<sup>&</sup>lt;sup>59</sup> Type of link classification for turn lanes in the center of streets typically located mid-block for entrances into driveways.

affected auto-oriented intersection counts, though some reduction in the number of multi-modal and pedestrian-oriented facilities also resulted from the application of this rule.

Street network intersection density [D3b] was calculated by creating a weighted sum of component intersection density metrics. Auto-oriented intersections were assigned zero weight to reflect that, in many instances, auto-oriented intersections are a barrier to pedestrian and bicycle mobility. Also, since three-way intersections do not promote street connectivity as effectively as four-way intersections, their relative weight was reduced accordingly.<sup>60</sup> The formula for [D3b] was calculated as follows:

D3b = (D3bmm3 \* 0.667) + Dbmm4 + (D3bpo3 \* 0.667) + D3bpo4

## Transit Accessibility (D4)

Transit service (D4) variables measure availability, proximity, frequency, and density of all public transit services. Two data sources were used to calculate transit metrics. First, transit service data was obtained in GTFS format from over 500 transit agencies<sup>61</sup> across the U.S. As part of the GTFS inventory, these data included the geographic location of all transit stops, as well as service schedules for all routes that serve those stops. Metrics that rely on transit service schedules ([D4a], [D4c], [D4d], and [D4e]) reflect GTFS data availability and completeness.<sup>62</sup> While all agencies follow the data definition standard, some agencies left values empty that were critical for building schedules, identifying valid services/routes or identifying transit stop departures by hour of day. See Table 9 in Appendix B for more information on which transit agencies are included within the SLD.

Secondarily, point location data of latitude and longitude coordinates were also obtained for all existing fixed-guideway transit service. Access to this type of transit service ([D3b025], [D3b050]) includes all rail transit (metro, light rail, streetcar, etc.), ferry and water taxis, and some bus rapid transit systems with dedicated right-of-way. All transit stops from the CTOD TOD database classified as existing were included in the database of fixed-guideway transit stations. Since no updates to this database had been performed since 2012, planned and proposed fixed-guideway transit systems were reviewed to identify those systems that have now been brought into service through 2020. Route type information was then gathered to select non-bus stops from the GTFS stop inventory to identify any other remaining fixed-guideway stations omitted from the CTOD TOD database.<sup>63</sup> A spatial selection was performed between the TOD database and the selected set of stops from the GTFS database to ensure no duplication of stops. See Table 8 in Appendix A for more information on the regions that have fixed-guideway transit service included in the SLD.

#### **Distance to Nearest Transit (D4a)**

Distance to the nearest transit stop [D4a] measures the minimum walk distance in meters between the 2010 population-weighted CBG centroid (as used by SLD version 2.0) and the nearest transit stop of any route type. To generate this metric, a custom geoprocessing model script was run. This processing model iteratively selected CBG centroids and identified all transit stops (from any GTFS file) within a three-quarter mile straight-line radius (approximately a 15-minute walk). The resulting sets of CBG to transit stop pairs were passed to the TravelTime API to estimate the walking distance between them in meters. The pedestrian network used by the TravelTime API includes walkable roads as well as pedestrian only

<sup>&</sup>lt;sup>60</sup> The weight of three-way intersections was diminished by one third. This weight was chosen to reflect the diminished choice of routes that a traveler faces when reaching a 3-way intersection when compared to a 4-way intersection (2 choices instead of 3).

<sup>&</sup>lt;sup>61</sup> A full list of transit agencies with GTFS data reflected in these metrics is available in Table 9 in Appendix B. <sup>62</sup> Although the SLD relies on GTFS data from 573 transit agencies, only 499 contained sufficient information to identify schedule details required for some SLD measures ([D4c], [D4d], [D4e] and [D5br], [D5be]).

<sup>&</sup>lt;sup>63</sup> Note that route information is often, but not always, included in GTFS data published by transit agencies.

facilities. Note that the initial selection of destinations was based on a straight-line distance, whereas the network solve is limited to finding those pre-selected destinations that are a 15 minute walk from a transit stop based on network distances. The initial selection is made simply to limit the number of potential destinations that are added to the OD matrix network problem.

The network analysis results were appended to a master table of stop-CBG OD pairs with the network travel distance included as an attribute. When all stop-CBG OD pairs had been found and listed in the master table, the table was then summarized by CBG to find the minimum network travel distance to a transit stop from that CBG centroid. This is the only measure in the SLD where the lower the value in each CBG, the better the access (in this case to nearby transit).<sup>64</sup> All CBGs with population-weighted centroids that were further than three-quarter miles from a transit stop were assigned a value of "-999999."<sup>65</sup>

Since the network problem was solved based on distance rather than travel time, there was no accounting for delays at intersections or bordering or alighting delays in determining the shortest path between a stop origin and CBG population-weighted centroid destination. The inclusion of stations from the CTOD TOD Database allowed stops that have fixed- guideway transit, but which do not provide GTFS data, to be included in the distance to nearest transit [D4a] tabulation.

#### Access to Fixed-Guideway Transit (D4b)

Fixed-guideway transit station locations (derived from the CTOD TOD Database and the GTFS database) were buffered using a crow-fly distance of one-quarter of a mile and then again at one-half of a mile. Each respective set of buffers was spatially intersected with the CBG unprotected areas polygons developed unprotected area variable. The resulting intersected features represent the polygons formed by the intersection of the CBG boundaries, all unprotected areas, and the transit station area crow-fly buffers. The area of each polygon was compared to the unprotected area of its corresponding CBG to determine the proportion of the polygon's unprotected area that is found within one-quarter or one-half mile of a fixed-guideway transit station. This value approximates the proportion of the CBG's activity (housing units and total employment) that were proximate to fixed-guideway transit.

The station area buffers were based on crow-fly distances, not network distances. The process could be improved in future versions of the SLD to include the development of network-based service area polygons around transit stations. A second potential improvement would involve assessing developed area in a CBG based on land cover data to define the portions of the CBG in which activities are located rather than referencing the CBG's unprotected area. However, this augmentation is expected to require a substantially higher level of effort to develop than that associated with defining protected areas.

Access to fixed-guideway stations within 0.25 miles [D4b025] and 0.50 miles [D4b050] were reported as proportions (values range from zero to one). These proportions may be applied to the CBG's activity variables (demographics and employment) to approximate the number of housing units and jobs that CBG contains that are located near rapid transit stations.

#### **Aggregate Frequency of Peak Hour Transit Service (D4c)**

GTFS transit schedule information was analyzed to calculate the frequency of service for each transit route during the weekday evening peak hour (4:00PM and 7:00PM local time). Transit routes with service that stops within 0.4 km (0.25 miles) crow-fly distance from the boundary of the CBG were then identified. Lastly, total aggregate service frequency was summed by CBG. Values for this metric are

<sup>&</sup>lt;sup>64</sup> Some CBGs have a value of "0" (indicating transit stops in close proximity) due to population-weighted centroids snapping directly on top of nearby transit stops on the network.

<sup>&</sup>lt;sup>65</sup> A value of "-99999" was assigned to SLD transit-based variables (D4 and D5b, D5d) that exceeded distance thresholds or did not have GTFS data coverage. Shoreline or CBGs in water bodies with no land area, no population and no jobs were also assigned a value of "-99999".

expressed as service frequency per hour of service. CBGs in areas that do not have transit service were assigned the value "-99999." Due to the distance threshold and buffer type differing from access to nearest transit stop, it may be the case that some CBGs have a valid access to nearest transit [D4a] value while not having an aggregate frequency of transit service [D4c] value or vice versa.

#### Aggregate Frequency of Peak Hour Transit Service Density (D4d)

This measure applies density characteristics to aggregate transit service frequency per square mile. This metric was calculated by dividing aggregate transit service frequency [D4c] by total land acreage [Ac\_Land], then converting to units per square mile. In a few instances where a CBG had no land acreage ([Ac\_Land] = 0), total CBG polygon acreage [Ac\_Total] was used as the denominator.<sup>66</sup> CBGs in areas that did not have transit service were given the value "-99999."

#### Aggregate Frequency of Peak Hour Transit Service per Capita (D4e)

Aggregate transit service frequency per capita [D4e] divides aggregate transit frequency [D4c] by total population [TotPop]. In the few instances where there was transit access and no population ([TotPop] = 0), the per capita transit access was set to  $0.^{67}$  All CBGs in areas where GTFS service data were unavailable were assigned a value of "-999999."

## **Destination Accessibility (D5)**

The most sophisticated variables to be included in the SLD address CBG-to-CBG accessibility. The primary variables ([D5ar], [D5ae], [D5br], [D5be]) all measure jobs or working-age population within a 45- minute commute via automobile (D5a) or 45 minute commute on a transit vehicle (which can be up to a 90 minute total travel time when walking access, walking egress, wait and transfer times are included) (D5b). Variable names with an "r" reflect accessibility from residences to jobs. Variable names with an "e" reflect accessibility from employment locations to working-age population (ages 18-64). A travel-time decay formula is used in each calculation to weight jobs/population closer to the origin CBG more heavily than those further away. D5c and D5d measure accessibility relative to other CBG within the same metropolitan region (CBSA). The approach to developing each of these measures is described below.

#### **Destination Accessibility via Automobile Travel (D5a)**

A geoprocessing model was developed using the TravelTime API to facilitate the calculation and tabulation of auto-accessible CBGs from a given origin CBG within a 45-minute drive time. The processing iterated through each CBG to identify candidate accessible CBGs (within a 45-mile radius). Auto travel times were then estimated for trips starting at each origin CBG at 8:00 AM local time (typical non-holiday Tuesday) and ending at each candidate destination CBG. If each trip's travel time was 45 minutes or less, the candidate CBG was selected as a match. For each match, the time-weighted access to jobs [D5ar] and working age population [D5ae] values were recorded. Values for all matches from each CBG origin were summed to estimate the final [D5ar] and [D5ae] accessibility metrics.

The decay function used to adjust accessibility values (population or employment) was the same equation used in SLD version 2.0. The original decay formula was derived from the report "Travel Estimation Techniques for Urban Planning" (NCHRP Report 365, Transportation Research Board, 1998) and is displayed below:

D5 Acc<sub>i</sub>=
$$\sum_{j=1}^{\infty} Emp_j * f(d)_{ij}$$

<sup>&</sup>lt;sup>66</sup> In the case where a CBG had no land area, no population and no jobs, the CBG was assigned a value of "-99999."

<sup>&</sup>lt;sup>67</sup> It is possible that some block groups that have transit service frequency in urbanized areas, however, they have no population and only have employment. These block groups were denoted as having a transit service frequency per capita of 0 in contrast to -99999 for block groups without transit service.

where

**D5** Acc<sub>i</sub> is the destination accessibility for CBG *i*, **Emp**<sub>j</sub> is the measure of Working-Age Population in the CBG *j*, and  $f(d)_{ij}$  is the measure of impedance between CBG *i* and CBG *j*.

$$f(d)_{ij} = a^* d_{ij}^{-b} e^{-c^*(d_{ij})}$$

Where,  $\mathbf{a} = 1$ ,  $\mathbf{b} = 0.300$ , and  $\mathbf{c} = 0.070$ ; please note that  $\mathbf{e}$ , is the exponential function.

This function  $f(d)_{ij}$  produces the curve displayed in Figure 1. The equation emphasizes close proximity, decaying rapidly as travel time increases up to about 10 minutes, at which point the friction resulting from marginal increases in travel time begins to ease. The decay factor approaches zero as travel time increases beyond 40 minutes.



Figure 1: 2017 NHTS travel time distance decay based on reported commute travel times.

The origin-destination (OD) matrix development process did not account for intrazonal travel. Although rows were added to the matrices where the destination CBG centroid was the same as the origin CBG centroid, the travel time reported for the OD pair was zero. A travel time of zero cannot be weighted using the distance decay formula described above, so to account for intrazonal destinations, intrazonal travel time

was estimated for each CBG. The formula for estimated intrazonal travel time was also taken from NCHRP 365:

$$T_{iz} = 0.5^* \sqrt{A_i}^* \frac{60}{s_i}$$

where

 $T_{iz}$  is the intrazonal travel time for CBG *i* in minutes,  $A_i$  is the unprotected area of CBG *i* in square miles, and  $s_i$  is the estimated travel speed within CBG *i* in miles per hour.

This equation required the estimation of a typical intrazonal travel speed. This was accomplished by classifying each CBG as "urban," "suburban," or "rural" based on activity density in the CBG. Activity densities were joined from the D1 – Density table and represent the total number of jobs and dwelling units per unprotected acre for each CBG. CBGs, where total activity density was less than 0.5 activity units per unprotected acre, were deemed "rural" and assigned an intrazonal travel speed of 35 miles per hour. CBGs with activity densities higher than six units per unprotected acre were classified as urban and assigned a travel speed of 15 miles per hour. All other CBGs were classified as suburban and assigned an intrazonal speed of 25 miles per hour. These designations were developed through visual inspection of areas well known to the study team. They only influenced the tabulation of intrazonal travel times and were not used in any other part of the analysis.

After all travel times had been fully tabulated - whether intrazonal derived from equations or intrazonal derived from the network analysis model – employment and working age population totals at destination CBGs were weighted by the decay curve described above and summed for each origin CBG. The sum of time-decayed employment accessible from each CBG is reflected in the variable [D5ar]; the corresponding figure for working-age population accessible from each CBG is reflected in the variable [D5ar].<sup>68</sup>

## Destination Accessibility via Transit (D5b)

Transit accessibility was assessed in essentially the same way as auto accessibility, although the development of CBG to CBG OD matrices was more complex. The following steps were applied to generate the D5b estimates:

- 1. All CBGs population centroids that were within a 15-minute walking distance of any transit stop (from the full set of all transit agencies with GTFS data) were selected and defined as trip end points.
- 2. The TravelTime API was used within a processing engine script to iterate through each trip endpoint, defining that point as a home destination. Candidate trip origins (work locations) were selected using a 45-mile radius (same values used in defining D5a candidates). A geoprocessing model used the TravelTime API to estimate origin (work) to destination (home) travel times and distances for transit trips starting between 5:00 PM and 5:45 PM (typical Tuesday in October, 2020). Results that contained origin-to-boarding or alighting-to-destination walk times greater than 15 minutes were excluded. Similarly, trips with time spent on a transit vehicle greater than 45 minutes were also excluded. A single transfer was allowed within the same transit system or to a separate transit system. The shortest valid travel time for each OD pair was saved. It should be noted that this estimate includes non-transit walk trips to candidate CBGs if that walk trip was less than 15 minutes.
- 3. Given that the TravelTime API was applied to conditions during the 2020 COVID-19 pandemic when some transit agencies reduced service, an effort was made to identify those changes and adjust values using older GTFS data from pre-COVID-19 periods. To test this, a second set of OD calculations was run for each valid OD candidate pair that was available in the raw GTFS files. This method used the same parameters as step #2 (TravelTime API) but was processed entirely using a local script. If the resulting set of OD pairs was larger using this approach, then the values from this approach were selected instead of the TravelTime API approach described in step #2. A primary and significant difference in this approach compared to the API approach is that transfers across separate GTFS files (different transit operators) were not possible using static and historic GTFS data, but they are available through the API. For this reason, the API approach was given first priority.
- 4. Once the final sets of matching OD pair travel times were identified, a time decay function was applied to adjust the access to employment and working-age population. The time-decay function applied to transit trips is different than the one applied to auto trips. The transit travel time decay

<sup>&</sup>lt;sup>68</sup> CBGs in shorelines or water bodies with no land area, no population and no jobs were assigned a value of "0."

function was generated from the 2017 National Household Travel Survey, where transit journey times were recorded for participants who made home to work trips. Figure 2 shows three different time decay functions. The decay function used for SLD version 2.0 and the 2020 auto work trip decay function is shown in red. The blue line shows the time decay function based on NHTS transit trips and was applied to the 2020 estimates of D5b job and worker accessibility. The green line is time decay for auto trips based on NHTS data and is only shown for comparison and was not used for any analysis.



Figure 2: Graph demonstrating the various time decay functions by source.

5. Just as in the auto accessibility calculations, intrazonal employment and population accessibility estimates were added to the transit accessibility estimates to account for non-auto access within a block group.

