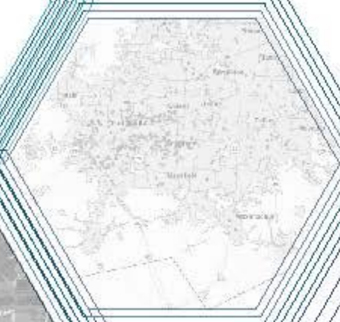

FINAL REPORT

Center for Transportation Equity, Decisions & Dollars

INCORPORATING MIXED AUTOMATED VEHICLE TRAFFIC IN CAPACITY ANALYSIS AND SYSTEM PLANNING DECISIONS

FINAL PROJECT REPORT

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16. Abstract

It is predicted that half of the vehicles sold and 40% of vehicle travels could be autonomous in the 2040s (Litman 2017). However, how the presence of connected and autonomous vehicles (CAV) impacts highway capacity and network system performance remains unclear. Without this knowledge, it is hard to understand and quantify the implication of the disruptive CAV technologies on the existing traffic operations. Also, it would be difficult for relevant agencies (e.g., MPOs and state DOTs) to make appropriate long-term planning for preparing the infrastructure systems for emerging mixed CAV traffic. This project aims to explore methods for tackling these challenges and demonstrating their applicability via real-world case studies. First, an analytical approach for quantifying highway capacity in mixed traffic environments is developed. This approach considers CAV technology uncertainties considering different headway distributions and vehicle platooning configurations. A generalized capacity function for mixed CAV traffic for the full spectra of traffic density, CAV penetration rates, vehicle types, platooning configurations and highway segment types is explored. The proposed model has a simple and practical form for easy applications by relative stakeholders. Then, we demonstrate applications of the proposed mixed traffic analysis approach to a transportation system with a case study on the Tampa Bay Regional Planning Model (http://www.tbrta.com/). Further, we propose simple traffic flow fundamental diagram formulations for ACC equipped vehicles from both macroscopic and microscopic perspectives. Then, a new methodological framework for measuring and visualizing place-based job accessibility in space and time is presented that overcomes the existing limitations. With the proposed methodological framework for job accessibility measurement, we can investigate how the evolution of traffic patterns from regular vehicles to CAV mixed traffics impacts the spatial patterns of job accessibility for the general population and the disparities across different socio-economic groups. The findings could offer policy implications related to transportation planning and urban design on job access for low-access areas.

17. Key Words Connected autonomous vehicles; capacity analysis; planning; network; traffic assignment, fundamental diagram, job accessibility	**18. Distribution Statement**

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Abstract

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CHAPTER I. INTRODUCTION AND LITERATURE REVIEW

This chapter discusses the existing studies toward mixed traffic capacity analysis and job accessibility measures.

BACKGROUND

Connected and autonomous vehicles (CAVs) are expected to improve highway traffic efficiency, safety, and energy efficiency through sensing the local environment, sharing information, and applying appropriate control measures (Ghiasi et al., 2017; Li et al., 2017; Kamrani et al., 2017). All these benefits are linked to the expectation that CAVs can largely improve highway traffic capacity by reducing time headways between consecutive vehicles through communications and automated control technologies. With CAV platooning, a pair of CAVs are similar to two concatenated cars in a train and thus shall have much less time headway compared with a pair of disconnected human-driven vehicles (HVs). Therefore, we envision that highway capacity will be improved in the far future when most vehicles are platooned CAVs as predicted by a number of studies on purely automated traffic with computer simulation (Ioannou and Chien, 1993) and analytical models (Kanaris et al., 1997; Swaroop et al., 1994; Fernandes and Nunes, 2012; Amoozadeh et al., 2015).

LITERATURE REVIEW

Mixed Traffic Capacity

Besides the consensus on the purely automated traffic, it is not yet completely clear how highway capacity is affected by CAVs in a mixed traffic containing both CAVs and HVs, which is expected to last for a relatively long transitional period. A number of studies conducted capacity analyses for mixed traffic, where most of them relying on computer simulation (e.g., Van Arem et al., 1997; Shladover et al., 2001; Vander Werf et al., 2002; Van Arem et al., 2006; Kesting et al., 2008; Kesting et al., 2010; Shladover et al., 2012). There are only a limited number of studies attempting building analytical models to characterize the capacity of mixed traffic. Tientrakool et al. (2011) evaluated the impact of Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) vehicles with deterministic headway rules on highway capacity. Levin and Boyles (2015) proposed a link capacity model as a function of automated vehicles' (AV) penetration rate and deterministic headway values. This model is extended by Levin and Boyles (2016) by considering different vehicle classes, while time headways are uniformly distributed across all vehicles in each class. Chen et al. (2016) proposed a deployment model to determine the locations of AV lanes on a general transportation network and provided elegant insights into network infrastructure design decisions. Fakharian Qom et al. (2016) performed a simulation analysis to evaluate the performance of Managed Lanes (ML) with CACC vehicles.

Although these studies provided impactful insight to the capacity analyses for mixed traffic, there lacks an analytical and scalable mixed traffic capacity model (e.g., comparable to HCM capacity formulas) for parsimoniously quantifying highway performance in the near future mixed traffic environment. Particularly, we need a model that is able to incorporate various uncertainties from technologies (e.g., uncertain headways) and traffic characteristics (e.g., market penetration rates and platooning configurations) perspective. Further, how to scale the capacity analysis from a segment to a network is not clear. This prevents transportation planners from accurately estimating and evaluating the impacts of the emerging CAV technologies on the transportation system and planning for the future infrastructure investments.

Job Accessibility

In the past decades, many research efforts has been devoted to studying accessibility, such as what it means, how to measure it, and what policy implications it offers. As a concept discussed in a number of disciplines, such as transportation, urban planning, geography, and environmental policy, accessibility has a variety of definitions (Geurs and van Wee, 2004; Le Vine et al., 2013; Song, 1996; Shen, 1998). For example, it measures the potential of various opportunities for interaction (Hansen, 1959), the relative ease with which opportunities can be reached from a given location with a choice of travel (Morris et al., 1979), the potential of an individual to reach opportunities (Burns, 1979), and the benefits an individual gains from a given transportation or land-use system (Ben-Akiva and Lerman, 1979). Regardless of the definition, opportunities can be employment, transportation, education, food, health care, landscape and natural resources, or other facilities (e.g., Antrop, 2004; Apparicio et al., 2007; Ikram et al., 2015; Luo and Wang, 2003; Murray and Wu, 2003; Rigolon, 2016; Shen, 1998; Talen, 2001). Owing to the strong link to urban planning and economic development, an emphasis on job accessibility has long been recognized (Cervero, 1989; Ihlanfeldt, 1993; Kain, 1968; Matas et al., 2010; Wang and Minor, 2002).

Accessibility measures can be infrastructure-based, place-based, person-based, and utility-based (Gerus and Wee, 2004). In terms of job accessibility, a commonly-accepted notion refers to that it measures the relative ease with which job opportunities can be reached from a given location with a choice of transportation mode, and hence place-based measures are more appropriate. Place-based measures are aggregated metrics that assess the number of job opportunities that are accessible to workers from a given location or zone. These include jobs-housing balance ratios, cumulative-opportunity measures, and gravity-based measures. Though they do not capture individual components of accessibility like they do in person-based measures (Kwan, 1998; Miller, 1991), place-based measures reflect accessibility at a zonal/regional level and hence are more favored by policy-makers (Dodson et al., 2007). Of the three groups of place-based accessibility metrics, gravity-based measures, such as the model by Shen (1998) and the 2SFCA model by Luo and Wang (2003) are generally most preferred, since they consider more components of accessibility, including the supply of jobs, the demand of workers, and the spatial barriers that separate them.

CHAPTER II. CAPACITY ANALYSIS OF MIXED TRAFFIC

This chapter discusses the developed analytical approach for quantifying highway capacity in mixed traffic environment. This chapter also describes a procedure on how to use mixed traffic capacity analysis in the traffic assignment step for transportation planning.

GENERALIZED MIXED TRAFFIC CAPACITY FORMULA

The methodology on capacity analysis is based on the generalized fundamental diagram analysis that converts microscopic vehicle dynamics (e.g., time and space headway) into macroscopic traffic flow measures (e.g., throughput, density). The capacity formulation will extend the maximum point of mixed traffic capacity in our preliminary study (Ghiasi et al. 2017) with our proposed generalized fundamental diagram method (Qian et al., 2017). In this framework, we consider a stream of N vehicles indexed as $n \in \mathcal{N} := \{1, 2, \dots, N\}$ moving along the highway segment. Let $A_n \in \{0, 1\}$ denote whether vehicle n is a CAV or an HV (human-driven vehicle); i.e., $A_n = 1$ if vehicle n is a CAV and $A_n = 0$ if vehicle n is an HV. Let h_n denote the time headway between vehicles n and $n + 1$, $\forall n \in \mathcal{N} \backslash \{N\}$. We allow h_n to be a random variable that follows a positive-valued distribution depending on vehicle types A_n and A_{n+1}, as illustrated in Figure 1.

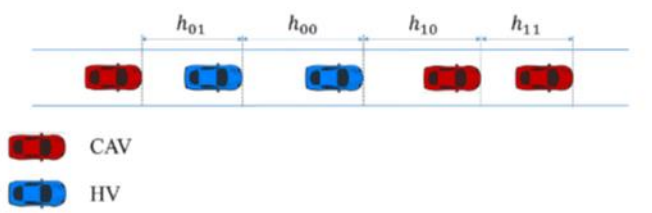


Figure 1. Illustration of headways in mixed traffic.

