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Environmental impact analysis of on-demand urban air mobility: A case study of the Tampa Bay Area

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ABSTRACT

Urban Air Mobility (UAM) uses electric vertical take-off and landing (eVTOL) vehicles to provide an alternative way of transporting passengers in urban areas. This study proposes a method of comparing air pollutant emissions from using ground transportation versus switching to multi-modal UAM, including greenhouse gases and other air pollutants (NO_x, SO_2, $PM_{2.5}$). A study by Wu and Zhang (2021) addressed planning questions regarding the optimal placement of vertiports and estimated diverted demand from ground transportation modes by combining network design and travel mode choice models. The proposed method is applied to the case study of Tampa Bay region. A sensitivity analysis was conducted to further evaluate the impacts. The study reveals that on-demand UAM (considering vertiport access and egress modes) generates more greenhouse gases and other air pollutants (except NO_x) in the case study region compared to ground transportation modes. The emissions depend on the structure of power production. A lower UAM service price and more vertiports will further increase emissions.

1. Introduction

UAM (Urban Air Mobility) is a new concept developed in recent years that uses electric vertical take-off and landing vehicles (eVTOLs) to carry passengers and payloads in an urban environment swiftly. As they operate much faster than ground vehicles, eVTOLs could provide an efficient and time-saving traffic mode to time-sensitive passengers when the urban road network is congested. Many private companies have invested in designing and producing efficient eVTOLs and UAM services. In addition, federal, state, and local stakeholders need to work with the private sector to integrate such new modes into existing multimodal transportation systems. High-density UAM operations in the future are expected to defer the need for capacity enhancement of roadway networks, and UAM could be a good example of private/public partnerships for improving the national transportation system.

Discussion on the ground infrastructure required for UAM concentrates on vertiports (areas for eVTOLs to take off and land), as vertiport locations will, by necessity, limit UAM service. In the early phases of UAM operations, the UAM network can serve only limited locations in cities with the highest travel demand, such as airports and urban Central Business Districts (CBDs). To allow UAM to serve larger areas and benefit more people, researchers (Wu & Zhang 2021; Shaheen et al., 2020) point out that UAM needs to mesh with the existing transportation system to unleash its potential fully. Reiche et al. (2018) recommended a hub-and-spoke structure to build the UAM network. Wu and Zhang (2021) answered several planning questions, including optimal vertiport locations and

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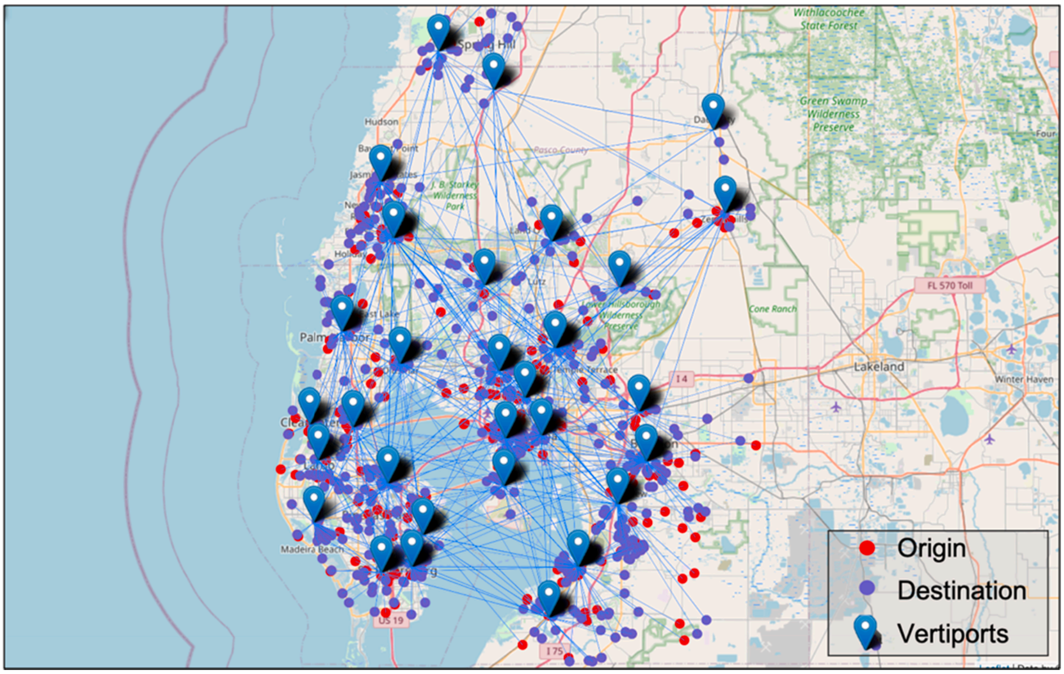


Fig. 1. Vertiport network design for station-based-UAM.

diverted demand from ground transportation, by establishing an integrated network design and travel mode choice model.

From the proposal of concepts to actual operation, stakeholders have proposed new products and concepts to turn UAM into reality. Manufacturers are developing new aircraft concepts, regulators are proposing operating rules, policymakers are discussing operational limitations, air traffic service providers are improving operation efficiency (Tang et al., 2022, 2021), and academia is trying to understand the requirements for public acceptance (Shaheen et al., 2018; Yedavalli & Mooberry, n.d.). Although the concept of on-demand UAM is advancing slowly, its implementation faces some urgent problems that need to be solved, such as infrastructure construction and public acceptance. For public acceptance, safety and environmental impact concerns must be addressed. Environmental concerns include noise (Antcliff et al., 2016; Holden & Goel, 2016) and emissions. Although eVTOLs may not generate emissions during flight (Holden & Goel, 2016), the generation of electricity is required and will emit air pollutants, including greenhouse gases and other by-products of the combustion of hydrocarbons. From a more macroscopic perspective, the emissions generated by the operation of multimodal UAM (i.e., the entire UAM trip including vertiport access, flight, and egress) need to be compared with pure ground transportation.

In the industrial area, life cycle assessment (LCA) is a common method to estimate the environmental impact over products' whole life (including production, transportation, operation, and disposition). In previous studies, researchers applied LCA to different transportation options, such as eVTOLs, electric vehicles, bikes, and high-speed railways (Chester & Horvath, 2010; Dave, 2010; Kasliwal et al., 2019; Kukreja, 2018). For the UAM environmental impact analysis, Pukhova (2019) conducted comprehensive research on the possible environmental impact of UAM adoption in Munich, adopting the simulation method proposed by Ploetner et al. (2020) and using an agent-based transportation system model to calculate the energy consumption and emission of CO_2 and NO_x with and without UAM. Travel demand data were obtained from a demographic survey and modeled into the baseline scenarios. Apart from the baseline scenarios, five scenarios with varying EV penetration, percentage of renewable energy, and new technologies in emissions were applied to compare the emissions. The results illustrate the relationship between emissions level and travel distance for different vehicles and show that the emission impact after introducing UAM is related to the energy mix. In our opinion, the author included some scenarios with bold assumptions regarding EV fleet penetration and the proportion of hydropower in the energy mix that are not realistic in the near term. The study does include scenarios with more realistic assumptions for EV penetration and fuel mix, and other kinds of air pollutants are considered.

