DEMAND FORECAST MODEL DEVELOPMENT AND SCENARIOS GENERATION FOR URBAN AIR MOBILITY CONCEPTS

Final Report

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Table of Contents

LIST OF FIGURES

1. Acknowledgments

The authors would like to thank Jeremy Smith and Ty Marien of the National Aeronautics and Space Administration (NASA) for their technical and financial support of this work. This project is part of a contract between Virginia Tech and the National Institute for Aerospace (NIA). The authors would also like to thank Sam Dollyhigh for his continuous support and critique of this analysis. Any opinions, findings, and conclusions or recommendations presented herein are those of the authors and do not necessarily reflect the views of NASA.

DEMAND FORECAST MODEL DEVELOPMENT AND SCENARIOS GENERATION FOR URBAN AIR MOBILITY CONCEPTS

2. Introduction

The purpose of this project is to estimate the demand for various Urban Air Mobility Concepts (UAM) of Operations and to generate scenarios for use in analysis and simulations. The demand forecast model, previously developed under NASA/NIA Contract No: NNL13AA08B; Task Order No: NNL16AA36T, for an urban on-demand air-taxi commuter concept is the basis for this work. The analysis presented addresses the following tasks:

Task 1: UAM Demand Forecast Model and Scenario Generation Development and Improvements. Virginia Tech improved the usability of the UAM Demand Forecast Model and associated Scenarios Generation codes so that they can be run by researchers who were not part of the code development process.

An integrated set of MATLAB scripts are developed for all four regions to facilitate optimal placement of vertiports, calculation of UAM demand, and capacity analysis. We delivered the Matlab code with NASA Langley. Modifications to the requirements of the project are maintained in a secure online server at Virginia Tech using software tracking (GitHub) that is protected by an incremental duplicate backup system.

Task 2: Demand Forecasts and Scenarios- Virginia Tech will generate a set of demand forecasts and scenarios for Northern California and three more regions in the United States to be selected in coordination with NASA, based on the existing On-Demand Mobility (ODM) or Urban Air Mobility (UAM) commuter concept.

The report presents in detail the data collection, mode choice calibration, and simulation analysis supporting the demand predictions for two UAM vehicle concepts with Vertical Take-Off and Landing (VTOL) capability. The analysis includes a sensitivity analysis of UAM demand under various UAM's cost per passenger mile (CPM) and the number of vertiports placed within a region. This report analyzes UAM demand in four U.S. regions, including Northern California (centered on San Francisco), Southern California, Dallas-Fort Worth, and New York City.

3. Task 2: Demand Forecasts and Scenarios Development

This section presents the steps undertaken to predict the UAM commuting trip demand. The analysis includes preliminary reviews to weather information of urban areas, analysis of travel survey data, calibration of urban-specific mode choice models, application or model choice models to the region's population, and generation of demand results to estimate person-trips. The demand results generated are for commuting trips only, specifically home-to-work and work-to-home trips, and do not include other possible sources of UAM demand outside of this project's scope, such as business or shopping trips.

3.1. Regions Selected and Defining the Study Area

In addition to building off findings from a previous project on the Northern California (San Francisco) region, three additional urban areas are part of the study. Table 1 outlines the analysis used to define the remaining three metropolitan areas. It presents the first-order evaluation of characteristics that would promote or inhibit the success of the UAM mode. The shaded cells indicate attributes of that city, which could significantly reduce the number of person-trips operated. Based on the population, socio-economic, and weather information, the three areas chosen were those surrounding Los Angeles, Dallas-Fort Worth, and New York City.

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

Metropolitan Area	Temperature		Wind	Precipitation	Snow	Population	Income
	% Time below 32°F**	% Time temp<32°F & (air-dew) temp is =<2°F**	% 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).
** From 6 AM–8 PM, Source: 2015 ASOS 1-min weather records by NOAA
*** Using 2009 dollars, Source: CEDDS, Woods and Poole, 2016.

To study UAM commuter demand, we consider all counties within 150 miles of each city center. Table 2 shows the characteristics of the selected metropolitan areas. Figures 1-4 show the details of counties included in the study for Northern California, Southern California, Dallas-Fort Worth, and New York, respectively.

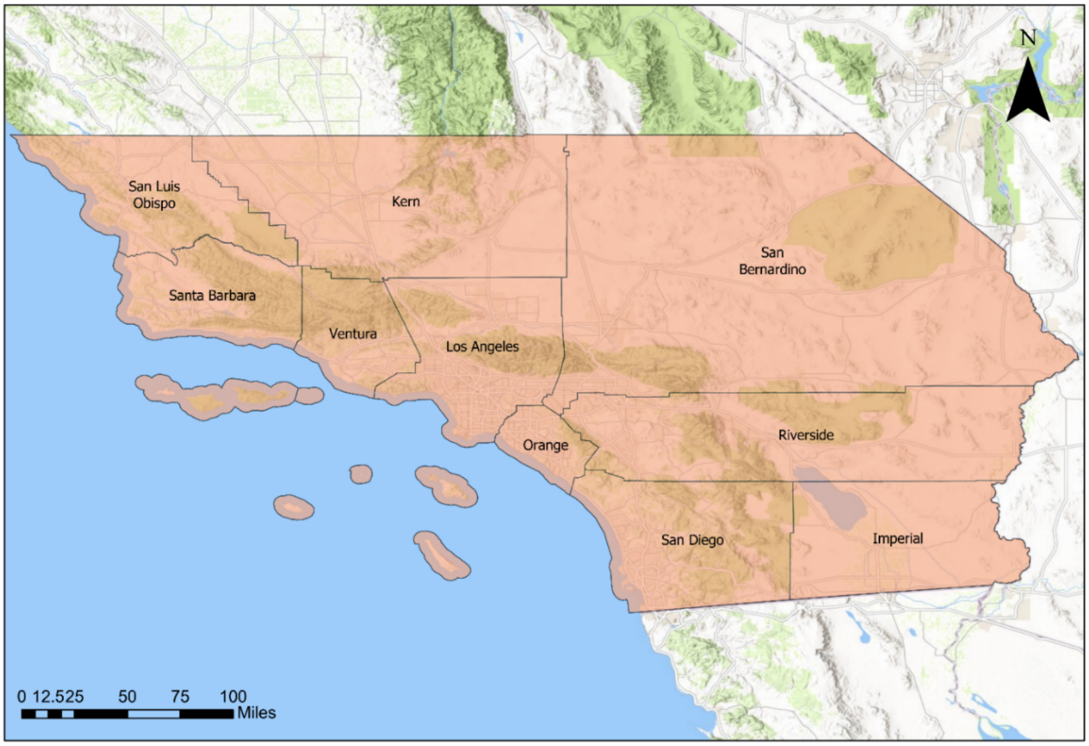
Table 2: Characteristics of the Selected Urban Areas

Region	Number of Counties Included in Study	Number of Census Block Groups	Number of Daily Commuters* (millions)
Northern California	17	7,106	4.63
Southern California	10	13,632	9.26
Dallas-Fort Worth	12	4,158	2.92
New York City	33	17,294	9.94

*LEHD LODES -2015 Data

Sources: Esri, HERE, DeLorme, increment P Corp., NPS, NRCan, Ordnance Survey, © OpenStreetMap contributors, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user

Figure 1: Northern California: Study Area



Sources: Esri, HERE, DeLorme, increment P Corp., NPS, NRCan, Ordnance Survey, © OpenStreetMap contributors, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS user community

Figure 2: Southern California: Study Area

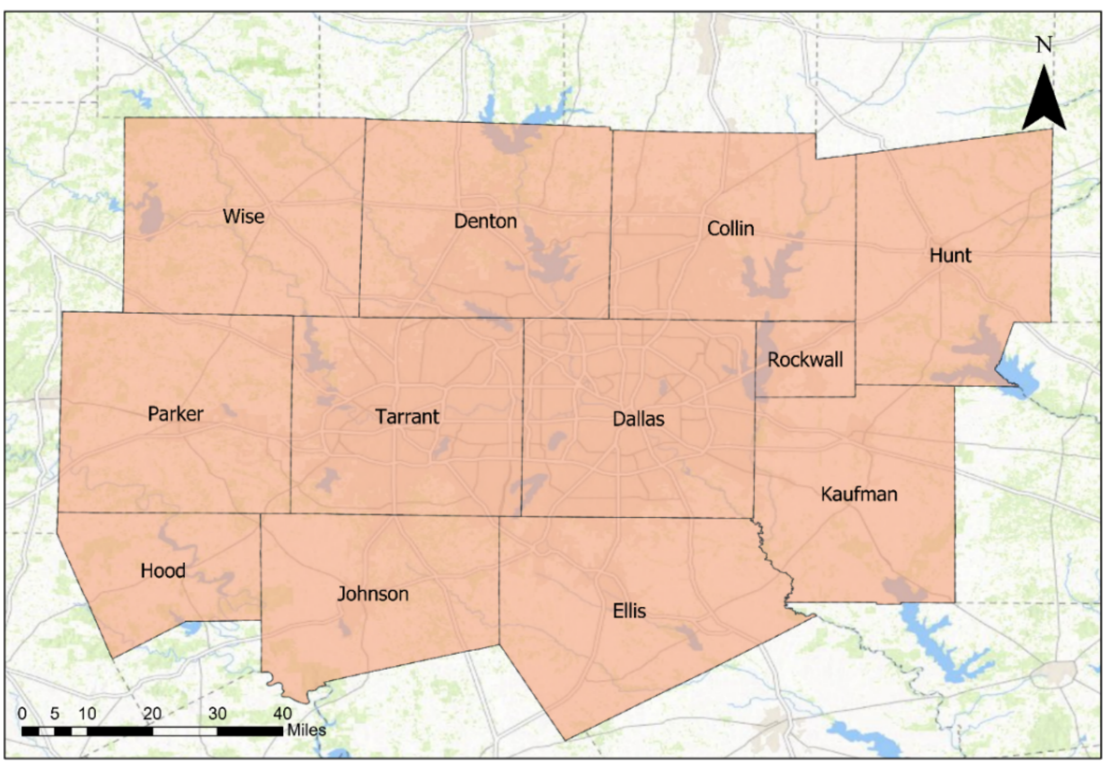


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Figure 3: Dallas-Fort Worth: Study Area

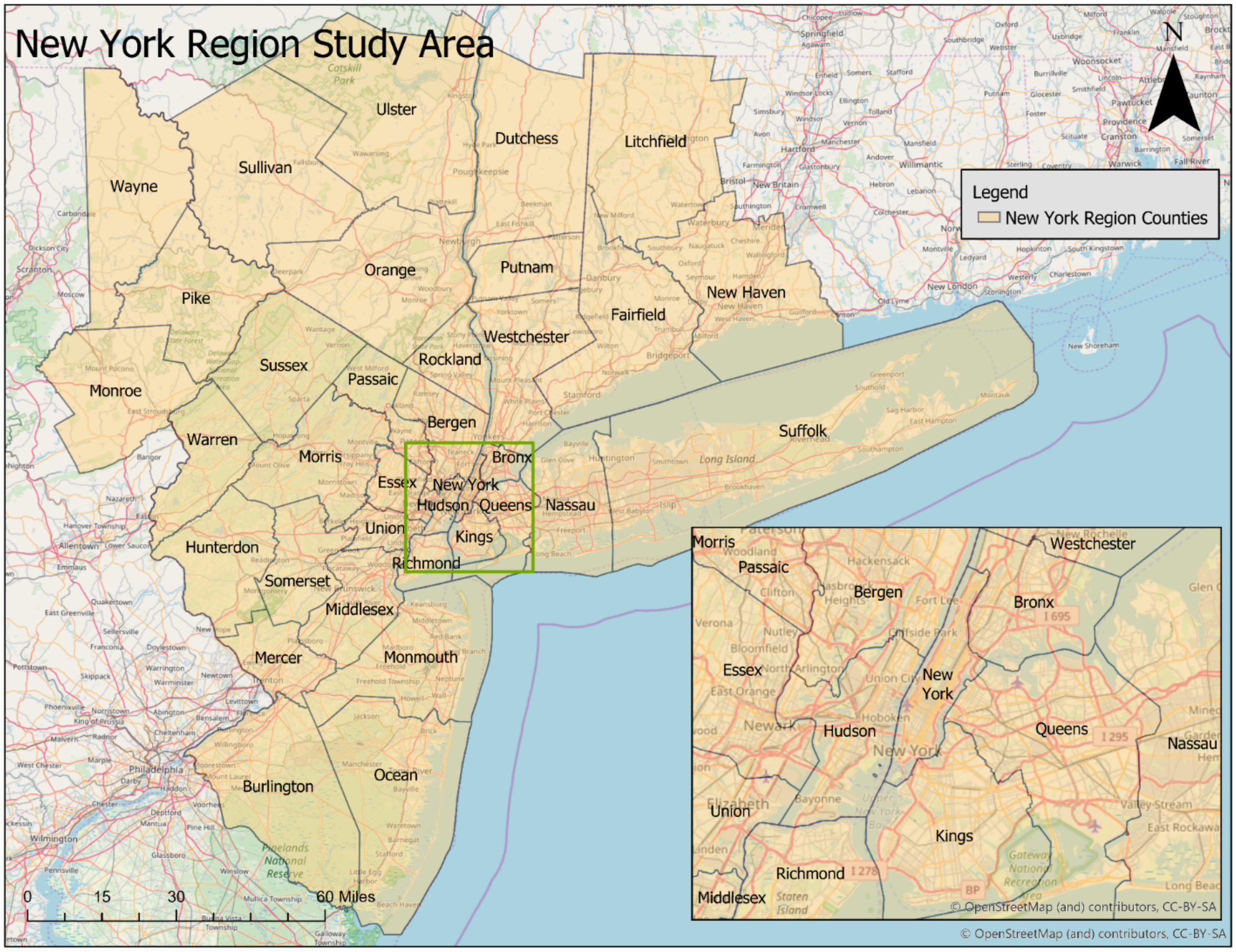

Figure 4: New York Study Area

3.2. Choice Model Estimation

Figure 5 presents the framework used to calibrate the trip mode choice models for each study area. The processes involve merging socio-economic databases, travel behavior data, model validation, and model calibration. We discuss the steps in the following sections of the report.

3.2.1. Mode Choice Datasets

To estimate UAM demand, we use a mode choice decision-making model on how commuters make decisions. The process involves reconstructing an individual's mode alternatives choice set (i.e., modes available to them) and estimating tradeoffs between time, cost, and convenience while commuting. The Value-Of-Time (VOT) is one metric defined when quantifying such tradeoffs.

To estimate the value of time for commuters, a revealed-preference mode choice data, as well as supplementary socio-economic information data, were collected, as listed in Table 3. We merge the datasets contained in Table 3 to include characteristics on both the trip (e.g., origin/destination) and the traveler (e.g., income information aggregated to the block-level).

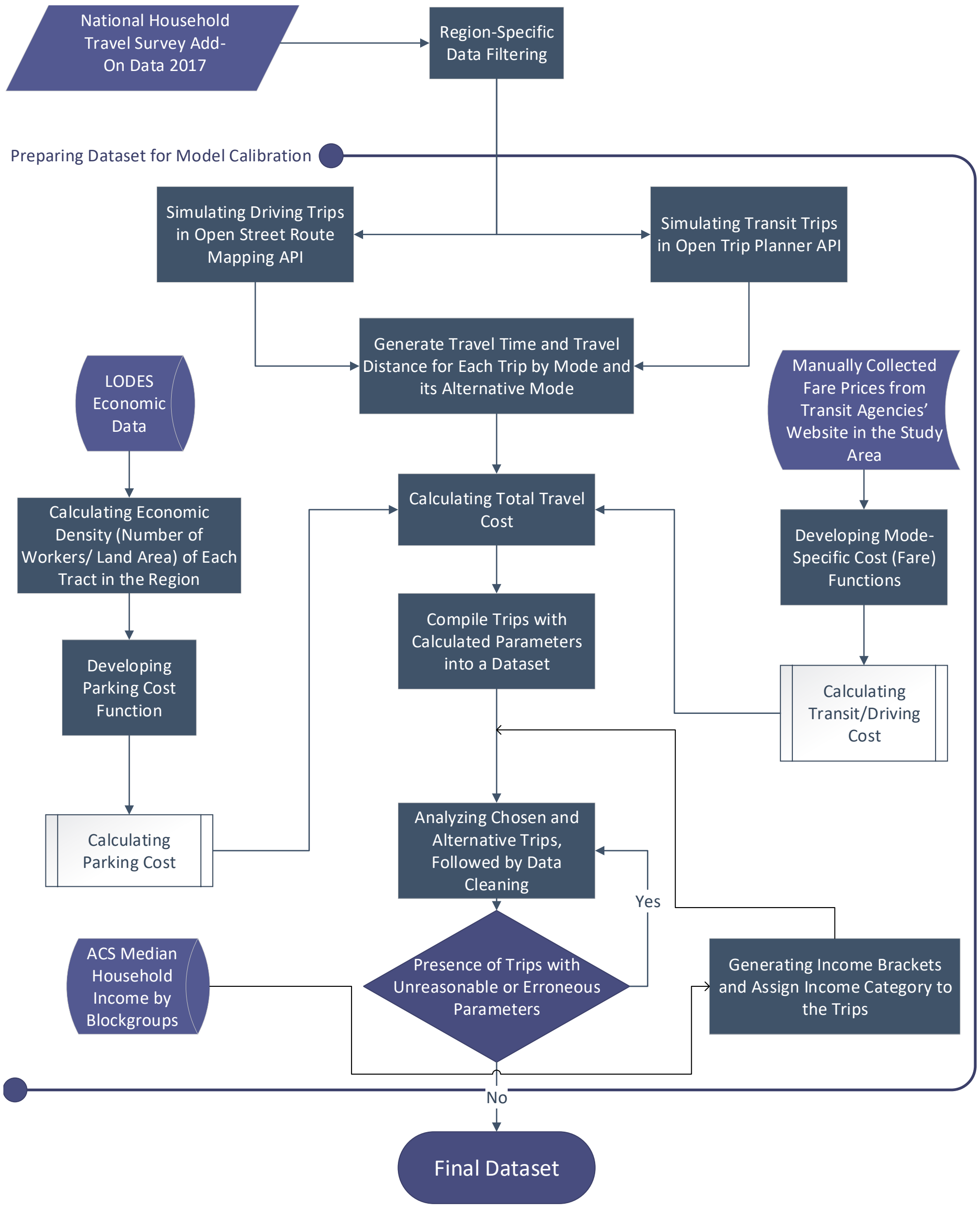

Figure 5: Workflow to Prepare Survey Data for Commuter Mode Choice Model Calibration

The National Household Travel Survey (NHTS) data is the basis for the travel survey used in the study. We collected add-on NHTS data to improve the quality and spatial scope of the data sets. We use an Application Programming Interface (API) to estimate travel time characteristics of the automobile and public transportation modes available to the commuter. The research team manually collected public transportation and automobile cost per mile and parking costs. The data collected applies to commuting trips. A trip was included in the study if it: 1) started and ended inside the study area; 2) linked home to work or vice-versa, and 3) was taken on a weekday. Table 4 shows a summary of the trip datasets used in the model calibration. For the New York Model, there were two mid-income categories as opposed to the other regions that had only one.

Table 3: Datasets Used in the UAM Commute Demand Analysis

Region	Datasets	Data Resolution
Northern California/ Southern California	• National Household Travel Survey-2017 Add-on Data • Longitudinal Employer-Household Dynamics LODES Data-2015 • American Community Survey-2016	• Location Coordinates • Block Group • Block Group
Dallas-Fort Worth	• Census Transportation Planning Products-2016 • Longitudinal Employer-Household Dynamics LODES Data-2015 • American Community Survey-2016	• Traffic Analysis Zone (TAZ) • Block Group • Block Group
New York City	• National Household Travel Survey-2017 Add-on Data • Longitudinal Employer-Household Dynamics LODES Data-2015 • American Community Survey-2016 • Yellow Cab Data: New York City Taxi and Limousine Commission	• Block Group • Block Group • Block Group • Taxi Zones

3.2.2. Spatial Income Distribution

The mode choice model calibration for Northern California, Southern California, and Dallas-Fort Worth includes three income categories. The model calibration of New York data employs four income categories. The maps shown in Appendix A illustrate the spatial distribution of median income levels. There are significant differences in the spatial distribution of income across the study regions. For example, the Northern California region has a higher percentage of the population in high-income level block groups. However, the cost of living is higher in Northern California compared to other areas.

In Northern California, high-income block groups reside around the San Francisco Bay Area. In Southern California and Dallas-Fort Worth, high-income block groups live in the suburbs and far away from the downtown areas. This difference could potentially decrease the demand in Northern California as UAM might not be attractive and viable for short commuting distances. The New York region has a high concentration of high-income population in Manhattan, Connecticut, the western suburbs of Jersey City, and parts of Long Island. High-income and upper-middle-income earners in the New York region have longer commutes making the area more attractive for UAM operations.

3.2.3. Model Calibration

The mode choice model uses a conditional logit model that includes independent variables that change between the modes for a single commuter (called generic variables- e.g., travel time, cost, distance traveled). The mode choice models do not include variables that remain consistent between the modes (called alternative-specific variables, e.g., commuter’s income, gender). Alternative-specific model variables could not because the NHTS data did not report UAM as a possible travel alternative, making it impossible to estimate those coefficients. Appendix A contains more information on conditional logit models and the derivation of their coefficients. Table 5 shows the list of variables included in the models. We include the travel time to go around airport approach surfaces in the region in the estimation of UAM mode travel time.