The overall traffic pattern can be characterized by two exogenous parameters that largely affect highway capacity. The first parameter, denoted by P_1, describes the percentage of CAVs in the mixed traffic. Further, let $P_0 = 1 - P_1$ denote the percentage of HVs. The second parameter, denoted by O indicates the CAV platooning intensity, i.e., the strength of CAV clustering in the mixed traffic. Basically, for a certain P_1 value, O determines the likelihood of the following vehicle type given a preceding vehicle type for each vehicle pair. For example, if O is set to its maximum value, the CAV clustering strength is maximum and thus, the type of the following vehicle matches the preceding vehicle's type. On the other hand, if O is set to the minimum value, we will have the weakest CAV clustering strength. Thus the probability that the following vehicle type follows the preceding one is minimum and the segregation between HVs and CAVs is maximum. With this, the probability of a type s vehicle follows type r can be represented as a function of CAV penetration rate and platooning intensity, denote by $t_{sr}(P_1, O)$. Let h_{sr} denote the average time headway between type s vehicles and type r vehicles. Then, Ghiasi et al. (2017) shows the maximum traffic capacity is

$$c := \frac{1}{\sum_{s=0}^{1}\sum_{r=0}^{1}(P_s t_{sr}(P_1, O) h_{sr})} \tag{1}$$

This result on the maximum capacity can be extended to the full spectrum of traffic flow density. The headway h_{sr} can be revised from the minimum headway to the actual headway determined by traffic density and compositions. This can be done by extending the multi-class fundamental diagram to consider different vehicle pair types distributed in mixed traffic. Technology uncertainties can also be considered in the analysis. Time headways of CAVs in mixed traffic environment will be highly uncertain and stochastic in future traffic. The effect of headway stochasticity on highway capacity is not captured in these results. The headway distributions in mixed traffic highly depend on CAV technologies that are yet to be fully developed and thus may have quite some uncertainties. From the literature, we see quite some discrepancies in describing CAV headway values ranging from 0.3 to 2.6 s. Further, different agencies report different expectations on CAV penetration rates in the future. It is also interesting investigating how sensitive the outcomes are to CAV penetration prediction errors. This way, for any possible traffic state, this method will be able to yield the mixed traffic throughput accordingly.

EXPERIMENTAL RESULTS

Following the capacity analysis, we propose a procedure in upgrading the traditional transportation planning model for regular HV traffic to near future mixed CAV traffic. In this project, we will focus on the static traffic assignment step (which is a key step in the four-step planning model widely adopted by a number of state DOTs). We propose a method to revise the static traffic assignment step in a commonly used planning modeling tool (e.g., Cube) to incorporate the mixed traffic throughput and travel time. The key to this step is to determine the relationship between the mixed traffic characteristics with link time as an extension of the classic BRP function. This can be obtained based on headway analysis from the previous analytical results in conjunction with queuing theory and simulation. Basically, we will investigate a generic link in a typical network. We will quantify the relationships between its travel time and mixed traffic characteristics (e.g., including traffic throughput demand, CAV penetration, platooning configurations) on this link via bottleneck queueing theory and simulation for a given peak hour demand pattern. This relationship will be used to replace the existing HV BPR function in the traffic assignment step. This way, the traffic assignment results will reflect the impacts of the mixed traffic.

As a preliminary study, version 8.2 of Tampa Bay Regional Planning Model (TBRPM v8.2) is adapted by replacing the BPR capacity with the maximum point capacity in Equation (1). We use the travel demand data of Florida district 7 from 2010 as the benchmark, where all vehicles are human-driven. Then, we simulate the mixed traffic case by applying the proposed formulation to modify the highways' capacity. CAV penetration rate P_1 assumed to be 50 percent in all road segments, where platooning intensity O assumed to be 0. Figure 2, shows that the capacities of all links increase from zero CAV penetration rate to 50 percent CAV penetration rate regardless of the highway type. As a result, the congestion along all road segments (defined by the ratio of velocity and capacity) decreases as the CAV penetration rate increases. As shown in Figure 3, some road segments meet saturated traffic flow in human-driven traffic. However, the number of road segments with saturated traffic flow decreases significantly. Note that this preliminary result uses the same BPR function except that the capacity is replaced with the calculated one for mixed traffic in Equation (1). In future, a generalized travel time function for mixed traffic will be used to reflect a more reasonable relationship between travel time and mixed traffic specific characteristics. Further, more traffic and planning scenarios can be considered. The associated cost savings/increases (e.g., changes of travel time, energy consumption and vehicle unit-distance travel costs) due to CAV technologies can be quantified as well.

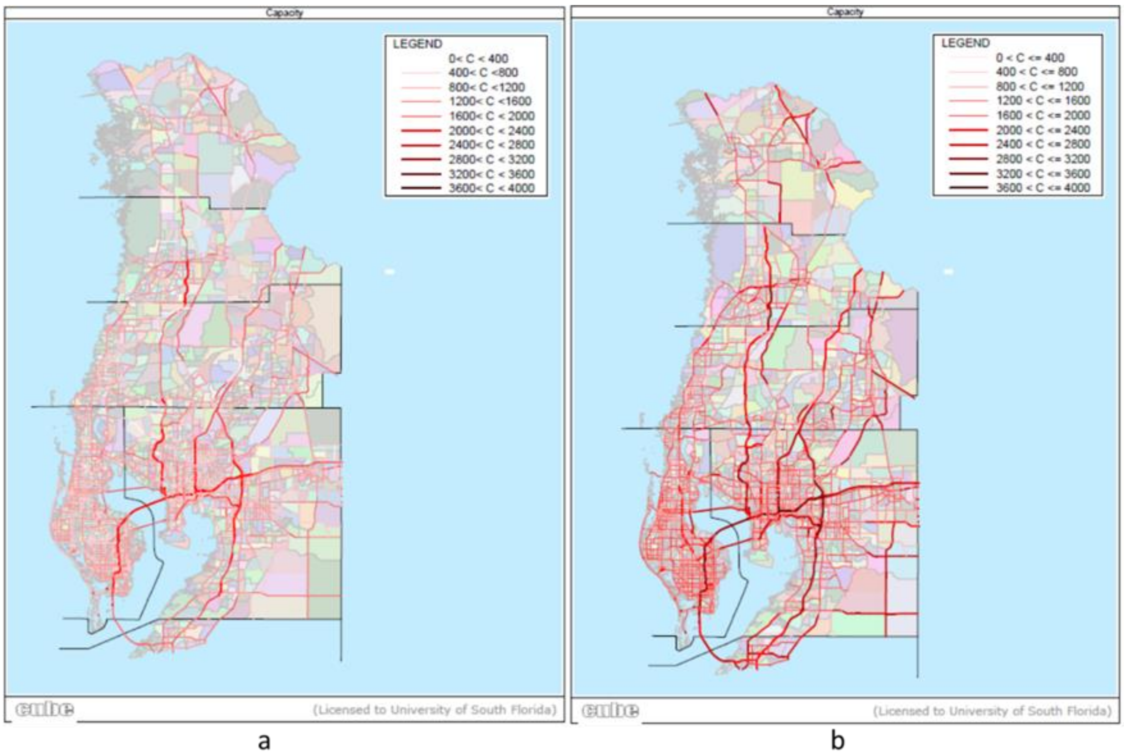
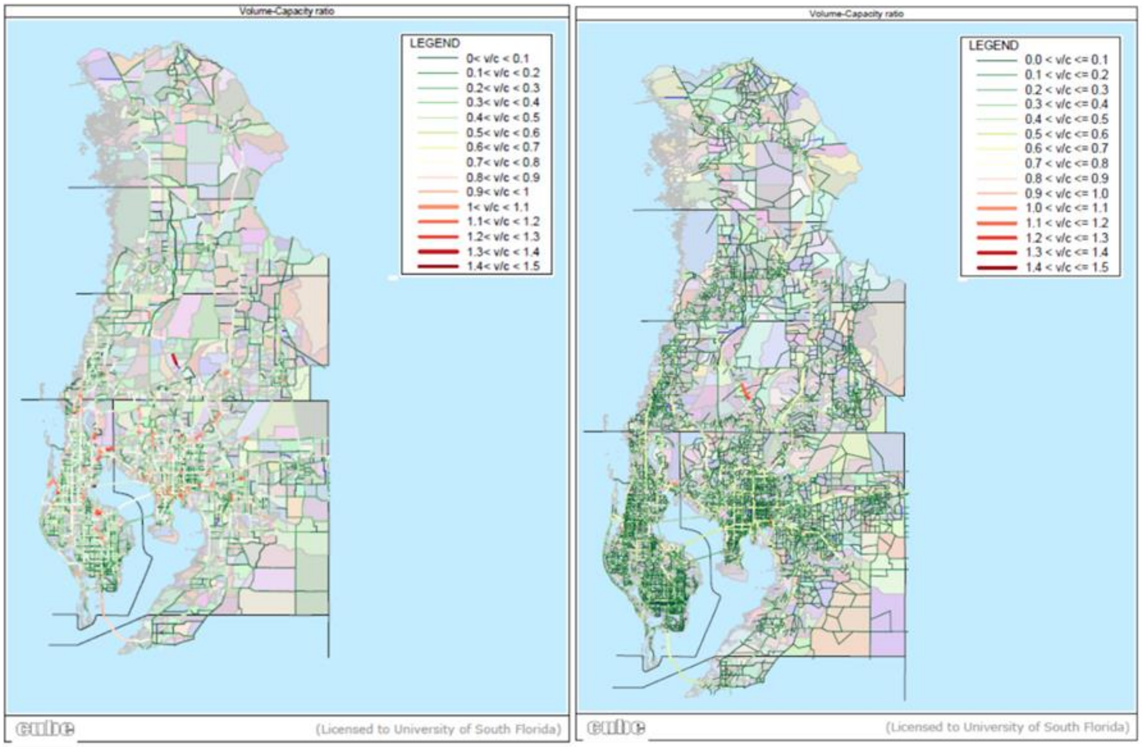