VTOL (Vertical Take-off and Landing) is not a new concept in aviation. Helicopters are the prevailing type of VTOL aircraft, used widely for civil and military purposes (Cohen et al., 2021); other types of VTOL aircraft using tiltrotor and directed jet thrust are used in military service as well. The recent eVTOL concept is targeted to be used for UAM. The eVTOL designs show large variation from type to type; according to the eVTOL Aircraft Directory (https://evtol.news/aircraft), there are five types of aircraft, and around 500 different models are undergoing testing and being readied for use. Andre and Hajek (2019) adopted three types of eVTOLs, including Quadrotor, Side-by-Side, and Lift + Cruise, to conduct an LCA analysis; both production and operational phases were considered. The configuration, range, and payload differences lead to different mission applications (Bacchini & Cestino, 2019); thus, the power required and speed vary at different flight phases. Silva et al. (2018) defined mission segments for the eVTOLs, dividing the mission profile into 10 phases, with detailed operational parameters for each phase. However, Silva assumed a higher cruise altitude than that

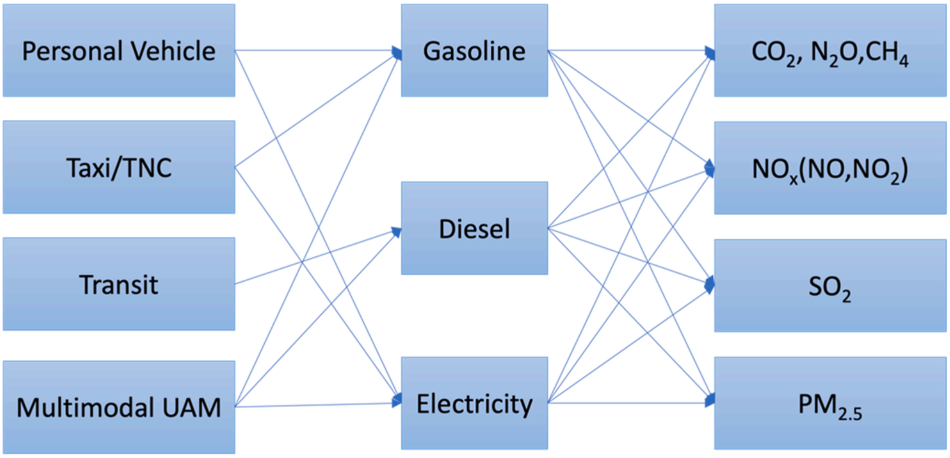


Fig. 2. General emissions calculation process.

proposed in the Federal Aviation Administration (FAA) Concept of Operations (FAA, 2020).

This study relied on the traffic demand data studied by Wu and Zhang (2021) and estimated the air pollutant emissions of diverted trips in the case study region. The emissions of the diverted trips before and after the introduction of multimodal UAM were compared, and four key factors were examined—penetration of pure electric vehicles in the automobile fleet, energy sources used in the production of electricity, price of on-demand UAM service, and the number of vertiports in the service region. These parameters were varied as part of the study's sensitivity analysis. The experiment results help illuminate the critical factors for determining the potential air pollutant emissions impact of on-demand UAM service and can serve as a reference for local policymakers considering UAM adoption.

2. Research scope and objectives

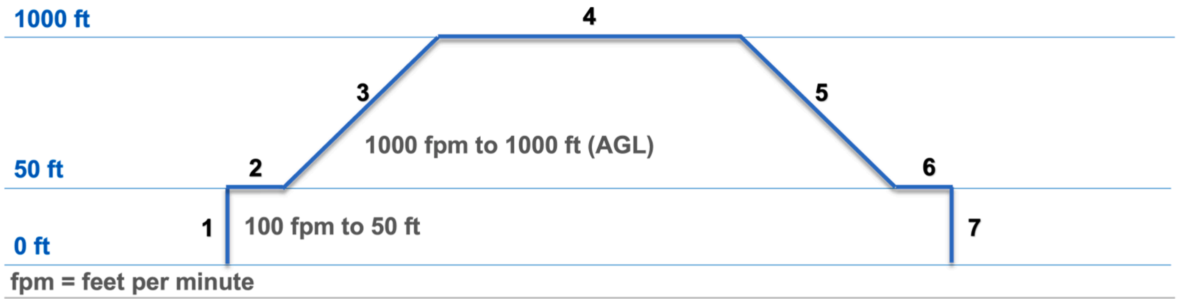
A previous study (Wu & Zhang, 2021) integrated vertiport network design with demand estimation to determine the optimal locations of vertiports and estimate diverted demand from ground transportation to station-based on-demand UAM service. Given the outcomes of that study, the objective of this study was to evaluate the environmental impacts of UAM service, with a specific focus on air pollutant emissions. Emission differences between pure ground transportation trips (before introducing UAM service) and trips after adoption of UAM service were compared. Sensitivity analysis was conducted to understand how the environmental impact changes with the variation of key parameters, e.g., number of vertiports, different UAM trip pricing, adoption of electric vehicles for ground transportation, and energy sources for electricity generation. Fig. 1 shows the on-demand UAM network in the Tampa Bay area from the previous study; marked sites are optimized locations of vertiports, and red and purple dots show the origins and destinations of diverted trips.

3. Research approach

This study focused on calculating and comparing several environmental impact indicators before and after introducing UAM. The research approach included the following steps:

1. Obtain regional emission rates of gasoline consumption, electric vehicle fleet penetration rate, energy sources for electricity production, and corresponding emission rates of different energy sources for electricity production.
2. Obtain diverted trip information from the previous work, including origin and destination, ground transportation distance, ground transportation modes and transit times, vertiport access and egress modes, and corresponding access and egress transportation distance and time and UAM flight distance.
3. For the diverted trips, calculate the air pollutant emissions for the pure ground transportation and the multimodal UAM trips and compare the difference.
4. Conduct a sensitivity analysis, varying the number of vertiports, pricing scheme for UAM trips, Electric Vehicle (EV) fleet penetration rates, and carbon intensity of electricity production.

As noted, the designs of proposed eVTOL vehicles vary greatly. Considering that on-demand UAM is proposed for high-density future operations, it was assumed that the eVTOL payload capacity is four passengers. It was also assumed that the eVTOLs have enough air space to operate without conflict. A sensitivity analysis regarding electricity generation energy sources was performed, and an average air pollutant emission rate for each energy source was used. All transit buses in this study were assumed to be powered by diesel engines, the primary bus type of transit agencies in the case study region. However, fleet types of different transit agencies vary;



No	1	2	3	4	5	6	7
Flight phase	Vertical Climb	Transition	Climb	Cruise	Descent	Transition & Hover	Vertical Descent
Time [s]	30	10	57	Time-related	57	40	30
Power	100%	100%	P_climb	P_cruise	P_descent	100%	100%
Power [kw]	345	345	310.5	264	124.2	345	345
Speed[kt]	-	-	56	98	56	-	-

Fig. 3. eVTOL flight phases and operational parameters.

some may have more powered by renewable energy, such as electricity or hydrogen. While implementing the method in this study to other regions, more detailed fleet information may be collected and used for calculating air pollutant emissions.

3.1. Calculation of air pollutant emissions

Fig. 2 illustrates the method of calculating air pollutant emissions for different transportation modes. Personal and for-hire service vehicles could be powered either by gasoline or electricity. For transit, it was assumed that buses were powered with diesel fuel. For multimodal UAM trips, although the eVTOLs are powered with electricity, vertiport access and egress trip segments could use any of six ground transportation modes involving different power sources, including manpower while walking and riding bikes. Thus, for calculating the air pollutant emissions of different modes, energy consumption was calculated as a function of distance or travel time, and the quantity of air pollutant emissions was calculated as a function of emission rates and energy consumed.

3.2. Calculation of energy consumption of ground transportation modes

This study considered six ground transportation modes for urban transportation—personal automobile, taxi/TNC (Transportation Network Company), transit, e-scooter, bike, and walk. There are three categories of energy consumption—gasoline, diesel, and electricity. Once the distance traveled by the vehicle was obtained, the distance was multiplied by the specific energy consumption rate to obtain total energy consumption. For gasoline vehicles and diesel transit, fuel consumption C_{fuel} was determined by specific energy consumption α in gallons per 100 miles. For electric vehicles, electricity consumption, C_{elec} was determined by β in kWh per 100 miles. For e-scooters, electricity consumption, $C_{scooter\_elec}$ was determined by γ in kWh per 100 miles.

$$C_{fuel} = \frac{distance}{100}*\alpha \tag{1}$$

$$C_{elec} = \frac{distance}{100}*\beta \tag{2}$$

$$C_{scooter\_elec} = \frac{distance}{100}*\gamma \tag{3}$$

Where,
distance = distance traveled.
α = fuel economy of gasoline vehicle.
C_{fuel} = fuel consumption for specific gasoline vehicle trip, in gallons.
β = energy efficiency of electric vehicle.
C_{elec} = energy consumption for specific electric vehicle trip, in kWh.
γ = energy efficiency of e-scooter.
$C_{scooter\_elec}$ = energy consumption for specific e-scooter trip, in kWh.

Table 1
Emission calculation input parameters.