In summary, the transit analysis focused on the basic phases of a transit trip: walking to access transit service, the in-vehicle trip, walking and/or waiting to make a transfer, the second in-vehicle trip (where available), and walk egress from a transit stop to a destination. Each phase is described below.

#### Walk Access to Transit

Walk access to transit was modeled as the network distance from a CBG population centroid to each accessible (within a 15-minute walk allowance) transit stop using either the TravelTime API or the static GTFS data set. A standard wait time of 5 minutes to make the first boarding was allowed.

#### In-Vehicle Time (first trip)

From walk accessible stops, additional ride accessible stops were located. These were stops to which a traveler could ride from the walk accessible stops based on the transit trips serving those stops. The maximum in-vehicle time permitted was 45 minutes. The total amount of in-vehicle time from the walk

accessible stop of origin was retained when modeling transfer opportunities.

## Transfers

For all ride accessible stop events, there may exist transfer opportunities. Ten minutes total transfer time was permitted, of which five could be spent walking to make the transfer. Transfers across transit systems from different operators were allowed for the TravelTime API estimates. Transfers using the static GTFS file method were only allowed within the same, single operator transit system.

## In-Vehicle Time (second trip)

A maximum of 45 minutes in-vehicle time was allowed. Thus, the stops accessible by riding during the second trip had to be reachable within 45 minutes minus the time spent on the trip's first in-vehicle leg. Stop events were linked to their stop locations, and pairs were summarized to find the fastest travel time between stop locations by any combination of walking, riding, and transferring during the analysis time period (PM peak).

## Walk Egress

Walk egress is developed using the same data as the walk access to transit, assuming that the alighting to destination walk time is the same travel time as the reverse direction. The TravelTime API approach provided total walk time and distance for each calculation, allowing controls of walk times and distances.

## Walk Competitiveness

For some OD pairs – especially in highly urbanized areas – walk travel times to neighboring CBGs were expected to be competitive with transit travel times, especially considering the five minute wait time required for the first boarding of a transit vehicle in the transit accessibility analysis. Thus, walk times between neighboring CBGs were analyzed for all CBGs that had some access to transit. A maximum 15 minute walk from origin to destination was permitted. The minimum travel time between zones by transit or by walking was compared and walking travel time was selected if it was more expedient than transit.

Transit accessibility was analyzed for the PM peak travel period only, as typically, this is a period of relatively intense transit service levels and during which a rich mix of commuting and discretionary tripmaking occurs. GTFS schedules were queried to isolate trips and their related stop events within the 5:00 PM to 6:30 PM time frame. There is no hard and fast departure time from the CBG origin. Rather, since all possible permutations of traveling by transit between stops were analyzed, the CBG to CBG travel times reported in the final matrix reflect the optimal transit trip connecting those CBGs in the PM peak period. The first transit trips had to be boarded prior to 5:45 PM. These and other key parameters of the transit analysis, as described herein, are summarized in Table 7.

Full Travel Period	5:00 PM to 6:30 PM
Travel Period of Walk Departure from CBG origin	5:00 PM to 5:45 PM
Travel Period of First Trip Boarding	5:00 PM to 5:45 PM
Maximum Possible Total Travel Time for the Transit Trip	90 minutes
Maximum Walk Time Allowed for Access	15 minutes
Wait time to Board First Trip	0-5 minutes
Maximum Total In-Vehicle Travel Time	45 minutes (first and second trips combined)
Number of Transfers Allowed	1
Maximum Time Allowed for Waiting to Make a Transfer	10 minutes
Maximum Time Allowed for Walking to Make a Transfer (subsumed within time for waiting to make a transfer)	5 minutes
Maximum Walk Time Allowed for Egress	15 minutes

#### Table 7: Attributes and Parameters of Transit Accessibility Analysis.

#### Accounting for directional transit service

The transit accessibility analysis was conducted for the PM peak period. However, several examples of places are served only by AM peak period service towards downtown and PM peak period service away from downtown. This analysis assumes that directional transit service always conforms to this symmetrical pattern. The transit analysis followed this pattern and all results are based on work to home transit travel accessibility.

## Proportional Regional Accessibility (D5c)

An additional set of accessibility variables were also calculated to measure accessibility by automobile (D5a) and transit (D5b) relative to other CBGs within the same metropolitan region. The CBSA for each block group was used to identify metropolitan areas.<sup>69</sup> Proportional regional accessibility for access to jobs ([D5ar] and [D5br]) and working age population ([D5ae] and [D5be]) were determined as a ratio of total CBSA accessibility. This was performed by summarizing the total access to jobs and working age population for each CBSA. Then access to employment and working age population in each CBG was divided by the total CBSA-level accessibility to attain proportional regional accessibility. Proportional regional accessibility to jobs ([D5cr] and [D5dr]) and working age population ([D5ce] and [D5de]) represent the ratio of CBG-level to CBSA-level access.

## **Relative Regional Accessibility (D5d)**

To further complement the regional accessibility to jobs ([D5ar] and [D5br]) and working age population ([D5ae] and [D5be]), a secondary set of measures were created to compare access in each CBG to the CBG with the highest access values in the metropolitan region. This relative regional accessibility measure, also known as a regional centrality index, was calculated by determining the maximum access to jobs and working age population for each CBSA. Then access to employment and working age population in each CBG was divided by the maximum CBSA-level accessibility to attain the regional centrality index. The relative regional accessibility to jobs ([D5cri] and [D5dri]) and working age population ([D5cei] and [D5dei]) represent the ratio of each CBG to the maximum CBG value within each CBG's region.

## National Walkability Index

Following the release of version 2.0 of the SLD, a subsequent set of measures was used to create a National Walkability Index (NWI) made available in 2015.<sup>70</sup> Walkability is characterized by components of the built environment that influence the likelihood or feasibility of walking as a form of utilitarian transportation. The NWI was intended to help address a growing demand for data products that enable users to consistently compare multiple places based on their suitability for walking as a means of travel. This measure was designed to also be a source input measure for transportation planning, including for scenario planning applications.

Along with the NWI data release, a user guide was developed to describe the methods and potential application . To create this measure of walkability, four SLD measures were combined into a composite index: 1) employment and household entropy [D2A\_EPHHM], 2) static eight-tier employment entropy [D2b\_E8MIXA], 3) street intersection density (weighted, auto-orientated intersections eliminated) [D3b] and 4) distance to nearest transit stop [D4a]. These four measures represent different characteristics of the built environment that are known to be supportive of walking, including a range of diversity in land uses, street connectivity and access to public transit. In this case, employment and household entropy and the static eight-tier employment entropy were both used as proxies for land use mix. A ranked score was calculated for each of the component measures by placing block groups into 4 quantiles (groupings each having an equal number, in this case, 25%, of CBGs). CBGs were then ranked from 1 (lowest relative

<sup>&</sup>lt;sup>69</sup> Values for this measure were not calculated for rural and small-town areas outside of metropolitan areas (not part of a CBSA).

<sup>&</sup>lt;sup>70</sup> National Walkability Index U.S. EPA

support for walking) to 20 (highest relative support for walking) based on their value within the quantiles.<sup>71</sup> The ranked scores were then weighted using the following formula: <sup>72</sup>

Walkability Index score =  $\binom{w}{3} + \binom{x}{3} + \binom{y}{6} + \binom{z}{6}$ 

Where w = CBG ranked score for intersection density x = CBG ranked score for proximity to transit stops y = CBG ranked score for employment mix z = CBG ranked score for employment and household mix

Using the formula above, all CBGs are assigned a National Walkability Index value between 1 (lowest walkability) and 20 (highest walkability). Scores are categorized into the following basic levels of walkability: 1) least walkable (1.0-5.75), 2) below average walkable (5.76-10.5), 3) above average walkable (10.51-15.25) and 4) most walkable (15.26-20.0).

<sup>&</sup>lt;sup>71</sup> Due to access to transit either not available (no transit service exists or transit service not producing GTFS data) or beyond the 0.75 mile (1,207 m) threshold in many CBGs in the country, any CBG given a "-99999" value was ranked in the first quantile. As a result, ranked CBGs only comprise rank 1 (without nearby transit service) and 15-20.

<sup>&</sup>lt;sup>72</sup> The elasticities (magnitude of impact) of intersection density, land use mix, and proximity to transit were all significant and similar in magnitude (Ewing and Cervero 2010). To keep the methodology behind the National Walkability Index as simple as possible while still incorporating the known impact of the built environment on walkability, the variables were weighted as follows: 1/3 to each of the three categories of street intersection density, land use mix, and proximity to transit. The land use mix category was divided into two to account for the two different techniques of measurement; employment mix and employment and household mix were each weighted by 1/6.

## Appendix A: Regions with transit service data reflected in SLD metrics

Table 8 provides a summary of regions with fixed-guideway transit service used in the development of SLD transit variables.<sup>73</sup> The type of fixed-guideway transit service for each metropolitan area is also described. Transit stations and stops shown in this table were specifically used in the development of the D4b variables related to access to fixed-guideway transit service.

Metropolitan Area	State	System Type*
Albany	NY	Intercity Rail
Albuquerque	NM	Commuter Rail
Atlanta	GA	Metro, Streetcar
Austin	TX	Light Rail
Baltimore	MD	Metro, Light Rail, Commuter Rail, Intercity Rail
Boston	MA	Metro, Commuter Rail, Ferry
Buffalo	NY	Light Rail
Charlotte	NC	Light Rail, Streetcar, Bus Rapid Transit
Chicago	IL	Metro, Commuter Rail, Intercity Rail
Cincinnati	OH	Streetcar
Cleveland	OH	Metro, Bus Rapid Transit
Dallas	TX	Light Rail, Commuter Rail, Streetcar
Denver	СО	Light Rail, Commuter Rail
Detroit	MI	Light Rail**
Eugene	OR	Bus Rapid Transit, Intercity Rail
Grand Rapids	MI	Bus Rapid Transit
Harrisburg	PA	Intercity Rail
Hartford	СТ	Commuter Rail, Bus Rapid Transit
Houston	TX	Light Rail
Jacksonville	FL	Light Rail**
Kansas City	MO	Bus Rapid Transit
Las Vegas	NV	Bus Rapid Transit, Monorail
Little Rock	AR	Streetcar
Los Angeles	CA	Metro, Light Rail, Commuter Rail, Bus Rapid Transit
Memphis	TN	Streetcar
Miami	FL	Metro, Commuter Rail, Light Rail**
Milwaukee	WI	Streetcar, Intercity Rail
Minneapolis	MN	Light Rail, Commuter Rail
Nashville	TN	Commuter Rail
New Haven	CT	Commuter Rail
New Orleans	LA	Streetcar
New York	NY	Metro, Commuter Rail, Ferry, Aerial Tram
Norfolk-Virginia Beach	VA	Light Rail, Ferry
Oklahoma City	OK	Streetcar
Orlando	FL	Commuter Rail
Philadelphia	PA	Metro, Commuter Rail
Phoenix	AZ	Light Rail
Pittsburgh	PA	Light Rail, Funicular
Portland	OR	Light Rail, Commuter Rail, Intercity Rail, Streetcar, Aerial Tram
Providence	RI	Commuter Rail
Sacramento	CA	Streetcar, Intercity Rail
Salt Lake City	UT	Light Rail, Commuter Rail
San Diego	CA	Light Rail, Commuter Rail, Streetcar, Bus Rapid Transit, Intercity Rail

*Table 8: Summary of metropolitan regions with fixed-guideway transit service incorporated into SLD variables.* 

<sup>&</sup>lt;sup>73</sup> This table may not include regions with only single stops that are part of intercity (commuter rail) or ferry terminals.

San Francisco	CA	Metro, Light Rail, Commuter Rail, Intercity Rail, Streetcar, Cable Car,
		Ferry
San Juan	PR	Metro
Seattle	WA	Light Rail, Commuter Rail, Intercity Rail, Streetcar, Monorail, Ferry
St. Louis	MO	Light Rail
Tampa	FL	Streetcar, Light Rail*
Tucson	AZ	Streetcar
Washington	DC	Metro, Commuter Rail, Streetcar

\* Fixed-guideway system types may vary or be classified using different terminology depending on region. \*\* Denotes tram or "People Mover" systems which may or may not be automated.

## **Appendix B: Transit Service Data: GTFS Transit Agencies**

Table 9 provides a listing, in alphabetical order, of all transit service agencies that had available GTFS data incorporated into SLD transit service and accessibility metrics. The table provides the agency name, as well as an alternative name or commonly used abbreviation, service name or stylization to identify service providers better. Each transit agency's service area is also included, which may consist of a principal city, county or state where transit service is offered. Lastly, the data release month and year of the GTFS for each agency is provided for reference.

#	Agency Name	Alternative Name	Service Area	GTFS Date
1	10-15 Transit		Ottumwa, IA	Dec, 2019
2	128 Business Council		Waltham, MA	Oct, 2017
3	ABO RIDE		Albuquerque, NM	Sep. 2020
4	Addison County Transit Resources		Middlebury, VT	Dec. 2018
5	Advance Transit		Wilder, VT	Sep. 2020
6	Airport (MAC)		Minneapolis-St. Paul, MN	Sep. 2020
7	Airport Valet Express		Bakersfield, CA	Jul. 2020
8	Alameda County Transit	AC Transit	Alameda County, CA	Aug. 2019
9	Albany Transit System		Albany, OR	Jul. 2020
10	Allegany County Transit		Cumberland, MD	Aug. 2019
11	Amador Transit		Amador, TX	Jul, 2020
12	Amarillo City Transit		Amarillo, TX	Apr. 2019
13	Anaheim Resort Transportation		Anaheim, CA	Sep. 2020
14	Anchorage People Mover		Anchorage, AK	Jul. 2019
15	Ann Arbor Area Transportation Authority	The RIDE	Ann Arbor, MI	Sep. 2020
16	Annapolis Transit		Annapolis, MD	Aug. 2019
17	Arcata & Mad River Transit System		Eureka-Arcata, CA	Sep. 2020
18	Arlington Transit		Arlington, VA	Sep. 2020
19	Asheville Rides Transit	ART	Asheville. NC	Sep. 2020
20	Asian Health and Service Center		Portland, OR	Jul. 2020
21	Athens Public Transit	The Bus	Athens, GA	Sep. 2020
22	Atlanta Streetcar		Atlanta, GA	Sep. 2020
23	Avon Transit		Avon, CO	Apr. 2020
24	Baltimore City Department of Transportation	Charm City Circulator	Baltimore, MD	Jan. 2020
25	Basin Transit Service		Klamath Falls, OR	Jun. 2020
26	Bay Area Rapid Transit	BART	San Francisco, CA	Sep, 2020
27	Bay Area Transportation Authority	BATA	Traverse City, MI	Sep, 2020
28	Bay State Cruise Company		Boston, MA	Jul, 2020
30	Bay Town Trolley		Panama City, FL	Jul, 2020
31	Beaumont Transit		Beaumont, TX	Aug, 2020
32	Beaver County Transportation Authority	BCTA	Beaver County, PA	Sep, 2020
33	Bee-Line Bus		Mount Vernon, NY	Sep, 2020
34	Beloit Transit System		Beloit, WI	Jul, 2020
35	Ben Franklin Transit	BFT	Richland, WA	Sep, 2020
36	Benton Area Transit		Corvallis, OR	Sep, 2020
37	Berkshire Regional Transit Authority		Pittsfield, MA	Aug, 2020
38	Big Blue Bus		Santa Monica, CA	Sep, 2020
39	Birmingham-Jefferson County Transit Authority	BJCTA	Birmingham, AL	Mar, 2020
40	Black Ball Ferry Line		Port Angeles, WA	Jul, 2020
41	Blacksburg Transit		Blacksburg, VA	Jan, 2020
42	Block Island Ferry		Narragansett, RI	Sep, 2020
43	Bloomington Transit		Bloomington, IN	Sep, 2020
44	Blue Lake Rancheria Transit System		Humboldt County, CA	Sep, 2020
45	Bluegrass Ultra-Transit Service		Lexington, KY	Dec, 2019
46	Boston Express		Concord, NH	Sep, 2020
47	Boston Harbor Islands National and State Park		Boston, MA	May, 2018
48	Brockton Area Transit Authority	BAT	Brockton, MA	Sep, 2020
49	Broward County Transit		Miami-Ft Lauderdale, FL	Sep. 2020