Table 4: Summary of Mode Choice Data used in Region-Specific Model Calibrations

<table>
<tr><th></th><th>Total Trips</th><th>Chose Driving</th><th>Chose Transit</th><th>Had Driving Available</th><th>Had Transit Available</th><th>Low Income Traveler</th><th colspan="2">Mid Income Traveler</th><th>High Income Traveler</th><th>Income Category Breaks</th></tr>
<tr><td>Dallas-Fort Worth</td><td>37,990</td><td>36,148</td><td>1,842</td><td>37,990</td><td>16,259</td><td>8,569</td><td colspan="2">21,854</td><td>7,567</td><td>$40k
$85k</td></tr>
<tr><td>New York</td><td>1,080</td><td>846</td><td>234</td><td>1,080</td><td>1,080</td><td>646</td><td>1,012</td><td>360</td><td>142</td><td>$50k
$100k
$150k</td></tr>
<tr><td>Northern California</td><td>7,471</td><td>6,982</td><td>489</td><td>7,399</td><td>2,568</td><td>916</td><td colspan="2">5,888</td><td>667</td><td>$45k
$152k</td></tr>
<tr><td>Southern California</td><td>8,084</td><td>7,947</td><td>137</td><td>8,042</td><td>3,095</td><td>1,698</td><td colspan="2">4,631</td><td>1,755</td><td>$45k
$152k</td></tr>
</table>

Table 5: Model Variable Definitions

Variable	Definition	Unit
TT	Total travel time: sum of IVTT and OVTT	Minutes
IVTT	In-vehicle travel time: time spent in a motorized vehicle, such as a car, subway train, or VTOL 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
Income Categories	Low, medium, and high-income group variables for all regions, except New York which has low, medium-low, medium-high, and high-income group variables.	Binary

Since UAM is not currently available in the regions studied, there is no revealed-preference data for the mode. The data does not show people's behavior when deciding to take this mode and, therefore, the model would not fully capture mode choice for UAM solely using the variables in the model. For example, a person may choose to drive instead of taking transit due to reliability, comfort, or safety, none of which are incorporated through the model's variables as these are not available in the data. For the same reason, we cannot estimate reliability, comfort, and safety for the UAM mode. Instead, this study utilizes the constants from Georgia Tech's mode choice stated-preference survey to capture unobserved biases towards a hypothetical UAM mode. These constants are shown in Table 6 and indicate that the unobserved characteristics, on average, increased the popularity of the UAM mode. Therefore, without the mode constants, the models would underestimate UAM demand.

We incorporate Georgia Tech's findings into this study considering the differences between the Georgia Tech model constants (i.e., drive minus UAM, transit minus UAM) to estimate the constants in the conditional logit models of our study. The ability to utilize the constants of another model is a unique feature of logit models in that it is the difference between the value of utility that determines the probabilities of selecting a mode. Table 7 shows an example to illustrate this point.

Table 8 shows the calibrated mode choice models for the four urban areas along with their corresponding values of time (VOTs). According to Louviere et al. [1], McFadden suggests that pseudo-R^2 values between 0.2 and 0.4 represent a model with a very good fit. Due to data quality in the Southern California and Dallas-Fort Worth regions, namely a low count of transit trips chosen and flat fare transit offerings, the Northern California model was ultimately applied to these regions. For the New Yor Region, we calibrated a separate model.

Table 6: Constants from Georgia Tech's Survey (Garrow, German, Patterson 2019)

Mode	Mode Constant
Drive	-0.580
Transit	-2.379
UAM	0

Table 7: Example showing Differences in Utilities to Determine the Probabilities of Selecting a Mode

Mode	Utility	Exponential (Utility)	Probability of choosing the mode
Drive	2	7.4	24%
Transit	1	2.7	9%
UAM	3	20.1	67%
Drive	1	2.7	24%
Transit	0	1.0	9%
UAM	2	7.4	67%

3.3. Mode Choice Model Application

The application of the logit models to estimate UAM demand requires known locations for UAM landing sites (hereon called vertiports). Vertiport locations determine the intermodal connections between the vertiport and the origin and destination of the trip. Figure 6 shows the framework used to place UAM vertiports, considering the potential demand for UAM. The location of vertiports is an iterative process to maximize the number of one-way commuter trips demand within the region. The process starts by locating one UAM vertiport at every block group in the study area and using the calibrated logit models to predict demand. Successive iterations follow while reducing the number of vertiports by half in every iteration and retaining the highest demand vertiports. The iterative process ends with the desired number of vertiports. The final result provides vertiport locations that maximize demand for a given set of UAM cost parameters and a target number of vertiports.

Table 8: Region-specific Calibrated Mode Choice Models

BASIC MODELS WITHOUT CONSTANTS				
	Dallas-Ft. Worth	**North California**	**South California**	**New York**
TT	-0.0550*	-0.0782*	-0.127*	-0.2365*
Cost	-0.207*	-0.242*	-0.368*	-0.4854*
Pseudo-R^2	0.514	0.468	0.789	0.890
TT VOT	$15.9	$19.4	$20.7	$29.2
ADVANCED MODELS WITHOUT CONSTANTS				
	Dallas-Ft. Worth	**North California**	**South California**	**New York**
TT				
IVTT		-0.0569*	-0.0721*	-0.2036*
OVTT		-0.111*	-0.180*	-0.2355*
Cost			-0.352*	-0.5714*
Transfers		0.417*	0.303*	-0.5325*
Low Income		-0.328*		-0.7183*
Lower-Mid Income				-0.6487*
Mid Income		-0.272*		
Upper-Mid Income				-0.5592*
High Income		-0.172*		-0.4196*
Pseudo-R^2		0.489		0.899
TT VOT				
IVTT VOT		$10.4, $12.5, $19.9	$12.3	$17.0, $18.8, $21.8, $29.1
OVTT VOT		$20.3, $24.4, $38.7	$30.7	$19.7, $21.8, $25.3, $33.7
Constraints			OVTT/IVTT=2.5	
ADVANCED MODELS WITH CONSTANTS				
	Dallas-Ft. Worth	**North California**	**South California**	**New York**
TT				
IVTT		-0.0472*	-0.0441*	-0.2027*
OVTT		-0.0845*	-0.110*	-0.2299*
Cost			-0.307*	
Transfers		0.343*	0.139*	-0.5384*
Low Income		-0.329*		-0.7157*
Lower-Mid Income				-0.6472*
Mid Income		-0.275*		
Upper-Mid Income				-0.5582*
High Income		-0.172*		-0.4187*
Transit Constant		-0.603*	-1.476*	-0.1038*
VTOL Constant		0.699	0.612	-0.7496
Pseudo-R^2		0.493		0.899
TT VOT				
IVTT VOT		$8.6, $10.3, $16.5	$8.6	$17.0, $18.8, $21.8, $29.1

OVTT VOT		\$15.4, \$18.4, \$29.5	\$21.5	\$19.3, \$21.3, \$24.7, \$33.0
Constraints			OVTT/IVTT=2.5	

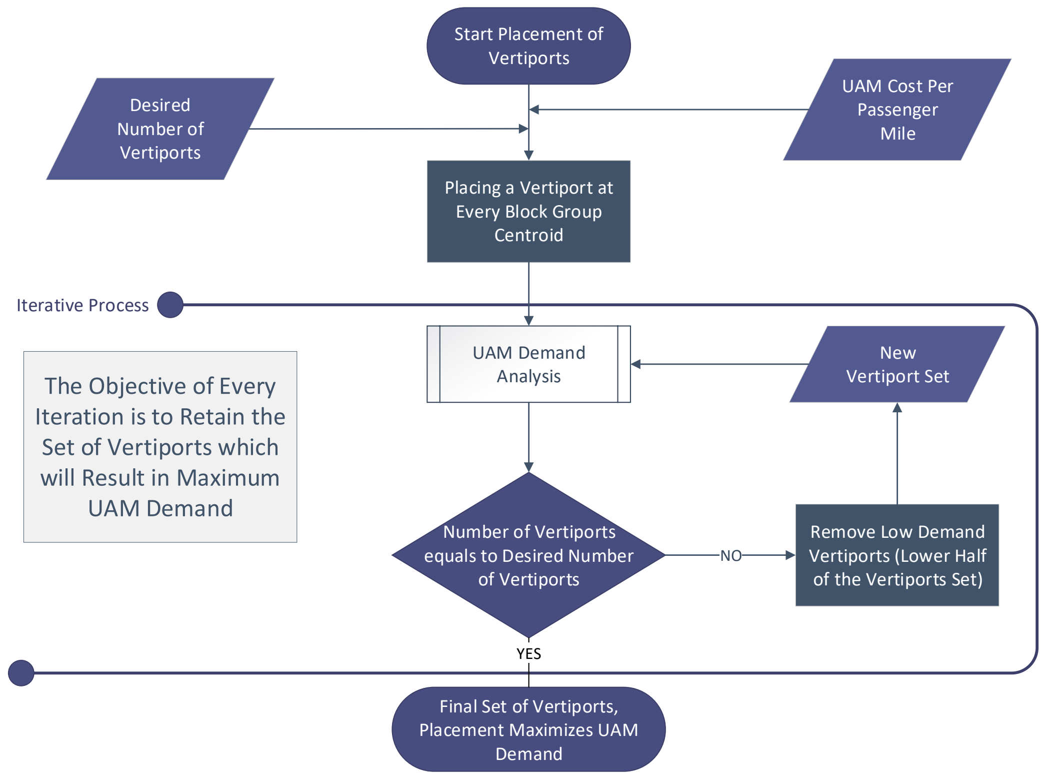

Figure 6: Demand-Driven Placement of Vertiports

3.3.1. UAM Demand Analysis Results

This section contains the demand results for each one of the four urban regions studied. We provide UAM demand parametric results under various vertiport sets and UAM cost per mile (CPM). UAM passenger commuter demand is sensitive to the cost of the UAM mode. An increase in cost per seat mile increase in price leads to a drop in the market share of the low- and mid-income household demand as those market segments are no longer able to afford the UAM mode for commuting. The model results highlight the importance of UAM's affordability to support its successful implementation. The UAM cost includes ground access from home to the nearest vertiport using a service such as UBER or Lyft, the UAM cost per mile, and the ground access from the destination vertiport to work. In total, these costs have to be affordable to capture a reasonable demand for the UAM system.

Northern California

Figure 7 shows the sensitivity of the UAM demand against the number of vertiports in Northern California. Even though the magnitude of UAM demand is different for both scenarios (UAM CPM of \$1.80 and UAM CPM of \$1.20), the sensitivity towards the number of vertiports is similar. The results show that, as the number of vertiports increase, the number of commuters in the catchment area increases as well. There are core vertiports that serve the majority of the UAM demand and feeder vertiports that provide UAM service from outlying areas. A comparison of UAM demand for 50 and 400 vertiport sets shows that increasing the number of vertiports by 700% increases UAM demand by 179% (156%) at CPM of $1.20. In Northern California, the areas with high-income levels are usually the densest (i.e., downtown areas). Therefore, increasing the number of vertiports does not increase the demand proportionately. The UAM demand for CPM $1.20 is slightly more sensitive, with an increasing number of vertiports as the mode is more affordable. Increasing the number of vertiports expands the network to service more medium and low-income areas.

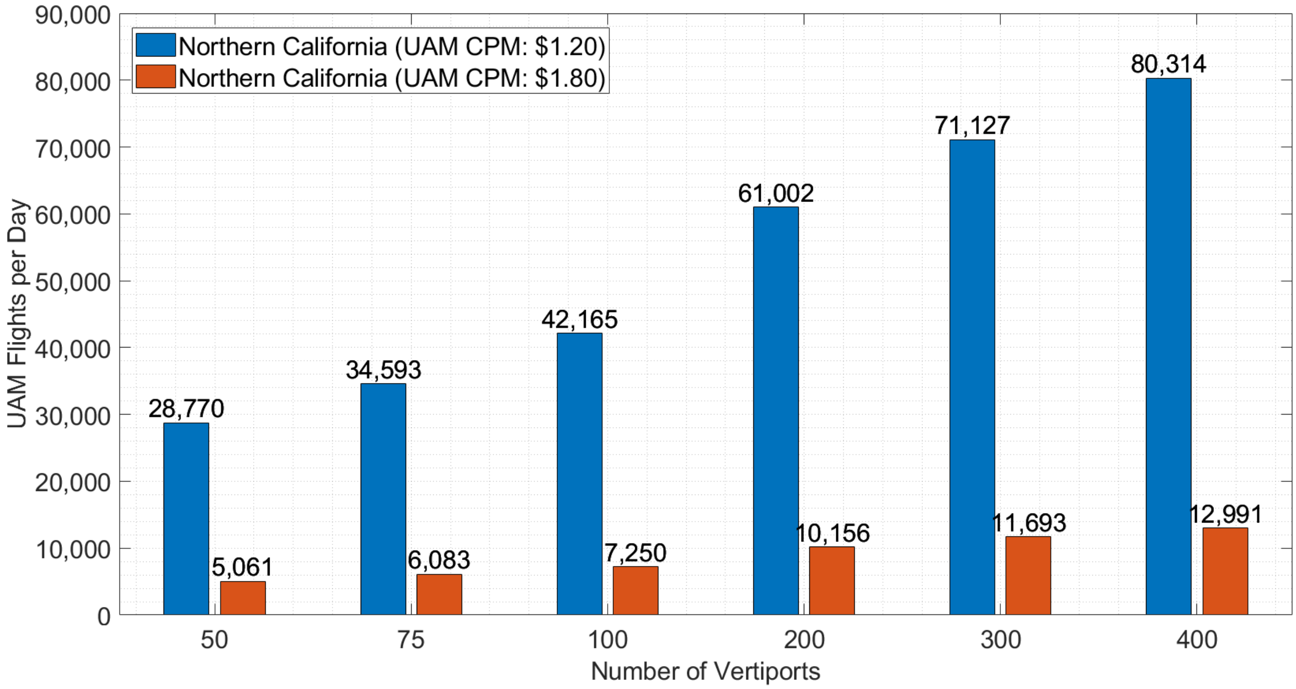

Figure 7: Northern California: UAM Demand by Number of Vertiports and CPM

Figure 8 shows the sensitivity of the UAM demand with the UAM cost per passenger mile. Figure 8 shows the sensitivity of the UAM demand with UAM CPM. In this study, we found that UAM demand in Northern California is slightly less sensitive to UAM cost per passenger mile compared to areas like Dallas and Southern California. The hypothesis is that a high percentage of high-income earners in the study area may be able to afford more costly UAM services. Figure 9 shows the composition of UAM demand by income category in Northern California. A feature of this region is the significant contribution from high-income earners even at the low UAM CPMs because high-income earners live in densely populated areas. Denser block groups are smaller in size and have lower intermodal connection times for UAM. Higher intermodal or travel time by UAM discourages high-income earners as they have a higher value of time. Therefore, if the intermodal and total travel times are low, high-income earners get significant utility from the UAM mode even at increased UAM CPMs. As the UAM CPM increases for the given UAM network size, the contribution from low- and mid-income households drops to a mere 9% market share at $3.00 UAM CPM.

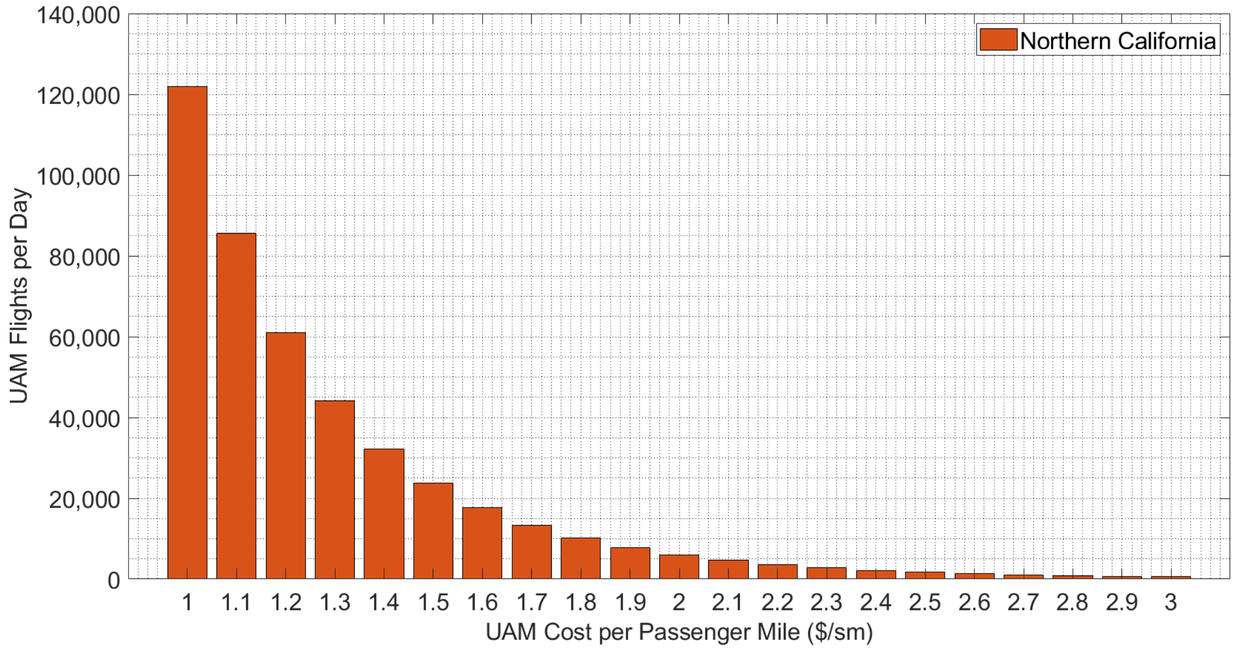

Figure 8: Northern California: UAM Demand Sensitivity with CPM and 200 Vertiports

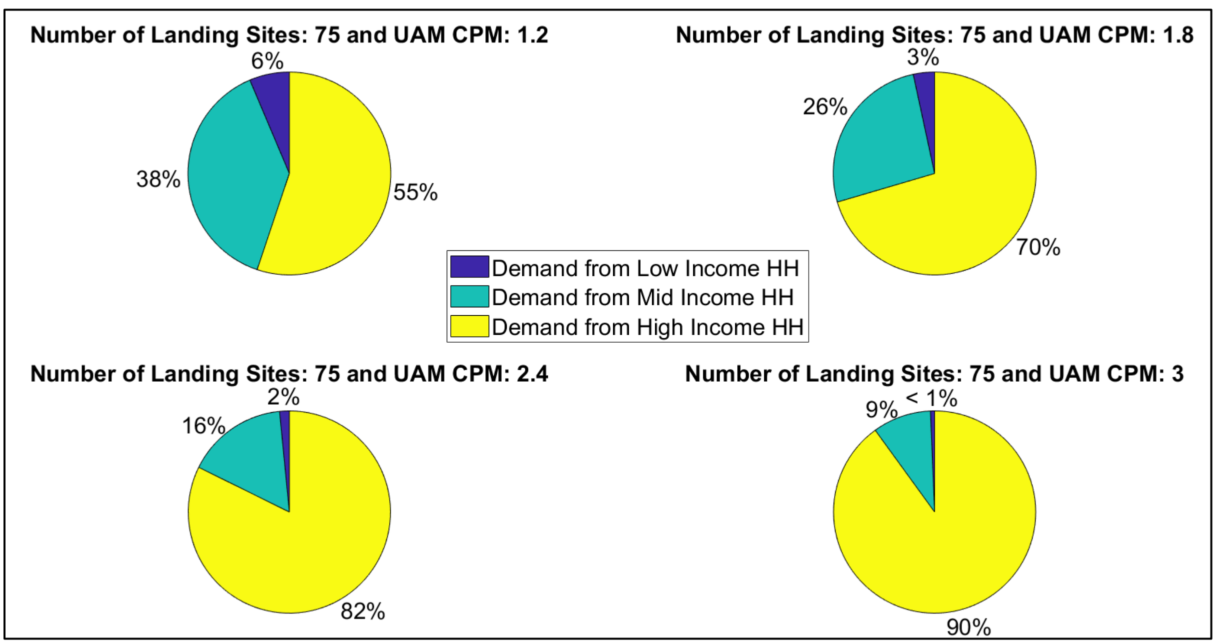

Figure 9: Northern California: Composition of UAM Demand by Income Category

Southern California

Figure 10 shows the sensitivity of the UAM demand against the number of vertiports in Southern California. In Southern California, the UAM demand is relatively much more sensitive to the number of vertiports due to the population density in the region. With the increasing UAM network size, the mode becomes more accessible to the people. Since the population density is relatively high in Southern California, the increase in UAM demand is almost four-fold when comparing the smallest (50) and the largest (400) UAM networks. As mentioned before, increasing number vertiports expand the service to include more low and mid-income households, but if the price-point is not attractive to those households, very little is added to the UAM demand generated.

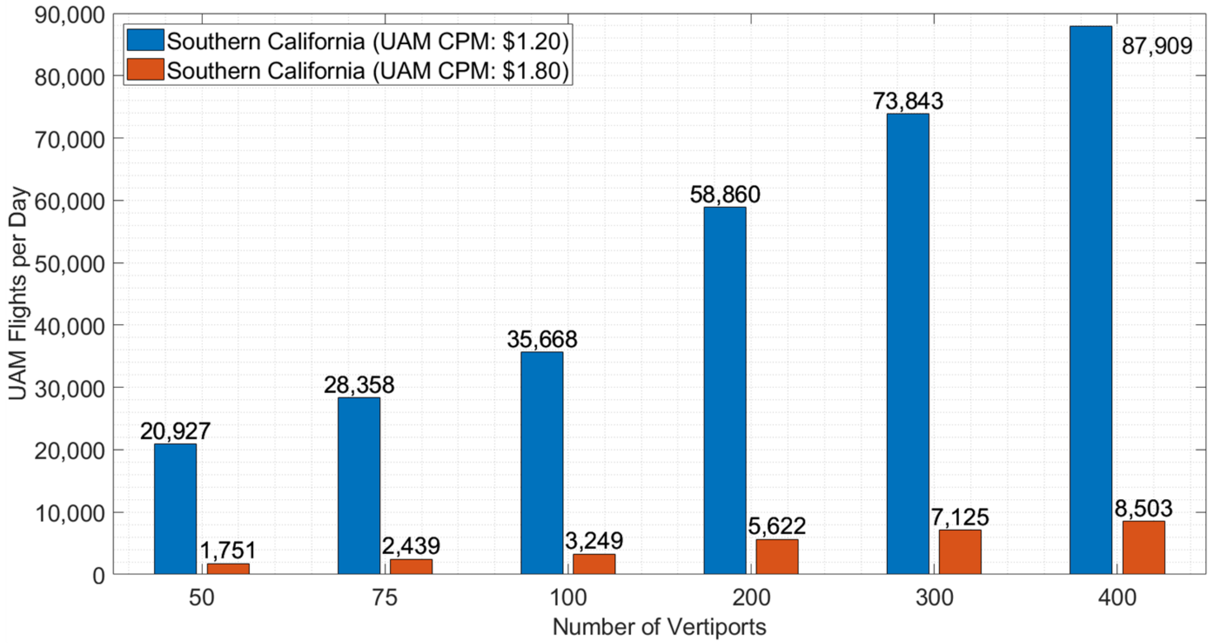

Figure 10: Southern California: UAM Demand by Number of Vertiports and CPM

Figure 11 shows the sensitivity of the UAM demand with the UAM cost per passenger mile. The UAM demand in Southern California is relatively more sensitive to the UAM CPM. This is attributed to the higher concentration of low- and mid-income households in the study region. As the cost of the UAM mode increases it becomes relatively less affordable to the low- and mid-income households. It can be observed from Figure 12 that the contribution from low- and mid-income households towards total UAM demand is significantly higher. Even at the $3.00 UAM CPM, almost one-third of the demand is coming from low- and mid-income households. This is due to the high percentage of people from low- and mid-income households in Southern California which can further be observed in spatial income distribution maps in Appendix B. Also, the plunging of UAM demand with increasing UAM CPM in Southern California is due to the same reason.