Parameter	Value	Unit	Source
CO_2 emission rate of gasoline	8780	g/gallon	EPA (2020b)
CH_4 emission rate of gasoline	0.38	g/gallon	EPA (2020b)
N_2O emission rate of gasoline	0.08	g/gallon	EPA (2020b)
CO_2 emission rate of diesel	10,180	g/gallon	EPA (2020b)
CH_4 emission rate of diesel	0.42	g/gallon	EPA (2020b)
N_2O emission rate of diesel	0.08	g/gallon	EPA (2020b)
CO_2 emission rate of electricity (FRCC)	422.676	g/kWh	EPA (2020b)
CH_4 emission rate of electricity (FRCC)	0.03	g/kWh	EPA (2020b)
N_2O emission rate of electricity (FRCC)	0.004	g/kWh	EPA (2020b)
Global Warming Potential of CO_2	1	–	EPA (2020b)
Global Warming Potential of CH_4	25	–	EPA (2020b)
Global Warming Potential of N_2O	298	–	EPA (2020b)
NO_x emission rate of gasoline vehicle	0.284	g/mi	BTS (2020b)
NO_x emission rate of diesel transit bus	8.19	g/mi	M.J. Bradley & Associates LLC (2019)
NO_x emission rate of electricity (FRCC)	0.161	g/kWh	EPA (2020b)
SO_2 emission rate of gasoline vehicle	0.001	g/mi	Argonne National Laboratory (2021)
SO_2 emission rate of diesel transit bus	0.024	g/mi	Darlington & Kahlbaum (1999)
SO_2 emission rate of electricity (FRCC)	0.126	g/kWh	EPA (2020b)
$PM_{2.5}$ emission rate of gasoline vehicle	0.0095	g/mi	BTS (2020b)
$PM_{2.5}$ emission rate of diesel transit bus	0.2016	g/mi	M.J. Bradley & Associates LLC (2019)
$PM_{2.5}$ emission rate of electricity (FRCC)	0.029	g/kWh	EPA (2020d)
Fuel economy of gasoline vehicle	24.4	MPG	BTS (2020a)
Fuel economy of diesel transit bus	4	MPG	Shauna et al. (2013)
Fuel economy of EV	0.3344	kWh/mi	Office of Energy Efficiency & Renewable Energy (2021)
Electricity consumption rate of e-scooter	0.0156	kWh/mi	GoTrax (2021)
eVTOLs max power	345	kWh	André & Hajek (2019)
eVTOLs cruise power	264	kWh	André & Hajek (2019)
Climb speed of eVTOLs	64.4(56)	mi/h(kt)	Bacchini & Cestino (2019)
Cruise speed of eVTOLs	112.7(98)	mi/h(kt)	Bacchini & Cestino (2019)
Personal Vehicle/Taxi occupancy	1.5	–	(Florida Department of Transportation Office of Policy Planning, 2011)
Transit occupancy	10	–	(Federal Highway Administration, 2018)

3.3. Calculation of energy consumption of eVTOL operations

The electricity consumption of eVTOLs is determined by the power required and operating time for different flight phases, e.g., climb, cruise, and descent. In this study, a seven-phase mission profile was used to calculate the energy consumption and emission of eVTOL operations (see Fig. 3). The operations parameters were based on Silva et al. (2018) and simplified according to the recent UAM ConOps (FAA, 2020).

As shown in Fig. 3, eVTOLs start with a vertical climb at 100 ft/min to 50 ft Above Ground Level (AGL). After 10 s of transition, they climb at 1,000 ft/min, adopting V_{be} (best endurance velocity) and 90 percent of maximum power. After that, they cruise at V_{br} (best range velocity) and an altitude of 1,000 ft AGL. Then, the eVTOLs descend at 1,000 ft/min to 50 ft AGL and descend at 100 ft/min in the final phase to ensure the accuracy and safety of the landing. The eVTOLs adopted in this study are the Quadrotor type with a maximum power of 345 kW and a cruise power of 264 kW. According to the helicopter's operation, the power required for descent is 40 percent of climb power (Rotaru, 2018). Speed and power relations were obtained from the work of Bacchini & Cestino (2019).

Flight energy consumption in total will follow Eq. (4), where P_i is the power required by flight phase i and t_i is the flight time in flight phase i. Note that for different eVTOL trips, all six other phases are the same, except cruise phase 4. The flight time in phase 4 is calculated by dividing cruise distance (distance of segment 4 in Fig. 3) with cruise speed. For the case study, the average eVTOL operation time was 14.88 min, and the average energy consumption was 55.83 kWh.

$$W = \sum W_i = P_i{}^*t_i \tag{4}$$

Where,
P_i = power required by flight phase.i
t_i = flight time in flight phase.i
W_i = work in flight phase.i

3.4. Air pollutants considered in this study

Four types of air pollutants were considered in this study—greenhouse gases (carbon dioxide [CO_2], nitrous oxide [N_2O], methane [CH_4]), oxides of nitrogen (NO_x), sulfur dioxide (SO_2), and particulate matter 2.5 ($PM_{2.5}$). Fluorinated gases were not considered; although they have a very high global warming potential (GWP) relative to other greenhouse gases, they are not produced by internal combustion engines or the production of electricity (EPA, 2020d). For the four air pollutants considered, GWP factors were used to convert different kinds of greenhouse gas into carbon dioxide equivalent (CO_2e). The transforming function is described in Eq. (5). For

Table 2
Mean value of travel time and distance on different travel modes.

	Travel Distance (mi) Pure Ground	Multimodal UAM	Travel Time(min) Pure Ground	Multimodal UAM
Personal Vehicle	32.75	26.60	47.01	25.12
TNC/Taxi	40.01	33.18	51.75	38.96
Transit Bus	14.10	14.75	93.76	37.50

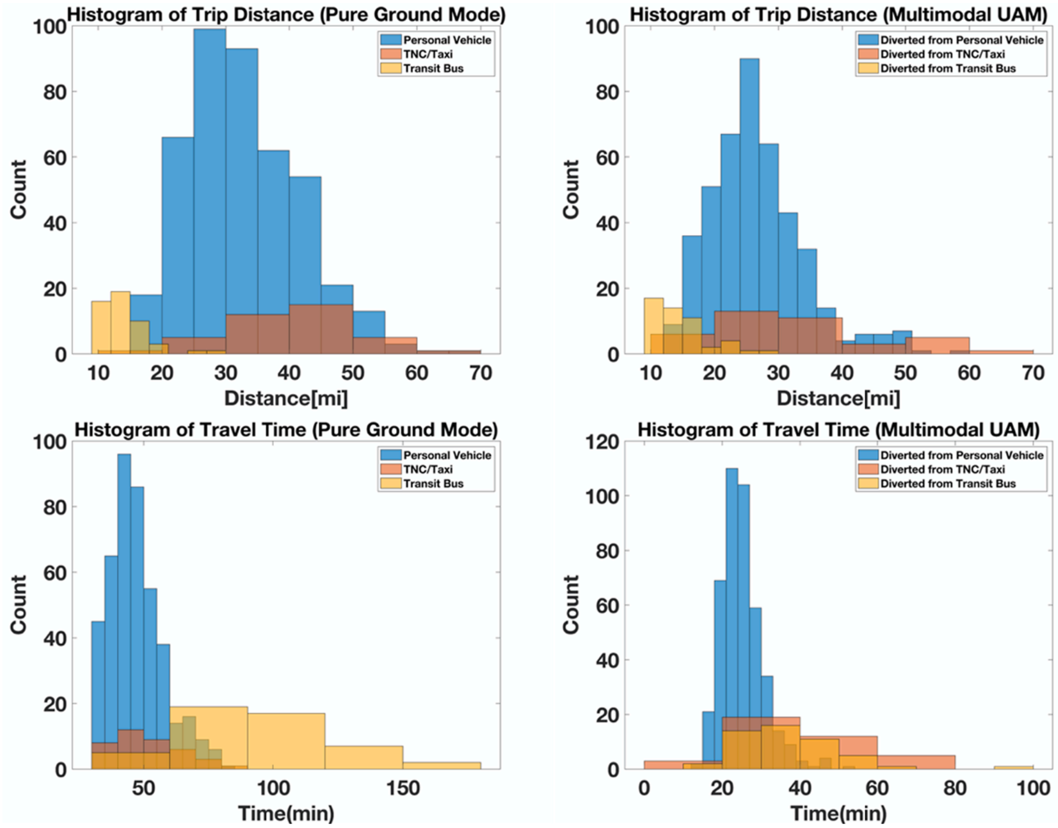


Fig. 4. Histogram of travel time and distance on different travel modes.

the emission of specific air pollutants E_{GHG_i}, there will be a related global warming potential factor GWP_i. Then, the total carbon dioxide equivalent was summed. The GWP for CO_2, CH_4, and N_2O are 1, 25, and 298, respectively (EPA, 2020b).

$$\sum_i CO_2e\ _i = \sum_i E_{GHG_i} * GWP_i \tag{5}$$

Where.
E_{GHG_i} = emission of greenhouse gas.i
GWP_i = global warming potential factor of greenhouse gas.i
$CO_2e\ _i$ = quantity of carbon dioxide equivalent.i

3.5. *Emission calculation for different types of energy*

3.5.1. *For gasoline and diesel*

As ground trip distance was known from the travel data, the vehicle's fuel economy was set as the average national level, the gasoline or diesel consumption for the vehicle was determined, and the greenhouse gases were determined using standard factors (see Table 1). For other air pollutants such as NO_x, SO_2, and $PM_{2.5}$, the emissions were determined by the emission rates and the distances traveled.

