Urban Air Mobility: Demand Estimation and Feasibility Analysis

Mihir Rimjha

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Susan Hotle Co-Chair

Antonio A. Trani Co-Chair

Kevin Heaslip

Feng Guo

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Abstract

This dissertation comprises multiple studies surrounding demand estimation, feasibility and capacity analysis, and environmental impact of the Urban Air Mobility (UAM) or Advanced Air Mobility (AAM). UAM is a concept aerial transportation mode designed for intracity transport of passengers and cargo utilizing autonomous (or piloted) electric vehicles capable of Vertical Take-Off and Landing (VTOL) from dense and congested areas. While the industry is preparing to introduce this revolutionary mode in urban areas, realizing the scope and understanding the factors affecting the attractiveness of this mode is essential. The success of UAM depends on its operational efficiency and the relative utility it offers to current travelers. The studies presented in this dissertation primarily focus on analyzing urban travelers' current behavior using revealed preference data and estimating the potential UAM demand for different trip purposes in multiple U.S. urban areas.

Chapter II presents a methodology to estimate commuter demand for UAM operations in the Northern California region. A mode-choice model is calibrated from the commuter mode-choice behavior observed in the survey data. An integrated demand estimation framework is developed utilizing the calibrated mode-choice model to estimate UAM demand and place vertiports. The feasibility of commuter UAM operations in Northern California is further analyzed through a series of sensitivity analyses. This study was published in Transportation Research Part A: Policy and Practice journal.

In an effort to analyze the feasibility of UAM operations in different use cases, demand estimation frameworks are developed to estimate UAM demand in the airport access trips segment. Chapter III and Chapter IV focus on developing the UAM Concept of Operations (ConOps) and demand estimation methodology for airport access trips to Dallas-Fort Worth International Airport (DFW)/Dallas Love Field Airport (DAL) and Los Angeles International Airport (LAX), respectively. Both studies utilize the latest available originating passenger survey data to understand arriving passengers' mode-choice behavior at the airport. Mode-choice conditional logit models are calibrated from the survey data, further used to estimate UAM demand. The former study is published in the

AIAA Aviation 2021 Conference proceeding, and the latter is published in ICNS 2021 Conference proceedings.

UAM vertiport capacity may be a barrier to the scalability of UAM operations. A heavy concentration of UAM demand is observed in specific areas such as Central Business Districts (CBD) during the spatial analysis of estimated UAM demand. However, vertiport size could be limited due to land availability and high infrastructure costs in CBDs. Therefore, operational efficiency is critical for capturing maximum UAM demand with limited vertiport size. The study included in Chapter V focuses on analyzing factors impacting vertiport capacity. A discrete-event simulation model is developed to simulate a full day of commuter operations at the San Francisco Financial District's busiest vertiport. Besides calculating the capacity of different fundamental vertiport designs, sensitivity analyses are carried to understand the impact of several assumptions such as service time at landing pads, service time at parking stall, charging rate, etc. The study explores the importance of pre-positioning UAM vehicles during the time of imbalance between arrival and departure requests. This study is published in ICNS 2021 Conference proceedings.

Community annoyance from aviation noise has often been a reason for limiting commercial operations at several major airports globally. Busy airports are located in urban areas with high population densities where noise levels in nearby communities could govern capacity constraints. Commercial aviation noise is only a concern during landing and take-offs. Hence, the impact is limited to communities close to the airport. However, UAM vehicles would be operated at much lower altitudes and have more frequent taking-off and landing operations. Since the UAM operations would mostly be over dense urban spaces, the noise potential is significantly high. Chapter VI includes a study on preliminary estimation of noise levels from commuter UAM operations in Northern California and the Dallas-Fort Worth region. This study is published in the AIAA Aviation 2021 Conference proceedings.

The final chapter in this dissertation explores the impact of airspace restrictions on UAM demand potential in New York City. Integration of UAM operations in the current National Airspace System (NAS) has been recognized as critical in developing the UAM ecosystem. Several pieces of urban airspace are currently controlled by Air Traffic Control (ATC), where commercial operation density is high. Even though the initial operations are expected to be controlled by the current ATC,

the extent to which UAM operations would be allowed in the controlled spaces is still unclear. As the UAM system matures and the ecosystem evolves, integrating UAM traffic with other airspace management might relax certain airspace restrictions. Relaxation of airspace restrictions could increase the attractiveness of UAM due to a decrease in travel time/cost and relatively more optimal placement of vertiports. Quantifying the impact of different levels of airspace restrictions requires an integrated framework that can capture utility changes for UAM under different operational ConOps. This analysis uses a calibrated mode-choice model, restriction-sensitive vertiport placement methodology, and demand estimation process. This study has been accepted for ICNS 2022 Conference.

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General Audience Abstract

Urban Air Mobility (UAM) or Advanced Air Mobility (AAM) are concept transportation modes currently in development. It proposes transporting passengers and cargo in urban areas using all-electric Vertical Take-Off and Landing (eVTOL) vehicles. UAM is a multi-modal concept involving low-altitude aerial transport. The high capital costs involved in developing vehicles and infrastructure suggests the need for meticulous planning and strong strategy development in the rolling out of UAM. Moreover, urban travelers are relatively more sensitive to travel time savings and travel time reliability; therefore, the efficiency of UAM is critical for its success. This dissertation comprises multiple studies surrounding demand estimation, feasibility and capacity analysis, and the environmental impact of UAM.

To estimate the potential for UAM, we need first to understand the mode-choice making behavior of urban travelers and then estimate the relative utility UAM could possibly offer. The studies presented in this dissertation primarily focus on analyzing urban travelers' current behavior and estimating the potential UAM demand for different trip purposes in multiple U.S. urban areas. The system planners would need to know the individual or combined effect of various parameters in the system, such as cost of UAM, network size of UAM, etc., on UAM potential. Therefore, sensitivity analyses with respect to UAM demand are performed against various framework parameters.

Capacity constraints are not initially considered for potential demand estimation. However, like any other transportation mode, UAM could suffer from capacity issues that can cause operational delays. A simulation study is dedicated to model UAM operations at a vertiport and estimating factors affecting vertiport capacity. After observing the demand potential for certain optimistic scenarios, we realized the possibility of a large number of low-flying vehicles, which could cause annoyance and environmental impacts. Therefore, the following study focuses on developing a noise estimation framework from a full-day of UAM operations and estimating a highly annoyed population in the Bay Area and Dallas-Fort Worth Region.

In our studies, modeling restricted airspaces (due to commercial operations at large airports) was always a critical part of the analysis. The urban airspaces are already quite congested in some urban areas, and we assumed that UAM would not operate in the restricted airspaces. The last study in this dissertation focuses on quantifying the impact of different levels of airspace restrictions on UAM demand potential in New York. It would help system planners gauge the level of integration required between the UAM and National Airspace System (NAS).

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1. Introduction

Urban Air Mobility (UAM) or Advanced Air Mobility (AAM) is a concept transportation mode which proposes to solve ground congestion problems by adding another dimension in urban mobility. The concept involves utilizing all electric Vertical Take-Off and Landing (eVTOL) vehicles for aerial transport of passengers and cargo inside urban ecosystem. Even though most of the developments in UAM occurred in recent years, the concept is not entirely novel. On-demand helicopter taxi services were offered during the 1970s in Boston and other cities [1]. New York Airways started offering helicopter taxis from the Pan Am Building to the airline's terminal at John F. Kennedy Airport (JFK) in 1965 [2]. However, these services could not sustain the operating cost and had strong opposition from the community due to increased noise and potential accident hazards [3]. Helicopter taxi services are still operating but limited to a few metropolitan areas due to high travel costs. BLADE currently offers airport shuttle services to all New York airports from three heliports in Manhattan [4]. Until recently, Voom used to offer helicopter services in São Paulo, Mexico City, and the San Francisco Bay Area [5]. Uber offers door-to-door multi-modal helicopter taxis from Manhattan to JFK airport [6]. While these services are currently being offered, they are far from the UAM ecosystem in development. UAM would involve autonomous (or piloted) electric vehicles with Vertical Take-Off and Landing (VTOL) capabilities to operate from congested urban spaces. UAM system plans to accommodate a larger population by offering services at lower cost by virtue of automation, economies of scale, and government subsidies [7].

Although the flying taxi concept sounds exciting, the system needs to be very efficient to attract travelers regularly. A system can only scale if there is sufficient demand. Therefore, for UAM to grow, it is paramount to attract passengers. Travel-time savings is the major attraction of UAM in urban settings. The UAM concept is multi-modal in design, putting it at a disadvantage as travelers dislike transfers in the urban transportation system. However, if the overall time-savings through UAM are significant compared to alternative modes, it could attract urban travelers.

Moreover, the travel-time savings should come at a reasonable marginal cost if UAM wants to target a larger population. Otherwise, it would be limited to a few similar to current helicopter taxi services. Therefore, analyzing the target population is essential for the scalability of UAM. UAM

attractiveness is subjected to travelers' Willingness-To-Pay (WTP) and their trip requirements. Hence, understanding the demographics of the target population, travel patterns, and mode-choice behavior is vital for efficient system design. A more efficient system can be tailored if the planners and operators know the factors influencing UAM demand.

Realizing the scope is the primary step in the development of the UAM system. Prior to demand estimation analysis, initial screening of the urban areas in the United States is performed using characteristics that would promote or inhibit the UAM mode's success. Based on the population, socio-economic, travel patterns, and weather information, the following four urban areas were chosen Northern California (San Francisco Bay Area), Southern California (Los Angeles Area), Dallas-Fort Worth, and New York City. Each of the four regions is at the focus of at least one study presented in this dissertation. The summary of the initial screening is included in Table 1.

Table 1: Weather and Socio-Economic Characteristics of Various Metropolitan Areas

Metropolitan Area	Temperature		Wind	Precipitation	Snow	Population	Income
	% Time below 32F**	% Time temp<32F & (air-dew) temp is =<2F**	% Records where wind speed is >= 15 knots**	Average annual inches	Days when >= 1 inch*	MSA population in millions***	HHs with income >100k in thousands ***
Atlanta	1.7	0.04	3.7	49.1	0.9	5.8	508.6
Boston	16.6	0.89	12.1	43	11	4.5	584.8
Chicago	18.2	1.41	11.5	40.4	12.6	7.2	709.6
Dallas	3.1	1.14	10.2	35.7	1	7.2	645.5
Los Angeles	0.04	0.05	15.7	9.4	0	13.4	1,204.1
Miami	0.9	0.97	3.1	67	0	6.1	437.4
New York	10.9	0.01	3	43.7	6.7	19.3	1,812.6
San Francisco	6.9	0.09	16.6	16.8	0	4.7	639.4
Seattle	9.1	0.12	3.2	41.7	1.7	3.8	433.4
Washington DC	11.1	1.34	4.8	40.2	4.2	6.2	996.9

* Source: 2007-2017 'Global Summary of the Year' records from Climate Data Online (NCDC). [8]
** From 6 AM–8 PM, Source: 2015 ASOS 1-min weather records by NOAA [9]
*** Using 2009 dollars, Source: CEDDS, Woods and Poole, 2016. [10]

Exploring different trip purposes for UAM potential is required to find UAM use cases to expand the reach to a greater population. The airport shuttle market has been identified as an early adopter of the UAM due to operational efficiency from demand concentration at one end, existing

infrastructure at one end, and the opportunity for collaboration with airlines for premium services [11]. However, the scalability of the UAM would require tapping into larger markets such as commuters.

Even if the UAM demand potential exists, capturing the demand would be challenging for the UAM system. Urban travelers are relatively more sensitive to cost and time. Therefore, the reliability and efficiency of the UAM system should be high. Major challenges include infrastructure development, landside and airspace capacity constraints, setting up the UAM network in already congested urban airspaces, community acceptance, handling potential annoyance from noise. Initial studies included in this dissertation focuses on building demand estimation frameworks for different trip purposes to understand factors influencing the UAM demand. Following studies analyze the factors affecting vertiport capacity and potential noise generated from a full day of operations. The last study quantifies the impact of different levels of airspace restrictions on UAM demand potential. This compilation of studies builds a comprehensive framework to understand the demand potential and feasibility of UAM operations.

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2. Commuter demand estimation and feasibility assessment for Urban Air Mobility in Northern California

2.1 Abstract

This study aims to estimate passenger demand for Urban Air Mobility (UAM) and analyze the feasibility of operating the system in Northern California. 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. This study focuses specifically on commuting trips, which are frequent and considered relatively more time-sensitive than other types of personal trips. The UAM mode's feasibility is studied using sensitivity analysis of UAM demand to cost per passenger mile and the number of vertiports placed in the region. This study also explores the spatial distribution of UAM demand in Northern California, which further helps in identifying the major commuter trip-attraction and trip-production zones for the UAM mode in the region. The results indicate that sufficient UAM demand for commuting trips can only be reached at optimistically low UAM offered fares. These fare levels could be challenging to obtain given the high real estate cost in Northern California's urban regions. Moreover, the reliability of the UAM mode must be comparable to the automobile mode; otherwise, it loses significant demand with increasing delays. The results also show that the commuting flows with promising UAM demand in Northern California are heavily one-directional, with San Francisco Financial District being a major attraction. Other types of trips should also be considered along with commuting trips to generate an economically viable system and reduce deadheading.

Keywords: On-Demand Mobility, Urban Air Mobility, Vertical Takeoff and Landing, Travel Demand

2.2 **Introduction**

On-Demand Mobility (ODM) could change how people travel in the future. With ODM, "vehicle routes and schedules are not fixed a priori; instead, they adapt dynamically to serve incoming transport requests" [1]. Today's society has seen implementations of ODM through mobile app-based taxi-hailing services, including Lyft and Uber. However, in the future, technologies such as autonomous vehicles and 2- or 4-person electric aircraft with vertical takeoff and landing (VTOL) capabilities are expected to be fully in service to the general public [2, 3]. ODM's impact will be two-fold by adding modes to a traveler's choice set and increasing the operational efficiency of existing transportation systems during peak-hour commutes.

The VTOL concept, also known as Urban Air Mobility (UAM), has gained considerable attention in recent years for its anticipated appeal to time-sensitive, price-inelastic travelers. It would provide a fast mode of transportation to bypass the congestion of ground transportation systems. America's most congested cities have the opportunity to receive the most significant benefit from UAM by reducing the delays and overall travel times. For example, in 2015, "the average San Francisco resident spent 230 hours commuting between work and home – that is half a million hours of productivity lost every single day" [4].

The UAM network will consist of vertiports, which, similar to helicopter pads, can be located in fields or on building rooftops. To use the UAM mode, commuters will first need to travel to the nearest vertiport to board a UAM aircraft. For this research, vertiport accessibility modes include walking or an ODM ground vehicle such as Uber or Lyft. We assume no public parking available at the vertiports. The commuter will then board a UAM aircraft to fly to the vertiport nearest to their destination, similarly relying on walking or ODM for the last-mile transportation. To date, a few companies have offered a similar service to UAM by using helicopters between helipads, such as BLADE with shuttle rides in the Bay area, Los Angeles, and New York [5]. However, these services are limited to very few Origin-Destination (OD) pairs. Helicopter commuter services are expensive compared to the UAM price estimated by Booz-Allen-Hamilton in a study supported by NASA [6] and an autonomous aerial vehicle manufacturer, E-hang [7]. The former estimated $6.25 per passenger mile in the near-term which could drop by 60% ($2.50) in the long-term, whereas the latter ran a

conservative financial model with the unit fare of $4 per passenger mile for the near-term, which could drop significantly considering economies of scale and efficiency gains.

In addition to vertiports, the UAM concept utilizes electric vehicles with advanced avionics and VTOL capabilities. UAM aircraft may be fully autonomous in the long-term, but they would include a safety pilot in the initial stages of deployment. The aircraft is expected to be a viable mode alternative for commuting. UAM aircraft will have a maximum range between 120-183 miles [4, 8] with a top cruise speed between 150-200 mph [4]. While this mode will be costly initially, similar to a helicopter, it could become more affordable over time, making it more feasible to use on a frequent basis [9]. Uber has already invested in VTOL by planning an initial offering of its UberElevate product in three test cities [10] by the year 2020.

This study aims to analyze the feasibility of offering UAM services to the commuter market in the Northern California region, centered on San Francisco. This study involves developing a model to estimate UAM commuter demand for different scenarios with varying vertiports in the region and cost per mile (CPM) to the traveler. The UAM demand model utilizes a calibrated mode-choice conditional logit model based on the add-on National Household Travel Survey (NHTS) data. The demand model is used to obtain a network of UAM vertiports placed optimally to maximize the UAM demand iteratively. The analysis considers the household income distribution in the region and the number of vertiports and CPM.

2.3   **Literature Review**

Existing literature contains several studies that assess the future of UAM. Booz Allen Hamilton performed a comprehensive market study of UAM for the National Aeronautics and Space Administration (NASA) [6]. They focused on ten major urban areas in the United States and witnessed high variability in UAM demand across the cities. A logit model was calibrated using two variables, travel time and travel cost per median hourly household income, using the American Community Survey (ACS) 2016 data and a general population survey that the company conducted. Their Monte Carlo simulations estimated a demand of close to 80,000 daily passengers across the United States served by 4,000 UAM vehicles for all trip purposes. This study assumed that UAM would use existing infrastructure for vertiports, specifically already built helipads and airports. However, the locations of

helipads and airports are not optimized to maximize demand. Using existing facilities could significantly disadvantage the UAM mode as intermodal distances could increase. The analysis was also performed at the census tract level, limiting the ability to estimate the mode choice of individuals and mode-specific trip characteristics.

Fu et al. [11] performed a mode-choice analysis in the UAM environment based in Munich, Germany. The study included data collection from an online stated-preference survey and the creation of several discrete choice models. The study found that for commuting, public transit is the most desirable choice, followed by auto, whereas UAM selection is the least likely. Their model estimates suggest a relative increase of acceptance for autonomous modes in the higher-Value-Of Time (VOT) group. Since this study is based on a stated-preference survey, it is possible that results could differ from actual, revealed-preference behavior.

Bulusu et al. [12] developed a traffic analysis method to estimate the maximum number of people that can benefit from UAM in a metro area. As a sample application, they applied their methodology to 327,57 commute trips in San Francisco Bay Area. Their study estimated multi-modal UAM trip itineraries and compared travel time savings by UAM compared to the car for different cases of vertiport transfer times. Commuters who only shift mode with 50% or more of travel time savings are considered to have a high value of time. They found that during high congestion and even with a long transfer time of 15 minutes, 45 % of commuters with the high value of time could benefit from UAM on a travel time basis. This indicates high UAM demand potential in the region. However, the study did not consider commuters' willingness-to-pay, which is essential to estimate total UAM passenger demand.

Balac et al. [13] explored the prospects of the UAM service in Zurich, Switzerland. They created experiments with combinations of various UAM passenger processing times, cruising speeds, and variable costs, assuming a base fare of 6 Swiss Francs (CHF). Their experiments found that when the variable costs exceed 1.8CHF/km, the UAM service failed to attract high passenger demand and, therefore, making the service only attractive to the very high-income market segment of the population. The study concluded that the UAM market share in small urban areas like Zurich is low, but for metro areas with dense populations, the UAM market share in the transportation system could

be significant. Limitations of this study include that the experiments were carried out on only a 10% population sample with a pre-defined network of nine-vertiports based on local expertise. Pre-defined vertiport locations might not maximize the UAM demand and, therefore, decrease the mode's demand potential. Building upon this study, Balac et al. [14] estimated demand for the aerial vehicle in the Zurich region using multi-agent-based simulation paired with a mode-choice model. Using Uber Black price for the aerial vehicle, the demand was found to be low, and the aerial vehicle would mostly serve mid-distance trips requiring high detour factors due to terrain. This study focused on the Zurich region, and its findings may not apply to an urban region in the USA due to differences in commuting patterns, terrain, congestion, demographics, public transit network, mode choice availability, etc. Nevertheless, the study provides significant reference and validation points.

Similar efforts are being put to explore the human factors involved in the integration of UAM into the current transportation system. Analyzing the user's perception and degree of public acceptance is equally important in the development of UAM. Al Haddad et al. [15] explored various factors affecting the adoption and use of UAM using a stated preference survey. After modeling adoption time using exploratory factor analyses and discrete choice models, they found safety and trust, affinity to automation, data concerns, social attitude, and socio-demographics as important factors in the adoption of UAM. Eker et al. [16] studied individuals' perceptions of benefits and concerns from UAM utilization, potentially affecting its adoption by the commuting population. They statistically analyzed data (collected through online-survey) using grouped random parameters bivariate Probit models. They found that an individual's perception towards the use of UAM is affected by various socio-demographic, behavioral, and attitudinal attributes. Behme and Planing [17] performed a qualitative analysis to study customer acceptance of UAM using individual interviews. They found that UAM acceptance would increase if the system is made more relevant and better known to the public. Furthermore, the study emphasized coherent intermodal connections for better acceptance of UAM in the current transportation system.

While the authors of this paper are aware of the factors affecting the adoption of UAM in the current transportation system, the study assumes full adoption of UAM and focuses on the feasibility of operating UAM from an economic perspective. The study presented in this paper builds upon previous work completed by Syed et al. [18], where a conditional logit model is calibrated to estimate

UAM demand in the Northern California region. This study builds on Syed et al. [18] by creating a new robust mixed conditional logit mode-choice model that captures the unobserved heterogeneity, which follows the method described in Greene et al. [19]. Eker et al. [20] discuss in detail the unobserved heterogeneity present with regards to the public's perceptions of UAM vehicles. The study presented in this paper incorporates segregated travel times (In-Vehicle Travel Time and Out-of-Vehicle Travel Time), income categories in the model, and other significant variables like the number of transfers. Additionally, the simulation of alternate trip modes in the model calibration and demand estimation (or model application) is improved by using Application Programming Interfaces (API) [21, 22], which uses real trip data for estimating the trip characteristics with high accuracy. Moreover, the parking cost is calculated by developing a function based on economic density and monthly parking costs [23]. The transit cost calculation is improved by including mode-based, OD cost functions built upon fare charts of respective transit agencies [24]. The resolution of the analysis is also refined from census tract to census block-group to improve accuracy.

2.4   **Study Area**

Northern California, centered on San Francisco, was defined as the study area for this analysis, given its UAM potential for commuting trips. Specifically, the success of the UAM depends on the performance of other modes in the region. The San Francisco Bay Area ranks consistently in the top five congested cities globally [25]. During peak hours, commuters in the San-Francisco area have lost nearly five days every year to traffic congestion [26]. The region's unique polycentric commuting pattern commutes by ground modes in peak hours even more difficult [27]. Also, UAM could be affordable to a high portion of the population as the Bay area has the second-highest household income levels in the United States, second only to Washington DC [28], and also has around 640,000 households with an annual household income greater than $100k [29].

The weather in Northern California also benefits the UAM mode with reduced inclement weather events. Inclement weather conditions can prevent the operation of UAM, similar to the operation of air transportation today. Even with advanced avionics and automation, it would be challenging to provide reliable passenger service in poor weather conditions. Using 11 years of aggregated weather data from National Climate Data Center (NCDC) [30] and 1-min weather records by National Oceanic and Atmospheric Administration (NOAA) [31], it was found that on average, the

San Francisco metro area receives only 16 inches of precipitation annually and has zero days of snow with more than an inch. However, San Francisco is impacted by wind, where 16% of the time the wind is above a 15-knot speed between 8 AM-6 PM [31], fog and seismic activity could affect the operation of a UAM system. The promising commute patterns, population demographics, and generally, favorable weather conditions compared to other U.S. regions support Northern California's selection to investigate UAM operations.

In total, the study area consists of 17 counties (7,106 block-groups) centered around the San Francisco area. The selection of counties in the study area matches the range of proposed UAM aircraft, where counties with population centroid within 150 miles of any of the Bay Area cities (San Francisco, San Jose City, Oakland) were selected. Figure 1 shows a map of the study area. No commuting trips from the county areas outside of the 150-mile radius were considered in this study.

Figure 1: Northern California 17-County Study Area

2.5   **Data and Methodology**

This study includes two tasks. The first was calibrating the mode choice model to quantify how commuters make decisions given the mode alternatives available to them and those alternatives' attributes. The second was applying the mode choice model to all of the commuters in the study area. In the application, the vertiports are first placed, and then the UAM demand for the region was quantified for the given set of vertiports. Table 2 summarizes the datasets supporting the tasks.

Table 2: Datasets Used in the Analysis

Datasets	Data Resolution	Task
National Household Travel Survey-2017 Add-on Data [32]	Location Coordinates	Mode Choice Model Calibration
Longitudinal Employer-Household Dynamics Origin-Destination Employment	Block-group	Parking Cost Estimation Model Application

Statistics (LODES) [33]		
American Community Survey-2017 [34]	Block-group	Mode Choice Model Calibration Model Application

2.5.1 Mode Choice Model Calibration

To estimate the demand for UAM, the mode choice decision-making process of commuters must be understood. This involved reconstructing each individual's mode alternatives choice set (i.e., modes available to them) and estimating how trade-offs are made between attributes of those alternatives such as time and cost. For the mode choice model, we calibrated a mixed conditional logit model. The conditional logit model is a type of logit model that only includes independent variables that vary between the modes for a single commuter (called generic variables- e.g., travel time, cost, distance). Alternative-specific variables that do not vary, such as number of household vehicles, could not be included because the coefficients for the UAM mode cannot be estimated as it is never the chosen mode in the study's revealed-preference mode choice dataset.

McFadden formulated the conditional logit analysis in detail [35], which became a popular method for mode choice studies in transportation, including [36, 37, 38, 39]. However, there are certain limitations to the conditional logit model. It assumes the same preferences for all individuals, which depend only on observable characteristics. The Independence of Irrelevant Attributes (IIA) property of the conditional logit model causes proportional substitution between the alternatives. The mixed logit model overcomes these limitations by allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over time [40]. In mixed conditional logit models, a commuter is expected to make mode choice decisions based on the utility derived from the mode. The utility that individual *n* derives from choosing alternative *j* on choice occasion *t* is given by $U_{njt} = \beta'_n x_{njt} + \varepsilon_{njt}$ [41], where β'_n is a vector of individual-specific coefficients, x_{njt} is a vector of observed attributes relating to individual *n* and alternative *j* on choice occasion *t,* and ε_{njt} is a random term that is assumed to be an independently and identically distributed extreme value. For known β_n, the probability of individual *n* choosing alternative *i* on choice occasion *t* is given by Equation 1, which is standard conditional probability.

$$L_{nit}(\beta_n) = \frac{\exp(\beta_n' x_{nit})}{\sum_{j=1}^{J} \exp(\beta_n' x_{njt})} \tag{1}$$

The unconditional probability of the commuter's observed sequence of choices is obtained by integrating L_{nit} over the distribution of β, given by Equation 2.

$$P_n(\theta) = \int S_n(\beta) f(\beta \mid \theta) d\beta \tag{2}$$

Where:

$f(\beta \mid \theta) = density\ for\ \beta, where\ \theta\ are\ the\ parameters\ of\ the\ distributions$

$S_n(\beta_n)$ is the probability of the observed sequence of choices for known β_n and is given by Equation 3, where $i(n,t)$ denotes the alternative chosen by individual n on choice occasion t and T is the total number of choices.

$$S_n(\beta_n) = \prod_{t=1}^{T} L_{ni(n,t)t}(\beta_n) \tag{3}$$

The coefficients are estimated by maximizing using a log-likelihood maximizing methodology dependent on characteristics of the trip when using that mode. The log-likelihood of the mixed logit model is given by $LL(\theta) = \sum_{n=1}^{N} \ln P_n(\theta)$, where N is the number of individuals. It is approximated using the simulation method because it cannot be solved analytically. The simulated log-likelihood is then given by Equation 4, where R is the number of replications and β^r is the rth draw from $f(\beta \mid \theta)$.

$$SLL(\theta) = \sum_{n=1}^{N} \ln\left\{\frac{1}{R}\sum_{r=1}^{R} S_n(\beta^r)\right\} \tag{4}$$

The mixed conditional logit was estimated using the National Household Travel Survey (NHTS) add-on data. Since the NHTS data contains multiple trip purposes and the focus of this study was solely on commuting trips, the following filters were applied to the NHTS data trips. A trip was only included in the study if it: 1) Started and ended inside the study area, 2) Linked home to work or

vice-versa, 3) Occurred on a weekday, and 4) Was not completed by walking or biking. Therefore, the trips included either chose auto or transit.

It is important to note that only the chosen mode is reported in the NHTS data, and the unchosen modes had to be generated. Also, some of the travel survey responses were suspicious (e.g., fare paid, travel time) as this is manually reported by the survey respondent and prone to human error. To overcome this data limitation, fare, mileage cost, and parking costs were collected separately for all samples in this study. Figure 2 and the following sections describe in detail how the data was cleaned and supplemented with data that had an automated collection.
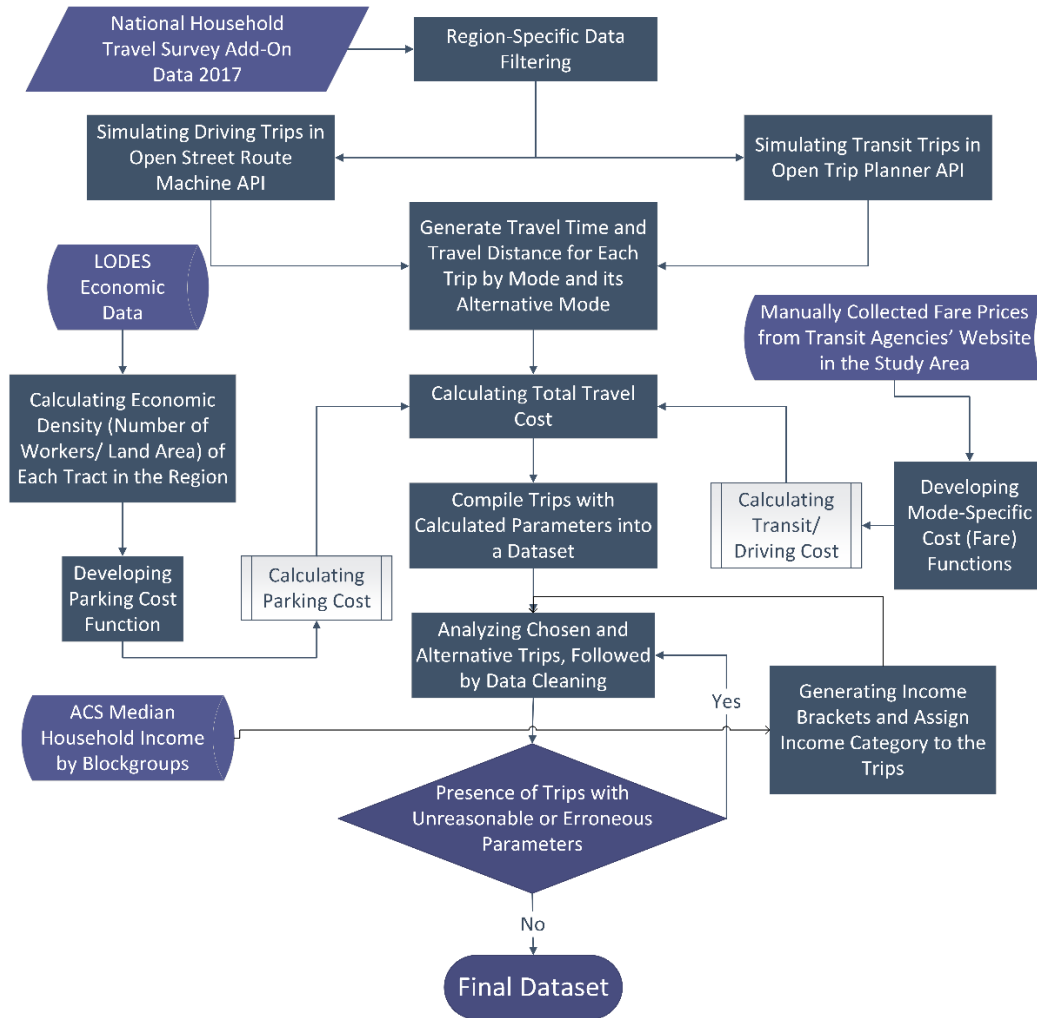
Figure 2: Framework Used to Prepare the Survey Data for Model Calibration

2.5.2 In-Vehicle Travel Time and Out-of-Vehicle Travel Time

Driving trips, including the unchosen driving alternatives for chosen transit trips, were simulated in Open Street Routing Machine (OSRM), which is an API built upon the open-source database of OpenStreetMap (OSM) [42]. It provided unimpeded IVTT travel time, travel distance, and routes between the OD pair. The unimpeded IVTT travel time was further adjusted using the Texas Transportation Institute Congestion Indices [43] to consider the impact of congestion. Travel time index (TTI) is a comparison between the travel conditions in the peak period to free-flow conditions [44]. The Congestion Indices are published by urban areas, where for example, the congestion factor

for the San Francisco-Oakland area is 1.41, and San Jose is 1.38. For the driving alternative OVTT, a constant 3-min OVTT was assumed.

Transit trips, including the unchosen transit alternates for chosen driving trips, were simulated in the Open Trip Planner (OTP) server. It is based upon a transit network built using General Transit Feeds Specifications (GTFS) from 52 transit agencies across the study area. The distribution of walking access distance was generated from the simulation output of the chosen transit trips in the NHTS data, and the 95th percentile of the distribution was selected as the reasonable walking distance to access the transit stations. Separate thresholds were estimated for heavy transit systems (commuter rail, subway) and light transit systems (bus, tram) as it is believed that people travel farther to access heavier modes [45]. The park-and-ride option was simulated for trips with the nearest heavy-rail mode station further than the reasonable walking distance. Transit alternatives involving more than three transfers or with a walking distance more than the reasonable walking distance for transit trips were considered infeasible and therefore discarded. The OTP simulation output included the travel time, distance, and travel mode for every segment of the trip. IVTT was then calculated by adding the time inside the transit vehicles or auto (in case of auto access trips). OVTT was calculated by adding time walking to the station, waiting at the station, walking between stations, and walking to the destination from the station.

2.5.3   Travel Cost

The driving cost was calculated using the AAA cost per mile [46] for a Sedan with an annual mileage of 15,000 miles, which was $0.60 per mile. For parking, costs vary drastically inside the central business districts and throughout the study area. Therefore, a constant parking cost was not suitable for all driving trips. Since no public datasets for parking costs were available, we developed a method to estimate the parking costs in the study area. After analyzing the parking rates provided by BestParking by Parkwhiz [23] for different urban regions inside the study area, we defined a relationship between economic activity and parking fares. The number of workers per square mile was extracted from the LODES-2015 data at the census tract level to quantify economic activity. Monthly parking rates were manually collected at the census tract level, and a function was generated to calculate the parking cost given the worker density of the census tract. Parking costs for the driving trips were calculated according to the work location's census tract.

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For transit, costs provided by the OTP API were often incomplete and used single-trip fares. For this study, it was assumed that transit commuters purchase monthly passes[1] for transit trips if offered by the agency; otherwise, a distance-based cost function was used. We developed transit cost functions for all major modes based on the region's transit costs for subway, commuter rail, bus, light rail, ferry, and cable car. We manually collected the transit fares for representative agencies in every transit sub-mode and generated a distance-based cost function using linear regression (see Table 3). Since the OTP API output has detailed information about the distance traveled in every segment of the trip, the transit cost is cumulative of costs incurred during every segment of the trip using the cost functions developed. For Park-and-Ride transit trips, a parking cost is added, which is half of the corresponding driving parking cost in the census tract of the origin transit station because parking at transit station is often subsidized to promote public transit use.

Table 3: Transit Cost Functions

Transit Sub-Mode	Fixed Cost ($)	Per-Mile Cost ($)
Commuter Rail	1.60	0.079
Subway	3.10	0.086
Bus	1.823	0.158
Light Rail (Tram)[1]	1.823	0.158
Ferry	6.0	-
Cable Car	2	-

[1]Light Rail and Bus services are usually provided by the same agency and follow a similar fare structure.

2.5.4   Income Categories

Besides attributes of the mode, the mode-choice is also influenced by the individual's characteristics, such as their Value Of Time (VOT). In transportation, the value of time for commuting is often estimated for different income levels as it is assumed that high-income individuals have a higher value of VOT than low-income individuals [47]. Due to the lack of records in the NHTS data, full segmentation, i.e., separate models for different income categories, was not feasible. Therefore, a partial segmentation (i.e., including variables interacting cost with income bins) was employed to account for the impact of income on an individual's mode choice. The model included three income

[1] Transit agencies monthly passes costs were either fixed or distance-based on origin-destination zones.

categories, *Low-Income, Mid-Income,* and *High-Income*. The brackets were estimated using the 30th percentile ($45,000) and the 90th percentile ($152,000) of the household income distribution in the region [48]. Since the LODES data lacked income information, the home block-group's median household income was used as an indicator. This information was extracted from the 2017 ACS 5-year estimates[2]. The block-group level was the finest resolution at which median household income is reported. Figure 3 shows the income distribution in the study area based on the categories employed in the analysis.
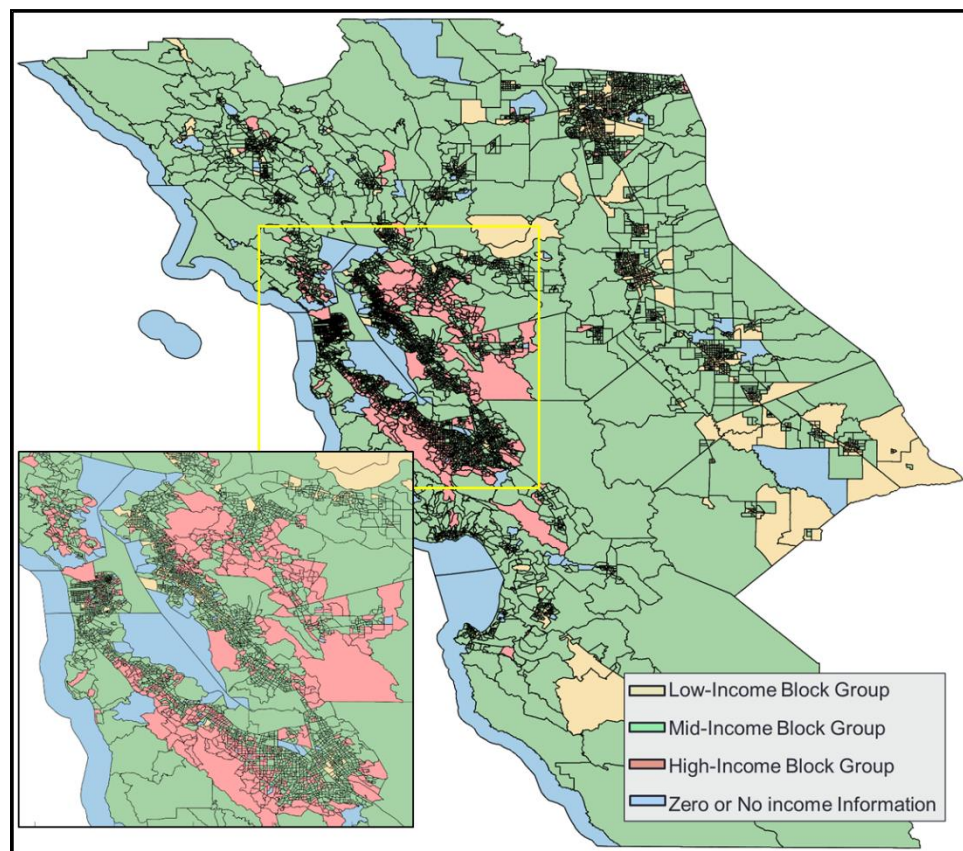
Figure 3: Income Distribution using Income Categories in the Study Area

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[2] Table B19013: Median household income in the past 12 months (in 2017 inflation-adjusted dollars)

2.5.5   Model Application

The calculation of UAM demand was an integrated process that worked in conjunction with the placement of vertiports. We developed an algorithm that used the calibrated mode choice model to place the vertiport in a way to maximize UAM demand for a given number of vertiports in the region. This model application used LODES-2015 data at the block-group level to estimate the number of commuting trips. The home block-group was the origin, and the work block-group was the destination for the home-to-work trip and vice-versa for the work-to-home trip. The commutes were then simulated to gather the trip characteristics needed to apply the mode choice model. The driving trips were simulated using the OSRM API, and transit trips were simulated using the OTP API. The UAM alternative was added to the mode choice set by considering both accessing the vertiport and the UAM trip itself. The access part of the trip was assumed to be completed by walking if the vertiport was within reasonable walking distance from the location. Walking time was estimated assuming an average walking speed of 3.1 mph; otherwise, the trip was simulated in OSRM API with taxi/cab characteristics. Similar assumptions were made for traveling from the destination vertiport to the final destination. In addition, the ingress and egress times were assumed to represent the out-of-vehicle time spent at the vertiport (ticketing, boarding, and alighting the UAM vehicle). The UAM part of the trip was simulated on the designated path, which was designed to avoid protected commercial airspace keeping a minimum distance between OD. Figure 4 shows an example of a UAM OD route avoiding approach and departure surfaces of precision runways at commercial airports in the Bay Area. Therefore, the total UAM trip travel time consisted of the following five parts; walking or taxi time to get to vertiport from origin location, ingress time (five-minutes), UAM flight time, egress time (five-minutes), and walking or taxi time to get to the final destination. Table 4 outlines the assumptions made for the UAM alternative.
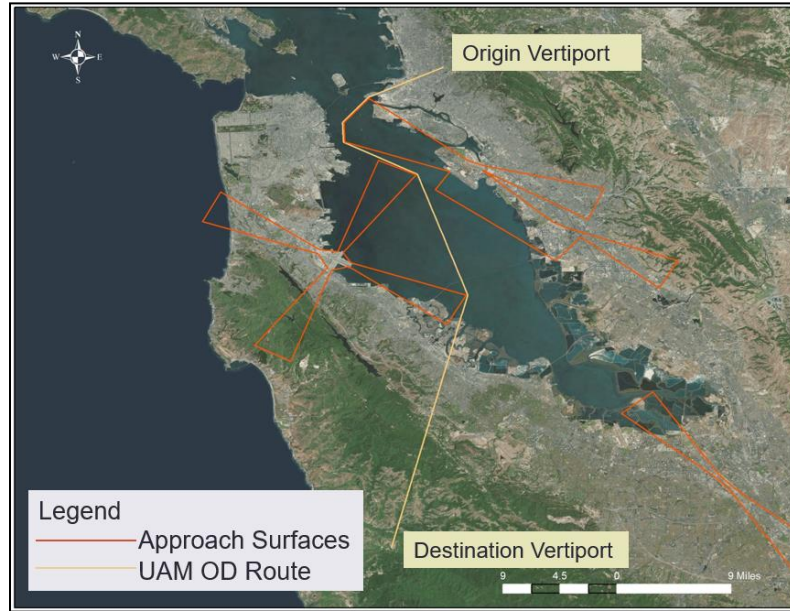
Figure 4: Example of a UAM OD Route Avoiding Approach and Departure Surfaces of Precision Runways at Commercial Airports

Table 4: Assumed Parameters for UAM Trip Calculations

Parameter		Value
Walkable Distance To/From Vertiport		0.40 mi
Ingress[1] 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
Taxi/Cab Fare Structure ($)	Base Fare	2.20
	Per Minute	0.42
	Per Mile	1.60
	Service Fee	1.70
	Minimum Fare	7.20

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

The probability of each available mode was calculated for every origin-destination (OD) pair in the LODES data. There were 4.63 million daily commuters inside the study area sharing 2.3 million OD pairs. Applying the mode choice probability and the total number of trips between the OD pair, the

mode-specific demand was calculated. The total UAM demand was calculated by combining the UAM demand for all OD pairs.