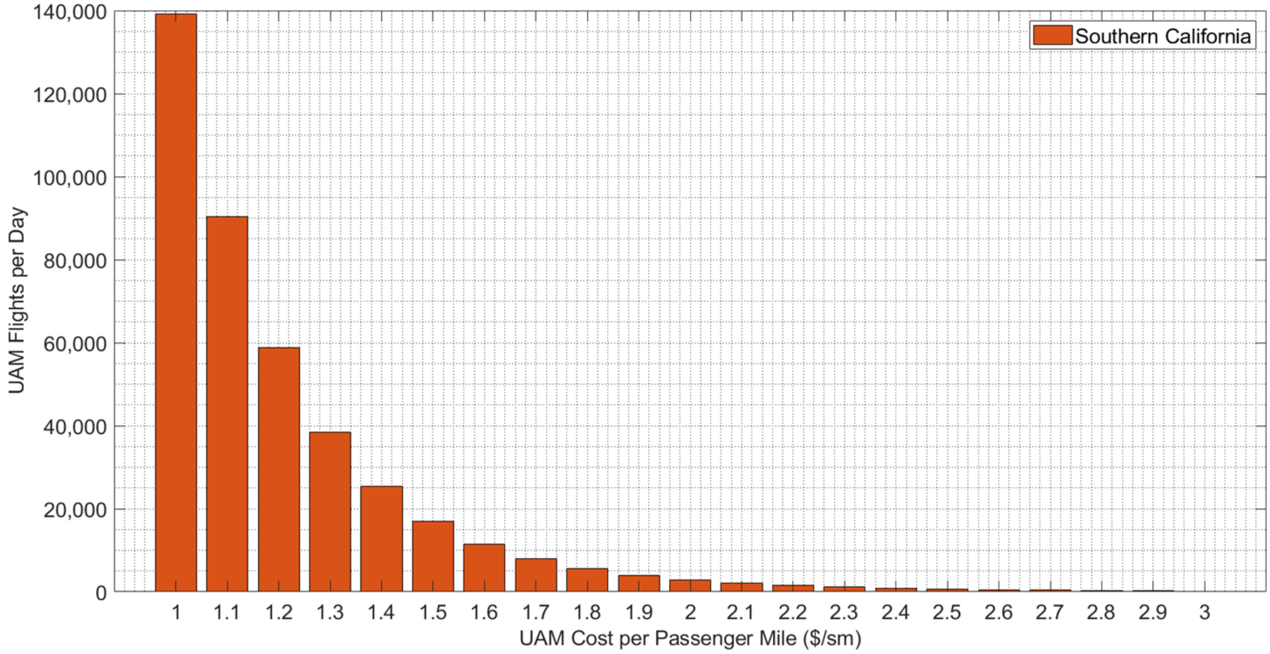

Figure 11: Southern California: UAM Demand Sensitivity with CPM and 200 Vertiports

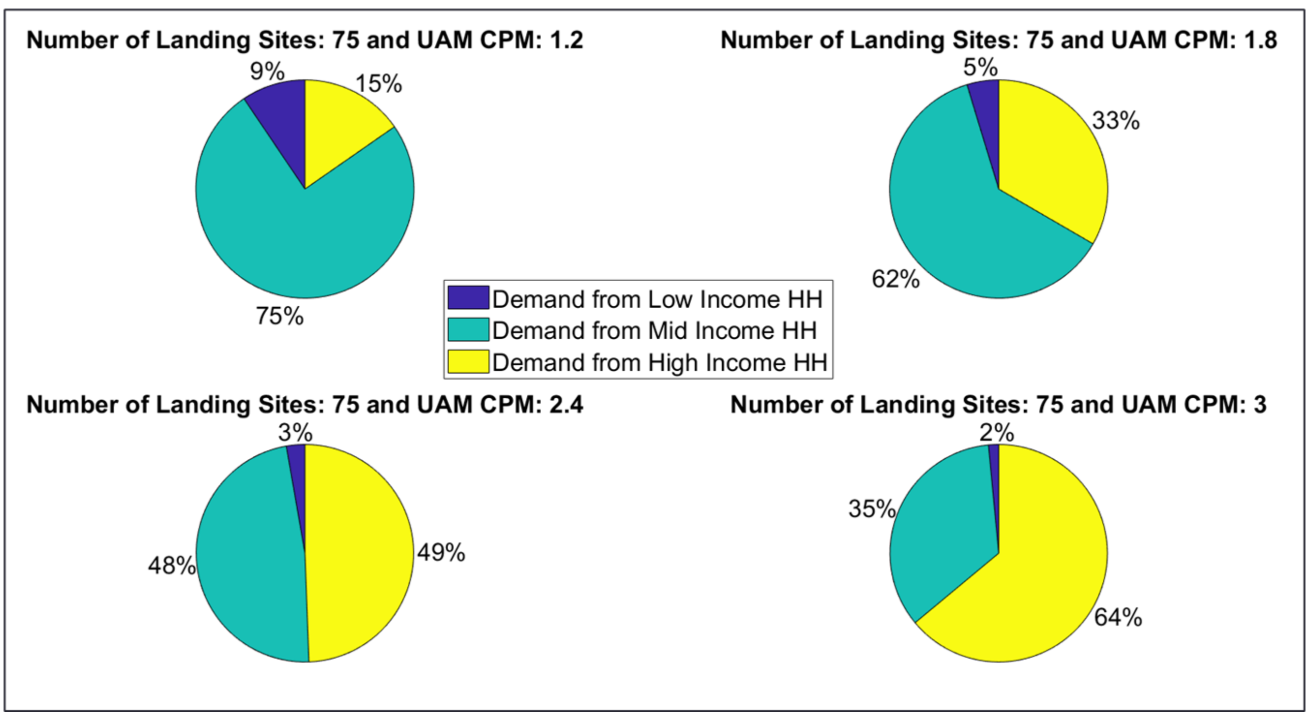

Figure 12: Southern California: Composition of UAM Demand by Income Category

Dallas-Fort Worth

Figure 13 shows the sensitivity of the UAM demand against the number of vertiports in Dallas-Fort Worth. The sensitivity of UAM demand is similar to Southern California because both regions have a lower percentage of high-income households. The magnitude of UAM demand is lower in Dallas-Fort Worth than in the Southern California region because Dallas-Fort Worth has a smaller population and fewer high-population density areas.

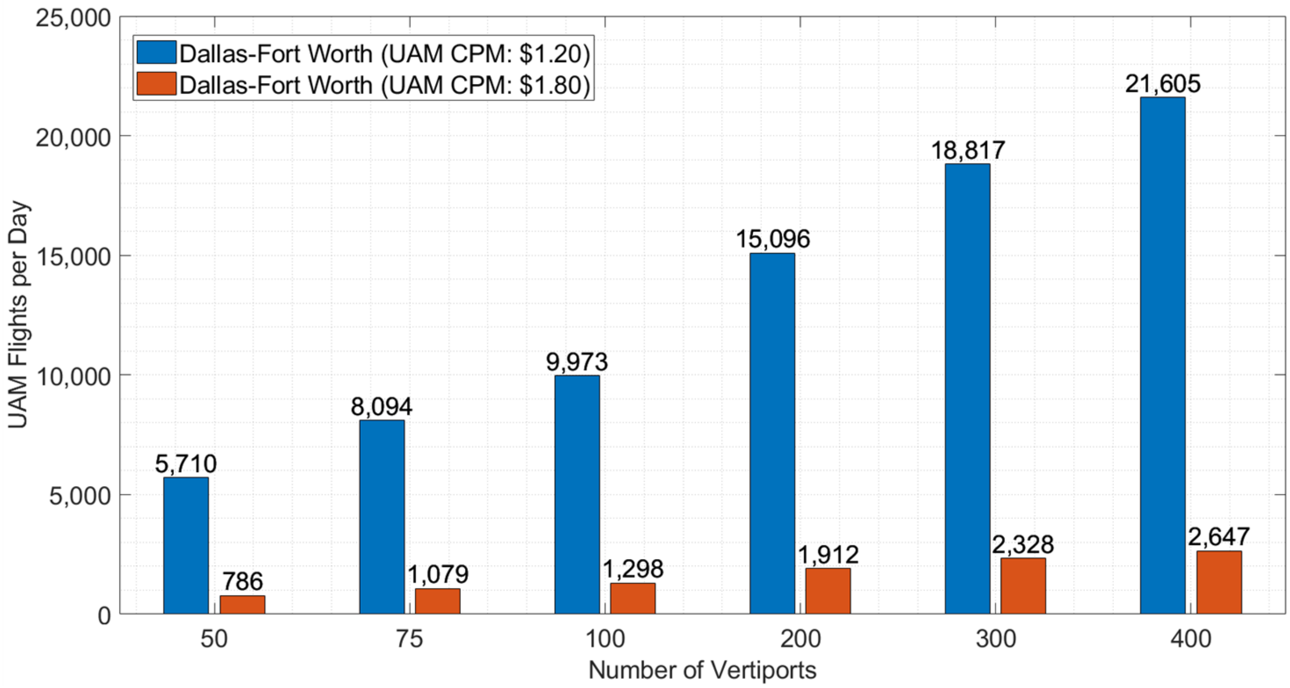

Figure 13: Dallas-Fort Worth: UAM Demand by Number of Vertiports and CPM

Figure 14 shows the sensitivity of UAM demand in Dallas-Fort Worth for various UAM costs per passenger mile. The UAM demand in the Dallas region is less sensitive compared to Southern California. The trend is due to the population density differences in the two areas. Southern California has a lower percentage of high-income households, but a larger population. Dallas-Fort Worth (Figure 15) shows a higher contribution to UAM demand from low-and mid-income household levels. Figure 15 shows a higher contribution to UAM demand from low-and mid-income household levels.

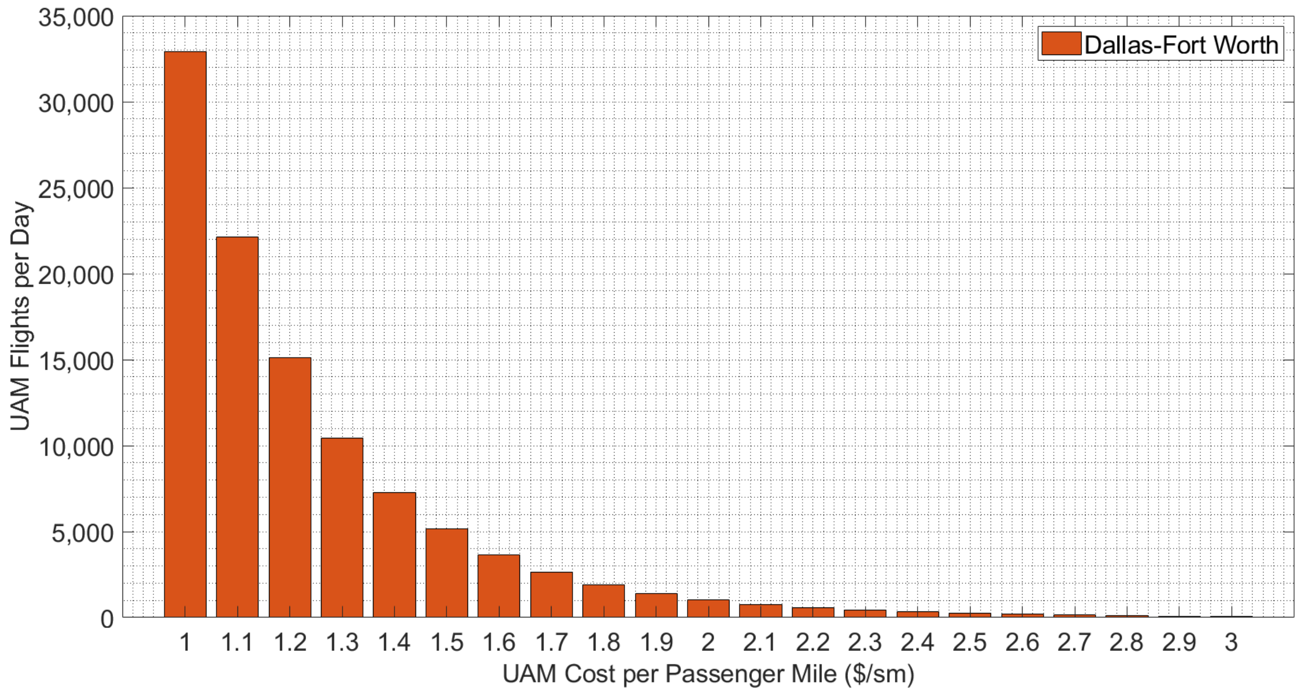

Figure 14: Dallas-Fort Worth: UAM Demand Sensitivity with CPM and 200 Vertiports

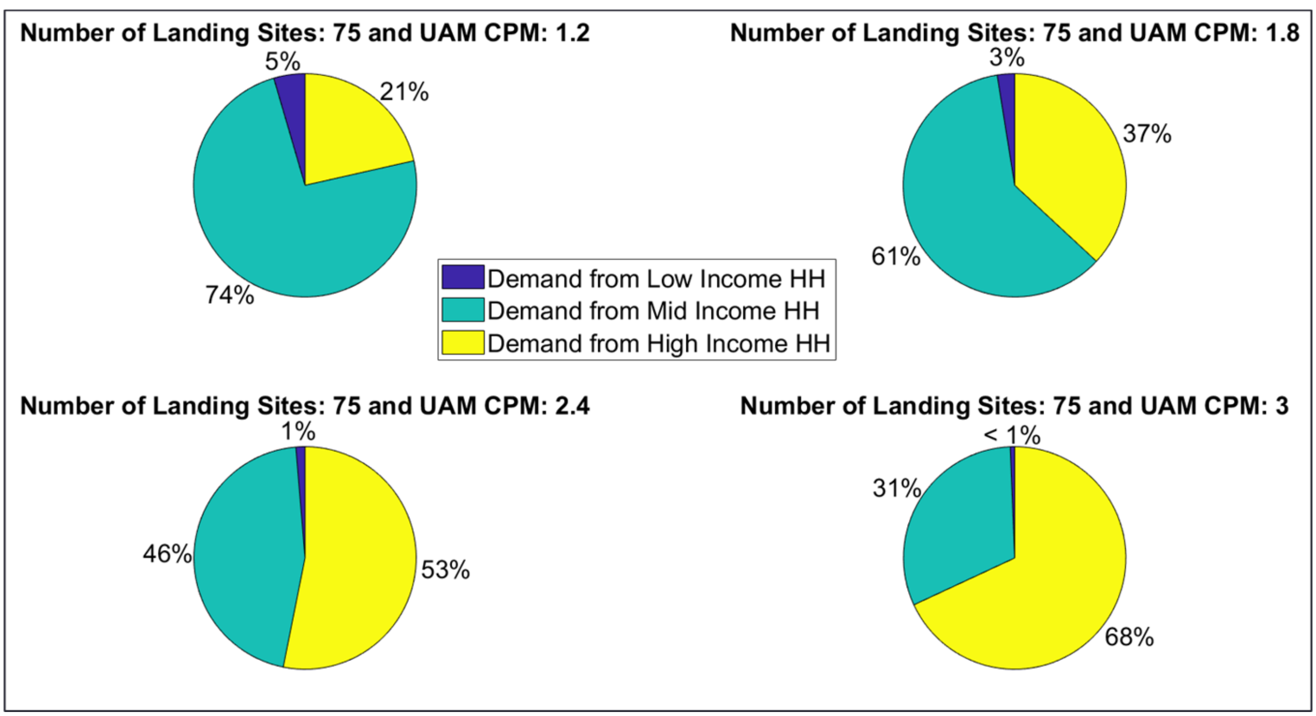

Figure 15: Dallas-Fort Worth: Composition of UAM Demand by Income Category

New York

For UAM demand estimates in the New York region, we use a different model calibrated using the NHTS add-on data. For other regions, we use the model calibrated for Northern California. New York has unique characteristics such as very high population density (Manhattan), relatively higher disutility in driving due to increased costs (parking, tolls, etc.), and traffic congestion, which could favor UAM. For New York, we developed highway travel congestion indices separately using Yellow Cab data from the Taxi and Limousine Commission (TLC). Figure 16 shows the distribution of the congestion indices for 1.16 million trips. The automobile travel time analysis uses a value of 2.77 for the travel congestion index.

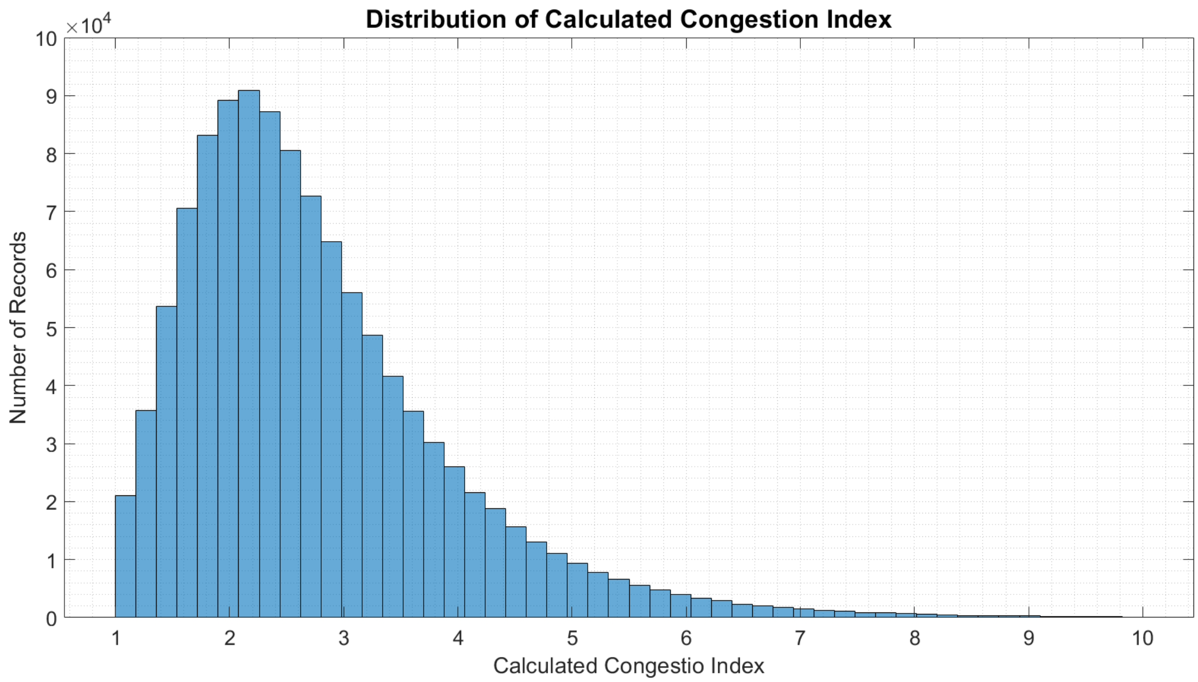

Figure 16: Congestion Index Distribution in New York City

Figure 17 shows the UAM demand for a different set of vertiports in New York with two different UAM CPM cost levels. The UAM demand increases by 114% when the number of vertiports increases from 50 to 400. There are four possible reasons for high-demand at $1.80 CPM for UAM. First, the monetary cost of driving in the region is high. Driving cost includes the cost of parking and tolls. Second, the UAM mode can take shorter routes than the ground modes because the area has numerous bodies of water. Third, the ground transportation congestion factor is high relative to the other three regions in the study. Fourth, the spatial distribution of income in the region is unique and found in Appendix B. In the New York area, a significant number of the upper mid- and high-income households live in the suburbs, offering an advantage to the UAM mode. Longer commutes, higher affordability, costly and slower alternative modes, and high population density all together results in high demand for UAM in the region. The unique features of the calibrated mode choice model contribute to the high demand results in New York. The mode choice model used has almost parity in the coefficients of in-vehicle and out-of-vehicle travel times, implying New Yorkers are less sensitive to out-of-vehicle travel times.

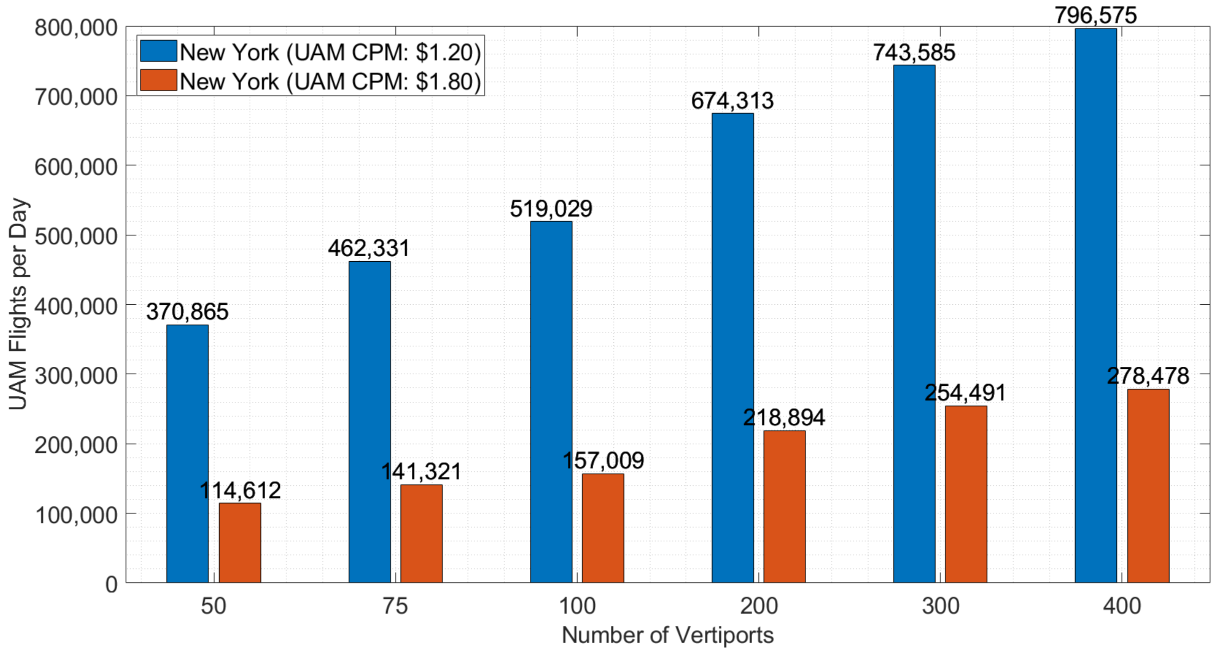

Figure 17: New York: UAM Demand by Number of Vertiports and CPM

Figure 18 shows the UAM demand sensitivity with UAM CPM for 200 vertiports. The UAM demand in New York is not as sensitive as other regions because of the high percentage of upper-mid and high-income households and costlier driving (both in cost and time). With a $2.2 UAM CPM and no base cost, the region could attract 100,000 daily UAM flights. Figure 19 illustrates the composition of the UAM demand by income category. As expected, the UAM demand from low and lower-mid income decreases with increasing UAM cost.