3.5.2. For electricity

For emissions associated with electricity generation, data from the eGRID database (EPA, 2020b) and FRCC were used (FRCC is a sub-region encompassing Florida). The unit for the air pollutant emission rates was g/kWh. Once electricity consumption was obtained, the corresponding air pollutant emissions were determined.

3.6. Data sources

3.6.1. Travel demand data

The travel demand data applied in this study were the optimization results of the previous study (Wu & Zhang, 2021), which encompasses diverted trips from the ground to multimodal UAM in the Tampa Bay area. These trip data contain 19 data elements, including the origin and destination coordinates of each diverted trip, ground modes of the trips and ground travel time before diverted to multimodal UAM, vertiports used by the trips after the introduction of UAM, and access and egress modes of the diverted trips. Such comprehensive data provide sufficient information to calculate and compare energy consumption and related air pollutant emissions before and after the introduction of UAM.

As shown in Table 2, the three main parts of pure ground mode are personal vehicle, TNC/taxi, and transit bus; the mean distance of these three traffic modes is 32.75 mi, 40.01 mi, and 14.10 mi, respectively. The mean distance of a trip diverted from personal vehicle and TNC/taxi decreases, and the distribution of trip distance moves slightly to the left (see Fig. 4). At the same time, the mean distance of the trips diverted from transit bus shows a slight increase. For all diverted trips, the mean distances of multimodal UAM and ground trips are 25.95 mi and 31.50 miles, respectively. For travel time, the mean value of travel time of trips switched from pure ground decreased, and the trips diverted from transit bus decreased to 40 percent of the original level. The mean travel times are 27.35 min for multimodal UAM and 51.86 min for ground trips.

For ground transportation modes considered in this study, both the pure ground trips and access/egress for multimodal UAM trips, the automobile (personal vehicles and TNC/taxi) was the favored choice (see Fig. 4). Based on the sales record for pure electric vehicles over the past 10 years in the U.S. (Department of Energy, 2021), it was assumed that 1.35 percent of vehicle fleets are electric vehicles. The air pollutant emissions of these vehicles were calculated based on electricity generation in the Tampa Bay area.

3.6.2. Vehicle operations data

It was assumed that a gasoline vehicle's average fuel economy is 24.4 MPG (0.041 gallons/mi), as reported in the U.S. Light-Duty vehicle database (Bureau of Transportation Statistics, 2020b) (accessed on May 10, 2021). For electric vehicles, EPA Fuel Economy websites (Office of Energy Efficiency & Renewable Energy, 2021) were referenced for 44 types of electric vehicles; the average energy consumption of electric vehicles is 33.44 kWh/100 mi (0.3344 kWh/mi). Diesel bus fuel consumption data are from Shauna et al. (2013). Diesel buses account for the bulk of the fleet of the local bus operator, Hillsborough Area Transit (HART).

3.6.3. Emission rate data

Emission rates for greenhouse gases are from an EPA report (2020b). For the air pollutants of gasoline vehicles, the data source for NO_x and $PM_{2.5}$ emissions rates is the Bureau of Transportation Statistics (2020b), and data for SO_2 emissions are from the GREET (Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies) model WTW Calculator (Argonne National Laboratory, 2021). The simulation settings represent today's fuel and vehicle technologies (simulation year 2019, vehicle model year 2014). For the air pollutants of diesel transit buses, the data source for NO_x and $PM_{2.5}$ emissions rates is a report by M. J. Bradley & Associates LLC (2019) written for the American Bus Association Foundation. As the emission standard of urban transit buses does not consider SO_2 to be a main air pollutant, the calculation method for SO_2 refers to Darlington & Kahlbaum (1999) and sets sulfur content as 15 ppm for the ultra-low-sulfur diesel. For electricity generation, the emission rates of NO_x and SO_2 are from EPA (2020a), and the emission rates of $PM_{2.5}$ also are from EPA (2020c). Emission rates for different sources of energy are summarized in Table 1.

3.6.4. Vehicle occupancy data

Vehicle occupancy data were used to calculate emissions per capita. For ground transportation, average occupancy was considered while calculating emissions per capita per trip. It was assumed that vehicle occupancy is 1.5 for the personal vehicle or TNC/taxi according to an FDOT document (FDOT ffice of Policy Planning, 2011). For transit bus, reference was made to a report of Federal Highway Administration (FHWA, 2018). The average bus occupancy of different cities was calculated and is shown in Table 2, which is 9.93; bus occupancy is 10. For eVTOLs, it was assumed that the passenger capacity is 4. Considering that eVTOLs are not always full, a 75 % average load factor was assumed, i.e., average eVTOL occupancy is three passengers.

4. Experimental results and Discussion

4.1. Case study

In the case study, emission metrics were computed for the same trips before and after introducing multimodal UAM and calculated the differences $\Delta Emission$ (see Eq. (6)).

$$\Delta Emission = Emission_{MultimodalUAM} - Emission_{pureground} \tag{6}$$

Table 3
Total emissions for different travel modes in case study (unit: kg).

		CO_2	CH_4	N_2O	CO_2e	NO_x	SO_2	$PM_{2.5}$
Pure Ground		4,147.739	0.179	0.037	4,163.329	4.276	0.020	0.132
Multimodal UAM	**eVTOL**	4,090.459	0.290	0.039	4,109.176	1.558	1.219	0.281
	Access	451.109	0.020	0.004	452.810	0.391	0.002	0.013
	Egress	499.995	0.022	0.005	501.875	0.339	0.002	0.013
	In Total	5,041.564	0.332	0.047	5,063.956	2.288	1.224	0.306
Difference		893.825	0.152	0.010	900.627	−1.987	1.204	0.174
% Difference		21.55 %	84.99 %	26.95 %	21.63 %	−46.48 %	5957.19 %	131.33 %

Table 4
Emissions differences for time benefit trips in case study (selected) (unit: g).

Trip ID	Items	Distance (mi)	Time (min)	CO_2e	NO_x	SO_2	$PM_{2.5}$
#159	Pure ground mode	26.2	43.9	6257.41	4.90	0.03	0.17
	Multimodal UAM	12.5	18.8	6019.42	4.03	1.52	0.40
	Difference	−13.7	−25.1	−238.00	−0.88	1.49	0.24
	Percent change	−52.42 %	−57.22 %	−3.80 %	−17.89 %	5484.71 %	142.21 %
#351	Pure ground mode	35.5	44.4	8484.18	6.65	0.04	0.22
	Multimodal UAM	17.2	17.6	7121.33	2.93	1.85	0.45
	Difference	−18.3	−26.8	−1362.85	−3.72	1.81	0.22
	Percent change	−51.63 %	−60.31 %	−16.06 %	−55.91 %	4911.42 %	98.17 %
#459	Pure ground mode	44.4	47.5	10605.83	8.31	0.05	0.28
	Multimodal UAM	19.2	17.9	7771.54	3.23	2.03	0.49
	Difference	−25.2	−29.6	−2834.29	−5.09	1.98	0.21
	Percent change	−56.78 %	−62.41 %	−26.72 %	−61.20 %	4302.60 %	73.90 %

Table 5
Total emissions differences for different travel modes (unit: kg/day).

