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AUTONOMOUS AIRCRAFT: CHALLENGES AND OPPORTUNITIES

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16. Abstract

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Autonomous Aircraft: Challenges and Opportunities

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ABSTRACT

The emerging field of advanced air mobility (AAM) presents myriad opportunities for disrupting traditional modes of transport, including passenger travel to cargo logistics. However, its path to full-scale adoption is fraught with regulatory, market, and logistical challenges. This report presents a nuanced understanding of AAM's complexities and its potential for transformative impact, particularly to reduce the impacts on surface transportation degradation. The research employs data-driven methodologies, machine learning algorithms, and geographic information system (GIS) techniques to explore the landscape of AAM. These studies reveal the crucial role of regulatory frameworks and gross domestic product in AAM adoption, the importance of accurate market forecasting, and the value of identifying key commodity and geographical targets for cargo drones. Additionally, this study highlights the potential of AAM in safely transporting dangerous cargo and improving pharmaceutical supply chains. The successful integration of AAM into global transportation systems requires a multi-disciplinary and multi-stakeholder approach. This study highlights the need for future research to build on this work to scale and optimize AAM technologies to meet the varying needs of nations and industries worldwide.

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1. INTRODUCTION

The emergence of autonomous vehicles of all types has created a new landscape of autonomous logistics that is complex and filled with uncertainties. Autonomous-electric taxis, trucks, trains, aircrafts, and ships are underway because of global *push* and *pull* factors [1]. Technological advancements in energy storage, capacity, computing, communications, and lightweight structural materials have reduced the cost, size, noise, and risks of vehicle operations. As a result, there has been a manufacturing *push* of many variants into the marketplace. Anticipated improvements in cost-efficiency, safety, reliability, speed, and pollution reduction have motivated a commercial *pull* for the technology [2]. As carriers began partnerships with major retailers and restaurants to deliver groceries and food with autonomous road and sidewalk robotic vehicles, the global pandemic of 2020 has solidified and accelerated those trends [3]. These developments resulted in a blossoming new field called *autonomous logistics*.

This research focuses on the subfield of autonomous aircraft logistics. Advancements in low-cost sensing and artificial intelligence have increased the affordability of unmanned aircraft systems (UAS), more commonly known as drones. Beyond cargo logistics, businesses are using drones for several other applications such as aerial photography, search and rescue, terrain mapping, safety inspections, crop monitoring, storm tracking, law enforcement, and air-taxis [4]. This report focuses on the subfield of autonomous aircraft *cargo* logistics (AACL) to directly contrast it with autonomous aircraft *passenger* logistics (AAPL), or flying taxis. The FAA Urban Air Mobility (UAM) program covers both cargo and passenger modes of autonomous aircraft logistics [5].

There are many uncertainties about AACL adoption. Wing Aviation LLC (a division of Alphabet, Google's parent company), UPS, and Amazon were among the first companies to gain FAA approvals for commercial package delivery drone operations beyond visual line of sight. Meanwhile, DHL, Uber, and Walmart have been testing drone-based delivery services in preparation to launch those services within the next few years. Hence, AACL will potentially compete with trucks and other modes of ground transportation. The potential disruptions from AACL are likely to upend business models and change the landscape for logistics.

This study addresses the United States Department of Transportation (USDOT) strategic goal of maintaining a state of good repair. The solution lies in the anticipation that low-cost aircraft can spur a mode shift away from surface transportation to relieve the load stress and burden of congestion. Moving traffic off roadways will prolong service life and reduce pollutive emissions. While the prospect of reduced pollution, lower transport costs, enhanced accessibility, and resilient supply chains makes AAM a compelling alternative, the regulatory landscape remains fragmented, posing challenges to widespread adoption.

The goal of this research is to understand the state of AAM regulatory frameworks, examine market forecasts, and explore the potential for using drones in cargo logistics, including case studies in the transport of dangerous goods and pharmaceuticals. By elucidating the current state of AAM, identifying predictive indicators, and highlighting market opportunities and key applications, this report aims to accelerate the deployment of AAM technologies and services in a way that is economically viable, environmentally sustainable, and socially responsible.

The organization of this report is as follows: Section 2 reviews the literature focused on the research goals. Section 3 reports the methods developed to forecast adoption and to explore real-world application opportunities in cargo logistics. Section 3 also discusses the results of applying the proposed methods. Section 4 addresses the limitations of this study and proposes further research. Section 5 concludes the report with suggestions about how stakeholders can benefit from the research and findings.

2. LITERATURE REVIEW

Advanced Air Mobility (AAM) has garnered increasing attention with retail giants like Walmart and Amazon leading the way in drone delivery services [6]. Figure 2.1 organizes a taxonomy of the authors' findings from the literature about the factors that affect AAM adoption.

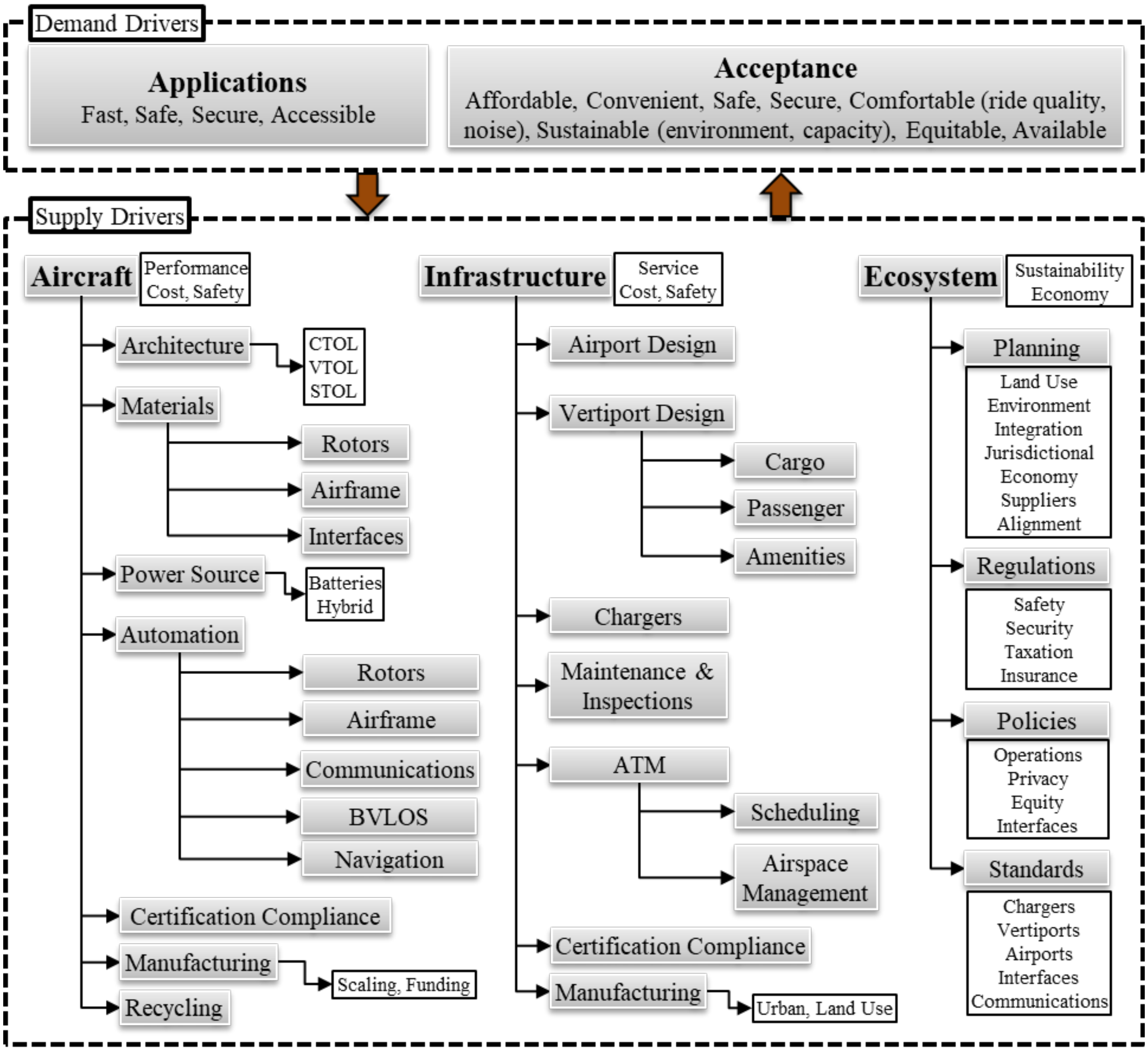

Figure 2.1 Empirical classification of key factors in the adoption of AAM

This section reviews the literature on the state of regulatory frameworks, market forecasts, cargo logistics, transport of dangerous goods, and pharmaceutical deliveries via AAM.

2.1 Regulatory Landscape

Studies highlight significant disparities in drone regulations across nations [7] [8]. For instance, African countries lag in promulgating drone regulations due to lack of expertise and resources [9]. There is also no centralized European data repository for remote pilots and legal entities [10]. Regulatory barriers include privacy and security threats, notably in the logistics sector [11].

2.2 Market Forecasting

Market projections for AAM are varied, with estimates ranging from $32 billion [12] to $641 million [13]. Traditional forecasting methods are insufficient to capture the nuanced demand influenced by e-commerce and community acceptance [14] [15]. Current methodologies lack integration between top-down and bottom-up approaches, leading to fragmented understandings [16].

2.3 Cargo Logistics

While researchers have extensively studied last-mile logistics, middle-mile transportation between intermediary facilities remains under-researched [17]. Companies like FedEx [18] and UPS [19] are looking to integrate Electric Aerial Aircraft (EAA) into their middle-mile logistics. BI Intelligence found that half of Walmart's potential customer base for a drone delivery service is within six miles of a store, which is within the current flight range of a typical drone [20]. According to Amazon's FAA petition, approximately 85% of the company's shipped orders weigh less than 5 pounds, which is within the current payload capacity of a typical drone [21]. An analysis by Ark Invest determined that based on conservative estimates for capital and operating costs, it would cost Amazon less than $1 to deliver a package within 30 minutes using drones as compared with $2 to $8 using ground transportation [22].

In addition to cost reduction, AACL could increase the population proportion that shippers can reach for same-day delivery. Direct path accessibility by air enables faster delivery by avoiding frequent stops and road traffic. Robots can work non-stop, day and night, and without a salary, holidays, or sick leave. The persistent shortage of truck drivers can accelerate AACL adoption [23]. Autonomous trucks in the future are not likely to compete with AACL for "last mile" logistics because autonomous truck operations are currently better suited for long-distance travel on highways versus local urban roads [24]. The significant reduction in cost of using drones instead of helicopters could drastically decrease the need for the latter in the short-term. However, the above hypotheses cannot be tested without further analysis to understand the prospects for AACL adoption.

2.4 Transport of Dangerous Goods

Challenges like road conditions, congestion, and environmental concerns continue to plague ground-based logistics [25]. Despite the evident risks associated with transporting hazardous materials [26], there's limited research on the utility of AAM for this purpose [27]. Preliminary work has started to explore the feasibility of carrying specific hazmat by air [28] [29].

2.5 Pharmaceutical Transport

In healthcare, AAM has shown promise for delivering essential medical supplies [30]. Drones have been beneficial for time-sensitive medical emergencies [31] [32] and have improved healthcare access in geographically challenging areas [33] [34]. There's a growing consensus on the transformative potential of AAM across various sectors. However, considerable gaps in the literature remain, particularly in regulatory frameworks, market forecasting, and specific applications like the transport of hazardous goods and pharmaceuticals.

3. METHODS AND RESULTS

The subsections that follow presents methods of forecasting adoption and an exploration of application opportunities for drones.

3.1 Adoption Forecasts

Advanced air mobility (AAM) is the use of electrified drones for cargo and passenger transport.

3.1.1 Predicting Worldwide Adoption

This section briefly reports on the author's work published in the following journal article:

Bridgelall, Raj. "Predicting Advanced Air Mobility Adoption by Machine Learning." *Standards*, 3(1):70-83, DOI:10.3390/standards3010007, March 2023.

This study identified indicators that can predict a country's propensity to adopt AAM. A review of the literature revealed that only developed nations like the U.S., China, and some European countries are actively working on drone technologies and regulations. This study used machine learning (ML) models to analyze 36 different indicators across 204 nations.

The workflow developed for this research is a three-stage process involving feature engineering, feature selection, and machine learning. Figure 3.1 illustrates the workflow, which starts with population data and merges attributes from various datasets, setting the stage for ML model development and predictions. The workflow compared the results from the following 12 ML models: artificial neural network (ANN), logistic regression (LR), support vector machine (SVM), naïve bayes (NB), k-nearest neighbor (kNN), random forest (RF), Catboost, extreme gradient boost (XGB), stochastic gradient descent (SGD), gradient boosting (GB), AdaBoost, and decision tree (DT.) For brevity, the authors refer the reader to Géron (2019) for a detailed description of how these models work and their implementation in Python code [35].

The first stage of the workflow included data acquisition based on reviewing the literature to identify relevant attributes for ML model development. Table 3.1 lists the various economic, environmental, and governance attributes utilized. They include gross domestic product (GDP), population, carbon dioxide (CO_2) emissions, and governance effectiveness index. The data sources were as follows:

- Vertical Flight Society (VFS) [36]
- World Bank Global Economic Prospects (WB-GEP) [37]
- World Bank World Development Indicators (WB-WDI) [38]
- Worldwide Governance Indicators (WGI) [39]
- World Bank Sustainable Development Goals (WB-SDG) [40]
- World Bank Jobs (WB-J) [41]
- World Bank Doing Business (WB-DB) [42]
- Social Progress Index (SPI) [43]

Table 3.2 lists the characteristics on land use, technology, and transportation, including attributes like land area, urban and rural areas, and agricultural land. Table 3.3 lists five predictive performance scores and their mean value for each ML model. The scores were area under the curve (AUC), classification accuracy (CA), precision (Pr), recall (Rc), F1 (harmonic mean of precision and recall), and training plus testing (T&T) time relative to the "constant" model. Géron (2019) provides further insights into the meaning and significance of these scores [35]. Based on the average of five scores, ANN emerged as the best performing model.