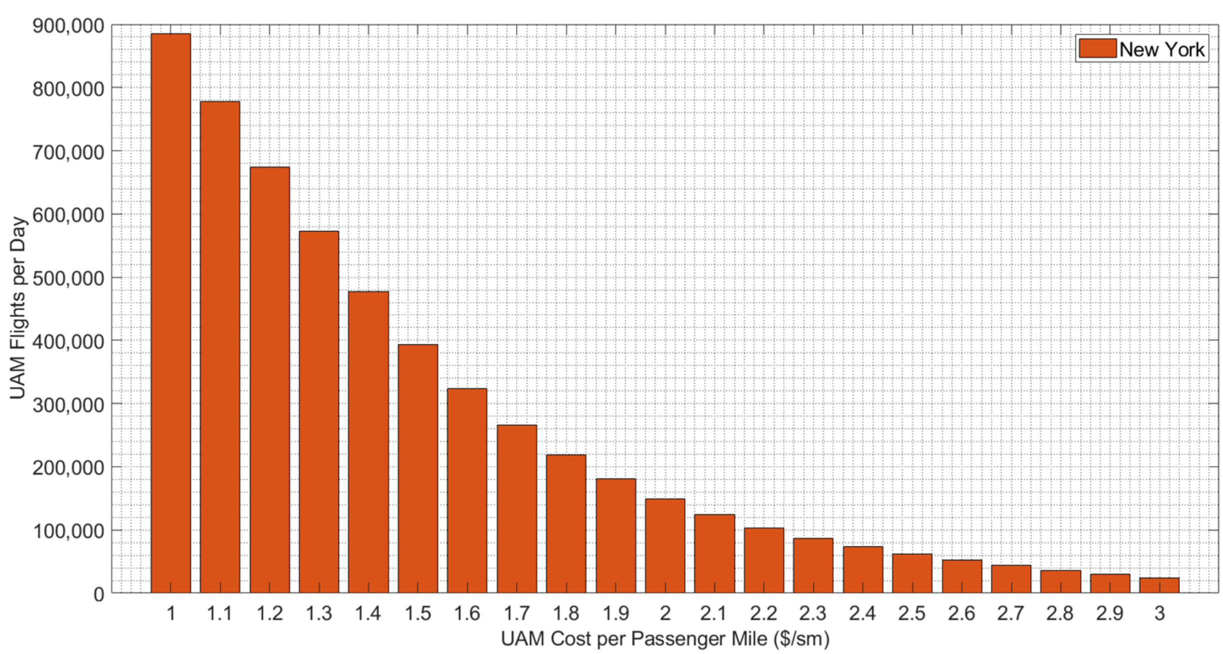

Figure 18: New York: UAM Demand Sensitivity with CPM and 200 Vertiports

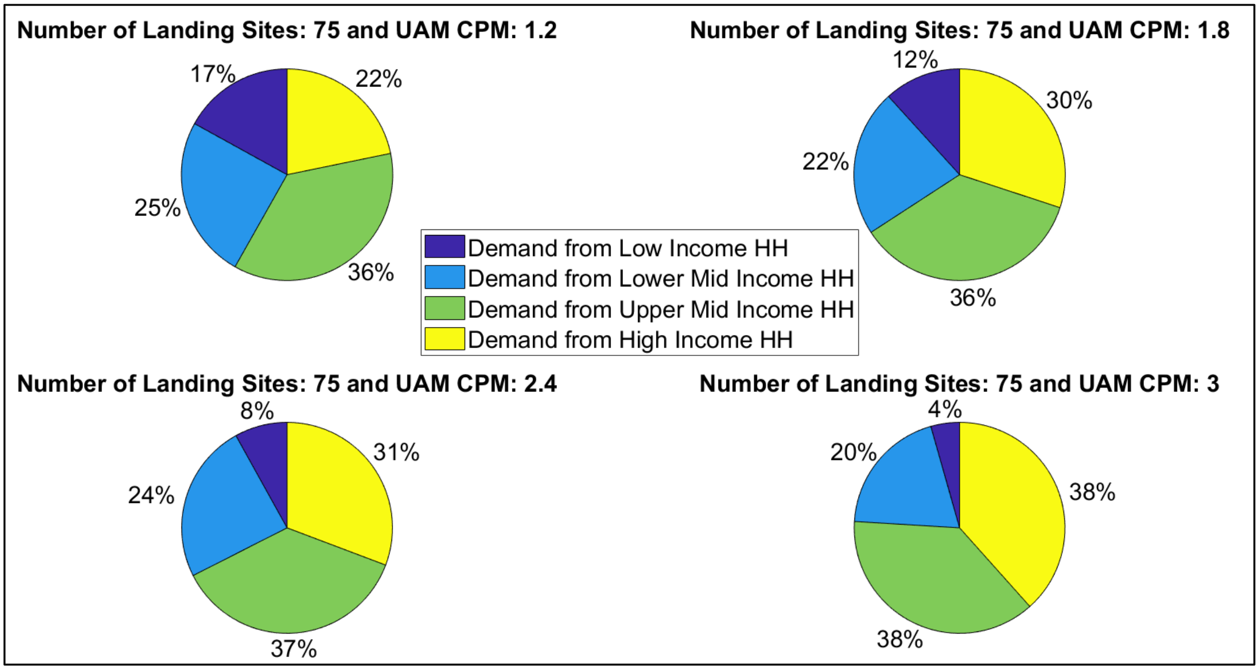

Figure 19: New York: Composition of UAM Demand by Income Category

3.3.2. Comparison of UAM Demand Results

Calculation of UAM demand is a complex process with high uncertainty. All urban regions are unique in their way, and the impact of regional characteristics on mode choice plays a vital role in the potential UAM demand. Figure 20 compares the UAM demand in all four regions for six UAM vertiport sets. Figure 20 shows the New York region's latent demand stands out from the four urban areas studied.

The number of UAM vertiports has a substantial impact on the UAM demand in Southern California and Dallas-Fort Worth. More so than in Northern California and New York City regions. Northern California and New York City have unique demographic characteristics such as high-income households in densely populated areas (see Figure 32). In Southern California and Dallas-Fort Worth, high-income households live in sparsely populated zones. Therefore, as the number of vertiports increases, UAM is accessible to less densely populated zones in Southern California and Dallas-Fort Worth, increasing UAM demand.

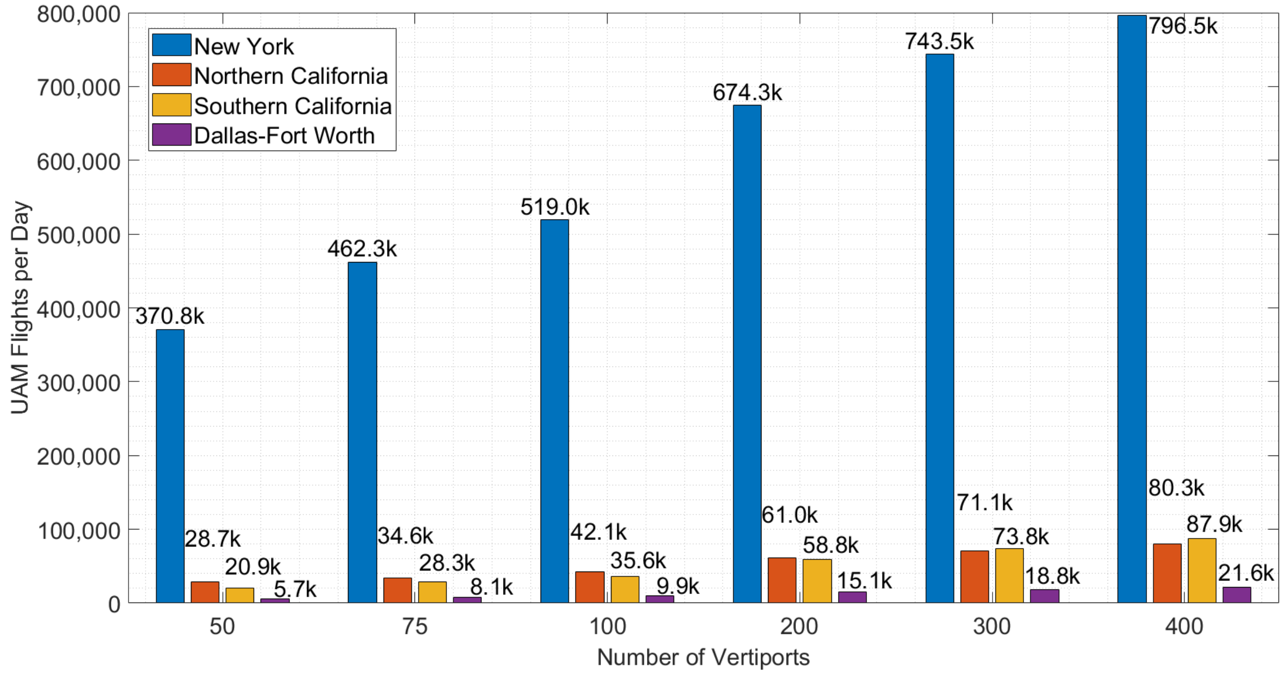

Figure 20: UAM Demand by Number of Vertiports for All Regions at CPM of $1.20

Figure 21 compares the UAM demand sensitivity with UAM cost per passenger mile across all regions with 200 UAM vertiports. Figure 21 provides insight into the cost of UAM services to offer a commuting alternative across all four regions. The UAM demand in Southern California and Dallas Fort-Worth areas is more sensitive to UAM CPM than in New York and Northern California due to a lower percentage of high-income households in the region.

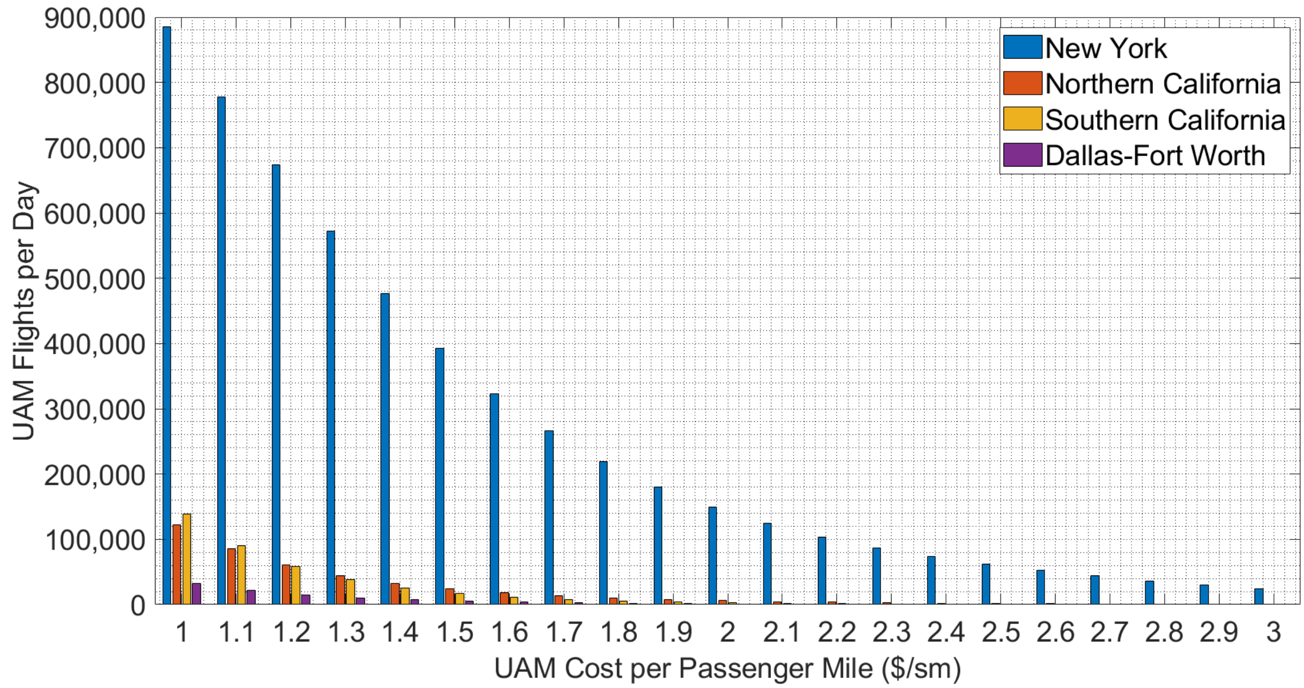

Figure 21: UAM Demand by CPM for All Regions at 200 Vertiports

3.3.3. Spatial Distribution of UAM Demand

Northern California

Figure 22 shows the spatial distribution of the UAM demand with 75 vertiports and UAM CPM of $1.20. The San Francisco Central Business District (CBD) is a significant attractor for the UAM trips. Most of the busiest vertiports in the region are inside San Francisco CBD. Although the study area for Northern California consists of 17 counties, all 75 vertiports get optimally placed around the bay area to maximize the UAM demand. Figure 23 shows the spatial distribution of UAM demand with 75 vertiports with UAM CPM of $1.80. Figure 23 shows most of the vertiports having fewer than 500 operations per day compared to 1000 operations per day at UAM CPM of $1.20. The busiest vertiports located in the SanFrancisco CBD, Mountain View, and San Jose CBD still have substantial demand. Figures 22 and 23 show the effect of increasing UAM cost on UAM demand at specific vertiports. Both figures show multiple vertiports with high demand within a small proximity. UAM vertiports that are close to others raises operational concerns. Appendix B contains ddditional maps with 200 vertiports and vertiports placed with higher UAM CPM costs.

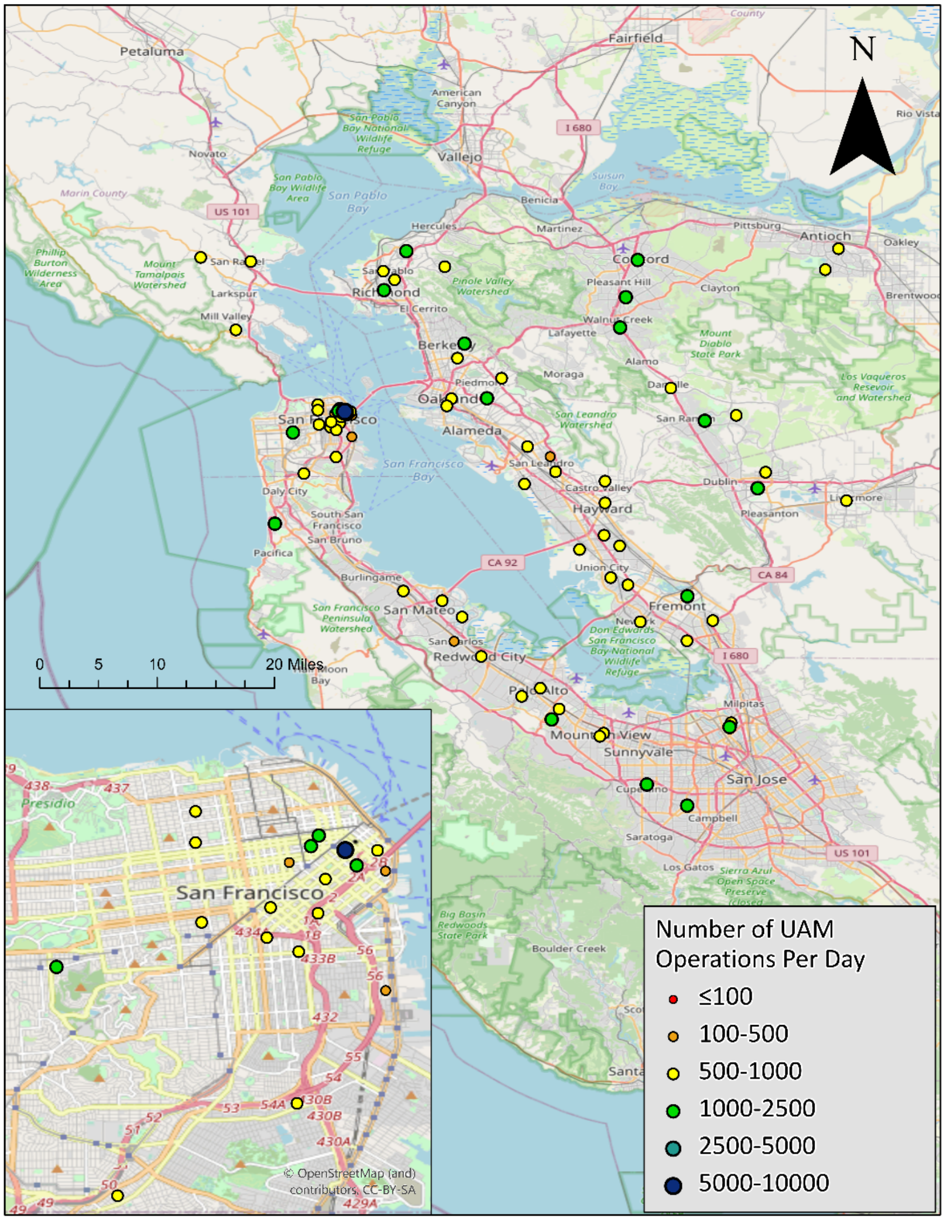

Figure 22: Northern California: 75 Vertiports Daily UAM Operations with CPM of $1.20

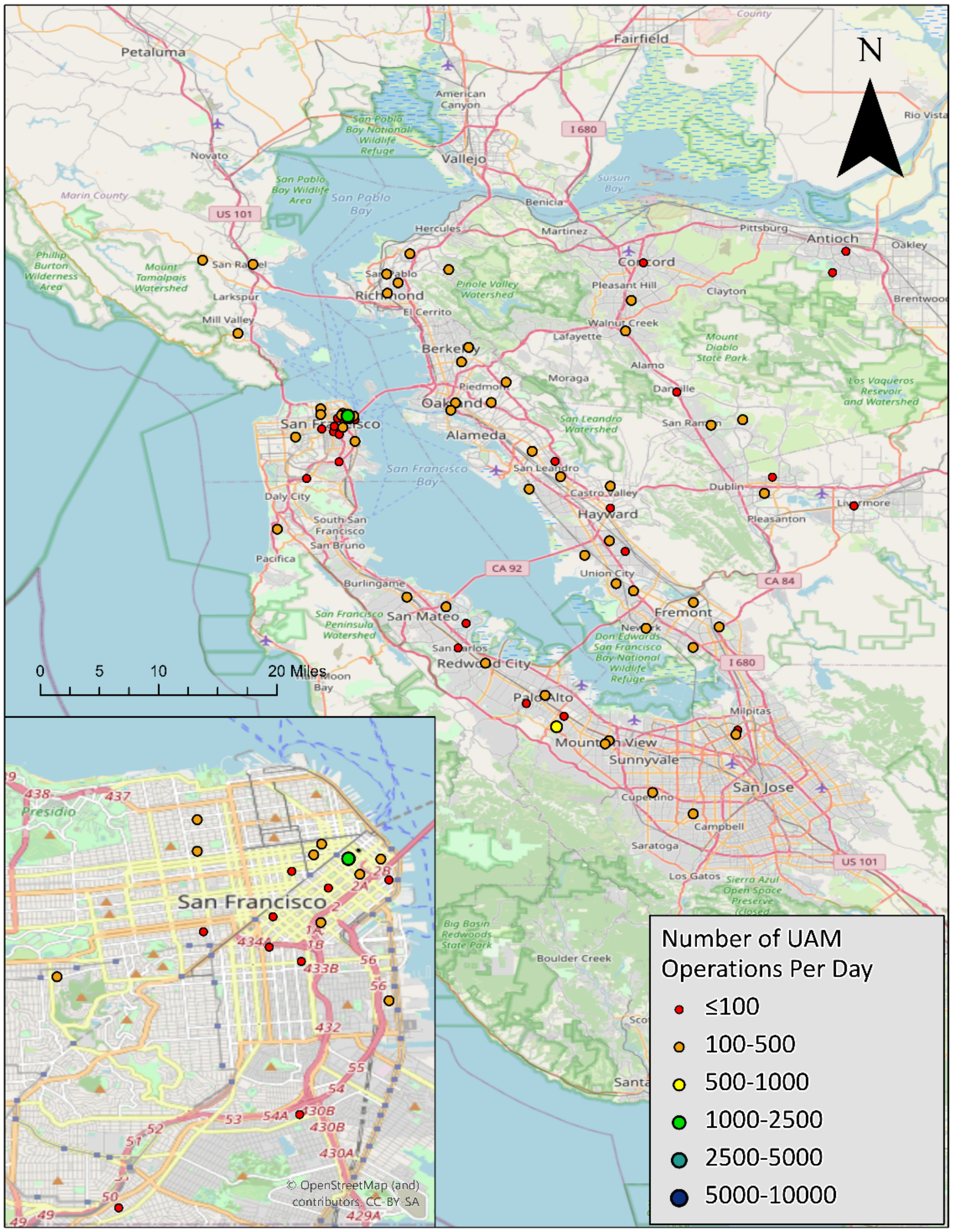

Figure 23: Northern California: 75 Vertiports Daily UAM Operations with CPM of $1.80

Southern California

Figure 24 shows the spatial distribution of the UAM commuter demand with 75 vertiports and UAM CPM of $1.20. Similar to Northern California, the vertiports in Southern California are placed in and around the Los Angeles County by the demand-driven algorithm. High population density zones in Southern California are particularly attractive to the placement of UAM vertiports. Lancaster (North of Los Angeles) attracts 13 vertiports even though the area contains mostly middle-income block groups. The corridor between Santa Monica and Beverly Hills has a higher proportion of high-income earners, and hence a cluster of vertiports can be found in that region. Unlike Northern California, Los Angeles Downtown is not among the most attractive areas to place vertiports. Figure 33 shows that low and mid-income households comprise the Los Angeles downtown area.