*Table 9: Summary of transit agencies that have GTFS data reflected in SLD measures.* 

#	Agency Name	Alternative Name	Service Area	GTFS Date
50	Bullhead Area Transit System	BATS	Bullhead City, AZ	Jan, 2020
51	Burlington Urban Service		Burlington, IA	Dec, 2019
52	Butler County Regional Transit Authority		Butler County, PA	Sep, 2020
53	Butte-Silver Bow		Butte, MT	Dec, 2019
54	BWI Thurgood Marshall Airport		Baltimore, MD	Dec, 2017
55	Calaveras Transit		Calaveras County, CA	Dec, 2019
56	Caltrain		San Francisco, CA	Aug, 2020
57	Canby Area Transit	CAT	Canby, OR	Dec, 2019
58	Cape Ann Transportation Authority		Gloucester, MA	Sep, 2020
60	Cape Cod Regional Transit Authority	CCRTA	Hyannis, MA	Sep, 2020
61	Cape Fear Public Transportation Authority	Wave Transit	Wilmington, NC	Sep, 2020
62	Capital Area Transit		Raleigh-Durham, NC	Sep, 2020
64	Capital Area Transportation Authority	CATA	Lansing, MI	Jan, 2020
65	Capital District Transportation Authority	CDTA	Albany, NY	Sep, 2020
66	Capital Metro		Austin, TX	Aug, 2020
67	Capital Transit		Juneau, AK	Apr, 2020
68	Capitol Corridor Joint Powers Authority		Sacramento, CA	Sep, 2020
69	Caravan Airport Transportation		Portland, OR	Jan, 2020
70	Cascades East Transit		Bend, OR	Sep, 2020
71	Cascades POINT		Eugene, OR	Jul, 2020
72	Casco Bay Lines		Portland, ME	Oct, 2019
73	Cecil Transit		Cecil County, MD	Aug, 2019
74	Cedar Rapids Transit		Cedar Rapids, IA	Sep, 2020
75	Central Arkansas Transit Authority		Little Rock, AK	Sep, 2020
76	Central Florida Regional Transit Authority	Lynx	Orlando, FL	Jul, 2020
77	Central Midlands Regional Transit Authority	The COMET	Columbia, SC	Sep, 2020
78	Central New York Regional Transportation Authority	Centro	Syracuse, NY	Sep, 2020
79	Central Ohio Transit Authority		Columbus, OH	Sep, 2020
80	Central Oregon Breeze		Bend, OR	Sep, 2020
81	Central Pennsylvania Transportation Authority	Rabbittransit	York, PA	Jun, 2020
82	Ceres Area Transit	CAI	Modesto, CA	Apr, 2016
83	Champaign Urbana Mass Transit District		Champaign-Urbana, IL	Sep, 2020
84	Chapter Area Designal Transmitter Arthurity	CADTA	Chapler Hill, NC	Jul, 2020
85	Charlette Area Transit System	CARIA	Charlette NC	Sep, 2020
87	Charlottecyille Area Transit	CAIS	Charlottesville VA	Sep, 2020
88	Chatham Area Transit	CAT	Savannah GA	Jul 2020
80	Chattanooga Area Regional Transportation Authority	CARTA	Chattanooga TN	Sep 2020
90	Cherriots	CARTA	Salem-Keizer OR	Jul 2020
91	Chicago Transit Authority		Chicago II	Sep 2020
92	Cities Area Transit	CAT	Grand Forks ND	Aug 2020
93	Citilink		Ft Wayne, IN	Sep. 2020
94	Citrus County Transit	Orange Line Bus	Lecanto, FL	Nov, 2015
95	City of Bandon Trolley	8	Bandon, OR	Aug. 2020
96	City of Fairfax City-University-Energysaver	Fairfax CUE	Fairfax, VA	Sep. 2020
97	City of Milton-Freewater		Milton-Freewater, OR	May, 2020
98	City of Palo Alto Shuttle		Palo Alto, CA	Jan, 2020
99	City of San Luis Obispo Transit	SLO Transit	San Luis Obispo, CA	Aug, 2020
100	City of Seattle		Seattle, WA	Sep, 2020
101	City of Seattle		Seattle, WA	Sep, 2020
102	City of South Portland Transit	South Portland Transit	South Portland, ME	Sep, 2020
103	City2City Shuttle		Portland, OR	Jul, 2018
104	CityLink		Coeur d'Alene, ID	Sep, 2020
105	Clackamas Community College	CCC Xpress	Clackamas County, OR	Aug, 2020
106	Clackamas County Consortium		Clackamas County, OR	Jul, 2020
107	Clallam Transit System		Clallam County, WA	Sep, 2020
109	Clark County Public Transit Benefit Area Authority	C-TRAN	Vancouver, WA	Sep, 2020
110	Clemson Area Transit		Clemson, SC	Apr, 2019
111	Clinton Municipal Transit Administration	Clinton MTA	Clinton, IA	Jun, 2020

#	Agency Name	Alternative Name	Service Area	GTFS Date
112	Clovis Transit		Clovis, CA	Jul, 2020
113	Coach Company - Massachusetts		Merrimac, MA	Jun, 2020
114	Coach Company - New York		New York, NY	Sep, 2020
115	Coach USA		New York, NY	Feb, 2010
116	CobbLinc		Cobb County, GA	Sep, 2019
117	Colorado Department of Transportation	Bustang	Denver, CO	Jul, 2020
118	Columbia Area Transit		Hood River, OR	Sep, 2020
119	Columbia County Rider	CC Rider	Columbia County, OR	Sep, 2020
120	Community Transit		Everett, WA	Jun, 2020
121	Community Transit		Everett, WA	Sep, 2020
122	Concord Kannapolis Area Transit	Rider	Concord, NC	Mar, 2020
123	Connect Transit		Normal, IL	Sep, 2020
124	Connecticut Transit - Hartford	CTTransit	Hartford, CT	Sep, 2020
125	Connecticut Transit - New Britain	CTTransit	New Britain, CT	Sep, 2020
126	Connecticut Transit - New Haven	CTTransit	New Haven, CT	Sep, 2020
127	Connecticut Transit - Stamford	CTTransit	Stamford, CT	Sep, 2020
128	Connecticut Transit - Waterbury-Meriden	CTTransit	Waterbury, CT	Sep, 2020
129	Coos County Area Transit		Coos Bay, OR	Aug, 2020
130	Coralville Transit		Coralville, IA	Aug, 2020
131	Corona Cruiser		Corona, CA	Dec, 2019
132	Corpus Christi Regional Transportation Authority		Corpus Christi, TX	Sep, 2020
133	Corvallis Area Transit		Corvallis, OR	May, 2016
134	Cottonwood Area Transit		Cottonwood, AZ	Dec, 2019
135	County Connection		San Francisco, CA	Sep, 2020
136	Culver CityBus		Culver City, CA	Sep, 2020
137	Curry Public Transit		Coos Bay, OR	Aug, 2019
138	Cuttyhunk Ferry Co.		New Bedford, MA	Sep, 2020
139	Cuyahoga Valley Scenic Railroad		Peninsula, OH	May, 2018
140	Dallas Area Rapid Transit	DART	Dallas-Ft Worth, TX	Sep, 2020
141	Dart First State		Wilmington, DE	Sep, 2020
142	DASH		Alexandria, VA	Sep, 2020
143	DATTCO		Fairhaven, MA	Jul, 2020
144	DC Circulator		Washington, DC	Jul, 2019
145	DC Streetcar		Washington, DC	Sep, 2020
146	Denton County Transportation Authority	DCTA	Denton County, TX	Aug, 2020
147	Des Moines Area Regional Transit Authority	DART	Des Moines, IA	Aug, 2020
148	Detroit Department of Transportation		Detroit, MI	Sep, 2020
149	Detroit People Mover		Detroit, MI	Sep, 2020
150	Diamond Express		Eugene, OR	Nov, 2019
151	Dodger Area Rapid Transit	DART	Fort Dodge, IA	Jul, 2020
152	Duarte Transit		Duarte, CA	Dec, 2018
153	Duke Transit		Durham, NC	Sep, 2020
154	Duluth Transit Authority		Duluth, MN	Aug, 2020
155	Eastern POINT		Bend, OR	Aug, 2020
156	Eastern Sierra Transit Authority		Inyo County, CA	Jul, 2020
157	El Dorado Transit		El Dorado County, CA	Jul, 2020
158	El Monte Transit		El Monte, CA	Nov, 2019
159	EMBARK	EMBARK	Oklahoma City, OK	Sep, 2020
160	Emery Go-Round		Emeryville, CA	Jul, 2020
161	Erie Metropolitan Transit Authority	EMTA	Erie County, PA	Jan, 2020
162	Escambia County Area Transit	ECAT	Pensacola, FL	May, 2020
163	Estuary Transit District	9 Town Transit	Middlesex County, CT	Jun, 2020
164	eTrans		Escalon, CA	Jul, 2020
165	Eureka Transit Service		Eureka-Arcata, CA	Sep, 2020
167	Everett Transit		Everett, WA	Sep, 2020
168	Express Arrow		Greeley, CO	Jun, 2020
169	Fairfax Connector		Fairfax, VA	May, 2020
170	Fairfield & Suisun Transit	FAST	Fairfield, CA	Sep, 2020
171	Fargo Moorhead Area Transit	MATBUS	Fargo, ND	Sep, 2020

#	Agency Name	Alternative Name	Service Area	GTFS Date
172	Florida Department of Transportation		Florida	Sep, 2020
173	Foothill Transit		West Covina, CA	Sep, 2020
174	Franklin Regional Transit Authority		Greenfield, MA	Sep, 2020
175	Franklin Transit		Nashville, TN	Dec, 2019
176	Frederick County Transit	TransIT	Frederick County, MD	Jul, 2019
177	Freedom Cruise Line		Harwich Port, MA	Jul, 2020
178	Fresno County Rural Transit Agency	FCRTA	Fresno, CA	Dec, 2018
179	Fresno Public Transportation	FAX	Fresno, CA	Jul, 2020
180	Gainesville Regional Transit System	RTS	Gainesville, FL	Sep, 2020
181	Georgia Regional Transportation Authority	GRTA	Atlanta, GA	Sep, 2020
182	Glendale Beeline		Glendale, CA	Sep, 2020
183	GO Transit (City of Oshkosh)		Oshkosk, WI	Mar, 2020
184	GoCary		Cary, NC	Jun, 2020
185	GoDurham		Durham, NC	Jul, 2020
186	Gold Coast Transit		Oxnard, CA	Sep, 2020
187	Golden Empire Transit District		Bakersfield, CA	Sep, 2020
188	Golden Gate Transit	GGT	San Rafael, CA	Sep, 2020
189	GoRaleigh		Raleigh, NC	Sep, 2020
190	GoTriangle		Raleigh-Durham, NC	Sep, 2020
191	Grays Harbor Transit	GH Transit	Hoquiam, WA	Aug, 2020
192	Greater Bridgeport Transit	GBT	Bridgeport, CT	Dec, 2019
193	Greater Cleveland Regional Transit Authority		Cleveland, OH	Sep, 2020
194	Greater Dayton Regional Transit Authority	Greater Dayton RTA	Dayton, OH	Aug, 2020
195	Greater Lafayette Public Transportation Corporation	CityBus	Lafayette, IN	Aug, 2020
196	Greater Lynchburg Transit Co.		Lynchburg, VA	Dec, 2019
197	Greater Portland Transit District	Greater Portland Metro	Portland, ME	Aug, 2020
198	Greater Richmond Transit Company	GRTC	Richmond, VA	Apr, 2020
199	Green Mountain Community Network, Inc.	GMCN	Bennington, VT	Aug, 2020
200	Green Mountain Transit	GMT	Burlington, VT	Aug, 2020
201	Greenlink Transit		Greenville, SC	Sep, 2020
202	Greenlink Trolley		Greenville, SC	Sep, 2020
203	Groome Transportation		Eugene, OR	Sep, 2020
204	Gunnison Valley RTA		Gunnison, CO	Mar, 2020
205	Gwinnett County Transit	GCT	Lawrenceville, GA	Jul, 2020
206	H & L Bloom, Inc.	Bloom Bus	Taunton, MA	Sep, 2020
207	Hampton Roads Transit	HRT	Hampton, VA	Sep, 2020
208	Harford Transit LINK		Harford County, MD	Feb, 2020
209	Harrisonburg Department of Public Transportation	Harrisonburg Transit	Harrisonburg, VA	Jan, 2018
210	Hartford Line		Hartford, CT	Jan, 2020
211	Hillsborough Area Regional Transit		Tampa, FL	Sep, 2020
212	Humboldt Transit Authority	RTS	Humboldt County, CA	Sep, 2020
213	Huntsville Shuttle Bus		Huntsville, AL	Sep, 2020
214	Hy-Line Cruises		Hyannis, MA	Sep, 2020
215	Impact Northwest	Impact NW	Portland, OR	Jul, 2020
216	IndyGo		Indianapolis, IN	Sep, 2020
217	Intercity I ransit		Olympia, WA	Sep, 2020
218	Intercity Transit	TT 4	Olympia, WA	Sep, 2020
219	Inter-Island Ferry Authority	IFA	Hollis, AK	Dec, 2019
220	Island Iransit	LATDAN	Coupeville, WA	Jul, 2020
221	Jackson Fransit System	JAIKAN	Jackson, MS	Jan, 2020
222	Jacksonvine Transportation Authority	JIA	Jacksonvine, FL Seguine WA	Sep, 2020
223	Jancsuville Transit System		Jonesville WI	Sep, 2020
224	Janesville Hallsti System		Arnold MO	Dec 2010
225	Jefferson Transit Authority		Port Townsend WA	Mar 2020
220	IFK Airtrain		New York NV	Sen 2020
2.28	Johnson County Transit	The JO	Johnson County KS	Sep. 2020
22.9	Josephine Community Transit	11000	Josephine County, RD	May, 2020
230	Kansas City Area Transportation Authority	KCATA	Kansas City, MO	Sep, 2020

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231	Kayak Public Transit		Pendleton, OR	Sep, 2020
232	Kern Transit		Bakersfield, CA	Sep, 2020
233	Key West Transit		Stock Island, FL	Apr. 2020
234	King County Marine Division		Seattle, WA	Sep. 2020
237	King County Metro Transit		Seattle, WA	Sep. 2020
238	Kings Area Rural Transit	KART	Hanford, CA	May, 2020
239	Kingsport Area Transit System	KATS	Kingsport, TN	Sep. 2012
240	Kitsap Transit		Bremerton, WA	Sep. 2020
241	Klamath Tribes		Chiloquin, OR	Jun. 2020
242	Knoxville Area Transit	KAT	Knoxville, TN	Jan, 2020
243	La Crosse Municipal Transit Utility	La Crosse MTU	La Crosse, WI	Jan, 2016
244	LA Go Bus		Los Angeles County, CA	Dec, 2019
245	Los Angeles Department of Transportation	LADOT	Los Angeles, CA	Sep, 2020
250	Laguna Beach Transit		Laguna Beach, CA	Sep, 2020
251	Lake Champlain Ferries		Burlington, VT	Jul, 2020
252	Lake Transit		Lower Lake, CA	May, 2020
253	Lakeland Transit		Lakeland, FL	May, 2011
254	Lakes Region Explorer		Bridgton, ME	Sep, 2020
255	Laketran		Lake County, OH	Sep, 2020
256	Lane Transit District		Eugene, OR	Sep, 2020
257	Lassen Rural Bus		Lassen County, CA	Aug, 2019
258	Lawndale Beat		Lawndale, CA	Dec, 2019
259	Lee County Transit	LeeTran	Lee County, FL	Sep, 2020
260	Lehigh and Northampton Transportation Authority	LANTA	Allentown, PA	Jan, 2020
261	Let'er Bus		Pendleton, OR	Aug, 2020
262	Lexpress		Lexington, MA	Jul, 2009
263	Lextran		Lexington, KY	Dec, 2019
264	Lincoln County Transit		Lincoln County, OR	Sep, 2020
265	Lincoln StarTran		Lincoln, NE	Jul, 2020
266	Link Lane		Eugene, OR	Jul, 2020
267	Link Transit		Chelan, WA	Nov, 2018
268	Linn Shuttle		Albany, OR	May, 2020
269	Linn-Benton Loop		Albany, OR	Jul, 2020
270	LINX Transit		Albany, OR	Jul, 2020
271	Livermore Amador Valley Transit Authority	LAVTA	Livermore, CA	Aug, 2017
272	Logan Express		Boston, MA	Mar, 2020
273	Long Island Bus		New York, NY	Aug, 2011
274	Long Island Rail Road		New York, NY	Mar, 2020
275	Los Angeles County Metropolitan Transportation	Metro	Los Angeles, CA	Sep, 2020
276	Los Angeles County Metropolitan Transportation	METRO	Los Angeles, CA	Sep, 2020
277	Lowell Regional Transit Authority		Lowell, MA	Jul, 2020
278	Madera Area Express	MAX	Madera, CA	Dec, 2019
279	Madera County Connection		Madera County, CA	Jul, 2020
280	Madison Metro Transit		Madison, WI	Sep, 2020
281	Makan Public Transit		Neah Bay, WA	Jan, 2019
282	Malheur Council on Aging & Community Services	MOAT	Ontario, OR	Jul, 2020
285	Manla Crowe	MUCAI	Minnace County, FL	Apr, 2019
284	Maple Grove	T1 D	Minneapolis-St. Paul, MN	Sep, 2020
285	Marble Valley Regional Transit District	The Bus	Rutiand, VI	Sep, 2020
200	Marshalltown Municipal Transit		Marshalltown IA	Sep. 2020
289	Martha's Vineward Transit Authority	VTA	Martha's Vinevard MA	Jun 2020
280	Maryland Transit Administration	ΜΤΔ	Baltimore MD	Sen 2020
209	Mason City Public Transit	141171	Mason City IA	Jan 2020
295	Mason Transit Authority		Mason County WA	Dec 2019
296	Mass Transportation Authority Flint	МТА	Flint MI	Sep. 2019
297	Massachusetts Bay Transportation Authority	MBTA	Boston, MA	Sep. 2020
298	Massport		Boston, MA	Mar, 2020
299	Memphis Area Transit Authoritiy	MATA	Memphis, TN	Aug, 2017