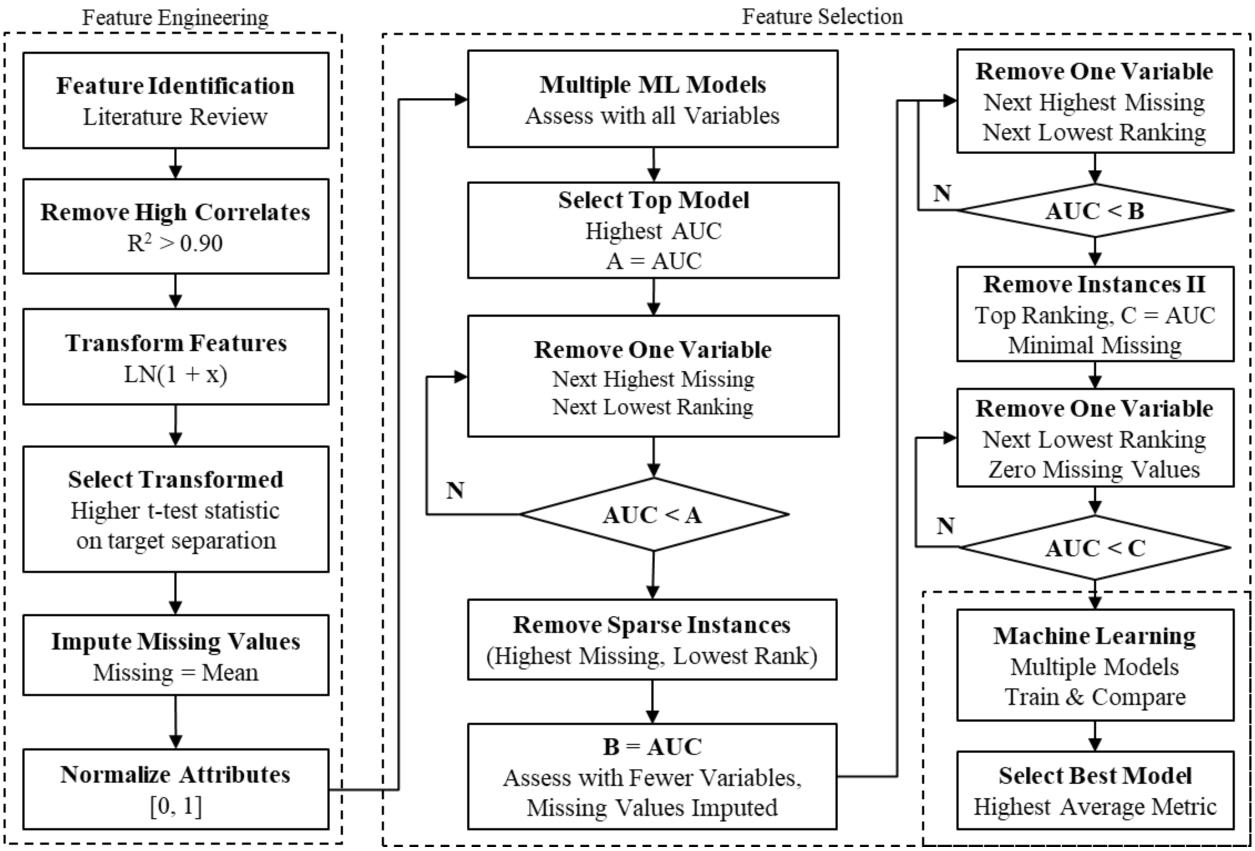

Figure 3.1 Feature engineering and machine learning workflow

Table 3.1 Drones, economic, social, environmental, and governance attributes selected

	Attribute	Description	Dataset	Year	N
Drones	Fly	Drone use regulated (target feature)	CAA Web	2022	222
	Designs_LN	Number of drone designs	VFS	2022	222
Economic	POP_M_LN	Population in millions (LN)	UN-WPP	2022	237
	POP_Gr	Population growth (annual %)	WB-PI	2021	222
	GDP_B_LN	GDP in $billion (LN) (current US$)	WB-WDI	2021	217
	GDPP_LN	GDP per capita (LN) (current US$)	WB-WDI	2021	217
	GDP_Gr	GDP growth (% since 2015 US$)	WB-GEP	2021	217
	Unemploy_LN	Unemployment (% of labor force)	WB-SDG	2020	261
	Arrivals_LN	Number of tourism arrivals	WB-WDI	2020	266
Environment	SPI	Social progress index	SPI	2021	168
	EQI-SPI	Environmental quality index	SPI	2021	168
	CO2_KT_LN	CO2 emissions (kilotons), LN	WB-WDI	2019	266
Governance	Gov_Eff	Governance effectiveness index	WGI	2019	214
	Polit_Stab	Political stability index	WGI	2019	214
	Reg_Qual	Regulatory quality index	WGI	2019	214
	Laws	Rule-of-law index	WGI	2019	214

Table 3.2 Land use, technology, and transportation attributes selected

	Attribute	Description	Dataset	Year	N
Land Use	Land_SqKM	Land area (sq. km)	WB-WDI	2019	268
	Urban_SqKM_LN	Urban area (sq. km), LN	WB-WDI	2010	268
	UrbanPop	Urban population (% of total)	WB-SDG	2020	261
	UrbanGr	Urban population growth (annual %)	WB-SDG	2020	261
	Rural_SqKM	Rural area (sq. km)	WB-WDI	2010	266
	Ag_SqKM	Agricultural land (sq. km)	WB-WDI	2018	266
	Rural_r	Rural/land area ratio	Derived	2010	266
	Urban_r_LN	Urban/land area ratio	Derived	2010	268
	Ag_r_LN	Agricultural/land area ratio	Derived	2010	266
	Forest_PCT_LN	Forest/land area ratio	WB-WDI	2019	266
	POP_SqKM	Population density (persons/sq-km)	WB-J	2016	242
	Land_Type	Landlocked (L), open ocean border (W), island (I)	Google	2022	222
Tech.	Electric_Cost	Cost to get in % of income per capita	WB-DB	2019	191
	ATM100K_LN	ATMs per 100,000 adults	WB-J	2016	242
	Phone100	Mobile phone subscriptions per 100 person	WB-J	2016	242
Transportation	LPI	Logistics performance index	WB-WDI	2018	266
	Infr_Qual	Infrastructure quality index	WB-WDI	2018	266
	Air_Cargo_LN	Air freight (million ton-km), LN	WB-WDI	2019	266
	Air_Pax_LN	Air passengers (year)	WB-WDI	2019	266
	Port_TEU_LN	Port traffic, 20 ft equivalent units (TEU)	WB-WDI	2019	266
	Road_Deaths	Road traffic mortality (per 100,000)	WB-WDI	2019	266

Table 3.3 ML model performance scores

Model	AUC	CA	F1	Pr	Rc	Mean	T&T
ANN	0.923	0.886	0.884	0.882	0.886	0.892	113.6
LR	0.912	0.873	0.864	0.867	0.873	0.878	6.5
SVM	0.885	0.867	0.861	0.860	0.867	0.868	10.0
NB	0.926	0.843	0.852	0.874	0.843	0.868	3.9
kNN	0.870	0.861	0.859	0.857	0.861	0.862	9.3
RF	0.889	0.855	0.850	0.848	0.855	0.859	47.0
Catboost	0.871	0.849	0.849	0.848	0.849	0.853	53.9
XGB	0.876	0.849	0.845	0.842	0.849	0.852	41.5
SGD	0.782	0.861	0.861	0.860	0.861	0.845	6.4
GB	0.853	0.837	0.835	0.832	0.837	0.839	36.9
AdaBoost	0.733	0.801	0.808	0.817	0.801	0.792	11.0
DT	0.658	0.795	0.793	0.791	0.795	0.766	6.1
No Skill	0.459	0.795	0.704	0.632	0.795	0.677	1.0

Figure 3.2 shows the feature ranking by a method called AUC reduction [35]. It indicates that GDP and regulatory quality were the top predictors for AAM adoption. For the top performing model, these attributes accounted for a 4% to 8% improvement in the model's predictive performance. This result suggests that practitioners should focus on these indicators when assessing a country's readiness for AAM. Interestingly, factors like social progress index, land use characteristics, and technology accessibility were poor predictors.

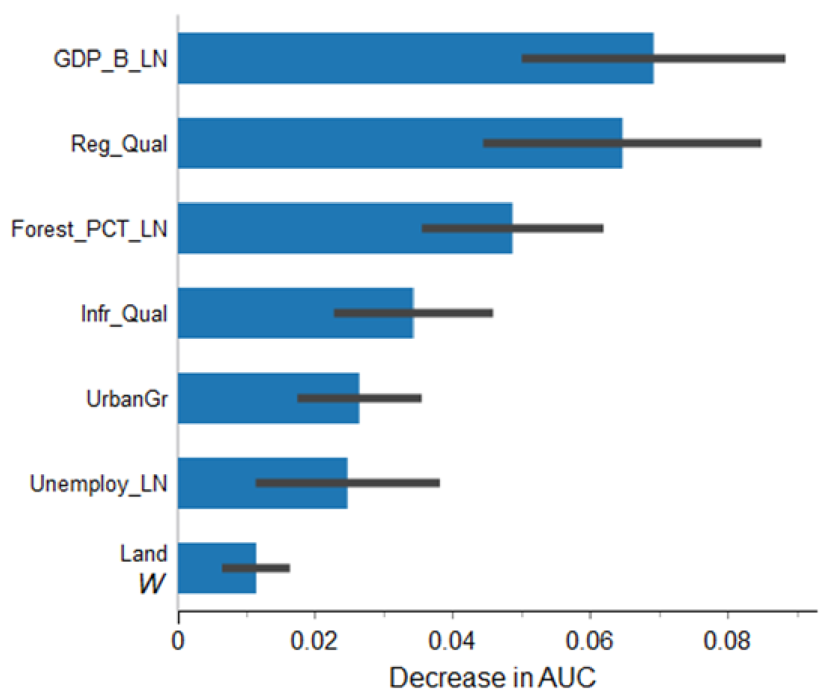

Figure 3.2 ANN feature ranking by AUC reduction

Figure 3.3 visualizes the relative likelihood of AAM adoption among nations based on their GDP and regulatory quality. Nations in the upper right quadrant are more likely to adopt AAM. The figure shows that the United States and China are outliers in regulating drone operations, testing more than 75% of all known designs.

Insights from this research can benefit technology developers, market prospectors, and international organizations. planners seeking to break into the AAM market should focus on countries with strong GDP and regulatory frameworks. Machine learning can be a powerful tool for predicting AAM adoption. However, the landscape is ever-changing, and today's laggards could be tomorrow's leader in AAM adoption.

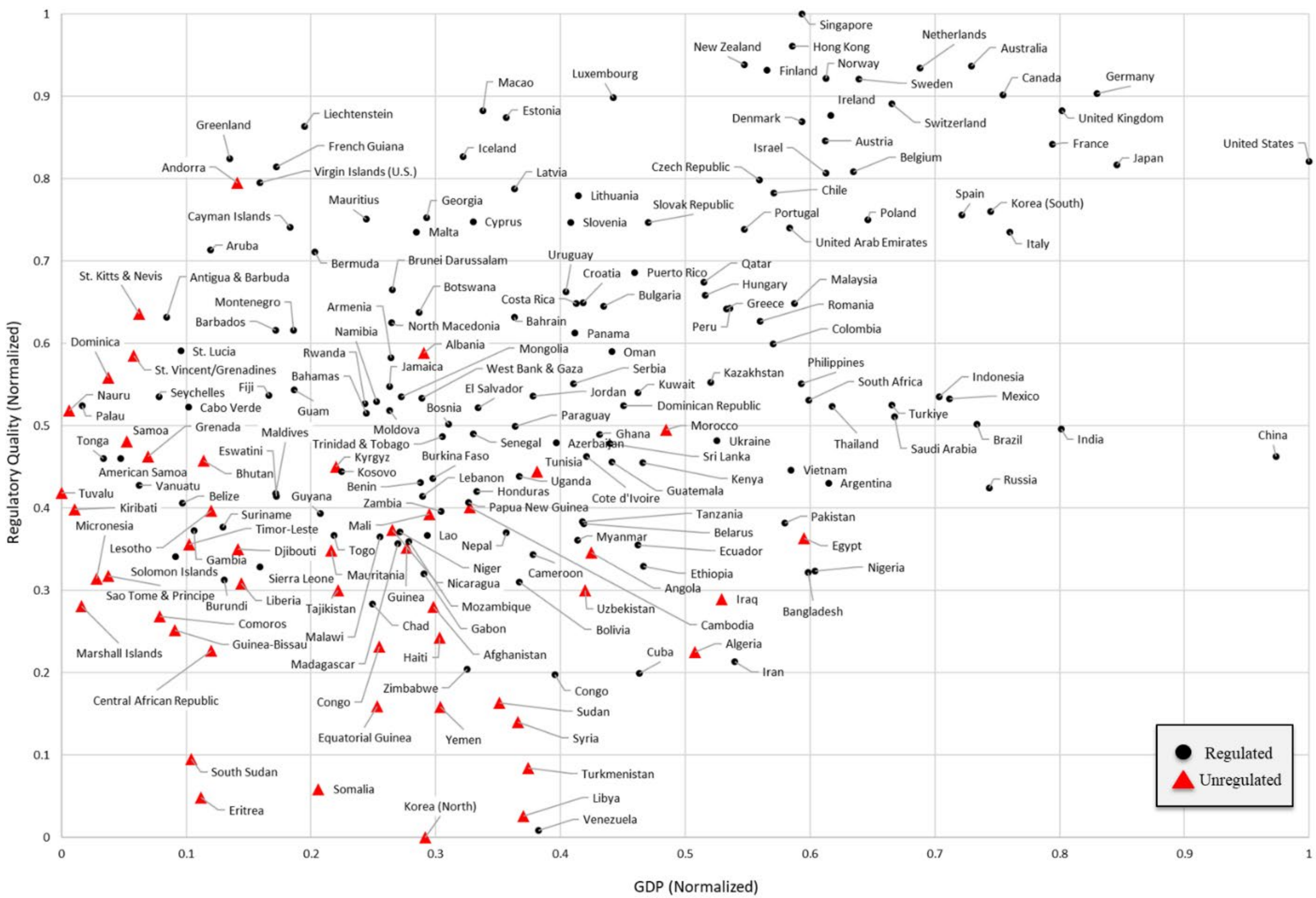

Figure 3.3 Normalized regulatory quality index and GDP

3.1.2 Forecasting Market Opportunities

This section briefly reports on the author's work published in the following journal article:

Bridgelall, Raj. "Forecasting Market Opportunities for Urban and Regional Air Mobility." *Technological Forecasting and Social Change*, 196(122835), DOI:10.1016/j.techfore.2023.122835, November 2023.

