



Urban Air Mobility: Airport Ground Access Demand Estimation

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This study aims to estimate passenger demand of Urban Air Mobility (UAM) for airport ground access trips while considering airspace restrictions in the Dallas-Fort Worth region. UAM is a concept mode of transportation designed to bypass ground congestion for time-sensitive, price-inelastic travelers using autonomous, electric aircraft with Vertical Takeoff and Landing (VTOL) capabilities. Airport ground access trips constitute a trip purpose that can utilize this mode. This study analyzes originating ground access trips for two major airports in the Dallas-Fort Worth region: Dallas-Fort Worth International Airport (DFW) and Dallas Love Field Airport (DAL). First, a mode choice model is calibrated on the existing airport ground access behavior. UAM demand is then estimated using the developed model, airspace restrictions, and the results from UAM demand stated-preference surveys in literature. Airspace restrictions consist of unusable pieces of airspaces based on current air traffic patterns, where the placement of UAM vertiports and overflying of UAM vehicles are prohibited. The demand model considers the trajectories of the UAM vehicles, which navigate on pre-defined routes inside Class-B airspace to prevent Air Traffic Control (ATC) involvement requirements. This study includes sensitivity analyses of UAM demand to the cost per passenger mile (CPM), number of vertiports placed in the region, and other secondary factors like vertiport location, intermodal cost, fixed cost, and average speed. Corridors with significant UAM demand are identified from the spatial distribution of demand and potential bottlenecks in the UAM network. The findings predict up to 4% market share of UAM for trips to the airport at the optimistically lower fare of \$2 per passenger mile (in addition to the fixed cost of \$23) and a 50-vertiport UAM network. Average Value of Times (VOTs) for business and non-business travelers are estimated to be around \$57/hr and \$36/hr, respectively. Business travelers comprise three-quarters of the total UAM demand because of relatively higher VOTs. Airport access trips in Dallas-Fort Worth region have considerable potential for UAM if the trip's price is below \$4 per passenger mile (in addition to the fixed cost of \$23).

I. Introduction

Urban Air Mobility (UAM) refers to an on-demand air transportation mode designed to avoid ground congestion. It uses electric vehicles equipped with advanced avionics and Vertical Take-Off and Landing (VTOL) capabilities [1]. The Concept of Operations (ConOps) consists of UAM passengers traveling to the nearest vertiport (VTOL airport)

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using a ground transportation mode, such as walking or car. After boarding the two or four-seater electric aircraft, the passenger is flown to the vertiport nearest their destination. Ground modes are then used for last-mile access to their final destination.

The initial timeline estimates urban public UAM operations as early as 2023 [2], where Uber announced plans to launch air-taxi service in Dallas, Los Angeles, and Melbourne with an eVTOL developed by Joby Aviation [3]. Several major players in the industry and government are working towards shaping the concept of UAM [4, 5]. Rapid developments in concept vehicles [6, 7, 8] and efforts to safely integrate UAM into the National Airspace System (NAS) [9] have further bolstered the UAM vision. However, for efficient development and operation of UAM, it is equally important to understand the demand side. Demand estimation for UAM is complex, where the system can be used for different trip purposes. Existing literature contains demand studies for commuting, cargo, airport access. [10, 11, 12, 13, 14, 15, 16].

Fu et al. [15] estimated UAM demand in the greater Munich area through agent-based transport simulation platform MATSim and Microscopic transportation orchestrator (MITO). However, their airport access UAM demand estimation does not capture the entire airport access traffic as MATSim and MITO focus on local inhabitants. Therefore, the share of airport passengers is underestimated. Roy et al. [16] estimated UAM demand for airport access trips to Atlanta International Airport (ATL) using a multi-commodity network flow approach. Their approach was limited to existing infrastructure and assumed a direct, straight-line path without considering airspace restrictions. The purpose of this study is to fill this gap in the literature. Dallas-Fort Worth region is among the top prospective regions for UAM [17]. Therefore, a UAM demand estimation framework focusing on full-day of airport access trips to/from Dallas-Fort Worth International Airport (DFW) and Dallas-Love Field Airport (DAL) is developed considering airspace restrictions in the region.

II. Background

Analyzing different trip purposes for their UAM potential is critical to tailor the concept development and infrastructure investment. Booz Allen Hamilton identified three focus markets for UAM; Airport Shuttle (transporting passengers to, from, or between airport over fixed routes), Air Taxi (on-demand point to point passenger transportation), Air Ambulance (travel to/from hospital for emergencies and potential hospital visits) [18]. Their market evaluation is based on the legacy market's value and size and technical, economic, and operational challenges. They predicted Airport Shuttle to be an early adopter of UAM due to operational efficiency from demand concentration at one end, existing infrastructure at the airport, and opportunity for collaboration with airlines for premium services [19]. McKinsey & Company studied UAM use cases for last-mile parcel delivery, Air Metro, and Air Taxi [20]. Their study predicts a commercially viable market for last-mile parcel delivery and Air Metro, whereas limited profitable cases for Air Taxi service. The Korean Urban Air Traffic (K-UAM) Roadmap includes plans to establish commercial UAM operation links for Incheon airport by 2025 [21]. Multiple studies have identified the potential for UAM in the airport ground access market. With Dallas-Fort Worth being one of the proposed early adopters of UAM operations, it is crucial to estimate potential ridership and factors affecting its feasibility in the airport access market.

Analyzing the airport ground access trips to develop predictive models is in practice for over 50 years. Ellis et al. [22] performed one of the earliest efforts to model airport ground passenger trips. Often airport access mode-choice models are developed for applied studies that are not published in the literature. Gosling surveyed 105 different organizations (airport authorities, regional and state planning agencies, surface transportation planning, airport consulting firms, selected universities, and other research organizations) and identified 52 studies between 1995-2005 that involved creating airport access mode-choice models [23]. The synthesis includes technical summaries of airport ground access studies performed at ten airports, including major US airports such as Hartsfield-Jackson Atlanta International Airport (ATL), Boston Logan International Airport (BOS), Chicago O'Hare International Airport (ORD), and Chicago Midway (MDW), etc. The motivation for calibrating an airport ground access mode choice model varied largely in these studies. However, they could be broadly categorized in either of the following: analyzing current trip generation [24], estimating ridership for a new mode [25] or an extension of an existing mode [26, 27], and planning of an integrated facility [28] or other airport elements like Automated People Mover (APM) [29, 30]. Calibrating a mode-choice model to estimate potential ridership for a new mode and understanding the factors that affect demand is a common practice in transportation analysis.

Tam [31] studied the factors affecting the demand for rail mode in the airport ground access market of Hong Kong International Airport (HKIA). A multinomial logit model was calibrated using the survey data collected at HKIA. Travel cost was identified as the key factor affecting the rail mode demand along with party size and the number of baggage pieces. Gupta et al. [32] developed a combined airport and ground access choice model for both business and

non-business travelers in the New York metropolitan region. They developed both a nested logit and a multinomial logit model but found the latter statistically significant. Access time and access costs were found to be significant for airport ground access mode choice. Access time was found to be relatively more onerous for business travelers due to higher VOTs. They also found that air passengers most appreciate airport access options guaranteeing fast and reliable service. This emphasizes the importance of mode reliability for airport trips, and the planning of UAM operations for airport trips should regard it as a critical factor.

Akar [33] examined ground access mode choice for passengers traveling to Port Columbus International Airport (CMH), Ohio. The factors affecting the mode choice were studied using the survey collected at the airport. Using binary logit models, the author analyzed the passenger's interest in taking alternative modes of transportation. Like DFW, mode share for ground access at CMH is dominated by automobile modes with a small public transit share. For alternative modes of transportation to be competitive with the automobile, they should offer reliability, shorter travel times, flexibility in departure time (which may require frequent service times), and comfort for more people to consider taking them. This indicates that in regions with a high automobile share in airport ground access, UAM mode could capture some market share if it is fast, reliable, and comfortable.