Figure 2. Highway capacity of a) Human-driven traffic b) Mixed traffic (50% penetration rate)



a b

Figure 3. Volume-Capacity ratio of a) Human-driven traffic b) Mixed traffic (50% penetration rate)

CHAPTER III. FUNDAMENTAL DIAGRAM FOR ADAPTIVE CRUISE CONTROL SYSTEM

This chapter discusses the formulated traffic flow fundamental diagram (FD) for commercially implemented adaptive cruise control system and mixed HV-CAV traffic.

TRAFFIC FLOW FUNDAMENTAL DIAGRAM FOR COMMERCIALLY IMPLEMENTED ADAPTIVE CRUISE CONTROL SYSTEM

The fundamental diagram (FD), also known as the flow-density relationship, is one of the most fundamental concepts in the traffic flow theory. An FD describes the relationship between flow and density of traffic in steady state (sometimes referred as equilibrium or stationary traffic), that is, traffic in which all the vehicles exhibit the same constant speed and spacing. Thus, FDs are utilized by a wide variety of academic and practical purposes in traffic science and engineering fields such as traffic flow modeling, analysis, and simulation.

An FD can not only describe the characteristics of the traffic (e.g., flow, density and speed at steady traffic) in macroscopic view, but also can explain some microscopic vehicle behaviors (e.g., spacing between two continuous vehicles at steady traffic). Currently autonomous vehicles are at the heart of academia and industry. Adaptive Cruise Control System (ACC), one of the most crucial parts of AV control systems, aims to maintain the safety space between the subject vehicle and its preceding vehicle by adjusting the speed or acceleration of the subject vehicle. . Several vehicle manufactories have already produced a series of vehicles equipped with ACC system and sold to customers. To know whether the commercially implemented ACC system impacts the characteristic of traffic flow, this study aims to explore the traffic flow FD considering commercially implemented ACC system. This study gives the insight that the traditional triangle fundamental diagram still is capable of describing the traffic flow characteristics for ACC quipped vehicles (VACC).

Macroscopic Method

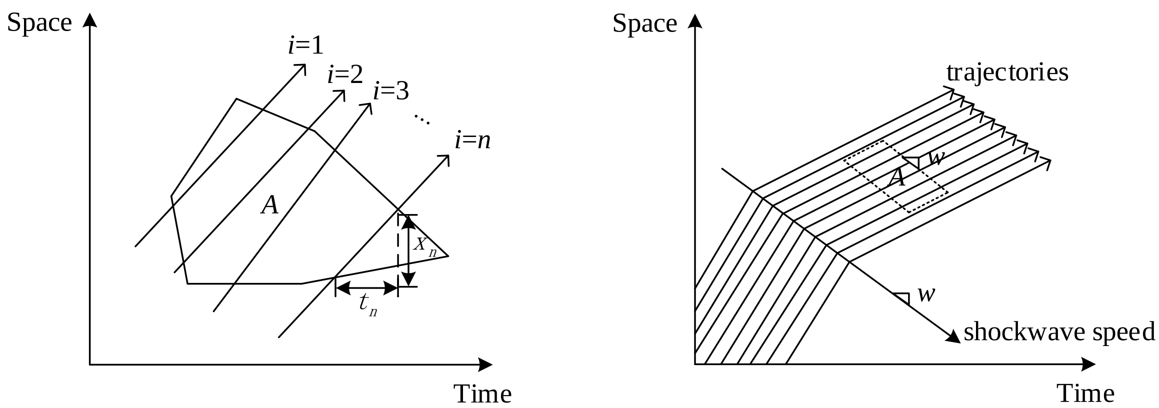
When platoon trajectory data are available, one can analyze the macroscopic traffic characteristics. Referring to Laval (2011), for a n-vehicles platoon inside an arbitrary region A in time-space, density k, flow rate q, and speed v can be calculated by equations (2)-(4).

$$k = \sum_{i=1}^{n} t_i / |A| \tag{2}$$

$$q = \sum_{i=1}^{n} x_i / |A| \tag{3}$$

$$v = q/k = \sum_{i=1}^{n} x_i / t_i \tag{4}$$

where $|A|$ denotes the area of region A, and t_i and x_i are the ith vehicle's travel time and distance traveled inside region A, as shown in Figure 4(a). In this study, following Laval (2011)'s study, A is a parallelogram area that is created by two opposite slides with slope w (i.e. shockwave speed) and the other two with a slope comparable to vehicles speed, as shown in Figure 4(b). This way, one maximizes the chances of having stationary conditions inside the considered area.



(a) (b)

Figure 4. Illustration to the arbitrary region for macroscopic method

Microscopic Method

For some reasons, the platoon trajectory data might not be available all the time or the available data might not contain sufficient information to study the traffic flow characteristics. In this section, we propose a microscopic method to study the traffic flow characteristics in a situation where the trajectory data does not include sufficient information, i.e., for a case where only two-vehicle trajectory data is available.

For a 2-vehicles-platoon trajectories inside an arbitrary region B in time-space, density k, flow rate q, and speed v can be calculated by equations (5)-(7).

$$v = x/t \tag{5}$$
$$k = 1/(L + |B|/t) \tag{6}$$
$$q = kv = x/(Lt + |B|) \tag{7}$$

where t and x denote the following vehicle's travel time and distance traveled inside region B, respectively, L is the average length of two vehicles, and $|B|$ is the area of region B. In this study, $|B|$ is an irregular area with four sides, two opposite sides that are comparable to the horizontal line (i.e. time line) and the other two that are part of the trajectories, as shown in Figure 5.
With these two methods, by successively moving the regions A or B throughout the platoon trajectories, the traffic flow characteristics (e.g., density, flow rate, and speed) can be obtained.

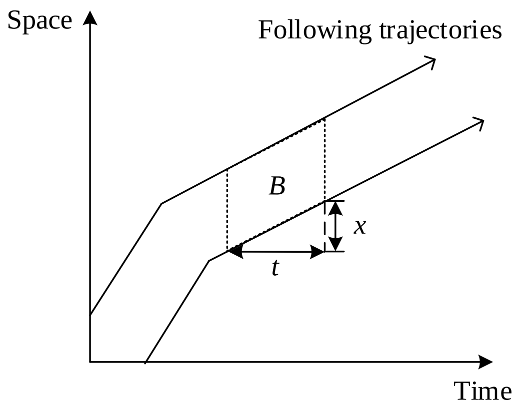


Figure 5. Illustration to the arbitrary region for microscopic method

DATASET

Thanks to the shared VACC trajectory dataset by Gunter et al. (2019), we have the opportunity to probe the traffic flow characteristics of VACCs. The data collections and experimental settings have been well described in Gunter et al. (2019). To avoid repetition, we briefly introduce the datasets we utilize in this study. Interested readers are referred to Gunter et al. (2019) for more details.

The obtained 1200 miles VACC trajectory datasets can be classified into two categories. The first one is seven-vehicles platoon trajectory data (include one leading vehicle and six VACC, i.e., vehicles A to F. The detailed information of these VACC are shown in Table 1). The second one is two-vehicles car-following trajectory data (include one leading vehicle and one VACC, i.e., one of vehicles A to F). The leading vehicles for these two datasets are a modified Ford Hybrid Escape vehicle and a 2018 model full size sedan, respectively. Two different kinds of flowing distance settings (one is relatively shorter than the other one) are tested The experiments are conducted at two different speed ranges, named by high (65-75 mph) and low (35-55 mph) speed ranges. All trajectory data are captured by high-accuracy GPS receivers during the experiment time horizons. In the experiments, the leading vehicle driving on a given lane executes a specific pre-defined speed profile (including quick acceleration and deceleration), and the following vehicles (six or one VACC) driving on the same lane follow the leading vehicle using the onboard ACC system.

Table 1. Tested VACCs (Gunter et al., 2019)

VACC	Style	Engine	Length (m)
A	Full-size sedan	Combustion	5.04
B	Compact sedan	Combustion	4.64
C	Compact hatchback	Hybrid	4.26
D	Compact SUV	Combustion	4.6
E	Compact SUV	Combustion	4.6
F	Mid-size SUV	Combustion	4.82

Further, thanks to the human-driven vehicles data shared by Federal Highway Administration (FHWA), we are able to make the comparison between VACC and human-drive traffic fundamental diagram.