This section presents a comprehensive study on the market opportunities for urban air mobility (UAM), with a spotlight on Uber Elevate. The study employed a multifaceted approach, combining data mining and analytics, to forecast demand across four distance bands: 100, 200, 300, and 400 miles. The study identified 2,083 viable routes among 859 U.S. cities and estimated that around 78,000 passengers will use 4,214 vertipads daily to fly on 3,023 four-passenger eVTOL aircraft by 2030.

The methodological framework developed was a hybrid data mining and analytical workflow, visually represented in Figure 1. The framework started with cleaning population datasets to enable their merging to forecast the 2030 population for each city. The model also incorporated Transportation Network Company (TNC) statistics and Uber trip data to estimate the number of trips generated and the likelihood of mode shift for each city.

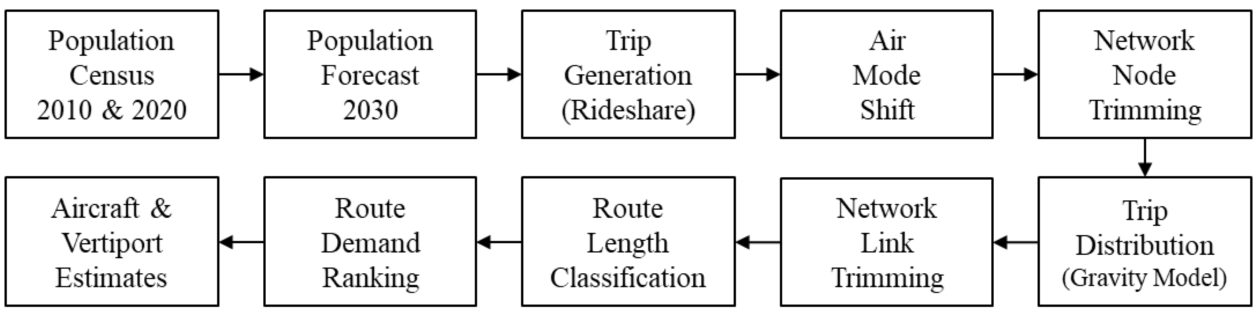

Figure 3.4 The data mining and analytical workflow of this study

Table 3.4 lists the data sources used in the study, including population datasets and TNC statistics. The data listed serves as the foundation for the hybrid methodology employed. The capacity of a vertipad under the above scenarios was

$$V_{\mathrm{c}} = \left\lceil \frac{60H_{\mathrm{O}}}{B_{\mathrm{c}} + T_{\mathrm{L}} + T_{\mathrm{D}}} \right\rceil = 26 \tag{1}$$

where $\lceil \cdot \rceil$ is the mathematical ceiling function that rounds up a value to the nearest integer. Table 3.5 summarizes the variables used in the calculations. Given that 30% of the population uses TNC and that the average annual trip rate is 10.4 (Table 3.4), the estimated average annual passenger departures from all vertiports at node *i* is

$$Y_i = P_i r_{\mathrm{p}} r_r r_{36} = \frac{P_i}{3.21} \cdot \tag{2}$$

where the value 3.21 = 1/(0.3 × 10.4 × 0.10). Therefore, the annual number of four-passenger drone departures from node *i* is

$$A_i = \frac{Y_i}{D_C} = \frac{P_i}{3.21 \times 4} = \frac{P_i}{12.82}. \tag{3}$$

Table 3.4 Data Used in the Analysis

Vars	Description	Value	Units	Source
D_m	Average eVTOL flight range advertised	91	Miles	[44]
B_N	Distance band category	{100, 200, 300, 400}	Miles	
S_m	Average eVTOL cruise speed advertised	125	MPH	[44]
S_e	Cruise speed for peak motion efficiency	125	MPH	[45]
B_c	Aircraft battery charge time	30	Minutes	[46]
T_L	Aircraft vertical lift time	1	Minute	[45]
T_D	Aircraft vertical descent time	1	Minute	[45]
H_O	Operating Hours (6 a.m. to 8 p.m.)	14	Hours	[47]
D_C	Drone passenger capacity + 1 pilot	4	Count	[45]
P_i	2030 population estimate for city at node *i*	Var	Count	[48]
XY_i	Centroid geospatial coordinates for node *i*	Var	degrees	[49]
r_p	Proportion of population using TNC rides	0.30	Proportion	[50]
r_r	Average annual TNC ride trip rate	10.4	per year	[51]
r_{AP}	Proportion of Uber trips accessing airports	0.17	Proportion	[45]
r_{36}	Proportion of rides longer than 36 minutes	0.10	Proportion	[51]
r_{60}	Proportion of rides longer than 60 minutes	0.06	Proportion	[45]
R_T	Average TNC ride trip time	14	Minutes	[51]
R_W	Average TNC ride wait time	5.8	Minutes	[52]
H_D	Haversine distance factor of road distance	0.71	Proportion	[45]

Table 3.5 Variables Used in the Analysis

Vars	Description	Units
Y_i	Average annual passenger departures from node *i*	Count
A_i	Average annual drone departures from node *i*	Count
$D\{i,j\}$	Average daily drone round trips on route $\{i,j\}$	Count
M_{ij}	Average daily trip-miles between nodes *i* and *j*	Trip-Miles
d_{ij}	Haversine distance between nodes *i* and *j*	Miles
F_{ij}	Flight time between nodes *i* and *j*	Minutes
Δ_{ij}	Time between availability of the same aircraft at node *i*	Minutes
R_{ij}	Road distance between nodes *i* and *j*	Miles
G_{ij}	Ground (road) travel time between nodes *i* and *j*	Minutes
r_{ij}	Flight time to road time ratio between nodes *i* and *j*	Proportion
$N\{i,j\}$	Number of drones serving route $\{i,j\}$	Count
$Q\{i,j\}$	Average daily departures per drone on route $\{i,j\}$	Count
$U\{i,j\}$	Average annual aircraft utilization on route $\{i,j\}$	Hours
V_c	Vertipad capacity (daily departures per vertipad)	Count
$V\{i,j\}$	Vertipads needed at each trip end of route $\{i,j\}$	Count
V_i	Minimum number of vertipads needed at node *i*	Count

This yields an average number of *daily* four-passenger drone departures from node *i* as

$$D_i = \frac{A_i}{365} = \frac{P_i}{4679.5}. \tag{4}$$

The above quantity is equivalent to 0.021% of the population at a node. For perspective, the above model predicts that a city of 9,359 persons will have 2,808 TNC users (30%) who would produce an average demand of two daily four-passenger drone departures. Hence, the strategy was to modify the model to reflect equal weight between the relative importance and relative impedance of locations with routes connecting to node *i*. That is, let {***J***} be the set of nodes *j* = {1, 2 ...} connected to node *i*. Hence, the number of departures that node *j* attracts from node *i* is

$$D_{ij} = D_i \left[\frac{1}{2} \left(\frac{D_j}{\sum_{j \in \{\boldsymbol{J}\}} D_j} \right) + \frac{1}{2} \left(\frac{1/d_j^2}{\sum_{j \in \{\boldsymbol{J}\}} (1/d_j^2)} \right) \right] \cdot \tag{5}$$

Airlines use the concept of "passengers daily each way" (PDEW) to measure the demand on a regional route [53]. PDEW assumes that passengers arriving at node *i*, especially commuters and business travelers, will return at some time. Therefore, returning passengers at node *i* will add to its departing passengers. Hence, the number of *round trips* on route $\{i, j\}$ was the sum of departures originated at each trip end such that

$$D\{i, j\} = \lfloor D_{ij} + D_{ji} \rfloor \tag{6}$$

where the operator $\lfloor \cdot \rfloor$ is the mathematical floor function that rounds down a value to the nearest integer. The number of *round trips* on route $\{i, j\}$ was the sum of departures originated at each trip end such that

$$D\{i, j\} = \lfloor D_{ij} + D_{ji} \rfloor \tag{7}$$

where the operator $\lfloor \cdot \rfloor$ is the mathematical floor function that rounds down a value to the nearest integer. The flight time from node *i* to node *j* is

$$F_{ij} = \frac{D_\mathrm{m}}{S_\mathrm{m}} + T_\mathrm{L} + T_\mathrm{D} \cdot \tag{8}$$

Based on round trips, the time between availability of the same aircraft at node *i* is

$$\Delta_{ij} = 2(B_\mathrm{c} + F_{ij}) \cdot \tag{9}$$

The number of four-passenger drones needed to serve route $\{i, j\}$ is

$$N\{i, j\} = \left\lceil \frac{D\{i, j\}\Delta_{ij}}{60 H_0} \right\rceil \cdot \tag{10}$$

The average number of daily one-way trips per drone that serve route $\{i, j\}$ is

$$Q\{i, j\} = \left\lceil \frac{2 \times D\{i, j\}}{N[i, j]} \right\rceil \cdot \tag{11}$$

The average daily trip-miles for route $\{i, j\}$ is

$$M_{ij} = 2 \times D\{i,j\}F_{ij} \cdot \tag{12}$$

The average aircraft utilization on route $\{i, j\}$ in annual flight hours is

$$U\{i,j\} = Q\{i,j\} \times F_{ij} \times 365/60 \cdot \tag{13}$$

The number of vertipads needed at each trip end of route $\{i, j\}$ is

$$V\{i,j\} = \left\lceil \frac{D\{i,j\}}{V_c} \right\rceil \tag{14}$$

Vertipads dedicated for specific routes may be underutilized. Hence, sharing a vertipad to serve multiple routes will increase utilization. Therefore, the lower bound for the number of route-shared vertipads needed at node *i* is

$$V_i = \left\lceil \frac{\sum_{j \in \{J\}} D\{i,j\}}{V_c} \right\rceil \tag{15}$$

The lower bound represents the theoretical scenario of 100% vertipad capacity utilization. Practically, however, more vertipads will be necessary to design some slack in the system that would accommodate operational variations such as flight, departure, and charge times.

Table 3.6, Table 3.7, Table 3.8, and Table 3.9 present the top ten cities within the 100-mile, 200-mile, 300-mile, and 400-mile bands, respectively. They provide a snapshot of where the highest demand is likely to be, based on the study's methodology. These tables offer metrics for the top ten routes within each distance band and summarize the demand forecast. They reveal that focusing on higher distance bands could be more lucrative on a per-seat-mile basis, but the first 100-mile band offers a larger market in terms of daily passenger volume. Table 3.10 present metrics for the top ten routes among all distance bands. Table 3.11 presents a summary of the overall demand forecast.

Table 3.6 Metrics for the Top Ten 100-mile Rand Routes

Top Ten (100-mile Band)	$\mathbf{M_{ij}}$	$\mathbf{d_{ij}}$	$\mathbf{F_{ij}}$	$\mathbf{R_{ij}}$	$\mathbf{G_{ij}}$	$\mathbf{r_{ij}}$	***D*{*i*, *j*}**	***N*{*i*, *j*}**	***Q*{*i*, *j*}**	***U*{*i*, *j*}**	***V*{*i*, *j*}**	$\mathbf{V_i}$	$\mathbf{V_j}$
New York_NY ↔ Philadelphia_PA	20,665	79	40.2	94	110	0.370	130	22	12	2,931	5	95	11
Austin_TX ↔ San Antonio_TX	3,107	74	37.5	80	77	0.490	21	4	11	2,510	1	10	14
Los Angeles_CA ↔ Bakersfield_CA	2,037	93	46.4	111	113	0.410	11	3	8	2,260	1	42	2
Denver_CO ↔ Colorado Springs_CO	1,985	62	31.8	71	68	0.470	16	3	11	2,126	1	7	4
New York_NY ↔ Hartford_CT	1,769	98	49.2	116	146	0.340	9	2	9	2,692	1	95	1
New York_NY ↔ Allentown_PA	1,636	82	41.3	93	106	0.390	10	2	10	2,510	1	95	1
New Haven_CT ↔ New York_NY	1,618	67	34.4	80	115	0.300	12	2	12	2,509	1	1	95
Chicago_IL ↔ Milwaukee_WI	1,546	86	43.2	92	89	0.490	9	2	9	2,366	1	16	1
Waterbury_CT ↔ New York_NY	1,511	76	38.3	95	121	0.320	10	2	10	2,327	1	1	95
New York_NY ↔ Bridgeport_CT	1,437	51	26.6	65	101	0.260	14	2	14	2,269	1	95	1
Average	3,731	77	38.9	90	105	0.384	24.2	4.4	10.6	2,450	1.4	45.7	22.3