UAM commuter demand decreases significantly when the UAM cost per passenger mile increases to $1.80 per mile. At $1.80 CMP, the UAM mode is now less affordable for low and mid-income household levels. The UAM demand for most of the vertiports in the region decreases to less than 100 operations per day. The Santa Monica to Beverly Hills corridor attracts UAM trips and several vertiports with high demand. All the vertiports in the Lancaster area have fewer than 25 operations per day, as the UAM model is less affordable.

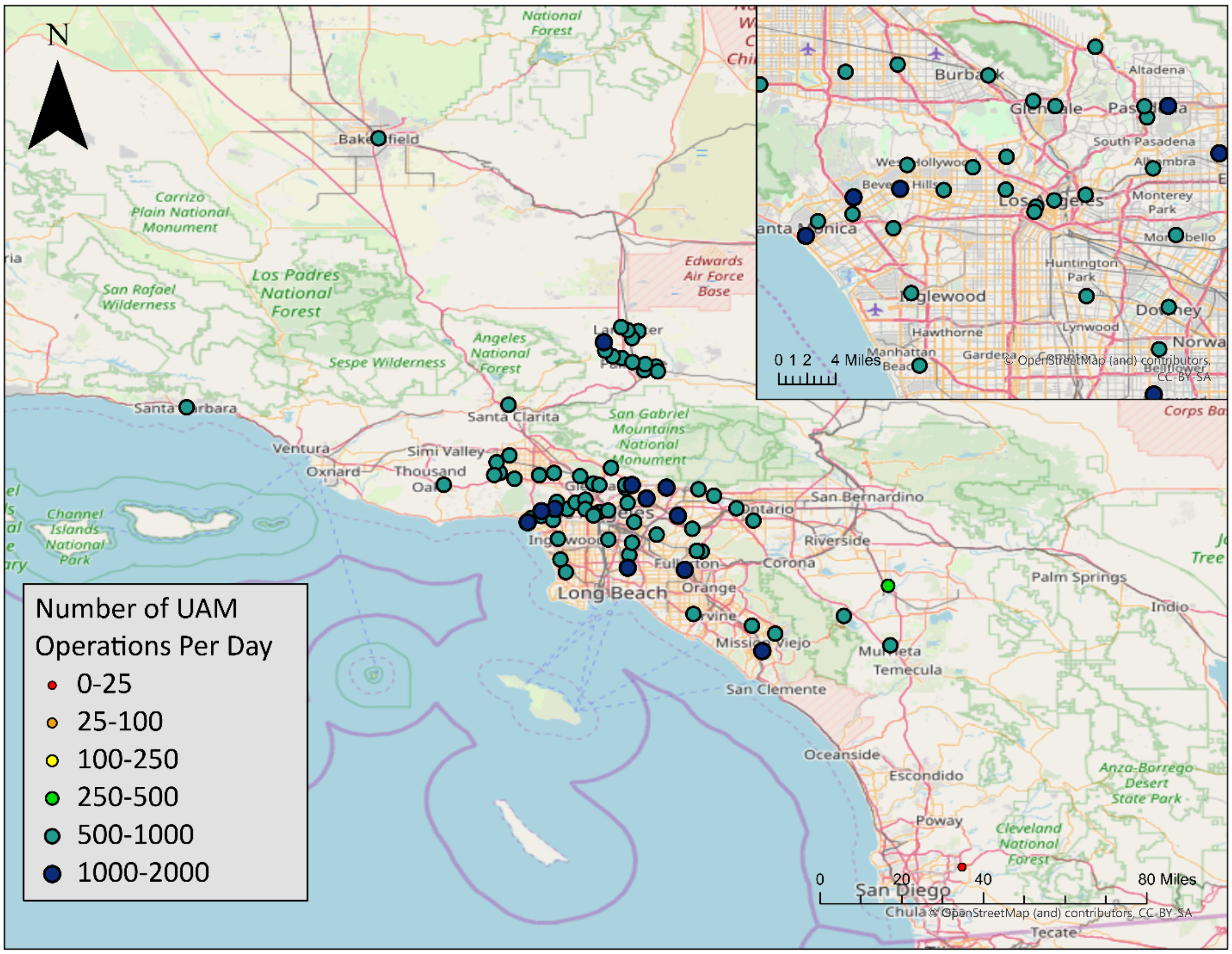

Figure 24: Southern California: 75 Vertiports Daily UAM Operations with CPM of $1.20

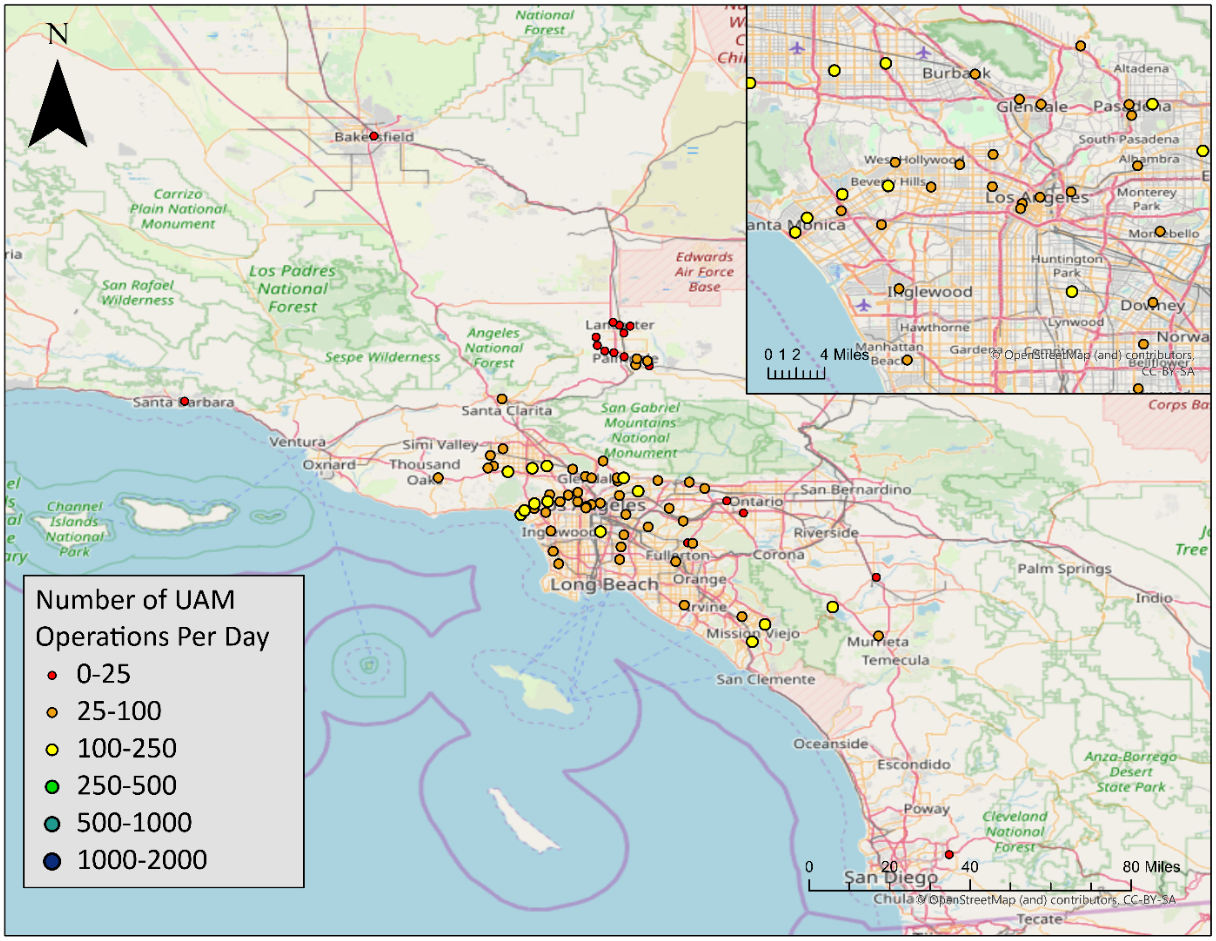

Figure 25: Southern California: 75 Vertiports Daily UAM Operations with CPM of $1.80

Dallas-Fort Worth

Dallas-Fort Worth is the smallest metropolitan area in terms of size and population. Apart from the Dallas-Fort Worth Metropolitan Statistical Area (MSA), the study area is sparsely populated and does not have many high-income households compared to other cities.

Figure 26 shows the spatial distribution of the UAM demand with 75 vertiports and UAM CPM of $1.20. Most of the high-income households in Dallas-Forth Worth reside in the northern suburbs of the city. The population density of the north suburbs is high, and the same area attracts many vertiports. Dallas-Fort Worth also has unique commuting patterns. The vertiports on the city suburbs act as feeders to the vertiports inside the Dallas CBD. As we move outside the Dallas CBD, the UAM demand keeps decreases until reaching the outskirts. The busiest vertiports are in Dallas CBD, slight north of Dallas CBD, and near the Centerport region (or near DFW Airport).

Figure 27 shows the vertiports for UAM cost $1.80 CPM. Similar to Southern California, the UAM demand in Dallas-Fort Worth decreases significantly with increasing UAM CPM cost. At UAM cost of $1.80 CPM, there is only one vertiport with more than 100 operations per day. Most of the vertiports have a demand of fewer than 25 operations per day.

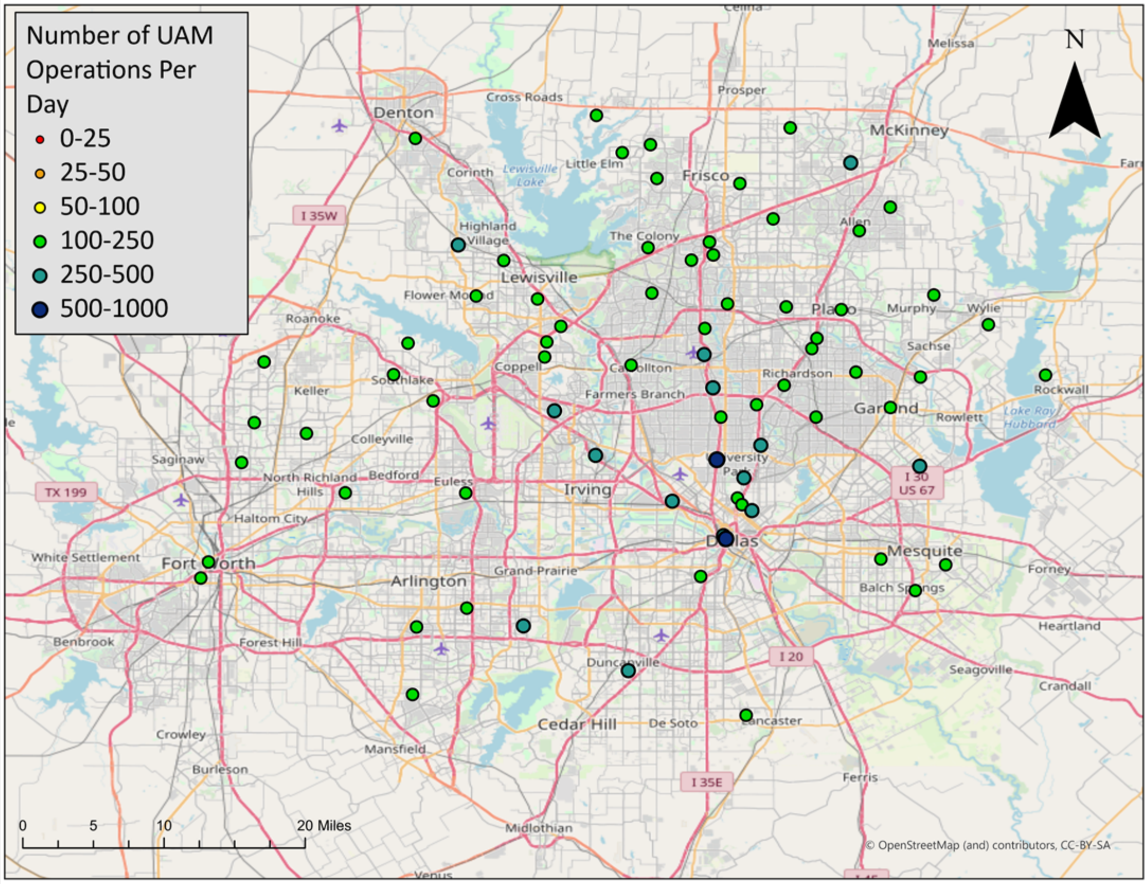

Figure 26: Dallas-Fort Worth: 75 Vertiports Daily UAM Operations with CPM of $1.20

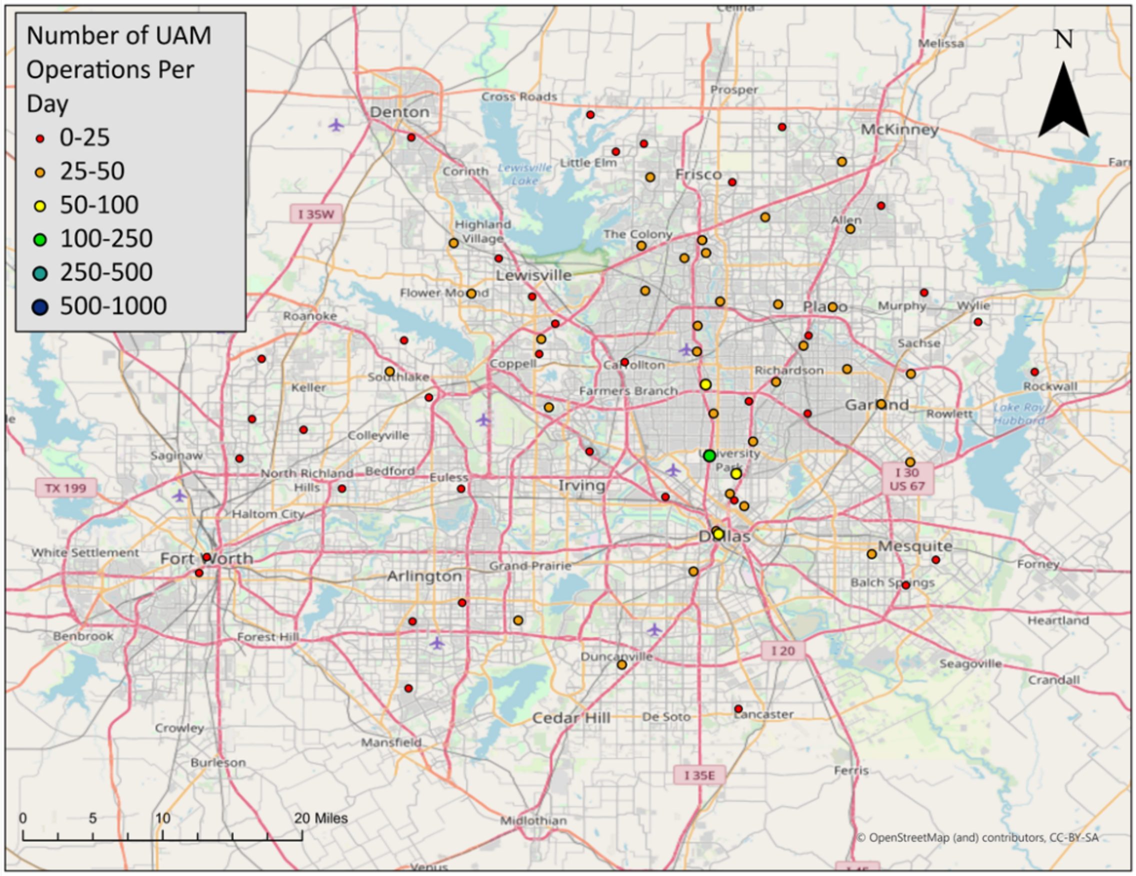

Figure 27: Dallas-Fort Worth: 75 Vertiports Daily UAM Operations with CPM of $1.80

New York

Figure 28 shows the impact of commercial airports in the New York region on the placement of vertiports and UAM demand. The approach and departure surfaces of precision runways at commercial airports, limit the vertiport placement in large portions of the New York area. Furthermore, avoidance of approach surfaces adds significant detours to UAM routes producing increased travel times and travel costs. For instance, surfaces at La Guardia Airport (LGA) and John F. Kennedy Airport (JFK) restrict the placement of vertiports in significant parts of Queens and also add travel time and cost to the commuting trips from Long Island to Manhattan.

High population density areas in New York, produce closely-spaced vertiports in areas like Manhattan. The next section introduces algorithms to split and consolidate vertiports that are closely-spaced. We also discuss methods to limit the vertiport demand at vertiports to contain their size to reasonable levels.

The UAM cost per passenger mile used in vertiport placement defines the vertiport location in a demand-driven approach. The UAM demand presented in this report use a UAM CPM cost of $1.20. This assumption favors the location of UAM vertiports near low and middle-income level areas (e.g., the Bronx). Figure 29 shows the UAM demand distribution with a UAM CPM of $1.80. Note a significant impact of UAM demand in vertiports located in the Bronx and Staten Island.

Figure 29 illustrates the importance of the UAM fare structure employed during the placement of vertiports.

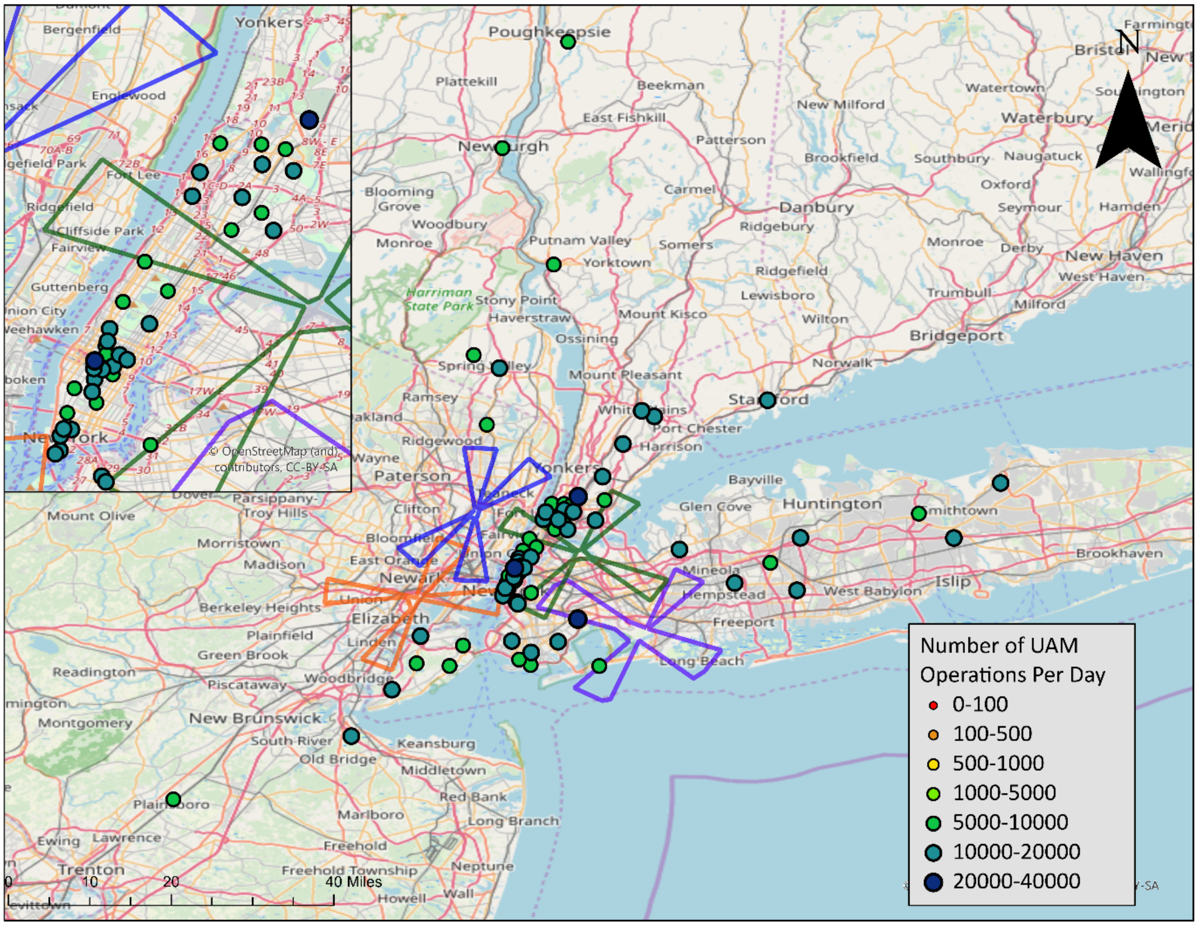

Figure 28: New York: 75 Vertiports Daily UAM Operations with CPM of $1.20

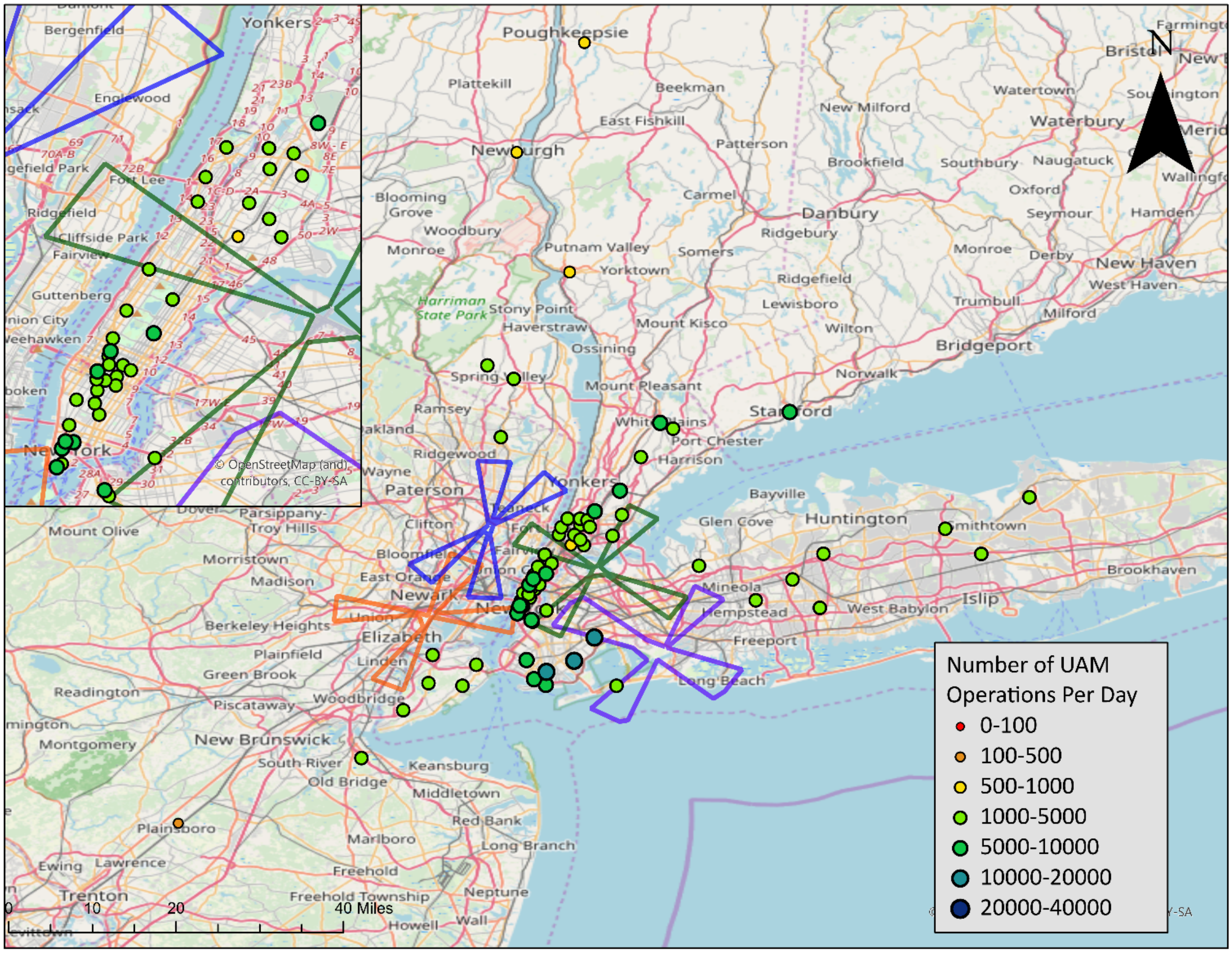

Figure 29: New York: 75 Vertiports Daily UAM Operations with CPM of $1.80

4. Vertiport Splitting and Consolidation Analysis

In the previous section, we presented the ideal placement of vertiports based on an iterative demand-driven approach. The demand-driven vertiport placement, coupled with the small size of block group regions, can sometimes produce closely-spaced vertiports. In this section, we present algorithms to split and consolidate vertiports after UAM demand estimation.