EXPERIMENTAL RESULTS

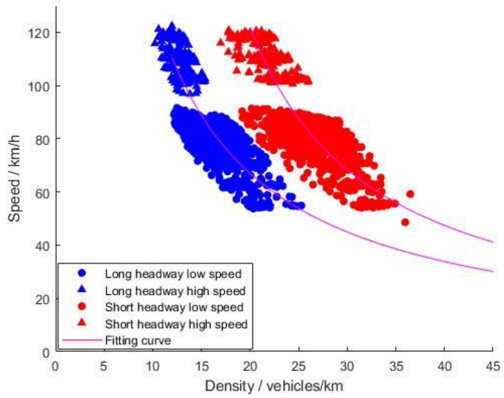
In this sub-section, first, the traffic flow characteristics of the VACCs using the VACC dataset processed by the methodology proposed in the previous sub-sections are presented. Then, trend analysis based on the presented results are addressed. Finally, the traffic flow characteristics of VACC and human-driven traffics are compared to analyze the impact of VACCs on the transportation system.

Figure 6 shows the scatter plots of traffic flow characteristics generated by the two-vehicle car-following and seven-vehicle platoon trajectory data. Due to the features of the obtained data (i.e., platoon trajectories and car-following trajectories data), it can be seen that all scatters are in a state at the right hand side (i.e., congested side) of the fundamental diagram. In addition, significant correlations among traffic density, flow rate, and speed are exhibited in the figure, and the detailed analysis are addressed as follows.

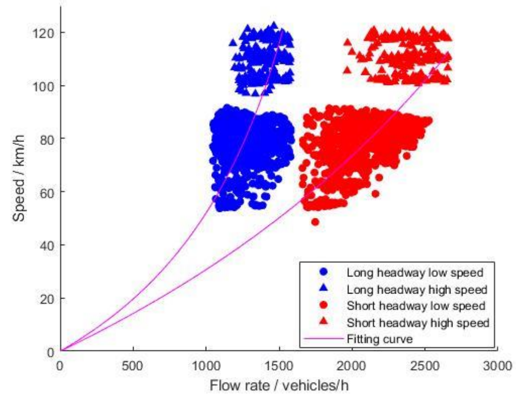
In the density-speed figure (see Figure 6(a)), it can be observed that the speed profile have a decreasing trend as the density increases. The scatters of the longer headway scenario show a larger radius of curvature than that the ones in the short headway scenario. For the longer headway scenario, the minimum density value is about 11 vehicles/km, which appears when the vehicles are operating with the maximum testing speed (i.e., 75 mph), and the maximum density value is about 25 vehicles/km, which appears when the vehicles are operating with the minimum testing speed (i.e., 35 mph). For shorter headway scenario, both the minimum and the maximum density values are increased (e.g., 17 vehicles/km and 38 vehicles/km), and they appear at the maximum and the minimum testing speeds, respectively. The results are consistent with the well-known traffic flow theory as the road segment can accommodate more vehicles with shorter headway.

In the flow-speed figure (see Figure 6(b)), it can be observed that as the flow rate increases, the speed of the traffic stream increases, and the scatters of the longer headway indicate a smaller radius of curvature than that of the short headway. For the longer headway scenario, the minimum flow rate value is about 1050 vehicles/h, which appears when the vehicles are operating with the minimum testing speed (i.e., 35 mph), and the maximum flow rate value is about 1600 vehicles/h, which appears when the vehicles are operating with the maximum testing speed (i.e., 75 mph). For the shorter headway scenario, both the minimum and the maximum flow rate values are increased (e.g., 1650 vehicles/h and 2700 vehicles/h), and they appear at the minimum and the maximum testing speed, respectively.

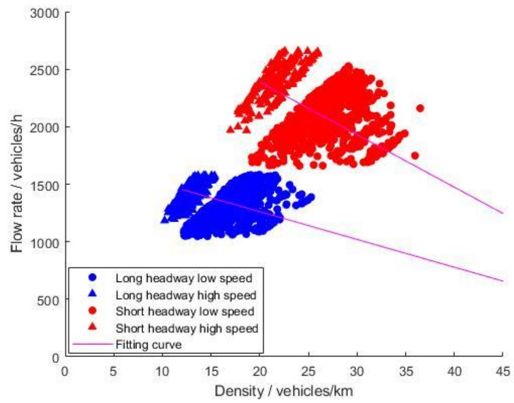
In the density-flow figure (see Figure 6(c)), it can be observed that as the density increases, the flow rate decreases, and the scatters of the longer headway exhibit larger slope gradients (slope gradients have negative values) than that of the short headway.



(a) Density-speed



(b) Flow-speed

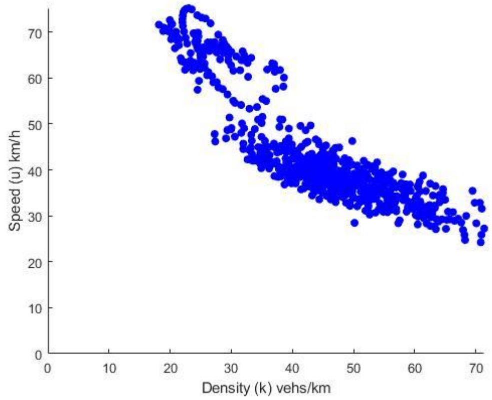


(c) Flow-density

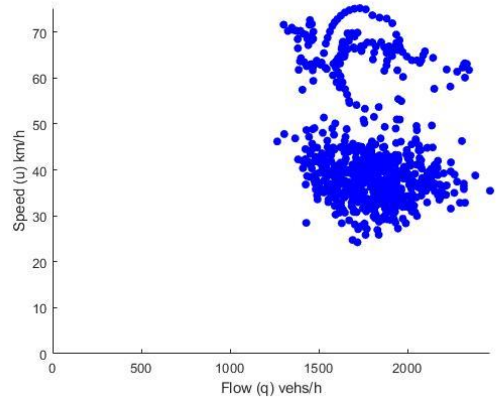
Figure 6. Scatter plots of VACC traffic data

It is well-known that the traditional triangle fundamental diagram has many merits (e.g., associated traffic flow characteristics among different trajectories) on traffic flow studies (Immers and Logghe, 2002). To this end, we fit the scatters with the triangle-fundamental-diagram-based functions. The fitting curves are shown in Figure 6. It can be seen that the traditional triangle fundamental diagram still can effectively describe the traffic flow characteristics of VACC.

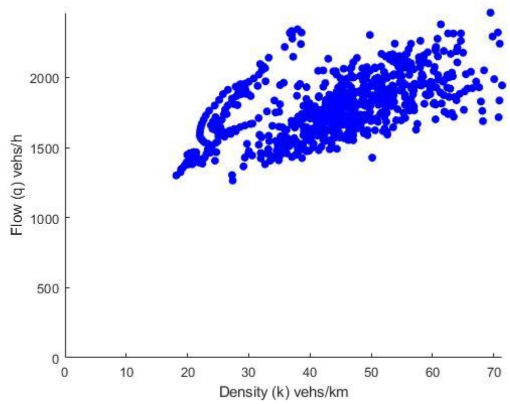
To study the impacts of VACC on the transportation system, we compared the traffic flow characteristics of VACCs and human-driven vehicles. In Figure 7, we plot out the density-speed, flow-speed, density-flow of the data obtained from human-driven vehicles. It can be observed that the capacity of the road segment in human-driven traffic is lower than the one in VACC traffic (the capacity of the road segment is about 2600 vehicles/h and 1600 vehicles/h for the short headway and the long headway scenarios, respectively, while the road capacity in human-driven traffic is about 2300 vehicles/h). This results show that VACCs have the capability to increase the road capacity up to 62.5% compared to the existing human-driven traffic.



(a) Density-speed



(b) Flow-speed



(c) Flow-density

Figure 7. Scatter plots of human-driven traffic data

CHAPTER IV. MEASURING AND VISUALIZING PLACE-BASED SPACE-TIME JOB ACCESSIBILITY

This chapter proposes a methodological framework for measuring and mapping place-based space-time job accessibility. It addresses the issues that are crucial to the study of job accessibility (and beyond). The integrated framework is demonstrated in the context of a case study of the Tampa Bay region of Florida. The methods can help inform transportation planning (e.g., transit management), economic development (e.g., affordable housing), and healthcare (e.g., EMS) resource planning and adjustment.

METHODS

A workflow describing the methods for computing the place-based space-time job accessibility measure is illustrated in Figure 8. This framework is described according to the chronological order of the workflow: (1) definition of study area and input data, (2) discretization of time and space, (3) calculation of space-time accessibility that is adapted from Shen's (1998) measure and implemented using a G2SFCA process, and (4) geovisualization of the results. Each of these steps are described in detail below.