The UAM demand analysis required the number of vertiports and UAM CPM value as inputs. For this study's purposes, vertiports are assumed to be open to operation 24 hours a day, 7 days a week. The framework for vertiport placement is shown in Figure 5. The process started with the highest resolution, i.e., placing a vertiport at each block-group centroid in the region. Every blockgroup has a vertiport assigned to it (closest to the blockgroup centroid). In each iteration, the mode choice model was used to calculate the UAM demand at each vertiport. At the end of the iteration, the vertiports set was sorted by descending UAM demand, and only the vertiports in the upper half of the set were retained. The location of some of the retained vertiports was modified to accommodate for the demand generated from blockgroups that lost their assigned vertiport in the last iteration. The iterations were stopped when the number of vertiports reached the desired number of vertiports. After the final iteration, vertiports in high-demand areas are generally found at blockgroup centroids, whereas vertiports in low-demand areas are generally found at the demand weighted mean of multiple blockgroup centroids. For this study's purposes, it is assumed that these final vertiports have the number of parking stalls and landing pads needed to serve all demand (i.e., the demand does not exceed the capacity). The sizing of vertiports is outside the scope of this study.
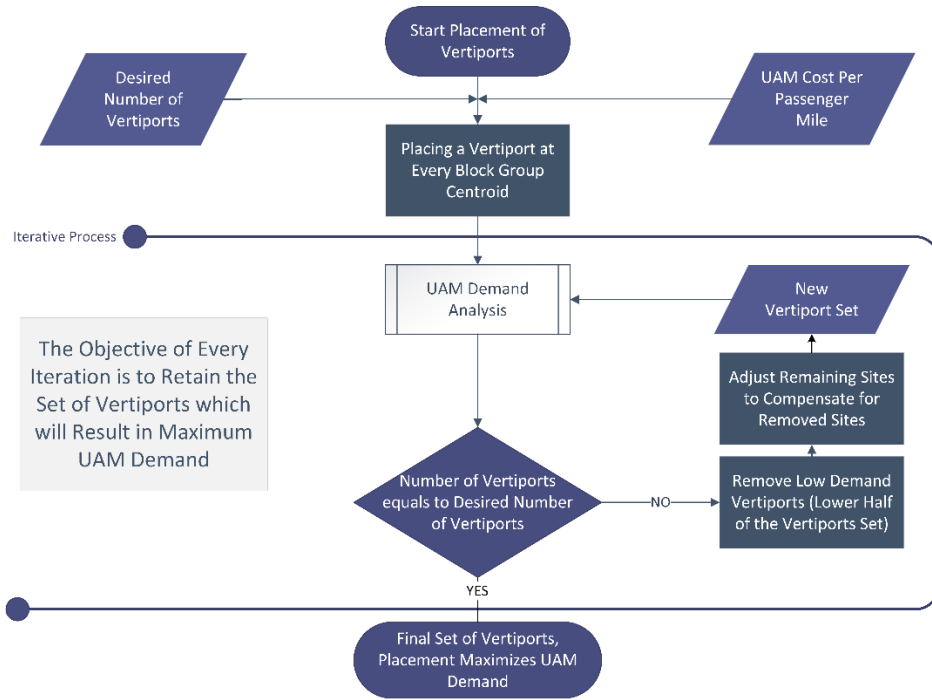
Figure 5: Placement of Vertiports Workflow

2.6   **Calibrated Mode Choice Model Results**

The selection of variables in the model was influenced by both prediction power and data capabilities. For data capabilities, variables that were in the NHTS mode-choice data but not in the LODES application data could not be included in the calibrated mode choice model. Table 5 includes the variables which resulted in the best fit for the calibrated model. In the final model, the income and cost variables interacted in order to allow for income to be incorporated as income by itself is an alternative-specific variable. The income interacted cost variables were then randomized to account for heterogeneity in the data. The negative sign of the income interacted cost variables is required for reasonable UAM demand estimation. If the mode choice analysis is performed with a positive coefficient for travel cost, an unreasonably high probability is observed for the UAM mode in mid to long-distance trips. The lognormal distribution was selected to avoid such infeasible demand estimates. The unavailability of variables related to traveler's characteristics in application data restricted us from capturing heterogeneity due to traveler's characteristics in the model. The number of steps for simulation in both model calibration and demand estimation was kept at 100 because there was a negligible improvement in model fit above 100.

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Table 5: Model Variable Definitions

Variable	Definition	Unit
IVTT	In-vehicle travel time: time spent in a motorized vehicle, such as auto, subway train, or UAM aircraft	Minutes
OVTT	Out-of-vehicle travel time: time spent out of a motorized vehicle, such as walking or waiting	Minutes
Cost	Monetary cost: includes costs such as transit fares, fuel costs, parking costs, etc.	$
Transfers	Number of transit-to-transit transfers on the route. Driving-to-transit or transit-to-driving do not count as transfers.	Transfers
Low Income	Income less than 30th percentile for the region (<$45,000)	Binary
Medium Income	Income between 30th and 90th percentiles for the region ($45,000-$152,000)	Binary
High Income	Income greater than 90th percentile for the region (>$152,000)	Binary

Table 6 presents the coefficients for the mixed conditional logit mode choice model for Northern California. The model is statistically significant because the p-value is less than 0.000. The model includes both IVTT and OVTT coefficients, the number of transfers required for the trip, and interactions between the trip cost and the traveler's household income. Validation of mode-share by distance is included in the Appendix.

Table 6: Mode Choice Logit Model

Variable	Coefficient	Standard Error	z	P>|z|	95% Conf. Interval
Mean					
IVTT	-0. 0517868	0.0000147	-1823.47	0.000	[-0.0518, -0.0517]
OVTT	-0. 0901427	0.0000129	-3529.78	0.000	[-0.0902, -0.0901]
Transfers	0. 3857525	0.000195	-4606.01	0.000	[0.3853, 0.3861]
Ln(-Low Income X Cost)	-1.059794	0.000201	1977.81	0.000	[-1.0601, -1.0593]
Ln(-Medium Income X Cost)	-1.214655	0.0001078	-5252.23	0.000	[-1.2148, -1.2144]
Ln(-High Income X Cost)	-1.689608	0.0004159	-1.1000	0.000	[-1.6904, -1.6887]
Transit Constant	-0.6572835	0.0003605	-4062.82	0.000	[-0.6579, -0.6565]
Standard Deviation					
Lognormal Std. Dev. (-Low Income X Cost)	0.0014603	0.0004115	3.55	0.000	[0.0006, 0.0022]
Lognormal Std. Dev. (-Medium Income X Cost)	0.3733613	0.0001538	2426.96	0.000	[0.3730, 0.3736]
Lognormal Std. Dev. (-High Income X Cost)	1.119758	0.0006354	1762.43	0.000	[1.1185, 1.1210]
Median IVTT VOT (per hr.)	$8.97, $10.47, $16.83				

Median OVTT VOT (per hr.)	$15.7, $18.22, $29.30
Number of estimated parameters	10
Log-likelihood$_{Initial}$	-2.42×10^8
Final Log-likelihood$_{Final}$	-2.3×10^8
Likelihood chi-square test statistic (Degree of Freedom:3)	6349661.4
Number of observations	10,012
Prob>χ^2	0.0000

Since UAM was not available in Northern California during the 2017 NHTS data collection, there was no revealed-preference data for the mode. This means that the UAM mode constant could not be estimated on the NHTS data. Instead, the UAM constant needed to be computed based on a stated-preference survey that captures the population's willingness-to-pay for the UAM mode. There are several UAM stated-preference surveys in literature, including [49] (used in this study) and [50].

To create our mode choice model, we first calibrated a mixed logit model using a lognormally distributed sampling of the income interacted cost variable. The distribution was bounded by the 5th and 95th percentile. This revealed-preference (RP) model had a transit constant with drive alone as a reference alternative, as shown in Equation 5. This model did not include a UAM constant as this mode is not an existing commuting alternative. V$_{RP}$ is the estimated utility for the ith commuter to take mode alternative j.

$$V_{RP_{ij}} = \beta_1 X_{ij} + \beta_2 X_{ij} + \cdots + \beta_n X_{ij} + \varepsilon_{RP\_Transit} \qquad (5)$$

Next, to transfer the constants, Dr. Garrow's research group calibrated a model on stated-preference (SP) survey data [49] using the same model methodology, sampling distribution type, and variables as the RP model. The exact SP model we requested from Dr. Garrow's research group (variables and estimation method) is not in the thesis [49]. It is important to note that the RP model was estimated only on Northern California travel behavior. The SP surveys were distributed across five U.S. cities. The Northern California income breaks would not be the same for the five regions, given the cost-of-living differences. Therefore, the SP model includes a continuous income variable. As shown in Equation 6, this model included the constants of transit and drive alone, with UAM as the reference alternative.

$$V_{SP_{ij}} = \beta_1 X_{ij} + \beta_2 X_{ij} + \cdots + \beta_n X_{ij} + \varepsilon_{SP\_Transit} + \varepsilon_{SP\_DriveAlone} \qquad (6)$$

The probabilities calculated from mixed logit models are driven by the differences in utilities between the available modes. Therefore, it was important to preserve the differences in constants from the SP model when creating the UAM constant in the RP model. Due to scalability between models, the differences between the SP constants were transferred by translating to an equivalent in-vehicle travel time utility. This followed the constants transferability method proposed by Cherchi et al. [51]. This made UAM is the new reference alternative in the RP model. Unfortunately, due to IRB restrictions, we were unable to calibrate an RP-SP pooled model, which could provide us the scaling parameter. Therefore, we resorted to the method presented in Chen and Naylor [52] where authors estimated the Bus Rapid Transit (BRT) constant for an RP-based model using the constants from an SP-based market research model. The constant coefficients are converted into bias time constants by dividing the constant-coefficient by the in-vehicle time coefficient.

$$b_m = \frac{c_m}{c_{\text{ivtt}}} \qquad (7)$$

Where b_m is bias time constant for mode m; c_m is constant-coefficient for mode m and c_{ivtt} is the in-vehicle travel time coefficient in the SP model. The bias time constants derived from the SP model were used in the estimation of UAM constants for the RP model. The UAM constant was calculated by a linear interpolation method using the auto constants, transit constants, and bias time constants estimated.

$$\Delta_{UAM} = \Delta_{PT} + (\Delta_{Auto} - \Delta_{PT})\left(\frac{b_{UAM} - b_{PT}}{b_{Auto} - b_{PT}}\right) \qquad (8)$$

Where Δ_{UAM} is UAM constant, Δ_{PT} is public transit constant, Δ_{Auto} is auto constant in the RP model; b_{UAM} is UAM bias time constant, b_{PT} is public transit bias time constant, and b_{Auto} is auto bias time constant. Δ_{UAM} was estimated to be 0.020569.

In this study, the SP data was not accessible for this study, so additional comparisons and statistical tests between the SP data and RP data could not be performed, such as in Washington et al.

[53]. Therefore, while this study's methodology for transferring constants from an SP survey to RP application aligned with the literature, this study was limited in the detailed comparison of the underlying data of the models.

2.7   **Demand Model Application Results**

The calibrated mode choice model, including the calculated UAM constant, was applied to Northern California commuting trips. Figure 6 outlines the sensitivity of demand with respect to the CPM offered by the UAM operating agency, assuming a constant 75 vertiports in the region. At a $1 CPM, there is a 42,140 UAM round trip demand per day, where increasing the CPM by just 20 cents reduces the demand by 34%. The sensitivity analysis results provide supportive evidence that a low CPM value is required for the system's success. The reduction in demand for higher CPMs reduces the revenue significantly and prevents the mode from covering fixed costs such as vertiport land and maintenance costs.
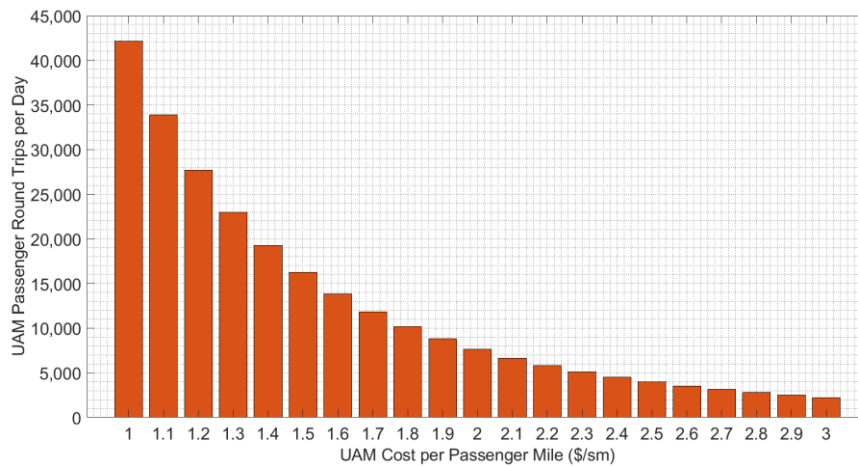
Figure 6: Daily UAM Demand Sensitivity to CPM (75 Vertiports)

Figure 7 illustrates the sensitivity of demand when the number of vertiports is changed, keeping the CPM at a constant $1.80. The vertiports for each scenario (e.g., 50, 75, 100 vertiports) are placed to maximize the UAM demand for a given number of vertiports in an iterative manner. To clarify, the vertiports location in the 50-vertiport set is not necessarily a subset of a larger vertiport set. As the number of vertiports increase, there is a direct relationship with the number of commuters in the

catchment area, which increases the demand for the mode. It is evident that there are core vertiports that serve the majority of the demand and feeder vertiports that provide UAM service in lowered demand areas. Comparing the 50 vertiport and 400 vertiport scenarios shows that reducing the number of vertiports by 87.5% reduces the demand by 47%. This concentration of demand at a small portion of the vertiports is similar to the current airport system in the United States with hub airports and regional airports. However, at a closer look, it becomes evident that a large number of vertiports is not economically viable for Northern California at a $1.80 CPM. For the 400 vertiport scenario, 196 of the vertiports have a demand of fewer than 50 UAM operations[3] per day.
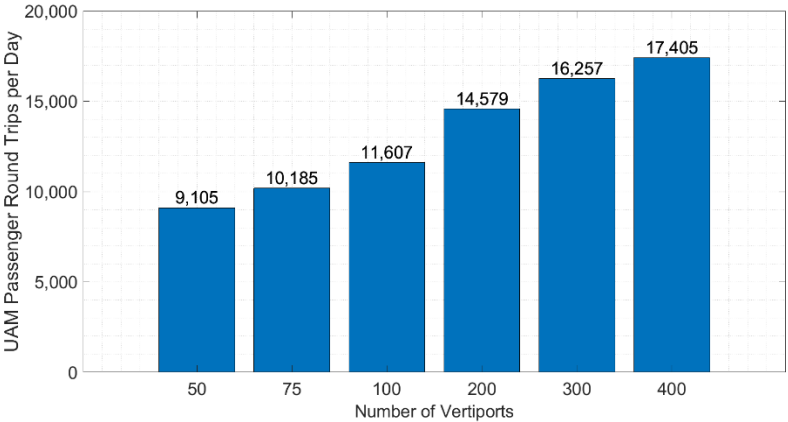
Figure 7: Daily UAM Demand Sensitivity to Number of Vertiports ($1.80 CPM)

The following sections analyze UAM demand further by evaluating two scenarios: 1) A high demand scenario with a large number of vertiports and low CPM (200 vertiports at $1.20) and 2) A low demand scenario with a small number of vertiports and high CPM (75 vertiports at $1.80). These two scenarios are used to provide a sensitivity analysis of demand and do not necessarily estimate the upper and lower bounds for demand in the region as it is possible that the UAM system, if built, would have to exceed a $1.80 CPM to recover costs. In both scenarios, vertiports are placed in an iterative manner, explained in Section 4.2.

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[3] UAM operation means a landing or a take-off. UAM operations are estimated from UAM passenger trips assuming 60% load factor or 2.4 passengers per flight.

2.7.1 High Demand Scenario (200 vertiports, $1.20 CPM)

To generate the high demand scenario, a 200 vertiport system offering trips at $1.20 CPM was estimated. Figure 8 shows the vertiport placement that maximizes the person-trip demand for this scenario in an iterative manner. It is shown that the areas with a higher concentration of vertiports have both a high worker density, high population density, and a high median income. An example of this is the Central Business District (CBD) of San Francisco, shown in Figure 8's inset. There are around 514,000 employees in San Francisco CBD and 196,000 people who live there (87,000 of which are employed inside CBD) [54]. Due to such a high concentration of work locations and households in CBD, the high demand vertiports are nearby.

The busiest vertiport is estimated to have 5,740 UAM operations per day. The Financial District is a big attractor of UAM trips because of the work location density and heavy disutility in driving due to parking rates and congestion. Unfortunately, the departure time information for application data was missing. To reflect the true nature of commuting trips, commuters' departure time distribution was extracted from NHTS data. Using that cumulative density function, the total person-trips between each OD pair were distributed over the day. Of that 5,740 UAM operations, 61% are expected to occur during the core commuting hours, between 6 AM - 9 AM and 4 PM – 7 PM.

There are more than ten vertiports placed with significantly high demand in the San Francisco CBD using the demand-driven approach. In the future, if the system increases to higher demand levels, it could be challenging to manage the peak-hour demand as it is concentrated in a small area from the perspective of airspace service providers. Moreover, results suggest that demand is very one-directional, where morning peak hour trips are into the city centers such as the San Francisco CBD, Mountain View, Cupertino, and the San Jose CBD, and the afternoon peak hour trips leave these city centers. This suggests that the commuter UAM system will require a large proportion of deadheading, where the aircraft will fly at times with a zero load factor. From Figure 3, the high-income areas can be observed around the bay and areas North-West of Oakland. It is evident that most of the feeder vertiports are placed in these areas, thereby reinforcing the influence of high-income earners on vertiport location when vertiports are placed for maximum UAM demand in an iterative manner.
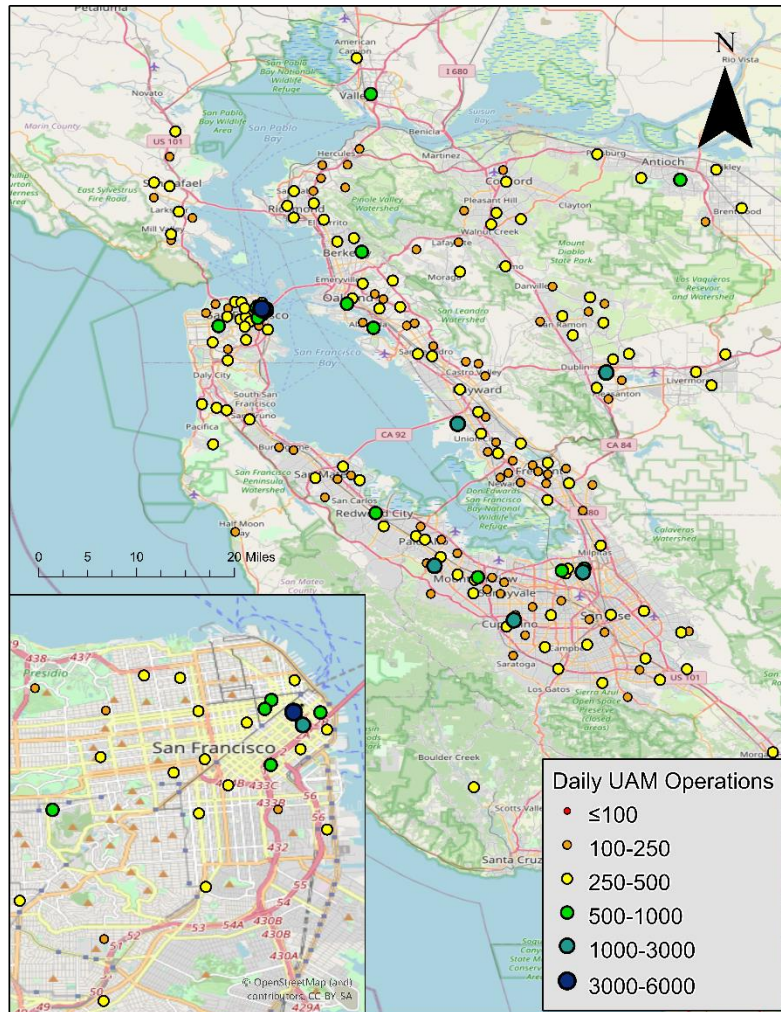
Figure 8: High Demand Scenario Vertiport Placement and Demand

Our analysis assumes a 5-minute ingress and 5-minute egress time of the UAM vehicle as well as a 0-minute delay waiting for the UAM vehicle to arrive. Figure 9 shows that UAM commuting demand is highly sensitive to any delay in the system, where the demand is cut in half by adding 10 minutes of delay. This inability for the system to take delay provides supportive evidence that for commuting purposes, the UAM system will either need to: 1) have low load factors as there is little time to group people up with the same OD pair or 2) rely on advanced trip bookings to group passengers resulting in a scheduled departure time that ideally would not be delayed.

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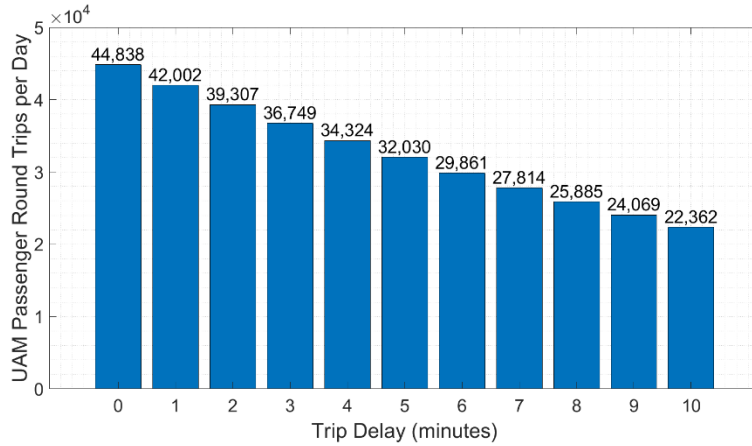
Figure 9: Sensitivity of UAM Demand with person wait time

2.7.2 Low Demand Scenario (75 vertiports, $1.80 CPM)

UAM is expected to be a costly mode and, therefore, will cater more towards higher-income households. Results indicate that the market share of high-income households will increase as the CPM increases. Specifically, in this low demand scenario, the market share of low-, mid-, and high-income households is 3%, 26%, and 71%, respectively. This is in comparison with the previous high demand scenario, where the low-, mid-, and high-income market shares were 2%, 39%, and 53%. Figure 10 shows that when the CPM is increased, and the number of vertiports are reduced, the surviving vertiports are located in dense employment areas or household areas with a higher than average income level. The feeder vertiports are cut due to low demand. Also, the largest vertiport in this scenario has 1,702 UAM operations, compared to the 5,740 UAM operations from the largest vertiport in the high-demand scenario.
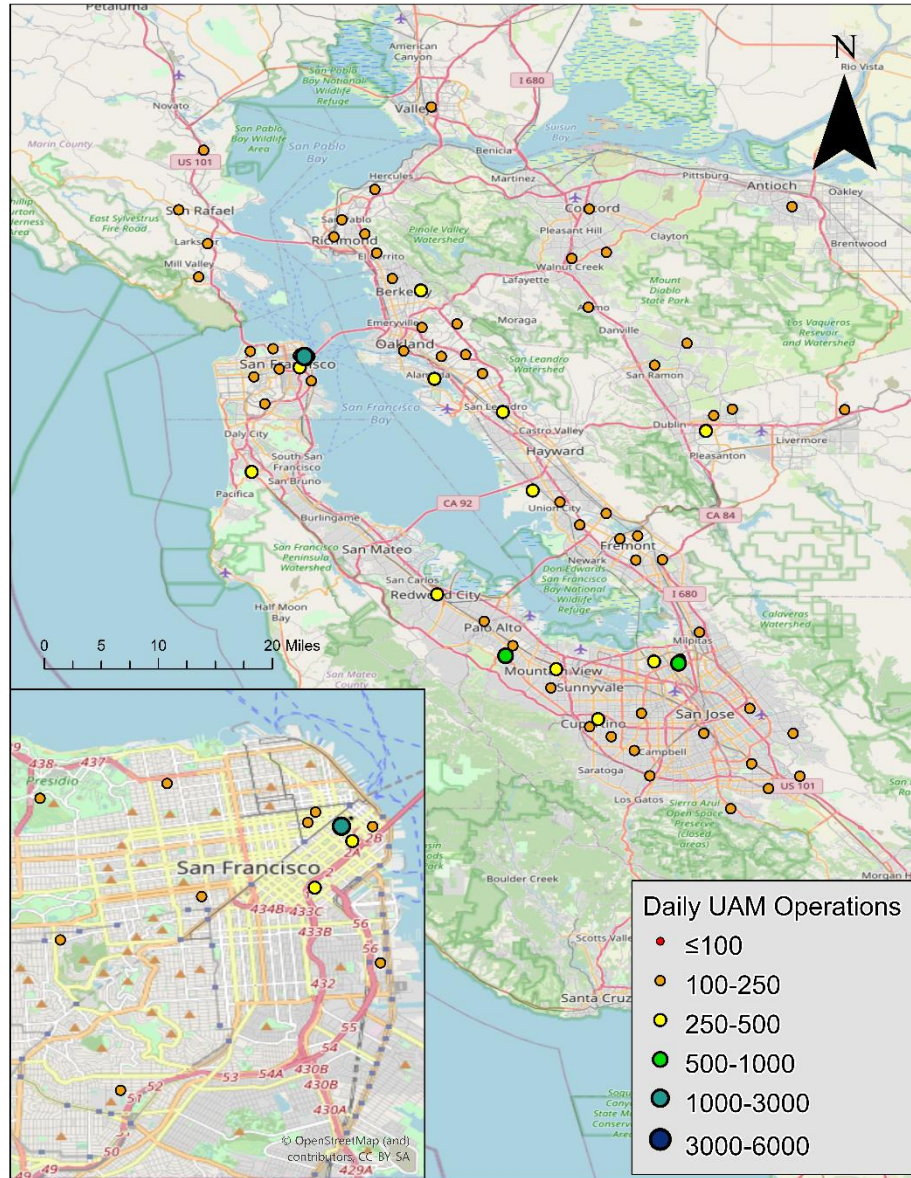
Figure 10: Low Demand Scenario Vertiport Placement and Demand

Figure 11 shows that the percent reduction per minute of added delay is similar to that of the high demand scenario, where 10 minutes of delay reduces the demand by half. This is especially problematic in this low-demand scenario, as with 10 minutes of delay, the system would have to rely heavily on other trip purposes to cover the system costs as it is estimated there is only a 4,569 commuting roundtrip demand total for the Northern California region.
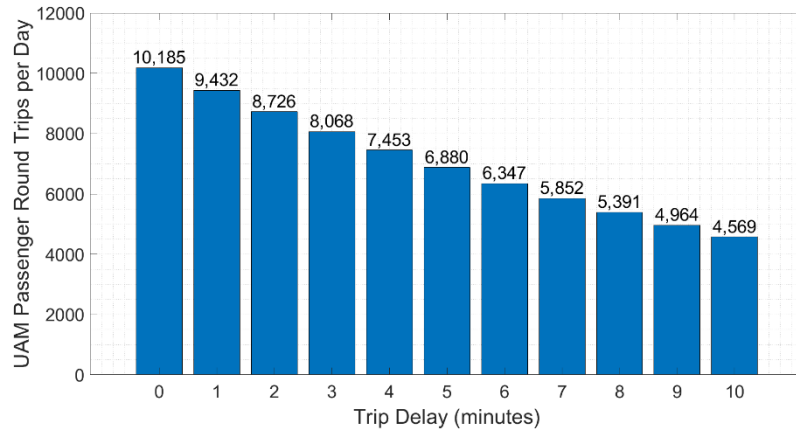
Figure 11: Sensitivity of UAM Demand with person wait time

2.8   **Conclusions and Policy Implications**

This study provided a sensitivity analysis of UAM demand in Northern California solely for commuting purposes. It considered the mode alternatives of UAM, drive alone, and transit. Findings include that, first, the UAM mode's success is hugely dependent on the mode's popularity with travelers in the high-income market segment. Therefore, it is essential for UAM to be a competitive mode for these travelers and to increase their level of trust and comfort in the system.

Also, the success of UAM is dependent on the operational efficiency of the system. Even without accounting for deadheading and higher fares levels due to vertiport costs, the demand is small, and it will be difficult for the system to be profitable on commuting trips alone. It seems this system has to be "errorless" for commuting purpose. The system's efficiency is a top priority as every very minute of additional wait time greatly impacts the mode's demand. The UAM system must have policies that lead to a minimum delay, or else the driving alternative quickly becomes a more attractive mode for commuters.

The construction and operation of a future UAM system will be complex and require intricate long-term planning. Based on our findings, several policies will be needed to promote the system's success and economic feasibility. Many of these policies are implemented in some form for other transportation systems (e.g., aviation or driving), so the lessons learned in their implementations will be of use to the UAM system.

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First, similar to road transportation, UAM commuting demand had morning and afternoon peak hours and is very concentrated in short time periods. Unless other trip purposes can make the UAM demand more uniform throughout the day, operators of the UAM system will need to implement some form of congestion pricing. Otherwise, the system's infrastructure will be overbuilt to serve the peak hours while being mostly empty the majority of the day. There is flexibility in how this congestion pricing would be implemented as the ticket purchase process is unknown at this time.

Second, as stated in the results, not only will UAM have peak hours for commuting, but also each peak hour will be very unidirectional, requiring a significant amount of deadheading. While UAM will be fully electric, policies to reduce energy consumption due to deadheading may need to be implemented. Deadheading is seen in ride-hailing services today, and the effects have been analyzed for environmental impacts. For example, due to increased carbon emissions of ride-hailing, California has proposed regulations on the industry [55].

Lastly, vertiports with the highest demand are located in downtown areas with limited land available. These two conflicting trends will require similar policies as expanding airports in downtown regions today (land acquisition, noise complaints, etc.). Vertiport constraints are different from airports (e.g., can build on the roof), but the general ideas are the same. Currently, the UAM system is described as being run and operated by a private company (e.g., UberElevate), but this land issue shows the large roles that the government will most likely have in the initial setup of the system. Policies similar to that of expanding airports in downtown regions may need to be considered in building the UAM system.

2.9   Study Limitations and Future Research

The findings presented in this paper are for scenarios that do not include the impacts of weather conditions on demand and operations, vertiport or airspace capacity issues, additional wait time for deadheading flight to arrive, and reliability issues of UAM. This study assumed ideal conditions in each of these areas. However, adding these factors to the analysis would improve the accuracy of the demand estimation. It is recommended for future region-specific UAM demand models, like the one presented in this paper, to include UAM system capacity as well as customer perception of the UAM system's reliability, safety [56], and trip experience. Important trip experience factors found in the

literature, for example, include "familiarity, value, fun factor, wariness of new technology, fear and happiness" [57].

Limited variables could be used in model calibration due to a lack of individual-level information in the application data (LODES). The model application could improve by including variables such as 'number of household vehicle' and 'household size,' which would improve the model's estimation of how travelers access the UAM system. This analysis assumed that the commuter would always choose the closest vertiport to the home/workplace and would either walk (if the distance is less than the walking threshold) or take a taxi to the vertiport. In future research, these assumptions could be relaxed by instilling some probabilistic behavior in vertiport selection and considering more ways to reach vertiport such as drop-off and parking if available.

Similarly, there are multiple routes one can choose from when commuting. The data collected through the OSRM API assumed that commuters take the fastest route available and would travel non-stop to their home or workplace, removing the effects of trip-chaining on UAM demand. This is a limitation that needs to be addressed in the future.

Estimating travel costs for transit connections depended on the transit agencies that involved both distance-based fare structures and flat-rate monthly passes. The flat-rate bias could impact the calibrated model, i.e., increased preference for the service offering flat-rate (monthly passes) instead of pay-per-use. Flat-rate travel cost functions could have caused bias in the public transit coefficient [58]. Although not addressed in this study, flat-rate bias should be considered in future research.

While our study included the effects of Willingness-To-Pay (WTP) with respect to travel time on mode choice, the literature suggests that the value of travel time reliability (VOR) is also a significant factor. When unaccounted for, VOR can impact WTP values [59]. Our study used deterministic travel times and, therefore, the WTP values were constrained to be negative. Future studies using stochastic travel times should consider the effects of VOR separately from WTP for travel time savings on mode choice.

Another limitation of the study is the inability to account for dynamic delays that occur in all modes. It used a congestion factor to account for road delays but considered the dynamic nature of congestion could certainly improve driving time estimation for driving trips and the intermodal

connection of UAM trips. Similarly, delays due to UAM charging should also be added to future simulations when this information becomes known about the new technology.

Lastly, future studies should consider additional trip purposes, including personal trips. This would give additional demand to the system without expanding the UAM system infrastructure by increasing trips to the non-peak hours. Adding these trips would provide more justification for the UAM system.

2.10 **Acknowledgments**

2.11 **References**

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2.12 Appendix: Model Validation
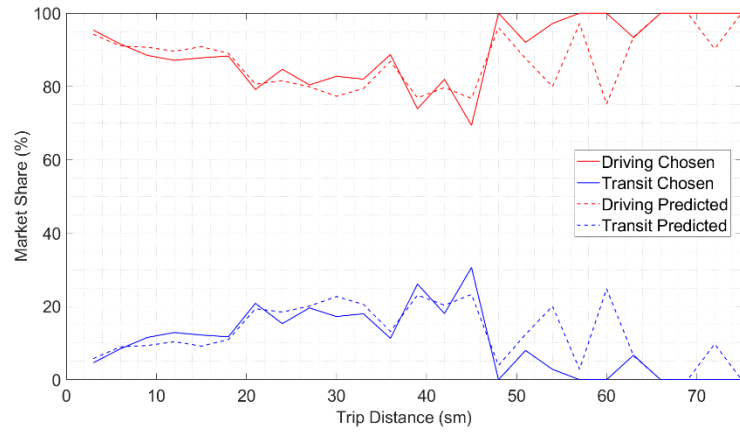
Figure 12: Market Share by Distance
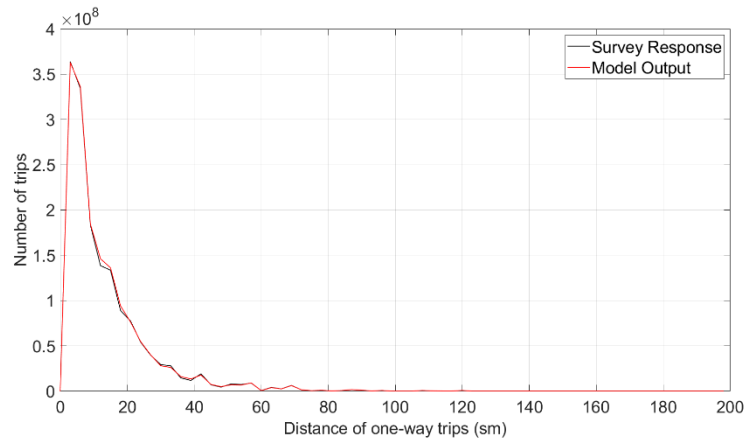
Figure 13: Comparison of Survey Responses and Model Predictions for Driving rips
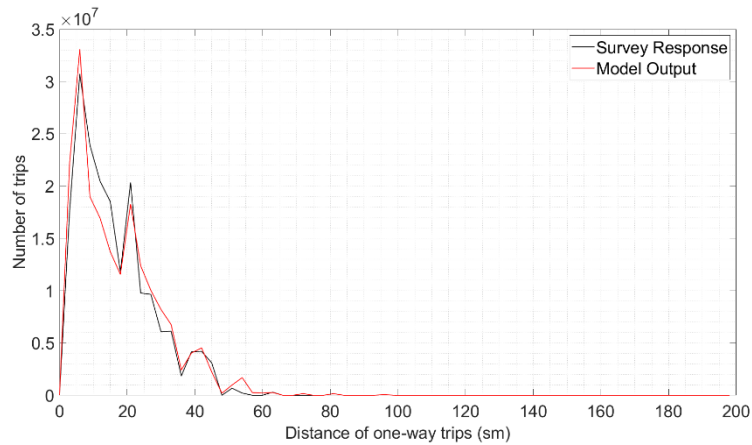
Figure 14: Comparison of Survey Responses and Model Output for Transit Trips

3.   Airport Ground Access Demand Estimation for Urban Air Mobility (Dallas-Fort Worth)

3.1   **Abstract**

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).

3.2   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) 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.

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3.3   **Background**

Analyzing different trip purposes for their UAM potential is critical to tailor the concept development and infrastructure investment. A study by 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.