Table 3.7 Metrics for the Top Ten 200-mile Band Routes

Top Ten (200-mile Band)	$\mathbf{M_{ij}}$	$\mathbf{d_{ij}}$	$\mathbf{F_{ij}}$	$\mathbf{R_{ij}}$	$\mathbf{G_{ij}}$	$\mathbf{r_{ij}}$	***D*{*i*, *j*}**	***N*{*i*, *j*}**	***Q*{*i*, *j*}**	***U*{*i*, *j*}**	***V*{*i*, *j*}**	$\mathbf{V_i}$	$\mathbf{V_j}$
New York_NY ↔ Boston_MA	24,434	185	90.9	215	234	0.390	66	19	7	3,869	3	95	5
San Antonio_TX ↔ Houston_TX	15,958	190	93.2	198	183	0.510	42	13	7	3,968	2	14	25
Baltimore_MD ↔ New York_NY	12,033	172	84.5	188	203	0.420	35	10	7	3,599	2	2	95
Austin_TX ↔ Houston_TX	9,053	146	72.1	165	156	0.460	31	8	8	3,508	2	10	25
San Diego_CA ↔ Los Angeles_CA	8,771	115	57.4	120	135	0.430	38	8	10	3,492	2	10	42
New York_NY ↔ Worcester_MA	6,493	155	76.2	176	195	0.390	21	6	7	3,245	1	95	1
Austin_TX ↔ Dallas_TX	5,803	181	89.0	195	173	0.510	16	5	7	3,792	1	10	12
Portland_OR ↔ Seattle_WA	5,791	145	71.5	174	166	0.430	20	5	8	3,479	1	5	7
Los Angeles_CA ↔ Fresno_CA	5,598	200	98.0	220	214	0.460	14	5	6	3,576	1	42	3
Indianapolis_IN ↔ Chicago_IL	5,233	164	80.5	183	178	0.450	16	5	7	3,427	1	4	16
Average	9,917	165	81.3	183	184	0.445	29.9	8.4	7.4	3,596	1.6	28.7	23.1

Table 3.8 Metrics for the Top Ten 300-mile Band Routes

Top Ten (300-mile Band)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i,j\}$	$N\{i,j\}$	$Q\{i,j\}$	$U\{i,j\}$	$V\{i,j\}$	V_i	V_j
New York_NY ↔ Washington_DC	24,269	206	100.7	226	255	0.390	59	19	7	4,289	3	95	5
Los Angeles_CA ↔ San Jose_CA	15,808	293	142.5	341	329	0.430	27	12	5	4,335	2	42	6
Dallas_TX ↔ Houston_TX	15,586	223	108.9	239	215	0.510	35	12	6	3,974	2	12	25
Houston_TX ↔ Fort Worth_TX	13,728	237	115.6	262	233	0.500	29	11	6	4,220	2	25	9
New York_NY ↔ Buffalo_NY	13,040	296	144.3	375	383	0.380	22	10	5	4,388	1	95	1
San Diego_CA ↔ Phoenix_AZ	11,840	296	144.1	355	329	0.440	20	9	5	4,382	1	10	17
Chesapeake_VA ↔ New York_NY	11,819	269	130.9	368	401	0.330	22	9	5	3,983	1	2	95
San Antonio_TX ↔ Dallas_TX	11,086	252	122.9	274	263	0.470	22	9	5	3,739	1	14	12
New York_NY ↔ Richmond_VA	10,203	269	130.9	340	388	0.340	19	8	5	3,981	1	95	1
Norfolk_VA ↔ New York_NY	9,887	291	141.6	363	395	0.360	17	7	5	4,306	1	1	95
Average	13,727	263	128.2	314	319	0.415	27.2	10.6	5.4	4,160	1.5	39.1	26.6

Table 3.9 Metrics for the Top Ten 400-mile Band Routes

Top Ten (400-mile Band)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i,j\}$	$N\{i,j\}$	$Q\{i,j\}$	$U\{i,j\}$	$V\{i,j\}$	V_i	V_j
Phoenix_AZ ↔ Los Angeles_CA	36,518	365	177.3	372	352	0.500	50	25	4	4,314	2	17	42
New York_NY ↔ Virginia_VA	26,518	390	189.2	**388**	454	0.420	34	18	4	4,604	2	95	2
San Francisco_CA ↔ Los Angeles_CA	16,901	338	164.3	383	365	0.450	25	12	5	4,996	1	5	42
El Paso_TX ↔ Phoenix_AZ	14,717	350	170.2	430	387	0.440	21	11	4	4,141	1	6	17
Mesa_AZ ↔ Los Angeles_CA	12,420	388	188.3	389	373	0.500	16	9	4	4,582	1	5	42
Pittsburgh_PA ↔ New York_NY	12,116	319	155.1	388	372	0.420	19	9	5	4,716	1	1	95
Nashville_TN ↔ Chicago_IL	11,028	394	191.1	442	462	0.410	14	8	4	4,649	1	4	16
Sacramento_CA ↔ Los Angeles_CA	10,540	351	170.6	386	367	0.460	15	8	4	4,152	1	2	42
Houston_TX ↔ New Orleans_LA	9,843	328	159.5	348	326	0.490	15	7	5	4,851	1	25	2
New York_NY ↔ Akron_OH	8,769	399	193.3	438	427	0.450	11	6	4	4,704	1	95	1
Average	15,937	362	175.9	396	389	0.454	22	11.3	4.3	4,571	1.2	25.5	30.1

Table 3.10 Metrics for the Top Ten Routes Among All Distance Bands

Top Ten (Overall)	M_{ij}	d_{ij}	F_{ij}	R_{ij}	G_{ij}	r_{ij}	$D\{i, j\}$	$N\{i, j\}$	$Q\{i, j\}$	$U\{i, j\}$	$V\{i, j\}$	V_i	V_j	B_N
Phoenix_AZ ↔ Los Angeles_CA	36,518	365	177.3	372	352	0.500	50	25	4	4,314	2	17	42	400
New York_NY ↔ Virginia_VA	26,518	390	189.2	388	454	0.420	34	18	4	4,604	2	95	2	400
New York_NY ↔ Boston_MA	24,434	185	90.9	215	238	0.380	66	19	7	3,869	3	95	5	200
New York_NY ↔ Washington_DC	24,269	206	100.7	226	255	0.390	59	19	7	4,289	3	95	5	300
New York_NY ↔ Philadelphia_PA	20,665	79	40.2	95	106	0.380	130	22	12	2,931	5	95	11	100
San Francisco_CA ↔ Los Angeles_CA	16,901	338	164.3	383	365	0.450	25	12	5	4,996	1	5	42	400
San Antonio_TX ↔ Houston_TX	15,958	190	93.2	198	183	0.510	42	13	7	3,968	2	14	25	200
Los Angeles_CA ↔ San Jose_CA	15,808	293	142.5	341	329	0.430	27	12	5	4,335	2	42	6	300
Dallas_TX ↔ Houston_TX	15,586	223	108.9	239	215	0.510	35	12	6	3,974	2	12	25	300
El Paso_TX ↔ Phoenix_AZ	14,717	350	170.2	430	386	0.440	21	11	4	4,141	1	6	17	400
Average	21,137	262	127.7	289	288	0.441	48.9	16.3	6.1	4,142	2.3	47.6	18.0	300

Table 3.11 Demand Forecast Summary

Band	Routes	Departures	Trip-Miles (K)	Drones	Vertipads
100	1,370	13,010	360	1,547	2,762
200	234	2,238	359	398	480
300	205	2,028	506	454	420
400	274	2,148	749	624	552
Total	2,083	19,424	1,973	3,023	4,214

Figure 3.5a graphically represents the revenue factors of departures and trip-miles. Figure 3.5b represents the capital factors of drones and vertipads. The figure shows that the number of one-way departures decreases significantly after the first 100-mile band but remains relatively stable for the subsequent distance bands. Figure 3.6 maps the cities with viable routes within the 100- and 400-mile bands. It visually confirms that the density of cities with routes is much higher within the first 100-mile band. Table 3.12 summarizes data related to travel time savings. It shows that the daily mean person years saved daily (PYSD) was 2.4 in the first 100-mile band and accumulated to 10.1 in the 400-mile band. Figure 3.7 shows the travel time savings graphically.

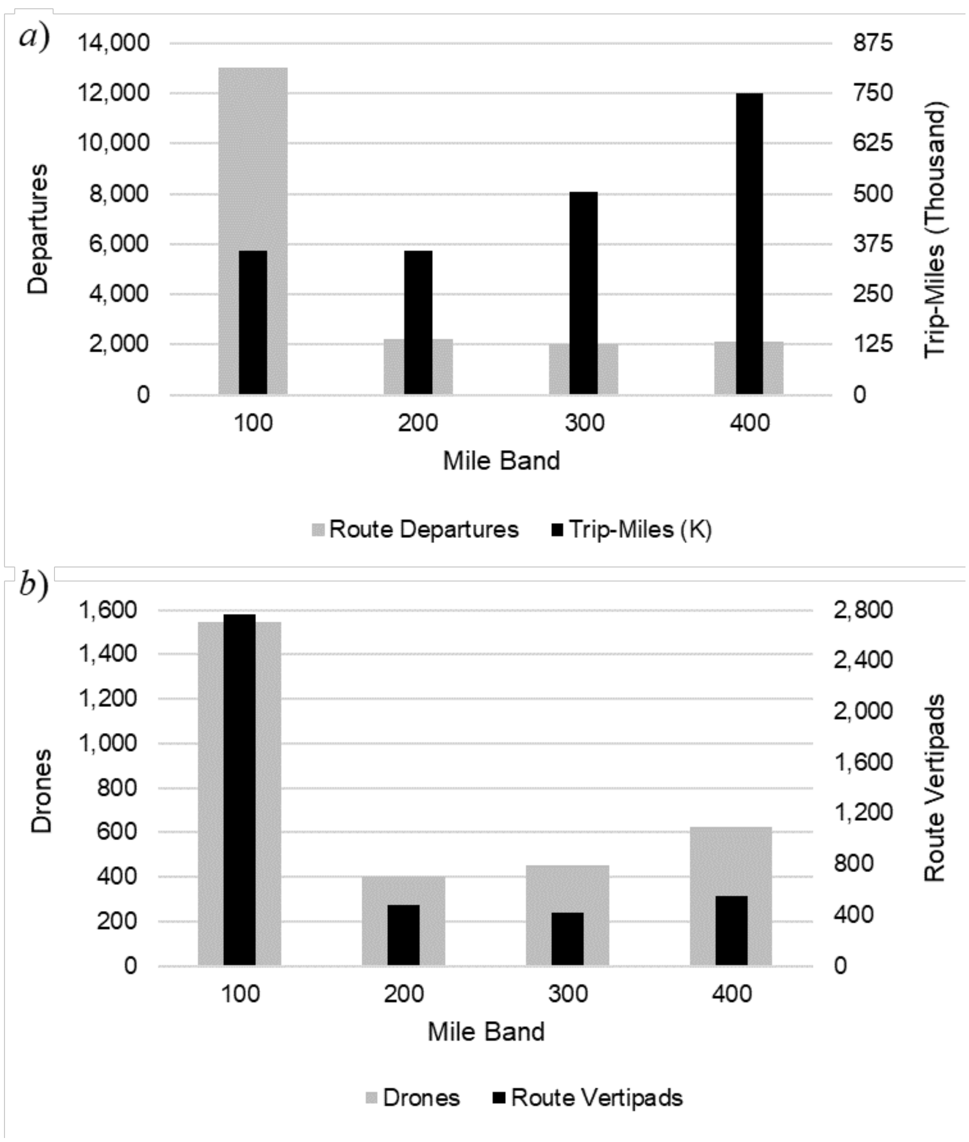

Figure 3.5 Revenue factors of *a*) departures and trip-miles, and *b*) capital factors of drones and vertipads.

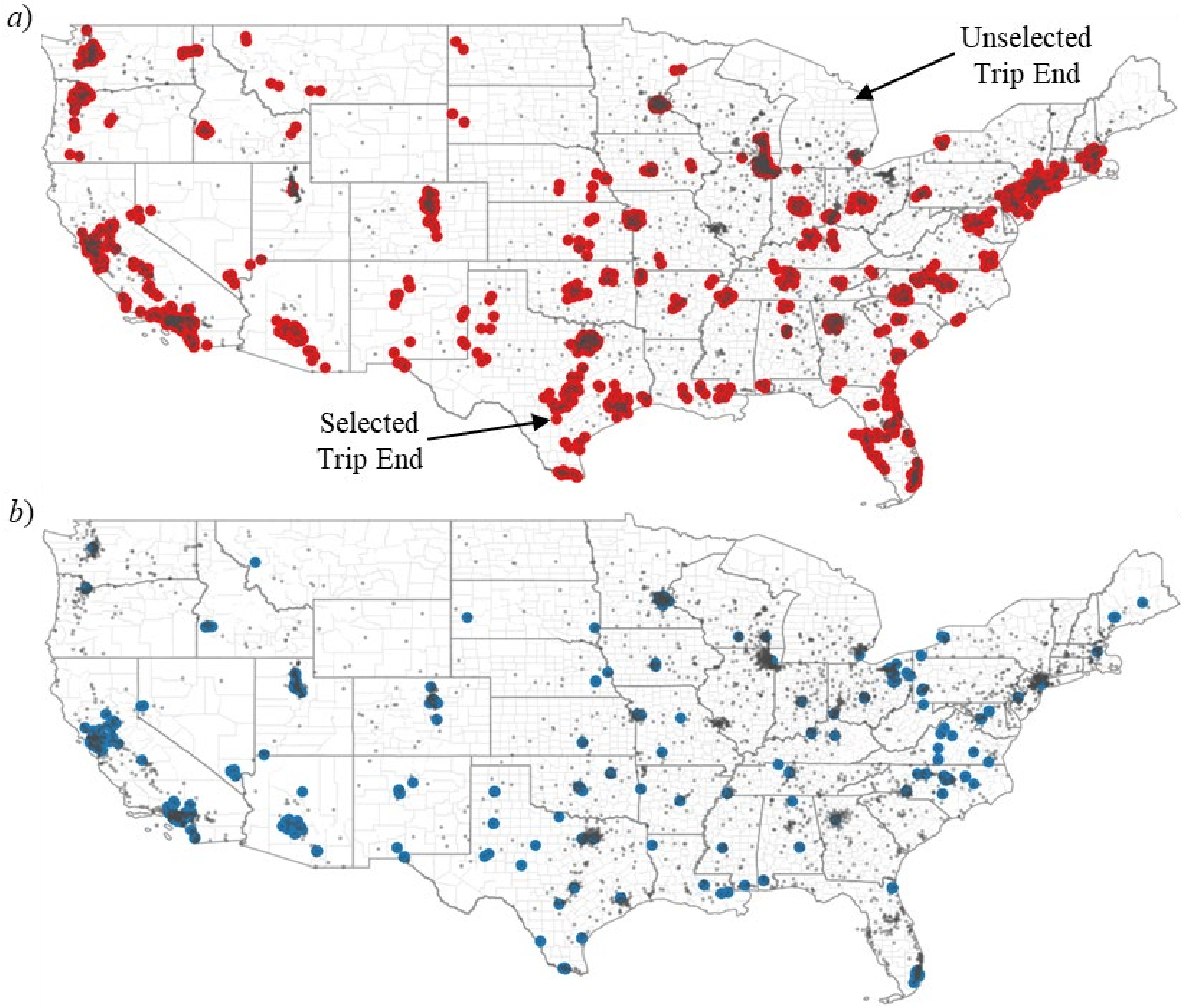

Figure 3.6 Trip ends selected *a*) within a 100-mile band, and *b*) within a 400-mile band