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300	Mendocino Transit Authority		Mendocino, CA	May, 2020
301	Merced County Transit	The Bus	Merced, CA	Sep, 2020
302	Merrimack Valley Regional Transit Authority		Boston, MA	Sep. 2020
303	Met Council		Minneapolis-St. Paul. MN	Sep. 2020
305	Metro St. Louis		St. Louis. MO	Sep. 2020
307	Metro Transit		Minneapolis-St. Paul, MN	Sep. 2020
308	Metro Transit	Root	Omaha, NE	Sep. 2020
310	Metrolink		Los Angeles, CA	May, 2020
311	Metro-North Railroad		New York, NY	Sep. 2020
312	Metropolitan Atlanta Rapid Transit Authority	MARTA	Atlanta, GA	Sep. 2020
313	Metropolitan Family Service		Portland, OR	Jul, 2020
314	Metropolitan Transit Authority of Harris County	METRO	Houston, TX	Sep, 2020
315	Metropolitan Tulsa Transit Authority		Tulsa, OK	Sep, 2020
317	MetroWest Regional Transit Authority	MWRTA	Framingham, MA	Sep, 2020
318	Miami-Dade Transit		Miami-Ft Lauderdale, FL	Sep, 2020
319	Michigan Flyer		East Lansing, MI	Dec, 2019
320	Middlesex 3 TMA		Middlesex County, MA	Jul, 2020
321	Milwaukee County Transit System		Milwaukee, WI	Sep, 2020
322	Minnesota Valley Transit Authority	MVTA	Burnsville, MN	Sep, 2020
323	Mission Bay Transportation Management Association	Mission Bay TMA	San Francisco, CA	Aug, 2020
324	MNR Hudson Rail Link		New York, NY	Sep, 2020
325	Modesto Area Express	MAX	Modesto, CA	Jul, 2020
326	Monroe County Transit Authority	MCTA	Monroe County, PA	Jul, 2020
327	Montachusett Regional Transit Authority		Fitchburg, MA	Sep, 2020
328	Monterey Park Spirit Bus		Monterey Park, CA	Oct, 2019
329	Monterey-Salinas Transit	MST	Monterey, CA	May, 2020
330	Montgomery County MD Ride On		Washington, DC	Jan, 2020
331	Montgomery Transit		Montgomery, AL	Dec, 2019
332	Morro Bay Transit		Morro Bay, CA	Aug, 2020
333	Mountain Area Regional Transit Authority	Mountain Transit	Big Bear, CA	Aug, 2020
334	Mountain Line		Flagstaff, AZ	May, 2016
335	Mountain Line		Missoula, MT	Sep, 2020
336	Mountain Metropolitan Transit		Colorado Springs, CO	Sep, 2020
337	Mountain Rides Transportation Authority	MRTA	Blaine County, ID	Sep, 2020
338	Mt. Hood Express		Clackamas County, OR	Aug, 2020
339	MTA Bus Company		New York, NY	Sep, 2020
346	MTA New York City Transit	MTA	New York, NY	Sep, 2020
347	MuscaBus		Muscatine, IA	Jul, 2020
348	MVgo Mountain View		Mountain View, CA	Aug, 2020
349	Mystic		Minneapolis-St. Paul, MN	Sep, 2020
350	Nantucket Regional Transit Authority	The WAVE	Nantucket, MA	Sep, 2020
351	Nassau Inter-County Express	NICE	Nassau County, NY	Aug, 2020
352	Navajo Transit System		Ft. Defiance, AZ	Jan, 2020
353	Neighborhood House		Portland, OR	Jul, 2020
354	Nevada County Gold Country Stage		Nevada County	Aug, 2020
355	New Orleans Regional Transportation Authority	NORTA	New Orleans, LA	Sep, 2020
356	New York City Department of Transportation		New York, NY	Aug, 2020
357	Niagara Frontier Transportation Authority	NFIA	Buttalo, NY	Sep, 2020
358	NJ Iransit	NOOLINE 16.	New Jersey (Statewide)	Sep, 2020
361	North Carolina State University Wolfline	NCSU Wolfline	Kaleigh-Durham, NC	May, 2020
362	North Lake Takes Errors		Demo NV	Jul, 2020
303	North Lake Tanoe Express		Reflor City, OP	Sep, 2020
304	Northern Indiana Commuter Transaction District	NICTD	Chastarton IN	Aug, 2020
365	NorthWest POINT	INICID	Astoria OP	Sep, 2020
367	Norwalk Transit System		Norwalk CT	Δμα 2020
368	NV Waterway		New York NV	Sep 2020
360	NVC Ferry		New York NY	Sep. 2020
370	Ocean City Transportation		Ocean City. MD	Aug, 2019

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371	OMNITRANS		San Bernardino, CA	Sep, 2020
372	Orange County Transportation Authority	OCTA	Orange County, CA	Sep, 2020
373	Other		Minneapolis-St. Paul, MN	Sep, 2020
374	Pacific Crest Lines		Bend, OR	Aug, 2020
375	Pacific Transit		Pacific County, WA	Aug, 2020
376	Palm Tran		Palm Beach County, FL	Sep, 2020
377	Palo Verde Valley Transit Agency	PVVTA	Blythe, CA	Sep, 2020
378	Palos Verdes Peninsula Transit Authority		Rolling Hills, California	Jul, 2020
379	Pasco County Public Transportation	PCPT	Port Richey, FL	Jun, 2020
380	Patriot Party Boats		Falmouth, MA	Aug, 2020
381	People for People		Yakima, WA	Nov, 2019
383	People Mover		John Day, OR	Aug, 2020
384	Petaluma Transit		Petaluma, CA	Aug, 2020
385	Peter Pan Bonanza Division		Springfield, MA	Jun, 2020
386	Peter Pan Bus Lines		Springfield, MA	Jun, 2020
387	Piedmont Authority for Regional Transportation	PART	Greensboro, NC	Aug, 2019
388	Pierce Transit		Tacoma, WA	Aug, 2020
389	Pierce Transit		Tacoma, WA	Sep, 2020
390	Pinellas Suncoast Transit Authority	PSTA	Tampa, FL	Sep, 2020
391	Pioneer Valley Transit Authority	PVTA	Springfield, MA	Sep, 2020
392	Placer County Transit		Auburn, CA	Aug, 2020
393	Plumas Transit		Plumas Transit, CA	Sep, 2020
394	Plymouth		Minneapolis-St. Paul, MN	Sep, 2020
395	Plymouth & Brockton Street Railway Co.	P&B	Plymouth, MA	May, 2020
396	Port Authority of Allegheny County		Pittsburgh, PA	Sep, 2020
397	Port Authority of New York and New Jersey		New York, NY	Aug, 2020
398	Port Authority Trans-Hudson Corporation		New York, NY	Aug, 2020
399	Port Authority Transit Corporation	PATCO Speedline	Philadelphia, PA	Dec, 2019
400	Port of Portland		Portland, OR	Aug, 2020
401	Portland Streetcar		Portland, OR	Aug, 2020
402	Potomac and Rappahannock Transportation	OMNIRIDE	Prince William County, VA	Jun, 2020
403	Public Oregon Intercity Transit (Klamath Shuttle)	Oregon POINT	Klamath Falls, OR	Aug, 2020
404	Puerto Rico Metropolitan Bus Authority	AII	San Juan, PR	Sep, 2020
405	Pulaski Area Transit	Deede	Pulaski, VA	Dec, 2014
406	Racine Transit	Ryde	Racine, WI	Mar, 2020
407	Radar Transit		Rodnoke, VA	Oct, 2015
408	Radiord Transit		Faultavilla A P	Aug. 2000
409	Razorback Transit		Fayetteville, AK	Aug, 2009
410	Red Apple Traisit		Partitington, NM	Dec, 2019
411	Redding Area Bus Authority Padwood Coast Transit	PCT	Euroka Araata CA	Aug, 2020
412	Regional Transportation Authority	DACE	Chicago II	Aug, 2020
413	Regional Transportation Authority Metra	RTA METRA	Chicago, IL	Sep, 2020
415	Regional Transportation Authority of Central Maryland	RTA Maryland	Howard County MD	I co, 2020
415	Regional Hansportation Rationaly of Central Maryland	icize wideyiand	Howard County, MD	Juli, 2020
416	Regional Transportation Authority of Middle Tennessee	RTA	Murfreesboro, TN	Sep, 2020
417	Regional Transportation Commission of Southern Nevada	RTC	Las Vegas, NV	Sep, 2020
418	Regional Transportation Commission of Washoe County	RTC RIDE	Reno, NV	Sep, 2020
419	Regional Transportation District		Denver, CO	Sep, 2020
420	Rhode Island Public Transit Authority	RIPTA	Providence, RI	Jan, 2020
421	Rhody Express		Eugene, OR	Jul, 2020
422	Ride Connection		Portland, OR	Jul, 2020
423	Rio Metro Regional Transit District	Rio Metro Rail Runner	Albuquerque, NM	May, 2020
424	Rio Vista Delta Breeze		San Francisco, CA	Jun, 2020
425	RiverCities Transit		Cowlitz County, WA	Jul, 2020
426	Riverside Transit Agency	RTA	Riverside, CA	Sep, 2020
427	Roaring Fork Transportation Authority	RFTA	Aspen, CO	Sep, 2020

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428	Rochester City Lines		Rochester, MN	Dec, 2014
429	Rochester-Genesee Regional Transportation Authority	RGRTS	Rochester, NY	Sep, 2020
430	Rockland County Department of Transportation	TOR	Rockland County, NY	Dec. 2012
431	Rocky Mountain National Park		Estes Park, CO	May. 2018
432	Rogue Valley Commuter Line		Medford, OR	May. 2020
433	Rogue Valley Transportation District	RVTD	Jackson County, OR	Jun. 2020
434	Roseville Transit		Roseville, CA	Dec. 2015
435	Rural Community Transportation		St. Johnsbury, VT	Jun. 2020
436	Sacramento Regional Transit		Sacramento, CA	Sep. 2020
437	Sage Stage		Modoc County, CA	Sep. 2014
438	Salina CityGo	CityGo	Salina, KS	Jan, 2009
439	San Benito County Express		San Benito County, CA	Aug, 2020
440	San Diego International Airport		San Diego, CA	Sep, 2019
441	San Diego Metropolitan Transit System	MTS	San Diego, CA	Sep, 2019
442	San Francisco Bay Ferry		San Francisco, CA	Jul, 2013
443	San Francisco Municipal Transportation Agency	SFMTA	San Francisco, CA	Sep, 2020
444	San Joaquin Regional Transit District	RTD	Stockton, CA	Aug, 2020
445	San Luis Obispo Regional Transportation Authority	RTA	San Luis Obispo, CA	Sep, 2018
446	Sandusky Transit System		Sandusky, OH	Jun, 2020
447	Sandy Area Metro	SAM	Sandy, OR	Aug, 2020
448	Sangamon Mass Transit Authority	SMTA	Springfield, IL	Sep, 2020
449	Santa Clara Valley Transportation Authority	VTA	San Jose	Aug, 2020
450	Santa Cruz Metro		Santa Cruz, CA	Sep, 2020
451	Santa Fe Trails		Santa Fe, NM	Aug, 2020
452	Santa Maria Area Transit	SMAT	Santa Maria, CA	Jul, 2020
453	Santa Ynez Valley Transit	SYVT	Solvang, CA	Nov, 2019
454	Sarasota County Area Transit		Sarasota, FL	Sep, 2020
455	Seastreak		New York, NY	Sep, 2020
456	Seattle Center Monorail		Seattle, WA	Sep, 2020
457	Seattle Children's Hospital		Seattle, WA	Aug, 2020
459	Selah Transit		Selah, WA	Dec, 2019
460	SEPTA		Philadelphia, PA	Sep, 2020
462	Shore Line East	SLE	New London, CT	Aug, 2020
464	Simi Valley Transit		Simi Valley, CA	Jan, 2020
465	Sioux Area Metro	SAM	Sioux Falls, SD	Dec, 2019
466	Sioux City Transit System		Sioux City, SD	Aug, 2020
467	Siskiyou Transit and General Express		Yreka, CA	Jul, 2020
468	Skamania County Public Transit	Gorge WET Bus	Skamania County, WA	May, 2020
469	Snowmass Village		Pitkin County, CO	Sep, 2020
470	Solano County Transit	SolTrans	Solano County, CA	Aug, 2020
471	Sonoma County Transit		Sonoma County, CA	Sep, 2020
474	Sound Transit		Seattle, WA	Sep, 2020
475	South Clackamas Transportation District	SCTD	Molalla, OR	Feb, 2020
476	South Florida Regional Transportation Authority	Tri-Rail	Miami, FL	Aug, 2019
477	South Metro Area Regional Transit		Wilsonville, OR	Jun, 2020
478	Southeast Area Transit District	SEAT	Preston, CT	Sep, 2020
479	Southeast Vermont Transit	MOOver	Wilmington, VT	Sep, 2020
480	Southeastern Regional Transit Authority	SRTA	New Bedford, MA	Aug, 2020
481	Southwest Ohio Regional Transit Authority		Cincinnati, OH	Sep, 2020
482	SouthWest POINT		Medford, OR	Dec, 2019
483	SouthWest Transit		Minneapolis-St. Paul, MN	Sep, 2020
484	Space Coast Area Transit		Melbourne-Palm Bay, FL	Jan, 2020
485	Special Services Transportation Agency		Colchester, VT	Aug, 2020
486	Spokane Transit Authority		Spokane, WA	Sep, 2020
487	Squaxin Island Transit		Shelton, WA	Jun, 2020
488	Stagecoach Transportation Services		Randolph, VT	Dec, 2018
489	Stanford Marguerite Shuttle		Stanford, CA	Sep, 2020
490	Stanislaus Regional Transit	StaRT	Modesto, CA	Jun, 2020
491	STAK Transit		I errell, I X	Aug, 2020