A companion, UAM landing site study, estimated the practical size of the largest vertiport to be six landing pads and 38 parking stalls. The size estimation included a capacity analysis and considered the typical commuting time distribution obtained in the NHTS survey data.

We split a vertiport if the demand during the peak hour requires more than the maximum number of landing pads (6 landing pads). Similarly, we consolidate vertiports within 0.5 statute miles of each other as long as the total demand does not exceed the maximum landing pad threshold. Splitting and consolidation run as a single algorithm that runs iteratively until reaching a desired number of the vertiports. The iterative algorithm involves replacing the vertiports (marked for splitting) by two or more vertiports placed using k-medoids (connected census blocks) algorithm, consolidating vertiports according to their respective UAM demand, and recalculating the UAM demand for the complete scenario.

Sometimes it is difficult to reach a vertiport set where all vertiports have less than the maximum number of landing pads. For such instances, we limit the UAM demand for the vertiports exceeding the maximum number of landing pads. Tables 9-12 show examples of UAM vertiport demand after split/consolidation and application of demand limits for Northern California, Southern California, Dallas-Fort Worth, and New York.

Table 9: Northern California Scenarios Post Split-Consolidation and Post Capping

Northern California				
Demand Set [Landing Sites, UAM CPM]	**Pre-Split/Consolidation**	**Post-Split/Consolidation**		**Post-Capping (if required)**
	No. of Flights	No. of Sites	No. of Flights	No. of Flights
[50, $1.80]	4,976	47	4,458	4,458
[100, $1.40]	22,400	91	20,514	18,808
[200, $1.10]	85,472	210	82,556	70,590

Table 10: Southern California Scenarios Post Split-Consolidation and Post Capping

Southern California				
Demand Set [Landing Sites, UAM CPM]	**Pre-Split/Consolidation**	**Post-Split/Consolidation**		**Post-Capping (if required)**
	No. of Flights	No. of Sites	No. of Flights	No. of Flights
[50, $1.55]	4,566	50	4,566	4,566
[100, $1.35]	18,356	97	18,360	18,360
[200, $1.20]	58,956	204	58,758	58,758

Table 11: Dallas-Fort Worth Scenarios Post Split-Consolidation and Post Capping

Dallas-Fort Worth				
Demand Set [Landing Sites, UAM CPM]	**Pre-Split/Consolidation**	**Post-Split/Consolidation**		**Post-Capping (if required)**
	No. of Flights	No. of Sites	No. of Flights	No. of Flights
[50, $1.20]	5,492	49	5,538	5,298
[100, $0.95]	26,488	102	26,198	25,747
[200, $0.80]	77,890	209	75,943	72,816

Table 12: New York Scenarios Post Split-Consolidation and Post Capping

New York				
Demand Set [Landing Sites, UAM CPM]	**Pre-Split/Consolidation**	**Post-Split/Consolidation**		**Post-Capping (if required)**
	No. of Flights	No. of Sites	No. of Flights	No. of Flights
[50, $3.20]	6,326	36	4,458	4,458
[100, $2.70]	31,250	120	35,236	33,884
[200, $2.20]	103,892	273	111,492	99,628

5. Conclusions

Calibrating a mode-choice model to estimate the demand for a new concept mode is the usual method adopted in transportation studies. However, it has been a challenge to calibrate a model that could calculate the demand for the UAM mode. When the focus is on any concept mode, either the existing survey data should include a similar transportation mode, or a robust stated preference survey should be adopted. A stated preference survey has its shortcomings; it is difficult for the survey taker to simulate the circumstances and arrive at the same mode-choice, which they would use in the future. Moreover, this study focused on the characteristics of the individuals, which could influence their mode-choice behavior. We believe that to predict UAM demand; mode choice decisions such as travel cost, travel time, transfers, safety, comfort, etc. will continue to be relevant irrespective of the mode (concept or in-use).

Developing a region-specific mode-choice model was a priority in this study. The Northern California model is robust, but calibrated models for Southern California and Dallas-Fort Worth have weaknesses which would result in erroneous UAM demand. The Southern California and Dallas-Forth Worth regions did not offer enough transit trips for robust calibration. The analysis shows that Southern California and Dallas-Fort Worth are not well-connected by public transportation and have low transit ridership nearing 5%. In such conditions, it is difficult for a travel survey to include significant numbers of transit trips needed in the calibration of a mode-choice model. Calibrating a mode-choice model requires data for all the modes (this study has driving and transit as the modes). For this reason, we adopted the Northern California model in the estimation of UAM demand for Southern California and Dallas-Forth Worth.

The selection of the income brackets is a critical step in the application of a mode choice model. It is required to have enough data in all income brackets to calibrate a robust model. In this study, the NHTS-2017 dataset could not support more than three income brackets. Moreover, the high variance of income distribution in Northern California resulted in a sizeable middle-income bracket ($45k-$152k). Having enough survey data for each desired income bracket could be an ideal situation for model calibration.

For urban commuter trips, parking costs and tools are essential to estimate the cost of driving trips (also park and ride transit trips), especially the ones in-and-out of CBD zones. Unfortunately, there is no publicly available dataset on the parking cost to estimate with precision such charges. In this study, we collected parking costs in zones with high economic activity to estimate parking costs based on spatial location.

The variables used in the model calibration are often constrained by the application process. The model application process to calculate the UAM demand is a computationally expensive process which deals with millions of trips in the region. Including more modes and the independent variable is an ideal step in improving the mode-choice model. However, the model should still be feasible in the application. For example, driving could be divided into drive alone and car-pooling but there is no method of simulating the car-pooling option for millions of commuters in each region. There are variables available in survey data that benefit the mode-choice model but make it difficult to apply the model. Information is not available for the application data and hence cannot be used. So, the selection of variables in model-calibration is influenced by the application process, only if the model application is part of the study.

The UAM demand results could benefit from a better understanding of the inter-modal connection for the UAM mode. Inter-modal connections mean 'Home to Vertiport' and 'Vertiport to Workplace '. There is no doubt that the UAM is the faster mode for trips over 10 miles. However, the inter-modal connections could be critical in the feasibility of this transportation mode. A better understanding of how UAM users will access the vertiports could help in a more credible estimation of UAM trip's parameters.

This study was limited to the commuter market. Commuter flows are usually one-directional, and hence UAM vehicles will have to serve a considerable number of deadhead trips. A challenge for UAM operations is to reduce deadheading to reduce overall UAM operating costs. A network simulator could enhance the realism of the projections presented in this report.

The following paragraphs provide are region-specific conclusions of this study.

Northern California

1) Northern California has the highest number of high-income zones and the highest percentage of high-income zones in the study area
2) Even at the low UAM CPM ($1.20), the majority of the UAM demand is contributed by high-income households (55%). The contribution of UAM demand from high-income households increases to 90% when the UAM CPM cost is $3.00
3) The UAM demand is most resilient to increasing UAM costs due to a higher concentration of high-income households. High-income households are more likely to afford the mode.
4) In Northern California, the commuter flows are highly (highest among all study areas) one-directional, where commuters from around the bay travel to San Francisco CBD for work.
5) San Francisco CBD has high economic activity concentration and significantly high travel times for people traveling to and from around the bay.
6) For 75 vertiports, the UAM demand in Northern California decreases from 65,020 to 14,020 to 3,605 flights per day when increasing the CPM from $1.00 to $1.50 to $2.00.

7) For 200 vertiports, the UAM demand in Northern California decreases from 121,900 to 5,964 flights per day when increasing the UAM cost per mile from $1.00 to $2.00.
8) The UAM demand in Northern California is less sensitive to the increases in the number of UAM vertiports. For a given UAM CPM, when increasing the number of vertiports from 50 to 400 (eight times), the UAM demand only increases by a factor of two. The pattern is unique to Northern California because high-income zones have a high population density. Therefore, increasing the number of vertiports does not increase the overall mode accessibility drastically.
9) San Francisco CBD presents a unique case and a challenge for operating such a service where demand is highly concentrated in a small area. For scenarios with UAM CPM less than $1.20, a vertiport in the Financial District is expected to handle 7,500 operations per day. Moreover, there are more vertiports in the CBD region with an expected demand of around 3,000 operations per day (for the same scenario). This could be a challenging problem for airspace management.
10) The high demand vertiports in Northern California are found in San Francisco CBD, Mountain View region, and San Jose CBD.

Southern California

11) Southern California region has a higher population than Northern California with the majority of the households residing in low- and mid-income households.
12) Only 15% of the UAM demand is generated from high-income households at a CPM value of $1.20.
13) The UAM demand in Southern California is not resilient to increasing UAM cost as it becomes less affordable for low- and mid-income households.
14) Unlike Northern California, Southern California has multiple zones with high economic activity and the trip attraction zones are distributed in multiple areas in and around Los Angeles county. This prevents from few vertiports having an exceptionally high concentration of UAM demand.
15) For 75 vertiports, the UAM demand in Southern California decreases from 67,310 to 7,710 to 1,232 flights per day when increasing the CPM from $1.00 to $1.50 to $2.00.
16) For 200 vertiports, the UAM demand in Southern California decreases from 139,100 to 16,930 to 2,916 flights per day when increasing the CPM from $1.00 to $1.50 to $2.00.
17) The UAM demand in Southern California is relatively more sensitive to the number of vertiports. In Southern California, high-income households are very few and usually reside in low population density zones, vice-versa for low- and mid-income households. Overall, population density is high in Southern California. Therefore, increasing the number of vertiports has a drastic impact on mode accessibility. For a given UAM CPM, when increasing the number of vertiports from 50 to 400 (eight times), the UAM demand increases four-folds.
18) In Southern California, the UAM CPM used during the placement of vertiports has a bigger impact than any other region. This is because of the high-income households being in the low population density region and low- and mid-income households being in high population density region generally. A higher UAM CPM places more vertiports near high-

income zones, whereas a lower UAM CPM places more vertiports in high-density zones as the mode is affordable to all categories. Therefore, the location of vertiports changes significantly according to the UAM CPM used in the placement of vertiports.

19) The high demand vertiports in Southern California are usually found near the Santa Monica-Beverly Hills corridor and south-east of Los Angeles city which is half-way between San Diego and Los Angeles.

Dallas-Fort Worth

20) Dallas-Fort Worth offers similar UAM demand patterns to Southern California with a smaller population and fewer high-income households. In the Dallas-Forth Worth region, the UAM demand is more resilient (relative to Southern California only) to increasing UAM CPM.
21) Only 21% of UAM demand is generated by high-income households at a $1.20 CPM cost.
22) High economic activity zones are found in Dallas CBD and slightly north of the Dallas CBD. Most of the high-income zones are located in suburbs in the north of Dallas city. Therefore, vertiports are mostly found in that part of the region.
23) The suburbs are spread across in a circular manner centered around Dallas City. This results in smaller feeder vertiports spread around the suburbs to feed into the Dallas CBD or economic zones in the northern part. There are a few vertiports with a significant concentration of UAM demand. The economic viability of feeder vertiports with very few operations could be a concern.
24) For 75 vertiports, the UAM demand in Dallas-Fort Worth decreases from 17,350 to 590 flights per day when increasing the CPM from $1.00 to $2.00.
25) For 200 vertiports, the UAM demand in Dallas-Fort Worth decreases from 32,930 to 1,028 flights per day when increasing the CPM from $1.00 to $2.00.
26) Due to smaller populations and fewer high-income households, there are fewer conditions under which the commuter market could be promising for the UAM concept.

New York

27) New York's characteristics are significantly different from other regions. The commuting patterns, variation in size of block groups, water body location, location of commercial airports, etc. Moreover, it has almost 10 million commuters with a higher proportion of high-income households than any other region. All these factors and heavy disutility in driving makes New York a big market for the UAM.
28) There are four income categories in New York. 58% of the demand comes from high-income and upper-mid income households in New York at $1.20 UAM CPM. There are significant numbers of long-distance commuters in the region who could gain from UAM.
29) The UAM demand in New York is relatively less sensitive and that could be attributed to costly driving, traffic congestion, and a larger high-income population.
30) For 75 vertiports, the UAM demand in New York decreases from 258,200 to 38,940 flights per day when increasing the CPM from $1.50 to $2.50.

31) For 200 vertiports, the UAM demand in New York decreases from 393,100 to 61,870 flights per day when increasing the CPM from $1.00 to $2.00.
32) Major trip attractors in the region are Manhattan, Brooklyn downtown, and JFK. Trips are produced from all over the region. However, since the UAM fare structure used in the analysis does not have a fixed cost parameter, it generated heavy UAM demand for short trips which are usually congested by driving. For example, Bronx to lower Manhattan, Brooklyn to Manhattan, etc., such trips would be eliminated if a UAM fixed cost is introduced.
33) This analysis includes five minutes of ingress and egress time each. However, it would be difficult to operate UAM from skyscrapers in Manhattan with such little ingress and egress times. As the ingress/egress or processing time increases, the UAM demand would start decreasing.
34) Even though the results include optimistically low-price points for UAM, it would be difficult to operate UAM in New York with lower costs given the high real estate costs in the region. Therefore, more realistic demand numbers could be found near the higher end of the UAM CPM scale.

6. Recommendations

This study is focused on only the commuter market. However, we believe the UAM could be beneficial for other types of trips too which are time-sensitive. Therefore, future research should also consider shopping, business, personal business, recreational, and trips to airports.

Since UAM is still a concept, there is little understanding of how users will access this mode. In this study, only walking and taxi services are considered as the access mode for UAM travelers. It is recommended that a detailed analysis of intermodal connections for UAM could provide better understanding of the dynamics of intermodal connection.

The study involved applying the model after calibration. Therefore, we were limited by the application process because not every mode choice can be simulated for millions of commuters. Similarly, there were significant variables in survey data that could not be used due to their absence in application data. For example, the umber of vehicles in the household, the number of workers in households, gender, etc.

The income brackets used in the study limit the analysis to 3-4 income groups. A mode-choice dataset with enough samples in various income groups could help in calibration of the model with more income groups, which in-turn could refine the UAM demand results.

The study shows that commuting flows are one-directional, and that would increase the dead-heading of flights. Network analysis could provide a better insight into the dead-heading flights, which would improve the travel cost estimation for the UAM mode.
The reliability of the modes of transportation modes should be considered in future research. In this study, we assumed that every mode of transportation is available when required. For example, public transit trips are assumed to be on schedule, and the UAM vehicle is always ready when

needed. Many factors affect the reliability of a mode of transportation such as weather and limited availability of UAM aircraft.

In this study, we use congestion indices of the Metropolitan Statistical Areas (MSA) from the Texas Transportation Institute. It was the only viable option when calculating the travel time for millions of trips. The drawback is that the TTI indices are single numbers that ignore the dynamic congestion of urban areas. Moreover, departure times are available in LODES data which could hamper in applying dynamic congestion to the trips. Both of which could help in a more realistic estimation of driving times.

In this study, we used the Open Trip Planner API for simulating transit trips/options in both calibration and application. Although the API's coverage is extensive, it could not replicate all the trips or connections. In Dallas-Fort Worth specifically, many transit trips were lost since they could not be simulated in the API.

Due to a lack of information on the ingress and egress process at the vertiports, currently, five minutes is used as a placeholder in this study. As the vertiports concepts start into shape, a better understanding of ingress and egress times at vertiports would emerge. It is believed that vertiport location or vertiport type (on a rooftop or vacant land) could influence the ingress and egress time. This could help in a better total travel time estimation for the UAM.

Due to the scope of this study and the unavailability of departure times in LODES data, this study could not use time-varying cost for any mode of transportation. Time-varying or dynamic cost functions would help in arriving at more realistic results.

In this study approach surfaces of the airports with precision, runways are safeguarded completely. If there is a better understanding of the interaction of commercial air traffic and UAM traffic in the future, this approach could be refined, and we could arrive at better UAM travel time and travel distance estimation.

7. References

[1] Louviere, J. J., A. D. Hensher, and D. J. Swait. Stated Choice Methods. Cambridge University Press, New York, NY, 2000.

[2] https://ocw.mit.edu/courses/civil-and-environmental-engineering/1-201j-transportation-systems-analysis-demand-and-economics-fall-2008/lecture-notes/MIT1_201JF08_lec05.pdf

8. Appendix A

Using the mode choice dataset, region-specific demand models were estimated using the conditional logit model methodology. An example of how logit models are estimated is shown in Figure 30. The coefficients in the model are estimated by maximizing the sum of the log-likelihood. As a mode's utility (i.e. benefit) increases, so do the probability of that mode being chosen.

Person O/D	Mode Alt.	Chosen (d)	In-Vehicle Time (Min)	Out-Vehicle Time (Min)	Num Transfers	Cost ($)	Income Level	Utility	Probability (P)	Log Likelihood (LL)
Pittsburg to Oakley	Drive	1	19.2	3	0	6.90	Mid	-3.303	97.4%	-0.02599
	Transit	0	49.15	27.83	1	5.44	Mid	-6.940	2.56%	0
San Francisco to Oakland	Drive	0	34.8	3	0	15.91	High	-5.044	55.7%	0
	Transit	1	22	29.95	0	4.12	High	-5.273	44.3%	-0.8144
Oakland to San Ramon	Drive	0	45.6	3	0	20.21	High	-6.398	87.7%	0
	Transit	1	55.67	38.28	1	8.03	High	-8.366	12.3%	-2.0991
									Sum of Log Likelihood		-2.9395

$$\text{Utility} = \beta_{IVTT}X_{IVTT} + \beta_{OVTT}X_{OVTT} + \beta_{NUMTRANSFERS}X_{NUMTRANSFERS} + \beta_{COST\_LOW\_INC}X_{COST\_LOW\_INC} + \beta_{COST\_MID\_INC}X_{COST\_MID\_INC} + \beta_{COST\_HIGH\_INC}X_{COST\_HIGH\_INC} + \beta_{DRIVE}X_{DRIVE} + \beta_{TRANSIT}X_{TRANSIT}$$

$$LL = d \times \ln(P)$$

$$P = \frac{e^{utility}}{\sum e^{utility}}$$

Figure 30: Example of Logit Model Coefficient Estimation.

Utility and the probability of a mode being chosen are not linear. For example, using the Pittsburg to Oakley sample above, a -3.303 utility for driving meant the individual had a 97.4% chance of choosing that mode. As shown in Figure 31, if $4 had been added to the trip's cost ($6.90+$4.00), that percentage would reduce to near 91%. Once a mode becomes too costly, it is not competitive with other modes. Therefore, adding $24 or $28 has very little change in the individual's probability of choosing the driving mode as both are nearly 0% chance of choosing driving. This non-linear shape aligns with the typical way people make choices between competing modes. Only in a certain utility range are modes very competitive with each other.