3.4   **Study Area**

Figure 15 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].
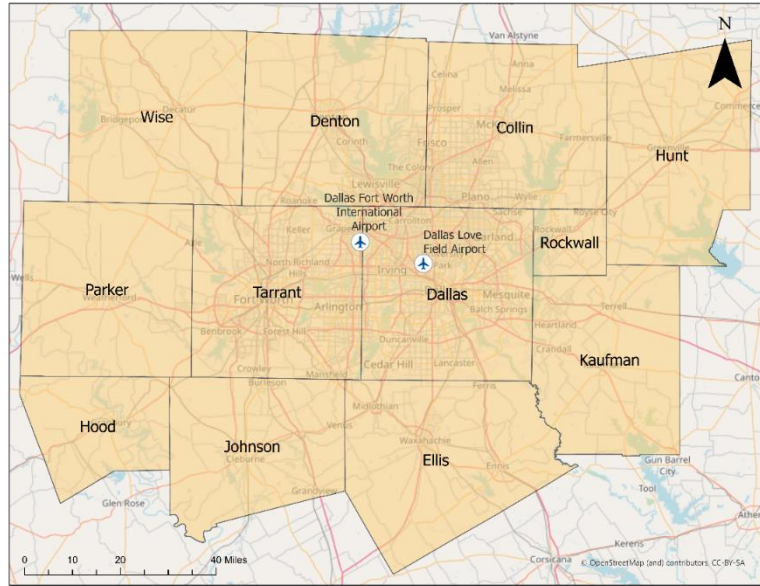
Figure 15: Dallas-Fort Worth Study Area

3.5   **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 7 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 7: 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%

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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. Figure 16 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. Visitor's 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.
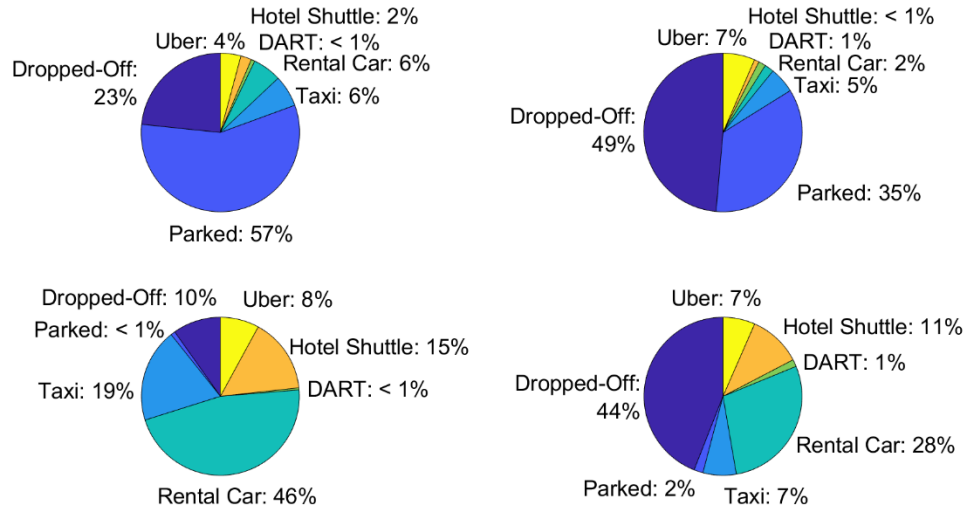
Figure 16: Observed Mode Share in Survey Data. Top Left: Resident Business, Top Right: Resident Non-Business, Bottom Left: Visitor Business, Bottom Right: Visitor Non-Business.

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. 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. Figure 17shows 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.
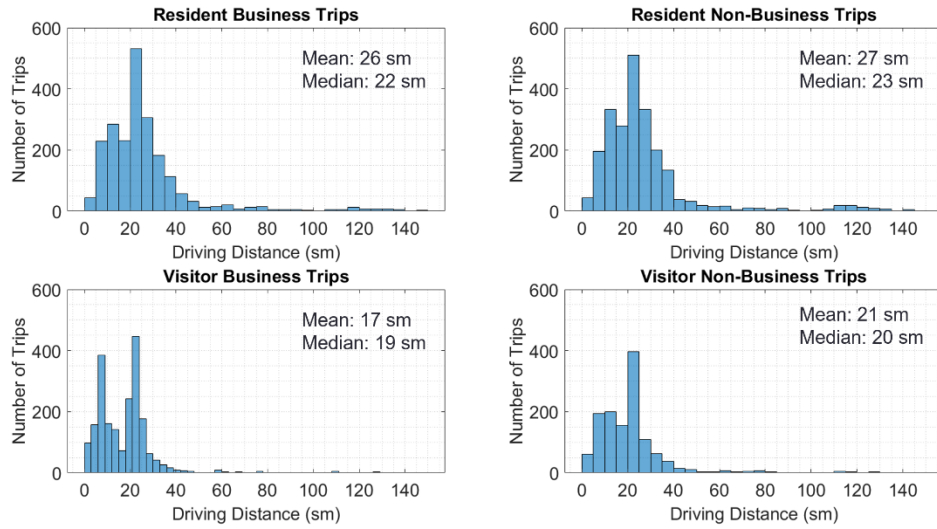
Figure 17: Distribution of Driving Distance of Airport Access Trips for Originating Passengers

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.

Figure 18 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.
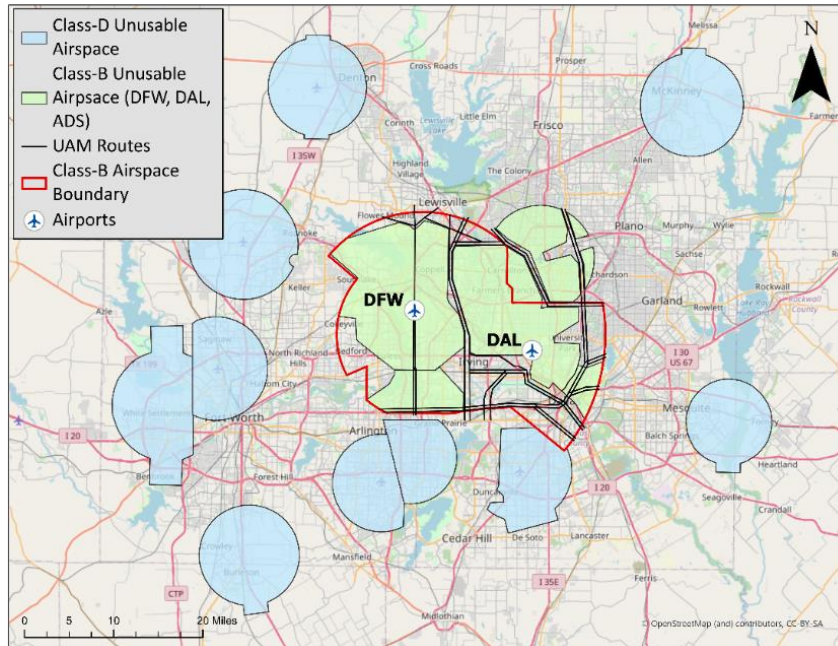
Figure 18: Unusable Airspaces and Routes Developed by NASA to Navigate UAM inside Class-B Airspace

3.6   **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. Figure 19 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.
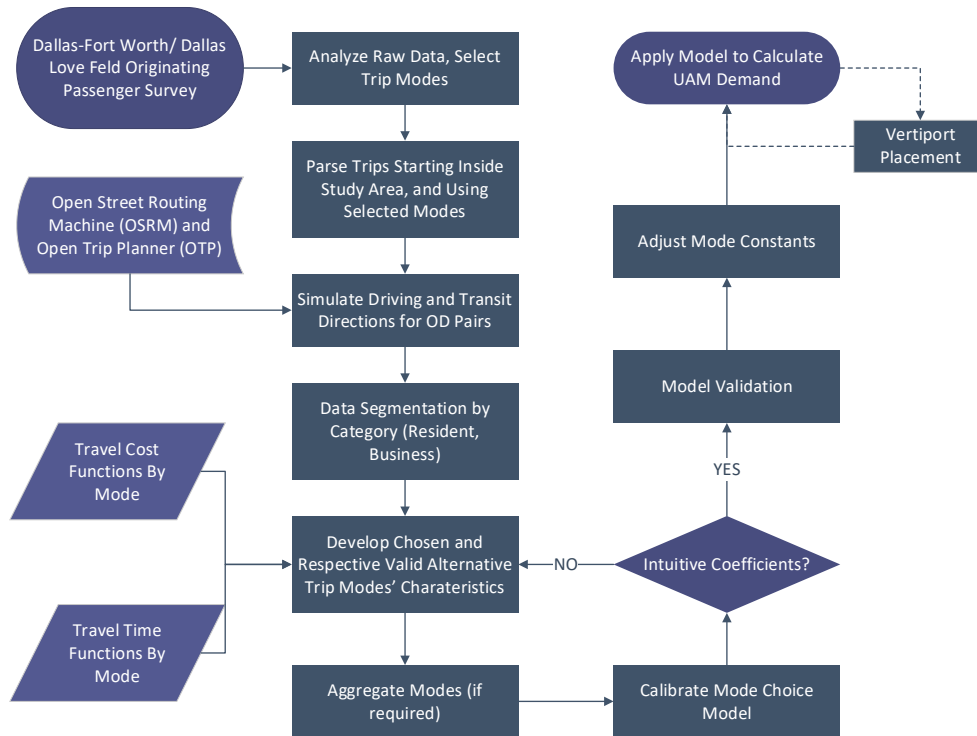
Figure 19: Workflow of UAM Demand Estimation for Airport Ground Access Trips

3.6.1 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].

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

(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 8 summarizes the estimation of travel times and travel costs for all the mode considered

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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 8: 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[4]	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 [45] for non-business travelers 3) Parking cost based on the parking lot[5]
Drop-off[6]	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	1) 3-min OVTT	1) 25% of the daily cost

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[4] Economy parking lot requires more waiting for shuttle than express parking lot. Terminal parking lot does not require shuttle.

[5] 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.

[6] 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.

	OSRM output 2) Shuttle time from rental car center	assumption 2) 15-min processing time at rental car center and waiting time for the shuttle	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[7]	Flat-rate ticket cost [48]
Rideshare	Congestion adjusted OSRM output	5-min waiting time assumption	Uber fare structure [49]

3.6.2 Vertiport Placement

UAM ConOps in this study requires the traveler to access the nearest vertiport by a rideshare service assumed to work in collaboration. 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 Figure 18). 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 blockgroups in the survey data. Survey methodology uses stratified sampling based on destination zones share, airlines market share, and time of day [43]. 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 blockgroup in

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[7] OTP does not include initial waiting time at the origin public transit stop.

daily UAM trips to the airports, utilizing the calibrated mode-choice model. UAM trip potential uses UAM trip parameters mentioned in Table 9 (further explained in section 3.7). Using the Fuzzy C-means clustering method [44], 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.

Table 9: Assumed Parameters for UAM Trip Calculations

Parameter		Value
Walkable Distance To/From Vertiport		0.10 mi
Ingress[8] 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

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[8] Ingress/Egress times account for processing and boarding/alighting the vehicle

at the vertiport. They do not account for trip delays.

3.7   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.

3.7.1   Calibrated Mode Choice Model Results

Table 10 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 10: Mode Choice Logit Model

Parameter		Coefficient (or Estimate)	
		Business Trips	Non-Business Trips
Mode	Drive & Park[#]	1.1613*	0.0384

Constants	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*
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 > chi^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

3.7.2 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-3.6.2 and assumptions mentioned in Table 9. 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 of $15 per passenger and a Landing Cost of $20 per vehicle was assumed. Figure 20 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 Base Cost and Landing Cost), there is a 3,202 UAM one-way airport trip demand per day, where increasing the CPM by 50 cents (25% increase in cost) 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 Base Cost and Landing Cost. Figure 21 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.
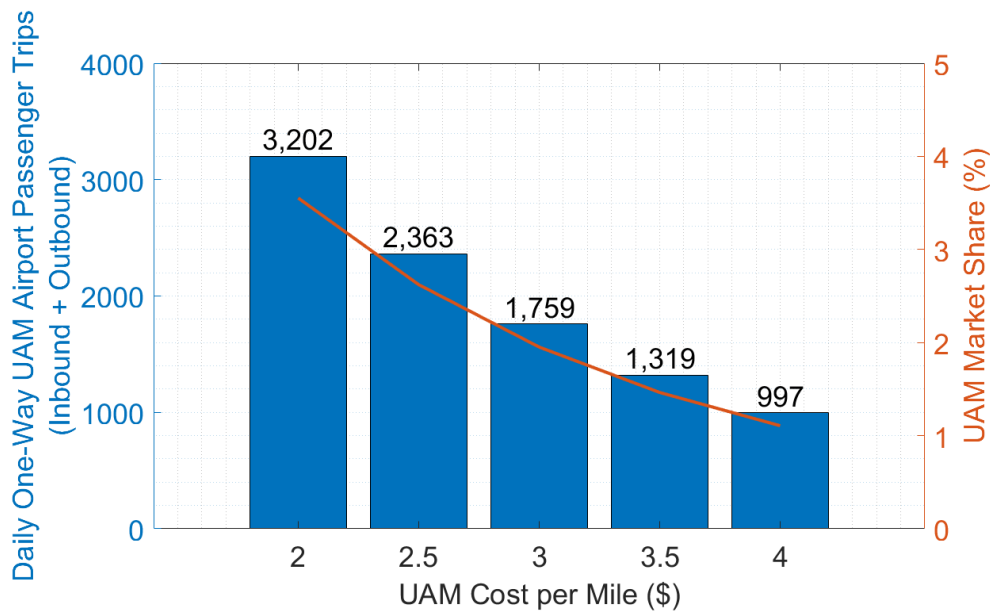
Figure 20: Daily Airport UAM Demand Sensitivity to UAM CPM (50 Vertiports)

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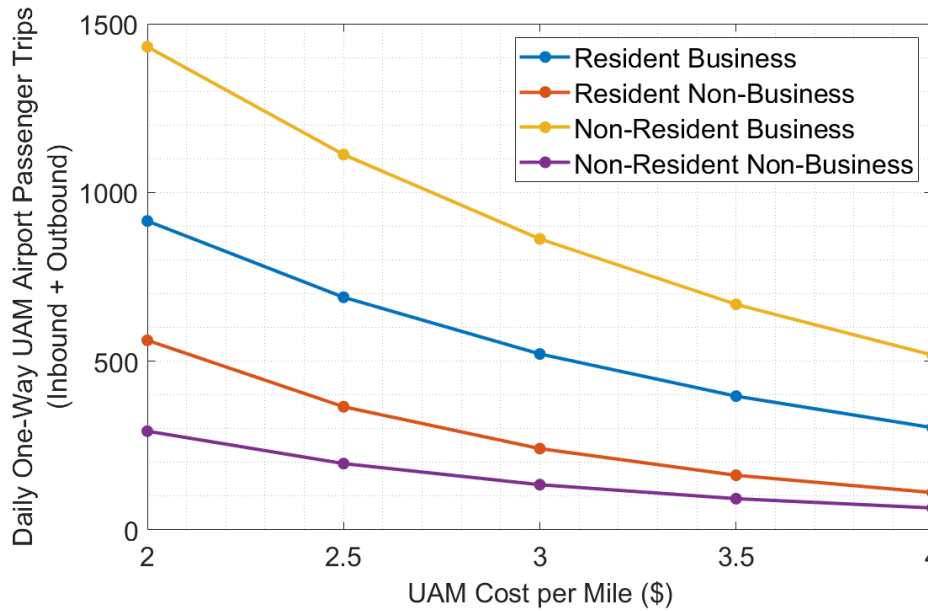
Figure 21: Daily Airport UAM Demand Sensitivity to UAM CPM (50 Vertiports) by Segment

Increasing the number of vertiports improves 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. Figure 22 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 Base Cost and $20 Landing Cost). Increasing the network size of 50 vertiports set by 50% increases daily UAM demand by 12.5%. Adding 25 vertiports to a 75 vertiport set increases the UAM demand by 2%. The increase in UAM demand is negligible adding vertiports beyond 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.

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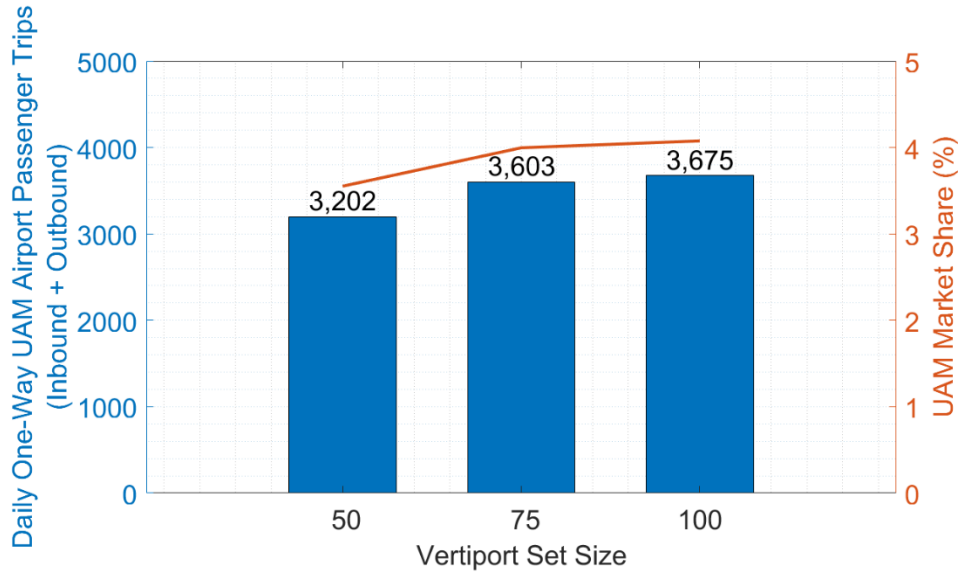
Figure 22: Daily Airport UAM Demand Sensitivity to UAM Vertiport Set Size (UAM CPM: $2)

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 Base Cost and $20 Landing Cost) that estimates 3,202 daily airport access UAM passenger trips. Figure 23 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%.
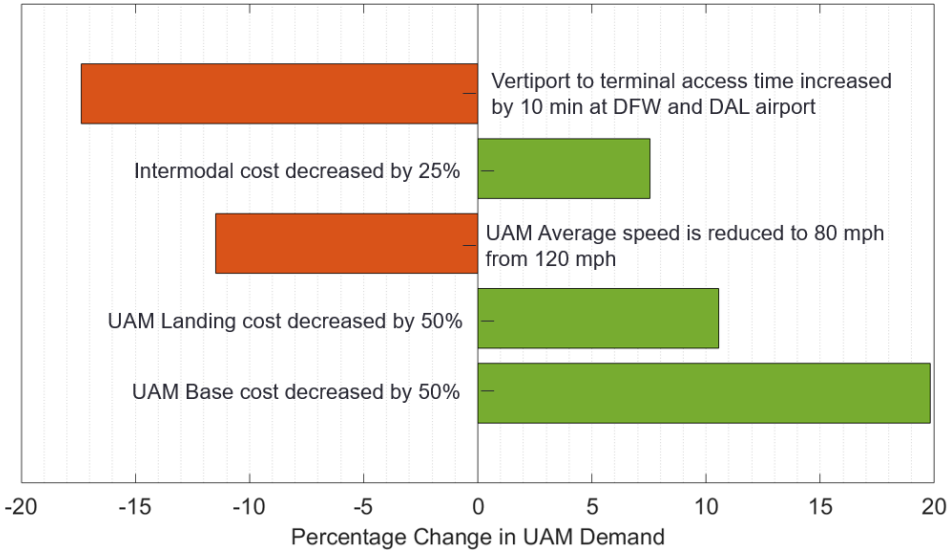
Figure 23: UAM Demand Sensitivity against Multiple Factors. Base Case: 50 Vertiports with $2 UAM CPM (additional to $15 Base Cost and $20 Landing Cost) generating 3,202 UAM One-way Passengers Trips

Figure 24 represents the spatial distribution of UAM demand for DFW airport trips with 50 vertiports and $2 CPM (additional to $15 Base Cost and $20 Landing Cost). 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. Figure 25 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.
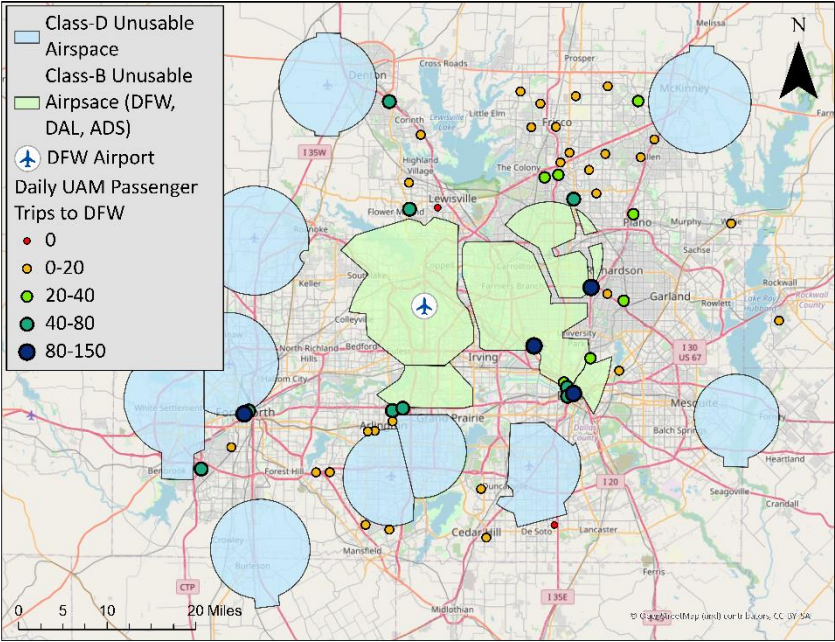
Figure 24: Spatial Distribution of UAM Trip Demand to DFW
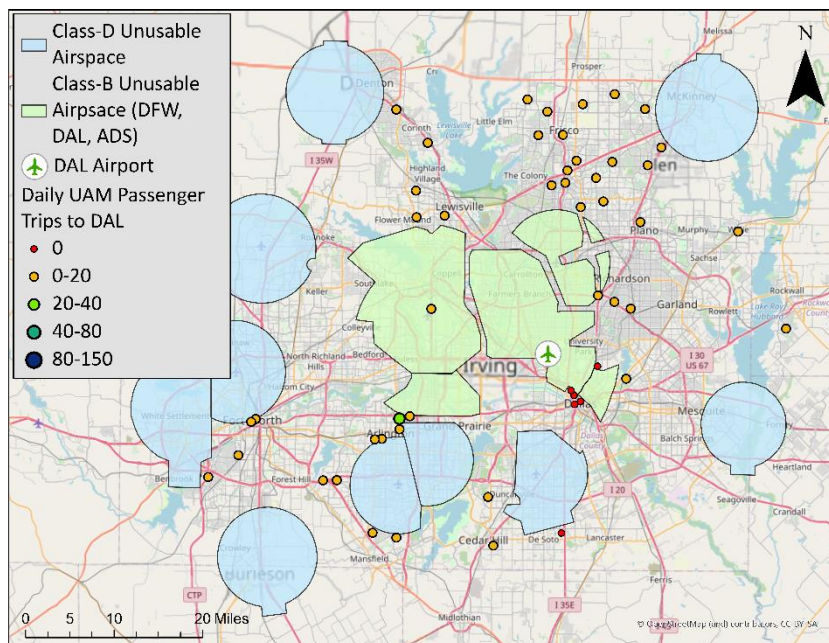
Figure 25: Spatial Distribution of UAM Trip Demand to DAL

3.7.3   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 Base Cost and $20 Landing Cost) 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 repositing

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. Figure 26 shows the number of daily flights on each route for the scenario with 50 vertiports and $2 UAM CPM (additional to $15 Base Cost and $20 Landing Cost). 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 UAM operations per hour. 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.
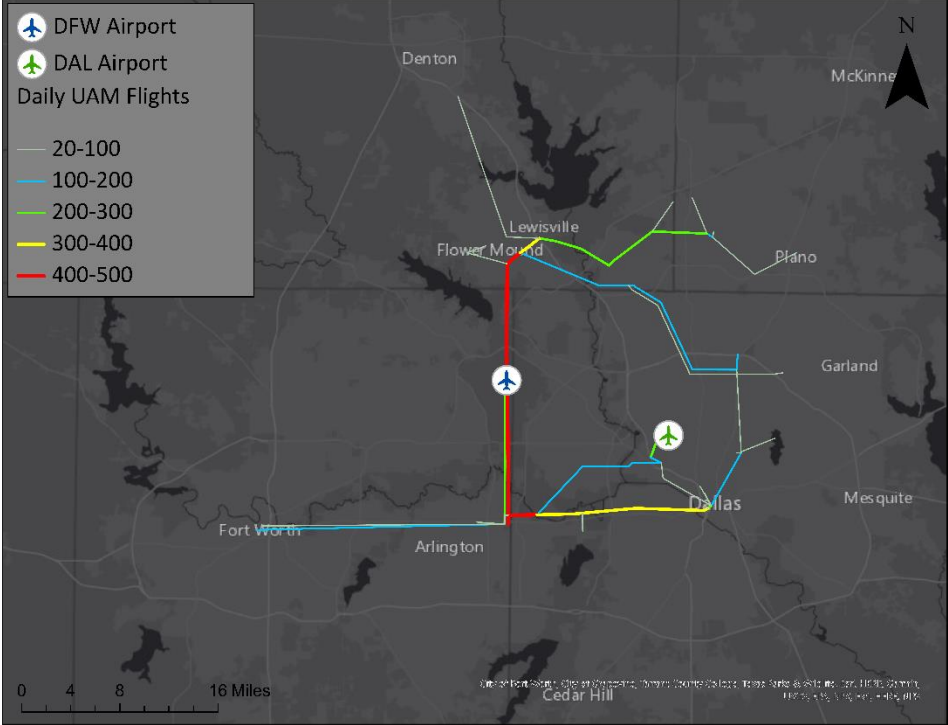
Figure 26: Daily UAM Flights by Route. Scenario: 50 Vertiports with $2 UAM CPM (additional to $15 Base Cost and $20 Landing Cost)

3.8   **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 Base Cost and $20 Landing Cost) 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

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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.

3.9 Acknowledgments

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3.11 **Appendix**
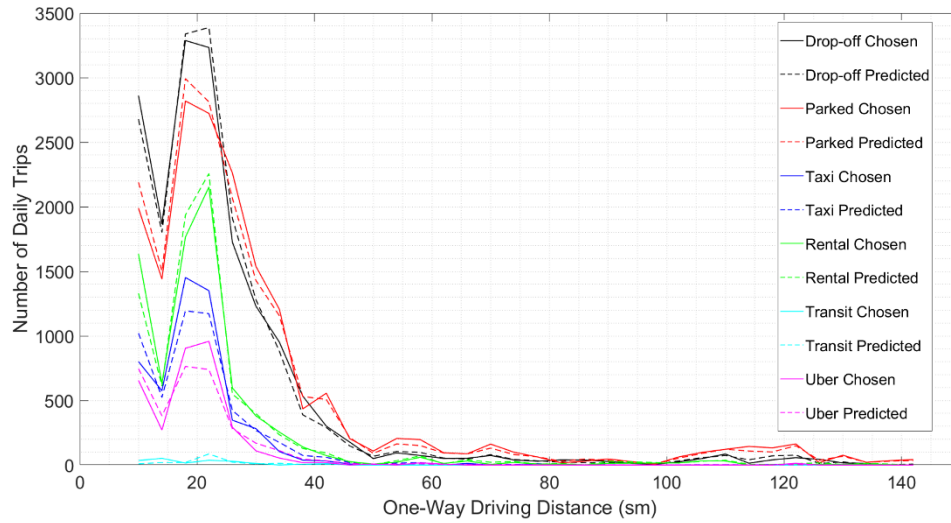
Figure 27: Comparison of Market Share by Distance: Chosen vs. Predicted
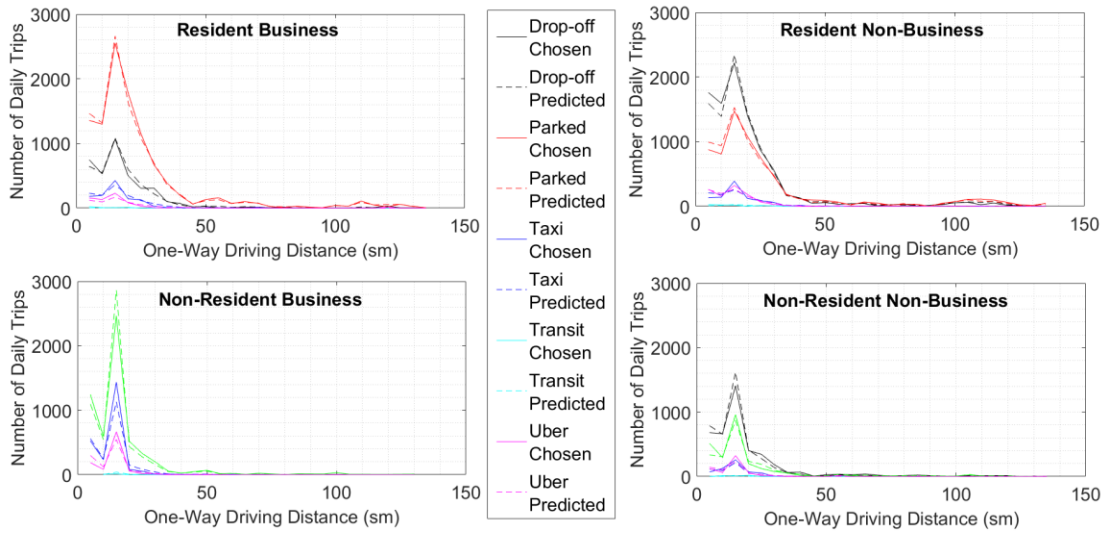
Figure 28: Comparison of Market Share by Distance: All Segments

4. Los Angeles Airport Ground Access Demand Estimation for Urban Air Mobility

Rimjha, Mihir, et al. "Urban Air Mobility Demand Estimation for Airport Access: A Los Angeles International Airport Case Study." *2021 Integrated Communications Navigation and Surveillance Conference (ICNS)*. IEEE, 2021.

4.1 Abstract

Urban Air Mobility (UAM) or Advanced Air Mobility (AAM) is a concept aerial transportation mode being designed for intracity transport of passengers and cargo utilizing autonomous electric vehicles capable of Vertical Take-Off and Landing (VTOL) from dense and congested areas. Airport ground access trips could be among the early adopters of UAM because of the high customer willingness to pay and substantial time savings for long-distance or significantly congested access trips. This study aims to estimate demand for UAM in the airport ground access segment of Los Angeles International Airport (LAX). Travel behavior is derived from the airport passenger survey 2019 provided by Los Angeles World Airports (LAWA). A mixed logit model captures the mode-choice behavior that is later modified to include UAM. Total daily originating passenger trips are estimated from the T-100 database. The calibrated model is then applied to calculate the UAM demand. Utilizing the developed UAM demand estimation framework, a feasibility analysis is performed through a series of sensitivity analyses with respect to UAM passenger cost per mile (CPM) and UAM network size (number of vertiports). Furthermore, the Also, UAM demand in specific high-demand corridors (according to the ground access traffic) is analyzed. UAM could capture an estimated 3.6% market share in airport access trips to/from LAX at $2.00 UAM cost per passenger mile, assuming 2.4 passengers per flight (additional to $15 base cost per passenger and $20 landing cost per flight).

4.2   Introduction

Los Angeles, California, is expected to be among the early adopters of UAM [1, 2]. Initially, commercial UAM services were expected to roll out in Los Angeles by 2023 [3], and the City of Los Angeles created a roadmap to support the UAM system planning [4]. Now, alongside the LA Department of Transportation (LADOT) and the city's Urban Movement Labs (UML), the City of Los Angeles has announced a UAM partnership to make Los Angeles the leader in UAM adoption [5, 6]. As the UAM concept is getting close to implementation, it is essential to estimate its demand potential, which will impact various system characteristics, including optimal vertiport placement and passenger cost per mile determination.

Existing literature contains demand studies exploring different trip purposes and their UAM potential. Fu et al. developed a simulation-based framework to estimate UAM demand for local commuters and airport passengers in the year 2030 for the greater Munich area [7]. They estimated around 0.62% market share of UAM with 74 vertiports and UAM cost of 2€/km (additional to 5€/trip). Balać et al. investigated the potential market for UAM in Zurich on a 10% population sample [8]. They suggest that UAM may only capture a small share of the transportation market in a small city like Zurich, but that might not be the case in heavily populated cities with congested ground traffic.

Roy et al. developed a multi-commodity network flow framework for UAM airport shuttle air taxi service in Atlanta [9]. While their focus was on optimizing flight scheduling of UAM vehicles, they analyzed the sensitivity of the UAM demand to the ticket price for two scenarios with 3 and 6 vertiports. Other demand studies in literature focus mainly on commuting, cargo, etc. [10, 11].

Booz Allen Hamilton explored market size and recognized three potential markets for UAM: Airport Shuttle, Air Taxi, and Air Ambulance [12] in their UAM market study for the National Aeronautics and Space Administration (NASA). They found Airport Shuttle and Air Taxi markets to be viable and expect the former to be early adopters of UAM because of operational efficiency. The need for supply/demand matching is minimized if demand is concentrated at one end of the flight.

The UAM's potential in airport access trips and in Los Angeles is recognized in literature, separately. However, the literature lacks UAM demand estimation efforts of this trip purpose in Los

Angeles. The analysis presented in this paper fills this gap by estimating UAM demand for airport access trips to LAX airport, which could be among the earliest commercial services of UAM [13, 14].

4.3   **Data**

Multiple datasets were used in this analysis. The *2019 Passenger Survey Los Angeles International Airport* conducted by Unison Consulting on behalf of LAWA is the primary data source in this analysis. This survey is part of LAWA's ongoing effort to modernize and improve airport ground transportation access, parking, and passenger and terminal facilities at LAX [15]. Nearly 15,000 survey responses were collected in two waves, February/March 2019 (non-peak) and July 2019 (peak), with a staggering daily schedule from 5 AM to 1 AM. Unison team claims the samples have a margin of error of no greater than ±3 percent at a 95 percent confidence level, which indicates each sample can be analyzed individually with a high level of statistical validity. The originating trips recorded in this survey are considered to be representative of all the traveler trips arriving at LAX. Hence, this dataset is used for mode-choice model calibration and determining regional trip origin distribution. The geographical resolution of this survey data was limited to the Zip-Code level.

This study is a follow-up to the UAM commuter study performed for NASA in 2019-20 [16]. The study area is kept consistent with the commuter study. Figure 29 illustrates the study area and geographical coverage of the survey data. There are 600 unique zip codes in the survey data, with trip origin having their centroid inside the study area. This study assumed the UAM vehicle has a range of 150 sm. All of these zip codes are within this distance of the LAX airport.
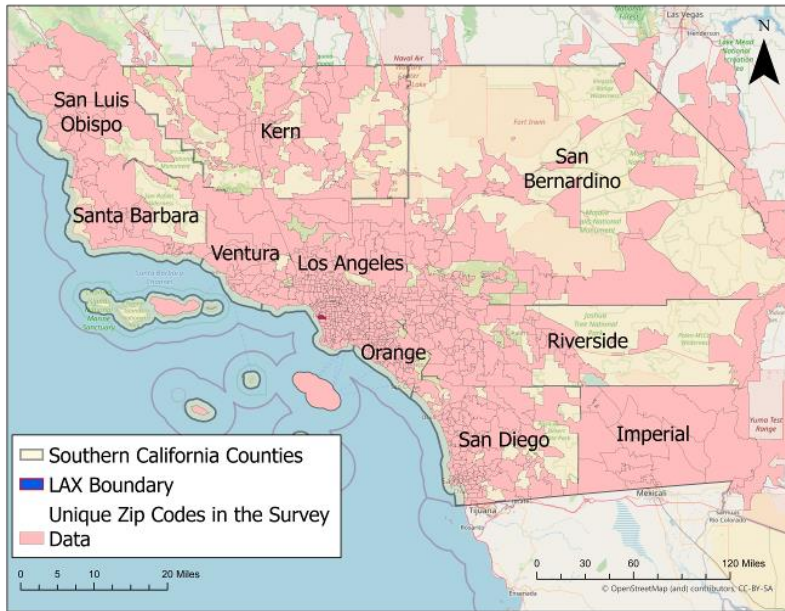
Figure 29: Study Area and Geographical Coverage of the Survey Data

Even though the survey included both originating passengers and connecting passengers, the trips by connecting passengers were filtered out as the analysis focuses on ground access trips. Originating passengers constituted 67% of the survey data. LAX region residents and visitors comprise an almost equal proportion of the originating passengers in the region, the former generating 53% of the trips whereas the latter generating the remaining 47%.

The data was segregated into four segments based on mode availability and expected mode-choice behavioral differences: Resident Business, Resident Non-Business, Visitor Business, and Visitor Non-Business. However, due to relatively fewer business travelers, there are not enough trips in all four segments for a credible four-segment analysis. Therefore, the data were re-segregated into two segments: Business trips and Non-Business trips. Since this UAM demand estimation is based on mode choice analysis, trips performed by captive modes like courtesy van, hotel shuttle are filtered out. Trips without trip-origin zip code information are also removed. Table 11 includes the remaining number of trips by segment.

Table 11: Originating Passenger Survey Data by Segment

Segment	Number of Trips	Percentage of Total Trips

Resident Business	1,802	13.6%
Resident Non-Business	2,729	34.5%
Visitor Business	1,257	15.8%
Visitor Non-Business	2,887	36.3%
Total	7,955	100%

Determining any new mode's feasibility requires a prior understanding of travel behavior in the region, especially mode-choice behavior. Figure 30 shows the mode choice proportions observed in the filtered data. Six modes are considered in this analysis: *Drop-Off, Drive and Park, Taxi* (traditional)*, Rental Car, Public Transit,* and *Rideshare*. There has been substantial change observed in the market share captured by *Transportation Network Companies (TNC)* (or *Rideshare*) compared to the previous edition of this survey (2015) [15]. The TNC market share grew by four times to 28% in 2019 considering raw survey data, i.e., without filtering. Most of these trips shifted from *Private Vehicle* and *Rental Car*. Such mode-shift is promising for UAM as it shares similarities with *TNC* (or *Rideshare*) mode.
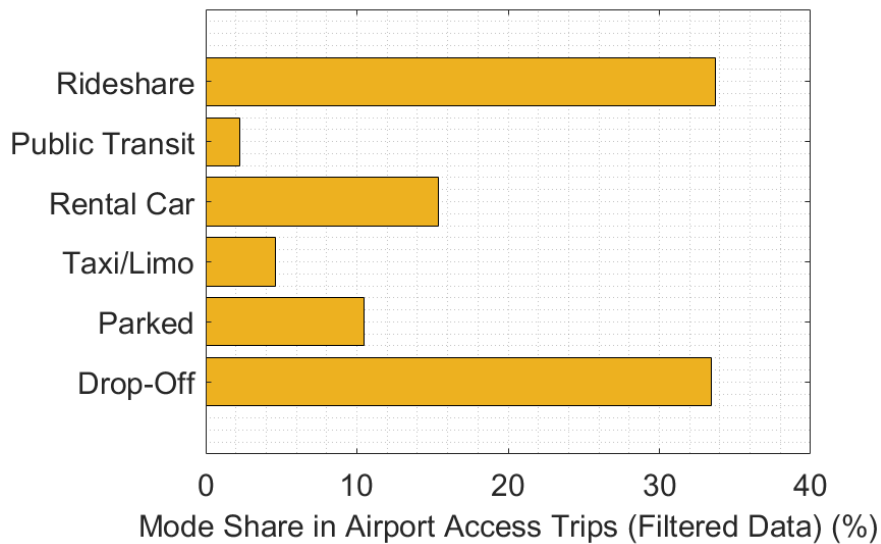
Figure 30: Observed Mode Share in Survey Data

UAM mode's utility depends mostly on marginal travel time savings, which can either come about by traveling over significantly congested ground traffic or when the Great Circle Distance (GCD) is considerably smaller than the alternative ground trip distance. Therefore, analyzing the trip distances of these ground access trips is essential for realizing UAM's scope.

Figure 31 and Figure 32 show the distribution of driving distances observed in the Business and Non-Business Segment survey data, respectively. Visitor business trips have a median distance of 15.7 statute miles (sm), the least among all categories. Many visitor business travelers tend to stay in hotels located close to the airport. Similarly, due to a large proportion (60%) of visitor non-business travelers residing in hotels close to LAX, the median driving distance is 17 miles. The second peak around 35 miles is due to several non-business visitors going to Anaheim, where Disneyland is located, making the most popular trip origin zip-code.