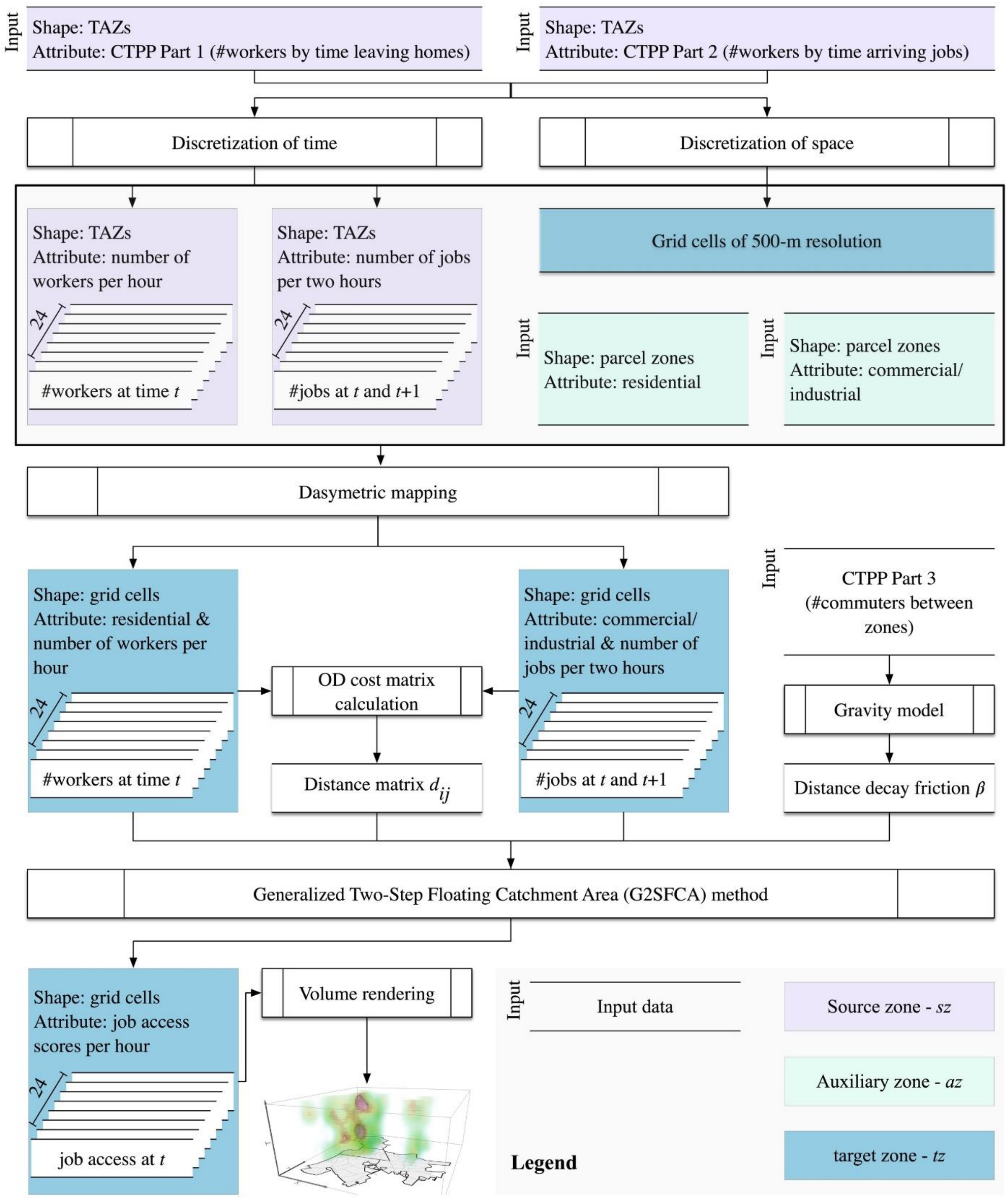


Figure 8. Workflow of the proposed methodology

Study Area Definition and Data Sources

Hillsborough and Pinellas Counties in the Tampa Bay Area of Florida is selected as the study area. Several major cities including Tampa, St. Petersburg, and Clearwater are within this area. Along with Hernando and Pasco Counties to the north, they make up the Tampa–St. Petersburg–Clearwater Metropolitan Statistical Area. According to the 2006-2010 American Community Survey (ACS) 5-Year Estimates data, there were 564,303 workers living in Hillsborough County; 89.5 percent of them stayed in the county for work and 5.2 percent commuted to Pinellas County. For Pinellas County, among 414,241 resident workers in total, 87.1 percent stayed for work and 1.1 percent commuted to Hillsborough County.

The major data source used in this research is the most recent 2006 to 2010 Census Transportation Planning Products (CTPP) data based on the 5-year ACS (http://ctpp.transportation.org/Pages/5-Year-Data.aspx). The CTPP consists of three parts: Part 1 reports the number of workers at residential places (total number, breakdowns by socioeconomic variables such as age, wage, and time leaving home); Part 2 records the number of workers at workplaces (total number, breakdowns by socioeconomic attributes such as wage and time arriving jobs); Part 3 provides detailed journey-to-work flow (total number of commuters, mean travel time by specific transportation modes) between residential and employment places (Hu and Wang, 2015). Temporal frequency distributions of workers and jobs and critical components to the measurement of space-time job accessibility are retrieved from the number of workers by their times leaving homes (Part 1) and the number of workers by their times arriving jobs (Part 2), respectively. They are provided in fifteen-minute increments from 5:00 a.m. to 11:00 a.m., one-hour increments from 11:00 a.m. to midnight, and a five-hour increment from midnight to 5:00 a.m. The data are aggregated at multiple zone levels such as Metropolitan Statistical Area (MSA), Census Tract, Traffic Analysis District (TAD), and Traffic Analysis Zone (TAZ). This research uses the TAZ-level data since TAZs are the most disaggregated zone units in the CTPP, and they are considered to be relatively uniform in terms of land use. There are 1,283 TAZs (compared to 567 census tracts) in the study area in 2010, averaging 3.78 km^2 in size. The TAZ boundary and other spatial datasets such as the road network were extracted from the TIGER Products 2010 from the U.S. Census Bureau. See Figure 9 for a map of the study area, where the major job centers, major roads, census tract boundaries, and the commuting flow patterns between tracts are shown. It should be noted that the use of tracts instead of TAZs in the visualizations is only for the sake of better visualization, since it would be too crowded to observe any pattern if mapped at the TAZ level.

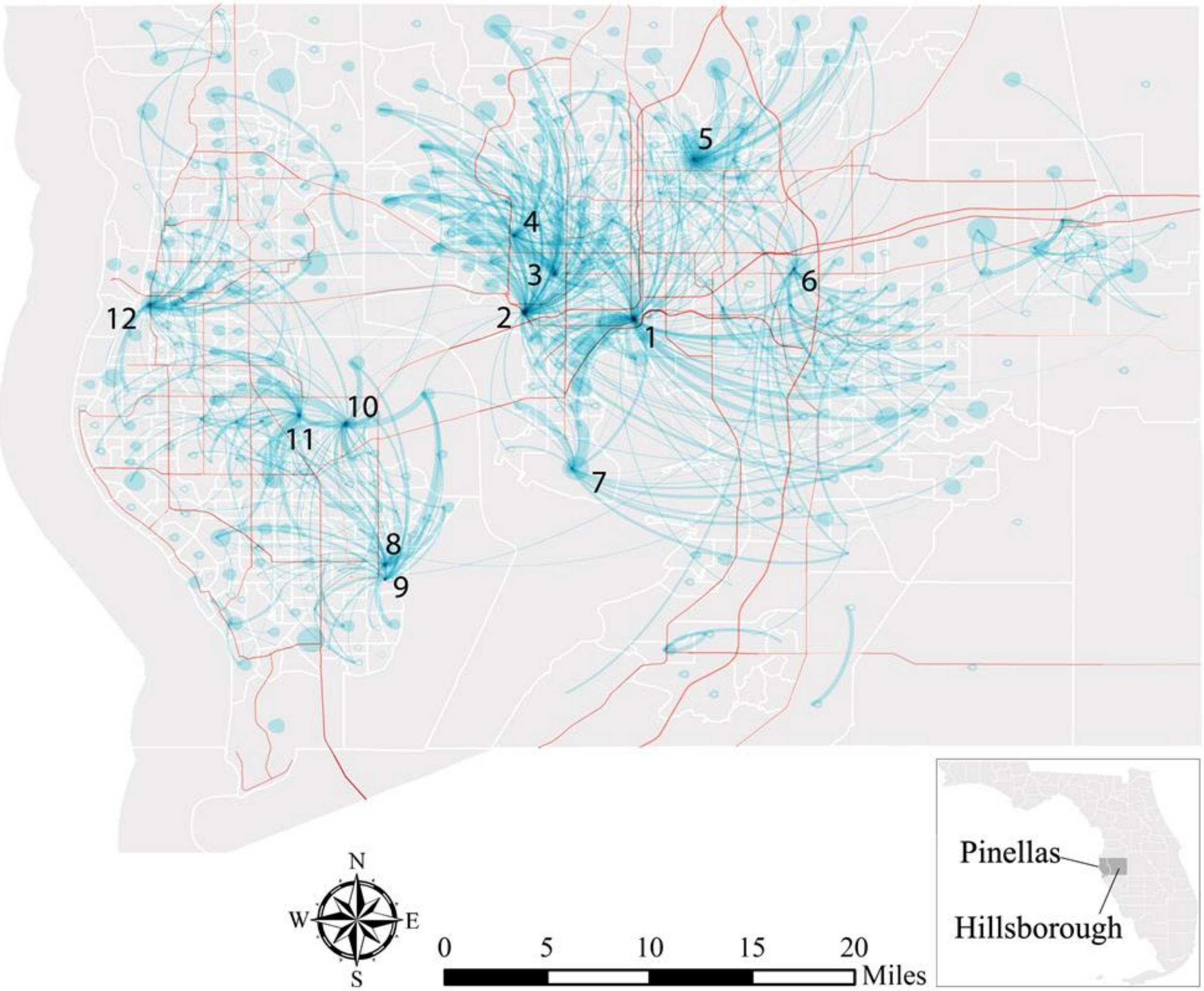


Figure 9. Census tracts overlaid with major roads and commuting flow in the study area. Major job centers are highlighted and labeled: 1. Tampa CBD, 2. Westshore Plaza, 3. International Plaza and Bay Street Shopping Mall, 4. USCIS Tampa Office, 5. University of South Florida, 6. Campuses of Hillsborough Community College, Springfield College, and Jersey College Nursing School, 7. MacDill Air Force Base, 8. St. Petersburg CBD, 9. University of South Florida St. Petersburg Campus, 10. Jabil Company (a US-based global manufacturing services company), 11. Pinellas Park (a major Gateway area of Pinellas County with many marine businesses), 12. Clearwater City Hall. [Note: The larger the line the more commuters, and lines with fewer than 100 commuters were cut off for better visualization.]