Table 3.12 Time Saving Statistics

Distance Band	μ AMiles	μ AMin	μ RMiles	μ RMin	μ A/R	μ PYSD
100	76.8	38.9	89.7	104.6	0.384	2.4
200	165.3	81.3	183.4	183.7	0.445	1.7
300	263.0	128.2	314.3	319.1	0.415	2.6
400	362.2	175.9	396.4	388.5	0.454	3.3

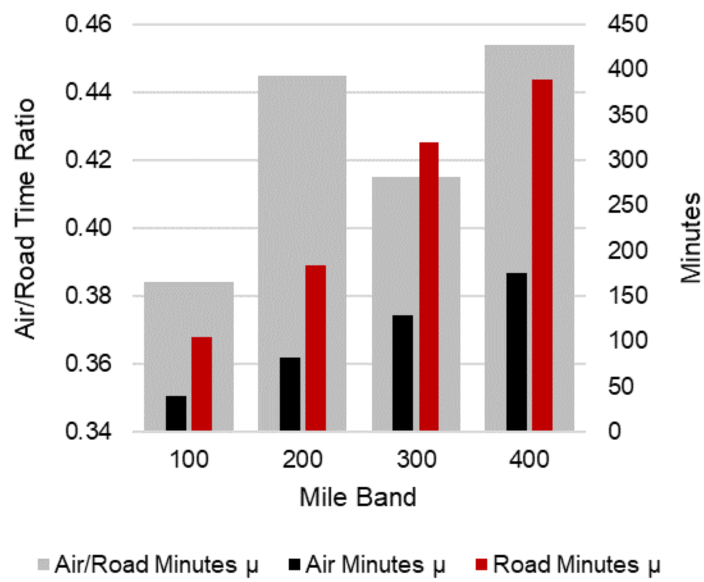

Figure 3.7 Average travel time savings with drones for each distance band

The study concluded that Advanced Air Mobility (AAM) has the potential to significantly disrupt traditional urban and regional travel. It emphasized that technological advancements in battery and airframe materials will extend the operating range of eVTOLs beyond 100 miles, making them increasingly viable for longer routes. The study also pointed out that while the capital needed to serve routes within the first 100-mile band will be significantly higher, the market potential in terms of passenger volume is also greater. Therefore, companies entering this space will need to carefully balance their short-term and long-term strategies to maximize both market capture and profitability.

3.2 Application Opportunities

The next subsections discuss commodities and routes that would be best suited for cargo drones, with dangerous cargo and pharmaceuticals as cases studies.

3.2.1 Commodities and Routes

This section briefly reports on the author's work published in the following journal article: Bridgelall, Raj. "Data-Driven Deployment of Cargo Drones: A U.S. Case Study Identifying Key Markets and Routes." *Algorithms*, 16(8), DOI:10.3390/a16080373, August 2023.

As analyst predict that the number of vehicles on the road will more than double between 2020 and 2050, the traditional trucking model will become increasingly unsustainable [54]. Air transport, particularly when electrified and autonomous, offers a safer and more efficient alternative, especially for high-value, low-weight, and time-sensitive goods. The term 'middle-mile,' which refers to cargo movement between intermediary facilities, is less prevalent in transport logistics compared to 'last-mile.' However, inefficiencies in the middle-mile can significantly affect last-mile deliveries. Previous studies have explored the potential of rlectric and autonomous aircraft (EAA) in various contexts, but this is the first study to have specifically focused on using a data mining and GIS workflow to characterize cargo shipping opportunities with EAA.

The workflow combined data from the 2017 commodity flow survey geographies database and the U.S. Census Bureau's TIGER® database. The former contained origin-destination data among 83 Metropolitan Statistical Areas (MSAs) and 46 other Freight Analysis Framework (FAF) zones. The GIS procedure of the workflow used the second database to calculate geospatial centroids for each zone, aiding in the estimation of flight distances among those regions. Figure 3.8 illustrates the three-stage data mining workflow, aimed at answering the "What", "Where", and "How" of the commodity flows targeted.

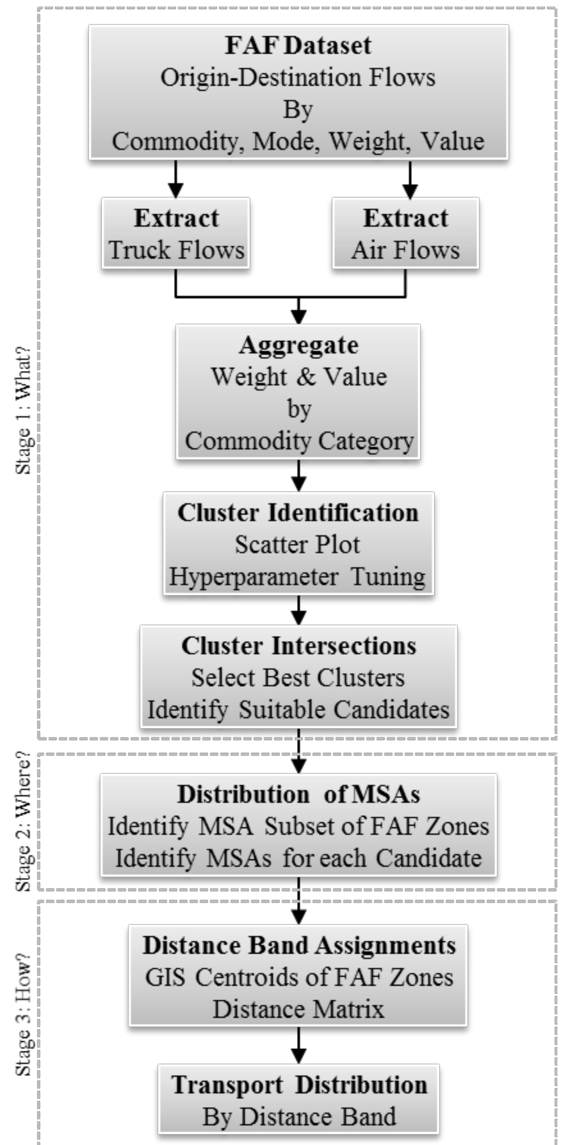

Figure 3.8 Three-stage data-mining workflow

Figure 3.9 shows the results from three clustering algorithms—Louvain, k-means, and DBSCAN—used to identify high-value, low-weight clusters for both truck and air transport. Figure 3.10 shows the clustered high-value, low-weight commodity categories transported by (a) air and (b) trucks. Electronics, machinery, and pharmaceuticals were common categories in both high-value clusters for truck and air.

Table 3.13 presents a summary of the representative composition of each selected commodity category. Table 3.14 summarizes the weight, value, and rank of the four selected commodities that have the highest propensity for mode shift to cargo EAAs. The table shows that these four commodity categories required the equivalent of 28 million semi-trailer trucks (truckload equivalent) in 2017.

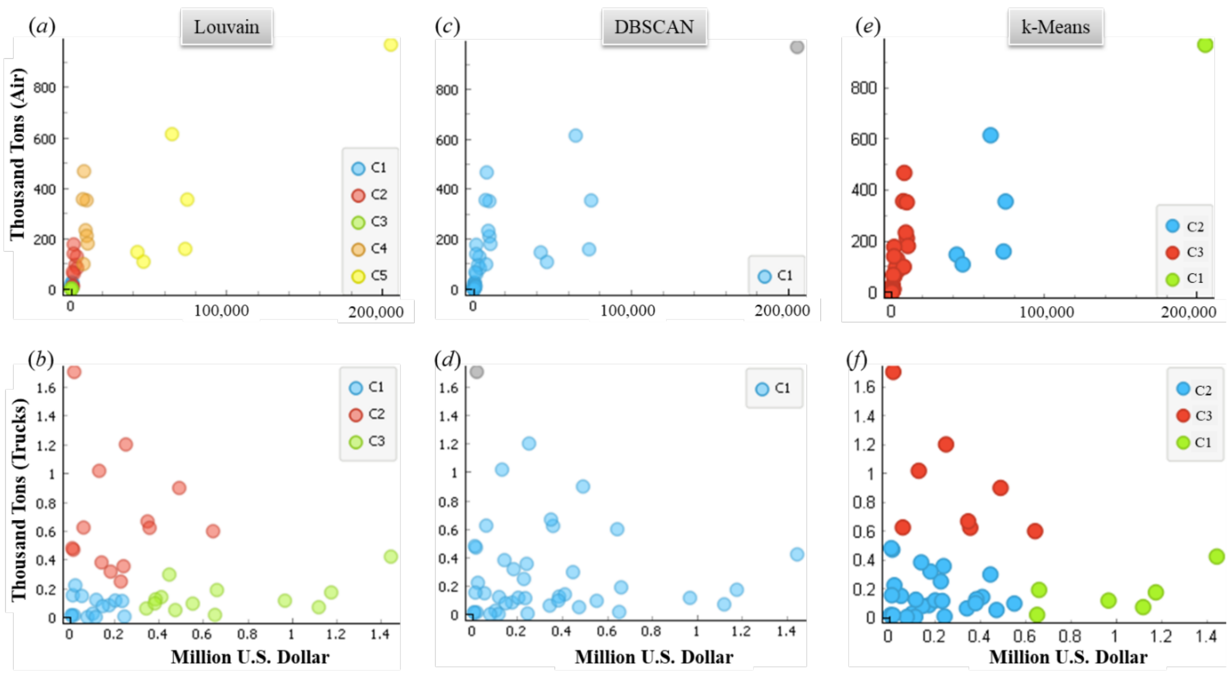

Figure 3.9 Comparison of clustering results for Louvain (**a**,**b**), DBSCAN (**c**,**d**), and k-means (**e**,**f**)

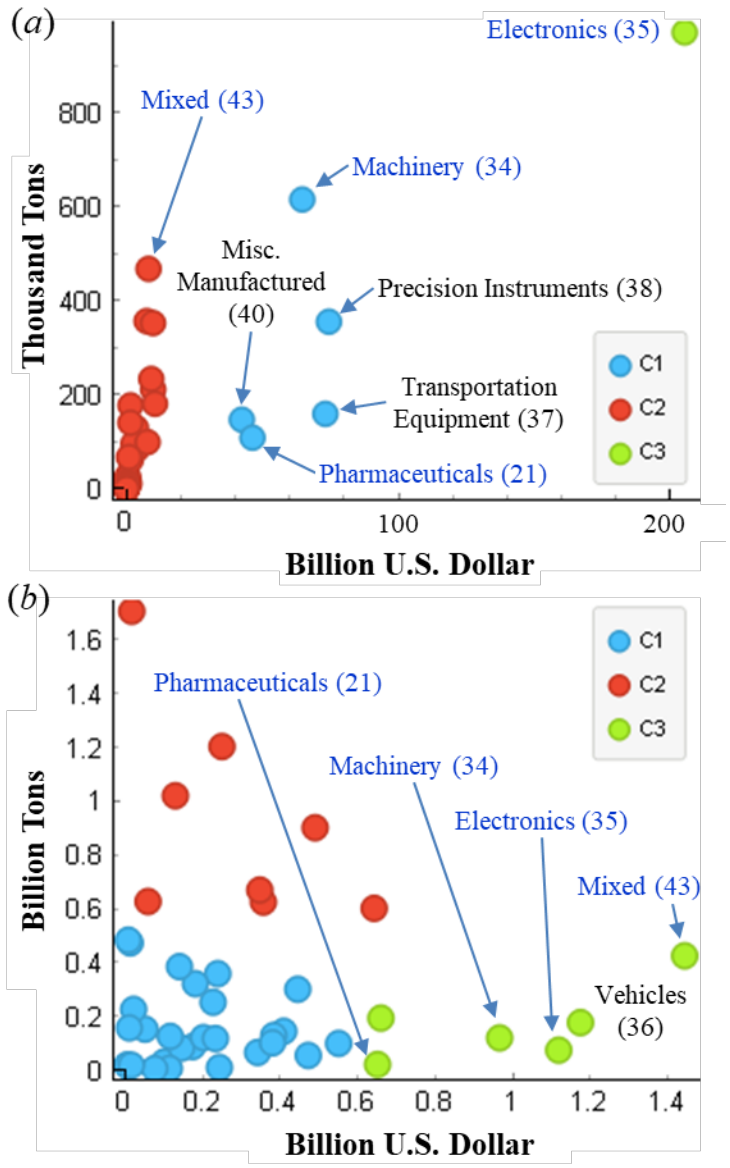

Figure 3.10 Clustered high-value, low-weight commodity categories by (**a**) air and (**b**) using trucks

Table 3.13 Representative content of the selected commodity categories

Commodity Category	Representative Content
Mixed Goods (43)	Food for grocery and convenience stores, supplies and food for restaurants and fast-food chains, hardware or plumbing supplies, and office supplies.
Electronics (35)	Cell phones, batteries, electronic entertainment products, electric cooking appliances, computers, office equipment, recorded media, computer software, electronic components and circuit boards, semiconductor manufacturing machinery, electric motors and generators, cooking appliances, domestic appliances, telephone, and communications equipment.
Machinery (34)	Non-electric motors and parts, pumps, compressors, fans, parts for air conditioning and refrigeration, dishwashers, manufacturing machines and tools, powered hand tools and apparatus, gears, and bearings for manufacturing equipment.
Pharmaceuticals (21)	Chemical mixtures for medical use, biological products, bandages, sutures, dental fillings, bone reconstructive cements, and other chemical preparations for medical use.