Rimjha et al. [34] estimated airport access demand for Los Angeles International Airport (LAX) trips. They calibrated a two-segment (business and non-business) mode-choice model, which is later utilized to calculate UAM passenger demand. Their methodology is broadly similar to the methodology adopted in this paper with significant region-specific modifications. They found that UAM could capture 3.6% of the LAX passenger trips at the cost of \$2 per passenger mile, in addition to a base cost of \$15 per passenger and a \$20 landing cost per flight. Roy et al. [35] developed a methodology to estimate the expected user base of a UAM business airport shuttle using discrete choice modeling. Their findings reveal a considerable potential user base for air taxi business airport shuttle services if the operating cost of UAM vehicles could be reduced and improved load factors could be obtained.

To summarize, multiple studies found the importance of travel time, travel cost, mode reliability, and comfort in airport ground access mode-choice decision. Party size and number of baggage pieces are also found to influence the access mode-choice among travelers. However, there is no airport ground access model developed recently for the Dallas-Fort Worth region, which is publicly-available. The study presented in this paper calibrates an airport ground access model for UAM demand estimation.

III. Study Area

Fig. 1 shows the study area of the analysis includes 12 counties surrounding the Dallas-Fort Worth metro area. Population centroid of all selected counties are within the operating range of reference vehicle (Joby S4) from Dallas CBD. The spatial resolution of the analysis is Census Block Groups. There are 4,801 Block Groups in the study area, with a total population of 6.82 million in 2015 [36].

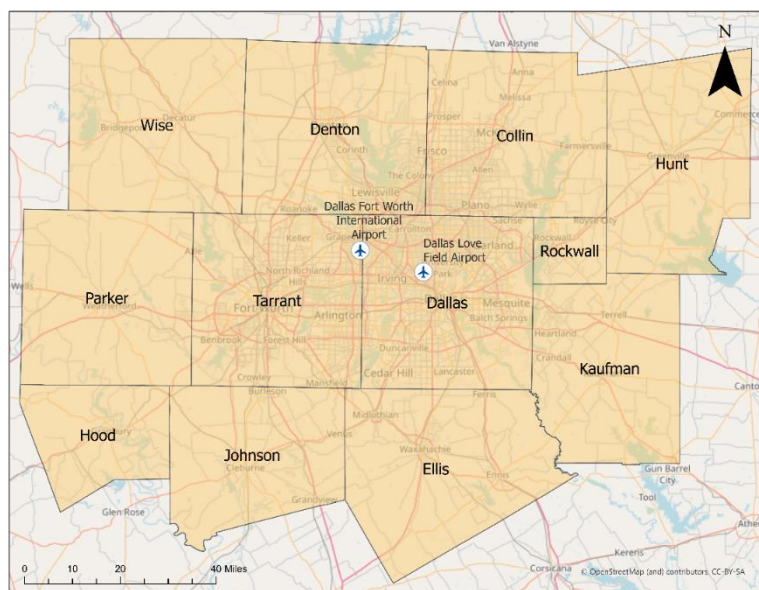


Fig. 1 Dallas-Fort Worth Study Area

IV. Data

The primary dataset used in this analysis is the 2015 originating passenger survey conducted by UNISON consulting at Dallas-Fort Worth International Airport (DFW) and Dallas Love Field Airport (DAL) on behalf of the North Central Texas Council of Governments (NCTCOG). The surveys were distributed to capture updated originating information regarding departing passengers' travel patterns and trip-making behavior. The survey data is used to analyze the regional distribution of trip origins and mode-choice behavior. First, records with trip origins outside the study area were filtered out. Data is segregated into four segments after observing significant mode selection and trip characteristics differences: Resident Business, Resident Non-Business, Visitor Business, and Visitor Non-Business. Table 1 includes the number of records and the daily number of trips estimated from provided weights, where 82.4% of the originating passengers in the region use DFW, and the remaining 17.6% of originating passengers use DAL.

Table 1: Originating Passenger Survey Data by Segment (DFW and DAL)

Segment	Number of Records		Number of Trips (Weighted)		Percentage of Total Trips	
	DFW	DAL	DFW	DAL	DFW	DAL
Resident Business	2,189	538	16,020	3,507	29%	30%
Resident Non-Business	2,342	620	17,037	3,990	31%	34%
Visitor Business	2,083	406	14,305	2,289	26%	19%
Visitor Non-Business	1,285	374	8,118	2,056	14%	17%
Total	7,899	1,938	55,481	11,852	100%	100%

Understanding current mode-choice behavior is required to identify the scope and estimate the demand for UAM. Fig. 2 illustrates the mode share observed in the survey data by segment. For residents, driving and parking their vehicle at the airport was the most common airport access method among business travelers, whereas drop-off was the most common among non-business travelers. Parking at the airport is relatively costly but convenient and preferred for shorter visits or when the cost is reimbursed. According to the survey data, travel cost is reimbursed for most business travelers (95% according to the survey data). This parking cost helps the UAM business case, where the UAM ConOps will have a higher CPM than other modes but no parking costs. For trips made by Visitors, a rental car is the most common airport access mode among business travelers, whereas drop-off is most popular among non-business. Visitors non-business travelers usually have family members or acquaintances who drop them off at the airport. Theoretically, the travelers who either park their vehicle, be dropped off at the airport, or use a taxi/uber could potentially benefit from UAM. UAM use cases for trips currently being done by courtesy vehicles such as hotel shuttle, courtesy van, etc., cannot be justified. Therefore, these trips are filtered out from the analysis.

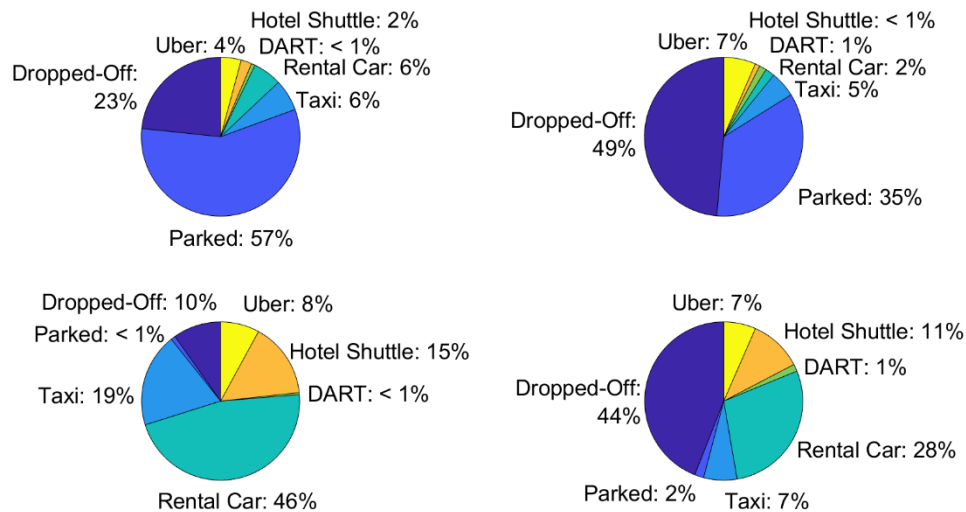


Fig. 2 Observed Mode Share in the Airport Survey Data. Top Left: Resident Business, Top Right: Resident Non-Business, Bottom Left: Visitor Business, Bottom Right: Visitor Non-Business

Significant travel time savings by UAM could occur in two scenarios: either long-distance ground trips or heavily congested ground trip alternatives. Origin-Destination (OD) pairs with a minimum of 10 miles flying distance are considered for UAM mode. UAM is assumed to be infeasible for any trip shorter than 10 miles since travel time savings are negligible, and flying UAM for short distances may not be economically feasible. Attributing to the location DFW in the region, the median driving distance of access trips is 20.1 miles. DFW is located close to the region's population center and almost equidistant from Dallas CBD and Fort Worth CBD. **Error! Reference source not found.** shows the distribution of driving distances for access ground trips in the survey data. Visitors tend to live closer to the airport during their stay. The distribution for visitor business travelers has two peaks. The segregation is probably attributed to some travelers staying at the airport or very close to the airport. Overall, a significant portion of the trips are shorter than the minimum distance for UAM eligibility and, therefore, not considered in the analysis. Resident ground access trips to the airport have a median driving distance of 22.5 miles, making them a promising segment for UAM.