Resident business and resident non-business both tend to travel longer distances because often residences are located in outskirts or suburbs. Unsurprisingly, 96% of the residents start from their homes. Trip distances of travelers from both segments have smoother distribution tail as residence zones could be found at different distances from the airport. Average trip distances are above 25 sm for all categories except visitor business which is a promising indicator for UAM as marginal travel time savings increase with increasing driving distance in general.
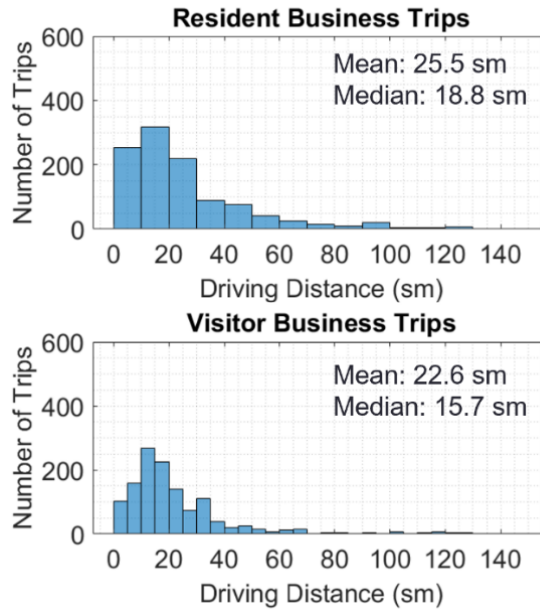
Figure 31: Distribution of Driving Distances of Access Trips to LAX (Business Segment)
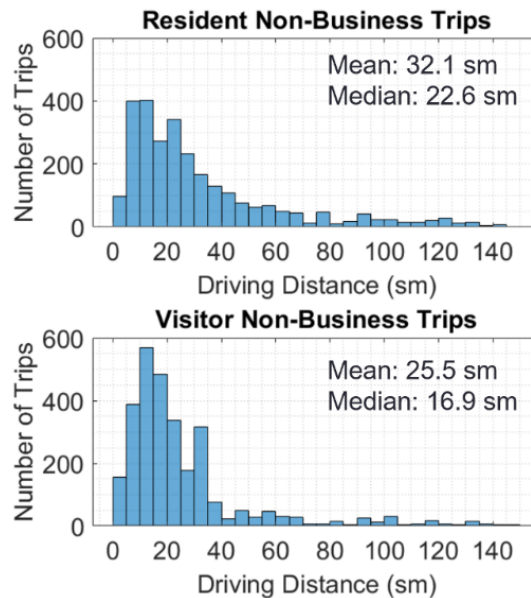
Figure 32: Distribution of Driving Distances of Access Trips to LAX (Non-Business Segment)

4.4 Airspace Restrictions

The LAX airport is the second busiest airport in the USA in terms of passenger traffic [17]. The commercial traffic in that region is complemented by 14 smaller airports producing a very congested airspace. Like all major airports, LAX is surrounded by Class-B airspace controlled by Air Traffic

Control (ATC). Class-B airspaces are individually designed and generally extend up to 10,000 feet vertically from Mean Sea-Level (MSL) and 30 nautical miles radially [18].

According to current guidelines, any unauthorized operation in Class-B airspace is prohibited. The UAM Concept of Operations (ConOps) is based on no ATC involvement as that could cause system delays and increase the workload of air traffic controllers and ATC resources. Class-D airspace requires two-way radio communications with ATC. In addition to LAX Class-B airspace, 14 Class-D airspaces surround the secondary or military airports present in the Los Angeles region. Savvy Verma and her research group at NASA AMES scrutinized the operations at these airports, and proposed restricted airspace envelopes shown in Figure 33. They develop boundaries of unusable airspaces and UAM operational conditions (recommended altitudes) near controlled airspaces.
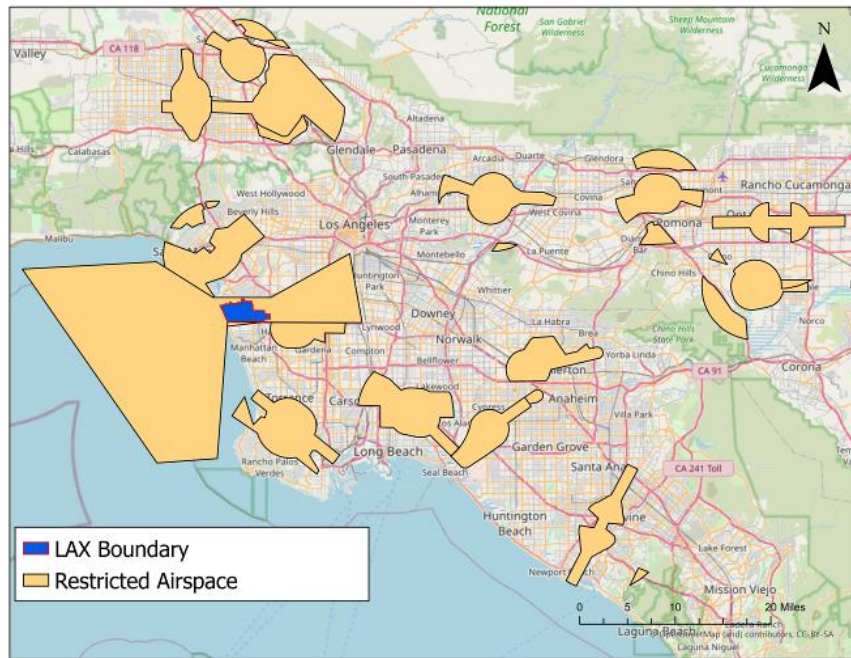
Figure 33: Restricted Airspace Boundaries (Source: NASA AMES)

These unusable airspaces are treated as restricted zones for UAM where the placement of vertiports and overflying of UAM vehicles are prohibited. UAM routes must detour if the GCD route pierces any restricted zones. To avoid placement of vertiports very close to the restricted zones, a 2,000 ft buffer is used for vertiport placement. Airspace restrictions result in relatively less optimal

placement of vertiports and extra travel distance and travel time for UAM trips. Both impacts expectedly decrease UAM utility to the traveler and demand for the UAM mode.

4.5 **Mode Choice Model Calibration**

A mode-choice model was calibrated model to capture the airport ground access travelers' mode-choice behavior. Specifically, a mixed conditional mode-choice model was found to be suitable for this purpose. The conditional logit model only includes trip-related variables or generic variables. Due to the lack of traveler-related information in application data, variables relating to traveler's characteristics could not be included in the model calibration.

Utilizing conditional logit models to capture choice behavior is in practice for several decades. Mixed logit models are warranted to capture unobserved heterogeneity in the data. Therefore, the mixed conditional logit model was significantly better in statistical fit than the conditional logit model because of the high variation observed in mode-choice behavior in this particular dataset. According to mixed conditional logit models, a traveler's mode-choice decision is based on the utility that can be derived from each available mode. The utility that individual n derives from choosing alternative j on choice occasion t is given by $U_{njt} = \beta_n' x_{njt} + \varepsilon_{njt}$ [19], where β_n' is a vector of individual-specific coefficients, x_{njt} is a vector of observed attributes relating to individual n and alternative j on choice occasion t, and ε_{njt} is a random error term.

The probability of individual n choosing alternative i on choice occasion t is given by standard conditional probability:

$$L_{nit}(\beta_n) = \frac{\exp(\beta_n' x_{nit})}{\sum_{j=1}^{J} \exp(\beta_n' x_{njt})} \tag{1}$$

The unconditional probability of the individual's choices is obtained by integrating L_{nit} over the distribution of β:

$$P_n(\theta) = \int S_n(\beta) f(\beta \mid \theta) d\beta \tag{2}$$

Where:

$f(\beta \mid \theta)$ is density according to the selected distribution.

$S_n(\beta_n)$ is the probability of the observed sequence of choices for known β_n:

$$S_n(\beta_n) = \prod_{t=1}^{T} L_{ni(n,t)t}(\beta_n) \tag{3}$$

The log-likelihood of the mixed logit model is given by $\text{LL}(\theta) = \sum_{n=1}^{N} \ln P_n(\theta)$, where N is the number of individuals. It is approximated using the simulation method because it cannot be solved analytically. The simulated log-likelihood is then given by:

$$\text{SLL}(\theta) = \sum_{n=1}^{N} \ln \left\{ \frac{1}{R} \sum_{r=1}^{R} S_n(\beta^r) \right\} \tag{4}$$

where R is the number of replications and β^r is the rth draw from $f(\beta \mid \theta)$. The coefficients are estimated by maximizing the simulated log-likelihood. The number of replications was fixed at 100 as little improvement was observed in statistical fit beyond that.

Originating passenger survey was a revealed-preference survey, and only chosen mode is included. The choice dataset is created by reconstructing each traveler's mode alternatives. Trip attributes are not part of the survey, and therefore, all trip attributes or model variables were estimated externally. Driving and transit directions were simulated for all the trips in the dataset using Open Street Routing Network (OSRM) [20] and Open Trip Planner (OTP) [21], respectively. The output of OSRM contains route directions, unimpeded travel time, and driving distance. Unimpeded travel times are adjusted for congestion using Texas Transportation Institute Congestion Indices [22]. Similarly, the OTP output contains transit itineraries which are processed to extract in-vehicle travel time, out-of-vehicle travel time, and number of transfers. If the walking distance to the closest transit station is more than the reasonable distance of a quarter-mile, car-and-park itineraries are chosen.

Trip attributes for the chosen and valid alternatives from all the modes considered in this analysis (Figure 30) are estimated based on certain derived functions and assumptions. In-vehicle travel time (IVTT) for all driving modes (Drop-Off, Drive-Park, Taxi, Rental, and Rideshare) is derived from congestion-adjusted driving time. Additional shuttle time is included if applicable (rental car, off-site parking). Assumed Out-of-Vehicle Time (OVTT) is included in Table 12.

Table 12: OVTT Assumptions

Mode	OVTT
Drop-Off	3-min
Drive-and-Park	3-min + Shuttle time if parked off-site
Taxi	5-min waiting time
Rental Car	3-min + 15 min processing and waiting time for the shuttle
Public Transit	OTP output
Rideshare	5-min waiting time

Travel cost estimations are based on standard fare structures and certain assumptions.

- Drop-Off is considered to have no cost.

- Drive-and-Park travel cost comprises driving cost and parking cost. For business travelers, driving cost is estimated from IRS per mile cost reimbursement rate [23], whereas AAA's 2019 operating cost of the car [24] is used for non-business travelers. Parking cost is based on parking location and number of days away. Only half of the total parking cost is applied to the one-way access trip.

- Taxi cost is based on the yellow cab fare structure in Los Angeles [25].

- Rental car cost comprises a quarter of the fixed rental daily cost, fuel cost, and daily insurance cost based on AAA 2019 [24].

- Public transit cost is based on the transit agency cost function [26, 27].

- Rideshare cost is based on Uber fare structure [28].

Selective mode availability is applied based on the traveler's category to avoid unreasonable mode alternatives. A rental car is not considered a valid alternative for residents. Similarly, Drive-and-Park is not considered a valid alternative for visitors. After estimating trip attributes for all chosen and their

valid alternatives, the model choice model is calibrated. Calibrated mode-choice model is included in Table 13, and its validation plot is included in Appendix-I.

Business and Non-Business travelers show a difference in mode-choice behavior because business trips are usually reimbursed, increasing the individual's willingness to pay. A partially segmented model is chosen to capture the differential mode-choice behavior of Business and Non-Busines travelers. Rideshare mode is chosen as the reference alternative for being the most popular. Lognormal distribution was selected for the travel cost variable to avoid positive values of travel cost coefficient in the application process. Normal distribution was selected for Number of Transfers. The heterogeneity in travel time was not significant; therefore, a fixed coefficient for travel time was selected.

Table 13: Mixed Logit Model Coefficients

Parameter		Coefficient (or Estimate)
Mean		
Mode Constants	Drop-Off	-2.9133*
	Drive & Park	1.1236*
	Taxi	-0.9381*
	Rental Car	0.4761*
	Public Transit	-0.1324*
Travel Time	Total Travel Time	-0.0358*
Travel Cost†	Travel Cost (Business)	-3.1694*
	Travel Cost (Non- Business)	-2.3487*
	Number of Transfers	-0.5648*
Standard Deviation		
Travel Cost†	Travel Cost (Business)	1.4928*
	Travel Cost (Non- Business)	1.7732*
	Number of Transfers	0.5487*
Model Fit	$Prob > chi^2$	0.0000*
Median Value of Time	Business VOT ($/hr)	52
	Non-Business VOT ($/hr)	22

*Significance: 0.01

†Logarithmic Coefficient

4.6   **UAM Concept of Operations**

UAM ConOps is briefly discussed to help readers understand the UAM system considered in this analysis and its demand estimation results. The centroid of the traveler's census blockgroup is the reference trip origin location for the access trip. The traveler is expected to always access the closest

vertiport from its origin location. If the vertiport is located further than 0.2 miles, the vertiport access trip is simulated using rideshare characteristics to access the vertiport. Otherwise, the vertiport access trip is assumed to be performed by walking. At all the vertiports, ingress and egress times of 5 minutes each are assumed to reflect processing time and boarding/alighting time. Since no vertiports are allowed inside restricted zones, a couple of vertiports are placed at the edge of restricted zones on the north and the south side of LAX, as shown in Figure 34. These are the two vertiports used for airport access.
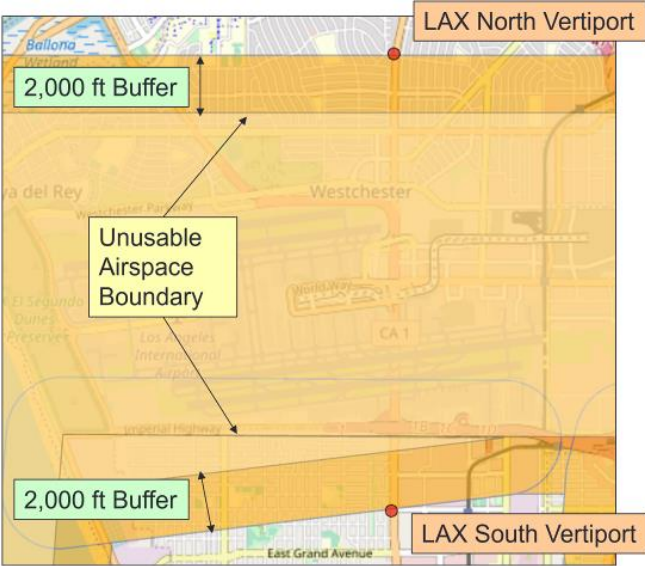
Figure 34: Vertiports Location at LAX

The closest LAX vertiport from the trip origin location is selected as the destination vertiport. The UAM trip is then simulated at an average speed of 120 mph on the UAM network using the shortest path algorithm. The UAM network consists of vertiports as nodes and valid edges that do not pierce restricted zones. While detouring, UAM vehicles are programmed to navigate slightly away (200 ft) but along the edge of a restricted zone to minimize detour factors. After exiting the destination vertiport near LAX, a shuttle with a headway of 10 minutes is assumed to take passengers to the terminal. The access travel time to the terminal from either vertiport is around 6 minutes. Hence, the total travel time by UAM is the sum of access time from trip origin to origin vertiport, ingress time at the vertiport, UAM trip time from origin vertiport to destination vertiport, egress time at the

destination vertiport, average shuttle wait time, and terminal access time from destination vertiport to the terminal.

Total travel cost for UAM consists of a base cost (payable per passenger), landing cost (payable per landing), and UAM trip cost. UAM trip cost includes access trip cost from the trip origin to origin vertiport using the Uber fare structure (if access trip is not made by walking), and distance-based fare using UAM cost per passenger mile (CPM) for origin vertiport to destination vertiport. The shuttle service from the destination vertiport to the terminal is assumed to be complementary. This analysis's reference vehicle is Joby S4 [29], with a capacity of 4 passengers. All UAM operations are assumed to operate at a 60% load factor (2.4 passengers per flight).

Since the model is calibrated on a revealed-preference survey that does not contain UAM mode, the mode constant for UAM could not be calculated. The mode constants' role is to capture mode-specific unobserved factors that influence mode-choice, such as safety, reliability, comfort, etc. The defined UAM ConOps is quite close to current operating models of rideshare modes, and UAM is sometimes referred to as aerial ridesharing. Therefore, it can be assumed that the unobserved factors would impact the traveler's utility of UAM, similar to Rideshare. Hence, UAM utility calculation uses the Rideshare mode constant.

4.7   Demand Estimation Methodology and Vertiport Placement

The originating passenger survey data is believed to have a credible geospatial distribution of LAX ground access trip origins. However, it does contain weights for the records to represent daily traffic. The daily number of originating passengers at LAX is required to estimate daily UAM airport access demand in the region. Monthly enplanements are extracted from the T-100 database maintained by the Bureau of Transportation Statistics (BTS) (shown in Figure 35), and the average daily combined enplanements are estimated at 121,379. These enplanements include both originating and connecting passengers.
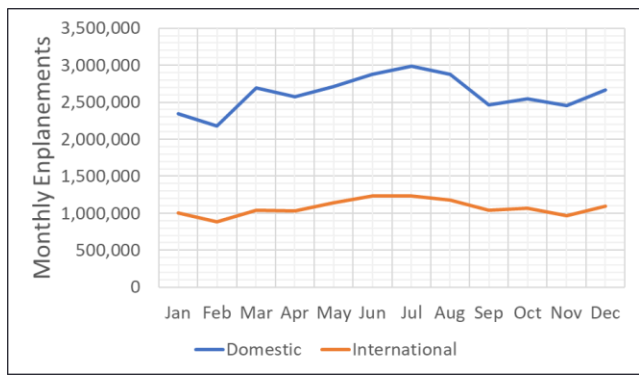
Figure 35: Monthly Enplanements in 2019 at LAX

LAWA reported in the *Fiscal Year 2019 annual Report* that approximately 81.6% of enplanements were from originating, and the remaining 18.4% enplanements were from connecting passengers [30]. Using the same ratio, the daily number of originating passengers at LAX was estimated to be 99,045. These daily originating trips were then distributed to the zip code level using the distribution ratio observed from the survey data. Figure 36 includes the trip origin ratios of zip codes, i.e., the number of trips (all categories) generating from each zip-code compared to the total number of trips (all categories).
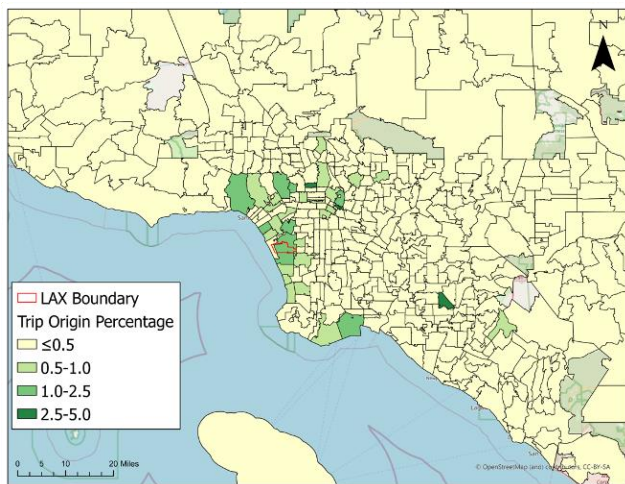
Figure 36: Trip Origin Percentage for all the Zip-Codes

This study is a follow-up to the commuter study [16], which was performed on census blockgroup level. To maintain consistency in the geographical resolution of demand results, Zip code-level trips were further distributed to census blockgroup level based on the population of each

blockgroup inside their zip code. Traveler's category was assigned to each trip based on the ratios observed in the survey. Unfortunately, the number of records in the survey data was not enough to capture resident/non-resident and business/non-business ratio credibly for every zip-code. Therefore, it was assumed that each zip-code would have the average ratio of resident/non-resident and business/non-business travelers observed in overall data.

Once the traveler's category and trip origin at blockgroup level were assigned, trip attributes for all valid mode alternatives were estimated for every Origin-Destination (OD) pair in the application dataset (Destination is LAX vertiports). Each mode's utility is calculated for every traveler using the calibrated model, and their mode-choice probability is estimated. UAM demand for each OD pair is cumulative of every traveler's probability on that OD pair. The total originating UAM demand is the sum of UAM demand on all OD pairs in the region. Due to the lack of data on returning passengers (airport to home), it is assumed that return UAM demand on each OD pair would be equal to its originating UAM demand.

4.8   **Vertiport Placement**

The placement of vertiport is critical for the success of UAM. Ideally, vertiports should be placed where there is potential for high UAM demand. This problem is quite complicated, and the process of optimally locating the vertiports is challenging. A demand-driven vertiport placement methodology has been developed in a parallel effort for NASA [31], which is utilized in this study. The method is discussed only briefly to avoid digressing from the focus of the paper.

After distributing the daily access trip to blockgroups, 12,699 unique blockgroups were present in the application dataset. The initial step in vertiport placement is to estimate blockgroup UAM demand potential. Blockgroup potential is calculated by running a demand model with a vertiport at every blockgroup centroid and estimating the number of UAM trips generated by each blockgroups. The idea is to calculate the maximum UAM trips a blockgroup can generate with an ideal vertiport location. Using blockgroup potential and the Fuzzy C-means clustering method, a certain number of clusters are placed in the region. Clusters falling inside restricted zones are removed, and a subset of clusters maximizing overall membership for the desired number of vertiports is selected as vertiports set location. Figure 37 shows the location of optimally placed vertiport sets for three different UAM network sizes: 50, 75, and 100 vertiports. A smaller set of vertiport is a subset of the more extensive

set. Therefore, all 50 vertiports are present in the 75 vertiport set, and all 50 and 75 vertiports are present in the 100 vertiport set. Due to overlapping with the subset, only new vertiports are visible in the 75 and 100 vertiport sets.
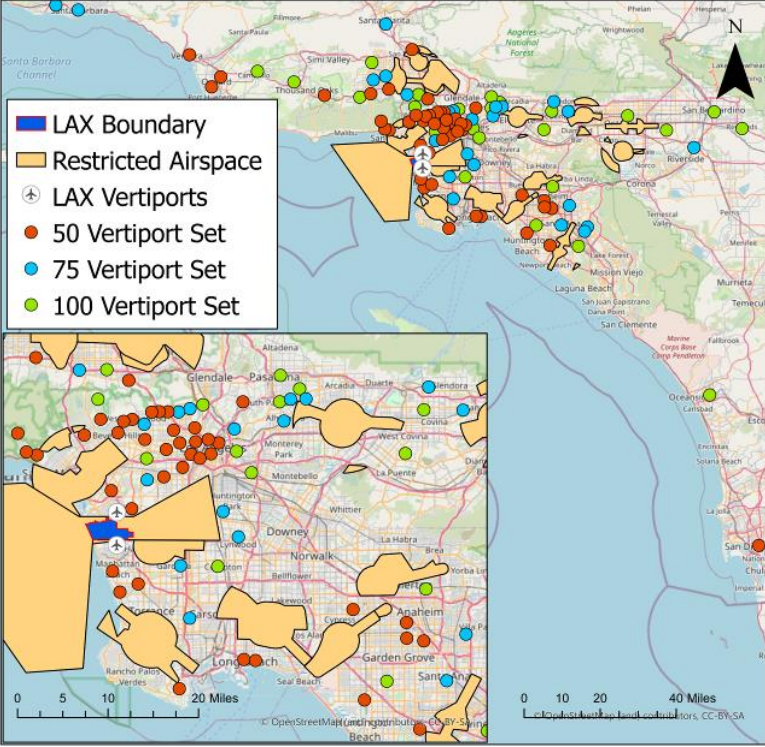
Figure 37: Vertiport Locations in 50, 75, and 100 Vertiport Sets

Vertiports are heavily concentrated in the Los Angeles Central Business District (CBD) and Santa Monica-Beverly hills corridor, even in the smallest vertiport set, suggesting high UAM airport access trips potential from these areas. As we move from 50 Vertiport Set to 75 Vertiport Set, more vertiports can be found in Santa Ana, Santa Clarita, San Marino, Riverside, and Santa Barbara. These areas had almost limited or no access to UAM with 50 vertiports. Moreover, with 100 vertiports, more vertiports can be found in suburbs or areas with relatively fewer airport trips.

4.9   **UAM Demand Estimation Results**

After placing the vertiport sets, UAM demand estimation simulations are performed for selected UAM fare structures to estimate daily UAM passenger trip demand. To analyze UAM demand's sensitivity towards changing UAM CPM, multiple demand estimation simulations are

performed with increasing UAM CPM values. Figure 38 shows estimated UAM demand at different UAM CPM for UAM network size of 75 vertiports. The blue bars correspond to the left Y-axis representing daily UAM LAX access passenger trips for originating and returning passengers combined. The orange line corresponds to the right Y-axis representing UAM market share at every UAM CPM. In addition to distance-based cost, $15 base cost per passenger and $20 landing cost per UAM landing fee is also charged for every UAM passenger trip. At $3 CPM, the UAM can capture a 2.4% market share in LAX airport access trips. The UAM demand dropped by 16.5% on increasing CPM cost by 40 cents from $1.80 to $2.20.
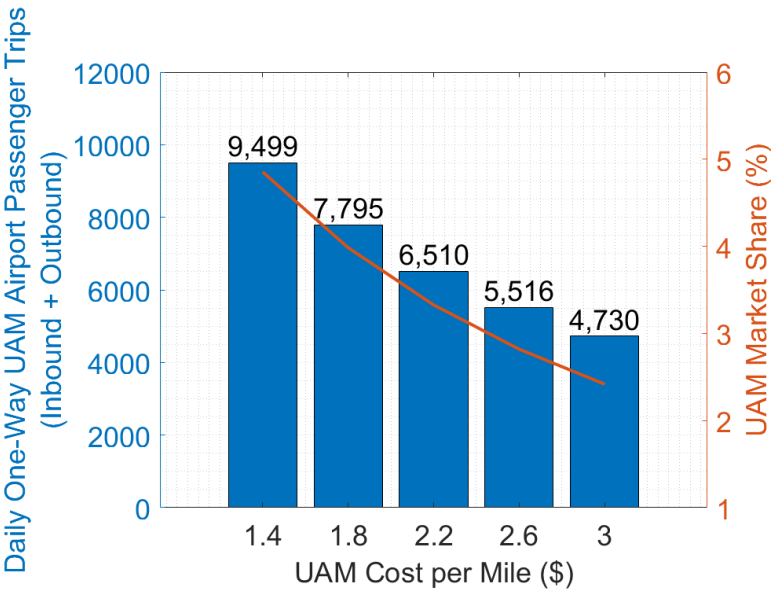
Figure 38: UAM Demand and its Sensitivity with UAM CPM (75 Vertiports)

Traveler's category (Business or Non-Business) has a significant impact on the sensitivity of UAM demand towards changing UAM. Figure 39 includes UAM market share by distance (all categories) for two different simulations at $2.0 UAM CPM and $3.0 UAM CPM. Due to the higher value of time, business travelers comprise a higher proportion of total demand than non-business trips. Business Visitors can benefit from UAM more than other categories because they do not have other convenient modes like Drop-Off and Drive-Park available to them. UAM demand by trip distance also varies significantly with changing UAM CPM values. UAM is not considered viable for trips with a driving distance of less than 10 sm. As expected, at higher CPM values, long-distance trips by UAM become costlier, and the demand decreases. Therefore, market share for all segments (blue line) is

almost the same in all distance ranges (Low distance: <20 sm, Mid-distance: 20-40 sm, and Long-distance:>40 sm) for a $2.0 UAM CPM run. Whereas the UAM market share drops steadily as trip distance increases for $3.0 UAM CPM run because of Mid- and Long-distance trips becoming substantially costlier.
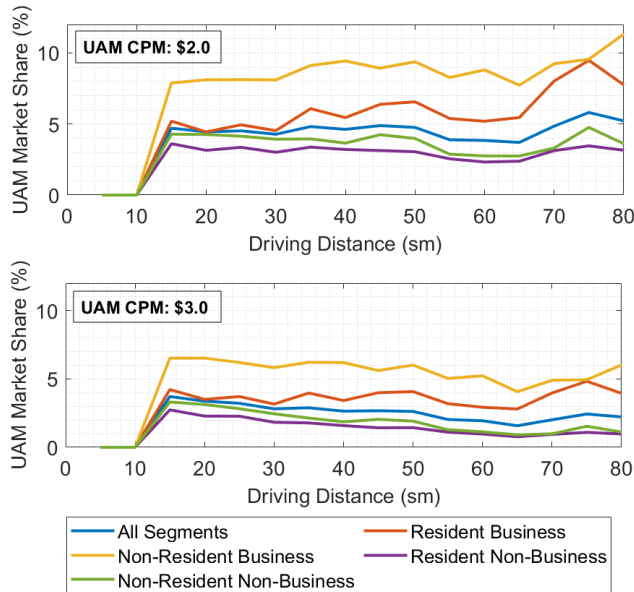
Figure 39: UAM Market Share by Distance (75 Vertiports)

4.9.1   Spatial Distribution of Demand

The spatial distribution of UAM demand is essential for regional planning of the UAM network. The importance of every vertiport must be identified before its feasibility is analyzed.

Figure 40 and Figure 41 illustrate the spatial distribution of UAM demand in terms of outbound passenger trip demand generated at individual vertiport with 75 vertiports set for $2.0 UAM CPM and $3.0 UAM CPM, respectively.

For the demand scenario with $2.0 UAM CPM, the vertiport in LA downtown has the highest demand, unsurprisingly. Other high demand (> 100 outbound passenger trips to LAX) vertiports are located in Long Beach, Riverside, San Marino, Covina, and North Hollywood. The corridor between Beverly Hills and Hollywood has more than a quarter of the mid-demand (50-100) vertiports in the region. Anaheim also has closely placed three mid-demand vertiports. Also, the vertiport in San Diego is generating more than 50 passenger trips per day to LAX. Vertiports near LAX airport have zero

demand because trips from these vertiports are too short to be feasible by UAM (minimum feasible distance is ten sm).

As UAM CPM is increased to $3.0, the outbound passenger trip demand decreases by ~33%. The most significant decrease in demand is observed at previously classified high-demand vertiports. There are no vertiports with more than 100 outbound passenger trips except the vertiport in LA downtown, which remains in the same category (150+ outbound passenger trips). Most of these high-demand vertiports (previously classified) were located far from the airport. As the UAM mode became 50% costlier in variable cost, trips from these vertiports became significantly costlier. The vertiports which lost less than average demand when UAM CPM increased are the ones with minimum or detour for trips to the airport. Detouring increases travel distance which in turn increases travel time and travel cost. Vertiports with UAM route to airport unaffected by airspace restrictions can better sustain increased cost in UAM CPM. UAM routes with significant detours lose demand more rapidly with the increasing cost of UAM because of added disutility from detours getting worse at higher costs.
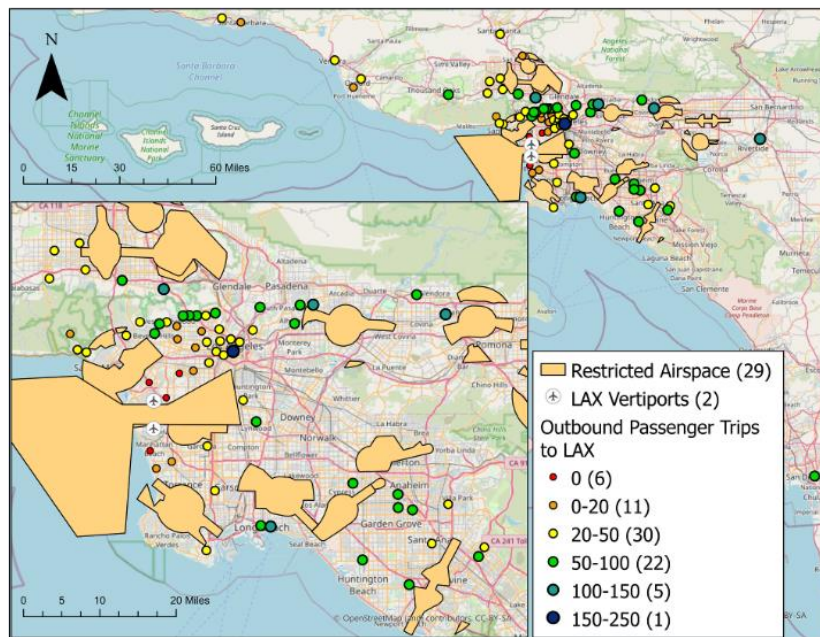
Figure 40: Spatial Distribution of Originating Demand. Daily Outbound Passenger Trips to LAX with 75 Vertiports and $2.00 UAM CPM. Total Originating Trips: 3,554
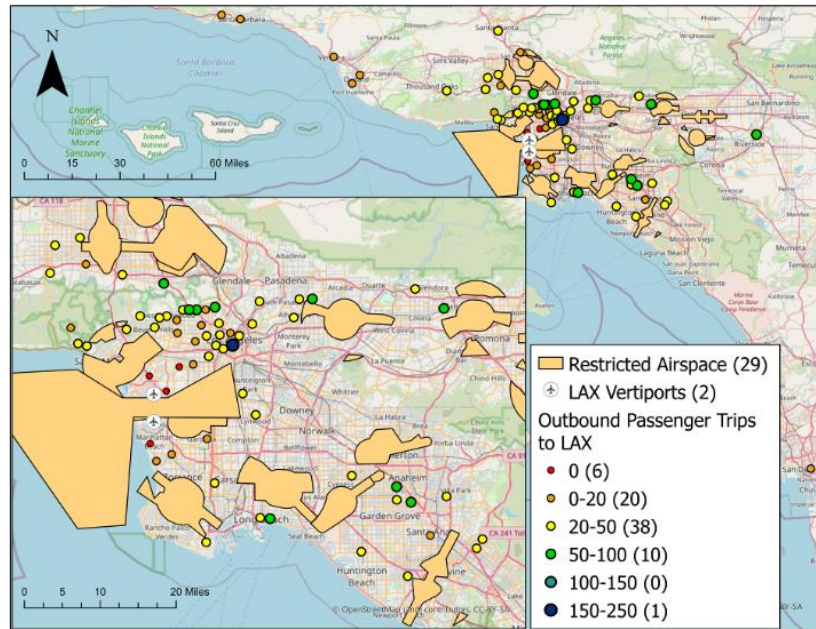
Figure 41: Spatial Distribution of Originating Demand. Daily Outbound Passenger Trips to LAX with 75 Vertiports and $3.00 UAM CPM. Total Originating Trips: 2,36

4.9.2 Top Demand Corridors

The final report of originating passenger survey [15] reported *Top 10 Areas of Origins* based on the number of trips originating from each zip code. These are popular corridors for airport access trips currently. The study analyzed UAM demand in these corridors using the 75-vertiport set and a UAM CPM of $2.0. Figure 42 shows the top 10 zip codes' location, and Table 14 includes the Areas (corresponding to these zip codes) and their respective share in current ground access trips to LAX. It also includes outbound UAM passenger trips demand to LAX from blockgroups inside these zip codes. Moreover, the percentage share of UAM demand from these areas is also reported.

Four of the ten top origin areas have zero demand for UAM because of UAM's infeasibility. They are either too close to the airport (LAX Area, El Segundo, Inglewood) or are located in restricted

zones, and their closest vertiport is too close to the LAX vertiports (Venice). Among the remaining areas, Downtown LA captures the highest share of total UAM demand (6%). Anaheim is the top area in terms of total trip origins and could capture 5.4% of outbound UAM demand. Hollywood and Long Beach both attract substantial UAM demand capturing 4.3% and 3.3% of the total UAM demand, respectively.
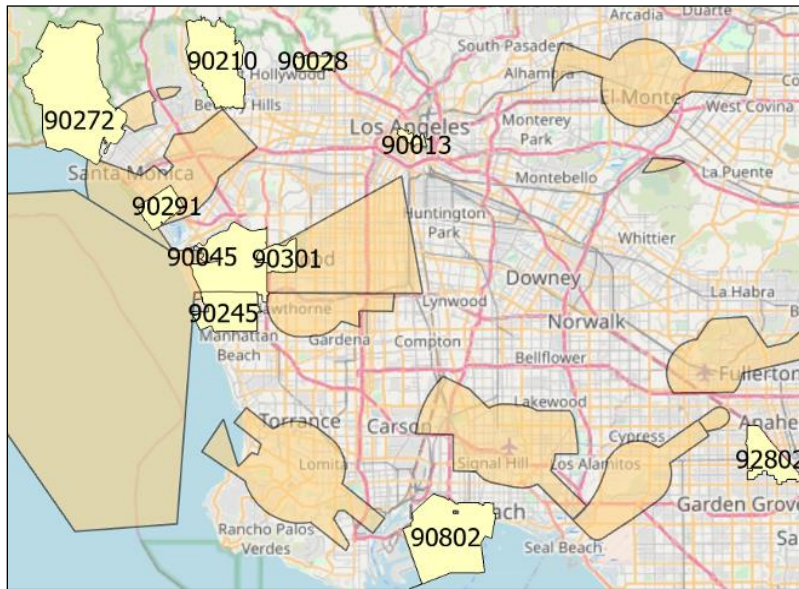
Figure 42: Top 10 Areas of Origin (Yellow Polygons)

Table 14: UAM Demand in Top 10 Areas of Origin by Current Ground Access Survey

Area	Zip Code	% of ground access trips	Outbound UAM Passenger Trips	% of Total Outbound UAM Passenger Trips
Anaheim	92802	4.1%	192.2	5.4%
Downtown LA	90013	3.8%	217.8	6.1%
LAX Area	90045	3.2%	0	-
Hollywood	90028	2.5%	154.0	4.3%
Long Beach	90802	2.4%	119.4	3.3%
Pacific Palisades	90272	2.2%	90.9	2.5%

El Segundo	90245	1.8%	0	-
Beverly Hills	90210	1.5%	80.3	2.2%
Inglewood	90301	1.5%	0	-
Venice	90291	1.4%	0	-

4.10 **UAM Demand Sensitivity with Number of Vertiports**

All demand results presented until this point use the 75 vertiport set. The number of vertiports or UAM network size is a critical element in the demand estimation process. As the number of vertiports increase, the mode becomes more accessible, and access time decreases. However, building more vertiports is not always better, especially from an economic point of view. Given the infrastructure and real estate cost in metro areas, building vertiports can be very costly. If they only serve a handful of passengers over the day, it is not economically feasible. Therefore, the potential demand impact of the addition/removal of vertiport should be analyzed.

Figure 43 shows the daily UAM demand by vertiport size, keeping the UAM CPM at $2.00. The total UAM demand increases by only 12% and 5.7% when vertiport size increases from 50 to 75 and 75 to 100, respectively. The small increase in UAM demand on adding more vertiports is probably due to the heavy concentration of airport access trip demand in certain areas of the region. When demand is concentrated in certain areas rather than evenly spread, a small vertiport set is more efficient, as witnessed.
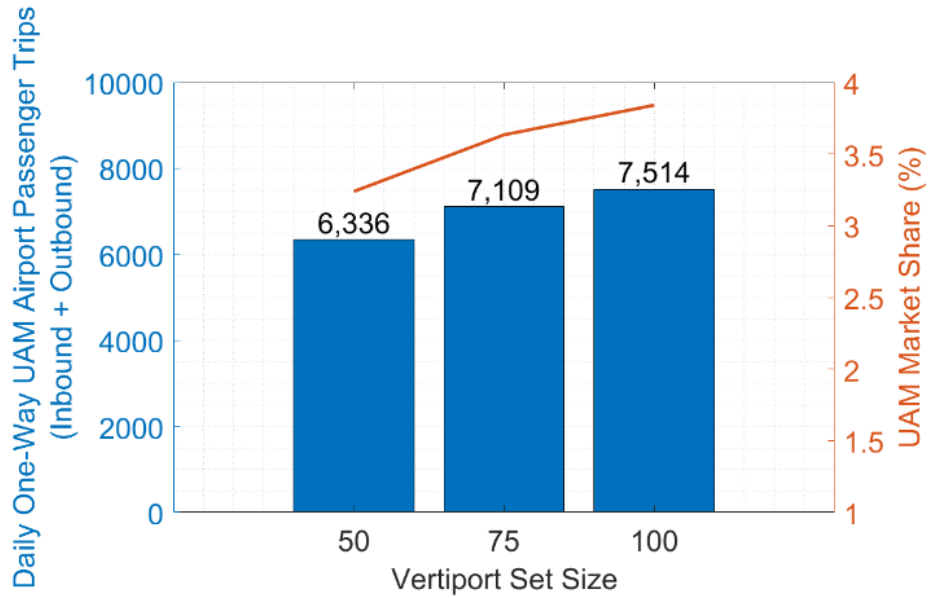
Figure 43: Total Daily UAM Demand by Vertiport Set Size (UAM CPM: $2.0)

4.11   Conclusions

UAM has considerable potential in airport access trips to LAX. With a network size of 75 vertiports, UAM could capture 3.6% (7,109 UAM passenger trips) and 2.4% (4,730 UAM passenger trips) market share at $2.0 UAM CPM and $3.0 UAM CPM, respectively (additional to $15 base cost per passenger and $20 landing cost per flight, assuming 2.4 pax per flight). The total airport access demand is geospatially concentrated in certain areas; therefore, the UAM demand is not very sensitive to UAM network size. Increasing the number of vertiports from 50 to 100 only increases UAM demand by 18.5%. LAX to LA downtown, Anaheim, Hollywood, and Long Beach, are the top four UAM corridors in order.