Table 3.14 Commodity categories selected for spatial demand analysis

Commodity	Million Tons	Trillion Dollars	% KTons	% USD M	Rank Truck	Rank Air	Truckload Equivalent
Mixed Goods	424.2	1.44	3.3%	10.6%	1	11	18,851,782
Electronics	73.2	1.12	0.6%	8.2%	3	1	3,253,678
Machinery	118.8	0.97	0.9%	7.1%	4	4	5,280,730
Pharmaceuticals	19.8	0.65	0.2%	4.8%	6	5	882,067
Total	636.0	4.2	5.0%	30.7%			28,268,257
All Commodities	12,669.0	13.6					563,065,851

Figure 3.12 ranks the commodity categories transported by value proportion. The figure maps the intersection of each high-value, low-weight cluster for trucks (cluster 3) and air (clusters 1 and 3). The figure shows that there is a point of diminishing returns in value proportion for commodity categories outside of each high-value, low-weight cluster. Figure 3.13 shows the MSA distribution by weight moved in thousand tons (KTons) for each of the four commodity categories selected in the data mining workflow and indicates their outliers. Table 3.15 summarizes the weight of the four commodity categories moved in the top eight MSAs. Figure 3.11 shows the MSAs and their centroids used to estimate the geodesic distances for drone flights.

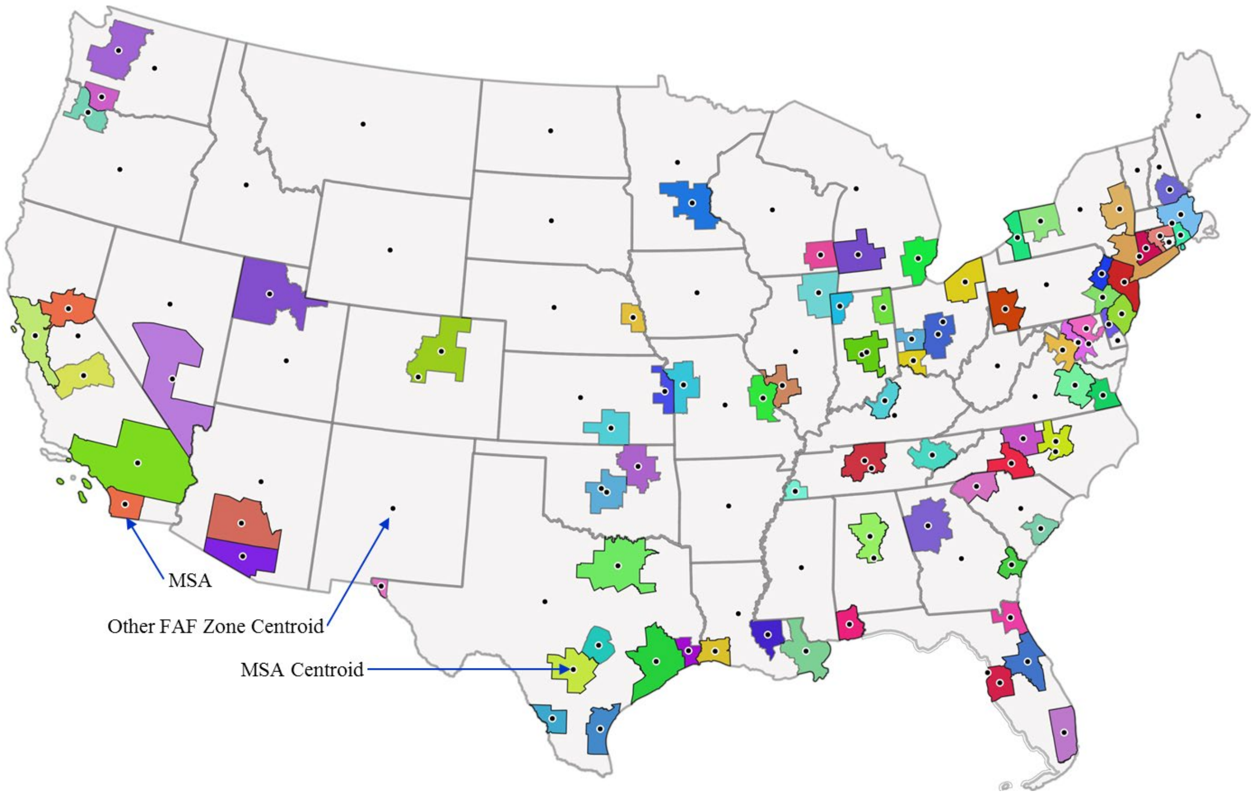

Figure 3.11 MSAs, other FAF zones, and their centroids

Table 3.16 displays the truckload equivalents transported among the top eight MSAs in four distance bands for each of the four commodity categories selected. Figure 3.14 shows the distribution of truckload equivalents across all distance bands. Truck transport within 100 miles accounted for 39.3% of the truckload equivalents for the four selected commodity categories. The accumulated proportion (% Acc) moved was 80.5% within a 400-mile distance band.

In summary, the method in this study identified four commodity categories and eight MSAs that could yield the highest initial demand for air transport. A distance band of 400 miles among these eight locations accounted for more than 80% of the transported weight. These results suggest that the shift from trucks to EAA transportation holds potential for achieving the United Nations' sustainable development goals, such as emission reduction and improved infrastructure longevity.

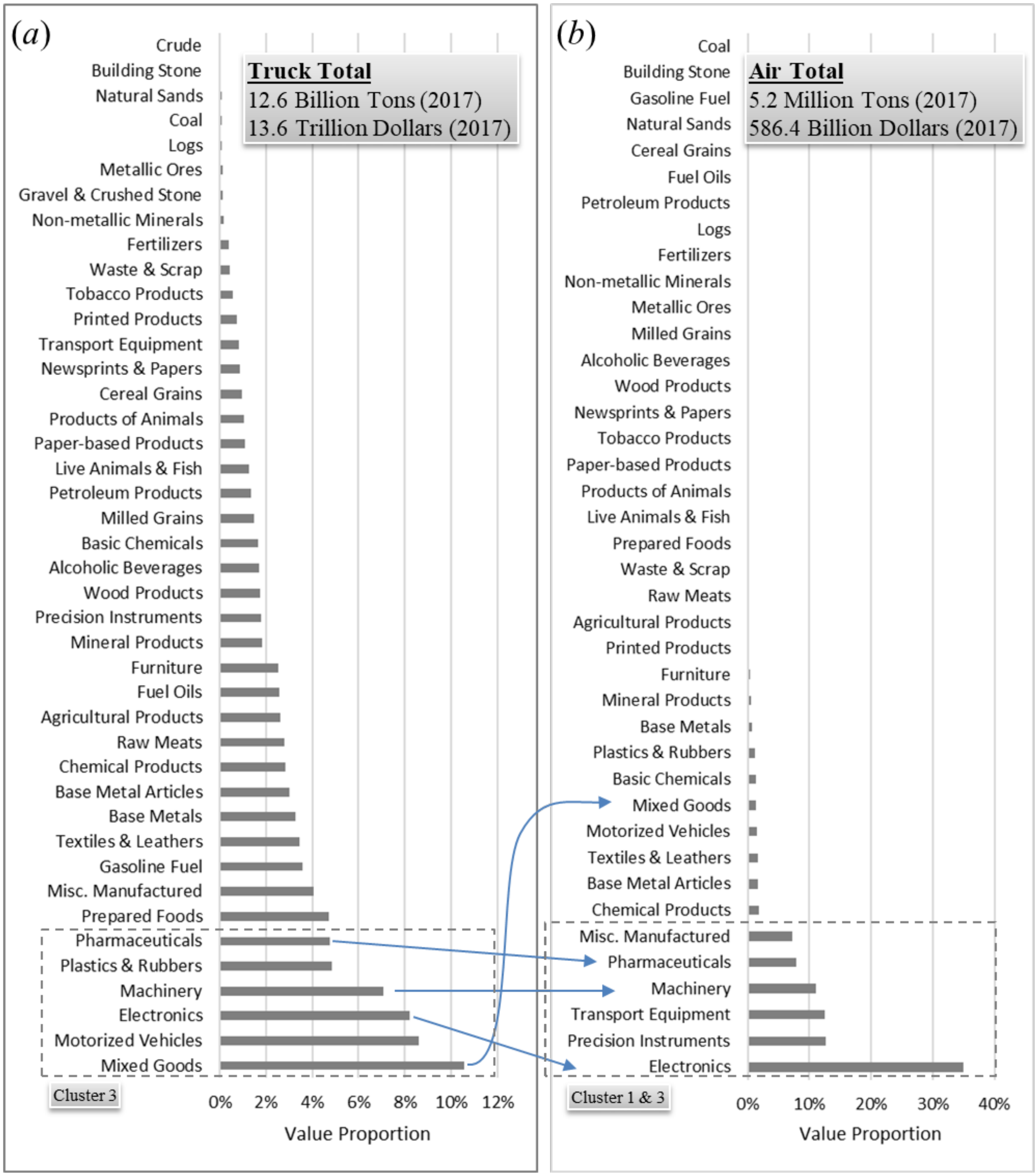

Figure 3.12 Commodity category distribution by value proportion carried using (**a**) trucks and (**b**) by air

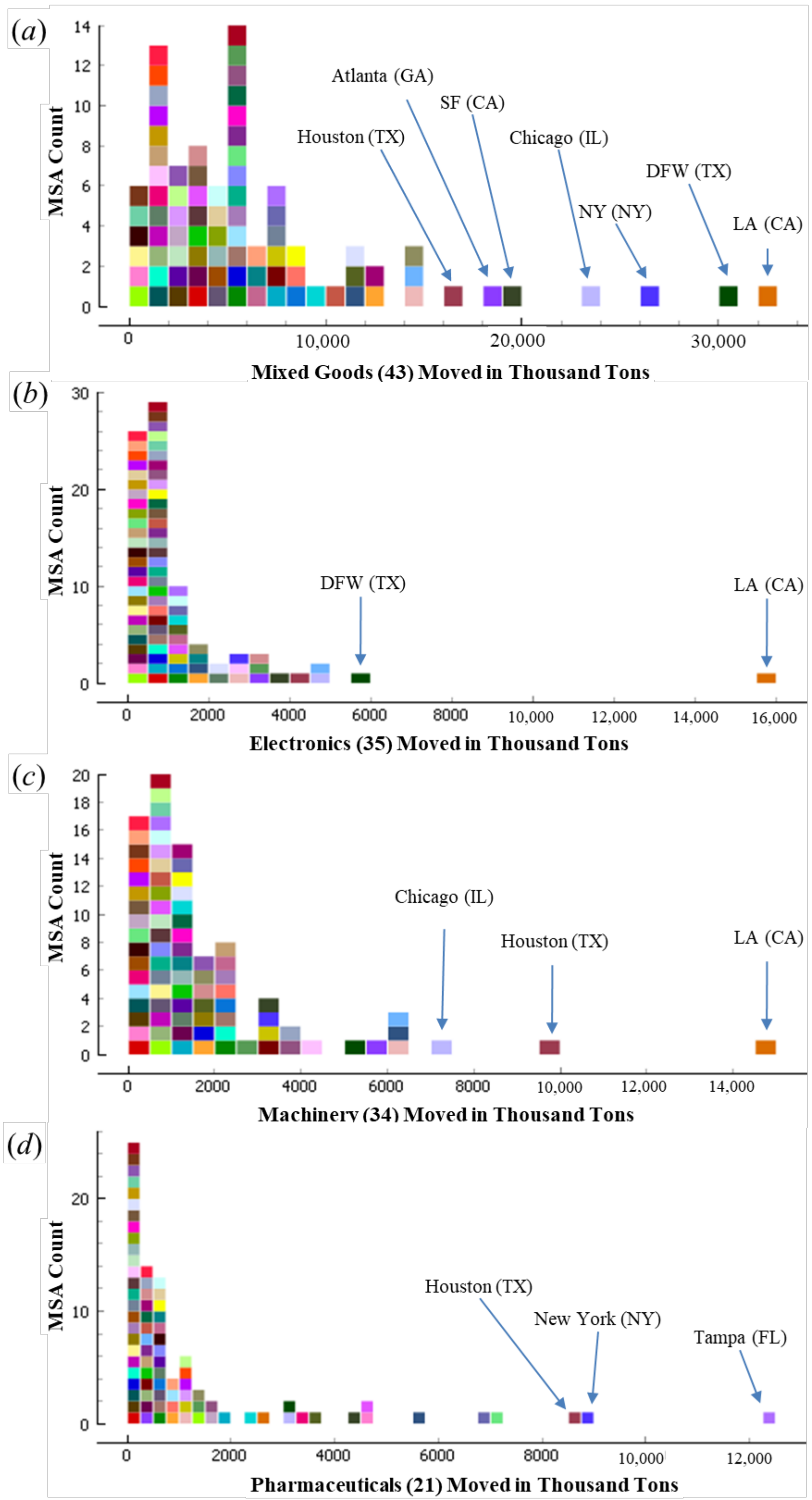

Figure 3.13 Weight distribution of (**a**) mixed goods, (**b**) electronics, (**c**) machinery, and (**d**) pharmaceuticals