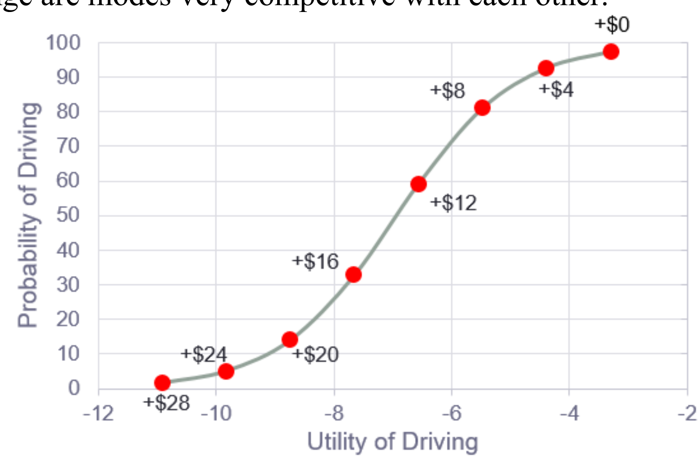

Figure 31: Example showing Utility and Probability of Mode being Chosen

The mode choice models incorporated the spatial income distribution, as shown in the following

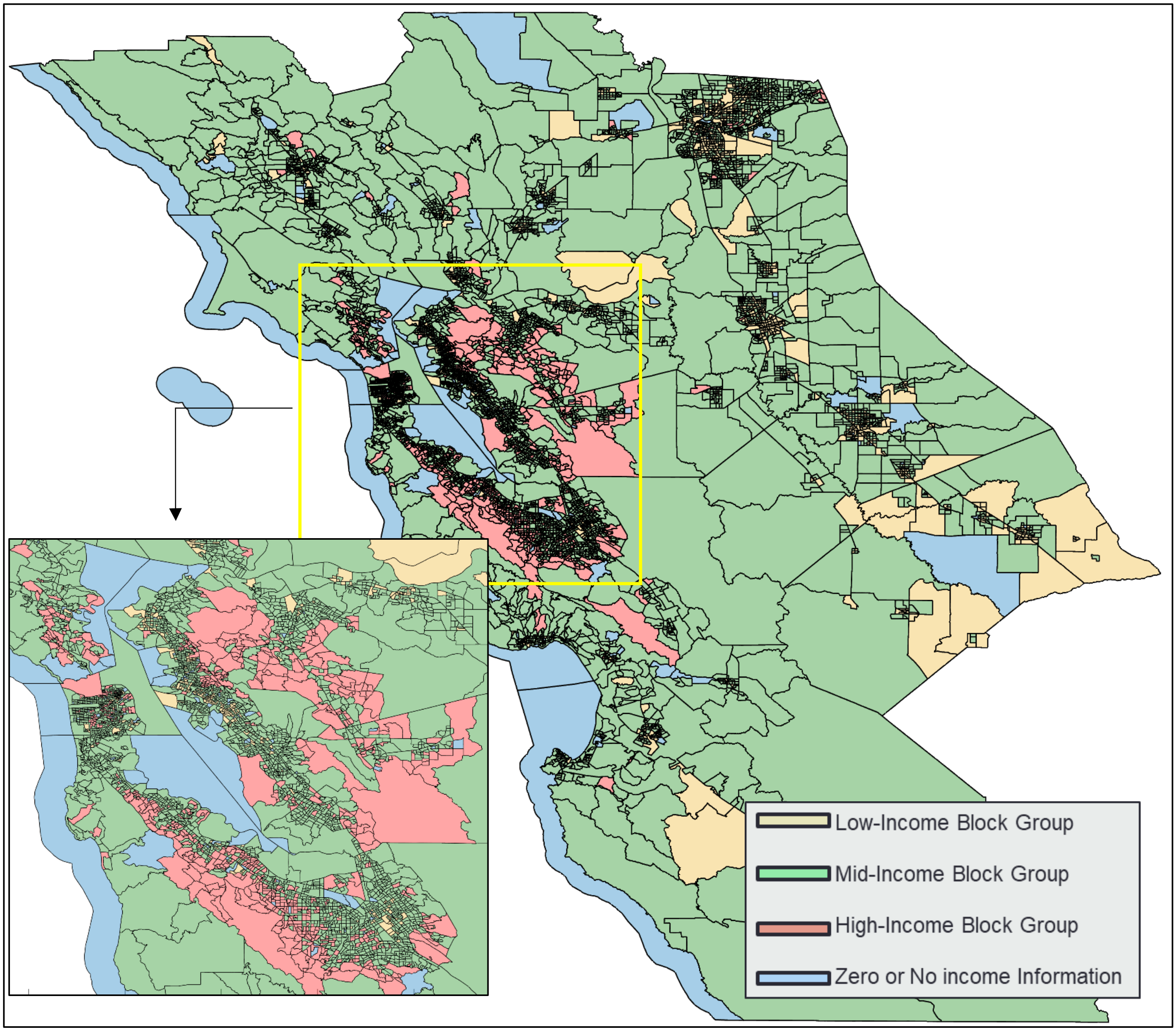

Figure 32: Northern California Income Distribution

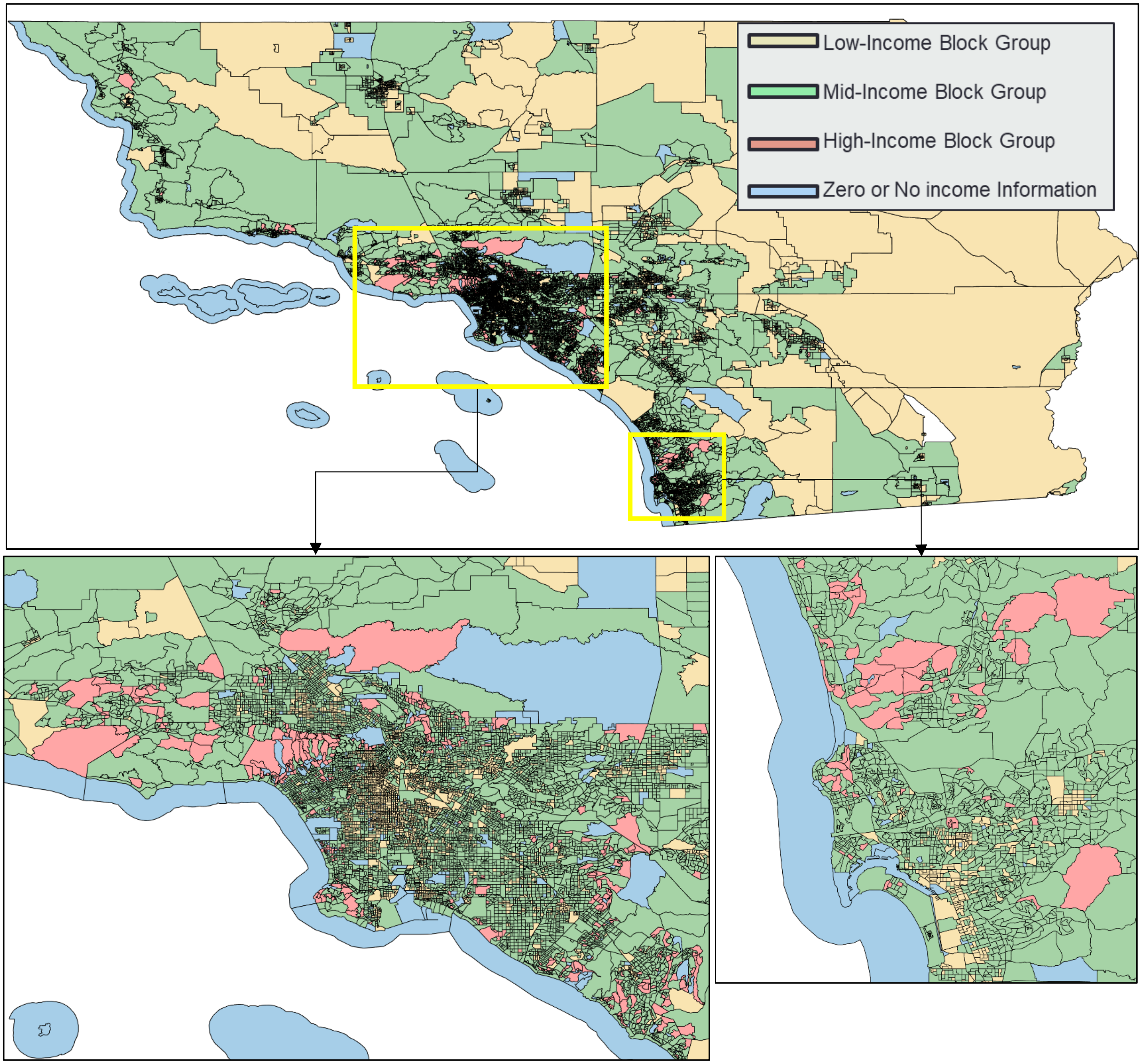

Figure 33: Southern California Income Distribution

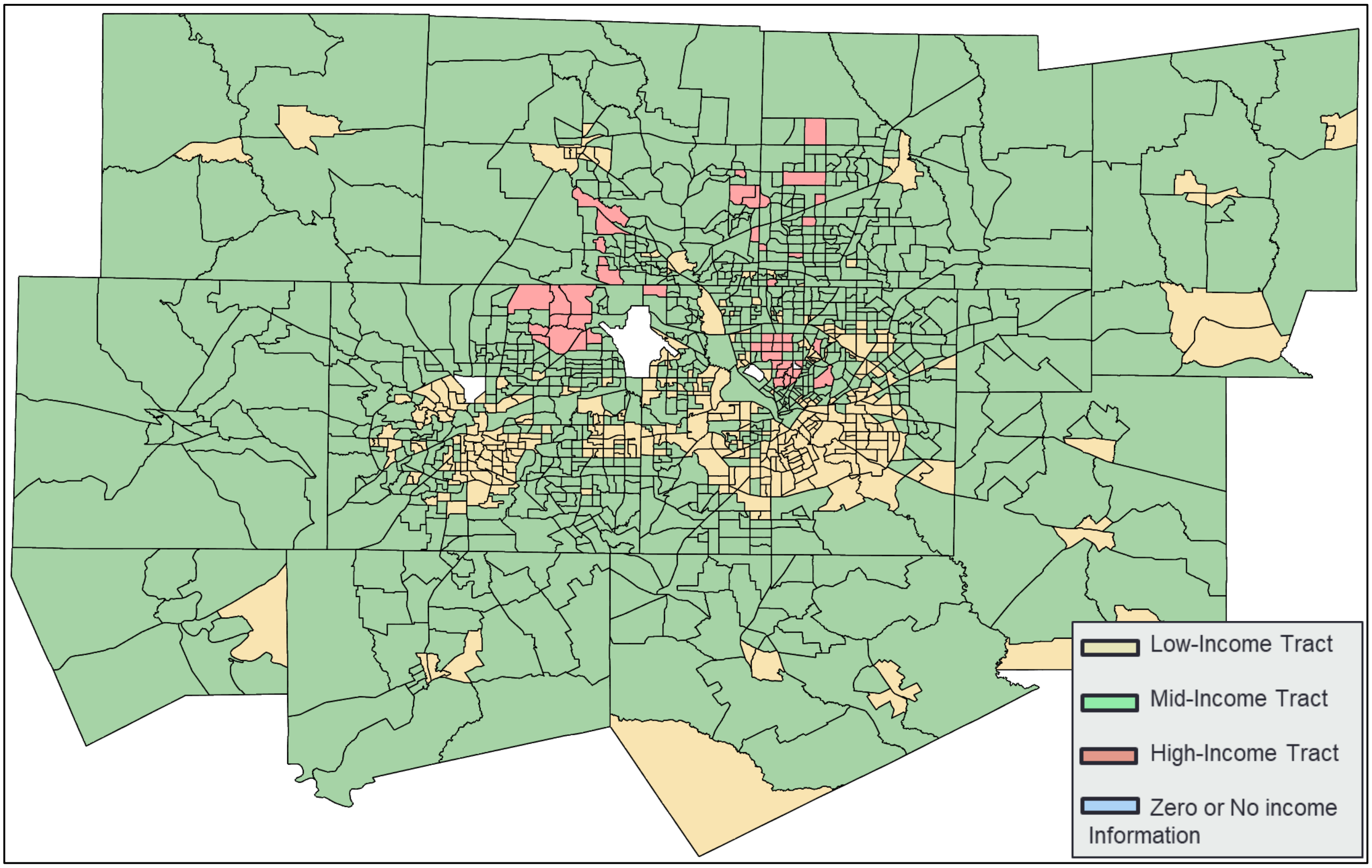

Figure 34: Dallas-Fort Worth Income Distribution

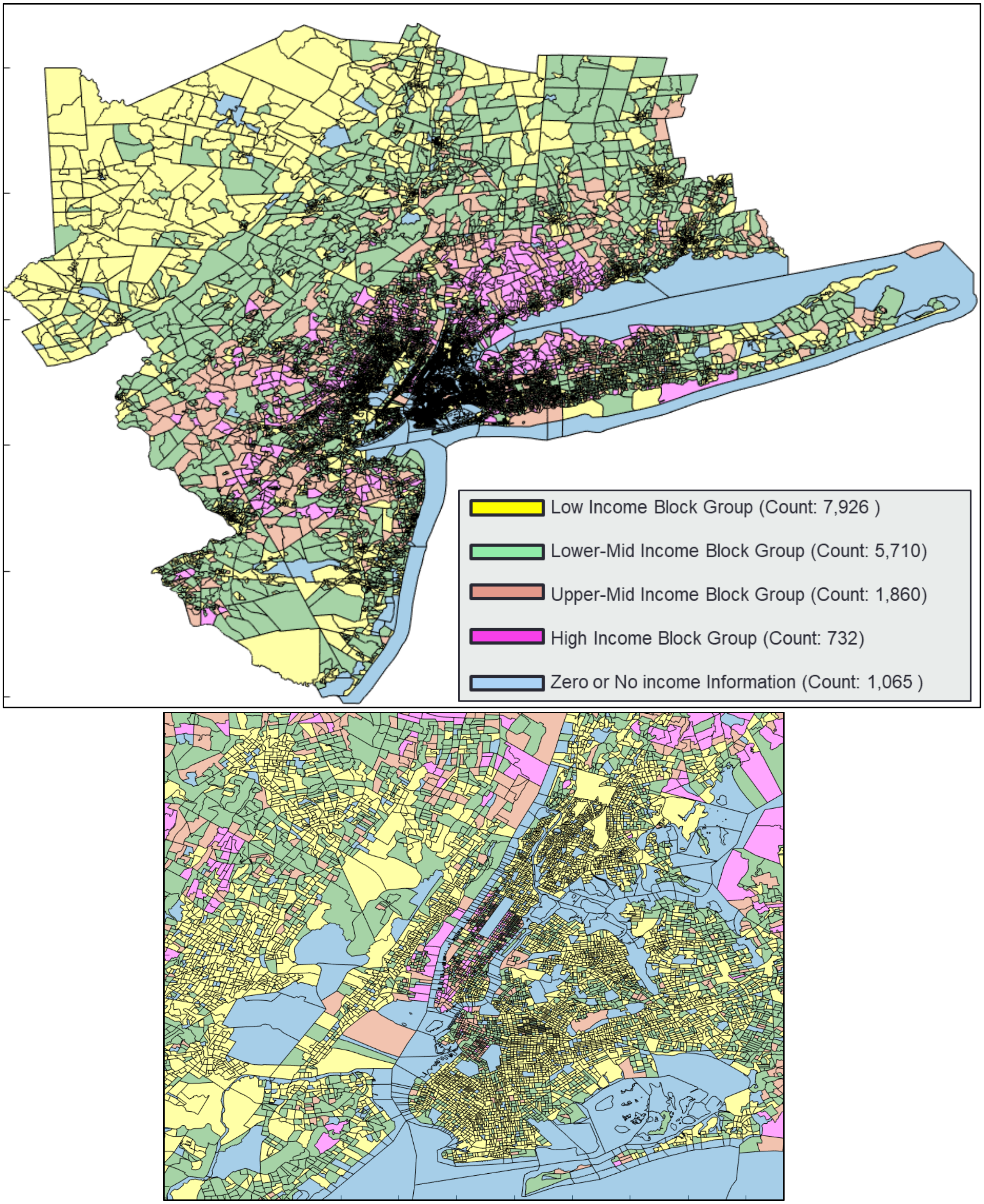

Figure 35: New York Region Income Distribution

9. Appendix B

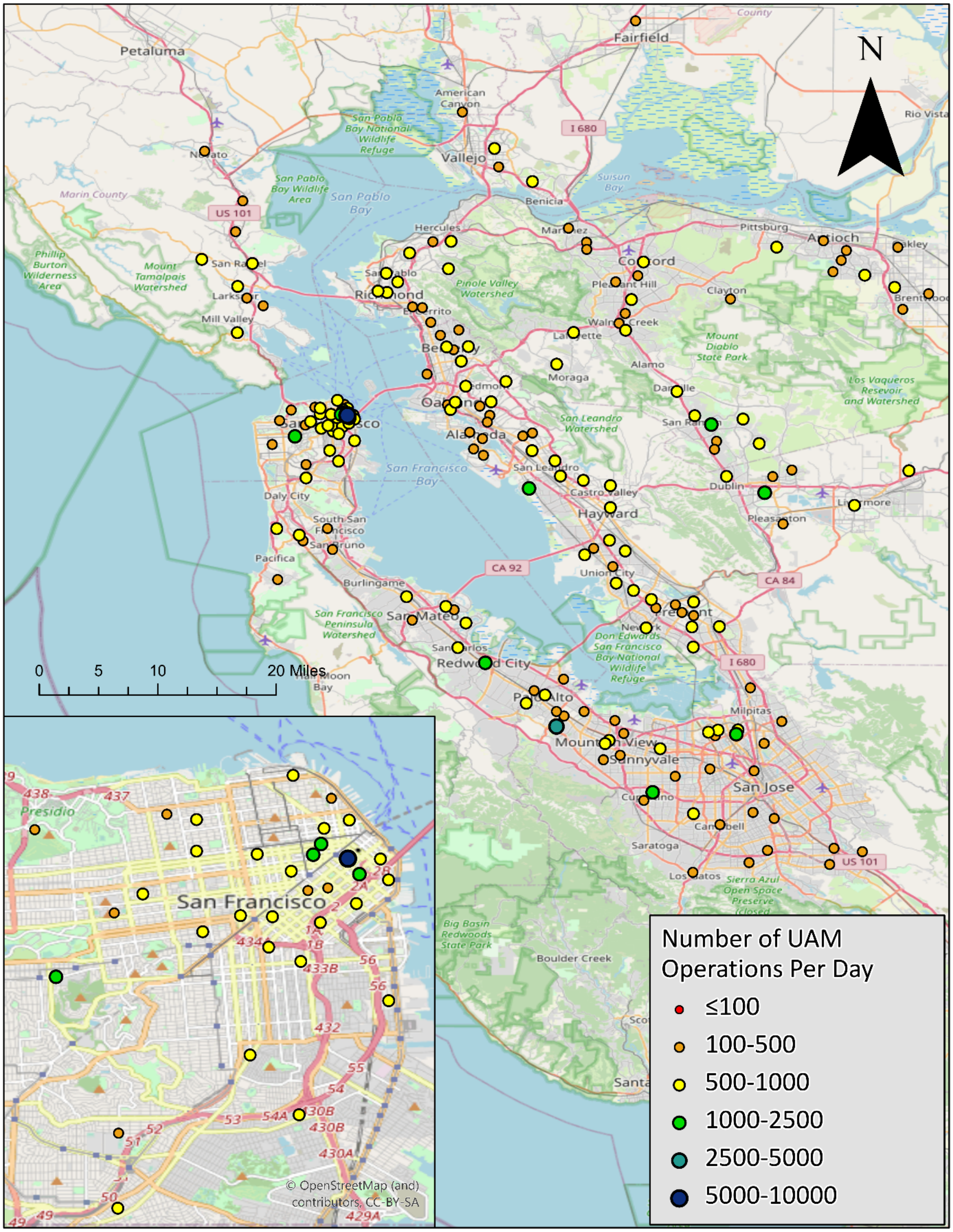

Figure 36: Northern California: 200 Vertiports Daily UAM Operations with CPM of $1.20

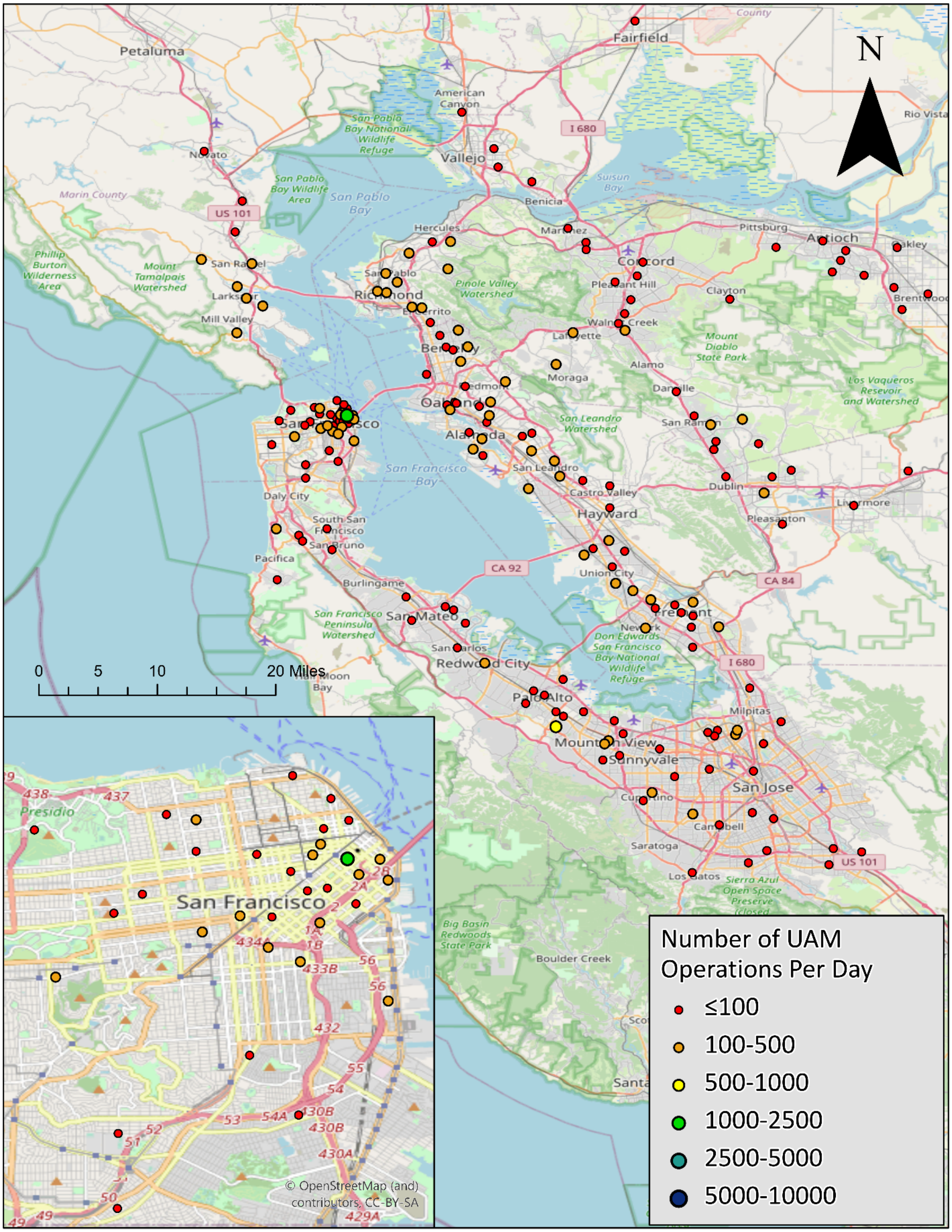

Figure 37: Northern California: 200 Vertiports Daily UAM Operations with CPM of $1.80