Discretization of time and space

The first step of the proposed methodology is to generate counts of jobs and workers at consistent, fine-scale spatial and temporal resolutions. For this study, this involved discretizing both the CTPP Part 1 (number of workers by time leaving homes) and Part 2 data (number of workers by time arriving jobs) into consistent representations in both time (hourly interval) and space (grid cells). In terms of time, CTTP counts of jobs and workers were either aggregated or disaggregated to hourly measures following Kobayashi et al. (2011)'s study. For data from 5:00 a.m. to 11:00 a.m., corresponding 15-min counts were summed to obtain hourly estimates. For data from 12:00 a.m. to 5:00 am, the five-hour count was evenly divided into 1-hour intervals. For 11:00 am to 12:00 a.m., the raw hourly counts were used. For example, if fifty people in TAZ *A* left their homes for work every fifteen minutes from 6:00 a.m. to 7:00 a.m., there would be a total of 200 resident workers in TAZ *A* for the whole hour. If 150 of those commuters arrived at work in TAZ *B* between midnight and 5:00 a.m., there would be thirty jobs assigned to each of the five hours in TAZ *B*. In this way, 24 groups of hourly counts of workers wt_i and jobs jt_i (i = 1,…, 24) were obtained for each TAZ. In terms of space, a regular grid was imposed over the study area for the purposes of redistributing the hourly count data associated with each TAZ to a uniform, finer scale in order to overcome issues associated with the large sizes of the TAZs and the potential uneven distribution of jobs and workers within them. For the study area, a raster of 22,646 grid cells of 500-m resolution was tessellated over the study area. This configuration was selected by trial and error in an attempt to balance accuracy and computational efficiency (i.e. a larger number of cells improves accuracy but demands more computation power).

The second step uses dasymetric mapping to redistribute the hourly count data associated with each TAZ to the grid cells. Dasymetric mapping is an area interpolation method that utilizes auxiliary data such as land use to disaggregate population data from a coarse spatial resolution to a finer resolution (Mennis and Hultgren, 2006). Owing to its integration of auxiliary data in the process, dasymetric mapping can provide more accurate small-area population estimation than other techniques not using such auxiliary data (Gregory, 2002). Parcel-based land use data of the study area in 2010 provided by the Florida Department of Revenue were used for this purpose. The data set includes several land use categories, such as residential, commercial, industrial, agricultural, and water. In total, there were 49,269 residential parcels and 18,703 commercial/industrial parcels in the study area. The former one is used to calibrate where workers live and the latter one is used to adjust jobs' spatial arrangement. Specifically, dasymetric mapping was applied to estimate the numbers of workers and jobs in each grid cell for each time *t*. Following the notions in Mennis and Hultgren (2006), the TAZs are referred to as *source zones* (*sz*), land use polygons are termed *auxiliary zones* (*az*), and the grid cells are called *target zones* (*tz*). The goal is to derive the numbers of workers and jobs at each *tz* based on the spatial overlap of *sz*, *az*, and *tz*. Equation 8 formulates the above process:

$$\hat{y}_{tz} = \sum_{sz \in tz} \left(\frac{y_{sz}}{\sum_{az \in sz} A_{az}} \times \sum_{az \in sz} A_{az \cap tz} \right) \tag{8}$$

where $\hat{y}_{tz}$ = the estimated count of workers (or jobs) for the target zone *tz*,

y_{sz} = the recorded count of workers (or jobs) of a source zone *sz* that overlaps *tz*,

A_{az} = the area of a given residential land use zone *az* (or a commercial/industrial land use zone to estimate jobs),

$A_{az \cap tz}$ = the area of the intersection between *az* and *tz*.

Figure 10 illustrates the process of dasymetric mapping using an example of the reported number of workers who leave home for work between 7:00 and 8:00 a.m. in TAZ 00136022 in the study area. Within the parenthesis in Equation 8, the first component of the product calculates the density of workers in a *sz* (a TAZ depicted in purple); instead of the whole area of a *sz*, the areas of all residential zones *az* (represented in green) within a *sz* are used to eliminate uninhabitable areas. Therefore, the density represents the number of workers per square kilometer of residential parcels in a TAZ. The second component computes the area of all residential parcels (or portions) associated with a *sz* in a *tz* (a cell outlined in dashed lines). Hence, the product returns the number of workers related to a *sz* in a *tz*. As a *tz* may contain regions belonging to multiple *sz*s, estimated workers for all *sz*s in a *tz* are summed. In this way, the counts of workers are redistributed to a set of grid cells from TAZs. Likewise, the counts of jobs at each grid cell can be obtained. After the dasymetric mapping process was applied to the study area, cells located outside residential and commercial/industrial areas were excluded, with 9,965 remaining residential cells and 5,898 employment cells (in comparison to 1,283 TAZs for either workers and jobs).

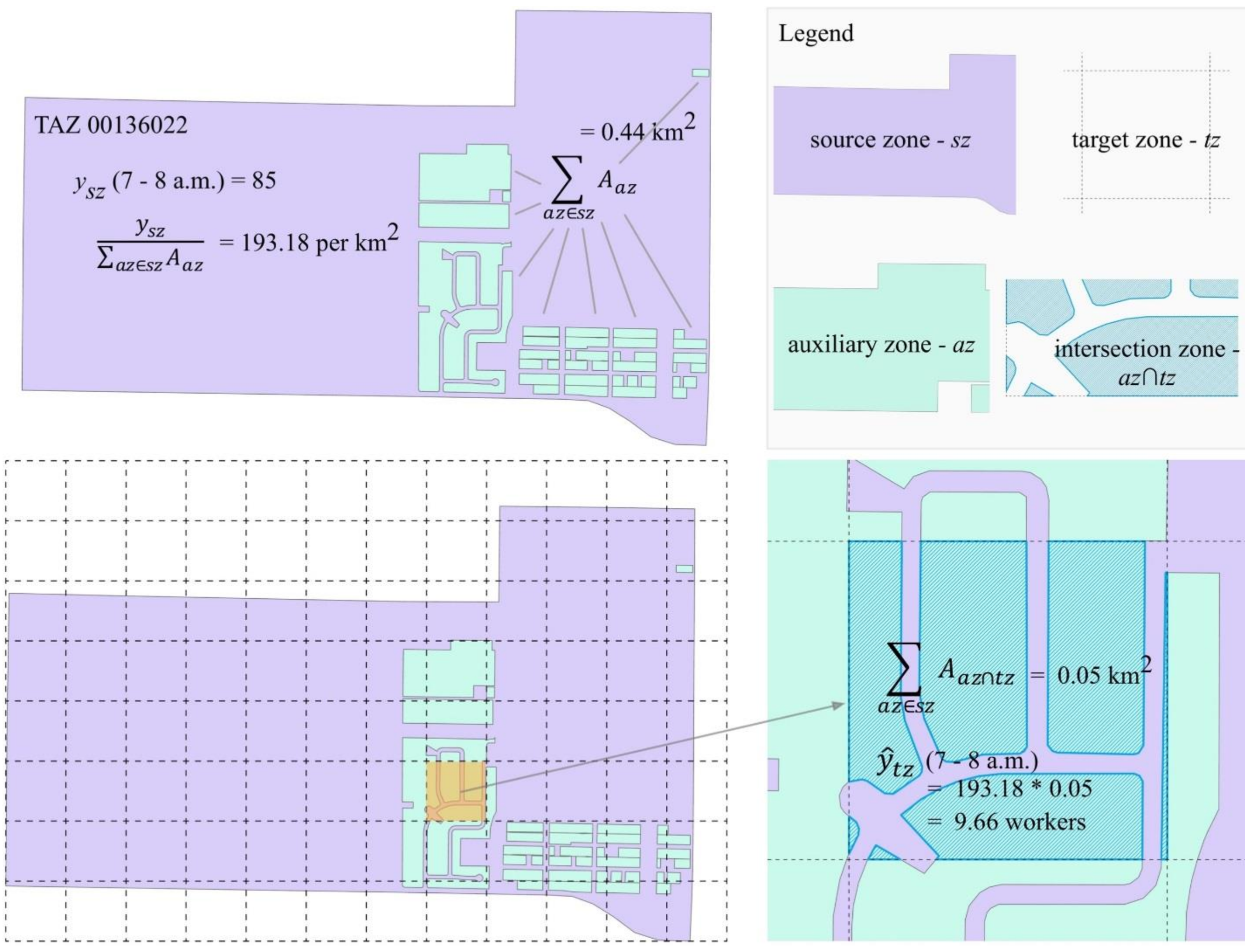


Figure 10. Illustration of the dasymetric mapping process

Measurement of space-time job accessibility

The third major step in the workflow involves modifying Shen's (1998) accessibility measure to incorporate a temporal dimension into the gravity equations. Shen's (1998) measure was adapted using the G2SFCA process (Wang, 2012; 2015) which simplifies the calculation by dividing it into two steps. In the context of job accessibility, the first step simply calculates the supply-to-demand ratio around each job location, while the second step sums up the ratios associated with all supply locations that are accessible to a demand location. Hence, G2SFCA can be interpreted as the ratio between supply of jobs and demand of workers and is equivalent to Shen's measure. Due to its simplified structure and interpretation, G2SFCA is more often used in spatial accessibility studies, in particular, access to health care research (e.g., Guagliardo, 2004; Ikram et al., 2015; Luo and Wang, 2003).