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492	StarMetro		Tallahassee, FL	Aug, 2020
493	Streamline		Bozeman, MT	Aug, 2020
494	Sun Metro Mass Transit Department	Sun Metro	El Paso, TX	Aug. 2020
495	Sunline Transit Agency	SunLine	Palm Springs-Indio, CA	Sep. 2020
496	Sunset Empire Transportation District		Astoria, OR	Sep. 2020
497	Sunshine Bus Company		St. Augustine, FL	Dec. 2019
498	SunTran		St. George, UT	Aug. 2020
499	SunTran (City of Ocala)		Ocala, FL	Dec. 2019
500	Susanville Indian Rancheria Public Transportation		Susanville, CA	Feb. 2020
501	Swan Island Evening Shuttle		Portland, OR	Dec. 2019
502	Tahoe Transportation District		Reno, NV	Sep, 2020
503	Tahoe Truckee Area Regional Transit		Reno, NV	Sep, 2020
504	Tar River Transit	TRT	Rocky Mountain, NC	Dec, 2019
505	Tehama Rural Area Express	TRAX	Tehama County, CA	Feb, 2020
506	Terre Haute Transit		Terre Haute, IN	Dec, 2019
507	The Current		Rockingham, VT	Aug, 2020
508	The Greater Attleboro Taunton Regional Transit	GATRA	Taunton, MA	Sep, 2020
509	The Hernando Express		Brooksville, FL	Dec, 2015
510	The LINK		Wenatchee, WA	Sep, 2020
511	The Rapid	The Rapid	Grand Rapids, MI	Sep, 2020
512	The Ride	The Ride	Boston, MA	Aug, 2020
513	The Victoria Clipper		Seattle, WA	Jan, 2020
514	TheBus		Honolulu, HI	Sep, 2020
515	Thousand Oaks Transit		Thousand Oaks, CA	Jul, 2020
516	Tideline Water Taxi		Tiburon, CA	Aug, 2020
517	Tillamook County Transportation District	The Wave	Tillamook, OR	Sep, 2020
518	Toledo Area Regional Transit Authority	TARTA	Toledo, OH	Sep, 2020
519	Topeka Metro		Topeka, KS	Jan, 2020
520	Torrance Transit System	TTS	Torrance, CA	Aug, 2020
521	Transfort		Fort Collins, CO	Aug, 2020
522	Transit Authority of Northern Kentucky	TANK	Fort Wright, KY	Jun, 2020
523	Transit Authority of River City		Louisville, KY	Sep, 2020
524	Transportation Reaching People	TPR	Clackamas County, OR	Jul, 2020
525	TriMet	TriMet	Portland, OR	Aug, 2020
526	Trinity Metro	FWTA	Fort Worth, TX	Sep, 2020
527	Trinity Transit		Trinity County, CA	May, 2020
528	UDASH - University of Montana		Missoula, MT	May, 2020
529	Union Gap Transit		Union Gap, WA	Dec, 2019
530	Unitrans		Davis, CA	Sep, 2020
531	University of AZ - Cat Tran - Free Shuttle Service		Tucson, AZ	May, 2020
532	University of Colorado Boulder		Boulder, CO	Sep, 2020
533	University of Iowa	CAMBUS	Iowa City, IA	Sep, 2020
534	University of Maryland College Park Transit Services	Shuttle UM	College Park, MD	Mar, 2010
535	University of Michigan Transportation Services		Ann Arbor, MI	Aug, 2020
536	University of Minnesota		Minneapolis-St. Paul, MN	Sep, 2020
537	Urban League		Portland, OR	Jul, 2020
538	Utah Transit Authority		Salt Lake City, UT	Sep, 2020
539	U-Trans		Roseburg, OR	Jul, 2020
540	Vacaville City Coach		Vacaville, CA	May, 2020
541	Vail Transit		Vail, CO	Jun, 2020
542	Valley Metro		Phoenix, AZ	Oct, 2015
543	Valley Metro	VDT	Phoenix, AZ	Sep, 2020
544	Valley Regional Transit	VKI	Neurant OD	Sep, 2020
545	Vanture County Transmontation Commission	VCTC	Newport, OK	May, 2017
540	Verde Lyny	VUIC	Cottonwood AZ	Sep, 2020
548	VIA Metropolitan Transit	VIA	San Antonio TY	Jul 2020
549	Via Mobility Services	* 1/3	Boulder CO	Δμα 2020
550	Victor Valley Transit Authority	VVTA	Hesperia, CA	Aug. 2020
1 220	· · · · · · · · · · · · · · · · · · ·			11005, 2020

#	Agency Name	Alternative Name	Service Area	GTFS Date
551	Vineyard Fast Ferry		North Kingstown, RI	Jun, 2020
552	Virginia Railway Express	VRE	Manassas, CA	Sep, 2020
553	Volusia County Public Transit System	Votran	Volusia County, FL	Feb, 2019
554	Washington Metropolitan Area Transit Authority	WMATA	Washington, DC	Sep, 2020
556	Washington Park Shuttle		Portland, OR	Sep, 2020
557	Washington State Ferries		Seattle, WA	Sep, 2020
558	Washington State Ferries		Seattle, WA	Sep, 2020
559	Waukesha County Transit		Waukesha County, WI	Aug, 2020
560	WeGo Public Transit		Nashville, TN	Sep, 2020
562	Western Contra Costa	WestCat	Contra Costa County, CA	Sep, 2020
563	Wichita Transit		Wichita, KS	Mar, 2016
564	Winter Park Transit	The Lift	Winter Park, CO	Apr, 2020
565	Woodburn Transit		Woodburn, OR	Jul, 2020
566	Worcester Regional Transit Authority	WRTA	Worcester, MA	Aug, 2020
567	Yamhill County Transit Area	YCTA	Yamhill County, OR	May, 2019
568	Yankee Line		South Boston, MA	Aug, 2020
569	Yolo County Transportation District	Yolobus	Woodland, CA	Sep, 2020
570	Yosemite Area Regional Transportation System		Yosemite, CA	Jul, 2020
571	Yosemite Valley Shuttle System		Yosemite, CA	Jul, 2020
572	Yuba-Sutter Transit		Marysville, CA	Jun, 2020
573	Yuma County Intergovernmental Public Transportation Authority	YCIPTA	Yuma County, CA	Sep, 2020

## Appendix C: Transit Service Data: GTFS Data Coverage by Ridership

Table 10 summarizes total ridership on transit systems with GTFS coverage in the SLD by metropolitan area. Many metropolitan regions are served by multiple transit agencies operating different types of transit services. Ridership information from the NTD, maintained by the FHWA, was acquired to compare the relative coverage of GTFS data by region. Census-designated areas with 50,000 people or more called urbanized regions (UZAs) were used to summarize the percentage of ridership where GTFS data is reflected in the SLD. This information is useful to determine the extent of SLD transit accessibility measure coverage for a specific region of interest.

Metropolitan Area †	Total	Ridership on GTFS	Ridership on Non-
· ·	Ridership (FY	Systems (FY 2019)	GTFS Systems
	2019) ‡		(FY 2019)
Aberdeen-Bel Air South-Bel Air North, MD †	0	-	-
Abilene, TX	0	-	-
Akron, OH	6,574,247	0 (0%)	6,574,247 (100%)
Albany-Schenectady, NY	15,683,929	15,683,929 (100%)	0 (0%)
Albany, GA	773,757	0 (0%)	773,757 (100%)
Albuquerque, NM	10,313,468	10,313,468 (100%)	0 (0%)
Alexandria, LA	0	-	-
Allentown, PA-NJ	4,732,570	4,732,570 (100%)	0 (0%)
Altoona, PA	567,624	0 (0%)	567,624 (100%)
Amarillo, TX †	0	-	-
Ames, IA	6,121,023	0 (0%)	6,121,023 (100%)
Anchorage, AK	4,173,959	3,750,404 (89.9%)	423,555 (10.1%)
Anderson, IN	0	-	-
Ann Arbor, MI	14,319,276	14,319,276 (100%)	0 (0%)
Antioch, CA	1,985,920	0 (0%)	1,985,920 (100%)
Appleton, WI	1,112,264	0 (0%)	1,112,264 (100%)
Asheville, NC	2,124,106	1.978,720 (93,2%)	145,386 (6.8%)
Athens-Clarke County, GA	7.272.198	1.280,266 (17.6%)	5,991,932 (82,4%)
Atlanta, GA	129.107.991	123,809,358 (95,9%)	5.298.633 (4.1%)
Atlantic City, NJ	113.081	0 (0%)	113.081 (100%)
Auburn, AL	0	-	
Augusta-Richmond County, GA-SC	668.888	0 (0%)	668,888 (100%)
Austin, TX	31.078.420	31.078.420 (100%)	0 (0%)
Bakersfield, CA	6.252.450	6.252.450 (100%)	0 (0%)
Baltimore, MD	96.816.359	96.521.182 (99.7%)	295,177 (0.3%)
Bangor, ME	0	-	
Barnstable Town, MA	5.041.758	1,179,775 (23,4%)	3,861,983 (76,6%)
Baton Rouge, LA	3.803.859	0 (0%)	3.803.859 (100%)
Battle Creek. MI	0	-	-
Bay City, MI	509.917	0 (0%)	509,917 (100%)
Beaumont, TX	416.352	416.352 (100%)	0 (0%)
Bellingham, WA	4.703.865	0 (0%)	4.703.865 (100%)
Beloit, WI-II. †	0	-	-
Bend, OR	745,968	745,968 (100%)	0 (0%)
Benton Harbor-St. Joseph-Fair Plain, MI	0	-	-
Billings, MT	470.975	0 (0%)	470.975 (100%)
Binghamton, NY-PA	1.866.060		1.866.060 (100%)
Birmingham AL	3 331 511	3 331 511 (100%)	0 (0%)
Bismarck, ND	0	-	-
Blacksburg, VA	4.659.053	4.659.053 (100%)	0 (0%)
Bloomington-Normal II.	2 533 469	2 533 469 (100%)	0 (0%)
Bloomington IN	3 197 637	3 197 637 (100%)	0 (0%)
Boise City ID	1 496 068	1 321 605 (88 3%)	174 463 (11 7%)
Bonita Springs FL	913 727	0 (0%)	913 727 (100%)
Boston MA-NH-RI	374 372 186	374 372 186 (100%)	0 (0%)
Bowling Green KY	0		
Bremerton WA	3 850 213	3 850 213 (100%)	- 0 (0%)
Diemerton, 1171	5,050,215	5,050,215 (10070)	0(0/0)

Table 10: GTFS transit data coverage summarized by total 2019 ridership by metropolitan area.

Metropolitan Area †	Total	Ridership on GTFS	Ridership on Non-
	Ridership (FY	Systems (FY 2019)	GTFS Systems
	2019) ‡		(FY 2019)
Bridgeport-Stamford, CT-NY	9,970,158	9,523,780 (95.5%)	446,378 (4.5%)
Brownsville, TX	1,553,994	0 (0%)	1,553,994 (100%)
Buffalo, NY	23,982,380	23,982,380 (100%)	0 (0%)
Burlington, VT	2,843,044	2,843,044 (100%)	0 (0%)
Canton, OH	2,330,539	0 (0%)	2,330,539 (100%)
Cape Coral, FL	3,180,902	3,180,902 (100%)	0 (0%)
Carbondale, IL	1.212.976	0 (0%)	1.212.976 (100%)
Casper, WY	0	-	-
Cedar Rapids, IA	1.333.692	1,333,692 (100%)	0 (0%)
Champaign, IL	11.620.837	11.620.837 (100%)	0 (0%)
Charleston-North Charleston SC	3 200 749	3 200 749 (100%)	0 (0%)
Charleston WV	1 632 201	0 (0%)	1 632 201 (100%)
Charlotte NC-SC	24 689 517	24 278 653 (98 3%)	410 864 (1 7%)
Charlottesville VA	316 547	0 (0%)	316 547 (100%)
Chattanaaga TN GA	2 642 200	2643200(100%)	0 (0%)
Chauanao WV	2,043,299	2,043,299 (10076)	0 (076)
Chieses II IN	554 752 (92	-	-
Chicago, IL-IN	1 095 027	333,013,278 (99.7%)	1,759,404 (0.5%)
Cincin city of the	1,965,057	0(076)	1,965,057 (100%)
Cincinnati, OH-KY-IN	1/,/4/,511	17,626,044 (99.3%)	121,467 (0.7%)
Clarksville, IN-KY	0	-	-
Cleveland, OH	32,985,936	32,879,681 (99.7%)	106,255 (0.3%)
Cleveland, TN	0	-	-
Coeur d'Alene, ID	0	-	-
College Station-Bryan, TX	438,979	0 (0%)	438,979 (100%)
Colorado Springs, CO	3,411,436	3,411,436 (100%)	0 (0%)
Columbia, MO	1,108,594	0 (0%)	1,108,594 (100%)
Columbia, SC	2,733,489	2,733,489 (100%)	0 (0%)
Columbus, GA-AL	0	-	-
Columbus, OH	19,572,009	19,430,144 (99.3%)	141,865 (0.7%)
Concord, CA	5,111,416	1,706,551 (33.4%)	3,404,865 (66.6%)
Conroe-The Woodlands, TX	691,409	0 (0%)	691,409 (100%)
Corpus Christi, TX	5,249,776	5,249,776 (100%)	0 (0%)
Corvallis, OR †	0	-	-
Cumberland, MD-WV-PA †	0	-	-
Dallas-Fort Worth-Arlington, TX	76,687,416	75,545,696 (98.5%)	1,141,720 (1.5%)
Danbury, CT-NY	682,224	0 (0%)	682,224 (100%)
Danville, IL-IN	0	-	-
Daphne-Fairhope, AL	133,765	0 (0%)	133,765 (100%)
Davenport, IA-IL	3.392.507	0 (0%)	3.392.507 (100%)
Davis, CA	3.741.782	3,741,782 (100%)	0 (0%)
Davton, OH	9.586.879	9.416.615 (98.2%)	170.264 (1.8%)
Decatur AL	141 928	0 (0%)	141 928 (100%)
Decatur, IL	1 120 171		1 120 171 (100%)
DeKalh II	509 527		509 527 (100%)
Delano CA	0	0 (070)	507,527 (10070)
Denton Lewisville TV	2 030 300	2 939 309 (100%)	0 (0%)
Denton-Lewisvine, 1A	2,939,309	105 227 078 (00 89/)	167 632 (0.2%)
Der Meiner, IA	103,304,710	4 205 222 (100%)	107,032 (0.276)
Detroit MI	4,393,323	4,393,323(10076)	0(070)
Detroit, MI	30,393,331	20,085,008 (72.9%)	9,909,005 (27.1%)
Dolnan, AL	0	-	-
Dover-Kocnester, NH-ME	427,023	0 (0%)	427,023 (100%)
Dubuque, IA-IL	0	-	-
Duluth, MN-WI	2,683,183	2,683,183 (100%)	0 (0%)
Durham, NC	15,290,515	15,290,515 (100%)	0 (0%)
East Stroudsburg, PA-NJ	336,825	0 (0%)	336,825 (100%)
Eau Claire, WI	913,567	0 (0%)	913,567 (100%)
El Centro-Calexico, CA	1,412,697	0 (0%)	1,412,697 (100%)
El Paso, TX-NM	11,513,869	11,513,869 (100%)	0 (0%)
Elizabethtown-Radcliff, KY	195,860	0 (0%)	195,860 (100%)