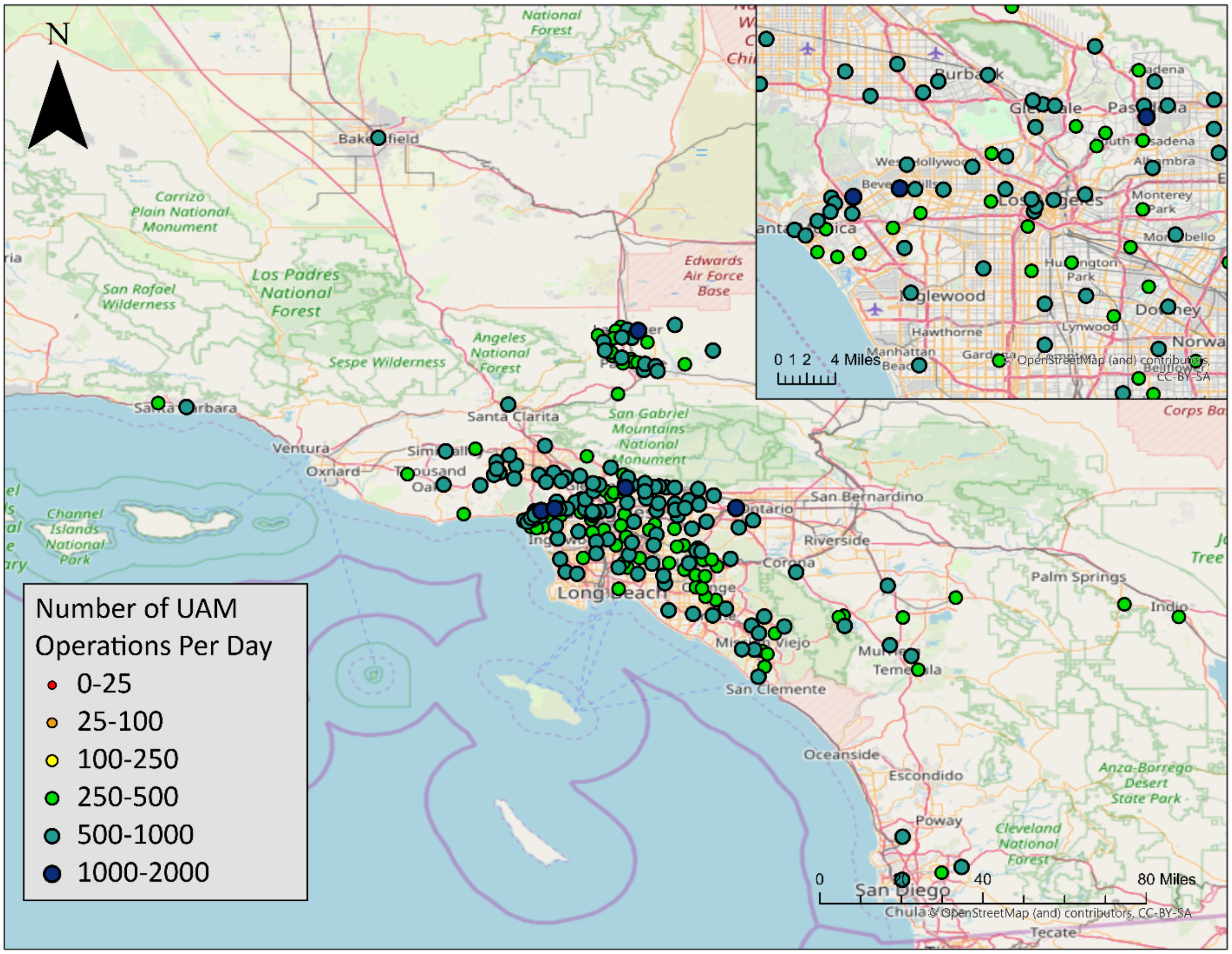

Figure 38: Southern California: 200 Vertiports Daily UAM Operations with CPM of $1.20

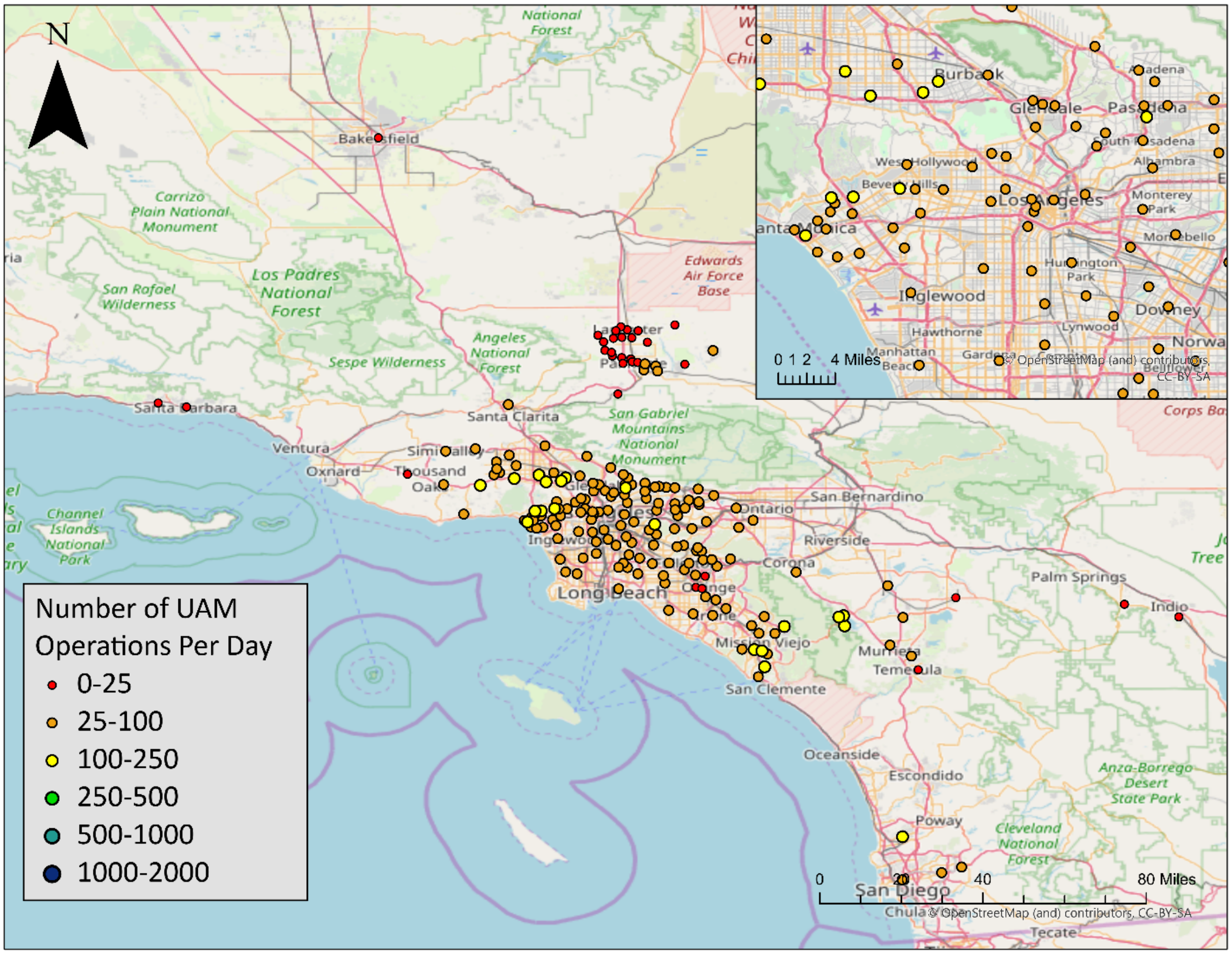

Figure 39: Southern California: 200 Vertiports Daily UAM Operations with CPM of $1.80

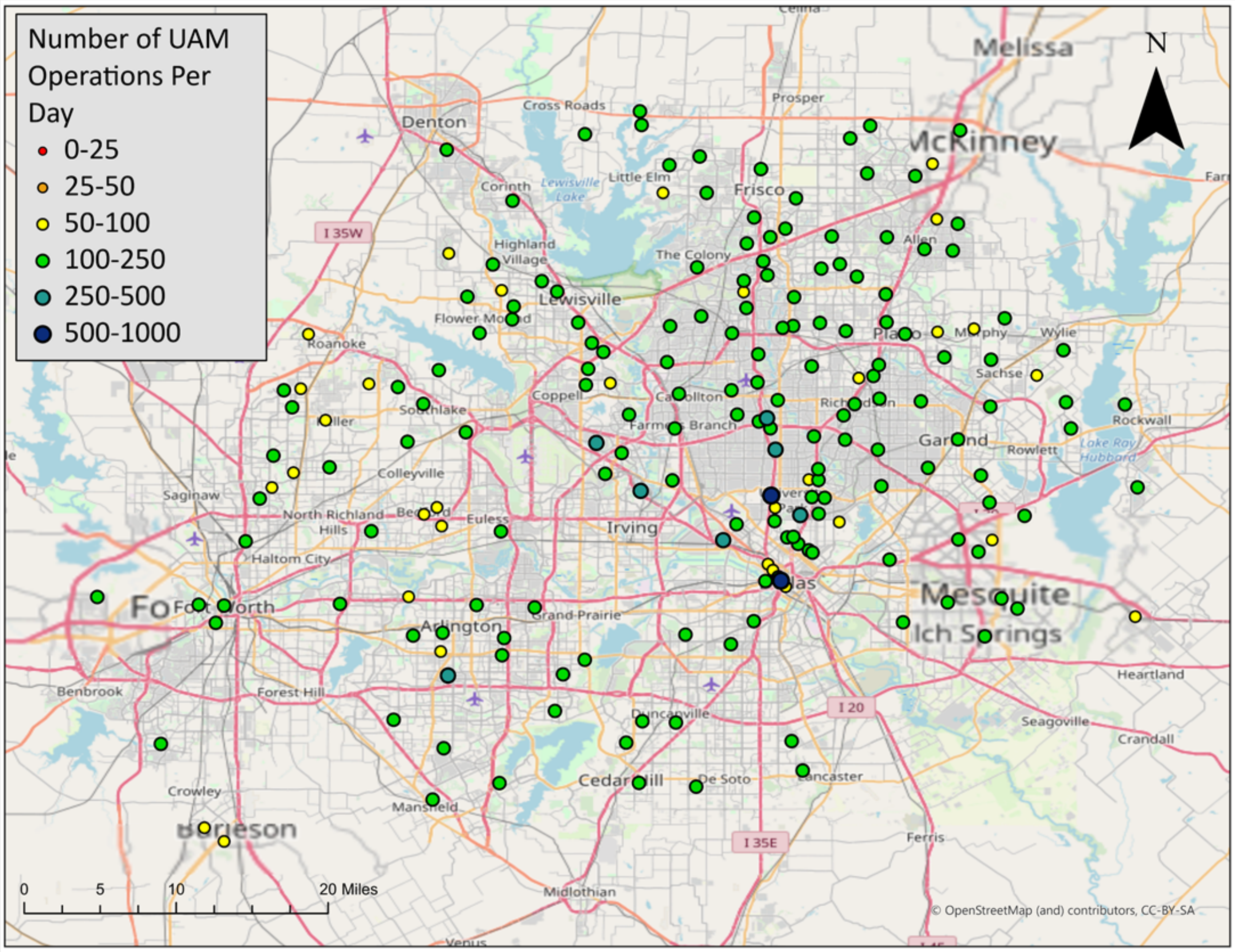

Figure 40: Dallas-Fort Worth: 200 Vertiports Daily UAM Operations with CPM of $1.20

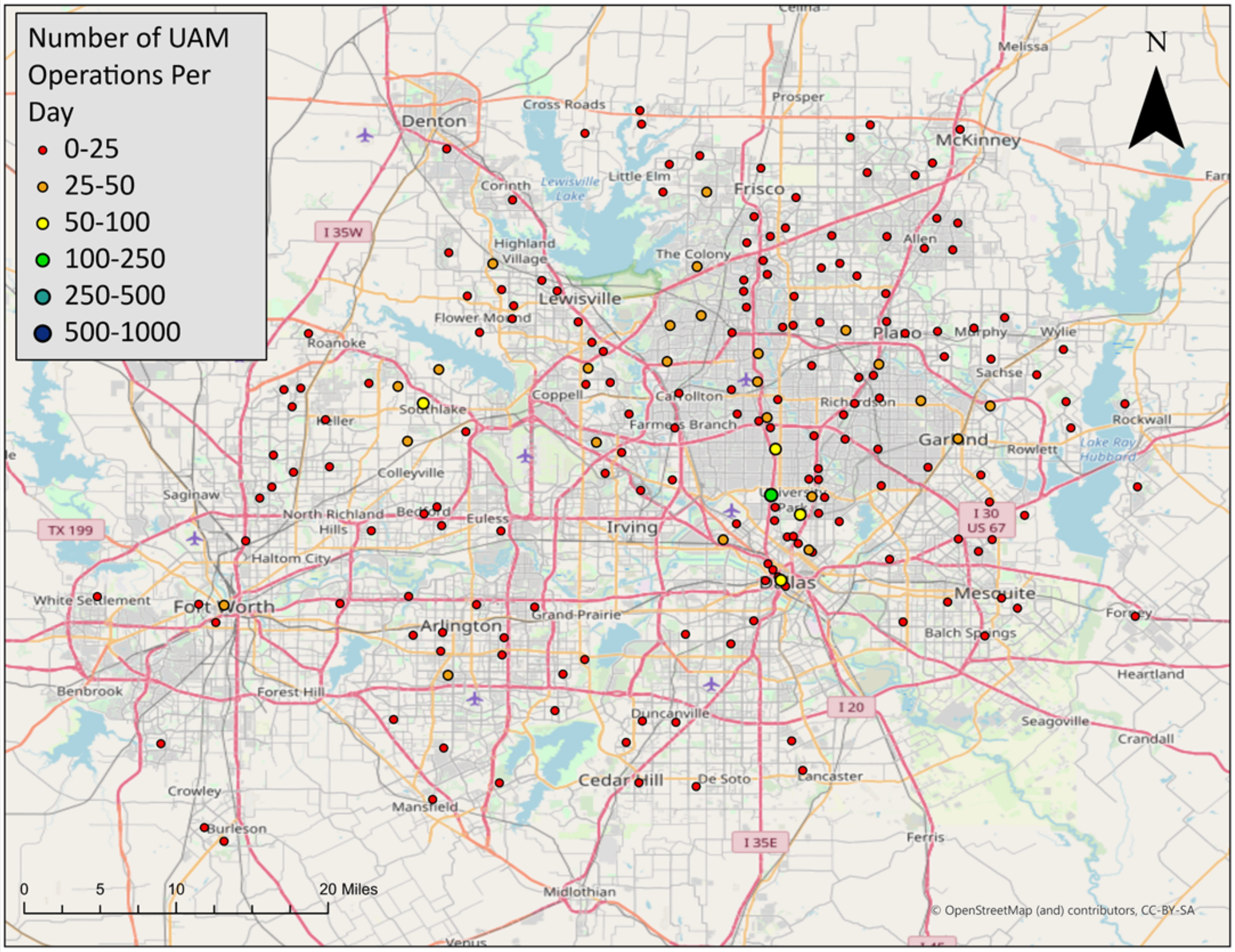

Figure 41: Dallas-Fort Worth: 200 Vertiports Daily UAM Operations with CPM of $1.80

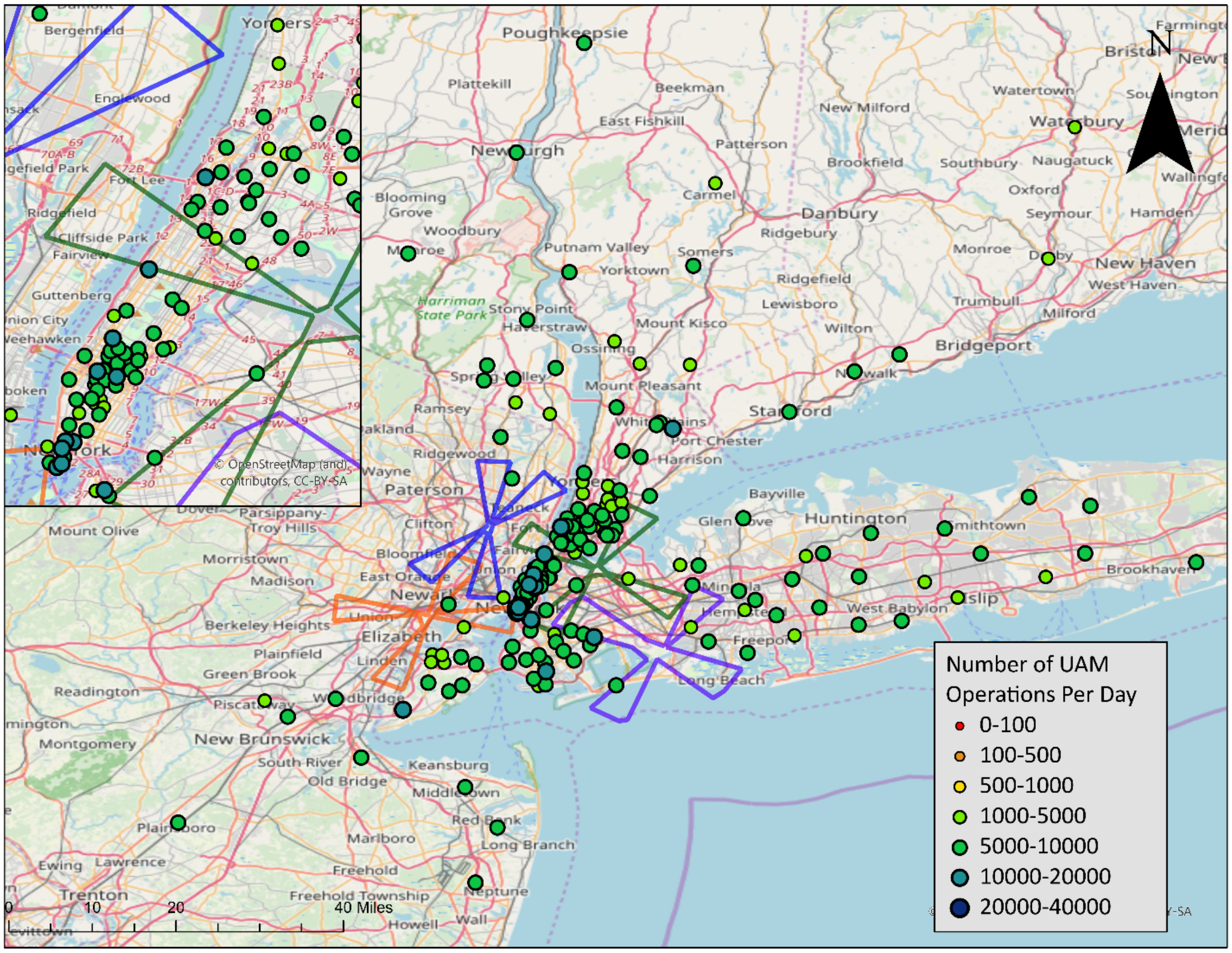

Figure 42: New York: 200 Vertiports Daily UAM Operations with CPM of $1.20

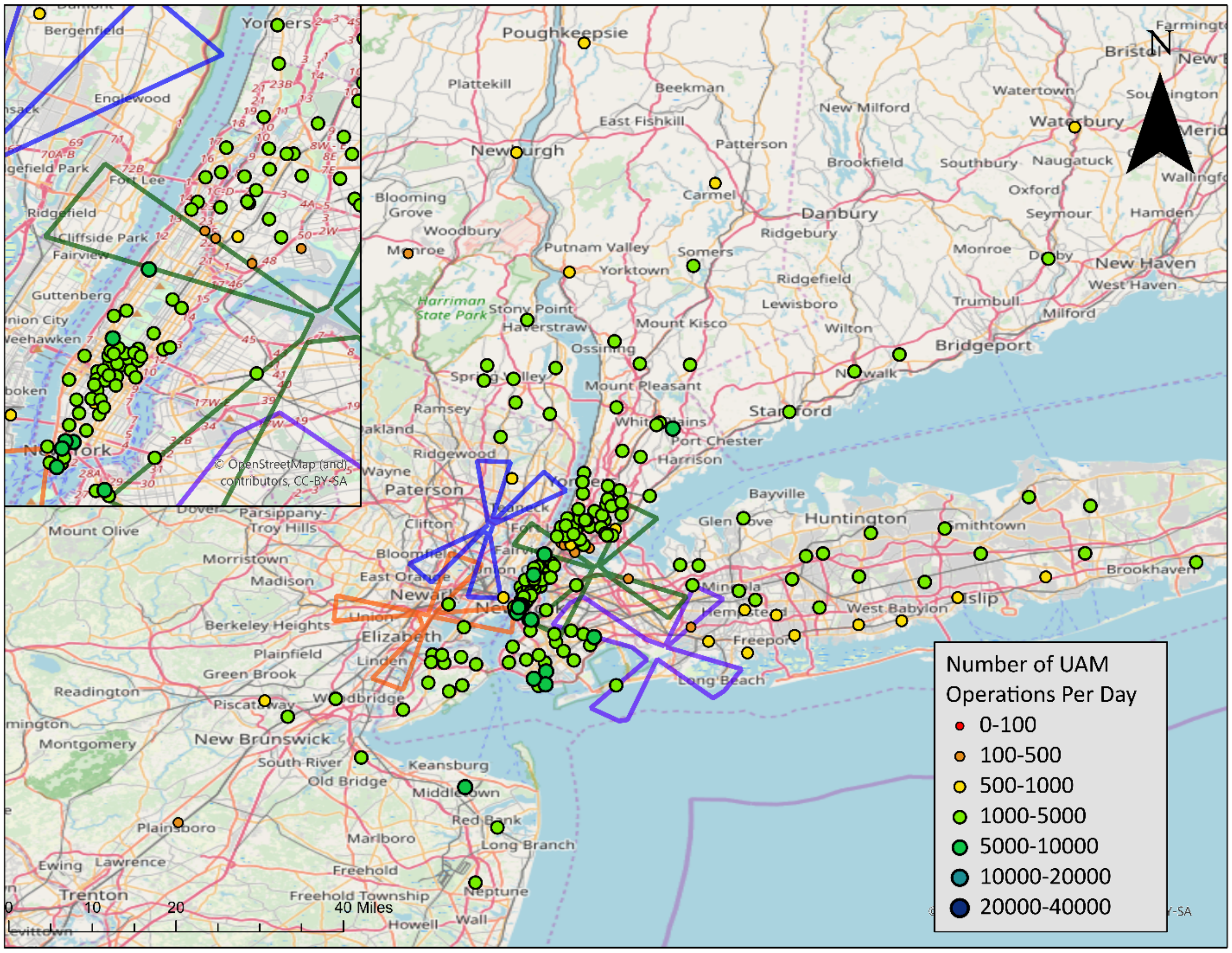

Figure 43: New York: 200 Vertiports Daily UAM Operations with CPM of $1.80