Based on the hourly counts of workers and jobs as well as the travel costs between them, the G2SFCA model was adapted to compute job accessibility scores for each time *t*. The first step of the revised model simply calculates the supply-to-demand ratio R_j around each job location *j* at time *t* using the following formula:

$$R_{j,t} = S_{j,t\in[t,t+1]} \Big/ \left(\sum_{k=1}^{m} D_{k,t} f_t(d_{kj,t}) \right) \tag{9}$$

where $D_{k,t}$ represents the number of resident workers at location *k* at time *t*, *m* is the total number of residential locations, $S_{j,t\in[t,\,t+1]}$ denotes the number of jobs at location *j* at time *t* and the following time *t*+1 (*t*+1was added to allow for longer travel times across the study area); for example, resident workers who leave home between 7:00 and 8:00 a.m. can access jobs with a start time range from 7:00 to 9:00 a.m., $d_{kj,t}$ is the travel time between location *k* and *j* at time *t*, and $f_t(d)$ defines a continuous distance decay function such as power, exponential, and Gaussian functions for time *t*. Since a particular residential location could have access to multiple job locations, a second step is then followed to sum up the ratio $R_{j,t}$ at any job location *j* that could be reached from a residential location *i* at the same time *t*:

$$A_{i,t} = \sum_{j=1}^{n} R_{j,t} f_t(d_{ij,t}) \tag{10}$$

where *n* represents the total number of job locations and $A_{i,t}$ denotes the job accessibility at residential location *i* at time *t*. The same $f_t(d)$ function is also integrated to take into account the continuous decay of access in distance between *i* and *j* at time *t*. Plugging $R_{j,t}$ into Equation 10, $A_{i,t}$ is then transformed as

$$A_{i,t} = \sum_{j=1}^{n} \left[S_{j,t\in[t,t+1]} f_t(d_{ij,t}) \Big/ \left(\sum_{k=1}^{m} D_{k,t} f_t(d_{kj,t}) \right) \right] \tag{11}$$

and a larger value of $A_{i,t}$ indicates a better job accessibility at residential location *i* at time *t*.

Here, the centroids of *tz*s (again, grid cells) are used to represent location i (or k) and j, network distances between cell centroids are employed to define the travel cost d_{ij}, and a power function is utilized to account for the distance decay effect as it is more suitable for analyzing short distance interaction at the city scale than other decay functions (Fotheringham and O'Kelly, 1989, pp. 12-13). The decay friction coefficient β is estimated using a gravity model (Hu and Wang, 2016; Wang and Minor, 2002; Wang, 2003):

$$C_{ij} = D_i S_j d_{ij}^{-\beta} \tag{12}$$

where C_{ij} represents the number of commuters residing in zone i and working in zone j, D_i and S_j are the number of workers in zone i and number of jobs in zone j, respectively. C_{ij} are extracted from CTPP Part 3, while D_i and S_j are obtained from CTPP Part 1 and Part 2, respectively. For the study area, 24 groups of hourly counts of workers (e.g., 12:00 – 1:00 a.m., 1:00 – 2:00 a.m., …, 11:00 p.m. – 12:00 a.m.) and jobs (e.g., 12:00 – 2:00 a.m., 1:00 – 3:00 a.m., …, 11:00 p.m. – 1:00 a.m.) for each grid cell tz were fed into the G2SFCA model for measuring the hourly job accessibility across Tampa Bay. This leads to an o-d cost matrix for 9,965 * 5,898 = 58,773,570 pairs to be solved and fed into the G2SFCA model for each time t. Since it would be unrealistic to obtain travel times based on the real-time or historical traffic data for such a massive matrix, instead, network distances for all o-d pairs were calculated, and a distance decay friction coefficient β was estimated to be -0.602 by using Equation 12 in order to calculate the accessibility measures. See the subsequent section for an exploratory analysis that adopts Google Maps travel times for job accessibility measurement.

Visualization of space-time job accessibility

The final step in the workflow involves creating a dynamic geovisualization of the hourly accessibility scores from the previous tasks. The resulting space-time job accessibility has a four-dimensional volume structure, (x, y, t, $A_{x,y,t}$), where $A_{x,y,t}$ denotes the job accessibility for location (x, y) at time t. Some popular approaches to the visualization of such four-dimensional data include: (1) volume rendering that assigns color and transparency to space-time cells (or, voxels) based on their accessibility scores (cells with poorer job access are less visible while high job access cells are more observable with different colors) and (2) isosurfacing that connects together points with the same accessibility value into a volume (Brunsdon et al. 2007; Demšar and Virrantaus 2010; Hu et al., 2018). The techniques have been commonly used to visually analyze spatio-temporal patterns such as human mobility (Kwan, 2000) and crime (Hu et al., 2018; Nakaya, 2013). Compared to the traditional side-by-side visualization of a series of two-dimensional maps, a four-dimensional visualization setting might allow for a more effective and interactive way to visualize and detect space-time dynamics of job accessibility. Here, a volumetric rendering technique is applied to combine the job accessibility estimations across different times through a trilinear interpolation and plot the results in a space-time cube environment. In this interactive environment, users can easily query data, alter the attributes of a scene (e.g., viewing angle and voxel transparency), add elements (e.g., contour lines), and see the results of these actions in real time. However, the two-dimensional displays of the space-time cube environment in this study would inevitably conceal some patterns that can be observed in the space-time environment (Kwan, 2000). For the study area, space-time cubes are used to map hourly job accessibility.

For comparison of the space-time cube representations, job accessibility is also measured using the original G2SFCA (static) implementation of Shen's (1998) model (refer to Wang, 2012 for the equations). Specifically, both the hourly counts of workers and jobs from the dasymetric grid were summed to derive daily counts at each grid cell. The daily counts, distance decay coefficient obtained from Equation 12, and the o-d distance matrix derived above are then fed into the original G2SFCA model to calculate the static job accessibility.

RESULTS AND DISCUSSION

When applying Shen's (1998) traditional gravity-based measure, job accessibility within the Tampa Bay region exhibits a concentric distribution pattern, decreasing gradually from the peninsular towards inland areas (Figure 11). Notably, the Tampa peninsular area has the best job accessibility due to the high-density of jobs and convenient, highly-developed transportation networks. Also evident from the map is a spillover pattern of high job access into areas that are immediately accessible from the Tampa peninsular through major highways. The extent of high job access areas largely matches the high-density employment areas identified in Figure 9. Inland areas, instead, have more residential than commercial/industrial activities and thus have lower job accessibility. This pattern is also present in Figure 9—a large number of commuting trips to the job centers start from inland suburban areas.

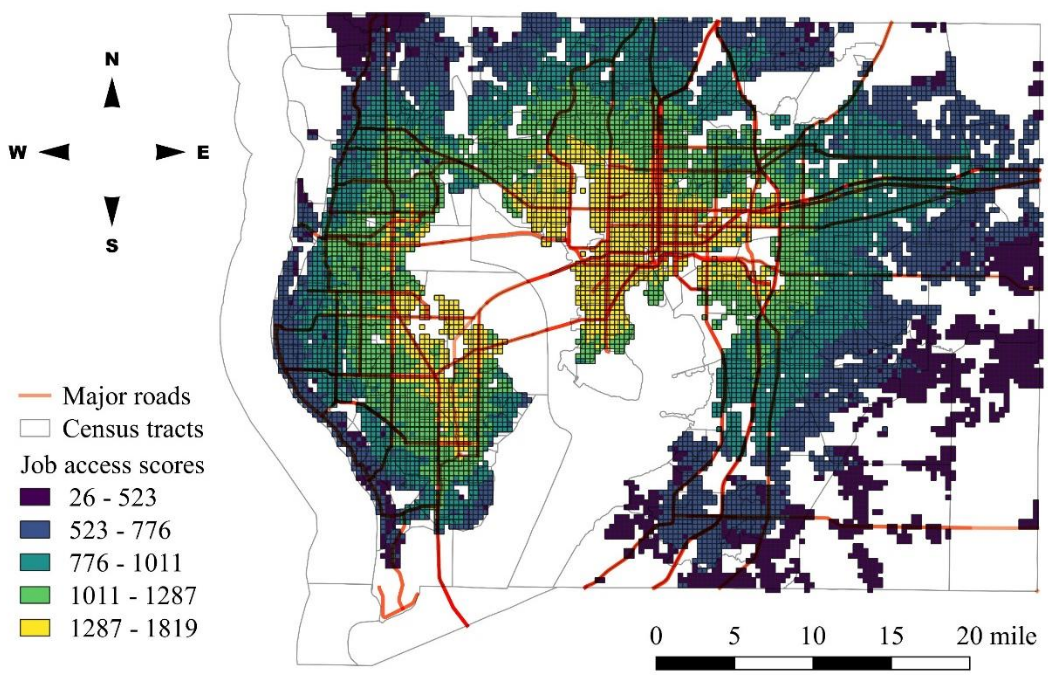


Figure 11. Job accessibility pattern measured by the static model

Although the traditional method illustrates broad spatial patterns of job accessibility in the region, the space-time approach presented here reveals the dynamic changes over the course of a day (Figure 12). Specifically, Figure 12a displays the pattern using the volumetric rendering approach that adjusts the color and transparency of each voxel based on its job accessibility score. As expected, job accessibility not only varies from place to place but also shifts throughout the day.