Metropolitan Area †	Total	Ridership on GTFS	Ridership on Non-
	Ridership (FY	Systems (FY 2019)	GTFS Systems
	2019) ‡		(FY 2019)
Elkhart, IN-MI	481,384	0 (0%)	481,384 (100%)
Elmira, NY	0	-	-
Erie, PA	2,638,723	2,638,723 (100%)	0 (0%)
Eugene, OR	10,528,027	10,528,027 (100%)	0 (0%)
Evansville, IN-KY	1,273,611	0 (0%)	1,273,611 (100%)
Fairbanks, AK	0	-	-
Fairfield, CA	905,023	905,023 (100%)	0 (0%)
Fargo, ND-MN	1,889,723	1,396,884 (73.9%)	492,839 (26.1%)
Fayetteville-Springdale-Rogers, AR-MO †	0	-	-
Fayetteville, NC	1,452,842	0 (0%)	1,452,842 (100%)
Flagstaff, AZ	2,570,838	2,570,838 (100%)	0 (0%)
Flint, MI	4,784,585	4,784,585 (100%)	0 (0%)
Florence, AL	108,577	0 (0%)	108,577 (100%)
Florence, SC	0	-	-
Fond du Lac, WI	0	-	-
Fort Collins, CO	4,685,846	4,503,616 (96.1%)	182,230 (3.9%)
Fort Smith, AR-OK	0	-	-
Fort Walton Beach-Navarre-Wright, FL	181,624	0 (0%)	181,624 (100%)
Fort Wayne, IN	1,676,800	1,676,800 (100%)	0 (0%)
Frederick, MD	593,853	593,853 (100%)	0 (0%)
Fredericksburg, VA	0	-	-
Fresno, CA	10,770,493	10,770,493 (100%)	0 (0%)
Gainesville, FL	9,255,107	9,255,107 (100%)	0 (0%)
Gainesville, GA	0	-	-
Galveston, TX	0	-	-
Glens Falls, NY	0	-	-
Grand Forks, ND-MN	290.323	290,323 (100%)	0 (0%)
Grand Junction. CO	0	-	-
Grand Rapids, MI	10.472.095	10,472,095 (100%)	0 (0%)
Great Falls, MT	441.765	0 (0%)	441.765 (100%)
Greeley, CO †	0	-	-
Green Bay, WI	1.324.579	0 (0%)	1.324.579 (100%)
Greensboro, NC	4,152,944	686.982 (16.5%)	3,465,962 (83,5%)
Greenville, SC	1.708.186	1.708.186 (100%)	0 (0%)
Gulfport, MS	809.534	0 (0%)	809.534 (100%)
Hagerstown, MD-WV-PA	0	-	-
Hanford, CA	4,136,576	702.428 (17%)	3,434,148 (83%)
Harrisburg, PA	2.203.193	2.203.193 (100%)	0 (0%)
Harrisonburg, VA	2,120,458	2.120.458 (100%)	0 (0%)
Hartford, CT	18,778,135	17.583.417 (93.6%)	1.194.718 (6.4%)
Hickory, NC	244.326	0 (0%)	244,326 (100%)
High Point, NC	0	-	
Holland, MI	412.143	0 (0%)	412,143 (100%)
Houma, LA	0	-	-
Houston TX	90 358 931	89 951 217 (99 5%)	407 714 (0 5%)
Huntington WV-KY-OH	952 911	0 (0%)	952 911 (100%)
Huntsville AL	749.063	749.063 (100%)	0 (0%)
Idaho Falls, ID	0	-	-
Indianapolis, IN	9.701.062	9.641.612 (99.4%)	59,450 (0.6%)
India-Cathedral City, CA	4 217 807	4 217 807 (100%)	0 (0%)
Iowa City IA	5 640 630	5 513 111 (97 7%)	127 519 (2 3%)
Ithaca, NY	4.291 946	0 (0%)	4,291,946 (100%)
Jackson, MI	516 837	0 (0%)	516 837 (100%)
Jackson MS	560 632	560 632 (100%)	0 (0%)
Jackson, TN	4/6 802	0 (N%)	446 803 (100%)
Jacksonville FI	11 7/2 867	11 614 452 (02 004)	120 /15 (1 10/)
Janesville WI +	11,/43,00/	11,017,452 (20.970)	127,415 (1.170)
Lefferson City MO	0	-	-
Johnson City, INO	162 792	- 0 (00/)	162 782 (1000/)
Johnson City, 110	102,782	U (U%)	102,702 (100%)

Metropolitan Area †	Total	Ridership on GTFS	Ridership on Non-
	Ridership (FY	Systems (FY 2019)	GTFS Systems
	2019) ‡		(FY 2019)
Johnstown, PA	1,220,538	0 (0%)	1,220,538 (100%)
Jonesboro, AR	0	-	-
Kahului, HI	2,084,376	2,084,376 (100%)	0 (0%)
Kalamazoo, MI	2,766,146	0 (0%)	2,766,146 (100%)
Kankakee, IL	671,555	0 (0%)	671,555 (100%)
Kansas City, MO-KS	15,162,331	14,596,578 (96.3%)	565,753 (3.7%)
Kennewick-Pasco, WA	3,126,689	3,126,689 (100%)	0 (0%)
Kenosha, WI-IL	1,404,305	0 (0%)	1,404,305 (100%)
Killeen, TX	502,048	0 (0%)	502,048 (100%)
Kingsport, TN-VA †	0	-	-
Knoxville, TN	2.895.316	2,752,602 (95,1%)	142,714 (4.9%)
Kokomo, IN	461.187	0 (0%)	461.187 (100%)
La Crosse, WI-MN	923.030	923.030 (100%)	0 (0%)
Lafavette, IN	5.099.775	5.099.775 (100%)	0 (0%)
Lafavette, LA	1.358.408	0 (0%)	1.358.408 (100%)
Lake Tahoe, CA-NV	338.726	338,726 (100%)	0 (0%)
Lakeland, FL	1.294.771	1.294.771 (100%)	0 (0%)
Lancaster-Palmdale, CA	2.352.468	0 (0%)	2.352.468 (100%)
Lancaster PA	7 259 514		7 259 514 (100%)
Lansing MI	11 110 771	11 049 330 (99 4%)	61 441 (0 6%)
Laredo TX	2 562 636	0 (0%)	2 562 636 (100%)
Lacou, IX	60 713	60 713 (100%)	2,502,050 (10070)
Las Vegas-Henderson NV	70 637 277	65 821 102 (03 2%)	4 816 085 (6 8%)
Las vegas-menderson, nv	3 306 184	0,00%	3 306 184 (100%)
Lawten OK	3,390,104	0 (078)	3,390,184 (10070)
Lawton, OK	262.459	-	262 458 (100%)
Leoahung Fustia Tayang El	303,438		472 605 (100%)
Leesburg-Euslis-Tavares, FL	472,095		4/2,093 (100%)
Leoninster-Fichburg, MA	1,120,810	1,120,810 (100%)	
Lewiston, ME	255,472		255,472 (100%)
Lexington-Fayette, KY	4,012,703	4,012,703 (100%)	0 (0%)
Lima, OH	0	-	-
	2,441,518	2,441,518 (100%)	
	2,304,700	0 (0%)	2,304,700 (100%)
Lodi, CA	0	-	-
Logan, UI	2,572,181	0 (0%)	2,572,181 (100%)
Lompoc, CA	0	-	-
Longview, WA-OR	390,598	390,598 (100%)	0 (0%)
Lorain-Elyria, OH	0	-	-
Los Angeles-Long Beach-Anaheim, CA	563,859,115	528,296,102 (93.7%)	35,563,013 (6.3%)
Louisville/Jefferson County, KY-IN	11,625,802	11,456,984 (98.5%)	168,818 (1.5%)
Lubbock, 1X	3,542,620		3,542,620 (100%)
Lynchburg, VA	2,018,554	2,018,554 (100%)	0 (0%)
Macon, GA	0	-	-
Madison, WI	12,969,815	12,969,815 (100%)	0 (0%)
Manchester, NH	0	-	-
Mansfield, OH	0	-	-
McAllen, TX	819,209	0 (0%)	819,209 (100%)
McKinney, TX	0	-	-
Medford, OR	1,232,952	1,232,952 (100%)	0 (0%)
Memphis, TN-MS-AR	6,477,372	6,410,327 (99%)	67,045 (1%)
Merced, CA	950,730	950,730 (100%)	0 (0%)
Miami, FL	125,231,477	122,415,568 (97.8%)	2,815,909 (2.2%)
Middletown, OH	0	-	-
Milwaukee, WI	32,021,507	29,998,223 (93.7%)	2,023,284 (6.3%)
Minneapolis-St. Paul, MN-WI	93,779,196	93,211,873 (99.4%)	567,323 (0.6%)
Mission Viejo-Lake Forest-San Clemente, CA	820,829	820,829 (100%)	0 (0%)
Missoula, MT	1,838,334	1,598,692 (87%)	239,642 (13%)
Mobile, AL	938,025	0 (0%)	938,025 (100%)
Modesto, CA	2,265,448	2,265,448 (100%)	0 (0%)

Metropolitan Area †	Total	Ridership on GTFS	Ridership on Non-
	Ridership (FY	Systems (FY 2019)	GTFS Systems
	2019) ‡		(FY 2019)
Monessen-California, PA	288,056	0 (0%)	288,056 (100%)
Monroe, LA	0	-	-
Monroe, MI	428,766	0 (0%)	428,766 (100%)
Montgomery, AL	602,397	602,397 (100%)	0 (0%)
Morgantown, WV	1,469,292	0 (0%)	1,469,292 (100%)
Morristown, TN	0	-	-
Mount Vernon, WA	896,118	0 (0%)	896,118 (100%)
Muncie, IN	1,408,230	0 (0%)	1,408,230 (100%)
Murfreesboro, TN	0	-	-
Muskegon, MI	0	-	-
Myrtle Beach-Socastee, SC-NC	0	-	-
Napa, CA	1,059,168	0 (0%)	1,059,168 (100%)
Nashua, NH-MA	462,549	0 (0%)	462,549 (100%)
Nashville-Davidson, TN	10.378.670	10.255.735 (98.8%)	122.935 (1.2%)
New Bedford, MA	2,749,070	2.749.070 (100%)	0 (0%)
New Haven, CT	7,799,900	7,567,553 (97%)	232,347 (3%)
New Orleans, LA	18,989,830	16.316.609 (85.9%)	2.673.221 (14.1%)
New York-Newark, NY-NJ-CT	4.373.931.006	4.262.515.596 (97.5%)	111.415.410 (2.5%)
Newark, OH	113.893	0 (0%)	113,893 (100%)
Norman OK	0	-	-
North Port-Port Charlotte, FL	130 125	0 (0%)	130 125 (100%)
Norwich-New London CT-RI	965.658	965 658 (100%)	0 (0%)
Ocala FL *	0	,005,000 (10070)	0 (070)
Odessa TX	0		
Oklahoma City, OK	3 122 065	3 122 965 (100%)	0 (0%)
Olympia Lacay WA	4 736 800	4 736 809 (100%)	0 (0%)
Omeha NE IA	4,730,809	2 268 050 (100%)	0(0/0)
Orlando, FL	26 400 172	26 400 172 (100%)	0(0/0)
Orlando, FL Ochkosh WI	20,490,172	<u>20,490,172 (10076)</u> <u>818 010 (100%)</u>	0(0/0)
Osiikosii, WI	151 244	0 (0%)	
Owensbolo, KI	131,344		131,344 (10076)
Dalma Day, Malhauma, El	4,363,132	4,383,132 (10076)	
Palm Day-Melbourne, FL Dalm Caast Daytona Daach Dart Oranga, FL	2,555,264	0(076)	2,555,264 (100%)
Panama City, EL	5,595,604	<u>5,492,723 (97.176)</u>	105,159 (2.970) 55 405 (10.09/)
Parlama City, FL	508,552	455,127 (89.176)	55,405 (10.976)
Parkersburg, wv-On	1 504 (25	-	-
Pensacola, FL-AL	1,304,023	1,304,623 (100%)	
Peoria, IL Detaluma CA	2,730,322		2,730,522 (100%)
Petaluma, CA	349,280	349,280 (100%)	
Philadelphia, PA-NJ-DE-MD	329,212,033	329,030,914 (100%)	101,141 (0%)
Phoenix-Mesa, AZ	84,024,737	(4, 940, 290, (05, 70/)	11,755,524 (15.9%)
Pillsburgh, PA	0/,/40,233	64,849,280 (93.7%)	2,890,955 (4.5%)
Plusheid, MA	524,796	524,796 (100%)	0 (0%)
Pocatello, ID	0	-	-
Port Arthur, 1X	1 505 000	-	-
Port Huron, MI	1,525,809		1,525,809 (100%)
Port St. Lucie, FL	886,510	0 (0%)	886,510 (100%)
Porterville, CA	0	-	-
Portland, ME	3,/58,994	2,111,881 (56.2%)	1,64/,113 (43.8%)
Portland, OR-WA	110,135,835	110,135,835 (100%)	0 (0%)
Portsmouth, NH-ME	0	-	-
Pottstown, PA	229,253		229,253 (100%)
Poughkeepsie-Newburgh, NY-NJ	1,558,043	0 (0%)	1,558,043 (100%)
Providence, RI-MA	17,508,354	17,465,668 (99.8%)	42,686 (0.2%)
Pueblo, CO	831,954	0 (0%)	831,954 (100%)
Racine, WI	1,041,115	1,041,115 (100%)	0 (0%)
Raleigh, NC	9,323,764	9,127,723 (97.9%)	196,041 (2.1%)
Rapid City, SD	0	-	-
Reading, PA	3,139,486	0 (0%)	3,139,486 (100%)
Redding, CA	630,122	630,122 (100%)	0 (0%)

Metropolitan Area †	Total	Ridership on GTFS	Ridership on Non-
	Ridership (FY	Systems (FY 2019)	GTFS Systems
	2019) ‡		(FY 2019)
Reno, NV-CA	7,863,626	7,863,626 (100%)	0 (0%)
Richmond, VA	9,283,520	9,283,520 (100%)	0 (0%)
Riverside-San Bernardino, CA	19,910,492	19,910,492 (100%)	0 (0%)
Roanoke, VA	1,970,807	1,970,807 (100%)	0 (0%)
Rochester, MN	2,155,230	2,155,230 (100%)	0 (0%)
Rochester, NY	14,712,832	14,712,832 (100%)	0 (0%)
Rockford, IL	1,650,532	0 (0%)	1,650,532 (100%)
Rome, GA	1,113,342	0 (0%)	1,113,342 (100%)
Sacramento, CA	23,524,697	22,364,647 (95.1%)	1,160,050 (4.9%)
Saginaw, MI	594,217	0 (0%)	594,217 (100%)
Salem, OR	3,272,941	3,272,941 (100%)	0 (0%)
Salisbury, MD-DE	325,096	0 (0%)	325,096 (100%)
Salt Lake City-West Valley City, UT	44,578,161	44,578,161 (100%)	0 (0%)
San Angelo, TX	472,045	0 (0%)	472,045 (100%)
San Antonio, TX	42,641,565	42,510,772 (99.7%)	130,793 (0.3%)
San Diego, CA	105,304,898	101,872,110 (96.7%)	3,432,788 (3.3%)
San Francisco-Oakland, CA	450,054,427	419,927,513 (93.3%)	30,126,914 (6.7%)
San Jose, CA	36,432,963	36,432,963 (100%)	0 (0%)
San Juan, PR	26,188,574	24,561,662 (93.8%)	1,626,912 (6.2%)
San Luis Obispo, CA	2,078,087	2,078,087 (100%)	0 (0%)
San Marcos, TX	2,942,220	0 (0%)	2,942,220 (100%)
Santa Barbara, CA	6,432,190	0 (0%)	6,432,190 (100%)
Santa Clarita, CA	2,681,213	0 (0%)	2,681,213 (100%)
Santa Cruz, CA	5,119,469	5,119,469 (100%)	0 (0%)
Santa Fe, NM	904,685	904,685 (100%)	0 (0%)
Santa Maria, CA	687,383	687,383 (100%)	0 (0%)
Santa Rosa, CA	3,534,449	1,682,482 (47.6%)	1,851,967 (52.4%)
Sarasota-Bradenton, FL	4,198,441	4,198,441 (100%)	0 (0%)
Savannah, GA	4,069,157	4,069,157 (100%)	0 (0%)
Scranton, PA	2,445,478	0 (0%)	2,445,478 (100%)
Seaside-Monterey, CA	4,428,381	4,428,381 (100%)	0 (0%)
Seattle, WA	225,876,041	225,876,041 (100%)	0 (0%)
Sebastian-Vero Beach South-Florida Ridge, FL	1,259,578	0 (0%)	1,259,578 (100%)
Sheboygan, WI	0	-	-
Sherman, TX	43,852	0 (0%)	43,852 (100%)
Shreveport, LA	2,618,604	0 (0%)	2,618,604 (100%)
Simi Valley, CA †	0	-	-
Sioux City, IA-NE-SD	876,826	0 (0%)	876,826 (100%)
Sioux Falls, SD	853,523	853,523 (100%)	0 (0%)
South Bend, IN-MI	1,596,172	0 (0%)	1,596,172 (100%)
South Lyon-Howell, MI	0	-	-
Spartanburg, SC	275,135	0 (0%)	275,135 (100%)
Spokane, WA	10,568,157	10,568,157 (100%)	0 (0%)
Spring Hill, FL †	0	-	-
Springfield, IL	1,573,175	1,573,175 (100%)	0 (0%)
Springfield, MA-CT	10,380,926	10,380,926 (100%)	0 (0%)
Springfield, MO	1,312,354	0 (0%)	1,312,354 (100%)
Springfield, OH	0	-	-
St. Augustine, FL †	0	-	-
St. Cloud, MN	1,680,763	0 (0%)	1,680,763 (100%)
St. Joseph, MO-KS	0	-	-
St. Louis, MO-IL	38,809.080	36,642,036 (94.4%)	2,167,044 (5.6%)
State College, PA	6,602.752	0 (0%)	6,602,752 (100%)
Stockton, CA	5,376.219	5,376,219 (100%)	0 (0%)
Sumter, SC	153.048	0 (0%)	153.048 (100%)
Syracuse, NY	11,219,473	11,219,473 (100%)	0 (0%)
Tallahassee, FL	3.643.431	3.643.431 (100%)	0 (0%)
Tampa-St. Petersburg, FL	28.403.299	27.943.719 (98.4%)	459.580 (1.6%)
Terre Haute, IN	237,867	237,867 (100%)	0 (0%)
	/ .		、 /