	Items	CO_2e	NO_x	SO_2	$PM_{2.5}$
Case study	Pure ground mode	4,163.33	4.28	0.02	0.13
	Multimodal UAM	5,063.96	2.29	1.22	0.31
	Difference	900.63	−1.99	1.20	0.17
	Percent change	**21.63 %**	**−46.48 %**	**5957.19 %**	**131.33 %**
0 % EV	Pure ground mode	4,194.28	4.31	0.01	0.13
	Multimodal UAM	5,071.50	2.29	1.22	0.31
	Difference	877.22	−2.01	1.21	0.17
	Percent change	**20.91 %**	**−46.74 %**	**8388.88 %**	**131.35 %**
5 % EV	Pure ground mode	4,079.65	4.19	0.04	0.13
	Multimodal UAM	5,043.57	2.27	1.23	0.31
	Difference	963.92	−1.92	1.19	0.17
	Percent change	**23.63 %**	**−45.76 %**	**3319.85 %**	**131.26 %**
10 % EV	Pure ground mode	3,965.02	4.07	0.06	0.13
	Multimodal UAM	5,015.65	2.25	1.23	0.31
	Difference	1,050.63	−1.82	1.18	0.17
	Percent change	**26.50 %**	**−44.73 %**	**2048.06 %**	**131.18 %**

Results are summarized in Table 3. Total emissions of CO_2e, SO_2, and $PM_{2.5}$ increase after the introduction of a multimodal UAM, and total emissions of NO_x decrease.

4.1.1. *Comparison of carbon dioxide equivalent*

As shown in Table 4, three kinds of greenhouse gas emissions were calculated individually and then converted to CO_2e by multiplying GWP factors (as described by Eq. (5)). For the overall CO_2e, the emission difference was positive, which means that the whole transportation system will generate more greenhouse gases when multimodal UAM is introduced. The emission of CO_2 dominates the greenhouse gas computation and contributes 99.24 percent of the CO_2e emission difference Table 5.

4.1.2. *Comparison of other air pollutants emission*

In Table 4, the total emission difference for SO_2, and $PM_{2.5}$ in multimodal UAM was higher than for the pure ground mode. The NO_x difference decreased 46.48 percent, and SO_2 and $PM_{2.5}$ increased 5957.19 percent and 131.33 percent, respectively. The eVTOL operation generated 81.85 percent of total UAM trip greenhouse gases, 68.09 percent of NO_x, 99.64 percent of SO_2, and 91.65 percent of $PM_{2.5}$. There was a notable increase in SO_2. The emission rate of gasoline is relatively small compared to the emission rate of electricity, thus causing a big emission difference. In this study, the possible traffic variation between weekdays and weekends was not

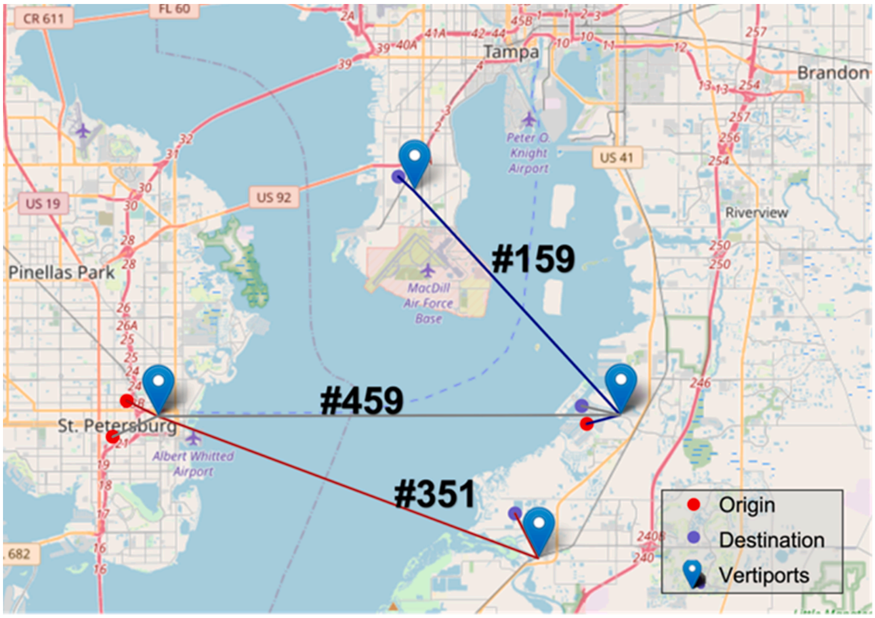


Fig. 5. Three selected time-saving trips.

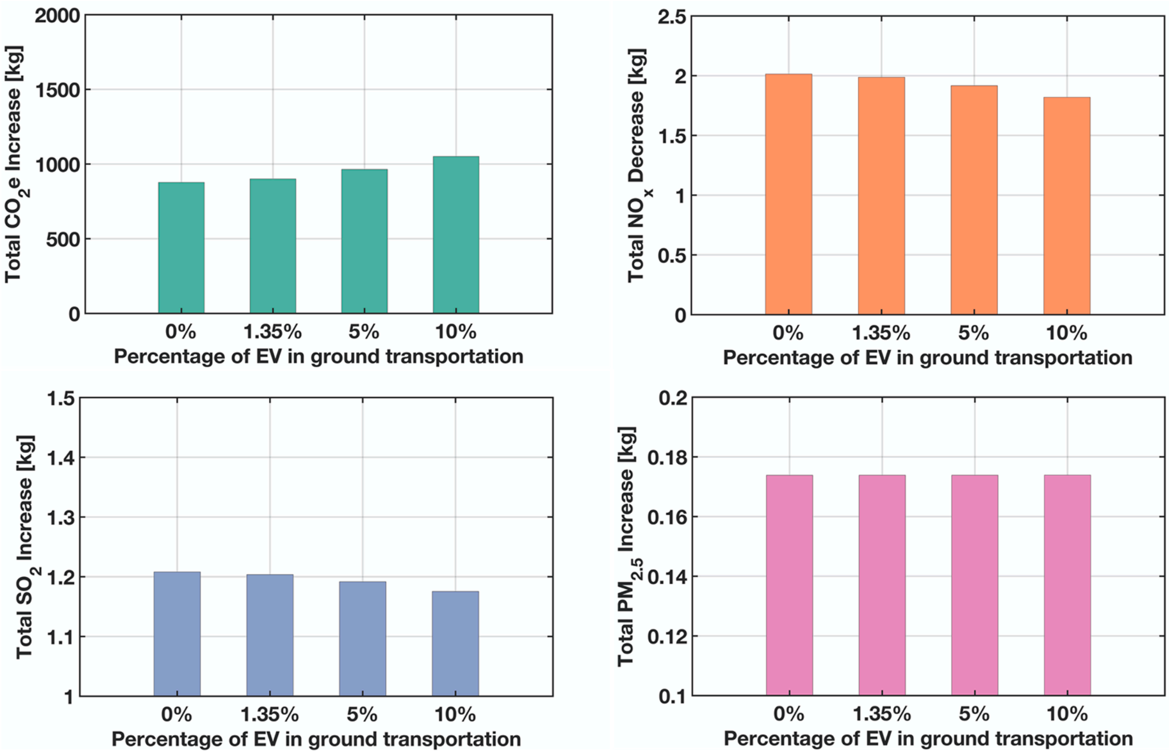


Fig. 6. Effect of EV fleet penetration on air pollutants.

used but was multiplied by the daily emission of 365 to get annual emission results. For the case study, annual CO_2e increase was 328.73 metric tons, annual NO_x decrease was 0.73 metric tons, and annual SO_2 and $PM_{2.5}$ increases were 0.44 and 0.06 metric tons, respectively, if multimodal UAM is introduced.