In general, job accessibility for the entire study area peaks at 5:00 – 7:00 a.m. (see the substantial areas of voxels with high job access in Figure 12a). As stated, it is assumed that a worker can access jobs in the current two-hour window. Therefore, workers who usually leave home around 5:00 – 7:00 a.m. have access to jobs starting between 5:00 and 8:00 a.m. In essence, the G2SFCA approach measures the ratio between jobs and workers. Despite that a large number of daytime jobs start between 7:00 and 9:00 a.m., the amount of competing demands during that time is the greatest as well. In comparison, the number of workers who leave home between 5:00 and 7:00 a.m. is much smaller relative to that of accessible jobs (starting between 5:00 and 8:00 a.m.). This big contrast gives rise to job accessibility reaching its highest point between 5:00 and 7:00 a.m. After this period, job accessibility in the whole region decreases significantly and remains at low levels in spite of two moderate spikes at noon (2:00 – 3:00 p.m.) and midnight (11:00 p.m. – 12:00 a.m.). The former period reflects job shifts starting from 4:00 p.m. (again, job access between 2:00 and 3:00 p.m. considers jobs starting between 2:00 and 4:00 p.m.) and the latter corresponds to night shifts starting at midnight.

Compared to the traditional two-dimensional maps, the space-time cube setting provides an interactive visualization environment, allowing for users to rotate the cube and examine results at any viewing direction. Figure 12b shows the top front view of space-time job accessibility in the region. The dark purple belt represents areas of the highest job accessibility (5:00 – 7:00 a.m.) and its spatial extent is largely consistent with the pattern spotted in Figure 11. Figure 12c illustrates the isovolumes generated using a threshold value of the 95th percentile of the space-time job accessibility scores. Consistent with Figure 12a, the same three major periods of high job accessibility in the entire region are identified. The substantial shrinkage of the spatial extent from the morning commuting peak to the noon and further to the midnight job shift hours is especially noticeable. None of these dynamic patterns can be readily diagnosed by the conventional static job accessibility models.

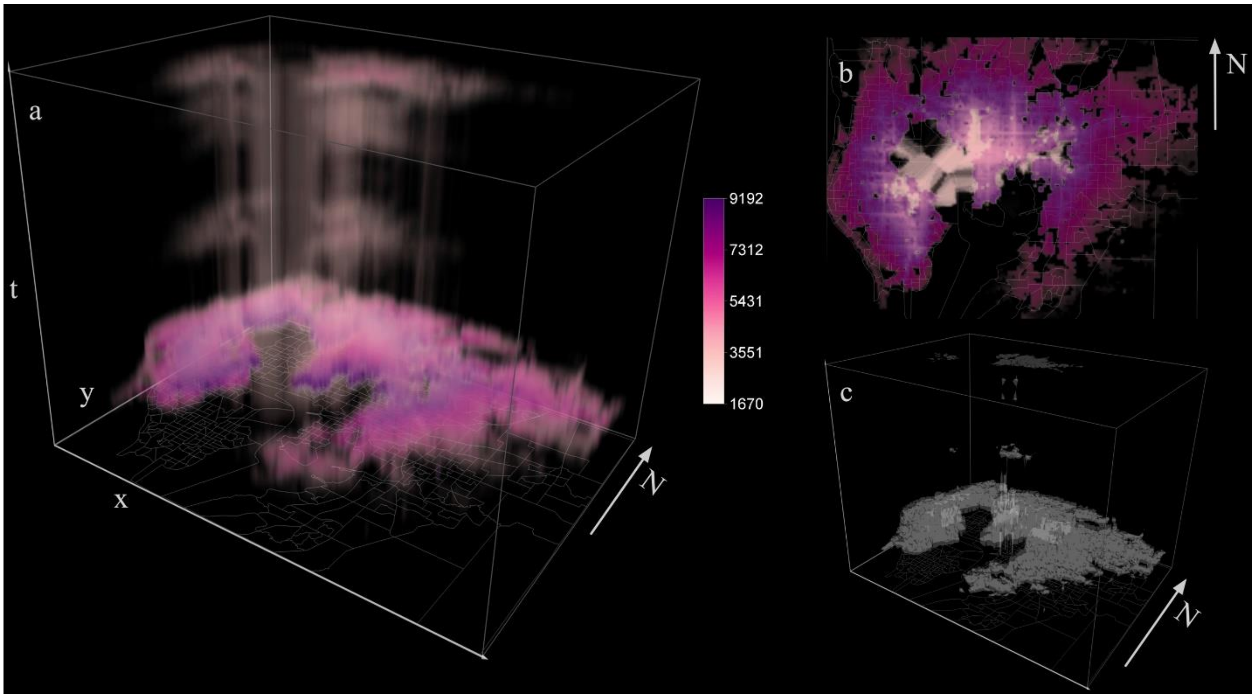


Figure 12. Space-time job accessibility pattern: (a) 135° viewing direction, (b) top front view, and (c) isovolumes generated using a job accessibility value of the 95th percentile

CHAPTER V. CONCLUSIONS

This study fills the fundamental gap in the lack of a capacity analysis methods for mixed CAV traffic considering different vehicle types, CAV market penetration rates and platooning configuration. We first developed a comprehensive analytical approach to quantify highway capacity in mixed traffic environments. CAV technology uncertainties considering different headway distributions and vehicle platooning configurations is considered in our development. A "generalized capacity function" for mixed CAV traffic for the full spectra of traffic density, CAV penetration rates, vehicle types, platooning configurations and highway segment types is proposed. Further, this research enables existing planning tools (e.g., Cube, MATSim) to be expanded to handle future mixed CAV traffic scenarios. The proposed model shall not only have a sound theoretical foundation but also render a simple and practical form (e.g., similar to BRP function or HCM capacity formulas) to be easily used in transportation planning for relative stakeholders (e.g., State DOTs, MPOs). Simple models can be used to replace the traffic assignment model in the existing planning tools. The preliminary study conducted on Tampa Bay Regional Planning Model (TBRPM v8.2) shows that the congestion along all road segments (defined by the ratio of velocity and capacity) decreases as the CAV penetration rate increases. Further, a traffic flow fundamental diagram (FD) for commercially implemented adaptive cruise control (ACC) system is presented in this study. Both macroscopic and microscopic procedures are described to formulate the fundamental diagram of ACC equipped vehicles. The experimental results of this study, obtained from the shared ACC equipped and human-driven vehicles' data, give the insight that the traditional triangle fundamental diagram is still capable of describing the traffic flow characteristics for ACC quipped vehicles (VACC). The results of these two studies help transportation planners and policymakers to be ready for the future transportation system by predicting the behavior of the future traffic system and the traffic congestion. The outcomes of these studies revealed that the presence of CAVs impact highway capacity and network system. These impacts however might not be always beneficial and the performance of the mixed traffic highly depends on the management policies that decide the overall operations of CAVs. The experimental results of this study show that the network system performance and highway capacity in mixed traffic environment is highly dependent on the CAV technology uncertainties considering different headway distributions and vehicle platooning configurations. It is shown that, as the CAV market penetration rate and platooning intensity increases, the highway capacity will also increase. Thus, providing manage lanes that allows only connected or connected and automated vehicles not only will improve the traffic system performance, but also encourages the use of CAVs.

Further, this study presents a new methodological framework for measuring and visualizing place-based job accessibility in space and time that enables us to investigate how the evolution of traffic patterns from regular vehicles to CAV mixed traffics will impact the spatial patterns of job accessibility for the general population and the disparities across different socio-economic groups. Also, results from the accessibility analysis show that the job accessibility in the Hillsborough and Pinellas Counties in the Tampa Bay region renders substantial variations over time and space. While traditional approaches illustrate the spatial patterns of job accessibility, these spatiotemporal variations cannot be captured. As a result, policy analysis and formulation based on the results from traditional methods can be biased and inefficient. Thus, these results offer a timely alert for transportation planners for also incorporating the spatiotemporal factors in accessibility analysis. The model and analysis tools developed during this project, after certain customization and refinement, can be used to facilitate planning practice. Additionally, although this project specifically focuses on job accessibility, accessibility to other activity locations (e.g., education, recreation, healthcare) can be analyzed with a similar methodological framework. The results from accessibility analysis can also be used as foundation for assessing the equity performance of a transportation system

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