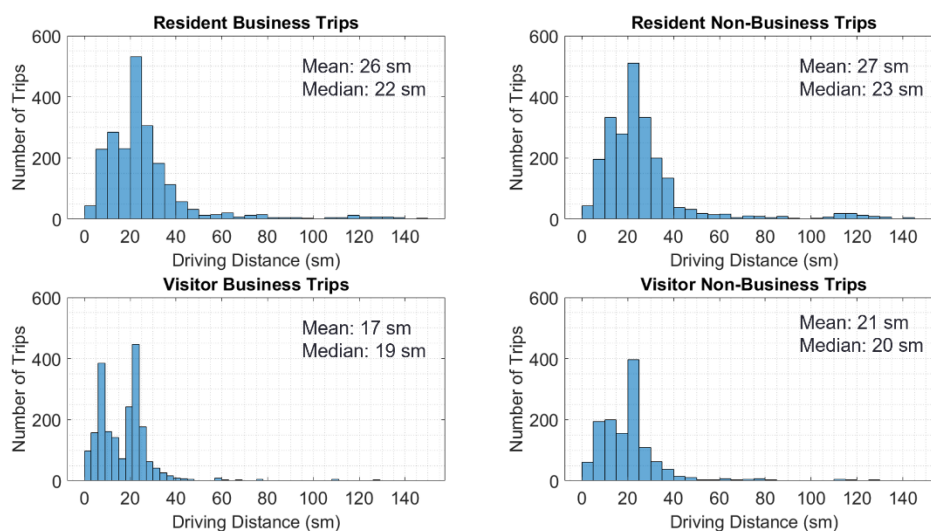


Fig. 3 Distribution of Driving Distance of Airport Access Trips for Originating Passengers

Class-B airspace is controlled airspace surrounding the nation's busiest airports. It is individually tailored and generally extends vertically up to 10,000 feet from Mean Sea-Level (MSL) and lateral limit up to 30 nm radius [37]. The innermost 10 nm area extends to the top, segment area between 10 nm and 20 nm has the floor between 2,800 feet to 3,000 feet above airport elevation. The area floor between 20 nm and 30 nm lies between 5,000 feet and 6,000 feet above airport elevation [38]. Currently, any operation in class-B airspace requires clearance from Air Traffic Control (ATC). The UAM ConOps developed for this study assumes the independence of UAM operations from ATC. However, it is only feasible when pre-defined ATC-approved routes are designed for UAM navigation inside class-B airspace.

Fig. 4 shows the unusable airspace pieces and routes developed by the National Aeronautics and Space Administration (NASA) Ames Research Center after analyzing flight trajectories for both south and north flow, with expert guidance from ATC controllers in the region. The routes are developed to navigate UAM vehicles inside class-B airspace and bring UAM in and out of the airports. Class-D airspace extends from the surface to 2,500 feet above airport elevation. Aircraft are required to establish two-way radio communication with ATC before entering and thereafter in class-D airspace. There are ten class-D controlled airspaces in the region centered at secondary or military airports. The ConOps in this analysis involves detouring the UAM around unusable class-D airspaces. It should be noted that the class-D airspace of Addison airport is considered similar to class-B airspaces due to the proximity to DAL airspace and the density of DAL commercial traffic.

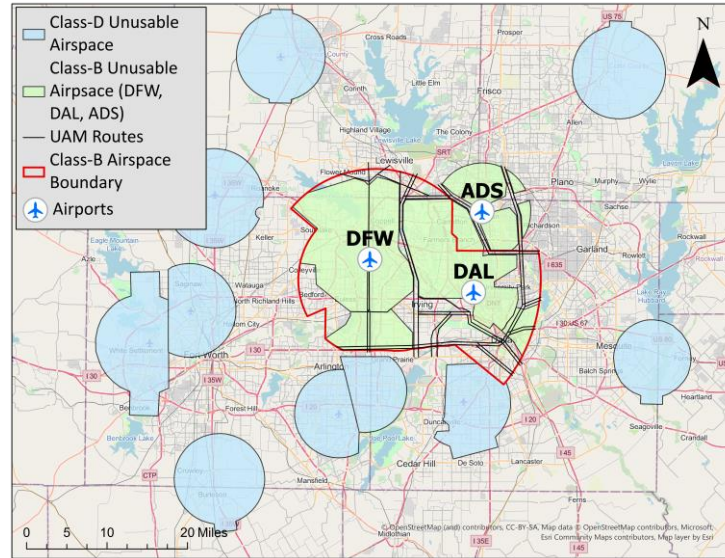


Fig. 4 Unusable Airspaces and Routes Developed by NASA to Navigate UAM inside Class-B Airspace

V. Methodology

There are three main tasks in estimating UAM demand for airport ground access trips: a) Mode-Choice Model Calibration, b) Vertiport Placement, and c) UAM demand estimation. The calibrated mode-choice model is adjusted to estimate UAM demand for a given number of vertiports. Fig. 5 illustrates the workflow adopted in this analysis. The vertiport placement method utilizes the mode-choice model to estimate the near-optimal location of vertiports, which are further used to estimate the final UAM demand for a given number of vertiports.

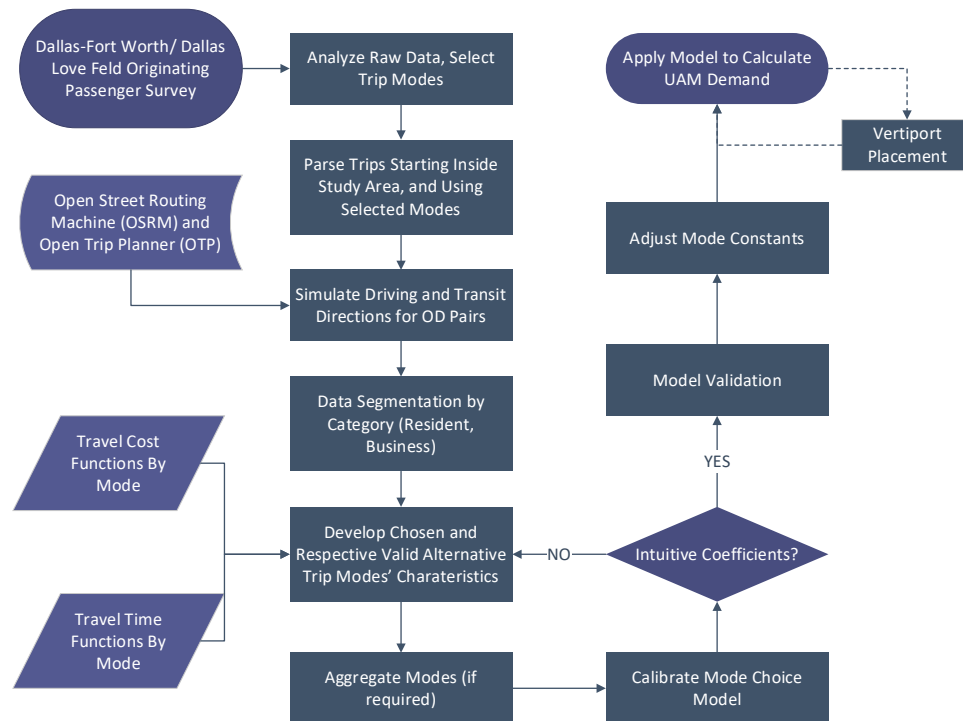


Fig. 5 Workflow of UAM Demand Estimation for Airport Ground Access Trips

A. Mode-Choice Model Calibration

Understanding existing modes of transportation and traveler's mode choice behavior is critical to estimating the demand for a new mode of transportation. Therefore, a mode-choice model is calibrated to understand the choice-making behavior of travelers for airport ground access. Airport trip characteristics are significantly different from other trips like commuting, shopping, and sightseeing. First, they are performed with less frequency. Second, reliability is more critical because delays in the access trip can be costly if one misses a flight. Third, a relatively high number of trips getting their cost reimbursed, which affects affordability. These differences can sometimes create challenges in airport ground access trip modeling, which is not uncommon [39].