4.12   Limitations and Future Research

The UAM demand results presented in this study are subjected to certain assumptions. Awareness and acceptance of UAM among travelers are assumed to be similar to current Rideshare modes (Uber, Lyft, etc.). The reliability of the UAM system should be high to achieve presented demand results. The analysis assumes that UAM is always available to travelers whenever requested. Potential delays due to vertiport congestion, inclement weather conditions, and unavailability of UAM

vehicles are recognized but not considered in the demand estimation process. Future research is recommended to include the impact of these factors to get more constrained UAM demand results.

The lack of information on travelers in application data restricted us from including traveler characteristics variables directly in the model. Household income, number of household vehicles, household size, and other traveler's related variables could strengthen calibrated model and result in more credible demand estimation results. Nevertheless, the UAM demand results presented in this paper are reasonable considering currently available data.

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4.14   **Acknowledgements**

4.15   **Appendix I: Model Validation Plot**
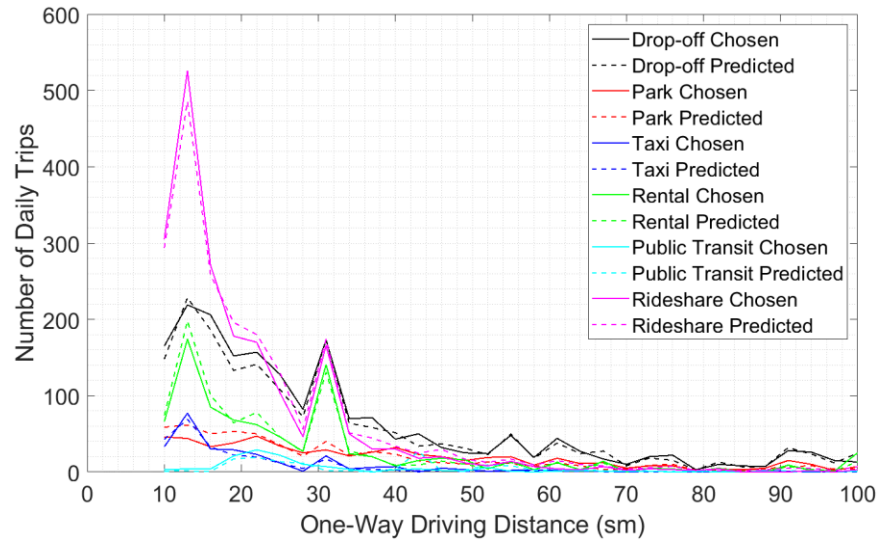
Figure 44: Comparison of Market Share by Distance

5.   Factors Affecting Vertiport Capacity

Rimjha, M., & Trani, A. (2021, April). Urban Air Mobility: Factors Affecting Vertiport Capacity. *2021 Integrated Communications Navigation and Surveillance Conference (ICNS)* (pp. 1-14). IEEE.

5.1   Abstract

This study aims at analyzing critical factors impacting vertiport capacity in urban areas. Urban Air Mobility (UAM) or Advanced Air Mobility (AAM) is a concept transportation mode being designed for intracity transport of passengers and cargo utilizing autonomous electric vehicles capable of Vertical Take-Off and Landing (VTOL) from dense and congested areas. The vertiports are expected to be placed on rooftops in Central Business Districts (CBD), limiting vertiports' size and suggesting high infrastructure costs. Therefore, vertiport capacity analysis is critical for an efficient UAM network as operations could be tailored for maximum efficiency. This analysis uses the vertiport designs developed for a previous study using current guidelines for heliports by Federal Aviation Administration (FAA). The minimum area of all designs was estimated for single and dual taxi-lanes configurations. From a preliminary geospatial analysis of San Francisco CBD, the rooftops' sizes are less likely to accommodate vertiports with more than three landing pads, even with tailored modifications. Therefore, this capacity analysis only considers vertiports with one, two, and three landing pads. A Discrete Event Simulation (DES) model is developed in MATLAB to simulate UAM operations and determine vertiport capacity. A high-demand vertiport in San Francisco Financial District is selected to understand the impact of unidirectional flows on a vertiport's passenger serving capacity. The analysis focuses on the utilization of various elements of vertiport, as they comprise the overall efficiency of the vertiport operations.   Moreover, vertiport capacity sensitivity against elements such as the charging rate, service times at landing pads, and parking stalls are included in the findings.

5.2 Introduction

As the industry is preparing its vehicles for commercial UAM operations [1, 2], cities and authorities are generating roadmaps for better adoption of this transportation mode [3]. The UAM is expected to create a significant impact on the economy [4, 5]. While the UAM vehicles could be ready to operate commercially by the year 2024 [6, 7], is the infrastructure ready? The early adopters of UAM would probably be the airport access trips [8] partly because the foundational infrastructure for takeoff/landing areas exists on at least one side of the flight. FAA also believes initial UAM operations could use existing helicopter infrastructure (routes, helipads, etc.), and no UAM unique structure is needed [9]. However, the UAM market is expected to grow rapidly at a compound annual growth of 11.3% over the next ten years [10]. It would be challenging to build an infrastructure capable of catering to high UAM demand levels in urban spaces with limited land availability, especially in CBDs. The operational efficiency of vertiports is crucial in capturing maximum UAM demand potential.

Vascik et al. developed an Integer Programming approach to determine deterministic vertiport capacity envelopes. They believe the ratio of gates to Touchdown and Liftoff (TLOF) pads as a key design factor [11] and found 7-8 gates per pad as "potentially efficient topology". Their analysis recommends having staging stands to handle unbalanced arrivals or departures. Even though staging stands require a smaller footprint than gates, they could increase the total vertiport footprint.

The vertiport designers and system planners could benefit from this analysis's results because the utility of the UAM depends significantly on the marginal time-savings, and any inefficiency in the system will affect the traveler's utility from UAM.

5.3 Data

The findings of a previous UAM demand estimation study [12] performed for the National Aeronautics and Space Administration (NASA) in the year 2019-20 comprise a significant part of the data used in this analysis. The demand estimation study focused only on commuters. It involved calibrating a mode-choice model using the National Household Travel Survey (NHTS) – 2017 Add-On data [13], developing a demand-driven vertiport placement method, and predicting the UAM demand using the LEHD Origin-Destination Employment Statistics

(LODES) data [14]. The demand analysis findings include the vertiport level Origin-Destination (OD) demand with departure and arrival times based on the actual departure times for commuters observed in NHTS data. The vertiport level OD demand acts as the input for the DES model developed in this analysis.

Even though the demand analysis was performed for four metro areas in the United States (Northern California, Dallas-Fort Worth, Southern California, and New York City), this analysis only focuses on Northern California. Nevertheless, the results could be easily extrapolated to other metro areas because Northern California poses a challenging case with a heavy UAM demand concentration in small airspace around San Francisco CBD. Also, high infrastructure costs, limited or no vacant land availability, and heavy congestion in road travel are standard features of other CBDs. The UAM demand results are dependent on the UAM cost structure and the UAM network size or number of vertiports. The demand model predicted a 0.04% market share for UAM at $2.50 per passenger mile with a $10 base cost and 75 vertiports, estimating around 1,923 UAM passenger commuter round trips from 4.6 million daily commuters in the region. Such demand levels are expected in the early to mid-term or when the UAM system gains some maturity. Hence, this demand set is considered suitable for the capacity analysis. Figure 45 illustrates vertiport locations in San Francisco CBD and their demand level for the selected demand set. There are five vertiports in/near the Financial District, and the study will be focusing on the one with the highest demand (322 operations). Passenger trip demand is converted to daily UAM flight demand assuming a 60% load factor with a four-seater UAM vehicle. An operation is defined as either a takeoff or a landing.
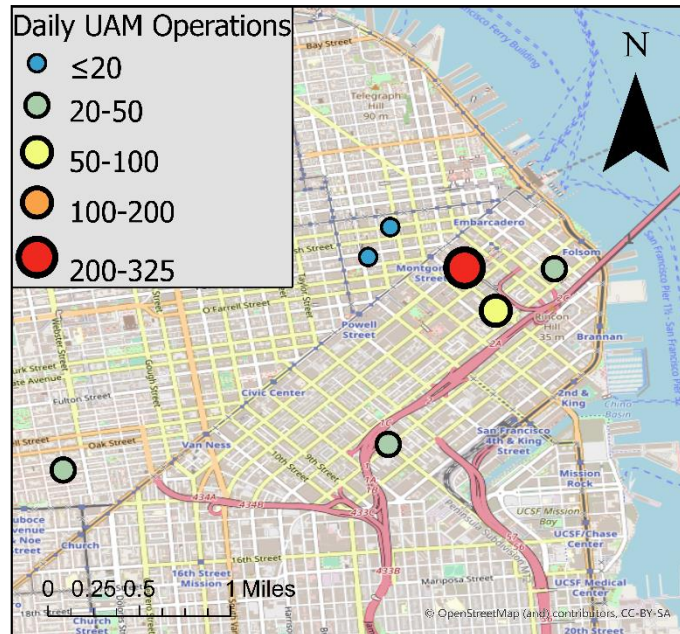
Figure 45: Daily UAM Operations at Vertiports in San Francisco CBD (Selected Demand Set)

The vertiport capacity is, of course, connected to the size of the vertiport. The demand analysis scope did not involve consideration of vertiport size or design. However, the vertiport locations and designs are closely studied in a parallel effort performed for NASA [15, 16]. There are no guidelines published yet for the UAM operations near and on vertiport. Therefore, the vertiport designs are developed using current guidelines for heliports by Federal Aviation Administration (FAA) in Advisory Circular 150/5390-2C [17]. Determining the minimum area required for vertiports of different configurations and compare it with land availability was the primary motive for developing vertiport designs. The designs include Clear Approach/ Departure Paths, Clear Area for Ground Maneuvers, FATO (Final Approach and Takeoff Area), TLOF (Touchdown and Liftoff Area), Safety Area Design, Parking Stalls, Safety Net (for elevated landing site), Wind Cone, Passenger Lounge Area/ Waiting Room, and Hangars and Lighting. Table 15 includes the minimum area required for vertiport designs considered in the capacity analysis. Appendix I includes the vertiport designs themselves.

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Table 15: UAM Vertiport Minimum Area Requirements

Landing Pads	Parking Stalls	Landing Pad Safety Area (acres)	Total Area in Ground Taxi Operation (acres)
1	8	0.25	1.97
2	16	0.25	3.87
3	24	0.25	5.84

5.4   Methodology

The basic framework involves utilizing a DES model to estimate the vertiport capacity with different configurations and in different settings. The DES model developed in MATLAB during this study involves a significant number of variables with assumed values because either the value of that variable is unknown or uncertain (for example, UAM range, UAM battery charging rate, etc.). The assumed values are based on either concept vehicle manufacturers or expected performance values based on current technology. Some of these variables have a more substantial impact on the capacity than the others, and it is crucial to study them through sensitivity analyses. The initial step in the analysis was the development of the DES model.

A DES model can model operations in a system as a series of events over time [18]. These events cause a change of state in the system, and no change is assumed between the events. Usually, a system consists of servers, resources, and queues. In this analysis, the *vertiport* is considered our system, and operations (arrival or departure) are considered entities. These entities move through the system and change the state of the system. The landing pads and the parking stalls are modeled as resources, and the UAM vehicles in the environment are modeled as modified resources. There are three First-In-First-Out (FIFO) queues in the system: Arrival Queue, Service Queue, and Departure Queue. The DES model and the simulation flow are shown in Figure 46.

Figure 46: Discrete Event Simulation Model Workflow

The DES model has three components that share common resources: *Arrival Section, Service Section,* and *Departure Section*. There are two independent entity generators (*Arrival and Departure*) that are not connected initially, but their mutual influence would be explained when introducing repositioning operations.

Arrival Section handles the arrival requests. If a pad is available, the pad is assigned the landing is completed by *Arrival Service Time* assigned to that operation. After landing, the operation is transferred to *Service Section* if any parking stall is available. Otherwise, the vehicle does not release the pad, and the operation is added to the service queue. The pad is released if a stall is assigned and there are no more arrivals in the queue. If the arrival queue is not empty, arrival operations in the queue are addressed before releasing the pad.

Once released from the pad, the vehicle is taxied to the assigned stall where the *Service* starts. *Service* includes bringing the vehicle to a complete stop for safely alighting the vehicle for passenger

arrivals. *Service End* is dictated by assigned *Service Time at Stall* for that operation. After *Service End*, the UAM vehicle is added to the available UAM vehicles at the vertiport and prepared for departure requests. Unlike arrivals, the service end does not release the stall as it is occupied by the vehicle, and the *Service* operation waiting in the queue must be processed at another available stall.

Departure Section handles all departure requests. When a departure request arrives, all UAM vehicles at the vertiport are checked for availability. If no vehicle is available, a repositioning arrival is requested. However, if vehicles are available, the one with the highest battery charge is assigned to the departure. The *Departure Launch* is scheduled after the assigned *Departure Service Time at Stall* for that operation. After the *Departure Service Time at Stall* is over, the vehicle battery level is checked against the minimum charge required for the assigned trip (including reserve). As soon as the vehicle is ready, landing pad availability is checked, and takeoff is scheduled.

5.5 Initial Vertiport Capacity Estimation

Baseline capacity metrics should be developed to understand the impact of various elements on vertiport capacity. The dissension between arrival and departure schedule is expected to reduce the passenger serving capacity of vertiport due to repositioning operations. However, the vertiports could achieve maximum passenger serving capacity with equal arrival and departure rates which would be an ideal scenario and rarely be the case in real-world UAM operations. UAM operations are simulated with arrivals and departures generated from the Poisson distribution with equal rates for baseline capacity. The simulations are carried out for 60 minutes to determine the maximum arrival and departure capacity of the vertiport configurations.

5.6 Passenger Serving Capacity of the Vertiport

The practical or passenger serving capacity of vertiports could be substantially less for actual commuting patterns. This part of the analysis focuses on the operations at the selected high-demand vertiport in San Francisco Financial District. There are 167 arrival flight requests, and an equal number of departure flight requests spanned across 24-hr. A full day of UAM operations is simulated with actual arrival and departure times of commuter flights estimated in the demand estimation study. Figure 47 shows the arrival/departure time distribution of passenger operations at the selected vertiport. The San Francisco CBD has a high employment density, making it the most significant trip attractor in the region. The selected vertiport does not produce any outbound commuter roundtrips,

which is expected given the vertiport location and surrounding expected given the location and surrounding demographics. All the inbound commuter trips arrive in the morning, starting before 5 AM and peaking around 8:45 AM. The return trips of these commuters peak at 5 PM. The commuter flow at this vertiport is completely unidirectional in both the morning and the afternoon.
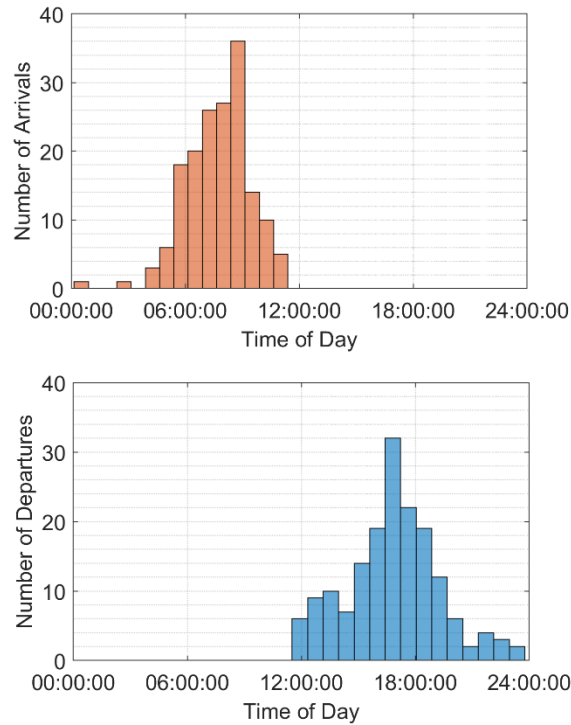
Figure 47: Distribution of Arrival and Departure Times of Flights at the Selected Vertiport

The flying distances of departures are also considered in the analysis, as they impact the service time of the departure or time taken to prepare for departure. The assigned UAM must have enough charge (with 20% reserve) for the flight. The UAM demand model assumes that UAM trips are infeasible below 10 miles. UAM provides significant travel time savings for mid-distance trips (20-30 miles) by bypassing ground congestion en-route to San Francisco Financial District. Also, UAM becomes very costly for long-distance trips; therefore, UAM trips in mid-range are relatively popular. Figure 48 shows the flight distances of departures from the selected vertiport.

As commuting traffic flows at the vertiport are unidirectional for a significant amount of time during the day, it poses a challenge for UAM operations as the proportion of UAM repositioning operations increases and the effective passenger carrying capacity of the system reduces. The

repositioning operations are an economic burden and also add to vertiport and airspace congestion. The imbalance between arrival and departure request times impacts the proportion of repositioning flights, which is analyzed in this study.
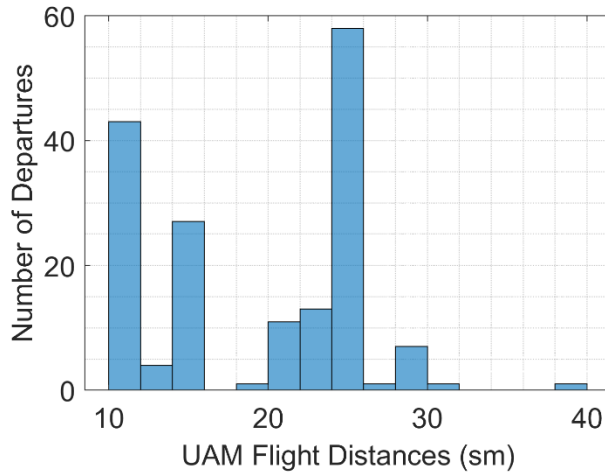
Figure 48: Distribution of Departure Flight Distances. Total Departures: 167

5.7 Repositioning Algorithm

Repositioning or dead-headed flight are generated when one type of operation (arrival or departure) dominates over another for a significant period of time. If arrival flight requests are dominating over departure flight requests, the rate of occupying the parking stalls at the vertiport would be higher than the release rate. This would eventually exhaust the vertiport capacity, and no more arrivals could be allowed before force releasing empty UAM vehicles through repositioning departures. Similarly, if departure flight requests are dominating over arrival flight requests, dead-headed arrivals would be required to bring empty UAM vehicles in order to serve departure requests once they exhaust the UAM availability at the vertiport.

Although repositioning operations are usually in response to instantaneous lack in supply, pre-planning repositioning operations could be conducive in efficient vertiport operation during peak periods, especially in this scenario where arrival and departure requests are heavily imbalanced. The reason for the recommendation of pre-planning is the use of the same resources at vertiport by repositioning operations and also the time it takes to perform repositioning operations. For example, if we wait till arrivals completely saturate the stall capacity and then force repositioning departure

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operation, it could cause significant delays as arrivals would be blocked till the vehicle is pushed and has departed from the vertiport. The repositioning departure would also use the same landing pads where the arrival queue has already started building up due to saturation. Similarly, if repositioning arrivals are only requested when no UAM vehicle on vertiport is available, significant delays could be incurred. Requesting repositioning flight, flying a dead-headed UAM vehicle, landing, and bringing it to a stall where departure service could proceed, would take a considerable amount of time and reliability issues.

In this study, knowledge of arrival and departure times is already fed to the system. Such information is not usually available to the operators of an on-demand service. However, predicting expected traffic using the data of completed trips (or traffic patterns of existing modes) as the system matures is already practiced and known to boost the system's operational efficiency [19]. This is also practiced in modern supply chains [20] for lower delays and higher productivity.

The DES model utilized in this study is programmed to enforce repositioning departures when 50% of the vertiport stalls are occupied and the number of completed arrival requests is less than the 95th percentile of all expected passenger-carrying arrivals. Similarly, the model requests repositioning arrivals if the occupied stalls are less than 50% of total stalls at the vertiport and the number of completed departures are more than the 5th percentile of all expected passenger-carrying departures. Besides pre-positioning, certain thresholds are embedded in the Simulation to enforce required repositioning operations and maintain stability in the system, such as requesting immediate repositioning arrival if no UAM is available at the vertiport for departure request or forcing immediate repositioning departure if service queue increases beyond taxiway limit of four vehicles.

5.8   Results

Variables with assumed values play a critical role in any discrete event simulation model. This model has assumed values for several variables such as *Arrival Landing Time or Departure Take-Off Time at Pads*, *Arrival or Departure Taxi Times*, *Service Times (Boarding or Alighting)*, etc. Some of these variables are later varied in the sensitivity analysis to quantify their impact on vertiport capacity or operational efficiency. Table 16 includes the assumed values for these variables in initial operations capacity estimation and actual passenger serving capacity estimation. Distribution is assumed for all

the service times instead of fixed values to provide randomness observed in real-time operations. The lognormal distribution is selected to avoid unrealistic negative service times.

Table 16: Assumed Parameters and their Values in the Simulation Model

Parameter	Value	Distribution	Variance
Arrival Service Time at Pad	90 sec	Lognormal	30 sec
Arrival/ Departure Taxi Time	60 sec	-	15 sec
Arrival Service Time at Stall (Passenger)	5 min	Lognormal	1 min
Arrival Service Time at Stall (Repositioning)	2 min	Lognormal	15 sec
Charging Rate (per min)	8%	-	-
Max. Charge (80% SOC)	100 mi	-	-
Reserve Ratio	20%	-	-
Departure Service Time at Stall (Passenger)	5 min	Lognormal	1 min
Departure Service Time at Stall (Repositioning)	1 min	Lognormal	15 sec
Departure Service Time at Pad	60 sec	Lognormal	15 sec

5.8.1   Initial Vertiport Capacity Results

The baseline simulation runs provide vertiport capacity metrics for balanced arrival, and departure operations generate from a Poisson distribution. All three vertiport configurations' operation handling capacity is calculated, keeping all assumptions mentioned in Table 16. Figure 49 illustrates the number of arrivals and departures handled by different vertiport configurations. Full utilization of Pads and Stalls was observed during multiple times during Simulation. Each configuration's interarrival times were tailored to avoid the arrival/service/departure queue threshold of five/five/six operations. Pre-staged UAM vehicles are defined as ready UAM vehicles already present at the vertiport at the Simulation start. Pre-staged UAM vehicles are kept at 33% of vertiport stall capacity. Table 17 includes the maximum number of passengers carrying operations observed in these simulations.

Table 17: Maximum Number of Operations in One-Hour Simulation

[Pads/Stalls]	Pre-Staged UAM Vehicles	Maximum Arrivals (Passenger Carrying)	Maximum Departures (Passenger Carrying)
[1 / 8]	3	16	20
[2 / 16]	5	22	25
[3 / 24]	8	43	35
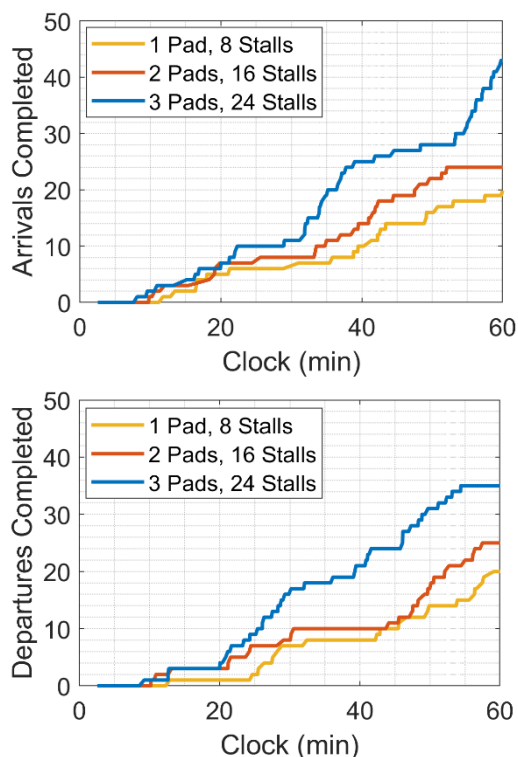
Figure 49: Hourly Capacity of Different Vertiport Configuration under Balanced Operation

5.8.2 Vertiport Capacity Results of Selected Vertiport

Following are the important observations from a full-day simulation of operations at the selected vertiport. Initial Simulation was attempted with three Pads – 24 Stalls vertiport configuration but, it could not handle the traffic, and vertiport resources were exhausted with infeasible queues. Figure 50 shows the queue limit breaching and exhausting resources, after which Simulation cannot continue without discarding arrival or departure operations.
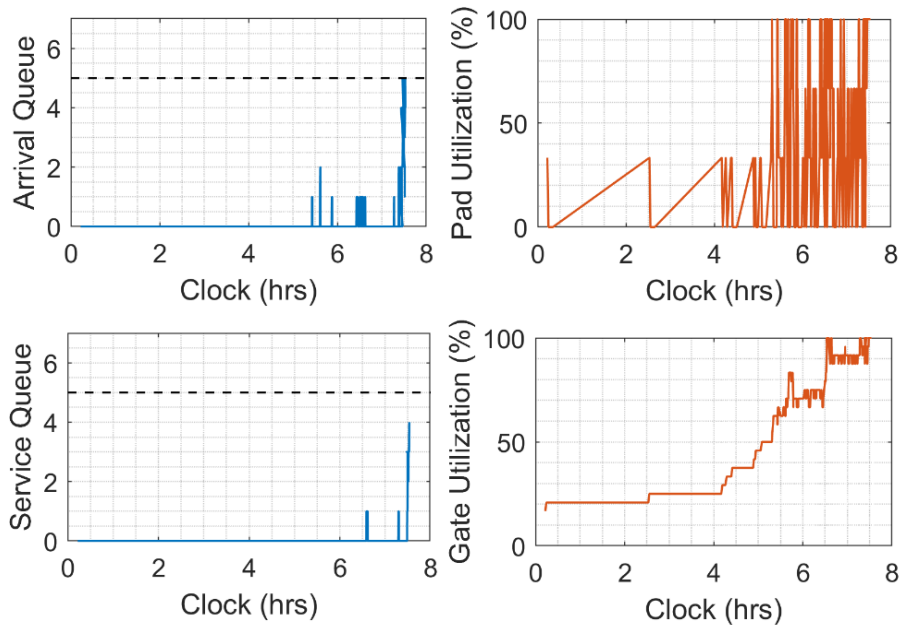
Figure 50: Queue and Utilization for 3 Pads - 24 Stalls

A minimum of four pads and 36 stalls would be required to serve the demand at our vertiport without discarding any operation. This configuration could be developed using combinations of the fundamental configurations and designs presented in this paper. A vertiport with four pads and 36 stalls would require almost 6.96 acres. Such a large area is difficult to find on rooftops or in vacant spaces in the Financial District. Perhaps, the vertiport could be split into two smaller (2 Pads -18 Stalls) vertiports or could be moved off-shore. Although convenient, the latter would add some extra access time and might decrease the demand.

Following are the simulation results with four Pads - 36 Stalls configuration. Figure 51 illustrates the utilization of resources (Pads and Stalls) at the vertiport during a full 24-hr Simulation. The increased utilization during peak periods is expected due to increased arrival and departure request rates. Arrivals are expected to take more time than departures at the pad and are programmed to occupy the pad for 30 seconds more than the departures (Table 16). Therefore, the pad-utilization is maximum for a more extended period of time during arrival peak (or morning peak) than during departure peak (or afternoon peak). The parking stall utilization is connected to the repositioning algorithm to some extent. The pre-positioning threshold dictates the maximum or the minimum number of UAM vehicles on the ground. The threshold is set at 50% or 18 gates for departures, i.e., if

the occupied gates drop below the threshold, repositioning arrivals are requested. This is evident from the stall-utilization profile during the afternoon.

Similarly, during morning peak hours, repositioning departures are forced if more than 50% of the stalls are occupied. However, due to minimum service time at stall and departures competing for same pads with arrival priority in place, the stall-utilization is rapidly increasing during peak arrival period, and stall-capacity gets exhausted by the end of arrival peak (around 9 AM). The highest number of hourly arrival requests is 42, from 7 AM-8 AM. However, due to the high proportion of repositing flights and short interarrival times, the vertiport operates at maximum capacity for a significant amount of time in the morning.
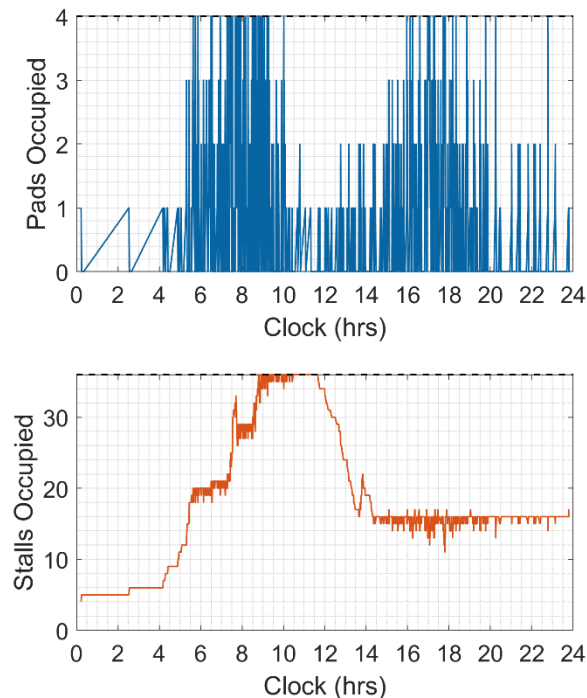
Figure 51: Pads' and Stalls' Utilization during 24-hour Simulation (4 Pads - 36 Stalls)

Analyzing the queue is a vital part of a discrete event simulation analysis. Understanding the factors controlling the queue helps in efficient planning. The vertiport in our model operates under arrival priority. Increasing service queue indicates gridlock potential at the vertiport, especially during peak periods when operation requests are on the higher side. Figure 52 shows the status of all three queues during the Simulation. Since the vertiport operates under arrival priority, the arrival queue does

not exceed two. During arrival peak hours, repositioning departures shoot the gap between passenger-carrying arrivals. Finding the gap becomes difficult as the rate of arrivals increases, and therefore, the departure queue extends to six during peak arrival hours. Without pre-positioning, this issue can aggravate as the system waits for capacity saturation before it starts forcing repositioning departures. The long queue of departures indicates a slow release of stalls, resulting in an increase of service queue if the vertiport stall occupancy is near maximum. This is also explained by the service queue's graph between 8 AM-10 AM.

Moreover, the abnormal increase in-service queue is attributed to the repositioning algorithm. The pre-positioning algorithm stops requesting repositioning departures if completed passenger arrivals are already over the 95th percentile (Clock~ 10.1 hours) of expected arrivals. Therefore, the remaining arrivals wait for service as vertiport stalls were already near exhaustion. It should be noted that besides pre-positioning, instantaneous repositioning requests can also be triggered by vertiport congestion.
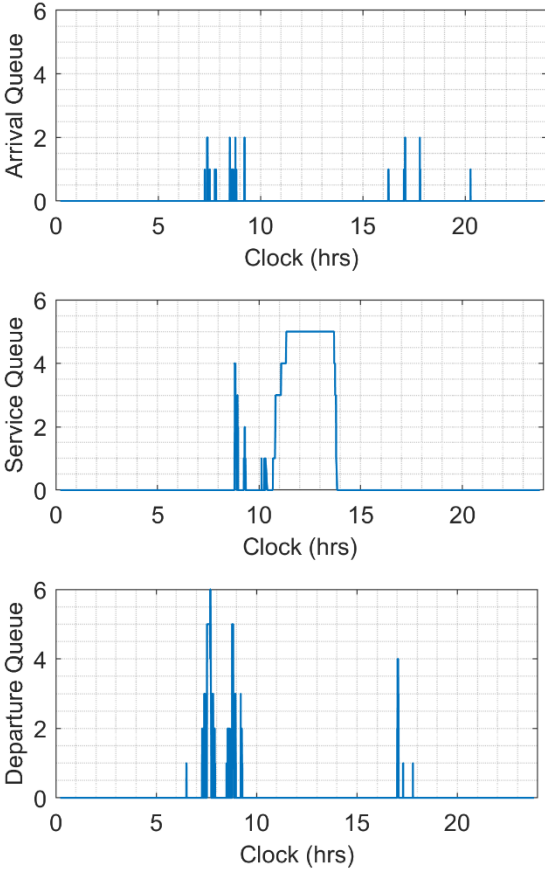
The imbalance between arrival request times and departure request times can affect the passenger-carrying operations a vertiport can handle. The 4 Pads- 36 Stalls vertiport is saturated because many repositioning flights are required consistently. Figure 53 depicts the steady requirement of repositioning departures and arrivals during arrival and departure peak periods, respectively. Repositioning operations are essential to keep vertiport operational for passenger operations.

Table 18 includes the total number of completed operations by the end of the Simulation. 46% of the arrival operations are repositioning operations, and 47% of the departure operations are repositioning operations. Due to the heavy imbalance, 0.90 repositioning departures are required per passenger arrival, and 0.85 repositioning arrivals are required passenger departure.
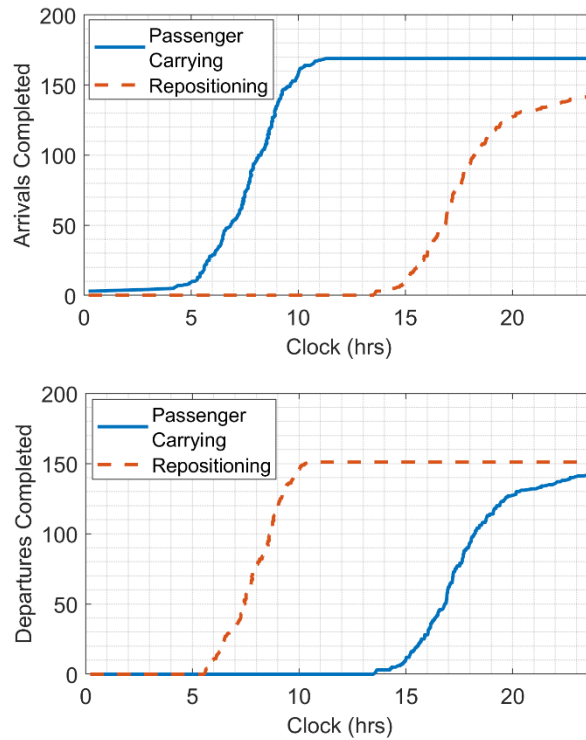
Figure 53: Number of Passenger Carrying and Repositioning Operations throughout Simulation

Table 18: Number of Completed Operations in a 24-hr Simulation

Operation Type	Total Number of Completed

	Operations
Passenger Arrivals	167
Repositioning Departures	151
Passenger Departures	167
Repositioning Arrivals	142

The UAM vehicles are considered a modified resource because individual vehicles are recorded and handled in the Simulation. The availability of UAM vehicles and departure wait times are closely related. The core motivation behind UAM vehicle pre-positioning is to make a vehicle available at the time of expected departure request. During departure peak hours, UAM vehicle availability drops quickly while repositioning arrivals are on the way or being processed. This can be observed in Figure 54. During arrival peak hours, the consistent gap between total UAM vehicles on the ground and available vehicles is due to the service time before the UAM is considered available for departures.
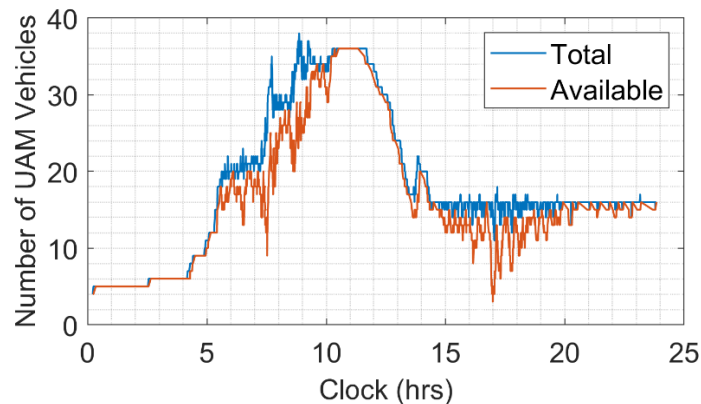
Figure 54: Number of UAM Vehicles on the Vertiport throughout Simulation

5.9   **Sensitivity Analysis**

Several factors are controlling the efficiency of the vertiport operations. Table 16 includes the default assumptions in the DES model. It is crucial to analyze the impact of these variables.

- Arrival Service Time at Stall: Figure 55 shows the Simulation service queue when the stall's arrival service time is increased by two minutes and variance by one minute. The service queue increases by three and exceeds the stable limit of five operations. Quick Service of the vehicles during peak arrival time is essential to avoid delays.
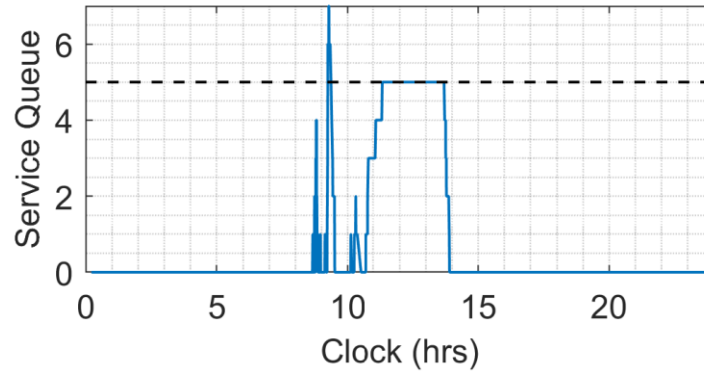
Figure 55: Increased Service Queue due to Increased Service Time and Variance for Passenger Arrivals

- Arrival Service Time at Pad: If the mean pad occupancy time of arrivals could be reduced by 30 seconds (90 seconds to 60 seconds per arrival), the same demand could be served by three Pads and 30 Parking Stalls without discarding any operation. The three Pads - 30 Stalls configuration requires almost 6.38 acres, 0.6 acres less than the default four Pads – 36 Stalls configuration. Figure 56 displays the pad utilization during a simulation with three Pads – 30 Stalls serving the same demand due to a 33% reduction in mean arrival service time at the pad.
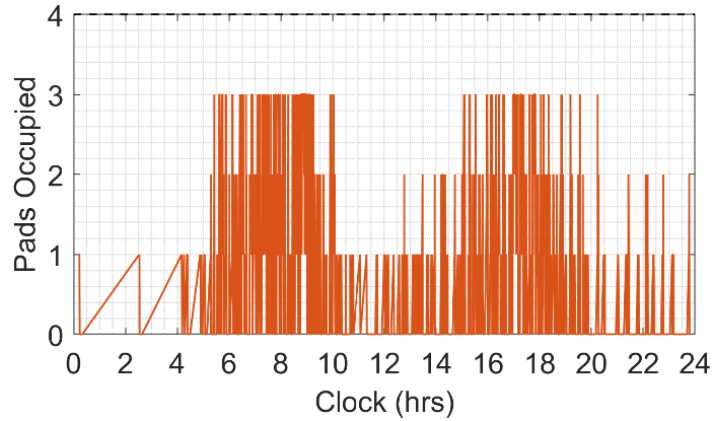
Figure 56: Pad Utilization during Simulation with Reduced Arrival Mean Service Time at Pad

- Repositioning Arrival Request Time: Since it is a single vertiport environment, UAM vehicle movement outside vertiport is not tracked. Repositioning arrival vehicle is assumed to arrive at the vertiport in 7.5 minutes from the time of the request. However, it could be argued. Also, the pre-positing algorithm is connected to the time it takes to bring repositioning the arrival vehicle. The impact of this variable is significant, which can be observed in Figure 57. Repositioning arrival request time is increased to 10 minutes keeping the same pre-positioning thresholds. The influx of repositioning arrivals during departure peak and when the vertiport operates under departure priority causes an infeasible arrival queue. This indicates the importance of the pre-positioning threshold in a multi-vertiport system or high variation in dead-headed arrivals' repositioning time.
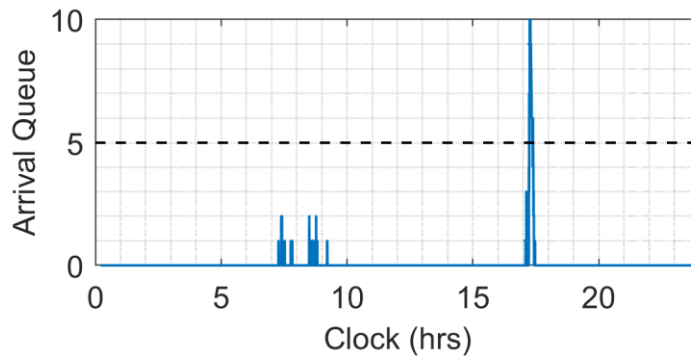
Figure 57: Increased Arrival Queue during the Departure Peak due to Increased Repositioning Arrival Request Time

The sensitivity of capacity against other variables such as battery charging rate and number of pre-staged vehicles was also analyzed. However, it was not found to be significant with given settings.