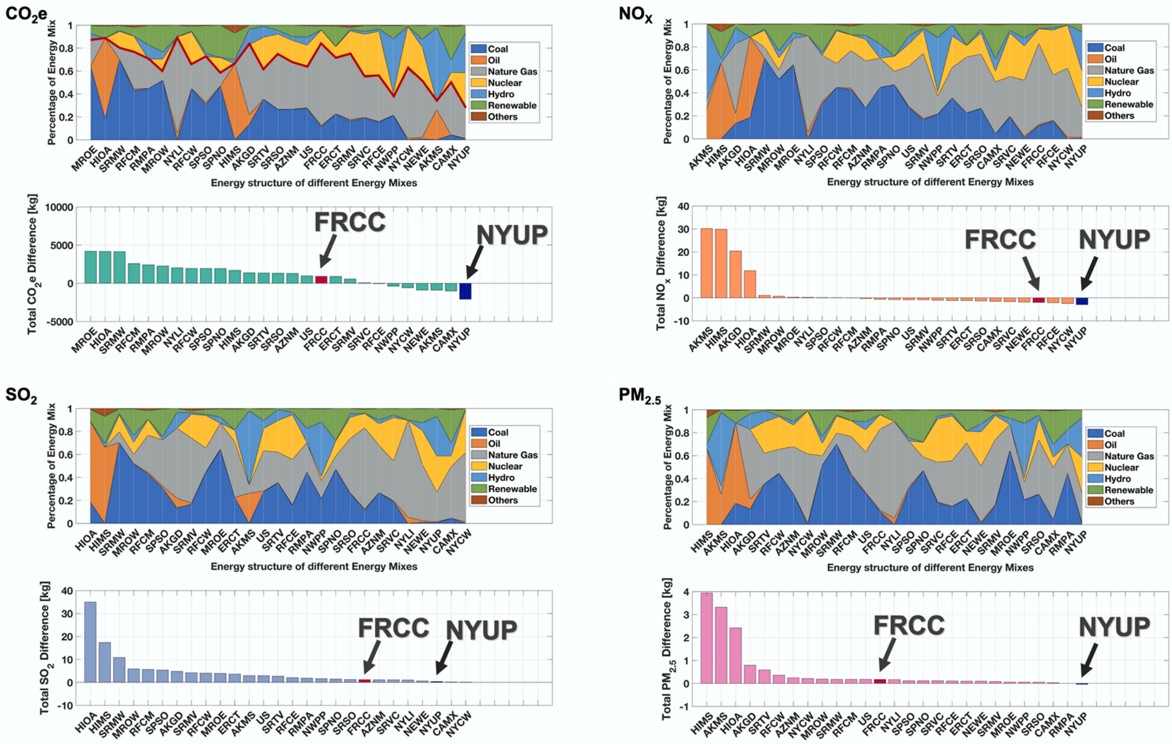


Fig. 7. Effect of electricity generation energy source on air pollutant emissions difference.

4.1.3. *Emission comparison of individual trip*

For the case study, the emission difference of greenhouse gas, SO_2, and $PM_{2.5}$ for entire trips increased significantly, but the time-saving benefits of multimodal UAM were significant as well. For selected trips shown in Table 4, after adopting multimodal UAM, travel times decreased more than 50 percent compared to pure ground trips. Multimodal UAM enabled convenient transportation in different areas and dramatically improved regional mobility and job accessibility in Tampa Bay Area (see Fig. 5).

4.2. *Sensitivity analysis of case study*

As initial results are highly sensitive to many parameters selected for the model, sensitivity analysis was conducted to understand the relationship between parameter changes and differences in environmental impact indicators. The parameters studied in the sensitivity analysis included market penetration of electric vehicles, power sources for electricity generation, price of UAM travel, and number of vertiports in the region of study. Emissions differences between pure ground transportation and multimodal UAM scenarios were compared. A positive $\Delta Emission$ means that the air pollutant emissions from multimodal UAM are higher than those from pure ground transportation.

4.2.1. *EV market penetration*

For the base case, the EV fleet penetration was 1.35 percent in Florida. For the sensitivity analysis, all other parameters were kept the same, and EV penetration was varied to 0, 5, and 10 percent.

As shown in Fig. 6, as the number of EVs in the automobile fleet increased, the CO_2e emissions for the pure ground mode decreased, so the difference between multimodal UAM and pure ground mode increased (i.e., multimodal UAM appears worse). NO_x was slightly worse, and the emission increment of SO_2 slightly decreased; there was very little change in $PM_{2.5}$.

4.2.2. *Energy mix for electricity generation*

In the baseline calculation, energy sources used in the FRCC region were adopted, which encompasses the Tampa Bay region. More than 80 percent of the energy used to generate electricity in this region comes from hydrocarbon fuels (i.e., coal, oil, natural gas). To understand how the carbon intensity of electric energy production affects the results of this environmental impact analysis, for the same diverted trips, electric production energy source profiles from other regions were used to calculate the air pollutant emission difference between pure ground transportation and multimodal UAM. The source of the energy mix data was EPA's eGrid database (https://www.epa.gov/egrid/data-explorer). Different eGrid subregions (see Appendix A) in the U.S. use different combinations of energy sources (see table in Appendix B), and these different sources will lead to a variation in emission rates. In the sensitivity analysis, 26 different combinations of the energy mix and the U.S. average energy mix were applied to the calculation. In Fig. 7, four

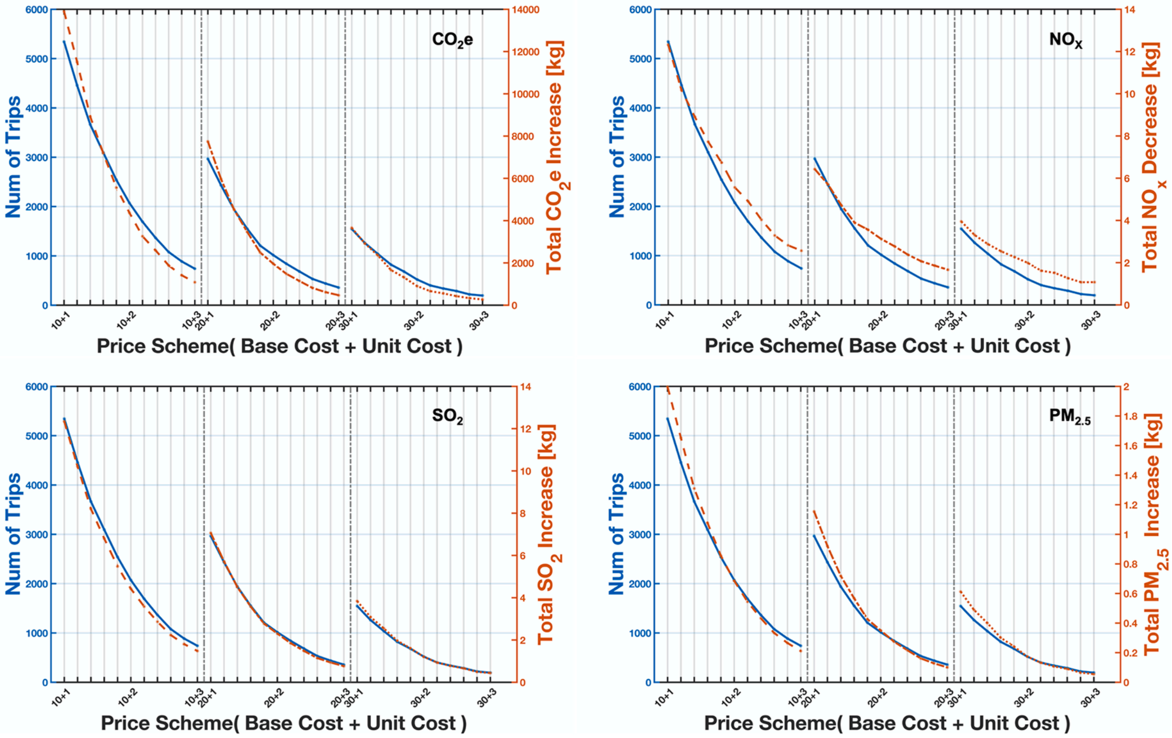


Fig. 8. Effect of pricing scheme on air pollutants emission differences.

panels illustrate the emission difference results for CO_2e, NO_x, SO_2, and $PM_{2.5}$. The bars are sorted in descending order of the emission difference for each panel. For CO_2e, the emission difference of FRCC is positive, and seven regions show negative emission differences, including NYUP. These regions own lower fossil fuels percentage in their energy mix than the others. For NO_x, one-third of the differences were positive, meaning that multimodal UAM produced more air pollutants than pure ground transportation, especially for the region with a higher percentage of oil; the others were negative. For SO_2, all emission differences were positive no matter which energy mix was adopted. For $PM_{2.5}$, most differences were positive, meaning that multimodal UAM produced more air pollutants than pure ground transportation, except the emission difference of $PM_{2.5}$ for NYUP was negative.