Two conditional logit models are calibrated for the mode-choice model, one for business trips and another for non-business trips. Each model partially segments the value of time by residents and visitors of the region. The conditional logit model only includes independent variables that vary between the modes for a single traveler (called generic variables- e.g., travel time, cost, distance). Alternative-specific variables that do not vary across the modes (e.g., income, gender) could not be included as the coefficients for UAM alternative-specific variables could not be calibrated because the mode is not chosen in the revealed-preference data. In conditional logit models, an individual is expected to make mode choice decisions based on the utility derived from the mode. The utility is estimated using a log-likelihood maximizing methodology dependent on the trip characteristics when using that mode. The traveler's probability of taking each mode in their choice set is then derived from the estimated utilities, as shown in Equation 1 [40].

$$P_{ij} = \frac{e^{U_{ij}}}{\sum_{j=1}^n e^{U_{ij}}} \quad (1)$$

Where:

P_{ij} = probability of selecting for mode j over n alternative modes for i^{th} traveler

U_{ij} = utility associated with mode j for i^{th} traveler

The conditional logit model was estimated using the dataset prepared from the Originating Passenger Survey. The originating passenger survey is a revealed-preference survey, and only the chosen mode is reported. Therefore, alternative mode characteristics have to be estimated. Required trip characteristics for a mode-choice model were not included in the survey, such as travel time, travel cost, etc. All trip characteristics for both chosen and alternative modes were estimated separately. There are six modes in the final dataset: drive-park, drive-drop, taxi, rental car, public transit, and ridesharing (Uber, Lyft, or similar). Driving trips for all OD pairs were simulated in Open Street Routing Machine (OSRM), which is an Application Programming Interface (API) built upon the database of OpenStreetMap [41]. It provided driving directions, unimpeded in-vehicle travel time (IVTT), and driving distance. Unimpeded travel times were further adjusted using Texas Transportation Institute Congestion Indices [42] to account for congestion.

Furthermore, three minutes of out-of-vehicle travel time (OVTT) was considered for all driving modes. Transit directions for all OD pairs were simulated in Open Trip Planner [43], and transit's IVTT and OVTT were extracted. Transit options with reasonable travel times were considered feasible. Table 2 summarizes the estimation of travel times and travel costs for all the mode considered in the analysis. Travel times and travel costs are measured in minutes and US dollars, respectively. Once the trip characteristics for chosen and available options were estimated, the mode-choice model is calibrated.

Table 2: Data Sources for Travel Time and Travel Cost Estimation

Mode	Travel Time		Travel Cost
	IVTT	OVTT	
Drive & Park	1) Congestion adjusted OSRM output 2) Shuttle time based on the parking lot	1) 3-min OVTT assumption 2) Based on Parking Lot ⁷	1) Driving cost based on IRS per mile cost reimbursement rate [44] for business travelers 2) Driving cost based on operating cost of the car according to AAA 2015

⁷ Economy parking lot requires more waiting for shuttle than express parking lot. Terminal parking lot does not require shuttle.

			[45] for non-business travelers 3) Parking cost based on the parking lot ⁸
Drop-off ⁹	Twice the congestion adjusted OSRM output	3-min OVTT assumption	No cost
Taxi	Congestion adjusted OSRM output	5-min waiting time assumption	Yellow cabs fare structure [46]
Rental Car	1) Congestion adjusted OSRM output 2) Shuttle time from rental car center	1) 3-min OVTT assumption 2) 15-min processing time at rental car center and waiting time for the shuttle	1) 25% of the daily cost of a rental car in 2015 from popular rental agencies [47] 2) Fuel and daily insurance cost from AAA [45]
Public Transit	OTP output	1) OTP output 2) Half of the headway ¹⁰	Flat-rate ticket cost [48]
Rideshare	Congestion adjusted OSRM output	5-min waiting time assumption	Uber fare structure [49]

B. Vertiport Placement

UAM ConOps in this study requires the traveler to access the nearest vertiport by a rideshare service assumed to work in collaboration with the UAM service provider. Travelers will access vertiport by walk if the walking distance is less than or equal to one-tenth of a mile. Luggage constraints are the reason for assuming a small plausible walking distance. After five minutes of assumed ingress time (processing and boarding), travelers would UAM vehicle, which would take them to their airport (DFW or DAL). The UAM vehicle is routed using the shortest path algorithm applied on a network made up of vertiports and the routes inside class-B airspace. Routes in the network are not allowed to overfly class-D airspaces and must detour around them. Also, no vertiports are allowed inside class-B and class-D unusable airspaces (see Fig. 4). Five minutes of egress time is added for alighting the UAM vehicle and reach the terminal. UAM vertiport at the airport is assumed to be located at an equivalent "curbside" location to avoid the involvement of shuttle services, which could increase the travel time and inconvenience for UAM travelers.

Vertiports' location is critical for UAM's success. Vertiport placement in this analysis aims at capturing maximum UAM demand for a given number of vertiports and placement restrictions. There are 1,932 unique Block Groups in the survey data. Survey methodology uses stratified sampling based on destination zones share, airline market share, and time of day [50]. The sampling and weighting methodology used in the survey resulted in a trip-origin distribution representative of daily airport trips. The initial step in the vertiport placement estimates UAM trip potential for each Census Block Group in daily UAM trips to the airports, utilizing the calibrated mode-choice model. UAM trip potential uses UAM trip parameters mentioned in Table 3 (further explained in section VI). Then, using the Fuzzy C-means clustering method [51], an appropriate number of clusters is developed. The fuzzy c-means method has a similar objective function as hard k-means. However, instead of assigning each data point to a cluster, the data point belongs to each cluster to some degree specified by a membership grade (based on its vicinity to the cluster centers). This feature of Fuzzy C-means is utilized since we were aware of the raw optimal solution's infeasibility caused by airspace restrictions. Data points for clustering are developed from a random selection of census blocks centroids of a census blockgroup weighted by its UAM potential. Random selection induced some variability in trip origin location inside a blockgroup and helped in better convergence. Clusters falling inside unusable airspaces are removed from the analysis. A subset of retained clusters that maximizes the overall membership for a given number of vertiports is selected as a vertiport set, e.g., top 50 or 75 clusters, which would maximize the combined membership of all data points in the clustering analysis.

⁸ The parking location for drive and park is included in the survey. Total parking cost was estimated using the rates reported on the airport website for different parking locations and stay duration reported in the survey. Only half of the total parking cost applies to the access trip cost for drive and park.

⁹ This analysis assumed zero travel cost because often drop-off is motivated by other factors like well-wishing and vehicle unavailability, and twice the driving time for drop-off, assuming the driver performs a round trip.

¹⁰ OTP does not include initial waiting time at the origin public transit stop.

Table 3: Assumed Parameters for UAM Trip Calculations

Parameter		Value
Walkable Distance To/From Vertiport		0.10 mi
Ingress ¹¹ Time		5 min
Egress Time		5 min
Average UAM Vehicle Speed		120 mph
Average Walking Speed		3.1 mph
Minimum Trip Distance for UAM Eligibility		10 miles
Average Occupancy		2.4
UAM Fare Structure	Base Cost (per- passenger)	\$15
	Landing Cost (per-vehicle)	\$20
	Cost Per Mile (CPM)	\$2.0

VI. Results

Results include the calibrated mode choice models and their adjustment to estimate UAM demand. This section also includes vertiport sets placed using the demand-driven clustering approach, followed by demand estimation for UAM and sensitivity analyses.

A. Calibrated Mode Choice Model Results

Table 4 includes the variables resulting in the best fit and their estimated coefficient for the calibrated model. The pseudo- R^2 suggests a good model fit as Lourviere et al. [52] consider values between 0.2 to 0.4 to be a very good fit. The model uses segment interacted cost variables that provide partial segmentation and captures subtle differences between residents' and visitors' travel cost perception. Drop-off is the base alternative in the model. Certain modes were only partially available to the segments. Rental car alternative was limited to visitor segment, and Drive & Park alternative was limited to residents. Model validation plots are included in the Appendix.