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Since simulation starts at midnight and arrivals precede departures, pre-staged aircraft are not useful in this circumstance. However, pre-staged aircraft is found to be useful in hourly simulations with balanced arrival and departure rates. The pre-positioning of the UAM vehicle allowed enough time for vehicles to be charged at the stall before being assigned to a departure. Therefore, the battery charging rate was not impacting vertiport capacity in these settings. However, vehicles often must wait for sufficient charge during mixed or balanced operations before they can be launched for departure.

5.10   Conclusions

Vertiports are a critical part of the UAM system, and the system's overall efficiency depends on them to a significant extent. Central Business Districts have the potential for UAM demand but at the same time building large vertiports is difficult due to high infrastructure and real estate costs. Therefore, the operational efficiency of limited-sized vertiports is essential. Hourly vertiport capacity for three basic vertiport configurations was estimated using a DES model with balanced arrival and departure rates. Furthermore, a full day of UAM operations at a busy vertiport in the San Francisco Financial District area were simulated to estimate the effective passenger serving capacity of vertiports under unidirectional flows. The disproportion between arrival and departure requests controls the requirement of repositioning operations at any vertiport. For the given passenger arrival and departure schedule at the selected vertiport, 0.9 repositing departures and 0.85 repositing arrivals are required of every passenger arrival and departure, respectively. The requirement of repositioning flights could be reduced by adding other trip purposes for UAM such as airport access trips, shopping, etc. The importance of pre-positioning UAM vehicles for efficient operations and avoidance of gridlock at the vertiport is explained in this study.

Sensitivity analysis found vertiport capacity to be sensitive against changes in service times at stalls, service times at pads, and time between repositioning request and its completion. On the other hand, vertiport capacity was not sensitive towards battery charging rate and the number of pre-staged vehicles in this particular simulation setting.

5.11   Limitations and Future Research

Certain simplifications were performed due to the limited scope of this analysis. The study environment included a single vertiport and assumed that repositioning flights are always available

within a reasonable time. However, repositioning flights would be requested from or forced to nearby vertiports subjected to the availability of resources in reality. A multi-vertiport analysis is recommended for a more credible analysis of repositioning operations. Although realistic, discarding or diverting arrival and departure requests was not in the scope of this Simulation. The analysis was limited to commuter operations, and it is recommended to include other trip types in future research.

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5.13   Appendix I: Vertiport Designs
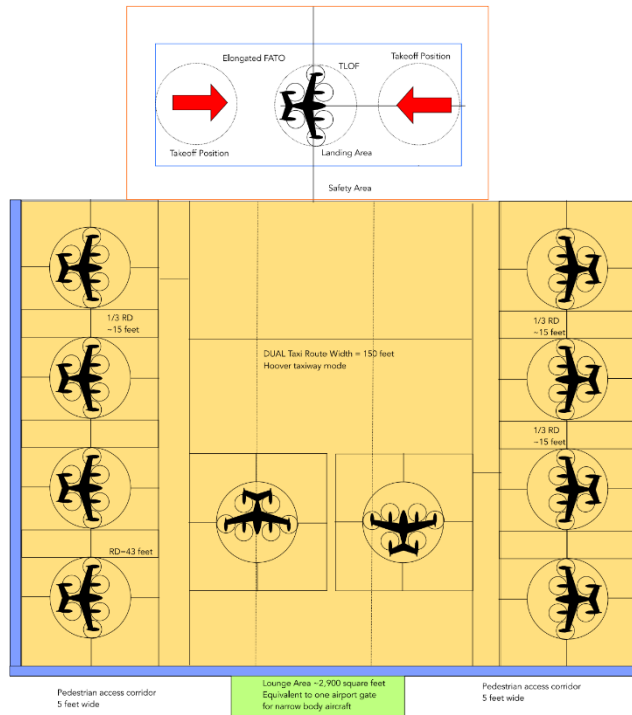
Figure 58: Vertiport Design using Current Heliport Standards for One Landing Pad and Eight Parking Stall Configuration
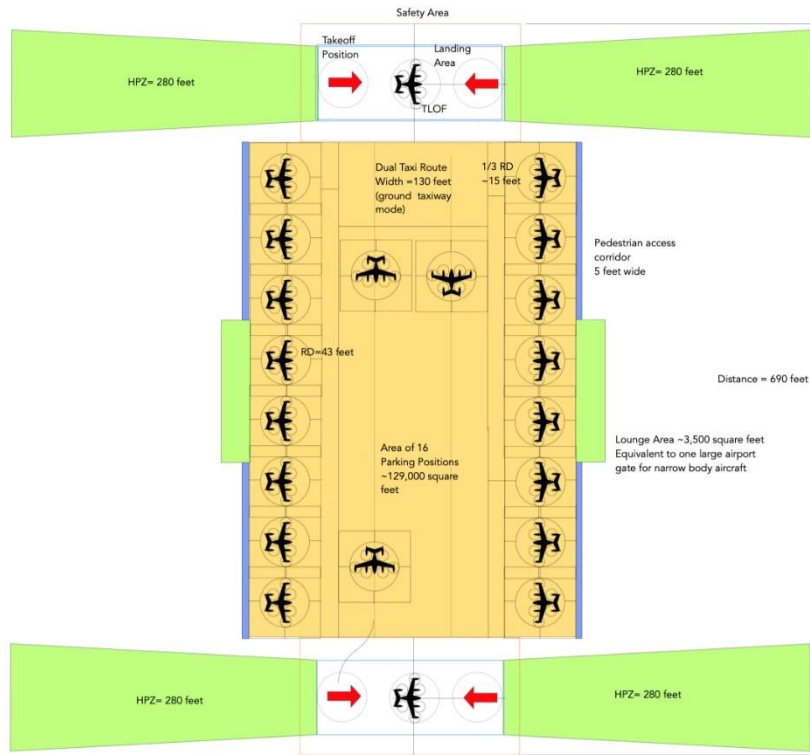
Figure 59: Vertiport Design using Current Heliport Standards for Two Landing Pads and 16 Parking Stall Configuration
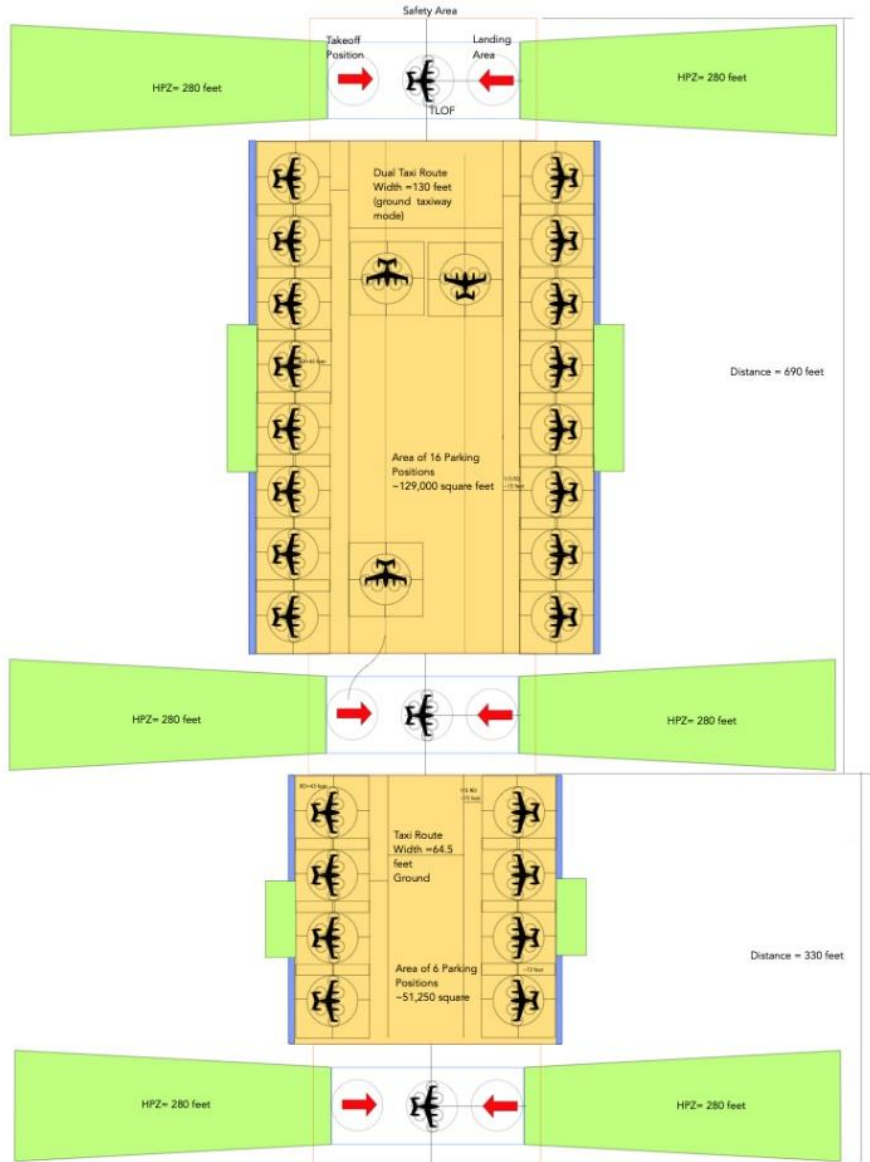
Figure 60: Vertiport Design using Current Heliport Standards for Three Landing Pad and 24 Parking Stall Configuration

6. Preliminary Noise Analysis of Commuter Operations

Rimjha, Mihir, et al. " Urban Air Mobility: Preliminary Noise Analysis of Commuter Operations." *2021 AIAA AVIATION FORUM* (p. 3204).

6.1 Abstract

This study aims to estimate potential noise levels generated due to Urban Air Mobility (UAM) commuter operations in the Northern California and the Dallas-Fort Worth regions. UAM is a concept aerial transportation mode designed to bypass ground congestion using an electric vehicle with Vertical Take-Off and Landing (VTOL) capabilities. UAM vehicles are expected to be significantly quieter than traditional helicopters, but operate on a much larger scale. Commuter travel demand will not be uniformly distributed with operations concentrated in a small geographical area such as Central Business Districts (CBD) and short time windows such as morning or evening peak periods. The objective of this study is to evaluate the aircraft noise annoyance generated by commuter UAM operations using flight trajectories developed in a previous study estimating UAM commuter demand. This study estimates the noise level from overflying UAM vehicles in a full day of operation (24 hours) and identifies areas where the noise levels may pose a challenge to future UAM operations. Noise estimation is performed at the Census Block group level using the Day-Night Level (DNL) metric. We run a parametric analysis considering two scenarios in each region: the UAM vehicle has a 10 dBA and 15 dBA noise reduction compared to the Robinson R-44 helicopter. The findings indicate a considerable difference between the 10 dBA and 15 dBA reduction scenarios. Although challenging, achieving a 15-dBA reduction compared to a 10- dBA reduction could reduce land area with DNL value above 50 dBA by 94% and highly annoyed population by 91% in Northern California. Similarly, in Dallas-Fort Worth, achieving a 15-dBA reduction compared to a 10-dBA reduction could reduce the land area with DNL value above 50 dBA by 80% and a highly annoyed population by 85%. Lastly, we analyze the high-demand vertiport in the San Francisco Financial District in the Aviation Environmental Design Tool (AEDT) to observe the DNL contours for the varying noise performance scenarios.

6.2 Introduction

Community annoyance due to aircraft noise around major airports has been a topic of interest for several decades [1, 2, 3]. Studies have shown that aviation noise disrupts sleep, adversely affects children's academic performance, and increases the risk for cardiovascular disease of people living in the vicinity of airports [4]. Urban Air Mobility (UAM) technology may be deployed in the National Airspace System (NAS) in significant numbers in urban areas and it is important to evaluate the magnitude of increased noise levels due to such operations.

UAM is a proposed aerial urban transportation mode involving advanced electric Vertical Take-Off and Landing (VTOL) vehicles. The concept of urban transportation using an aerial vehicle is not entirely novel. Multiple companies offered transportation services in New York using helicopters between Manhattan and airports in the region from the mid-1950s to the late 1970s [5, 6]. Besides safety concerns, the locals opposed these operations due to the high noise level generated [7]. Companies like BLADE, Uber, and Voom offer scheduled and on-demand helicopter trips between urban centers and airports [8, 9]. Even after utilizing advanced and relatively quiet helicopters like the Bell 206L-4, these services generated noise annoyance for Brooklyn residents [10]. Helicopter services operate on a considerably smaller scale than proposed UAM concepts, which indicates that UAM could significantly impact urban noise levels and potentially contribute to community annoyance. The UAM system demand is likely to be small in the initial phase of deployment. However, under favorable economic conditions, the UAM system could achieve maturity requiring thousands of flights daily in the U.S. [11, 12, 13, 14, 15, 16]. Unless the vehicles are considerably quieter compared to present helicopter technology, demand is unlikely to reach such numbers unprotested from the community, especially in densely populated regions.

This study presents a preliminary assessment of noise generated from a full day of UAM operations in two major urban areas in the United States: Northern California Bay Area and Dallas-Fort Worth. While multiple studies have estimated noise impacts through trajectory and concept vehicle simulations, there has not been much work performed on the potential noise levels generated from a mature UAM system with data based on a UAM demand analysis. This study fills this gap in the literature and creates critical links between UAM forecasted demand, vehicle noise performance, and expected noise annoyance. In addition, we extend the analysis to include a high-demand vertiport

in San Francisco Financial District in the Aviation Environmental Design Tool (AEDT) tool to closely observe the DNL contours for the varying noise performance of UAM vehicles.

6.3   Background

Yedavalli and Mooberry performed a study to understand public perception of UAM utilizing expert interviews and 1,540 survey responses across Los Angeles, Mexico City, New Zealand, and Switzerland [17]. The findings show that communities ranked noise generation as second in their top concerns (both the type of sound and volume), with UAM vehicle safety ranking first. The individual parameters producing the highest average concern from overflying UAMs across all combinations are: the resemblance between the sound of a UAM and that of a helicopter at 51%, the low flying UAMs at 51%, and the frequency of UAMs flying (100 times per hour) at 51%. The study concluded with an emphasis on noise mitigation in the UAM system design for better adoption of the mode.

Vascik and Hansman identified decreased community acceptance due to UAM noise as one of the strong scaling constraints for UAM [18]. The study identified the significant non-acoustic factors and mapped the acoustic and non-acoustic impacts of UAM operations to noise annoyance. The authors point out the challenge of representing community acceptance of aircraft noise constraints with a single metric. Furthermore, they determined the percentage of people highly annoyed in a community to be a salient metric for community acceptance in their proposed two-stage approach to understanding scalability limitations due to community acceptance.

Bent et al. studied the barriers associated with UAM noise that may hamper UAM vehicle entry into service and recommended high-level goals to address them [19]. The study focuses on four areas of interest: Tools and Technologies, Ground and Flight Testing, Human Response and Metrics, and Regulation and Policy. The authors recognize the importance of the human response to UAM noise for public acceptance and the success of UAM. Therefore, the study recommends the development of surrogate or other reduced order models so that designers can quickly determine the effects of design changes on noise early in the design process.

There has been a great interest and rapid development in the UAM vehicle sector from many aviation and automobile industry leaders in recent years [20, 21, 22, 23]. Polaczyk et al. summarized current technology (2019) and research in UAM [24]. Their report discusses forty-four eVTOL

prototypes currently being designed and implemented. The UAM vehicle concepts vary broadly from multi-rotors, multi-rotors with fixed wings, multi-rotors with foldable wings, etc., with different passenger capacity, payload capacity, battery, etc. Aircraft noise is an intrinsic property partly influenced by various factors such as structural design, the number of rotors/engines, operational noise of rotors/engines installed, and other design factors incorporated to mitigate noise specifically. Since all design concepts have varying components and the Federal Aviation Administration (FAA) is yet to certify a UAM vehicle capable of transporting passengers safely, the aircraft noise profiles of this vehicle are a major unknown.

Glaab et al. performed system-level simulations for a fleet of notional UAM vehicles for two different scenarios in New York [25]. The noise analysis is performed with AEDT using linearly scaled-down (20% lower) version of Noise Power Distance (NPD) curves of the Eurocopter AS350D light helicopter. The first scenario analyzes trips to the airport from current heliports in Manhattan representing near case, whereas the second scenario involved "hubs" located inside Manhattan based on the assumption of "early adopters" representing a farther term use case with commuters. The study assumes the number of operations parametrically (8, 32, and 128 operations per hour) to develop DNL contours at the airports for the first scenario and at the hubs in the second scenario. Using a notional target of 50 dBA, the findings suggest that the first scenario using 32 vehicles per hour did not exceed the target value for populated areas outside the vertiport vicinity. However, with 128 vehicles per hour, the study estimated 55 dBA in the interior of Manhattan and 65 dBA near vertiports. For the farther term scenario, the study found noise levels of less than 50 dBA. While the study displays the ability to simulate a different number of operations and estimate DNL contours around vertiports, it lays little emphasis on noise generated by overflying vehicles along the route and focuses only on areas around vertiports. The parametric analysis helps understand the cause-effect relationship but does not 3 reflect the region's actual travel patterns. Nevertheless, the study developed a sound methodology to estimate noise levels from NPD curves available in AEDT.

The typical UAM vehicle is likely to be a multi-rotor with a capacity of 2-4 passengers. We use the Robinson R-44, a two-bladed, single-engine four-seat, light utility helicopter, as the baseline vehicle for this analysis. The assumption is that the UAM vehicle would likely be quieter than the R-44, but the magnitude is unknown. Uber indicated that VTOLs would initially be 15 dBA or more

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quieter than existing helicopters [26]. Jia and Lee studied the acoustics of a one-passenger and a six-passenger quadrotor Urban Air Mobility (UAM) aircraft designs in level flight based on high-fidelity Computational Fluid Dynamics (CFD) approach [27]. The study found significantly lower noise from their UAM aircraft than a traditional 4-seat helicopter (such as the Bell 430). However, the difference reduces to less than 10 dBA at 1,000 Hz, where the human ear perception of noise annoyance is critical. The study concludes that a goal of 15 dBA quieter UAM than a traditional helicopter would be challenging to achieve. Eißfeldt suggests a potential reduction of 3-5 dBA from reduced tip speed, swept blades, increased blade count, or 1-2 dBA from reduced blade loading [28]. Due to the wide variation of the potential reduction in noise generated from UAM vehicles in literature, the study presented in this paper performs a parametric analysis concerning the noise profile (SEL curves) of UAM vehicles, i.e., multiple noise profiles are generated from different reduction values from baseline noise profile (SEL curves) of Robinson R-44. This analysis is performed at two reduction levels from the baseline noise profile: 10 dBA, 15 dBA.

6.4   Data

The analysis presented in this paper utilizes the UAM demand estimated during the commuter demand estimation study [29, 13]. The four-dimensional flight trajectories are generated after distributing daily UAM demand using departure time distribution of commuter trips extracted from the National Household Travel Survey -2017 Add-on data (Figure 61). A flight trajectory consists of a set of waypoints generated every second, keeping track of the flight's coordinates, altitude, and timestamp. The UAM Coordination and Assessment Team (UCAT) at the National Aeronautics and Space Administration (NASA) 's Aeronautics Research Mission Directorate has defined a series of UAM Maturity Levels (UMLs) [30]. UML levels represent development levels of UAM ecosystem through density and complexity of UAM operations. This analysis uses a UAM traffic level, which corresponds to "Intermediate State" or UML-3 and UML-4 [31, 32]. In Northern California, the desired daily UAM traffic level is obtained with 100 vertiports and $1.85 UAM Cost per Passenger Mile (CPM). Figure 62 shows the two-dimensional view of all flight trajectories (5,818) with 100 vertiports placed via a demand-driven approach. The scope of the demand analysis was seventeen counties surrounding the bay area. However, the scope shrinks to five or six counties around the bay area when the demand-driven approach places the vertiports to extract maximum UAM demand for a given number of

vertiports. The Concept of Operation (ConOps) in the demand analysis assumes UAM operations being independent of Air Traffic Control (ATC). Therefore, UAM flights are routed to avoid approach and departure surfaces of precision runways to avoid any conflict with aircraft operations at commercial airports [33, 34].
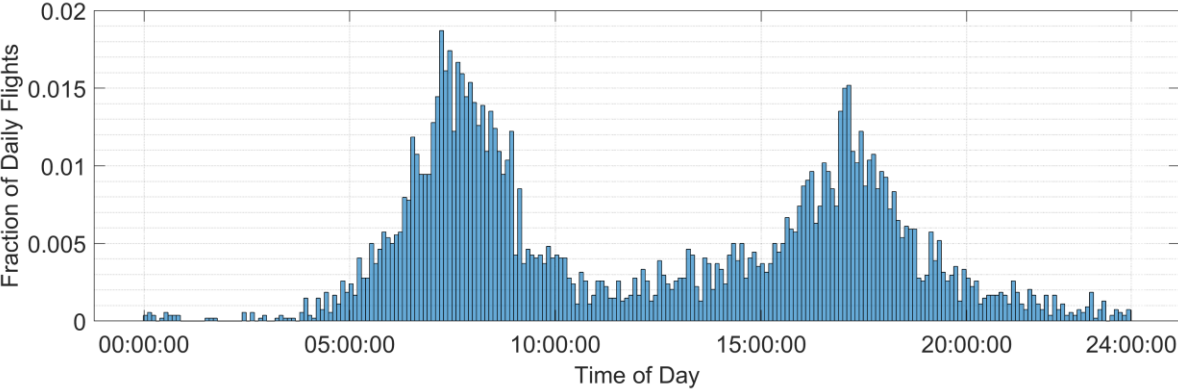
Figure 61: Distribution of Departure Times of UAM Commuter Trips
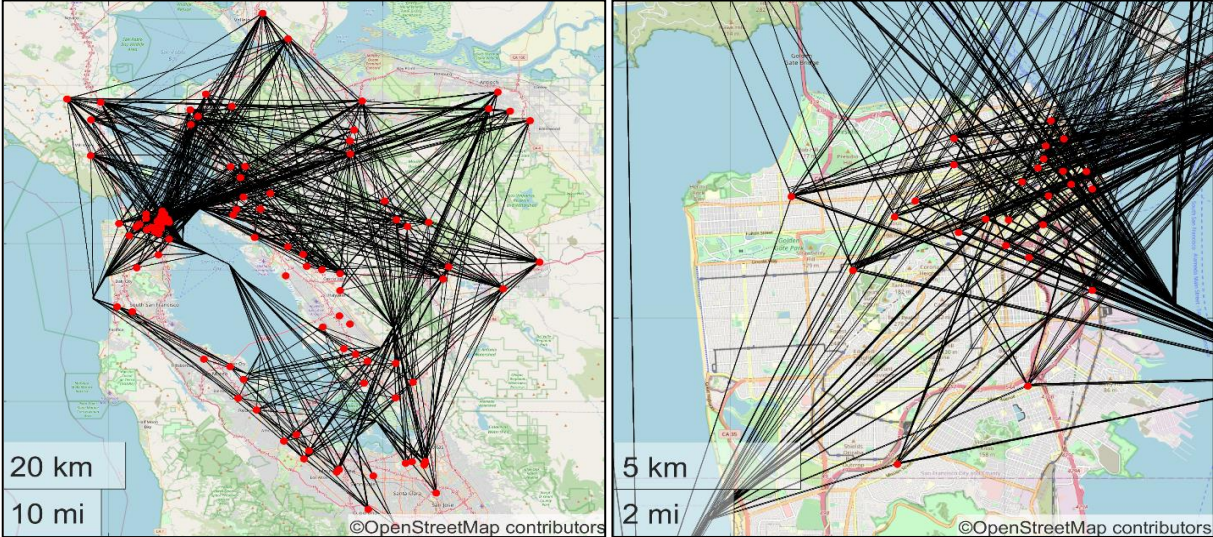
Figure 62: UAM 2-D Flight Trajectories. Left: All 100 Vertiports. Right: Focused on San Francisco CBD

Similarly, in Dallas-Fort Worth, the desired daily UAM traffic level is obtained with 75 vertiports and $1.30 UAM CPM. Figure 63 shows the two-dimensional view of all flight trajectories

(5,398), with 75 vertiports placed via the demand-driven approach. The scope of the demand analysis was 12 counties surrounding the Dallas-Fort Worth area. Similar to the Bay Area, the approach and departure surfaces at Dallas-Fort Worth International Airport (DFW) and Dallas Love Field (DAL) are protected.
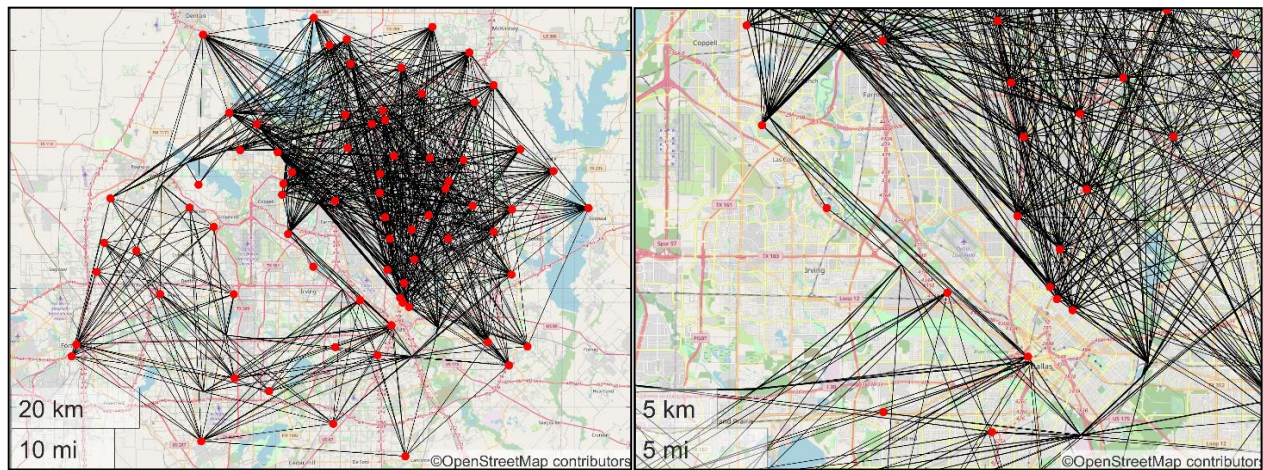
Figure 63: UAM 2-D Flight Trajectories. Left: All 100 Vertiports. Right: Focused on Dallas CBD

6.5 Methodology

Noise generated by a flying event (flyover, approach, departure) is measured in Sound Exposure Level (SEL). SEL is a single event metric that combines the acoustic energy generated by an event accumulated in one second. The AEDT tool developed by the Federal Aviation Administration (FAA) contains NPD curves for several airplanes and helicopters in their database. NPD curves model the variation in SEL with the distance of measuring point, i.e., noise generated by an event at a certain distance. NPD curves vary by event type, i.e., they are different for approach, departure, and flyover. Moreover, different NPD curves apply to different engine types. Using the baseline NPD curves of R-44, UAM vehicle NPD curves are developed for different reductions. Figure 64 shows the NPD curves developed from R-44 for all three operations (approach, departure, and level-fly) and the assumed NPDs for UAM vehicles for two scenarios (10 dBA and 15 dBA levels of noise reduction).
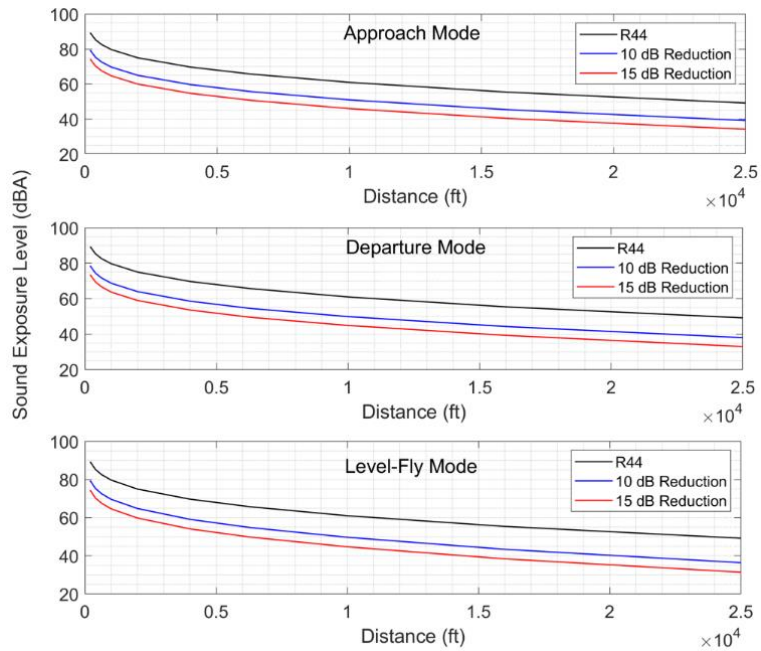
Figure 64: Noise Power Distance Curves of R44 and UAM for Different Modes

Figure 65 illustrates the workflow adopted for block group level noise analysis. The steps or data sources outlined in red are found to have the most decisive influence on final DNL values or annoyance levels. The following subsections explain the DNL value and annoyance level estimation in detail.
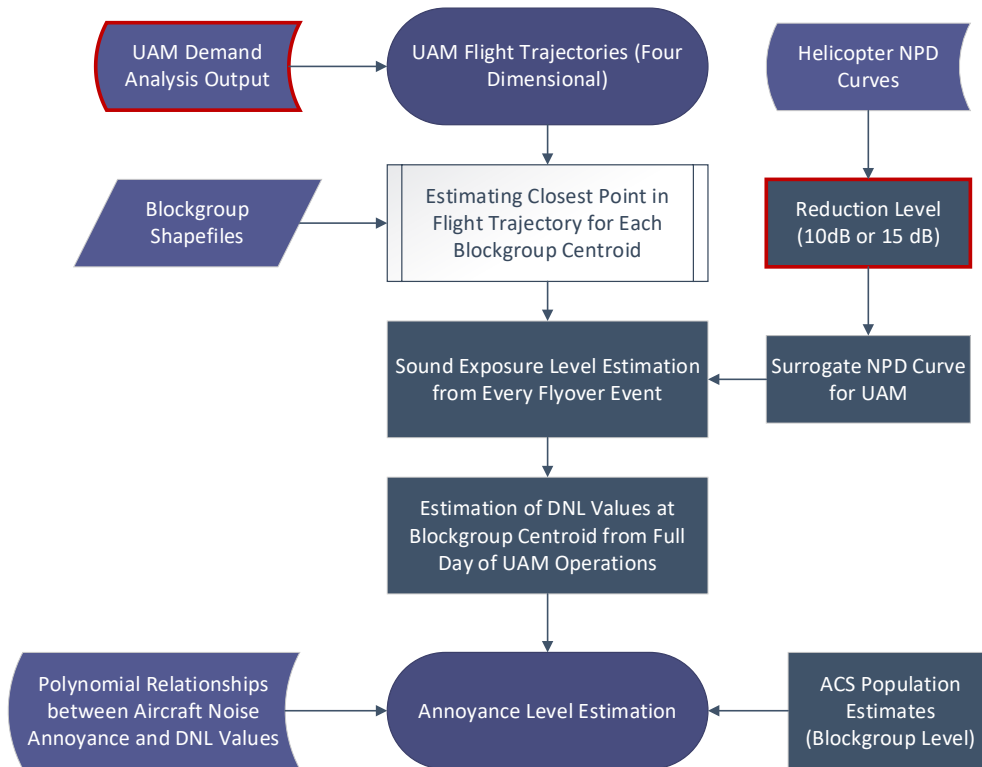
Figure 65: Adopted Workflow for Blockgroup Level Noise Analysis

6.6   **Estimation of Block Group Level DNL Values**

There are 7,106 and 4,158 block groups in the Northern California and Dallas-Fort Worth study area. For every Block Group, taking the population centroid as the representative point, SEL generated by each flying event is calculated. It is assumed that the flight trajectory's closest point is the most impactful part of the event. Therefore, the waypoint in the flight trajectory closest to the concerned Block Group centroid is selected to determine the SEL. Figure 66 shows an example of the closest point in the trajectory to a Block Group population centroid. A flight trajectory is made from 3-dimensional waypoints (blue) and population centroid is denoted by the red dot. The NPD curve selection depends on the relative position of the selected waypoint in its trajectory, i.e., if the closest waypoint is during the approach phase of the flight, the approach NPD curve is selected.
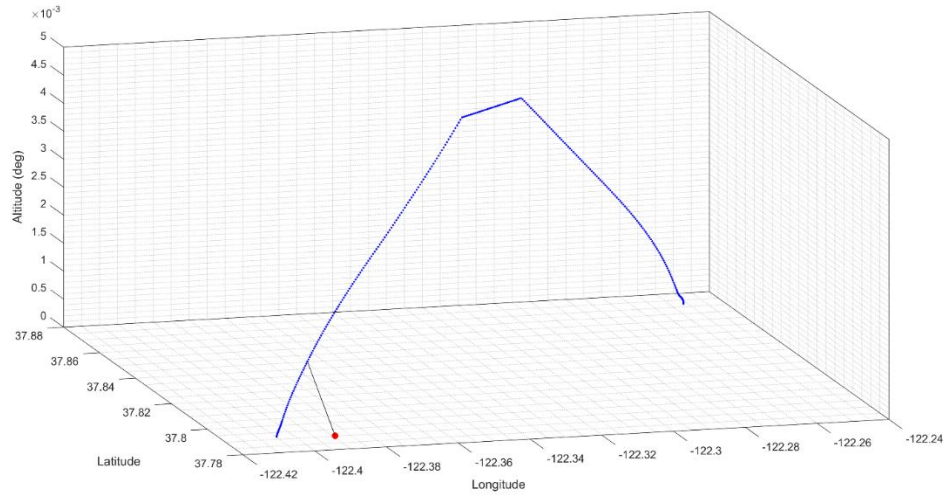
Figure 66: Example of Closest Point in the Flight Trajectory

Furthermore, the combined metric used to understand the noise generated by all the flying events in a day is the Day-Night Average Sound Level (DNL). Equation 1 calculates the value of DNL value at each Block Group centroid due to all flying events combined.

$$L_{DN} = 10 \log \left[\frac{1}{T} \sum_{i=1}^{N} 10^{\frac{(SEL_i + W)_i}{10}} \right] \tag{1}$$

$$L_{DN} = Day - Night\ Sound\ Level\ (dBA)$$

$$SEL_i = Sound\ exposure\ level\ associated\ with\ the\ i^{th}\ flyover$$

$$T = Reference\ Time\ (86{,}400\ seconds\ in\ a\ day)$$

$$W = 10\ if\ Operation\ is\ during\ Night\ (10\ PM\ to\ 7\ AM)$$

6.7 Estimation of Annoyance Levels

Human annoyance levels are estimated from DNL values for better interpretation of noise levels generated. Annoyance summarizes people's adverse reactions towards the noise that causes interference with speech, sleep, and the desire for a tranquil environment [35]. The noise was recognized as an environmental pollutant in l950's, and since then, several social surveys have been

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conducted to understand the societal impact of noise. Schultz developed one of the first dose-response relationships between noise exposure and subjective responses from eighteen social surveys on noise annoyance worldwide [36]. FAA's current noise policy uses the updated dose-response curves developed by Schultz. Miedema and Oudshoorn modeled the distribution of noise annoyance with the mean varying as a function of the noise exposure measured in DNL or Day-Evening-Night-Level (DENL) [37]. They fitted the model to data from several noise annoyance studies and developed a polynomial approximation of these relationships, which can be used for practical applications.

FAA undertook a multi-year research effort to quantify the impacts of aircraft noise exposure on communities around commercial service airports in the United States (U.S.) [38]. In this effort, their research team performed the Neighborhood Environmental Survey targeting communities around airports with at least 100 daily jet operations and where at least 100 people exposed to DNL higher than 65 dB and between 60 dB- 65 dB each. They analyzed "highly annoyed" responses and associated DNL to generate dose-response curves for each individual airport and a national dose-response curve. Their findings revealed that substantially more people are highly annoyed for a given DNL aircraft noise exposure level compared to previous studies. Therefore, we used the national dose-response relationship 7 to estimate the fraction of the "Highly Annoyed" population at the Census Block Group level. The logistic relationship is shown by equation 2. Further, we used the American Community Survey (ACS) Population Estimates [39] to estimate the number of annoyed people at the Census Block Group level.

$$\text{Percent HA} = \frac{100 \exp(-8.4304 + 0.1397 DNL)}{1 + \exp(-8.4304 + 0.1397 DNL)} \tag{2}$$

6.8   Generation of DNL Contours using AEDT

High noise levels are observed in San Francisco CBD. The second part of the analysis involves developing noise contours around the busiest vertiport from a full day of observation. The DNL contours provide a better understanding of noise propagation at the vertiport level and could be conducive to planning noise-mitigation techniques on the operations front. The operations (landing and take-off) are simulated in AEDT 3c, and noise contours are examined closely. The vertiport in the San Francisco district is generated as a heliport in the AEDT scenario. The UAM equipment is generated from Robinson R44 Raven/Lycoming O-540-F1B5 equipment in the AEDT database but with a

modified noise profile based on the reduction level scenario (10-dBA or 15-dBA). Multiple flight tracks are generated from analysis of popular azimuths in arrival and departure flight trajectories. A receptor grid of 300 latitudinal and 300 longitudinal points separated 0.05 nm with vertiport in the center is generated for the analysis. Based on the arrival and departure times of the UAM flights, hourly-binned operations are created in the AEDT environment. A full day of operations is simulated to estimate DNL levels at each receptor, which are then used to develop noise contours around the vertiport.

6.9   Results

The estimated Block Group level DNL values and annoyance levels are presented in this Section. In addition, both metrics' results are compared to understand better the impact of vehicle noise performance on noise level generated from a full day of operation.

6.9.1   Northern California

Figure 67 displays the spatial distribution of DNL values for both scenarios; the map on the left represents the 10-dBA reduction scenario, and the map on the right represents the 15-dBA reduction scenario. As suspected, high DNL values are observed in the San Francisco CBD due to the high concentration of UAM demand. It was found from the demand analysis that high employment density (especially high-income earners), high congestion levels, and costly parking costs resulted in high UAM demand for San Francisco CBD [13]. In the 10-dBA reduction scenario, the Financial District's DNL value reaches 63 dBA, with several block groups in the CBD region experiencing DNL values above 50 dBA. Besides San Francisco CBD, DNL values of 50 and above are observed all around the bay, in San Jose CBD and Oakland CBD. The DNL values drop significantly in the 15-dBA reduction scenario all around the region. DNL levels drop below 60 dBA in the Financial District and below 50 dBA in most of the CBD. DNL values have also dropped considerably all around the bay and on the east side of the bay. Due to the detouring of UAM around the approach and departure surfaces of precision runways at commercial airports, the block groups falling below the protected surfaces have a low noise level. However, it should be noted that expected UAM noise would be in addition to existing noises due to aviation, industry, ground transportation, etc.

Figure 67: Spatial Distribution of DNL Values in dBA. Inset Focuses on San Francisco CBD. Left: 10 dBA Reduction Scenario. Right: 15 dBA Reduction Scenario.