The results indicate that CO_2e emissions are related to the proportion of the hydrocarbon fuels (coal, oil, natural gas) used in electricity production (portion below the red line in the top-left area of Fig. 7), especially the proportion of oil and coal, as would be expected. Note that the HIOA (Hawaii) and FRCC (Florida) regions use a similar percentage of non-renewable sources, but the emission difference of CO_2e is greatly different due to the different proportions of hydrocarbon fuels. Oil dominates electricity production in the HIOA, and natural gas dominates in the FRCC. The regions with a lower percentage (less than 50 %) of non-renewable energy supply show a carbon dioxide emission decrease (e.g., NYUP) (see Fig. 7).

For NO_x emissions, the difference seems to have a strong relationship with the use of oil-fired generators. The NO_x emissions difference is very low for regions that do not use oil. For the SO_2 emission difference, three regions dominate—HIOA, AKMS, and SRMW (see Appendix A for specific locations); these regions have higher oil and coal usage than the others. For $PM_{2.5}$, HIMS, AKMS, HIOA, and AKGD have much higher emission differences than the other regions because they use a relatively high percentage of oil in electricity production.

The analysis can provide hints on the environmental impacts of UAM in other regions or in the same region but with improved energy sources for electricity production. Among the different combinations of the energy mix, some regions, e.g., NYUP, use more renewable energy and clean energy (nuclear energy) for electricity production. NYUP can be considered one scenario of future energy structure of FRCC. In Fig. 7, the air pollutant emission difference with emerging UAM with FRCC and NYUP energy source profiles are highlighted. As shown, with NYUP energy source profiles, introduction of UAM will help reduce CO_2 equivalent, NO_x and PM2.5, with slight increase of SO2.

In summary, emissions difference is related to overall emissions intensity, which is related to the energy mix used for electricity generation. The CO_2e emissions are more related to fossil fuel use, whereas NO_x, SO_2, and $PM_{2.5}$ are related to the share of oil and coal in the energy mix.

4.2.3. Price schemes of on-Demand UAM service

The pricing of UAM trips and the number of vertiports will influence traveler willingness to switch from pure ground transportation to multimodal UAM. Wu & Zhang (2021) applied sensitivity analysis to determine how the change of price schemes of on-demand

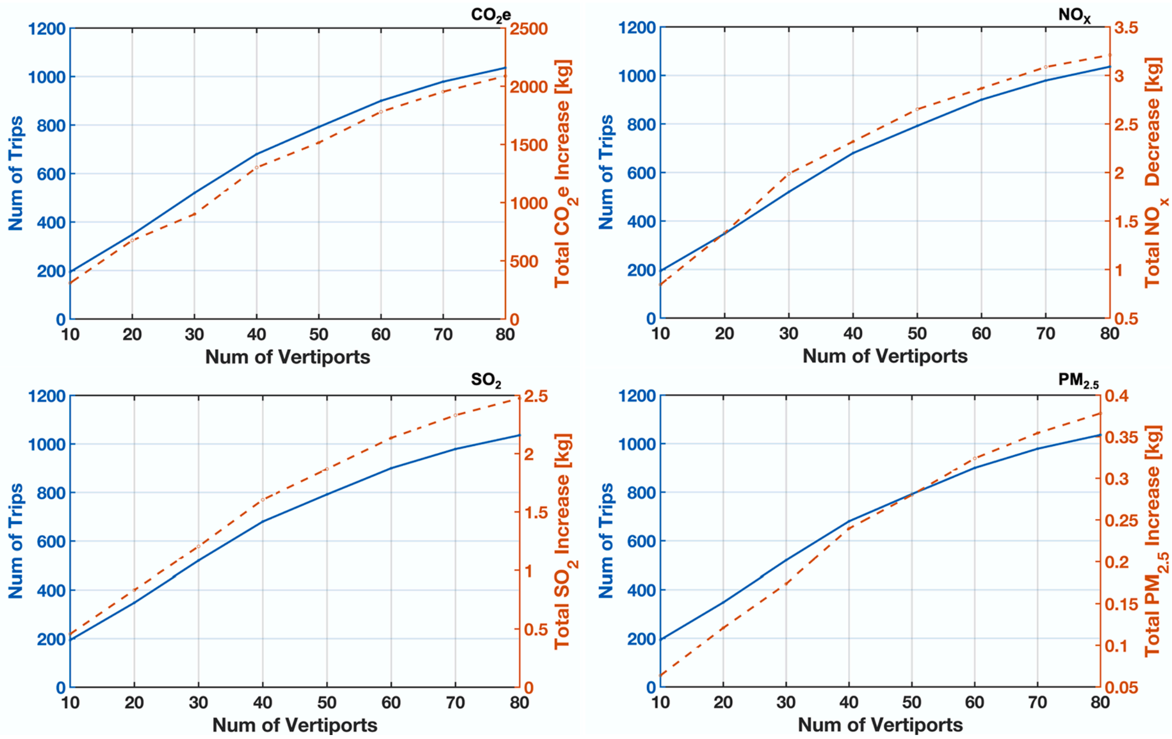


Fig. 9. Effect of number of vertiports on air pollutant differences.

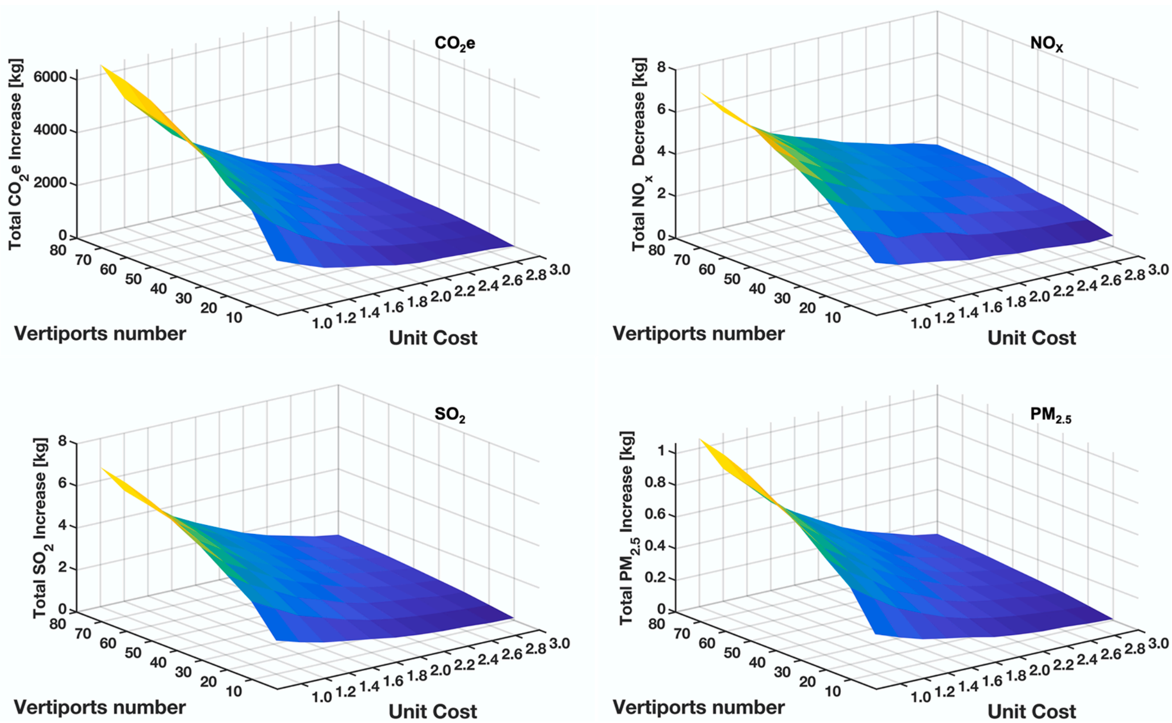


Fig. 10. Effects of pricing scheme and vertiport numbers on air pollutant differences.

UAM service leads to different locations of vertiports and diverted demand from pure ground transportation to multimodal UAM. A sensitivity analysis from the environmental impact aspect was conducted using this information. The baseline scenario assumed that the on-demand UAM service charges a fixed price of $30 plus $2 per mile variable (or unit) price for each trip. In the sensitivity analysis, the fixed price varied among [10, 20, 30], and variable price varied among [1.0, 1.2, …, 3.0]. Different combinations of fixed and variable prices were used for obtaining outcomes.