Since the UAM mode was not a part of the survey data, the UAM mode constant could not be estimated during model calibration. Mode constants capture unobserved factors such as safety, reliability, comfort, personal preference, etc., which influence mode choice decisions. UAM ConOps defines the mode as an aerial ridesharing mode [53]. Therefore, it can be assumed that the unobservable factors affect the mode choice for UAM, similar to rideshare modes. This analysis uses rideshare mode constant for UAM mode constant. Similar assumptions have been made in UAM studies. In a Munich-based study, Ploetner et al. found similarities in terms of excluded attributes of UAM and train [54]. They assigned the UAM mode to the transit nest and used train mode's variables for UAM except for travel costs, travel time, and assumed VOT values.

Table 4: Mode Choice Logit Model

Parameter		Coefficient (or Estimate)	
		Business Trips	Non-Business Trips
Mode Constants	Drive & Park [#]	1.1613*	0.0384
	Taxi	-0.7247*	-1.4141*
	Rental Car ^{##}	0.5772*	-0.2281*
	Public Transit	-2.333*	-1.9685*
	Rideshare (Uber, Lyft, etc.)	-1.8706*	-1.8531*
Travel Time	Total Travel Time	-0.0207*	-0.0192*

¹¹ Ingress/Egress times account for processing and boarding/alighting the vehicle at the vertiport. They do not account for trip delays.

Travel Cost	Travel Cost (Residents)	-0.0220*	-0.0353*
	Travel Cost (Visitors)	-0.0216*	-0.0316*
	Number of Transfers	-0.2277*	0.3337*
Model Fit	ρ^2 (Pseudo R^2)	0.2952	0.2763
	Prob > χ^2	0.0000*	0.0000*
Value of Time	Resident VOT (\$/hr)	56.45	32.54
	Visitor VOT (\$/hr)	57.50	36.38

Note: Significance: *0.01

#Only applicable to Resident Business Trips

##Only applicable to Non-Resident Business Trips

B. UAM Demand Estimation

The UAM alternative was added to the mode choice set after estimating UAM trip characteristics for each OD pair. The UAM trips are simulated based on the ConOps described in section IV-B and assumptions mentioned in Table 3. All mode probabilities are recalculated for all the trips in the dataset using Equation 1. The total number of daily inbound airport trips eligible for UAM is 45,070 (to DFW: 38,701 and to DAL: 6,369). The UAM demand is estimated using the traveler's UAM probability and daily weight provided in the survey. Joby S4 is the concept vehicle used in this analysis; it has a capacity of four passengers. The analysis assumes a 60% load factor (2.4 passengers per vehicle) for the UAM trips. After exploring prices for various ridesharing and on-demand services in the region, a Base Cost (BC) of \$15 per passenger and a Landing Cost (LC) of \$20 per vehicle was assumed. **Error! Reference source not found.** outlines the sensitivity of demand with respect to the CPM offered by the UAM operating agency, considering a constant 50 vertiports in the region. Due to the lack of data on returning passengers (airport to home/hotel/work), an equal number of UAM originating and returning trips is assumed on OD pair level. At a \$2 CPM (additional to BC and LC), there is a 3,202 UAM one-way airport trip demand per day, where increasing the CPM by 50 cents reduces the demand by 26%. Even though the UAM demand drops quickly on increasing the per-mile cost, a considerable number of trips could be observed at a high per-mile cost of \$4, which is in addition to the BC and LC. Fig. 7 shows segmented demand based on traveler's category. The proportion of business travelers in UAM demand is high due to their relatively higher VOT than non-business travelers. Even though business travelers make up to 54% of the total ground access market in the Dallas-Fort Worth region, they comprise three-quarters of the UAM demand for a scenario with 50 vertiports and \$2 UAM CPM. The higher cost of UAM is expected to affect non-business travelers relatively more due to their relatively lower VOT. Therefore, the share of non-business travelers in UAM demand drops to only 17% in the high-cost scenario with \$4 UAM CPM.

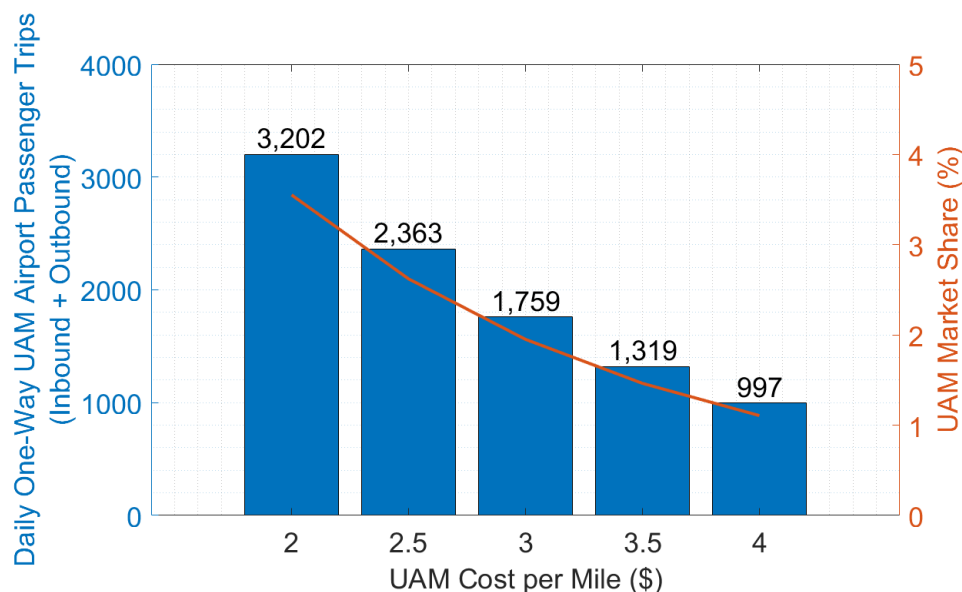


Fig. 6 Daily Airport UAM Demand Sensitivity to UAM CPM (50 Vertiports)

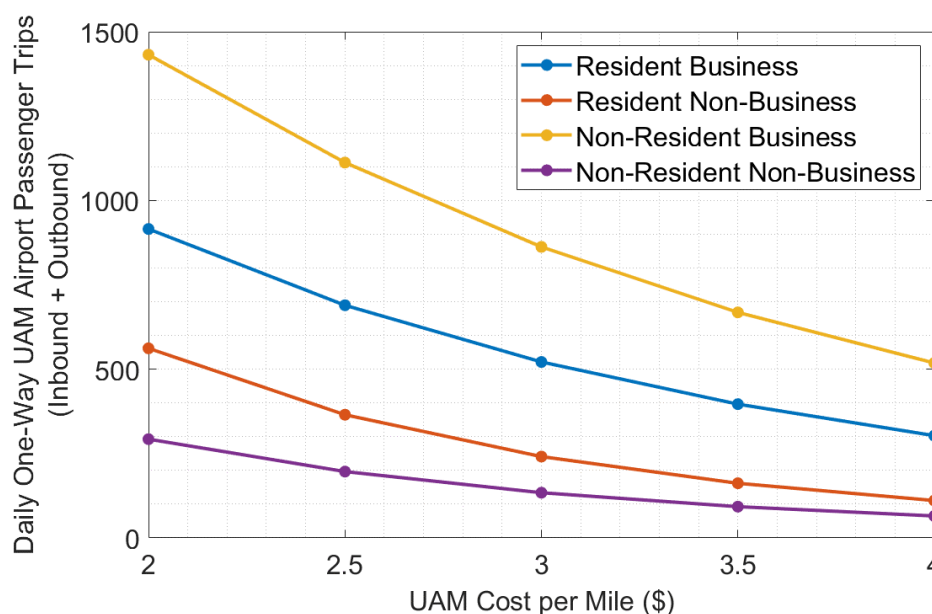


Fig. 7 Daily Airport UAM Demand Sensitivity to UAM CPM (50 Vertiports) by Segment

Increasing the number of vertiports should improve the accessibility of UAM as access times would decrease. However, building and operating a large number of vertiports could be an economic burden. Therefore, it is essential to evaluate the change in demand with changing network size of vertiports. Three vertiport sets with 50, 75, and 100 vertiports are generated where a smaller set is a subset of the larger sets. Fig. 8 illustrates the sensitivity of UAM demand with the UAM network, i.e., the number of vertiports. UAM demand is estimated for all three vertiport sets and \$2 UAM CPM (additional to \$15 BC and \$20 LC). Increasing the network size of 50 vertiports set by 50% increases daily UAM demand by 12.5%. Adding additional 25 vertiports to 75 vertiport set increases the UAM demand by 2%. The increase in UAM demand is negligible on adding vertiports to the 100 vertiport set. The reason for a nominal increase in UAM demand on increasing the size of vertiport set is a heavy concentration of airport trip demand in certain areas. Airport trip access demand in Dallas-Fort Worth is concentrated in a few parts of the region and, therefore, effectively served by a smaller network of vertiports. Additional vertiports are placed in areas with scarce airport access demand and thus, resulting in only a minor increase in UAM demand.