The percentage of the highly annoyed population is calculated using the estimated DNL values. Figure 68 shows and compares the highly annoyed population's spatial distribution for both the reduction scenarios. As expected, the majority of the highly annoyed population is in San Francisco. For the 10-dBA reduction scenario, the highly annoyed population can be found in significant numbers (>500 per blockgroup) near San Jose CBD, Oakland CBD, Mountain View, Cupertino, Dublin, Antioch, San Rafael, and Livermore. However, the highly annoyed population drops substantially in the 15-dBA reduction scenario than the 10-dBA reduction scenario. In the 15-dBA reduction scenario, very few block groups have more than 200 highly annoyed people.

It should be noted that achieving a 15 dBA reduction compared to a helicopter could be challenging for UAM vehicle designers. Since the demand scenario analyzed in this study belongs to an intermediate maturity level (expected at the end of the decade), achieving a 15 dBA reduction maybe possible in that timeframe. Moreover, the noise level generated in the region could be reduced substantially if a 15 dBA reduction is achieved. Table 19 compares the DNL values and annoyance

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level output for both scenarios. If the noise levels of future UAM vehicles achieve a 15 dBA reduction, the land area affected by noise could decrease by 80%. The total highly annoyed population would be reduced by 80%.

Table 19: Comparison of DNL values and Annoyance levels for both Scenarios (Northern California)

DNL Category	Area under Influence (sq. mi.)		Population Impacted by Noise		Highly Annoyed Population	
Reduction Scenario	10 dBA	15 dBA	10 dBA	15 dBA	10 dBA	15 dBA
45-50 dBA	97.0	22.7	657,946	159,270	87,126	21,828
50-55 dBA	22.7	1.15	159,270	12,844	38,435	2,870
55-60 dBA	1.15	0.32	12,844	3,317	4,699	1,209
60-63 dBA	0.32	0	3,317	0	1,776	0
Total	**121.2**	**24.2**	**833,377**	**175,431**	**132,036**	**25,907**

Figure 68: Spatial Distribution of Highly Annoyed Population. Inset Focuses on San Francisco CBD. Left: 10 dBA Reduction Scenario. Right: 15 dBA Reduction Scenario.

6.9.2 Dallas-Fort Worth

Figure 69 illustrates the spatial distribution of Block Group level DNL values for both the scenarios; the map on the left represents the 10-dBA reduction scenario, and the map on the right represents the 15-dBA reduction scenario. For the 10-dBA reduction scenario, high DNL values could be observed in Dallas CBD, Carrollton, Lewisville, Plano, Duncanville, Mesquite, and Dallas suburbs. Compared to the Bay Area, the generated noise is spatially more distributed in Dallas-Fort Worth and relatively smaller levels in the CBD region due to lesser concentration. Moreover, a significant part of Dallas downtown falls under the protected surface of DAL. For the 15-dBA reduction scenario, like the Bay Area, the DNL values drop substantially compared to the 10-dBA reduction scenario. A limited number of block groups have DNL values of more than 45 dBA.
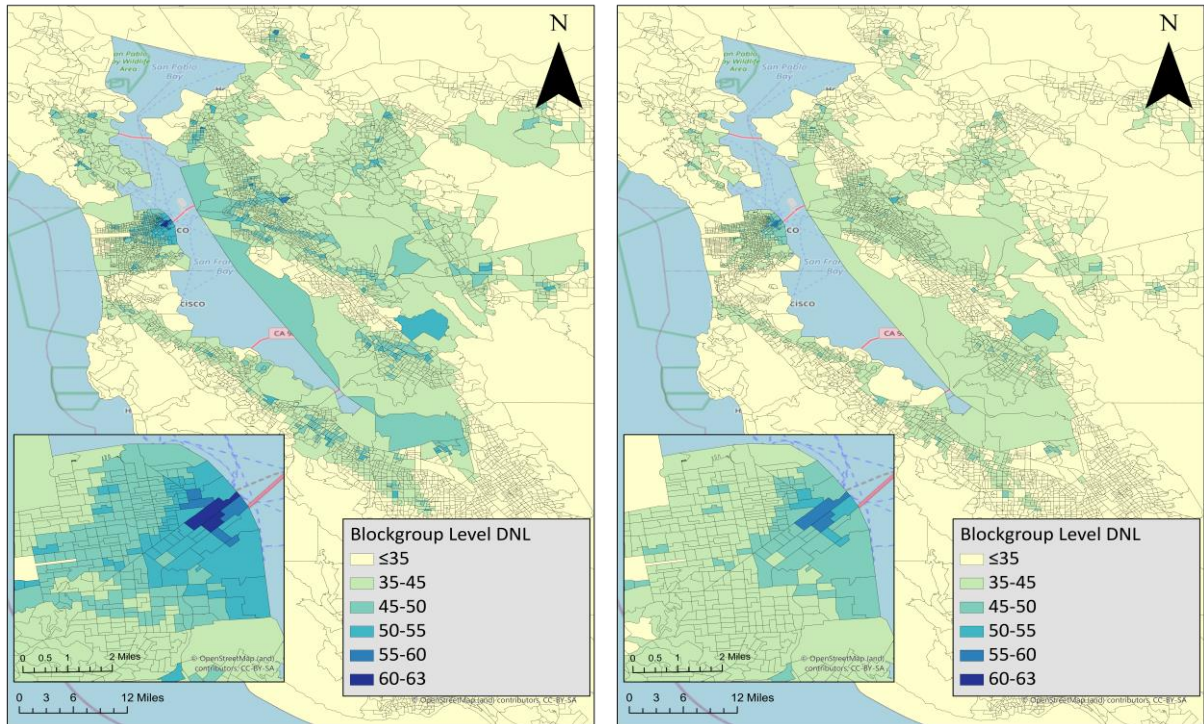
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Figure 69: Spatial Distribution of DNL Values. Inset Focuses on Dallas CBD. Left: 10 dBA Reduction Scenario. Right: 15 dBA Reduction Scenario.

Figure 70 compares the spatial distribution of the highly annoyed population by Census Block Group. Dallas-Fort Worth has a smaller population density compared to Northern California. With lower DNL values, the total number of highly annoyed people is significantly less than the Bay Area for a similar UAM maturity level. For the 10-dBA reduction scenario, the Census Block Groups with more than 250 highly annoyed people can be found near major feeder vertiports, forming a circular pattern around the Dallas CBD. The same block groups can also be observed distinctively in the 15-dBA reduction scenario but with fewer highly annoyed populations. The annoyance caused in the 15-dBA scenario is significantly lower than the annoyance in the 10-dBA scenario. Table 20 compares the DNL values and annoyance level output for both scenarios. Suppose the reduction level could be increased from 10 dBA to 15 dBA. In that case, the area under the influence could decrease by 78%. The total population under the influence could reduce by 72%. The total highly annoyed population could reduce by 74%.

Table 20: Comparison of DNL values and Annoyance levels for both Scenarios (Dallas-Fort Worth)

DNL Category	Area under Influence (sq. mi.)		Population under Influence		Highly Annoyed Population	
Reduction Scenario	10 dBA	15 dBA	10 dBA	15 dBA	10 dBA	15 dBA
45-50 dBA	50.6	11.2	188,688	58,284	24,832	8,776
50-55 dBA	11.2	2.8	58,284	14,514	15,252	3,121

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| 55-60 dBA | 2.8 | 0 | 14,514 | 0 | 5,145 | 0 |
| Total | 64.6 | 14.0 | 261,486 | 72,798 | 45,229 | 11,897 |

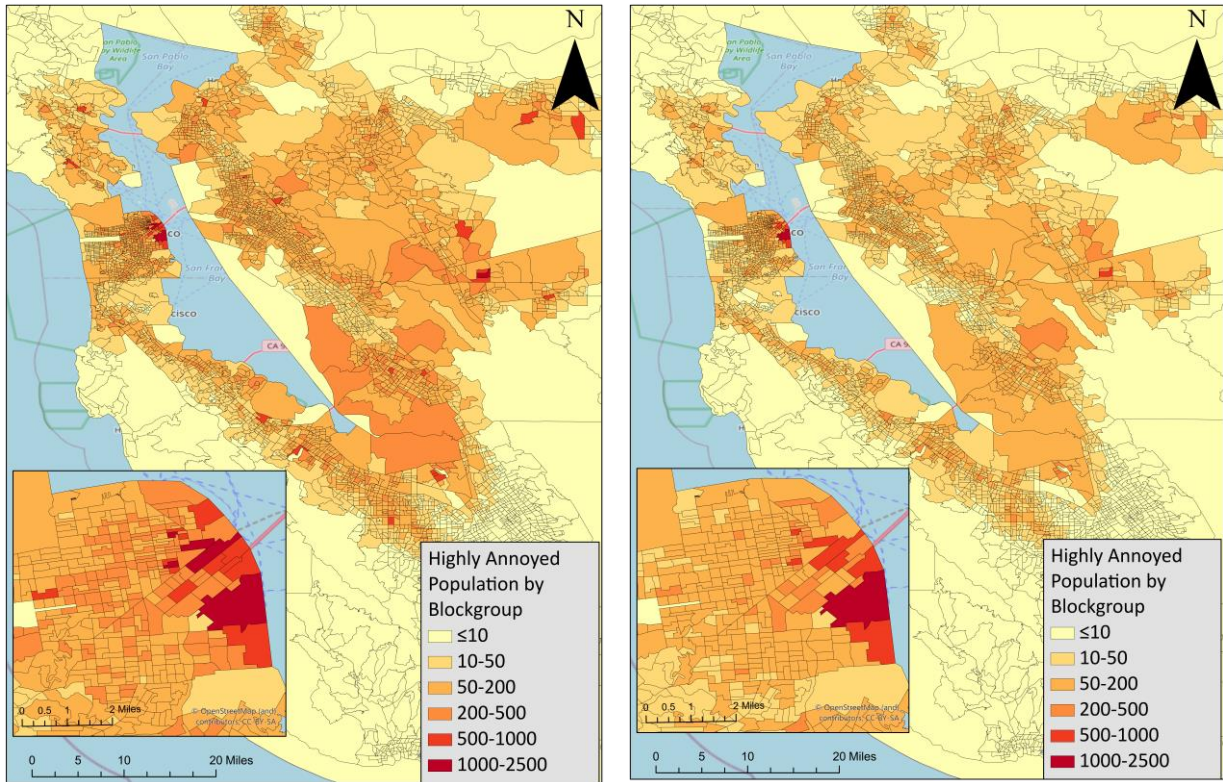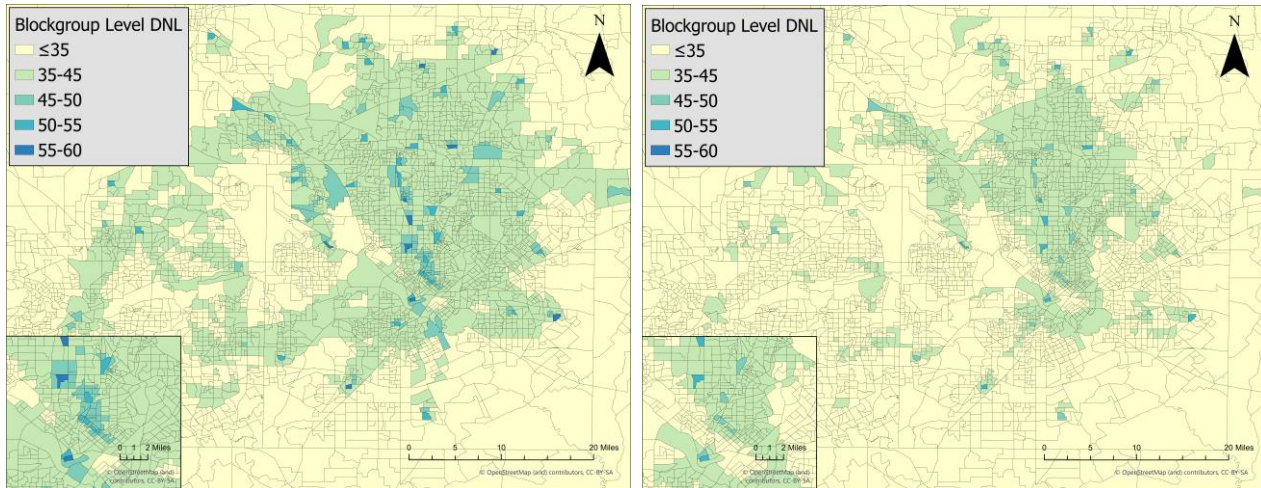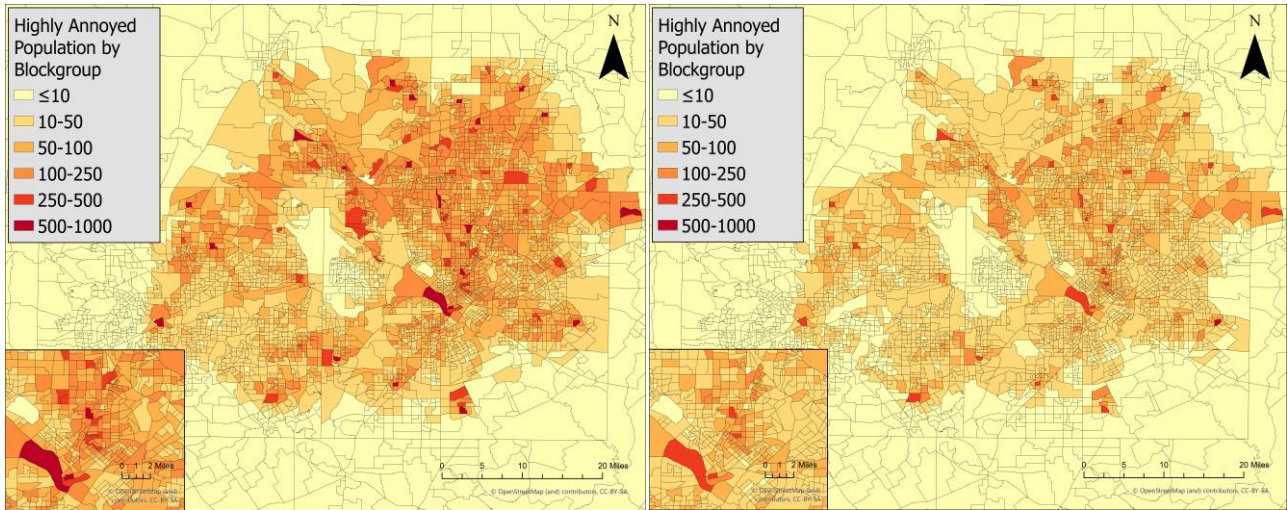

Figure 70: Spatial Distribution of Highly Annoyed Population. Inset Focuses on Dallas CBD.
Left: 10 dBA Reduction Scenario. Right: 15 dBA Reduction Scenario.

A full day of simulation at the Financial District vertiport in AEDT consists of 458 arrivals and an equal number of departures. Figure 71(left panel) shows the first and last three-mile segment of all departures and arrivals, respectively. Figure 71 (right panel) displays the distribution of arrival and departure times of operation at this vertiport. This vertiport has a unique operation schedule because no commuters live near that vertiport who wants to commute to other parts of the region using UAM. Therefore, all of the arrivals are concentrated in the morning hours when commuters are flowing into that vertiport. All the departures are concentrated in evening hours when the same commuters return. The analysis in this paper only considers passenger-carrying operations. However, such an unbalanced operations schedule leads to many repositioning flights (i.e. deadheading), as observed in Rimjha and Trani [40]. They found that the 0.9 repositioning departures and 0.85 repositioning arrivals are required of every passenger arrival and departure, respectively. Considering repositioning operations would significantly inflate the noise levels generated from operations at this vertiport. The DNL contours presented in this Section are generated from passenger-carrying operations only.

UAM routes are designed to detour approach and departure surfaces at commercial airports following the shortest path. All the traffic to/from any place south of SFO detours around protected surfaces of 1-19 runways at SFO; thus, there is a heavy concentration of flight trajectories on that path. Similarly, a significant portion of flights to/from the other side of the bay detours around the protected surface at 12-30 runway at Oakland International Airport (OAK), causing a concentration of flight trajectories on that path (Figure 71). The heavy concentration of flight trajectories on both paths will influence the shape of noise contours significantly. DNL calculation considers nighttime operations (10 PM to 7 AM) to be more onerous and, therefore, artificially increases noise level measurements for night operations by 10 dB. Out of 916 operations, 15.2% of operations occur during nighttime hours.
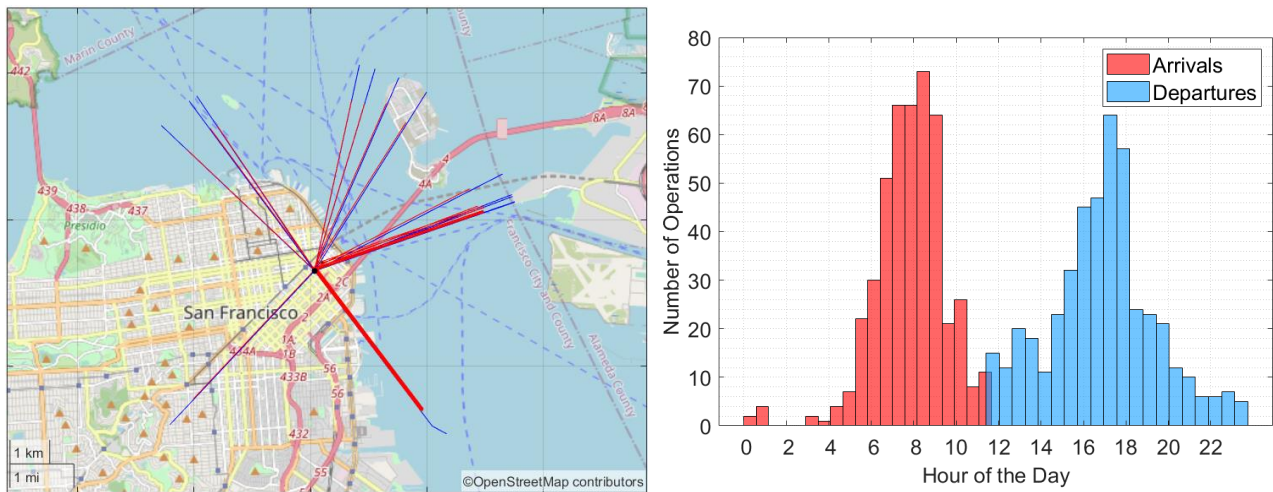
Figure 71: Flight Operations at Financial District Vertiport. Left: Flight Trajectories of Departures (Blue) and Arrivals (Red). Right: Time of Operations.

Figure 72 illustrates the DNL contours developed from a full day of operations at the Financial District vertiport. The varying concentration of flight trajectory defines the shape of noise contours around the vertiport. Unsurprisingly, the basic shape of noise contour is concentric circles, and it has concentration-based elongated spikes along the flight tracks. The length of elongation depends on the reduction scenario too. DNL contours for the 10-dBA reduction scenario encompass a significantly large area than DNL contours for the 15-dBA reduction scenario. The 45 DNL contour extends at least 1.2 miles and 0.75 miles in all directions for 10-dBA and 15-dBA reduction scenarios, respectively. The length along flight tracks is greater in the 10-dBA scenario and extends across the bay. Table 21 summarizes the comparison of DNL contours from both the reduction scenarios. In contrast to 10-dBA

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reduction scenario, the area under 45, 55, 65, and 75 DNL contour in 15-dBA reduction scenario shrink by 83%, 53%, 50%, and 48%, respectively. The population exposed under each DNL contour is estimated using the population exposure functionality in the AEDT tool based on Census Data. The highly annoyed population is further calculated from the exposed population and national dose-response curve discussed in Section IV-B. In contrast to the 10-dBA reduction scenario, the highly annoyed population under 45, 55, 65, and 75 DNL contour in the 15-dBA reduction scenario reduce by 74%, 64%, 58%, and 66%, respectively.
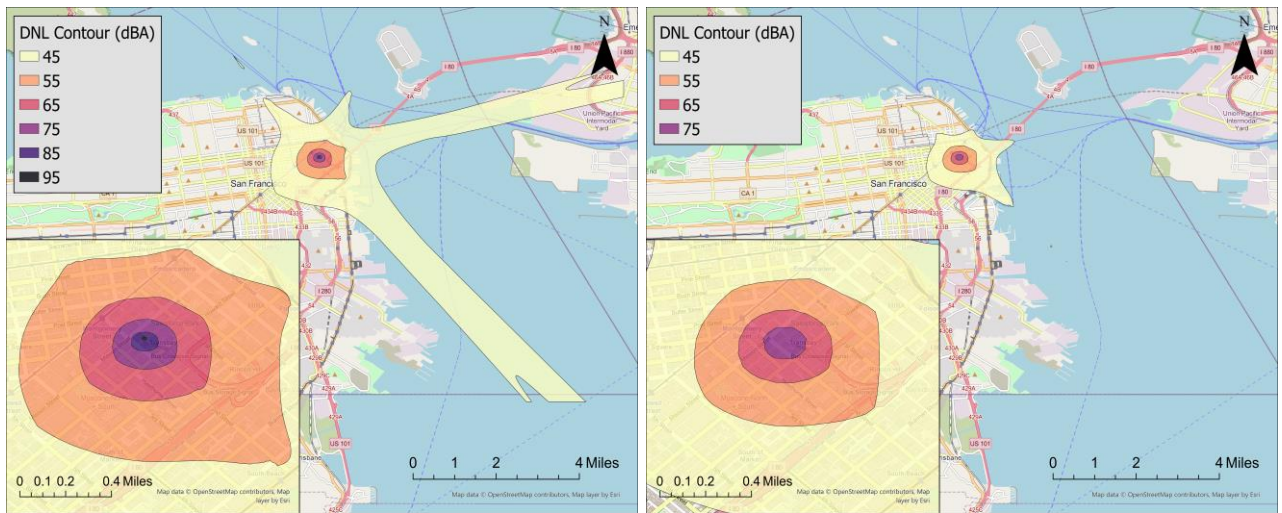
Figure 72: DNL Contours from Operations at Financial District Vertiport. Left: 10 dBA Reduction Scenario. Right: 15 dBA Reduction Scenario.

Table 21: Comparison of DNL Contours from both Reduction Scenarios

DNL	Area under DNL Contour (sq. mi.)		Population under DNL Contour		Highly Annoyed Population	
Reduction Scenario	10-dBA	15-dBA	10-dBA	15-dBA	10-dBA	15-dBA
45	10.89	1.81	110,811	28,764	21,133	5,485
55	0.70	0.33	11,655	4,213	5,687	2,055
65	0.16	0.08	1,596	677	1,267	537
75	0.03	0.0155	272	93	256	87
85	0.006	-	2	-	2	-
95	0.0002	-	-	-	-	-

San Francisco CBD has a high employment density. Although current regulations in 14 CFR Part 150 Airport Noise Compatibility do not address noise levels below 70 dB in commercial zone [41], high noise levels could cause nuisance to employees as people are now more sensitive to aviation noise [38]. Moreover, we have only considered single vertiport and passenger-carrying operations. With multiple vertiport and repositioning flights, noise levels in CBD can reach excessive levels. Therefore, the impact on the daytime population should also be considered. Daytime population from ESRI demographics [42] is analyzed inside DNL contours for both reduction scenarios, as shown in Figure 73. The finest resolution of the daytime population is census tracts which are unfortunately too big for individual contour analysis. Therefore, we calculated the daytime population under 45 DNL outer boundary for both reduction scenarios. The daytime population of 22 census tracts encompassed by 45 DNL boundary is 379,527 for 10-dBA reduction scenarios. Whereas in the 15-dBA reduction scenario, the daytime population inside the 45 DNL boundary is 207,256, 45% lower than that of the 10-dBA scenario.
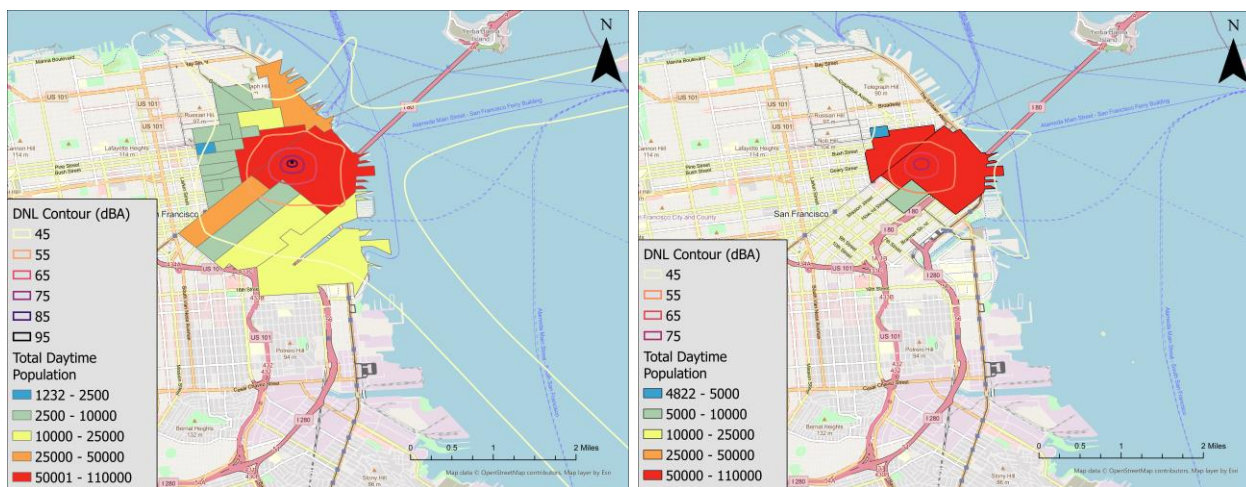
Figure 73: DNL Contours and Daytime Population. Left: 10-dBA Reduction Scenario, Right: 15-dBA Reduction Scenario

6.11 Conclusions

This paper presents a framework to estimate noise levels from a full day of UAM operations in Northern California and Dallas-Fort Worth regions. UAM flight trajectories are derived from an output of mature-state demand analysis. Using Robinson R44 as a surrogate UAM vehicle and modifying its NPD curves, Block Group level DNL values are estimated for two reduction scenarios (10-dBA and

15-dBA). According to the current state of knowledge, 10-dBA reduction from the traditional helicopter is achievable, but 15-dBA reduction could be challenging. Noise results from both scenarios are compared to understand the impact of extra 5-dBA reduction. In Northern California, the area impacted (>45 DNL) decreases by 80% and population under influence decreases by 79%, on increasing reduction level from 10 dBA to 15 dBA. In Dallas-Fort Worth, the area and under influence (>45 DNL) decreases by 78% and population impacted decreases by 72%, on increasing reduction level from 10 dBA to 15 dBA.

The Highly Annoyed population is estimated from DNL values for every scenario for a better interpretation of results. The total highly annoyed population is calculated using the national dose-response curve from Neighborhood Environmental Survey and ACS 5-year population estimates at the block group level. In Northern California, the total highly annoyed population for the 10-dBA scenario is estimated at 132,036, which reduces by 80% on increasing the reduction level to 15-dBA. Similarly, in Dallas-Fort Worth, the total highly annoyed population for the 10-dBA scenario is estimated at 45,229, which reduces by 74% on increasing reduction level to 15-dBA.

A vertiport level analysis was performed in the AEDT tool to develop DNL contours from UAM operations at Financial District vertiport in San Francisco. The area, population, and daytime population under DNL contours significantly change based on the reduction levels. The shape of the DNL contour is influenced by geographic travel patterns and airspace restrictions. The findings indicate that a massive reduction in the noise footprint of UAM operations is observed on an increasing reduction level. Therefore, achieving reduction levels close to 15-dBA is recommended for mature state operations.

The results presented in this paper only consider passenger-carrying operations. We believe a significant fraction of repositioning operations would be required to serve commuting demand. Considering repositioning operations is recommended for future studies as that would increase noise footprint. Since the noise performance of the UAM vehicle is not available at the time of this analysis, we assumed noise reductions of 10 dBA and 15 dBA compared to the Robinson R44 light helicopter. Future research should use the noise performance of UAM vehicles once the exact noise profiles are

known. Noise level estimation could also be improved by simulating the operations for an entire network in the AEDT tool, which would be computationally expensive.

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7.   Impact of Airspace Restrictions on Urban Air Mobility Commuter Demand Potential

7.1   Abstract

This study aims to understand the impact of airspace restrictions on Urban Air Mobility (UAM) commuter demand potential in the New York City region. The potential for UAM is higher in congested cities with substantial commuter populations, but often these cities are served by one or more airports with congested airspaces encompassing over a large part of the urban area. The integration between commercial airspaces and future UAM airspace is among the major challenges to overcome. This study analyzes UAM demand potential with three scenarios of airspace restrictions- No Restrictions, Class-B restrictions only, Class-B/D restrictions. Close to 10 million commuters reside in the New York City area. The city is served by three major commercial airports (JFK, EWR, LGA), making it ideal for this study. A UAM demand estimation framework is built to estimate UAM demand potential for different scenarios. The airspace restrictions significantly affect the UAM demand potential by resulting in less optimal placement of vertiports and increased travel distances. Based on the UAM fares used in the simulation, the airspace restrictions decrease UAM demand by 40% - 57%, compared to the unrestricted scenarios.

7.2 Introduction

Urban Air Mobility (UAM) or Advanced Air Mobility (AAM) is a concept transportation mode being designed for intracity transport of passengers and cargo utilizing autonomous electric vehicles capable of Vertical Take-Off and Landing (VTOL) from dense and congested areas. Urban transportation is currently limited to the surface modes, and UAM proposes adding another dimension to the urban travel ecosystem. It is a multi-modal concept involving aerial transport at lower altitudes within urban and suburban spaces [1]. However, the urban airspaces are not unoccupied. On the contrary, the airspaces are most congested above urban regions due to the heavy commercial aviation operations. Therefore, the integration of UAM in the current airspace is considered a critical step in developing a safe and sustainable UAM ecosystem [2, 3]. The spatial distribution of airspace congestion depends on the runway configuration and operational flow configuration adopted at every airport. The airspace management is relatively more complicated, and airspace congestion is more complex in multi-airport cities (e.g., Dallas-Fort Worth, New York, Washington D.C.).

The UAM system could only sustain if there is enough demand. Therefore, some aspects of the systems would be tailored to capture maximum UAM demand while considering several operational constraints [4]. The system planners and authorities recognize the requirement of different levels of integration at different maturity levels [3]. The integration policies are often governed by safety standards, expected technology, and arrangements in the system. However, the development and innovation in integration could be driven by the demand, i.e., if the UAM demand is sensitive to different integration levels between the UAM ecosystem and current airspace system, it could motivate innovative and unprecedented changes in airspace management. The UAM system's development would thrive on its ability to capture as much UAM demand potential as it can. Therefore, it is crucial to analyze the impact of different integration policies on the UAM mode's attractiveness. The New York region is selected for this analysis because its urban airspace is quite congested and presents a challenging case due to three major commercial airports and Newark Liberty International Airport (EWR), LaGuardia Airport (LGA), and John F. Kennedy International Airport (JFK) and other small airports. Moreover, the unique characteristics of the New York region portray a promising scenario for the UAM, such as very high population and employment density (Manhattan), relatively higher

disutility in driving due to increased costs (parking, tolls, etc.), and traffic congestion, longer commuting times [5].

The study involves developing a region-specific demand estimation framework using a mode-choice model calibrated from the commuting behavior observed in the National Household Travel Survey-2017 (NHTS)- Addon data and creating a demand-driven vertiport placement methodology that could accommodate spatial restrictions. Three different scenarios are built for airspace restrictions depicting different integration levels between UAM and airspace management. The impact of airspace restrictions on critical UAM trip-related parameters such as vertiport access times and UAM aerial trip time are analyzed to understand the sensitivity of scenario-based demand estimations. The findings elucidate on UAM demand potential trade-off with relaxation or constraining of airspace restrictions. The analysis could help system planners gauge the requirement for integration between the UAM ecosystem and current commercial airspace.

7.3   **Background**

The importance of airspace integration for UAM operations has been realized in the literature. Thipphavong et al. [6] developed high-level initial airspace integration concepts for emergent and early expanded UAM operations. They believe that UAM aircraft should be safe, efficient, and predictable. UAM operations should have minimal impact on existing airspace operations to integrate UAM into the airspace system. The authors emphasize the requirement of UAM vehicles and systems to be interoperable with each other and those of existing airspace users to overcome the safety and efficiency barriers of airspace restrictions. While they believe that the initial UAM flights would require ATC to provide air traffic services and management, ATC workload might limit the expansion of UAM in the early expanded stage. They also suggest that the key to achieving higher-density, higher-frequency UAM operations is developing concepts, technologies, and procedures that will enable UAM integration into the airspace system and manage without tactical intervention from ATC.

Vascik et al. [7] explored various challenges that upcoming UAM operations could present for ATC in the United States. The authors believe that the ATC scalability constraint would hamper addressing the challenges created by UAM through increased number of

operations, increased density of operations, and low altitude operations. When ATC-managed airspaces reach saturation, no more aircraft (or UAM) would be allowed to enter the airspace. Their analyses in Los Angeles, Boston, and Dallas found ATC-controlled airspaces covered approximately 43%, 65%, and 56% of the urban area, respectively. Henceforth, if the airspace is saturated, the ATC may not allow UAM to access more than half of the city's surface area. These findings further emphasize the importance of advanced integration of UAM operations in the current airspace system.

Vascik and Hansman [8] studied the effectiveness of airspace cutouts in mitigating ATC restrictions to Advanced Air Mobility (AAM) scaling. They developed multiple "ATC ConOps Scenarios" to study the effect of airspace cutouts and other airspace integration strategies. Their study involved estimating potential demand for AAM services. The potential commuter demand was estimated from The Census Transportation Planning Product (CTPP), assuming commuters who travel more than 60 minutes one way represent potential demand for UAM. They studied mission coverage for different ATC scenarios, ranging from current-day baseline scenarios that prohibit UAM operations in controlled airspaces to scenarios that open up special use airspaces and low-traffic controlled airspaces for UAM operations. The authors observe highly varying UAM mission coverage by urban areas. They conclude that UAM could access only 34% of long-distance commuter workplaces in the median U.S. city without ATC interaction. However, allowing UAM operations in special use airspace and low traffic controlled airspaces increase median mission coverage for long-distance commuters to 54% and 35%, respectively. This study provides a fundamental framework for analyzing the impact of different ATC ConOps on UAM mission coverage. However, it does not calculate UAM demand for different scenarios.

While there are studies focusing on integration concepts and analyzing UAM potential for different integration scenarios, the direct impact of varying airspace restriction levels on UAM demand is missing in the literature. This study proposes to fill that gap in the literature by developing an integrated framework to analyze different levels of airspace restrictions and their direct impact on UAM demand.

7.4   Study Area

The study area selection is driven by the concept vehicle range and commuter flow patterns in the region. Most economic activity in the region is concentrated in New York City, comprising five counties: Manhattan, Bronx, Queens, Kings, and Hudson counties. Joby S4 is selected as the reference vehicle. It has a design range of 150 miles. Considering NYC as the center, counties with their centroid within the design range of the Joby S4 are included in the study area. Figure 74 shows the study area, consisting of 33 counties made up of 17,294 census blockgroups with 9.94 million daily commuters [9].
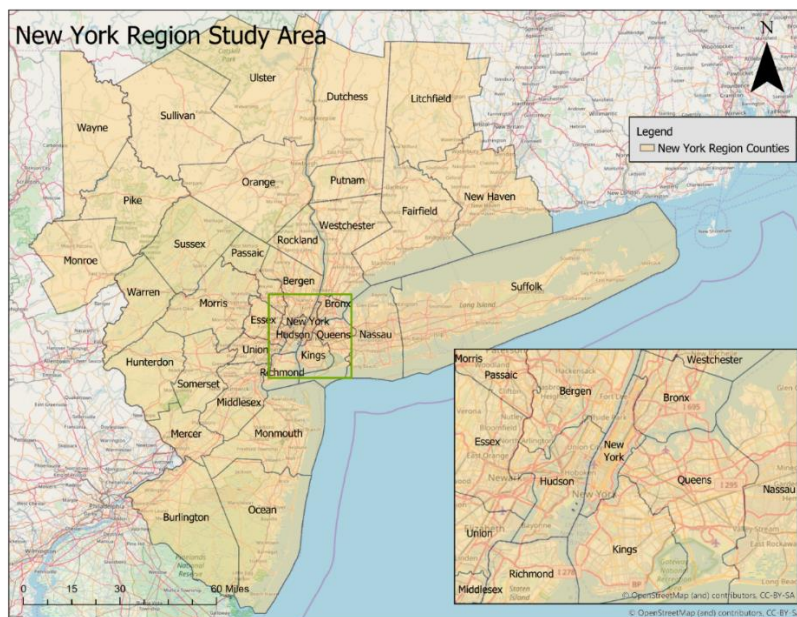
Figure 74: Study Area. Inset focuses on New York City.

7.5   Data and Methodology

The airspace restriction scenarios are developed using the Class Airspace data published by the U.S. Department of Transportation, Federal Aviation Administration-Aeronautical Information Services [10]. Restricted airspaces are designated by different classes and have varying levels of restrictions. 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 [11]. The Class-B airspaces in our study areas extend up to 7,000 ft. The Class-B airspace has several layers with varying altitudes. Generally, the innermost 10 nm area extends to the top, segment area between 10 nm and 20 nm

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has a 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 [12]. Parts of Class-B airspace which extend from the ground are considered in this analysis, assuming UAM could navigate below the restricted pieces of airspaces that have a bottom layer above the ground. Air Traffic Control (ATC) clearances are required for operating in Class-B airspace. Figure 75 illustrates all the 19 restricted airspaces in the study area. There are two Class-B airspaces; one surrounds JFK and LGA airport, and the other surrounds EWR airport.
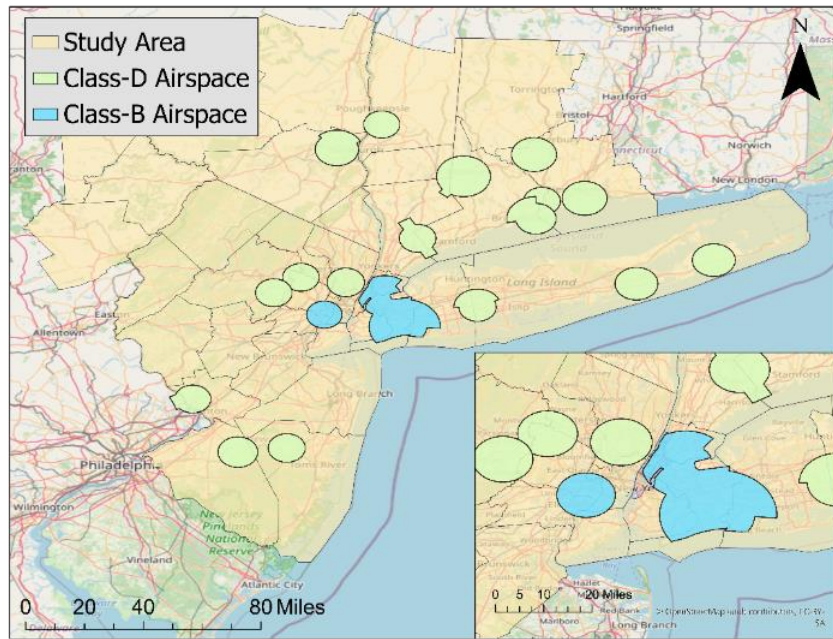
Figure 75: Restricted Airspaces in the Study Area. Inset focuses on New York City.

The other 17 restricted airspaces in the study area are Class-D airspaces. Class-D airspace is also part of controlled airspaces and generally surrounds smaller or military airports. Class-D airspace extends from the surface to 2,500 feet above airport elevation. Current guidelines require aircraft to establish two-way radio communication with ATC before entering and thereafter in class-D airspace. Three scenarios of airspace restriction applicable to UAM operations are built based on different levels of integration. We believe that the highest integration level would result in maximum relaxation in airspace restrictions for UAM operations.

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Moreover, completely independent operations would represent the lowest level or no integration. Scenario 1 is the ideal or baseline scenario with no airspace restrictions for UAM operations which can only be achieved when UAM traffic is managed by the ATC or with a seamless transition between UAM traffic management and the ATC. There are no restrictions in vertiport placement and overflying of UAM in Scenario 1. Scenario 1 may not be entirely realistic considering current regulations, but the relaxation in airspace restrictions in mature state ecosystems could tend towards the Scenario 1 environment.