Fig. 8 shows the results of the sensitivity analysis. The solid blue line represents the number of trips, and the dotted orange line represents the emission difference. Note that the positive number indicates that multimodal UAM yields greater emissions than pure ground transportation. From Fig. 8, it can be concluded that the number of UAM trips and the CO_2e increase are positively related. With a price increase, the total number of trips will decrease, total CO_2e will decrease, and the decrease of NO_x and increase of SO_2 and $PM_{2.5}$ will also decrease. It also can be seen from Fig. 8 that with a lower fixed cost, e.g., $10, the same change in unit cost will lead to a more significant change in the number of diverted trips and environmental impact indicators than in higher fixed cost cases, e.g., $30.

4.2.4. Number of vertiports

Also examined was the effect of vertiports numbers on the change in emissions. As the number of vertiports increases, the attractiveness of the UAM trip increases. The number of vertiports varied from 10 to 80 in increments of 10. In Fig. 9**,** the solid blue line represents the number of trips, and the dotted orange line represents the emission difference. It shows that as the number of vertiports increases, the number of UAM trips increases. When the number of vertiports is greater than 40, the increase of UAM trips slows, as does the increase of CO_2e. For NO_x, SO_2, and $PM_{2.5}$, the emission difference goes with the increment of vertiports. After the number of vertiports exceeds 40, the emission difference of greenhouse gases and other air pollutants slows.

4.2.5. Combinations of vertiports and pricing schemes.

The number of vertiports and the pricing scheme were simultaneously varied to understand their combined effects. The fixed cost was set at $30, the unit cost varied from $1 to $3, and the number of vertiports varied from 10 to 80. Fig. 10 illustrates the resulting response surfaces. It was found that a higher price and lower vertiport number will lead to a lower total air pollutant emission difference.

5. Conclusion

In this study, emission rate data were collected for different transportation modes, and the air pollutant emission difference between ground transportation and multimodal UAM were compared. The method was applied to the case study of the Tampa Bay region and shows that compared to ground transportation modes, on-demand UAM (including considering access and egress modes) emits more greenhouse gas, SO_2, and $PM_{2.5}$ while emitting less NO_x based on the FRCC's hydrocarbon fuel-dominated electricity structure. As the proportion of electric vehicles in the automobile fleet increases, greenhouse gas differences will increase further, and the NO_x, SO_2, and $PM_{2.5}$ difference will decrease. The comparison results depend on the structure of electric power production, as greenhouse gas emissions are related to the proportion of non-renewable energy in electricity production, and the other air pollutants are positively related to the proportion of oil and coal. A lower UAM price and increased number of vertiports will spur the diverted demand, and, as a result, the greenhouse gas emission and other air pollutants (SO_2, $PM_{2.5}$) emissions difference increase and NOx will decrease more. Although the method can be applied for other regions, the comparison results of Tampa Bay area are not transferrable to other regions directly because geographic features, roadway structure, and resource mix for electricity generation could vary significantly from region to region.

In an ongoing effort, network design and demand estimation for future years in the Tampa Bay area are being explored. Also, information is being collected on a future resources mix for electricity generation and applying that to the additional environmental impact analysis of UAM. Another ongoing study is investigating how to predict induced demand that could be caused by the introduction of UAM. The anticipated outcomes will enhance understanding of emerging UAM and advance public awareness of the integration of UAM with the existing multimodal transportation system.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Transportation.

Appendix. A: Map of eGRID subregions

Appendix B: Energy source profiles of electricity production in different subregions.

Region	Coal	Oil	Gas	Nuclear	Hydro	Biomass	Wind	Solar	Geothermal	Other Fossil	Other Unknown	CO_2 total output emission rate (lb/MWh)
US	27.46 %	0.60 %	35.13 %	19.36 %	6.88 %	1.65 %	6.54 %	1.53 %	0.38 %	0.35 %	0.12 %	947.182
AKGD	13.54 %	8.29 %	61.05 %	0 %	13.63 %	0.92 %	2.63 %	0 %	0 %	0 %	0 %	1039.635
AKMS	0 %	26.29 %	7.15 %	0 %	64.36 %	0.17 %	2.07 %	0 %	0 %	0 %	0 %	525.083
AZNM	26.70 %	0.04 %	41.10 %	18.81 %	3.37 %	0.38 %	1.77 %	4.38 %	3.44 %	0 %	0.01 %	1022.355
CAMX	4.38 %	0.04 %	45.18 %	9.10 %	10.99 %	2.83 %	7.30 %	14.92 %	4.19 %	0.73 %	0.33 %	496.536
ERCT	22.62 %	0.03 %	48.55 %	10.00 %	0.22 %	0.24 %	17.02 %	0.77 %	0 %	0.44 %	0.11 %	931.672
FRCC	11.62 %	0.89 %	70.64 %	12.56 %	0.10 %	2.63 %	0 %	0.93 %	0 %	0.01 %	0.62 %	931.842
HIMS	0 %	66.20 %	0 %	0 %	3.52 %	1.86 %	14.63 %	2.89 %	4.01 %	0 %	6.89 %	1110.689
HIOA	18.59 %	69.93 %	0 %	0 %	0 %	6.35 %	2.84 %	1.49 %	0 %	0.79 %	0 %	1669.943
MROE	64.10 %	0.50 %	22.58 %	0 %	5.30 %	4.25 %	3.07 %	0.03 %	0 %	0.07 %	0.10 %	1678.016
MROW	51.81 %	0.10 %	8.03 %	10.62 %	6.00 %	1.06 %	21.68 %	0.47 %	0 %	0.03 %	0.19 %	1239.848
NEWE	0.98 %	1.18 %	48.93 %	29.75 %	6.74 %	7.66 %	3.37 %	1.14 %	0 %	0.15 %	0.10 %	522.312
NWPP	21.32 %	0.18 %	15.71 %	3.29 %	47.66 %	1.23 %	8.28 %	1.32 %	0.60 %	0.28 %	0.13 %	639.037
NYCW	0 %	1.42 %	60.11 %	37.55 %	0 %	0.91 %	0 %	0.02 %	0 %	0 %	0 %	596.414
NYLI	0 %	5.49 %	84.25 %	0 %	0 %	8.97 %	0 %	1.29 %	0 %	0 %	0 %	1184.241
NYUP	0.81 %	0.57 %	25.90 %	31.30 %	34.60 %	1.98 %	4.68 %	0.17 %	0 %	0.00 %	0 %	253.112
RFCE	15.55 %	0.47 %	39.65 %	38.95 %	1.96 %	1.73 %	0.99 %	0.51 %	0 %	0.19 %	0.00 %	715.966
RFCM	43.10 %	1.27 %	32.46 %	13.60 %	0 %	1.96 %	5.69 %	0.11 %	0 %	1.80 %	0.00 %	1312.56
RFCW	44.41 %	0.33 %	20.98 %	28.28 %	0.89 %	0.64 %	3.61 %	0.11 %	0 %	0.71 %	0.05 %	1166.096
RMPA	44.76 %	0.02 %	25.47 %	0 %	12.46 %	0.25 %	15.33 %	1.62 %	0 %	0 %	0.09 %	1273.615
SPNO	46.95 %	0.15 %	11.69 %	12.95 %	0.15 %	0.11 %	27.95 %	0.05 %	0 %	0.00 %	0.01 %	1163.187
SPSO	30.94 %	1.70 %	39.99 %	0 %	2.81 %	1.44 %	22.40 %	0.40 %	0 %	0.26 %	0.06 %	1166.582
SRMV	16.78 %	0.97 %	56.54 %	20.68 %	1.32 %	1.62 %	0 %	0.11 %	0 %	1.68 %	0.30 %	854.645
SRMW	70.21 %	0.05 %	9.41 %	14.80 %	0.97 %	0.13 %	4.16 %	0.04 %	0 %	0.03 %	0.19 %	1664.15
SRSO	26.33 %	0.20 %	47.25 %	18.47 %	3.03 %	3.65 %	0 %	1.03 %	0 %	0.03 %	0.00 %	1027.928
SRTV	35.47 %	0.08 %	26.50 %	27.46 %	9.53 %	0.75 %	0.02 %	0.17 %	0 %	0.03 %	0 %	1031.537
SRVC	19.10 %	0.55 %	34.63 %	37.80 %	2.29 %	2.82 %	0.45 %	2.18 %	0 %	0.10 %	0.07 %	743.328

Source: US EPA, 2018.

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