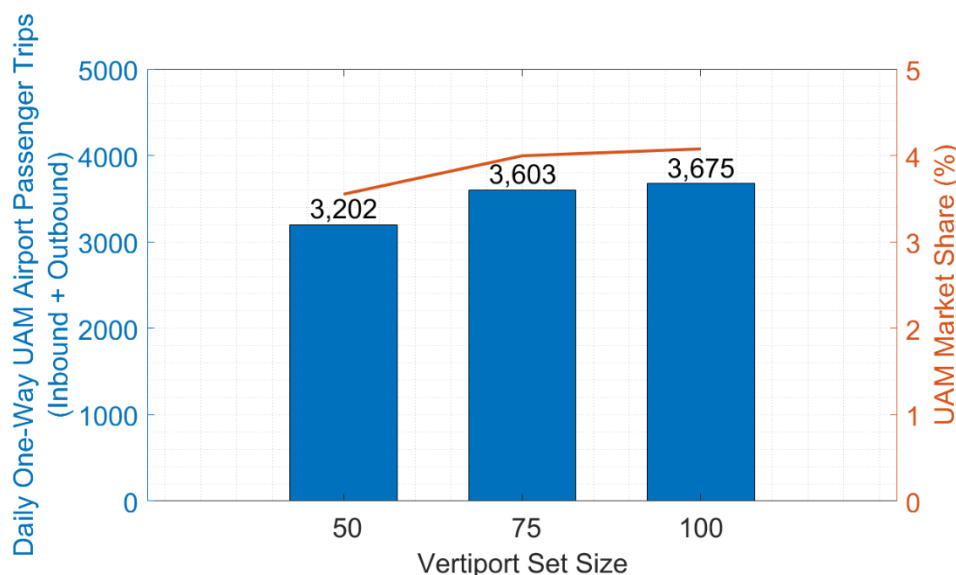


Fig. 8 Daily Airport UAM Demand Sensitivity to UAM Vertiport Set Size (UAM CPM: \$2)

Sensitivity analysis is extended to secondary factors influencing UAM demand in the system. Certain parameters usually kept constants during the demand estimation process are varied to understand their impact on the UAM demand. The base scenario selected for reference is 50 vertiports with \$2 UAM CPM (additional to \$15 BC and \$20 LC) that estimates 3,202 daily airport access UAM passenger trips. Fig. 9 shows the impact of changes in secondary factors on UAM demand. The demand estimation process is repeated for every change, with the discussed change being the only deviation from the reference scenario. The base cost for a UAM trip in the reference scenario is \$15 per passenger, which aligns with the base cost of mid to premium rideshare services. Decreasing the base cost by 50% to \$7.5 per passenger could increase the overall UAM demand by almost 20%.

Similarly, the UAM demand could increase by 10.5% if the landing cost charged per flight (assuming 2.4 passengers per flight) is reduced by 50% to \$10 per flight. The UAM average speed assumed in the reference scenario is 120 mph based on the reference vehicle's speed. UAM vehicles would travel on designated routes inside Class-B airspace and sometimes make frequent turns. In the case of a slower vehicle or congested airspace, maintaining a 120-mph average speed over the entire aerial trip could be challenging. UAM's primary attractive feature is travel-time savings, and any drop in average speed is expected to curb UAM demand. UAM demand could reduce by almost 12% if the average UAM speed is reduced to 80 mph.

Intermodal trip or access trip to the origin vertiport is a crucial part of the UAM trip. The ConOps assumes intermodal trip would be completed via cab/taxi service if the access distance is more than the threshold of one-tenth of a mile. The intermodal cost is calculated using the Uber fare structure in the Dallas-Fort Worth region. The intermodal cost is a significant part of the total cost for many travelers. If the intermodal cost could be brought down by virtue of collaboration, automation, economies of scale, etc., UAM affordability would increase. UAM demand could increase by 7.5% if the intermodal cost could get 25% cheaper. On the other hand, vertiport location at the airport could affect the UAM's inconvenience and total travel time. The commercial traffic pattern at DFW allowed a narrow passage to bring UAM vehicles near the terminal, which was not viable at DAL airport. The analysis assumes vertiport to terminal access time of zero and ten minutes at DFW and DAL, respectively. However, physical restrictions in vertiport placement could increase the vertiport to terminal access time. If vertiport to equivalent curbside access time is increased by 10 minutes at both the vertiports, the UAM demand could decrease by 17.5%.

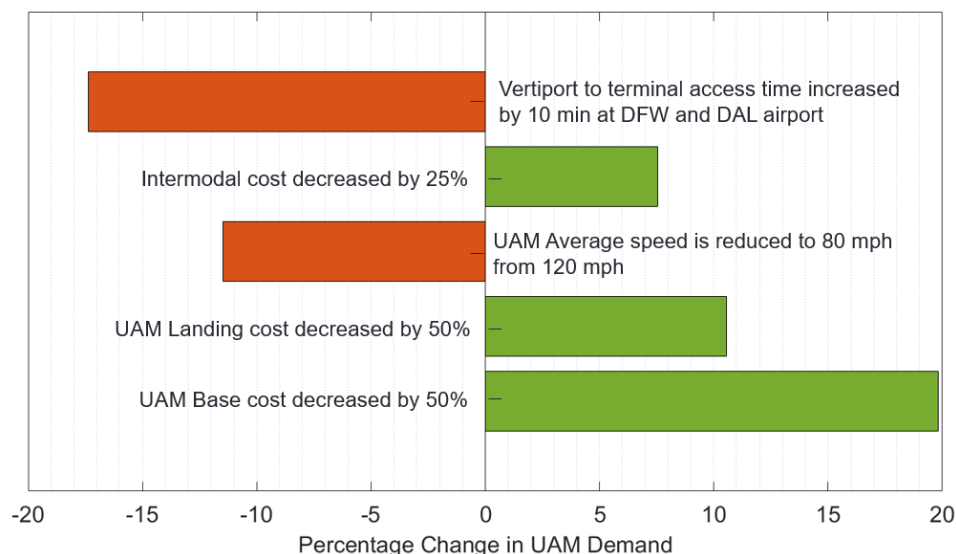


Fig. 9 UAM Demand Sensitivity against Multiple Factors. Base Case: 50 Vertiports with \$2 UAM CPM (additional to \$15 BC and \$20 LC) generating 3,202 UAM One-way Passengers Trips

Fig. 10 represents the spatial distribution of UAM demand for DFW airport trips with 50 vertiports and \$2 CPM (additional to \$15 BC and \$20 LC). Vertiports with high demand are located in Dallas downtown, DAL airport, Fort Worth downtown, and near Richardson. The high demand at DAL vertiport suggests the scope for an airport shuttle. Several mid-demand vertiports are found in Denton, Arlington, near Benbrook, Dallas and Fort-Worth downtowns, and Dallas suburbs. Major corridors can be established between Dallas downtown, Fort-Worth downtown, and the DFW airport. The high demand for UAM on these corridors is probably attributed to the high number of business travelers. Fig. 11 represents the spatial distribution of UAM demand for DAL airport trips for the same demand scenario. Since DAL only attracts 14% of UAM eligible trips to the airports in the region, the demand at the vertiports is relatively low. There is only one vertiport near Arlington with more than 20 daily UAM passenger trips to DAL. The vertiports in Dallas downtown have zero for trips to DAL because the flying distance is less than the minimum UAM eligible flying distance of ten statute miles. All remaining vertiports have a similar demand level with less than 20 daily UAM passenger trips to DAL.