Class-B airspaces are more congested than Class-D airspaces. A mid-term scenario of airspace restrictions for UAM operations could represent partial integration. Scenario 2 describes the mid-term scenario where vertiport placement and UAM overflying are still prohibited inside congested Class-B airspaces but allowed in Class-D airspaces. Furthermore, Scenario 3 is built to represent minimum integration. No ATC involvement in UAM traffic management, i.e., vertiport placement and UAM overflying, is prohibited inside Class-B and Class-D airspaces. Scenario 3 represents a near-term scenario from an integration perspective. Prohibition of vertiport placement means vertiports are not allowed to be placed inside certain areas because operations (landings or take-offs) at vertiports, if not managed by ATC, could be a safety concern for commercial aviation.

Similarly, the prohibition of UAM overflying means UAM routes cannot pass through restricted spaces and must detour around them. The introduction of such restrictions would result in certain disutility in UAM operations compared to the ideal scenario. For example, detouring increases UAM travel time and could also increase UAM travel costs. Spatial restrictions in vertiport placement could result in less optimal placement, causing a relative increase in access time to/from the vertiports. These inefficiencies transfer to a decrease in the UAM demand as the mode becomes less attractive. UAM operations in Scenario-I are expected to experience minimum delays and detours with relatively efficient placement of vertiports.

Table 22: Defining Scenarios of Airspace Restrictions

Scenario	Restrictions	
	Vertiport Placement	**UAM Overflying**
Scenario-1	None	None

Scenario-2	Only in Class-B Airspace	Only in Class-B Airspace
Scenario-3	In Class-B and Class-D Airspace	In Class-B and Class-D Airspace

Comparison of different scenarios for their quantitative impact on UAM demand requires building a demand estimation framework. Several UAM demand studies have been carried in recent years [13, 14, 15, 16, 17]. The demand estimation framework uses the UAM demand estimation methodology adopted in Rimjha et al. [18]. The demand estimation framework includes three fundamental pillars: region-specific calibrated mode-choice model, vertiport network, and model application, as shown in Figure 76. Different scenarios have different sets of airspace restrictions. Airspace restrictions impact vertiport placement and calculation of UAM trip characteristics (travel time, travel cost, etc.), thereby affecting total UAM demand.
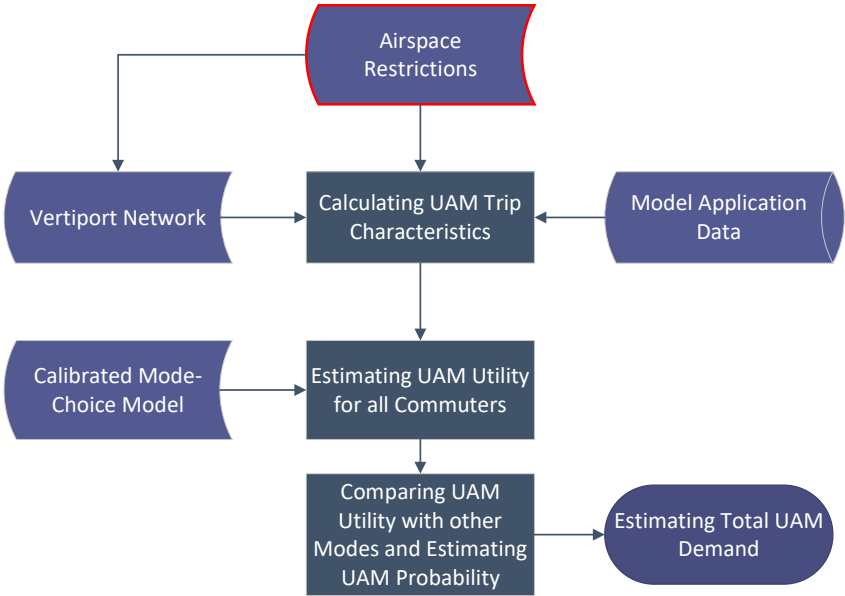
Figure 76: Upper-Level Demand Estimation Framework

7.5.1 Mode-Choice Model Calibration

Understanding the commuters' current mode-choice behavior in the region is critical for the estimation of UAM demand. A conditional logit model is calibrated using the methodology mentioned in Rimjha et al. [18]. A brief overview of the calibration workflow is presented here; please refer to Rimjha et al. [18] for detailed methodology. Commuter trips from NHTS-2017

New York Add-On Data are extracted, and a choice dataset is created. NHTS-2017 is a revealed preference survey and includes only the chosen mode. The trip-related characteristics for survey responses had to be estimated separately due to limited accuracy in travel time and travel cost information reported in the survey. The geographical resolution of trip origin and destination is census-blockgroup, and therefore, blockgroup centroids are used as a surrogate for trip origin/destination location. Estimating mode-specific trip characteristics for every Origin-Destination (OD) pair is performed using the methods mentioned in Rimjha et al. [18], with a few modifications required to address New York-specific data issues.

A significant modification is applied in the calculation of congested travel time for driving trips. Unimpeded travel time obtained from the driving simulator is adjusted to account for congestion using Texas Transportation Institute's (TTI) congestion indices in Rimjha et al. [18, 19, 20]. However, this method was not suitable for the New York region in its raw form. The congestion indices are reported at the urban area level. New York - New Jersey - Connecticut (NY-NJ-CT) is one urban area with a single value for congestion index, i.e., the variation in congestion could not be captured inside the urban area (shown in Figure 77a). New York City is among the most congested cities [21], and using a single congestion index reported in TTI results in underestimating congestion levels in New York City.
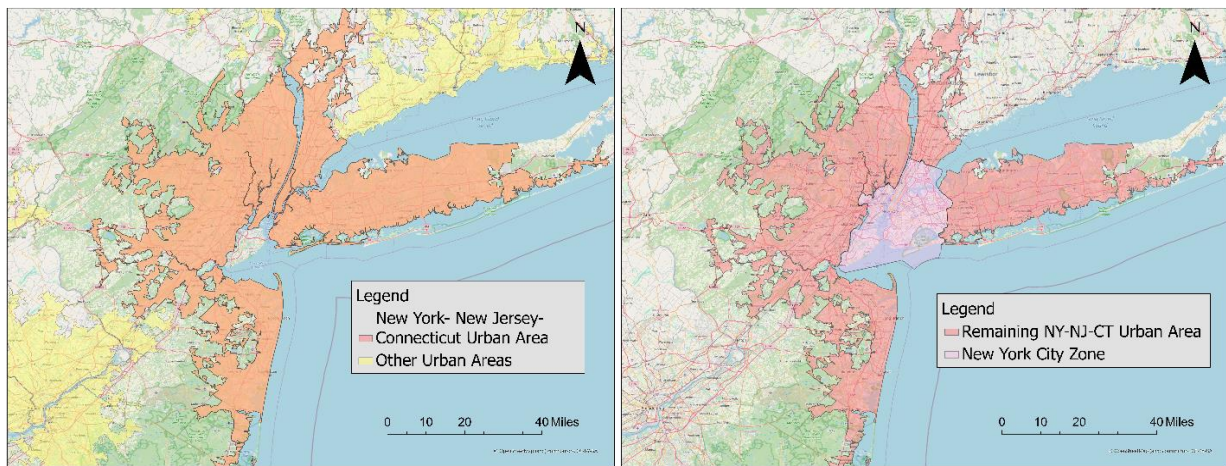

Figure 77: Left (a): Spatial Extent of NY-NJ-CT Urban Area. Right (b): New NYC Zone for the Congestion Index Calculation

To address this issue, we estimated the congestion index for New York City region from empirical data. Using more than 5 million yellow cab trips data reported by New York City Taxi

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Limousine Corporation [22], a distribution of congestion indices is generated. Only peak period trips within five boroughs (Manhattan, Bronx, Queens, Brooklyn, and Staten Island) of New York City are used in the analysis. The trips are simulated in a driving simulator to estimate unimpeded travel time using the origin and destination taxi zones reported in the data. The unimpeded travel time is then compared to the travel time reported in the taxi data to calculate the empirical congestion index. As expected, a slight variation is observed among indices in each borough. However, due to computational limitations and the given scope of the study, all five boroughs were combined to form New York City Zone, as shown in Figure 77b. The mean value from the distribution of empirical congestion indices is selected for New York City Zone. The corresponding TTI congestion indices are used for remaining and other urban areas. Figure 78 shows the distribution of empirical congestion indices calculated from the taxi data. The mean value of the distribution is 2.77.
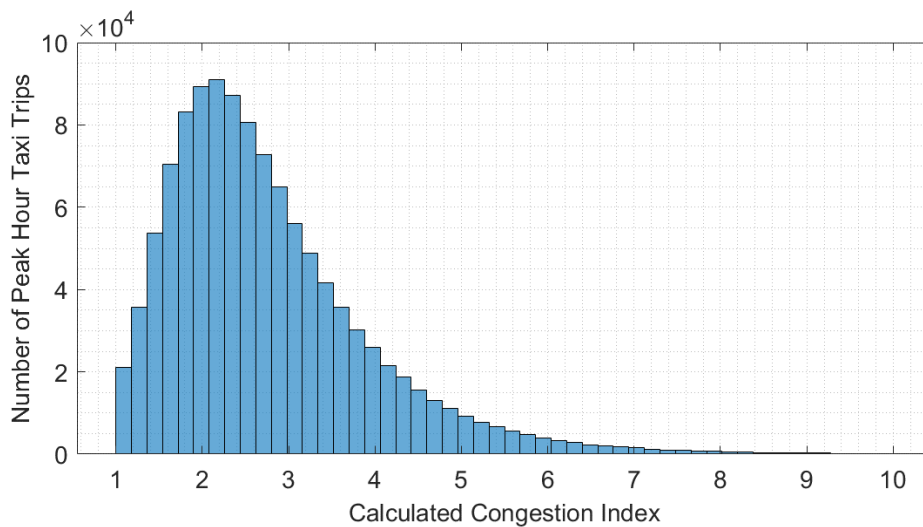
Figure 78: Distribution of Calculated Congestion Indices

The mode-choice dataset is prepared after estimating trip characteristics for every commuter in the survey dataset. A conditional logit model is calibrated to capture the mode choice behavior. A conditional logit model predicts the probability of choosing a particular mode based on trip-related characteristics. The probability of a mode depends on the relative utility an individual can gather from it. Conditional logit models only contain generic variables such as travel time, travel cost, etc., or interacted variables but do not contain alternate-specific variables. The logit models expect travelers to behave fully rationally. Therefore, the probability of

choosing a mode depends on the utility a traveler can gather from the mode. The household income often influences mode-choice decisions as Value Of Time (VOT) or Willingness To Pay (WTP) varies with income. Therefore, partial segmentation concerning household income is used in the calibration process to capture varying VOTs. After observing the data, it is segmented using four income (annual household income) categories: Low-income (less than $50,000), Lower-mid ($50,000-$100,000), Upper-mid ($100,000-$150,000), and High-income (greater than $150,000). The UAM constant is later estimated according to the method mentioned in Rimjha et al. [18].

7.5.2 Vertiport Placement Methodology

The network of vertiports is a critical element in the UAM system. Ideally, vertiports should be placed to capture maximum UAM demand. There are various elements of the vertiport network which affect the utility of UAM and thereby affect UAM demand. Therefore, the problem of optimal placement of vertiports is complicated. Moreover, the placement methodology should be able to accommodate spatial restrictions. The proposed methodology is based on a demand-driven clustering approach. The method is based on the vertiport placement methodology used in Rimjha et al. [19], which was limited to airport access trips. Blockgroup level commuter demand potential is first estimated by placing vertiport at every blockgroup centroid and calculating UAM demand potential. Based on initial demand results, vertiports are placed using Fuzzy-C means clustering method while considering airspace restrictions. The methodology is explained in detail in Rimjha et al. [19]. Moreover, a minimum separation of 2,000 ft is maintained between the vertiports considering air traffic management feasibility. All vertiports in this analysis are assumed to have the required capacity. However, studies in the literature have analyzed the potential problem with commuter flows and effective vertiport capacity [23].

7.5.3 Model Application

The calibrated mode-choice model is applied to the application dataset to calculate daily UAM passenger demand. The LEHD Origin-Destination Employment Statistics (LODES) data [9] at the census blockgroup-level is used for model application. It provides the home and work location (or blockgroup) of the commuters in the region. Assuming all workers commute daily, OD pairs are generated at blockgroup levels. For the home-to-work trip, the home blockgroup

centroid is assumed as the trip origin location, and the work blockgroup centroid is assumed as the trip destination, and vice-versa for the return trip. Trip characteristics for the application dataset would be estimated from simulation of driving and transit directions for each OD pair. For calculating UAM trip characteristics, a traveler is expected to choose the closest vertiport at both ends of the trip. The access parts of the UAM trip, i.e., home (or work) to origin vertiport and destination vertiport to work (or home), are expected to be done by walking if the access distances are less than the reasonable walking distance of a quarter-mile. Otherwise, the access part is simulated in the driving simulator using taxi/cab characteristics. Five minutes of ingress and egress time are assumed at origin and destination vertiport, respectively, to account for processing, boarding, and alighting time. The aerial part of the UAM trip is simulated on the network of vertiports using the shortest-path algorithm. The In-Vehicle Travel Time (IVTT) comprises time spent inside the UAM vehicle and access time (if access trip is made by taxi). Out-of-Vehicle Travel Time (OVTT) comprises ingress/egress time and walking time (if access trip is made by walking). Similarly, total travel costs consist of distance-based flying cost, base cost, and access cost (if access trip is made by taxi).

After calculating UAM trip characteristics for every OD pair in the application data, utilities from different modes are calculated using a calibrated model for each available mode in every OD pair. Furthermore, the UAM demand for every OD pair is estimated. This demand estimation process is repeated for all the scenarios.

7.6 **Results and Discussion**

Table 23 includes the calibrated mode choice model for the New York region. The p-value (less than 0.000) suggests the model is statistically significant. All the variables included in the final model are also statistically significant with reasonable coefficients. In-vehicle Value of Time per hour (IV-VOT) of Low, Lower Mid, Upper Mid, and High-Income travelers is estimated at $16.9, $18.8, $21.8, and $29.0, respectively. Similarly, the Out of Vehicle Value of Time per hour (OV-VOT) is estimated at $19.3, $21.3, $24.7, and $32.9. The estimated UAM constant is 0.7496.

Table 23: Mode Choice Logit Model

Variable	Coefficient	Standard Error	z	P>|z|

IVTT	-0.2027318	0.0000355	-5757.46	0.000
OVTT	-0.2299768	0.0000662	-3501.37	0.000
Transfers	-0.5384475	0.000457	-1006.55	0.000
Low Income X Cost	-0.7157321	0.0014569	-1544.01	0.000
Lower Mid Income X Cost	-0.6472583	0.001233	-5458.31	0.000
Upper Mid Income X Cost	-0.5581929	0.000993	-6141.34	0.000
High Income X Cost	-0.4187676	0.000948	-4454.54	0.000
Transit Constant	-0.1033775	0.0011107	-91.02	0.000
Log-likelihood$_{Initial}$	-3.138e8			
Final Log-likelihood$_{Final}$	-0.503e8			
Likelihood chi-square test statistic (Degree of Freedom:8)	9.010e8			
Number of observations	12,168			
Pseudo Rsq.	0.8995			

The vertiport placement method uses the calibrated model to place vertiports through a demand-driven approach. Due to the higher VOTs, High and Upper-mid income commuters are relatively more likely to attract UAM travel time savings. Therefore, commuters' household/workplace density, especially those of the High and Upper-mid income category, dominates the placement of vertiports. Figure 79 and Figure 80 shows population density and income distribution in the area. It should be noted that only commuters traveling more than ten miles are eligible for UAM. Therefore, short-distance commuters' home/workplace density does not affect vertiport placement.
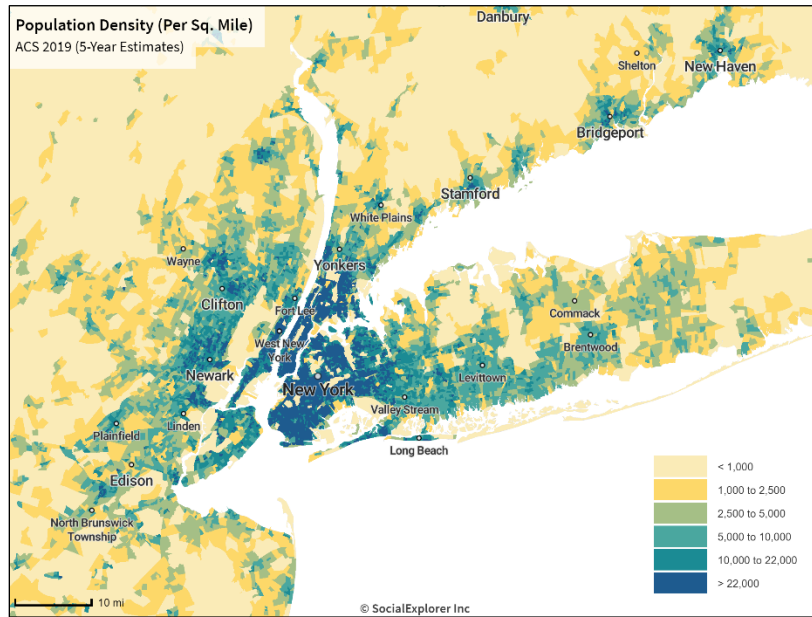
Figure 79: Population Density Distribution [24]

Figure 80: Median Household Income Distribution [24]

New York Boroughs surrounding Manhattan, i.e., Bronx, Brooklyn, Queens, have high population density but consist primarily of short-distance commuters and high density of low to mid-income households. Therefore, the demand-driven approach places vertiports where demand is high due to either longer/congested commutes or large detours due to water bodies. Figure 81

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includes 100 vertiports placed via a demand-driven approach for all three scenarios. In Scenario 1, vertiports are placed most optimally as there are no airspace restri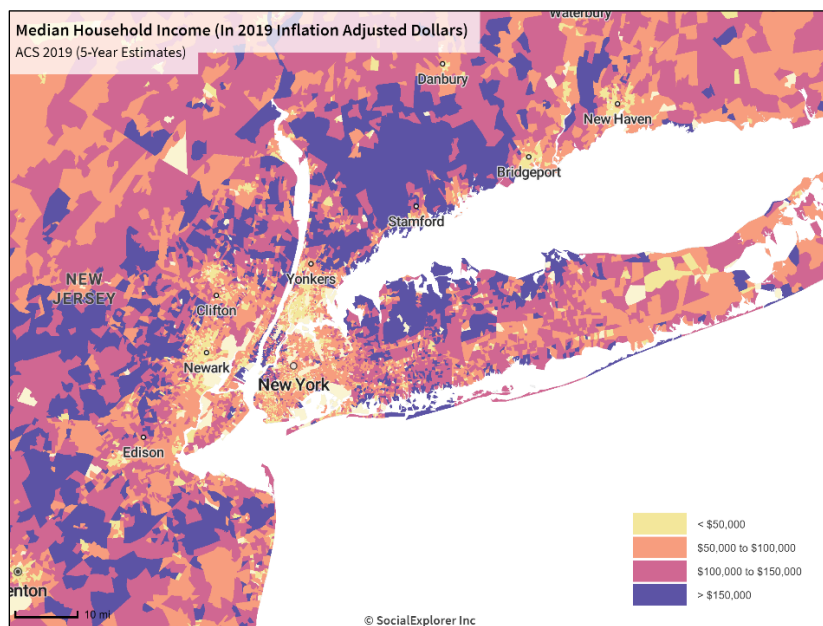ctions. Vertiports are heavily concentrated in the Manhattan region due to high employment density. Other smaller clusters can be seen in western Queens and south-east Kings because a large number of commuters commute to Manhattan.

Similarly, significant high-income commuters from Long Island and Connecticut coast commute to Manhattan, Jersey City, and Brooklyn. In Scenario 2, a large portion of Manhattan, Queens, and Kings County is blocked by restricted airspace surrounding JFK, LGA, and EWR airports. Therefore, more vertiports are located in Long Island, Westchester, and Connecticut. In Scenario 3, the additional airspace restrictions have a relatively more minor impact on vertiport placement. Connecticut coast is the most impacted by additional restrictions.
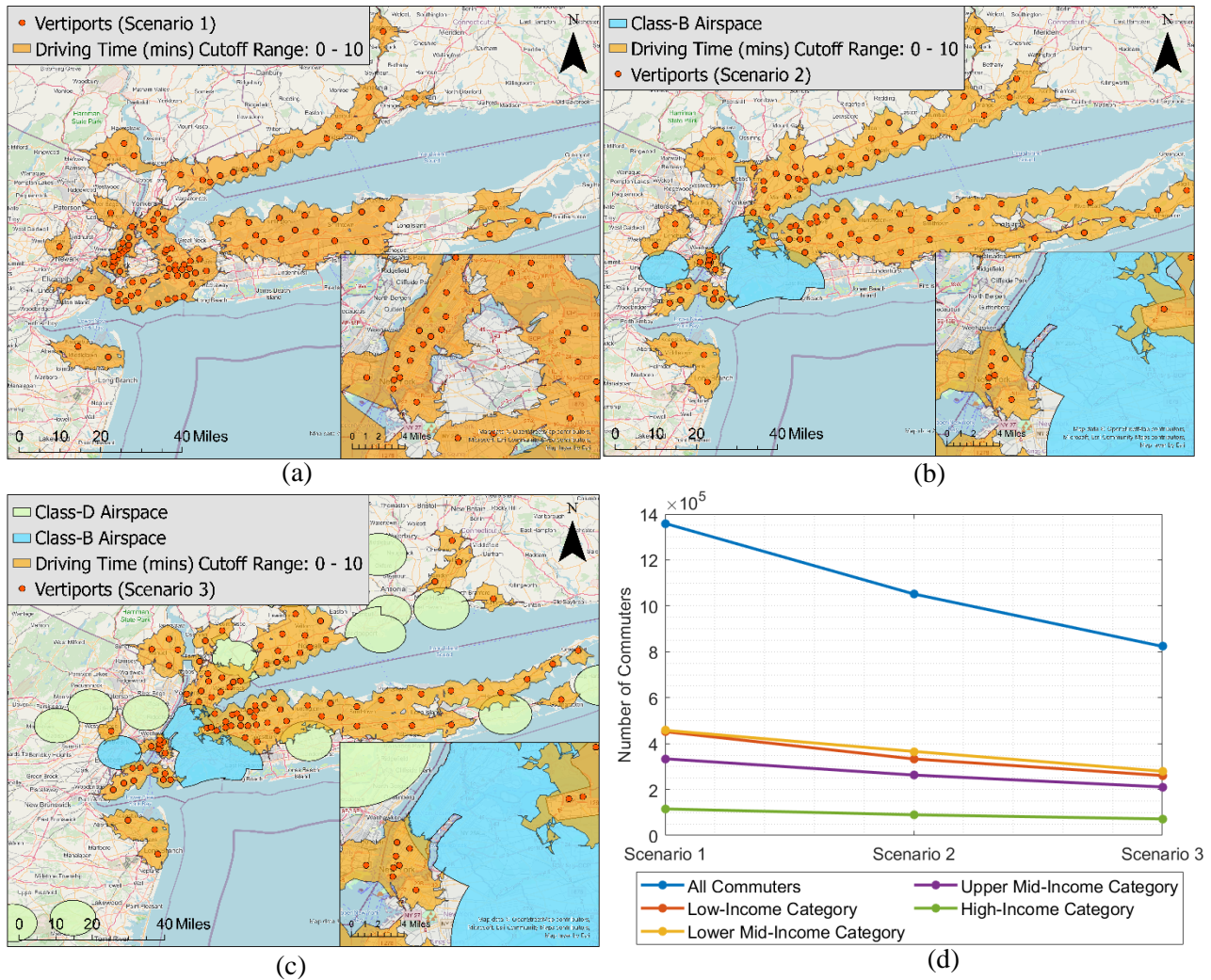
Figure 81: 100 vertiports placed via demand-driven approach in (a) Scenario 1, (b) Scenario 2, (c) Scenario 3. (d)- Number of commuters with a vertiport within 10 minutes of drive-time

The airspace restrictions result in less optimal placement of vertiports, thereby decreasing UAM accessibility. Figure 81 (a, b, c) also includes a 10-min drive time polygon from the whole vertiport network. The changes in overall vertiport network accessibility Figure 81 (d) illustrates the comparison of the number of commuters having a vertiport within 10-minutes of driving time across the scenarios. The number of those commuters drops by 22.6% in Scenario 2 compared to Scenario 1 and further drops by 21.7% in Scenario 3. The commuters in Low and Lower-Mid income categories are affected relatively more because of the JFK-LGA Class-B airspace blocking the majority of Queens and Kings County.

In addition to less optimal placement of vertiports, airspace restrictions add to the disutility of UAM mode in two major ways: (a) Increasing intermodal times and (b) Increasing aerial trip time/cost. The former is due to the closest vertiport being relatively far at either or both ends of the trip, and the latter is because of detouring around the restricted airspaces. Figure 82 (left) illustrates the intermodal or access times distribution for commuter OD Pairs with at least one daily UAM round trip demand. The average intermodal time is 15.7 mins, 17.5 mins, and 20.9 mins in Scenario 1, Scenario 2, and Scenario 3, respectively. However, the introduction of airspace restrictions significantly changes UAM travel's feasibility compared to the unrestricted scenario. The average intermodal times for the Scenario-1 commuter OD pairs increase from 15.7 mins to 47.9 mins and 56.2 mins in Scenario 2 and 3, making it highly unfavorable.
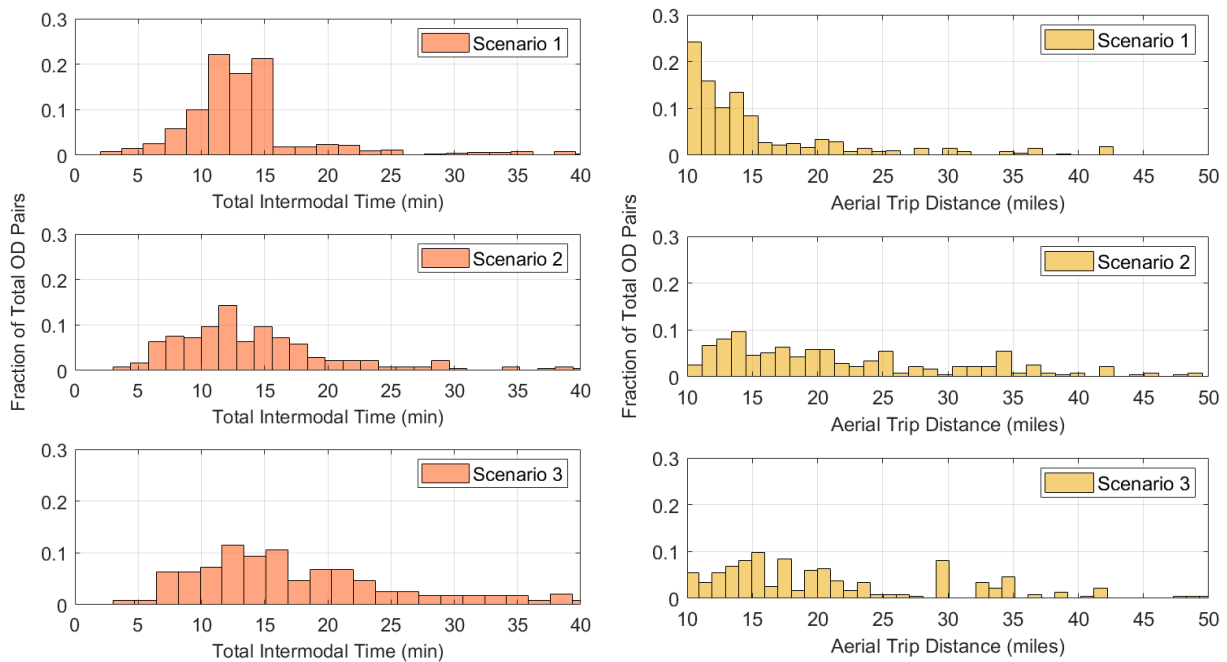
Figure 82: Left: Distribution of UAM Intermodal Trip Times. Right: Distribution of UAM Aerial Trip Distances.

Figure 82 (right) compares the distribution of aerial trip distances of commuter OD Pairs with at least one daily UAM round trip demand. Since there are no restrictions in Scenario 1, the UAM vehicle travels a great circle path from origin to destination vertiport. However, when airspace restrictions are in place (Scenario 2 and 3), UAM vehicle is detoured around the restricted airspaces along the great circle path, increasing travel time and travel cost. The average

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aerial trip distances are 15.6 miles, 21.0 miles, and 22.1 miles in Scenario 1, Scenario 2, and Scenario 3, respectively. The increase in average aerial trip distance causes UAM trips to be longer and costlier. The extra disutility in UAM travel in restricted scenarios compared to an unrestricted scenario affect the UAM demand.

Figure 83 includes the UAM demand results for each scenario and their respective sensitivity with UAM cost. UAM cost consists of a fixed cost ($10 per person) and a variable cost based on aerial trip distance (cost per passenger mile). The cost of the intermodal trip is also added if they are completed via taxi/cab. The expected decrease in UAM demand due to airspace restrictions can be observed. For UAM CPM of $2.50, the UAM demand in Scenario 2 is 45% less than in Scenario 1, and the UAM demand in Scenario 3 is 9.5% less than in Scenario 2. Overall, Class-B airspace restrictions result in a decrease of 15%-54% (depending on the UAM cost) in UAM demand compared to the unrestricted scenario. Additional Class-D restrictions result in a further 8%-29% decrease, depending on the UAM cost. The commuters consisting major share of the UAM demand at lower fares are more sensitive to increased cost due to detours. Therefore, the effect of airspace restrictions on total UAM demand is more prominent at lower UAM fares.
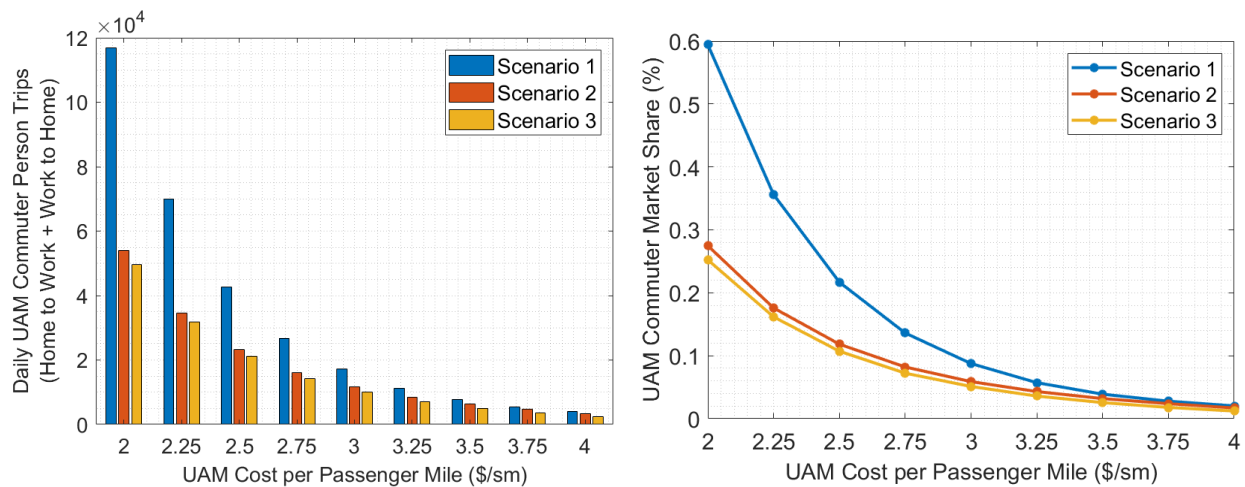

Figure 83: Daily UAM Demand with 100 Vertiports. Left- UAM Demand Sensitivity. Right-UAM Commuter Market Share.

Increasing UAM cost causes demand to decrease quickly as UAM utility drops significantly. In Scenario 1, increasing the UAM CPM by 25 cents (from $2.00 to $2.25) decreases the UAM demand by 40%, also the UAM market share drops from 0.60% to 0.35%.

Similar sensitivity towards UAM cost is observed for restricted scenarios too. Lower UAM fares are essential to capture significant demand because, at $4 UAM CPM, which is the expected fare by multiple vehicle manufacturers, the demand is negligible in all the scenarios. At $3 UAM CPM, UAM could capture 0.50% market share in the restricted scenario and 0.80% in unrestricted scenarios. Due to being a big and dense commuter market, even this tiny market share results in 10,000 to 18,000 commuter passenger trips. It must be noted that all the scenarios are simulated with 100 vertiports. The UAM demand is found to be sensitive to the number of vertiports in previous studies.

7.7 Conclusions

This study examines the impact of different levels of airspace restrictions on UAM commuter demand potential in the New York region. A UAM demand estimation framework is developed and utilized to estimate the UAM demand for different scenarios of airspace restrictions. A conditional logit model calibrated on NHTS-2017 Add-on data captures the travel behavior in the region. The in-vehicle value of time and out-of-vehicle value of time of the commuters in the region is estimated to be $17 - $29 per hour and $19 - $33 per hour, respectively, based on the income category.

The impact of airspace restrictions on UAM demand potential and vertiport placement is substantial.   The demand-driven vertiport placement method places several vertiports in Manhattan and Queens in the unrestricted scenario. A sizeable part of Manhattan and Queens is blocked by Class-B airspace of JFK-LGA airports, decreasing UAM accessibility in restricted scenarios. The airspace restrictions also increase the average UAM travel time and travel cost due to detours. The extra disutility in UAM travel caused by airspace restrictions affects the UAM demand. At lower UAM CPM of $2 to $3, the UAM demand in restricted scenarios decreases by as much as 55%, compared to the unrestricted scenario.

Several assumptions and some limitations in the process adopted in this analysis can be overcome in future research. The consideration of airspace restrictions is rather rudimentary, and future studies should consider custom-tailored pieces of Class-B/C/D airspaces based on the density of flight tracks. Future research should also consider the impact of inclement weather on UAM operations in New York City. However, this study builds the foundation to assess the

broader impact of airspace restrictions on UAM demand potential and help develop airspace integration policies.

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8. Chapter VIII: Conclusions

Studies presented in this dissertation explore multiple aspects of Urban Air Mobility (UAM). The first study presents a methodology to build a UAM demand estimation framework and presents the potential commuter demand for UAM in the Northern California region. The study concludes that the UAM fares have to be optimistically low to capture a significant market share in Northern California. Sensitivity analysis indicates that UAM could lose almost half of the demand with a ten-minute average delay. Hence travel time reliability is vital for UAM to attract commuters. The travel time savings from UAM comes at a relatively higher cost which attracts high-income individuals in higher proportions. Therefore, UAM must gain their trust and become a competitive alternative. San Francisco CBD has a high economic activity concentration and significantly high travel time/cost for commuters traveling to and from the bay. Therefore, UAM demand is heavily concentrated in San Francisco CBD, which presents a challenging case for airspace management and infrastructure development. Moreover, UAM cannot rely on commuter flows because of their unidirectional nature. Commuter flows are concentrated temporally (in peak periods) and geographically, requiring a high proportion of repositioning flights, thereby decreasing the system's efficiency.

Building on the recommendations of the first study, the following two studies presented in this dissertation analyze the feasibility of UAM in airport access market segments in two metro areas: Dallas-Fort Worth and Los Angeles. Airport travelers are expected to be among the early adopters of UAM due to relatively longer access trips and higher value of time. The higher value of time is because airport access trips are performed less frequently, and business travelers can get the cost reimbursed. The findings of both studies indicate significant potential for UAM in the airport ground access market. Modeling UAM routes considering airspaces restrictions due to commercial operations at DFW, DAL, and LAX was a critical part of both the studies. Considering airspace restrictions, UAM in the airport ground access market could capture 3.2% and 3.7% share in Los Angeles and Dallas-Fort Worth, respectively, with a 50-vertiport set and $2.0 UAM CPM (additional to $15 base cost per passenger and $20 landing cost per flight). Even though the predicted market share of UAM is smaller in Los Angeles, the daily number of airport access UAM flights estimated in Los Angeles is 2,630, about 85% more than that in Dallas-Fort Worth (1,418). The airport access UAM demand is slightly more sensitive against

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UAM CPM in Los Angeles than in Dallas-Fort Worth because 54% of the travelers to DFW/DAL are business travelers, which is significantly more than the proportion at LAX (30%). Business travelers are less sensitive to increasing costs as their costs are reimbursed. The airport access UAM demand drops by 26% and 20% in Los Angeles and Dallas-Fort Worth, respectively, when increasing UAM CPM from $1.50 to $2.0.

All demand estimation studies in this dissertation assume that the vehicle is always available at the desired vertiport without delay, and also, there are no capacity constraints at the vertiport. Most of the high demand vertiports are located in the CBDs, where infrastructure for UAM is limited and costly. Therefore, understanding factors affecting the vertiport capacity is essential for efficient operations. In the fourth study, a discrete-event choice model is developed to simulate operations at the San Francisco CBD vertiport, the busiest vertiport with unidirectional flows. The findings indicate that pre-positioning UAM vehicles at the vertiport are critical for minimizing delays. However, that reduces the effective passenger serving capacity of the vertiport. For the given passenger arrival and departure schedule at the selected vertiport, 0.9 repositing departures and 0.85 repositing arrivals are required of every passenger arrival and departure, respectively. Several important variables in the simulation were varied in the sensitivity analyses to understand their quantitative influence on vertiport capacity.

Some optimistic demand scenarios estimate thousands of UAM flights daily in an urban area in a mature UAM ecosystem. Even though the UAM vehicles are expected to be much quieter than existing rotorcraft technology, their proposed scale of operation at low altitudes could possibly create significant community annoyance due to noise. The fifth study estimates the blockgroup level noise generated from a full day of UAM operations in Northern California and Dallas-Fort Worth. The flight trajectories and schedule generated in the demand estimation study are used as input in the noise estimation study. Using the modified NPD curves of the Robinson R-44 helicopter, the blockgroup level DNL values are estimated, which are used along with the new dose-response curves developed in the Neighborhood Environmental Survey (NES) to calculate the highly annoyed population. In Northern California, the total highly annoyed population for the 10-dBA scenario is estimated at 132,036, which reduces by 80% on increasing the reduction level to 15-dBA. Similarly, in Dallas-Fort Worth, the total highly annoyed

population for the 10-dBA scenario is estimated at 45,229, which reduces by 74% on increasing reduction level to 15-dBA.

Modeling airspace restrictions is a crucial part of the UAM simulation, where UAM trip characteristics are calculated. All the demand estimation studies in this dissertation assumed no interaction between commercial aviation and UAM traffic. To model that, airspace restrictions are considered. The first commuter-based study uses approach and departures surfaces at commercial airports as restricted airspaces for UAM, where the placement of vertiports and UAM routing is prohibited. More sophisticated restricted airspaces are used in the airport access studies, which are developed at NASA AMES research center after scrutinizing commercial traffic at DFW/DAL and LAX airport. Either way, the airspace restrictions result in less optimal placement of vertiports and extra disutility in UAM travel due to increased travel time/cost. The quantitative impact of the restriction on-demand potential is an intricate problem that depends on commercial airports, runway layouts, trip production/attraction zone's location, and UAM fare structure. The final study in this dissertation sheds light on this problem by modeling the UAM system and estimating demand potential for commuters with different levels of airspace restrictions. The presence of three big commercial airports and a large commuter population made New York the ideal choice for this analysis. A sizeable part of Manhattan and Queens is blocked by Class-B airspace of JFK-LGA airports, decreasing UAM accessibility in restricted scenarios. At lower UAM CPM of $2 to $3, the UAM demand in restricted scenarios decreases by as much as 55%, compared to the unrestricted scenario.

The models included in all the studies are built on revealed preference and have a little knowledge of traveler's perception of UAM. Future research should calibrate pooled models with stated and revealed preference, both. The demand estimation studies assumed a vehicle is always available at the nearest vertiport. However, that's an ideal scenario and therefore, future demand estimation research should consider repositioning delays. Even though the vertiport capacity is analyzed in a separate study, demand studies have assumed that required airspace and vertiport capacity is always available. It is recommended that the future studies should consider capacity related delays in the network. The noise profiles of Robinson-R44 are modified and considered as a surrogate for the UAM vehicle. Future noise analyses should use noise profiles of a prototype or actual UAM vehicle.

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