Table 3.15 Commodity weight moved in the top MSAs

MSA	Pharmaceuticals	Machinery	Electronics	Mixed Goods	Total KTons
Los Angeles CA, USA	2,725.7	14,866.3	15,523.6	32,170.3	65,286.0
San Francisco CA, USA	4,441.2	3,331.6	3,707.0	19,142.1	30,622.0
Tampa FL, USA	12,360.8	759.9	1,040.1	7,532.0	21,692.8
Atlanta GA, USA	411.1	5,975.9	3,195.6	18,506.3	28,088.8
Chicago IL, USA	3,026.0	7,069.2	4,867.2	23,411.6	38,374.0
New York NY, USA	8,794.0	3,132.8	2,646.3	26,132.2	40,705.3
Dallas–Fort Worth TX, USA	3,061.4	5,071.5	5,716.2	30,506.5	44,355.6
Houston TX, USA	8,724.7	9,928.9	4,367.9	16,874.2	39,895.7
Total	43,545.0	50,136.1	41,064.0	174,275.2	309,020.2
CONUS	302,783.0	237,632.8	146,415.5	848,330.2	1,535,162
Top MSA %	14.4%	21.1%	28.0%	20.5%	20.1%

Table 3.16 Truckload equivalent flows between the top MSAs

Miles Band	Mixed Goods	Electronics	Machinery	Pharma	Total	%	% Acc
100	2,583,396	299,612	419,312	80,519	3,382,840	39.3%	39.3%
200	1,357,662	257,587	288,219	44,434	1,947,902	22.6%	61.9%
300	591,588	154,589	236,029	46,440	1,028,646	12.0%	73.9%
400	326,591	122,995	98,965	14,829	563,380	6.5%	80.5%
Totals	4,859,238	834,782	1,042,526	186,222	6,922,768	80.5%	

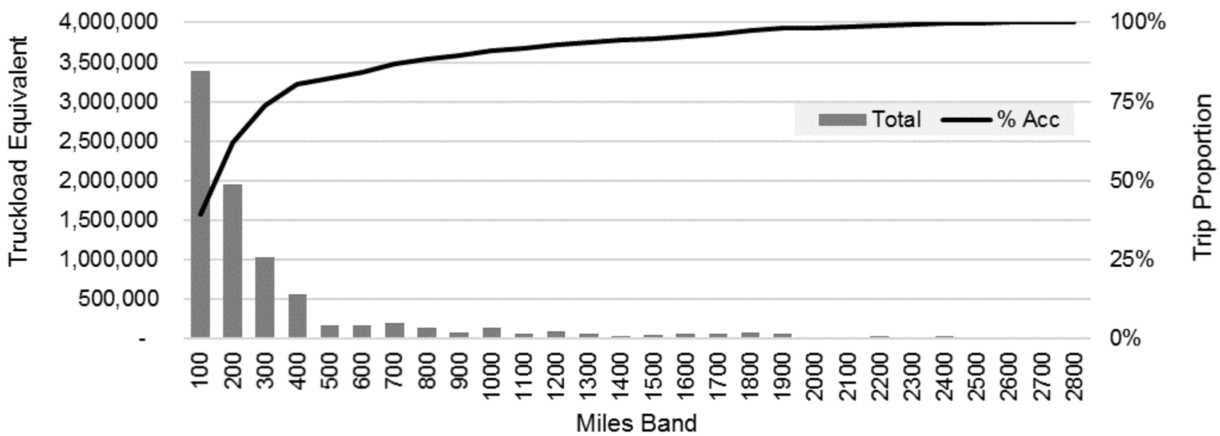

Figure 3.14 Truckload equivalent and accumulated trip proportion for the selected commodities and MSAs

3.2.2 Dangerous Cargo Transport

This section briefly reports on the author's work published in the following journal article: Bridgelall, Raj. "Reducing Risks by Transporting Dangerous Cargo in Drones." Sustainability, 14(20), DOI:10.3390/su142013044, October 2022.

A potential benefit of Advanced Air Mobility (AAM) is the reduction of road congestion and greenhouse gas emissions. Another potential benefit is the reduction of human-caused railroad and truck accidents involving Hazmat. This section explores the potential of using drones for the transportation of hazardous materials (Hazmat) in urban systems. The study aims to identify a minimal set of metropolitan areas where early cargo drone deployments could yield the most significant initial benefits. Table 3.17

classifies various dangerous goods, providing a framework for understanding the types of materials that drones could potentially transport.

Table 3.17 Classification of Dangerous Goods

Class	Description & Examples	Typical Uses	Risks
Explosives	Substance, article, or device that can explode. Examples: gun powder, safety flares, and fireworks.	War, demolition, mining, avalanche control [55].	Explosion triggered by heat, radiation, vibration, or chemical reaction.
Gases	Non-solid and non-liquid matter. Examples: butane, aerosols, oxygen, methane, acetylene, carbon monoxide and hydrogen sulfide.	Industrial uses, cooking grills, household cleaners, cosmetics.	Accidental release from pressurized containers, and possible contact with ignition sources.
Flammable Liquids	Liquids with flash points between 100 °F and 140 °F. Examples include gasoline, acetone, toluene, diethyl ether, and alcohols.	Fuels, cleaning solutions, paints, polishes, varnishes, adhesives, paint thinners.	Exposure to heat can bring a liquid to its flash point (release of vapor) when ignition can occur.
Flammable Solids	Ignitable solids. Examples: alkali, coal, carbon, magnesium, metallic hydrides, sulfur, cellulose nitrate, matches.	Battery manufacturing, cooking, composting.	Ignitable by heat, friction, contact with other substances such as oxidants or acids.
Oxidizing Substances & Organic Peroxides	Chemicals that oxidize other substances and/or provide fuel to burn. Examples: ammonium nitrate, potassium nitrate, nitric acid, halogens, and potassium bromate.	Manufacturing of plastics and rubbers and agricultural uses such as fertilizers.	Unstable—prone to exothermic decomposition [56].
Toxic and Infectious Substances	Poisons, infectious, and irritating materials. Examples: bacteria, blood samples, cyanide, methyl bromide, tear gases, medical waste, and forensic materials.	War, pesticides, medicines, fuel additives, disinfectants.	Accidental releases can harm humans.
Radioactive Material	Materials with specific activity greater than 0.002 microcuries per gram. Examples: Cobalt-60, Americium-241, Cesium-137, Iridium-192, and Plutonium-239.	Weapons manufacturing, power production, smoke alarms, and medical imaging [57].	Accidental releases can harm humans.
Corrosive Substances	Chemicals that destroy materials or cause irreversible alterations of living tissue. Examples: sulfuric acid, sodium hydroxide, hydrofluoric acid, and some battery fluids.	Cleaning solutions, drain unclogging, paint stripping.	Accidental release can cause severe burning and irritation of human skin.
Other	Examples: batteries (lithium-ion, lithium metal), magnetized material, asbestos, dry ice.	Batteries for electric vehicles, electronics, electric scooters, drones.	Known to be combustible under certain circumstances.

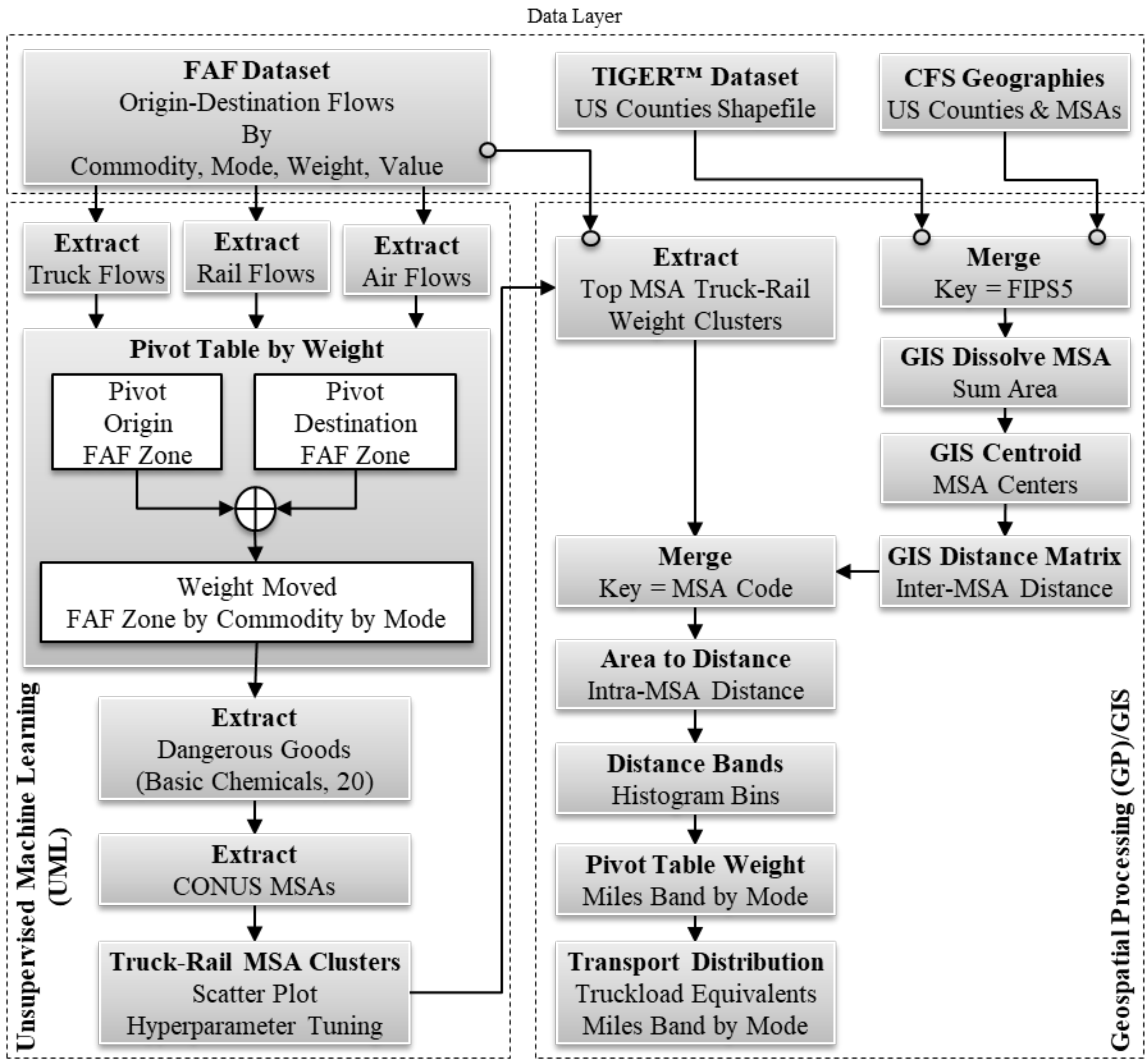

Figure 3.15 The HDM workflow

This analysis considers the commodity category of basic chemical materials (BCMs) for the U.S. case study.

The study employs a Hybrid Data Mining (HDM) workflow that combines Unsupervised Machine Learning (UML) and Geospatial Processing (GP) to identify optimal metropolitan areas for drone deployments. Figure 3.15 illustrates the hybrid data mining workflow. The workflow uses the Freight Analysis Framework (FAF) dataset, which is the most comprehensive source of multimodal commodity flows available for locations within the United States. The “Pivot Table by Weight” procedure partitions the data into three modal subsets of commodity flows: truck, rail, and air. Figure 3.16 and Figure 3.17 provide clustering results and MSA rank of BCMs moved by truck, rail, and air, respectively. Table 3.18 summarizes the basic theory of operation of the clustering algorithms, their advantages (A) and disadvantages (D). Table 3.19 lists the tuned hyperparameter settings for each clustering algorithm.

Table 3.20 lists the distance band distribution of truckload equivalents and their proportion for the selected outlier MSAs and Figure 3.18 plots the data for visualization. The results show that deployments in only nine metropolitan areas in four states could move 38% of all basic chemicals within 400 miles. Achieving initial success in these deployments will guide policy-making and new logistical standards for transporting dangerous goods. For urban planners and policymakers, this research offers a data-driven methodology to identify optimal locations for drone deployments for Hazmat transportation. It also provides a framework for understanding the risks and benefits associated with such deployments, thereby aiding in informed decision-making.