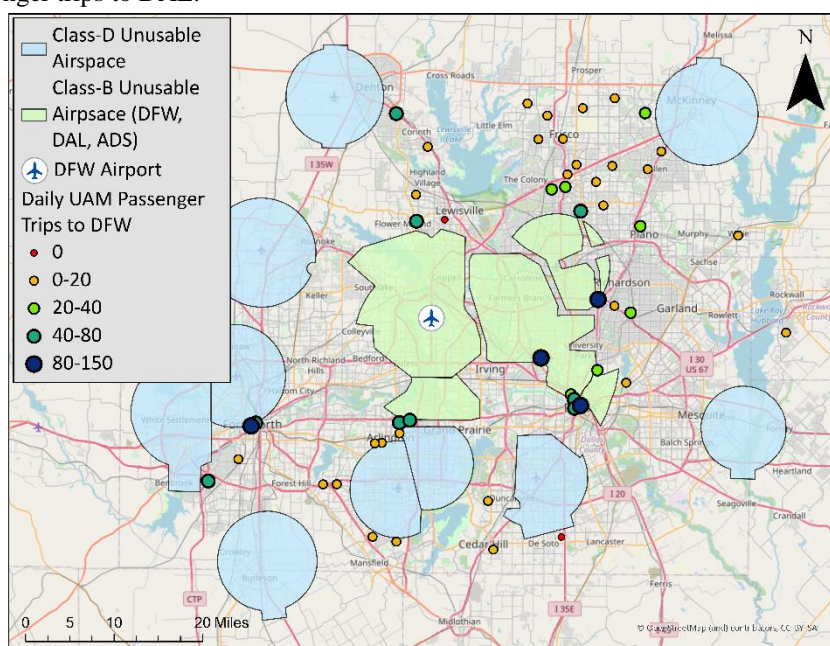


Fig. 10 Spatial Distribution of UAM Trip Demand to DFW

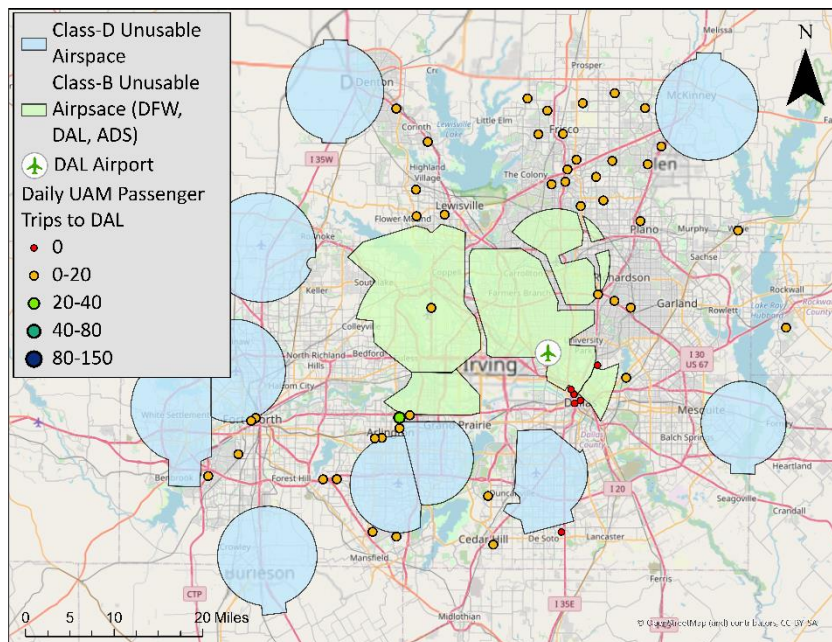


Fig. 11 Spatial Distribution of UAM Trip Demand to DAL

C. Capacity Discussion

The demand estimation process does not consider any capacity constraints. It assumes the required capacity is always available at the vertiport and in the airspace. However, capacity constraints would be a common operational constraint as the demand levels increase. This subsection sheds light on the feasibility of UAM operations at DFW vertiport predicted by the demand model with 50 vertiports and \$2 UAM CPM (additional \$15 BC and \$20 LC) from a capacity perspective.

Passenger trips are converted to UAM flights assuming 2.4 passengers per UAM flight, i.e., 60% load factor for the reference vehicle with a capacity of four passengers. Using the scheduled flight time reported in the survey and pre-departure distribution observed at the airport, departure times for UAM trips are generated. A full day of operations (617 arrivals and 617 departures) at the DFW vertiport are then simulated in the discrete-event simulation model developed in Rimjha and Trani [55]. According to the simulation results, the operations at the DFW vertiport would require a minimum of five pads and 48 parking stalls with reasonable service queues and service waiting times. Approximately 0.17 repositioning departures were required for every arrival, and 0.15 repositioning arrivals were required for every departure. These ratios are relatively low compared to the ratio found in Rimjha and Trani [55] during the simulation of a full day of UAM commuter operations. This is due to limited unidirectionality in airport access trips along with little concentration in peak periods. In contrast, commuter trips are usually heavily concentrated in peak periods with a high degree of unidirectionality. According to the analysis presented in Tarafdar et al. [56] and Tarafdar et al. [57], a five pad and 48 parking stall vertiport configuration would require almost 10.5 acres of land. Vertiport of that size is difficult to build close to the terminal. Either a smaller vertiport could be built close to the terminal, or a vertiport with the required capacity be built relatively far from the terminal. In the former option, vertiport would operate under capacity constraints causing delays and increasing operational inefficiency, whereas the latter option would increase the access time and thereby decrease the UAM demand as observed in the feasibility analysis.

UAM trips in the analysis are simulated on the designed network, which uses a total of three routes in the narrow corridor to bring UAM vehicles in and out of the DFW vertiport. Two of these routes are on the south side, and one is on the north side. These routes were designed assuming the exceptional navigational performance of the UAM vehicle. While the demand estimation process does not account for airspace restrictions, we recognize potential route capacity saturation while operating a high number of operations in and out of the DFW vertiport. Fig. 12 shows the number of daily flights on each route for the scenario with 50 vertiports and \$2 UAM CPM (additional \$15 BC and \$20 LC). Routes in and out of the DFW vertiport are critical and called spine road routes. The spine road route from the north has a demand of almost 500 UAM flights, whereas the spine road routes in the south have a demand of 436 (red) and 290 (green) UAM flights. The peak-hour demand in airport access trips has a proportion of 8% of the daily demand. Using that fraction, the peak-hour demand in the northern spine road route could reach 40 flights/hr.

Moreover, peak-hour demand for southern spine road routes could reach 35 flights/hr. (red) and 23 flights/hr. (green). Assuming separation minima of 2 nm and an average UAM speed of 80 knots in that corridor, the route capacity of any spine road route is estimated at 33 homogenous operations per hr. Even without considering mixed operations, the spine road route in the north and one spine road route in the south would be capacity constrained. Route capacity constraints could cause delays and thereby decrease the UAM demand. Therefore, the spine road routes could potentially become bottlenecks in the UAM network.