Ridership (FY 2019) ‡         Systems (FY 2019) (FY 2019)         GTFS Systems (FY 2019)           Texarkana-Texarkana, TX-AR         0         -         -           Texas (Civ, TX         0         0         -         -           Tobusand Oaks, CA †         0         0         -         -           Toledo, Oll-MI         2.007,259         (2,007,259         (0,00%)         0 (0%)           Tucson, AZ         15.844.953         141.958 (0.9%)         15.702,995 (99.1%)           Tulson, OK         2.717,580         2.717,580 (100%)         0 (0%)           Tuscaloosa, AL         0         -         -           Uniontown-Connellsville, PA         251,169 (100%)         362,076 (0.6%)           Utica, NY         1,338,743         1,314,656 (98.2%)         24,087 (1.8%)           Vaaville, CA †         0         -         -         -           Victorin, TX         0         -         -         -         -         -           Vistorville-Hesperia, CA         2,240,374         12,240,374 (100%)         0 (0%)         -         -           Vistorville-Hesperia, CA         2,240,374         13,332,764 (100%)         0 (0%)         -         -           Vistoria, TX         1,257,	Metropolitan Area †	Total	Ridership on GTFS	Ridership on Non-
$\begin{array}{ c c c c c c c c c c c c c c c c c c c$		Ridership (FY	Systems (FY 2019)	GTFS Systems
Texarkana-Texarkana, TX-AR         0         -           Texas City, TX         0         -           Thousand Oaks, CA †         0         -           Tolecdo, OH-MI         2,007,259         2,007,259 (100%)         0 (0%)           Tusos, AZ         15,844,953         141,958 (0.9%)         15,702,995 (99,1%)           Tuson, AZ         15,844,953         141,958 (0.9%)         15,702,995 (99,1%)           Tuson, AZ         15,844,953         141,958 (0.9%)         15,702,995 (99,1%)           Tuska, OK         2,717,580         2,007,259 (100%)         0 (0%)           Tuscaloosa, AL         0         -         -           Uniontown-Connellsville, PA         251,169         0 (0%)         251,169 (100%)           Urica, NY         1,338,743         1,314,656 (98,2%)         24,087 (1.8%)           Vaaeville, CA †         0         -         -           Valeio, CA         2,114,933         1,446,163 (68,4%)         668,770 (31.6%)           Victoria, TX         0         -         -         -           Viristriik Bach, VI         0         -         -         -           Viristriik Bach, VI         0         -         -         -           Viristriik Sa<		2019) ‡		(FY 2019)
Texas City, TX         0         -           Toledo, OH-MI         2,007,259         2,007,259         0.00%)         0.0%)           Toledo, OH-MI         2,007,259         2,007,259         0.00%)         0.0%)           Tueson, AZ         15,844,953         141,958 (0.9%)         15,702,995 (99,1%)           Tueson, AZ         15,844,953         141,958 (0.9%)         15,702,995 (99,1%)           Tueson, AZ         15,844,953         141,958 (0.9%)         160,00%)           Tuescalosa, AL         0         -         -           Uniontown-Connellsville, PA         251,169         0.0%)         251,169 (100%)           Urban Honolulu, HI         64,427,861         64,407,861         64,872,801         24,087 (1.8%)           Vacaville, CA         2,114,933         1,314,656 (98,2%)         24,087 (1.8%)         Vacaville, CA         -         -           Victori, TX         0         - <td< td=""><td>Texarkana-Texarkana, TX-AR</td><td>0</td><td>-</td><td>-</td></td<>	Texarkana-Texarkana, TX-AR	0	-	-
Thousand Oaks, CA $\uparrow$ 0         -         -           Toledo, OH-MI         2,007,259         (2,007,259         (0,0%)         0 (0%)           Tucson, AZ         15,844,953         141,958 (0.0%)         0 (0%)           Tulsa, OK         2,717,580         (2,717,580         (0,0%)           Turlock, CA         188,450         0 (0%)         188,450 (100%)           Turlock, CA         188,450         0 (0%)         188,450 (100%)           Uniontown-Connellsville, PA         251,169         0 (0%)         251,169 (100%)           Uriantown-Connellsville, PA         251,169         0 (0%)         251,169 (100%)           Uriantown-Connellsville, PA         2,114,933         1,314,656 (98,2%)         24,087 (1.8%)           Vacaville, CA †         0         -         -         -           Victoria, TX         0         -         -         -           Victoria, TX         0         -         -         -           Vireitoria, NJ         0<	Texas City, TX	0	-	-
Toledo, OH-MI         2.007,259         2.007,259         0.00%)           Topeka, KS         1.310,702         1.0,1072         1.00%)         0.0%)           Tucson, AZ         15,844,953         141,958         0.0%)         0.0%)           Turlox, CA         2,717,800         2,717,800         0.0%)         0.0%)           Turlox, CA         188,450         0.0%)         188,450         0.0%)           Tuscon, AL         0         -         -         -           Uniontown-Connellsville, PA         251,169         0.0%)         251,169 (100%)           Utran, Honolulu, HI         64,427,861         64,065,785 (99,4%)         362,076 (0.6%)           Valcio, CA         2,114,933         1,314,656 (98,4%)         668,770 (31.6%)           Victorville-Hesperia, CA         2,240,374         1,240,374 (100%)         0 (0%)           Victorville-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Virgin Islands, VI         0         -         -         -           Virgin Islands, VI         10         -         -         -           Virgin Islands, VI         0         -         -         -         -           Virgin Islands, VI         0	Thousand Oaks, CA †	0	-	-
Topeka, KS         1,310,702         1,310,702         1,310,702         0,0%)           Tucson, AZ         15,844,953         141,958 (0.9%)         15,702,995 (99.1%)           Turka, OK         2,717,580         0,07%)         0,07%)           Turka, CA         188,450         0,07%)         0,07%)           Turka, CA         0         -         -           Uniontown-Connellsville, PA         251,169         0,07%)         251,169 (100%)           Urban Honolulu, HI         64,427,861         64,065,785 (99.4%)         362,076 (0.6%)           Valeig, CA         0         -         -         -           Valaville, CA †         0         -         -         -           Victoria, TX         0         -         -         -           Victoria, TX         0         -         -         -           Vineland, NJ         0         -         -         -           Vineland, NJ         206,661         0 (0%)         1,615,012 (100%)           Virginia Baach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Virginia Baach, VA         12,87,009         0 (0%)         1,615,012 (100%)           Waeo, TX         1,287,009         <	Toledo, OH-MI	2,007,259	2,007,259 (100%)	0 (0%)
Tucson, AZ         15,844,953         141,958 (0.9%)         15,702,995 (99.1%)           Tulsa, OK         2,717,580         2,717,580         0.00%)         188,450         0.00%)           Turlock, CA         188,450         0.00%)         128,450 (100%)         0         168,450 (100%)           Uniontown-Connellsville, PA         251,169         0.00%)         251,169 (100%)         251,169 (100%)           Uthan Honolulu, HI         64,427,861         64,065,785 (99.4%)         362,076 (0.6%)           Vacaville, CA †         0         -         -           Vallejo, CA         2,114,933         1,446,163 (68.4%)         668,770 (31.6%)           Victorville-Hesperia, CA         2,240,374         2,240,374 (100%)         0.00%)           Victorville-Hesperia, CA         2,240,374         13,332,764 (100%)         0.00%)           Virgin Islands, VI         0         -         -	Topeka, KS	1,310,702	1,310,702 (100%)	0 (0%)
Tulas, OK         2,717,580         2,717,580         00%)         00%)           Turlock, CA         188,450         00%)         188,450         00%)           Turlock, CA         0         -         -           Uniontown-Connellwille, PA         251,169         00%)         251,169           Utica, NY         1,338,743         1,314,656         98.2%)         24,087           Vacaville, CA         0         -         -         -           Vacaville, CA         0         -         -         -           Vallejo, CA         2,114,933         1,314,656         98.2%)         24,087         (1.8%)           Vallejo, CA         2,214,374         2,240,374         0.240,374         0.0%)         -         -           Victoria, TX         0         -         -         -         -         -         -         -           Virgin Islands, VI         0         -<	Tucson, AZ	15,844,953	141,958 (0.9%)	15,702,995 (99.1%)
Turlock, CA         188,450         0 (0%)         188,450 (100%)           Tuscaloosa, AL         0         -         -           Uniontown-Connellsville, PA         251,169         0 (0%)         251,169 (100%)           Urban Honolulu, HI         64,427,861         64,065,785 (99,4%)         362,076 (0.6%)           Utica, NY         1,338,743         1,314,656 (98,2%)         24,087 (1.8%)           Vacaville, CA †         0         -         -           Vallejo, CA         2,2114,933         1,446,163 (68,4%)         668,770 (31.6%)           Victorville-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Vitotrville-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Virgini Islands, VI         0         -         -           Virgini Bach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Virgini Bach, VA         1,287,009         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,668,701 (1.1%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Washington, DC-VA-MD         40,043,9406         405,975,689 (98,98%)         44,63,717 (1.1%)	Tulsa, OK	2,717,580	2,717,580 (100%)	0 (0%)
Tuscalossa, AL         0         -           Uniontown-Connellsville, PA         251,169         0 (0%)         251,169 (100%)           Urban Honolulu, HI         64,427,861         64,065,785 (99,4%)         362,076 (0.6%)           Urica, NY         1,338,743         1,314,656 (98.2%)         24,087 (1.8%)           Vallejo, CA         2,114,933         1,446,163 (68.4%)         668,770 (31.6%)           Victoria, TX         0         -         -           Victoria, TX         0         -         -           Victoria, TX         0         -         -           Vineland, NJ         0         -         -           Vingini Islands, VI         0         -         -           Virginia Baech, VA         13,332,764         13,332,764 (100%)         0 (0%)           Virginia Baech, VA         1287,009         0 (0%)         1,615,012 (100%)           Washington, DC-VA-MD         410,439,406         405,975,689 (98.9%)         4,463,717 (1.1%)           Waterbory, CT         4,933,139         4,933,139 (100%)         0 (0%)           Washington, DC-VA-MD         1,066,007 (100%)         0 (0%)         2,1194,421 (10%)           Waterbory, CT         4,933,139 (40%)         0 (0%)         2,1194,42	Turlock, CA	188,450	0 (0%)	188,450 (100%)
Uniontown-Connellsville, PA         251,169         0 (0%)         251,169 (100%)           Urban Honoluk, HI         64,427,861         64,065,785 (99,4%)         362,076 (0.6%)           Vacaville, CA ↑         0         -         -           Valeo, CA ↑         0         -         -           Vallejo, CA         2,114,933         1,344,656 (98,2%)         24,087 (1.8%)           Victoria, TX         0         -         -           Vineland, NJ         206,661         0 (0%)         226,661 (100%)           Virginia Beach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Virginia Beach, VA         1,287,009         0 (0%)         1,287,009 (100%)           Waldorf, MD         400,439,406         405,975,689 (98,9%)         4,463,717 (1.1%)           Washington, DC-VA-MD         410,439,406         405,975,689 (98,9%)         4,463,717 (1.1%)           Washington, DC-VA-MD	Tuscaloosa, AL	0	-	-
Urban Honolulu, HI         64,427,861         64,065,785 (99,4%)         362,076 (0.6%)           Utica, NY         1,338,743         1,314,656 (98,2%)         24,087 (1.8%)           Vacaville, CA †         0         -         -           Vallejo, CA         2,114,933         1,446,163 (68,4%)         6668,770 (31.6%)           Victorvile-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Victorvile-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Virgin Islands, VI         0         -         -           Virginia Beach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Virginia Beach, VA         1,287,009         0 (0%)         1,287,009 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Watorf, MD         806,460         0 (0%)         1,287,009 (100%)           Waterbury, CT         4,933,139 (4933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139 (4933,139 (100%)         0 (0%)           Waterbury, CH         0         -         -           Weatchee, WA         1,036,007         1,036,007 (100%)         0 (0%)           Waterbury, CH         379,457         0 (	Uniontown-Connellsville, PA	251,169	0 (0%)	251,169 (100%)
Utica, NY         1,338,743         1,314,656 (98.2%)         24,087 (1.8%)           Vacaville, CA †         0         -         -         -           Vallejo, CA         2,114,933         1,446,163 (68.4%)         668,770 (31.6%)           Victoria, TX         0         -         -           Victoria, TX         0         -         -           Victoria, TX         0         -         -           Victoria, NJ         0         -         -           Vineland, NJ         206,661         0 (0%)         206,661 (100%)           Virginia Beach, VA         13,332,764         13,332,764 (13,332,764 (100%)         0 (0%)           Visalia, CA         1,615,012         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,846,460 (100%)           Washington, DC-VA-MD         410,439,406         405,975,889 (98.9%)         4,463,717 (1.1%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139 (100%)         0 (0%)	Urban Honolulu, HI	64,427,861	64,065,785 (99.4%)	362,076 (0.6%)
Vacaville, CA †         0         -           Vallejo, CA         2,114,933         1,446,163 (68,4%)         668,770 (31.6%)           Victoria, TX         0         -         -           Victoriylle-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Vinland, NJ         0         -         -           Virgini Islands, VI         0         -         -           Virgini Bands, VI         0         0.00%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waco, TX         1,287,009         0 (0%)         306,460 (100%)           Wacobary, CT         4,933,139         4,933,139 (100%)         0 (0%)           Watobary, CT	Utica, NY	1,338,743	1,314,656 (98.2%)	24,087 (1.8%)
Vallejo, CA2,114,9331,446,163 (68.4%) $668,770 (31.6\%)$ Victoria, TX0Victorille-Hesperia, CA2,240,374 (100%)0 (0%)Villas, NJ0Vineland, NJ206,6610 (0%)206,661 (100%)Virgini Baach, VA13,332,764 (13,332,764 (100%)0 (0%)Virsilia, CA1,615,0120 (0%)1,615,012 (100%)Visalia, CA1,615,0120 (0%)1,615,012 (100%)Waldorf, MD806,4600 (0%)806,460 (100%)Washington, DC-VA-MD410,439,406405,975,689 (98.9%)4,463,717 (1.1%)Waterbury, CT4,933,1394,933,139 (100%)0 (0%)Waterbury, CT4,933,1394,933,139 (100%)0 (0%)Waterbor, IA0Wenatchee, WA1,036,0071,036,007 (100%)0 (0%)Wichita, KS1,366,9601,366,960 (100%)0 (0%)Williamsburg, VA2,119,4420 (0%)2,119,442 (100%)Williamsburg, VA0Winchita, KS1,366,9601,366,960 (100%)0 (0%)Williamsport, PA0Winkindawa, RL00Winkindawa, RA1,056,9181,056,918 (100%)0 (0%)Williamsburg, VA00Winkindawa, RL000 <t< td=""><td>Vacaville, CA †</td><td>0</td><td>-</td><td>-</td></t<>	Vacaville, CA †	0	-	-