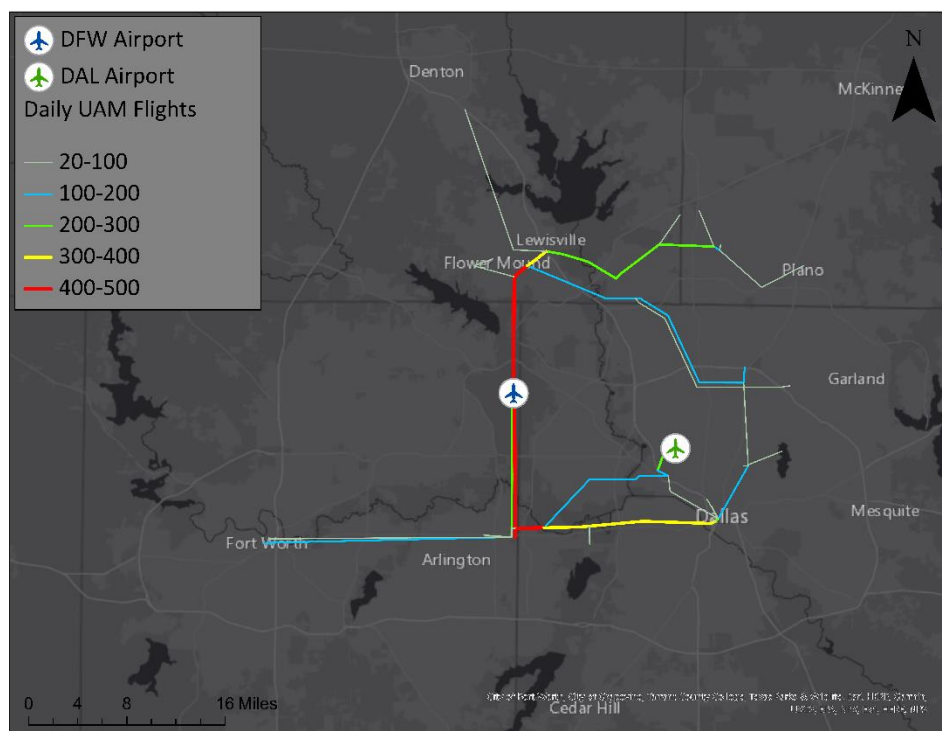


Fig. 12 Daily UAM Flights by Route. Scenario: 50 Vertiports with \$2 UAM CPM (additional to \$15 BC and \$20 LC)

VII. Conclusions

This paper analyzes the latest originating passengers survey at Dallas-Fort Worth International airport and Dallas Love Field to understand current travel patterns and trip-making behavior of travelers in the airport ground access segment. Mode-choice models are developed to capture the mode-choice behavior of the travelers and estimate UAM demand for airport access trips. UAM could capture around 4% market share (3,202 one-way passenger trips) with 50 vertiports and UAM CPM of \$2 (additional to \$15 BC and \$20 LC) in the Dallas-Fort Worth region. Almost three-quarters of that total UAM demand is from business travelers due to their relatively higher value of time than non-business travelers. The sensitivity analysis of UAM demand against UAM CPM found that UAM demand drops by 26% if the UAM cost per passenger mile increases by 50 cents. Even at a high price of \$4 CPM, UAM could capture about 1% of the market share. Increasing the vertiport network size does not significantly impact the UAM demand as airport access demand is concentrated in certain areas in the region, therefore, comfortably catered by a smaller vertiport set. UAM demand only increases by 12.5% and 2% on increasing number of vertiports from 50 to 75 and 100, respectively.

Sensitivity analysis of UAM demand against changes in secondary factors revealed that UAM demand could increase by almost 20% and 10% on 50% reduction in UAM base cost and UAM landing cost, respectively. UAM demand could also increase by about 7.5% if intermodal access gets 25% cheaper by virtue of collaboration, automation, economies of scale, etc. On the other hand, the UAM demand could drop by 12% and 17.5% if the average speed of UAM is reduced to 80 mph from 120 mph and if vertiport to terminal access travel time is increased by 10 minutes at both airports, respectively. Therefore, the location of vertiport at the DFW airport should be close to the equivalent "curbside" location to reduce access inconvenience. The spatial distribution of UAM demand advocates a

significant potential of high-demand corridors between DFW airport and Dallas downtown, DAL airport, Fort Worth downtown, and Richardson area. Since UAM trips to DAL only comprise 14% of all total demand and most of which are spread near uniformly over the region, no high demand corridor potential is recognized for DAL airport trips, except the shuttle corridor between DAL and DFW. Demand estimation does not consider capacity constraints, but a post-estimation analysis suggests potential vertiport capacity constraints at DFW vertiport and route capacity constraints for the given route network and UAM demand scenario with 50 vertiports and \$2 UAM CPM. Even with congested airspace and other scaling constraints, airport access trips in the Dallas-Fort Worth region are a promising market for UAM operations.

Future research should incorporate capacity constraints in the demand estimation process. The analysis could be enhanced by UAM perception-related information from airport access travelers specifically. The impact of other factors like luggage handling, inclement weather, system delays should be explored. This analysis assumed no interaction with commercial ATC, and therefore a significant part of airspace is unusable. Policies to dynamically reduce unusable airspace through limited ATC incorporation should be studied as reducing detours would improve UAM vehicle routing. Mature state UAM operations could generate significant noise levels [58]. However, future research should investigate whether the UAM's contribution to noise levels around the airport is significant, considering default noise levels from commercial aviation operations.

Appendix

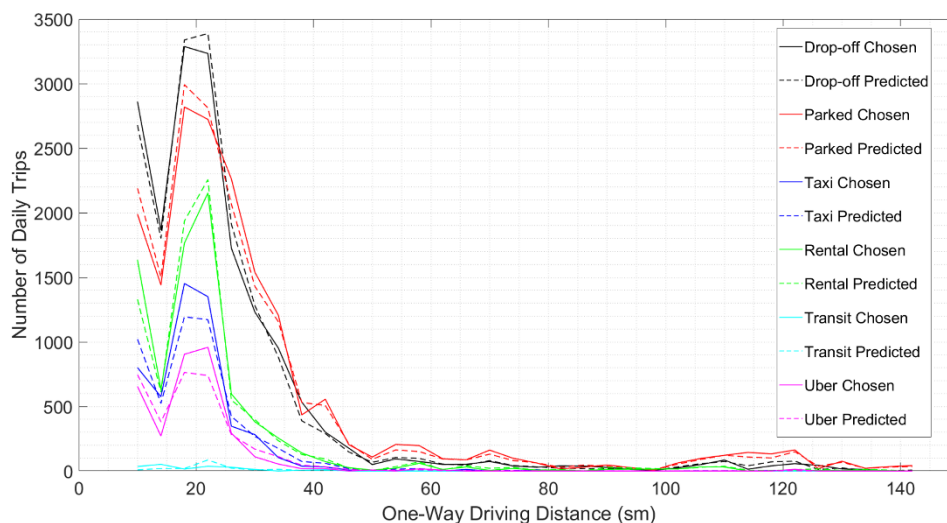


Fig. 13 Comparison of Market Share by Distance: Chosen vs. Predicted

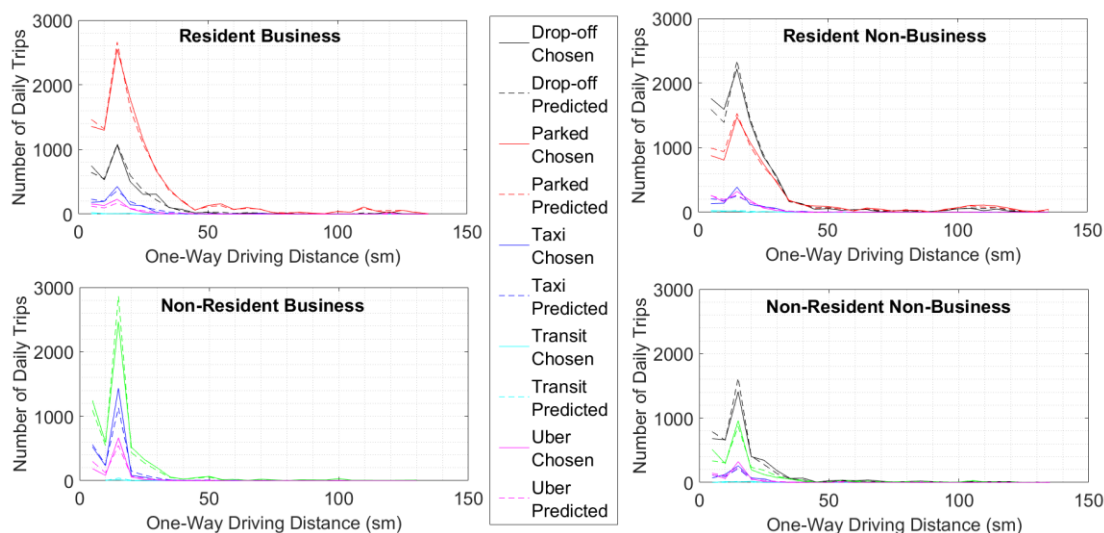


Fig. 14 Comparison of Market Share by Distance: All Segments

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