Victoria, TX         0         -           Victorville-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Villas, NJ         0         -         -           Vincland, NJ         206,661         0 (0%)         206,661 (100%)           Virgin Islands, VI         0         -         -           Virgini Beach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Visalia, CA         1,615,012         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waldorf, MD         806,460         0 (0%)         806,460 (100%)           Waterbury, CT         4,933,139 (100%)         0 (0%)         0 (0%)           Waterbury, CT         4,933,139 (100%)         0 (0%)         0 (0%)           Weatchee, WA         0         -         -           Weatcher, Eldersburg, MD         0         -         -           Wheeling, WV-OH         379,457         0 (0%)         2,119,442 (100%)           Williamsburg, VA         2,119,442         0 (0%)         2,134,550 (100%)           Williamsburg, VA         1,258,731         1,258,731 (100%)         0 (0%)           Williamsport	Vallejo, CA	2,114,933	1,446,163 (68.4%)	668,770 (31.6%)
Victorville-Hesperia, CA         2,240,374         2,240,374 (100%)         0 (0%)           Vilals, NJ         0         -         -         -           Vineland, NJ         206,661         0 (0%)         206,661 (100%)           Virgin Islands, VI         0         -         -           Virginia Beach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Virginia Beach, VA         1,615,012         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waldorf, MD         806,460         0 (0%)         1,287,009 (100%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139         -         -           Wausau, WI         0         -         -           Wausau, WI         0         -         -           Wheeling, WV-OH         379,457         0 (0%)         1,314,850           Williamsburg, VA         1,366,960         1,366,960 (100%)         0 (0%)	Victoria, TX	0	-	-
Villas, NJ         0         -           Vineland, NJ         206,661         0 (0%)         206,661 (100%)           Virgini Islands, VI         0         -         -           Virginia Beach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Visalia, CA         1,615,012         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         806,460 (100%)           Waldorf, MD         806,460         0 (0%)         806,460 (100%)           Washington, DC-VA-MD         410,433,406         405,975,689 (98,9%)         4,463,717 (1.1%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbor, IA         0         -         -           Weatchee, WA         1,036,007 (100%)         0 (0%)         0 (0%)           Westminster-Eldersburg, MD         0         -         -           Wheeling, WV-OH         379,457         0 (0%)         379,457 (100%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsburg, VA         1,258,731 (105%)         0 (0%)           <	Victorville-Hesperia, CA	2,240,374	2,240,374 (100%)	0 (0%)
Vineland, NJ         206,661         0 (0%)         206,661 (100%)           Virgin Islands, VI         0         -         -           Virgini Beach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Visalia, CA         16,15,012         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waldorf, MD         806,460         0 (0%)         806,460 (100%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterboo, IA         0         -         -           Wasu, WI         0         -         -           Wenatchee, WA         1,036,007         1,036,007 (100%)         0 (0%)           Wischita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Withingsport, PA         1,314,850         0 (0%)         2,119,442 (100%)           Williamsburg, VA         2,119,442         0 (0%)         2,194,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, PA         2,696,733         0 (0%)         2,696,733 (100%)           Winchester, VA         0         -         -	Villas, NJ	0	-	-
Virgin Islands, VI         0         -           Virginia Beach, VA         13,332,764         13,332,764 (100%)         0 (0%)           Visginia Beach, VA         1,615,012         0 (0%)         1,615,012 (100%)           Visalia, CA         1,615,012         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waldorf, MD         806,460         0 (0%)         806,460 (100%)           Washington, DC-VA-MD         410,439,406         405,975,689 (98.9%)         4,463,717 (1.1%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterloo, IA         0         -         -           Wasuau, WI         0         -         -           Wenatchee, WA         1,036,007         1,036,007 (100%)         0 (0%)           Wischita, KS         13,366,960         1,366,960 (100%)         0 (0%)           Wischita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Winchester, VA         0         -         - <td>Vineland, NJ</td> <td>206,661</td> <td>0 (0%)</td> <td>206,661 (100%)</td>	Vineland, NJ	206,661	0 (0%)	206,661 (100%)
Virginia Beach, VA         13,332,764         13,332,764         10,332,764         00%           Visalia, CA         1,615,012         0.0%         1,615,012         0.0%         1,615,012         100%           Waco, TX         1,287,009         0.0%         1,287,009         0.0%         806,460         0.0%         806,460         100%         100%         100%         100%         100%         100%         100%         100%         100%         100%         100%         100% <td>Virgin Islands, VI</td> <td>0</td> <td>-</td> <td>-</td>	Virgin Islands, VI	0	-	-
Visalia, CA         1,615,012         0 (0%)         1,615,012 (100%)           Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waldorf, MD         806,460         0 (0%)         806,460 (100%)           Washington, DC-VA-MD         410,439,406         405,975,689 (98,9%)         4,463,717 (1.1%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         0         -         -           Waseu, WI         0         -         -           Wenatchee, WA         1,036,007         1,036,007 (100%)         0 (0%)           Westminster-Eldersburg, MD         0         -         -           Wenatche, WA         1,366,960         1,366,960 (100%)         0 (0%)           Wichita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         2,696,733 (100%)           Williamsport, NC         2,696,733         0 (0%)         2,696,733 (100%)           Wincester, VA         0         -	Virginia Beach, VA	13,332,764	13,332,764 (100%)	0 (0%)
Waco, TX         1,287,009         0 (0%)         1,287,009 (100%)           Waldorf, MD         806,460         0 (0%)         806,460 (100%)           Washington, DC-VA-MD         410,439,406         405,975,689 (98,9%)         4,463,717 (1.1%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterbury, CT         4,933,139         4,933,139 (100%)         0 (0%)           Waterloo, IA         0         -         -           Wenatchee, WA         1,036,007         1,036,007 (100%)         0 (0%)           Westminster-Eldersburg, MD         0         -         -           Wheeling, WV-OH         379,457         0 (0%)         379,457 (100%)           Williamsport, PA         1,366,960         1,366,960 (100%)         0 (0%)           Williamsport, PA         1,314,850         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,258,731         1,258,731 (100%)         0 (0%)           Winchester, VA         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918	Visalia, CA	1,615,012	0 (0%)	1,615,012 (100%)
Waldorf, MD $806,460$ $0.0\%$ $806,460.(100\%)$ Washington, DC-VA-MD $410,439,406$ $405,975,689.(98.9\%)$ $4,463,717.(1.1\%)$ Waterbury, CT $4,933,139$ $4,933,139.(100\%)$ $0.0\%$ Waterloo, IA $0$ Wausau, WI $0$ Wenatchee, WA $1,036,007.(100\%)$ $0.0\%$ Westminster-Eldersburg, MD $0$ -Wolding, WV-OH $379,457.00\%$ $0.0\%$ Wichita, KS $1,366,960.1,366,960.(100\%)$ $0.0\%$ Williamsburg, VA $2,119,442.00\%$ $0.0\%$ Williamsport, PA $1,314,850.00.00\%$ $0.0\%$ Winchester, VA $0$ -Worester, NA $0.0.0\%$ $$	Waco, TX	1,287,009	0 (0%)	1,287,009 (100%)
Washington, DC-VA-MD $410,439,406$ $405,975,689 (98.9\%)$ $4,463,717 (1.1\%)$ Waterbury, CT $4,933,139$ $4,933,139 (100\%)$ $0 (0\%)$ Waterloo, IA $0$ $ -$ Wausau, WI $0$ $0$ $-$ Wenatchee, WA $1,036,007 (100\%)$ $0 (0\%)$ Westminster-Eldersburg, MD $0$ $-$ Wheeling, WV-OH $379,457 (00\%)$ $379,457 (100\%)$ Wichita, KS $1,366,960 (13,66,960 (100\%)$ $0 (0\%)$ Williamsburg, VA $2,119,442 (00\%)$ $0 (0\%)$ Williamsport, PA $1,314,850 (0\%)$ $0 (0\%)$ Winchester, VA $0$ $-$ Winchester, VA $0$ $-$ Winter Haven, FL $0$ $-$ Worcester, MA-CT $3,232,569 (3,232,569 (100\%))$ $0 (0\%)$ Yakima, WA $1,056,918 (1,056,918 (100\%))$ $0 (0\%)$ Yakima, WA $1,056,918 (100\%)$ $0 (0\%)$ Youngstown, OH-PA $1,568,483 (00\%)$ $0 (0\%)$ Yuung, AZ-CA $844,374 (844,374 (100\%))$ $0 (0\%)$ Yuung, AZ-CA $9 846 93 5 77 (2) 9 306 541 641 (05.4\%)$ $450 394 131 (4.6\%)$	Waldorf, MD	806,460	0 (0%)	806,460 (100%)
Waterbury, CT $4,933,139$ $4,933,139$ $1,90\%$ $10\%$ Waterloo, IA0Wausau, WI0Wenatchee, WA $1,036,007$ $1,036,007 (100\%)$ $0 (0\%)$ Westminster-Eldersburg, MD0Wheeling, WV-OH $379,457$ $0 (0\%)$ $379,457 (100\%)$ Wichita, KS $1,366,960$ $1,366,960 (100\%)$ $0 (0\%)$ Williamsburg, VA $2,119,442$ $0 (0\%)$ $2,119,442 (100\%)$ Williamsport, PA $1,314,850$ $0 (0\%)$ $1,314,850 (100\%)$ Winchester, VA0Worcester, MA-CT $2,696,733$ $0 (0\%)$ $2,696,733 (100\%)$ Worcester, MA-CT $3,232,569$ $3,232,569 (100\%)$ $0 (0\%)$ Yakima, WA $1,056,918$ $1,056,918 (100\%)$ $0 (0\%)$ Youngstown, OH-PA $1,568,483$ $0 (0\%)$ $1,568,483 (100\%)$ Yuba City, CA931,948 (931,948 (100\%) $0 (0\%)$ Yuba City, CA9346 935 772 $9,396 541 541 (454\%)$ $450,394 131 (456\%)$	Washington, DC-VA-MD	410,439,406	405,975,689 (98.9%)	4,463,717 (1.1%)
Waterloo, IA         0         -         -           Wausau, WI         0         -         -         -           Wenatchee, WA         1,036,007         1,036,007 (100%)         0 (0%)           Westminster-Eldersburg, MD         0         -         -           Wheeling, WV-OH         379,457         0 (0%)         379,457 (100%)           Wichita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Wilnington, NC         1,258,731         1,258,731 (100%)         0 (0%)           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winer Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)	Waterbury, CT	4,933,139	4,933,139 (100%)	0 (0%)
Wausau, WI         0         -         -           Wenatchee, WA         1,036,007         1,036,007 (100%)         0 (0%)           Westminster-Eldersburg, MD         0         -         -           Wheeling, WV-OH         379,457         0 (0%)         379,457 (100%)           Wichita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, NC         1,258,731         1,258,731 (100%)         0 (0%)           Winchester, VA         0         -         -           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%) </td <td>Waterloo, IA</td> <td>0</td> <td>-</td> <td>-</td>	Waterloo, IA	0	-	-
Wenatchee, WA $1,036,007$ $1,036,007 (100\%)$ $0 (0\%)$ Westminster-Eldersburg, MD0Wheeling, WV-OH $379,457$ $0 (0\%)$ $379,457 (100\%)$ Wichita, KS $1,366,960$ $1,366,960 (100\%)$ $0 (0\%)$ Williamsburg, VA $2,119,442$ $0 (0\%)$ $2,119,442 (100\%)$ Williamsport, PA $1,314,850$ $0 (0\%)$ $1,314,850 (100\%)$ Williamsport, NC $1,258,731$ $1,258,731 (100\%)$ $0 (0\%)$ Winchester, VA0Winston-Salem, NC $2,696,733$ $0 (0\%)$ $2,696,733 (100\%)$ Worcester, MA-CT $3,232,569$ $3,232,569 (100\%)$ $0 (0\%)$ Yakima, WA $1,056,918 (1,056,918 (100\%)$ $0 (0\%)$ Youngstown, OH-PA $1,568,483$ $0 (0\%)$ $1,568,483 (100\%)$ Yuba City, CA $931,948 (931,948 (100\%)$ $0 (0\%)$ Yuma, AZ-CA $844,374 (844,374 (100\%)$ $0 (0\%)$	Wausau, WI	0	-	-
Westminster-Eldersburg, MD         0         -         -           Wheeling, WV-OH         379,457         0 (0%)         379,457 (100%)           Wichita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, PA         1,258,731         1,258,731 (100%)         0 (0%)           Winchester, VA         0         -         -           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)         0 (0%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)         0 (0%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)         0 (0%)	Wenatchee, WA	1,036,007	1,036,007 (100%)	0 (0%)
Wheeling, WV-OH         379,457         0 (0%)         379,457 (100%)           Wichita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, PA         1,258,731         1,258,731 (100%)         0 (0%)           Winchester, VA         0         -         -           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Westminster-Eldersburg, MD	0	-	-
Wichita, KS         1,366,960         1,366,960 (100%)         0 (0%)           Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, PA         1,258,731         1,258,731 (100%)         0 (0%)           Windester, VA         0         -         -           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Wheeling, WV-OH	379,457	0 (0%)	379,457 (100%)
Williamsburg, VA         2,119,442         0 (0%)         2,119,442 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Williamsport, PA         1,258,731         1,258,731 (100%)         0 (0%)           Windester, VA         0         -         -           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Wichita, KS	1.366.960	1,366,960 (100%)	0 (0%)
Williamsport, PA         1,314,850         0 (0%)         1,314,850 (100%)           Wilmington, NC         1,258,731         1,258,731 (100%)         0 (0%)           Winchester, VA         0         -         -           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Williamsburg, VA	2,119,442	0 (0%)	2,119,442 (100%)
Wilmington, NC         1,258,731         1,258,731 (100%)         0 (0%)           Winchester, VA         0         -	Williamsport, PA	1,314,850	0 (0%)	1,314,850 (100%)
Winchester, VA         0         -         -           Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winston-Salem, NC         0         -         -           Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Wilmington, NC	1,258,731	1,258,731 (100%)	0 (0%)
Winston-Salem, NC         2,696,733         0 (0%)         2,696,733 (100%)           Winter Haven, FL         0         -         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Winchester, VA	0	-	-
Winter Haven, FL         0         -         -           Worcester, MA-CT         3,232,569         3,232,569 (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Winston-Salem, NC	2.696.733	0 (0%)	2.696.733 (100%)
Worcester, MA-CT         3,232,569         3,232,569         (100%)         0 (0%)           Yakima, WA         1,056,918         1,056,918 (100%)         0 (0%)           York, PA         2,231,826         2,231,826 (100%)         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)	Winter Haven, FL	0	-	-
Yakima, WA       1,056,918       1,056,918 (100%)       0 (0%)         York, PA       2,231,826       2,231,826 (100%)       0 (0%)         Youngstown, OH-PA       1,568,483       0 (0%)       1,568,483 (100%)         Yuba City, CA       931,948       931,948 (100%)       0 (0%)         Yuma, AZ-CA       844,374       844,374 (100%)       0 (0%)	Worcester, MA-CT	3.232.569	3,232.569 (100%)	0 (0%)
York, PA         2,231,826         2,231,826         0 (0%)           Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)           Total         9 846 935 772         9 396 541 641 (95 4%)         450 394 131 (4 6%)	Yakima, WA	1.056.918	1,056.918 (100%)	0 (0%)
Youngstown, OH-PA         1,568,483         0 (0%)         1,568,483 (100%)           Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)           Total         9 846 935 772         9 396 541 641 (95 4%)         450 394 131 (4 6%)	York, PA	2.231.826	2,231.826 (100%)	0 (0%)
Yuba City, CA         931,948         931,948 (100%)         0 (0%)           Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)           Total         9 846 935 772         9 396 541 641 (95 4%)         450 394 131 (4 6%)	Youngstown, OH-PA	1.568.483	0 (0%)	1.568.483 (100%)
Yuma, AZ-CA         844,374         844,374 (100%)         0 (0%)           Total         9 846 935 772         9 396 541 641 (95 4%)         450 394 131 (4 6%)	Yuba City, CA	931,948	931,948 (100%)	0 (0%)
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Yuma, AZ-CA	844,374	844.374 (100%)	0 (0%)
	Total	9 846 935 772	9 396 541 641 (95 4%)	450 394 131 (4.6%)

† GTFS data available, but no ridership available. Assumed 100% on GTFS systems.‡ Did not report ridership information to National Transit Database in 2019.

Source: National Transit Database (NTD), Federal Highway Administration (FHWA), 2020.