Table 3.18 Unsupervised Machine Learning Algorithms Compared for Cluster Detection

Algorithm	Theory of Operations	Hyperparameters
DBSCAN	Density-based spatial clustering of applications with noise (DBSCAN). Separates densely packed points from outliers. Initializes core points as those that are within distance *d* of *k* points. Grows a cluster by randomly labeling a core point as a cluster, and then grows that cluster by sequentially adding other core points that are within distance *d* until all core points are assigned to a cluster. Finally, it assigns non-core points to clusters that are within distance *d.* The unassigned points are labeled as outliers. A: finds clusters that linear hyperplanes cannot separate. D: specification of *d* of *k* requires heuristics, which can be impractical for large feature spaces.	Normalize features? Number of points (*k*) Distance (*d*) Distance measure
Louvain	Extracts communities from networks by constructing a k-nearest neighbor graph with edges weighted by the number of shared neighbors. Clusters are labeled based on edge density inside communities relative to between communities. A: algorithms and process large networks quickly. D: the resolution parameter adjusts the cluster size, which can make it difficult to cluster small communities.	Normalize features? PCA preprocess vectors Distance measure Number of neighbors (*k*) Resolution (*r*)
k-means	Randomly selects one point per cluster, and then iteratively recalculates centroids while reassigning points to their nearest centroid. The algorithm converges once cluster reassignments stops or the number of specified iterations is complete. Produces a silhouette score, which is a measure of within-cluster similarity and outside-cluster separation. A: performs well when clusters are symmetrical. D: specifying the number of clusters require heuristics, but the silhouette score can help the analyst.	Normalize features? Number of clusters (*k*) Initialization method Number of reruns (*n*) Number of iterations (*i*)

Table 3.19 Tuned Hyperparameter Settings for the Clustering Algorithms

Hyperparameter	DBSCAN	Louvain	k-means
Features normalized	Yes	Yes	No
Distance	Euclidean	Euclidean	Squared-Euclidean
Initialization	n/a	PCA = 2	k-means ++
Parameters	$k = 4$; $d = 12.99$	$k = 4$, r = 5.0	$n = 10$, $i = 300$

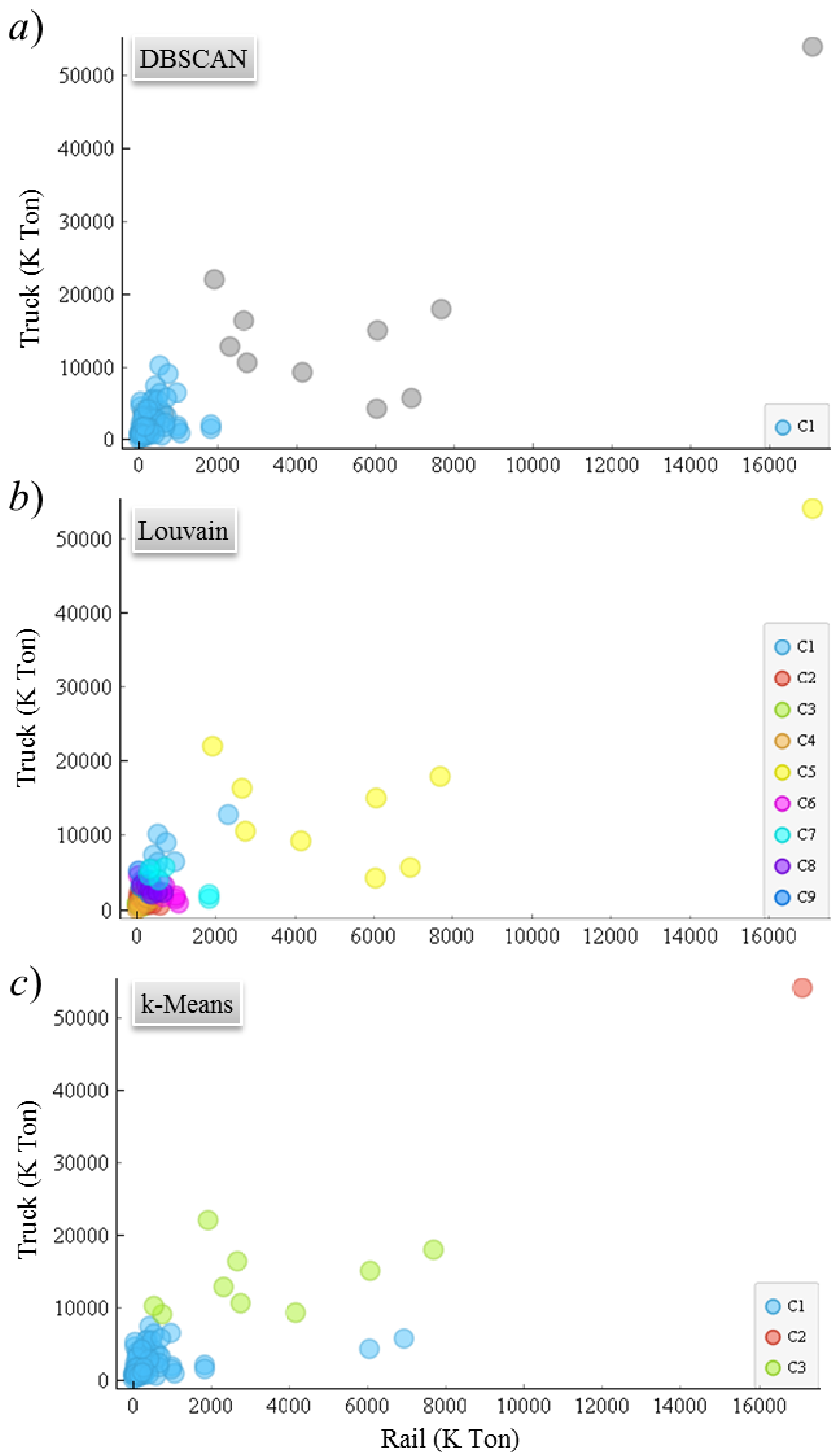

Figure 3.16 Comparison of clustering results for a) DBSCAN, b) Louvain, and c) k-means

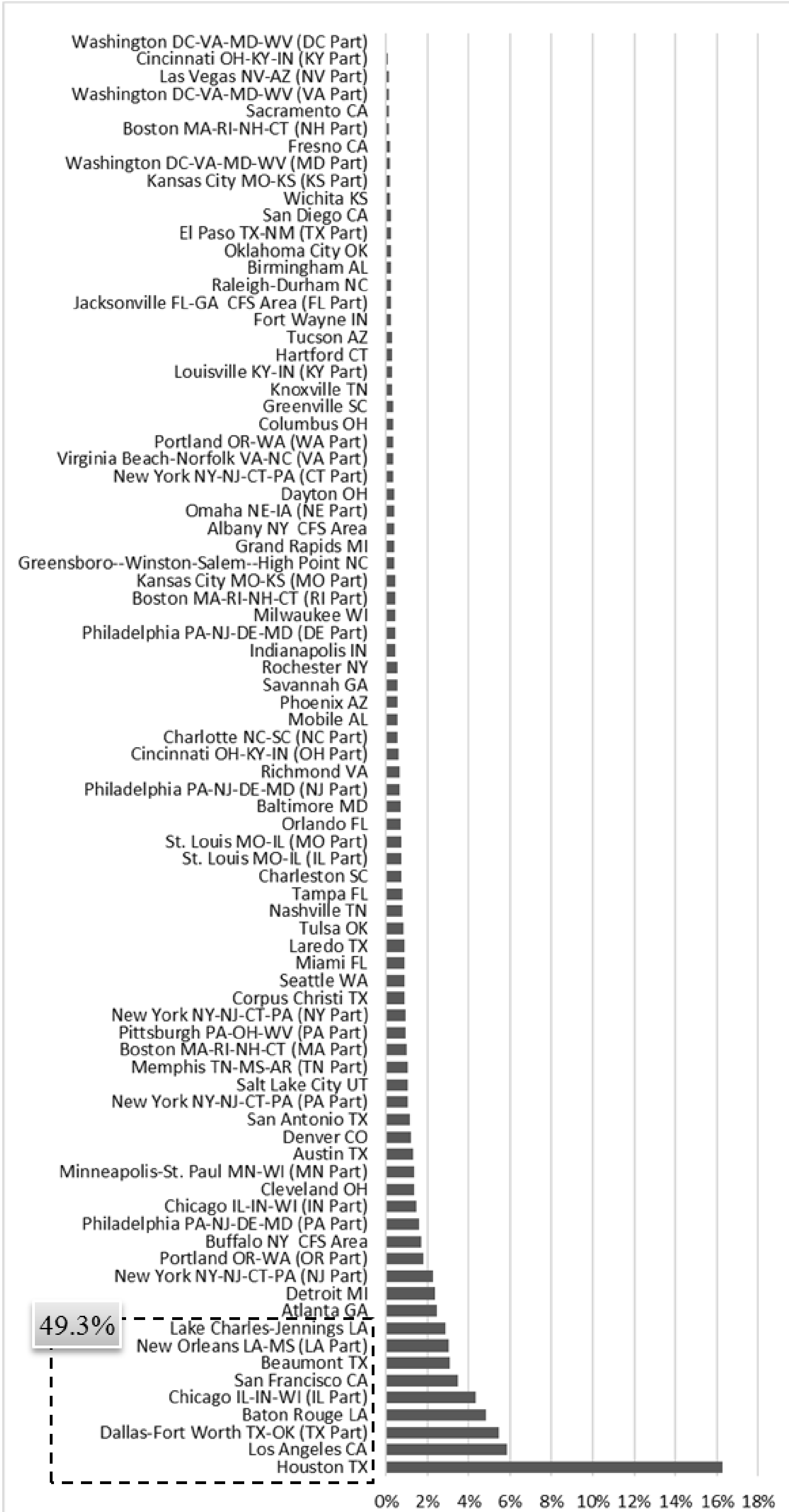

Figure 3.17 MSA rank of BCMs moved by truck, rail, and air

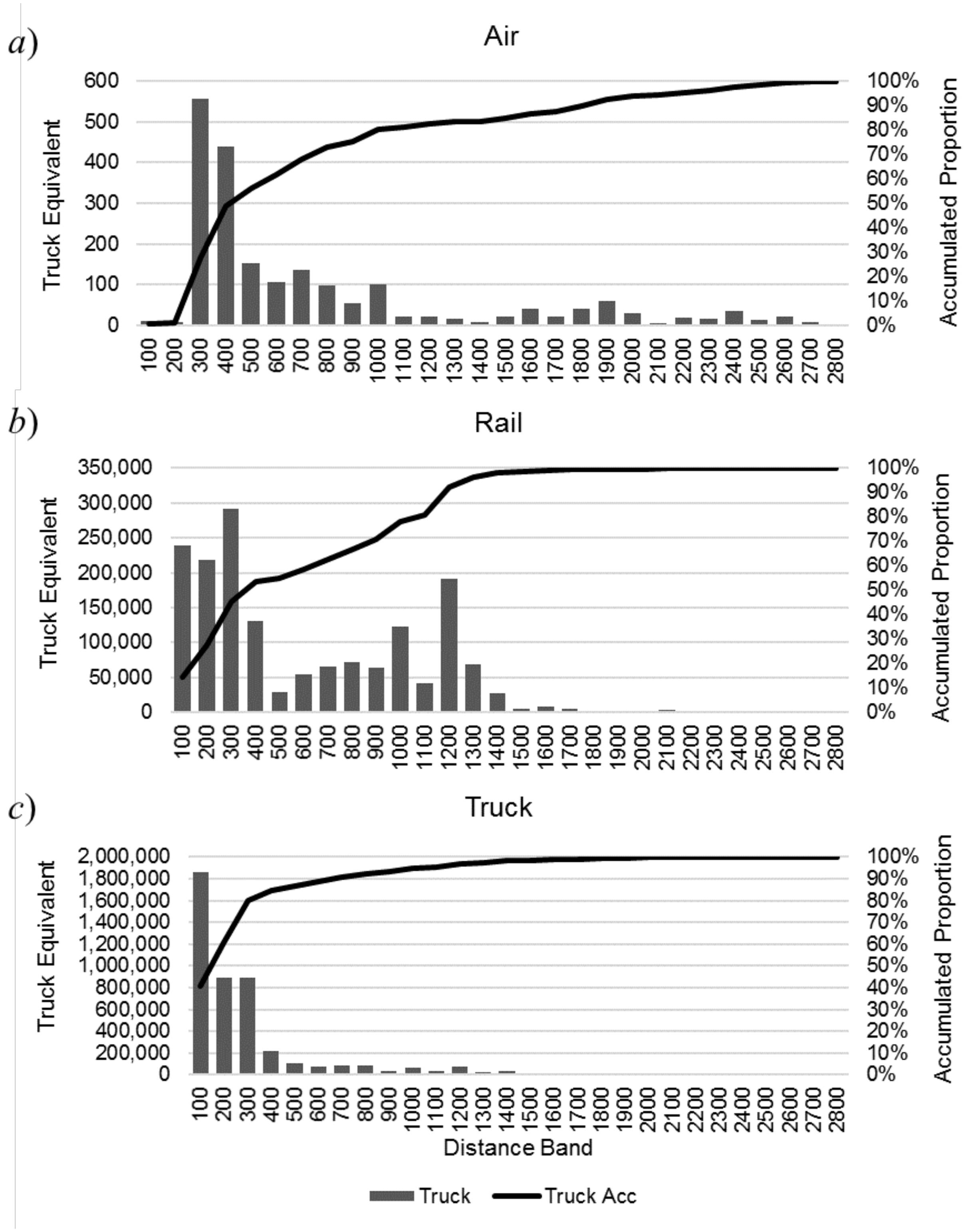

Figure 3.18 MSA rank of BCMs moved by truck, rail, and air

Table 3.20 Truckload Equivalent and Proportion Moved by Miles Band and Mode in the Outlier MSAs

Band	Air	Air Acc.	Rail	Rail Acc.	Truck	Truck Acc.	3-Modes	3-Modes Acc.
100	11.4	0.5%	239,468.1	14.5%	1,858,411.2	40.8%	2,097,890.7	33.8%
200	8.8	1.0%	217,816.7	27.7%	892,520.1	60.4%	1,110,345.6	51.7%
300	555.1	27.7%	291,106.7	45.4%	892,206.9	80.0%	1,183,868.7	70.8%
400	440.1	48.9%	130,613.3	53.3%	213,958.3	84.7%	345,011.7	76.3%
500	151.9	56.3%	29,614.7	55.1%	102,053.0	86.9%	131,819.5	78.5%
600	107.8	61.5%	54,879.4	58.4%	75,802.3	88.6%	130,789.5	80.6%
700	137.3	68.1%	65,460.3	62.4%	88,755.7	90.6%	154,353.3	83.1%
800	99.1	72.9%	71,947.0	66.8%	79,644.7	92.3%	151,690.7	85.5%
900	53.4	75.4%	63,921.1	70.6%	38,083.4	93.1%	102,057.9	87.2%
1000	99.9	80.2%	123,533.8	78.1%	66,995.1	94.6%	190,628.7	90.2%
1100	21.6	81.3%	41,494.4	80.6%	36,211.3	95.4%	77,727.3	91.5%
1200	22.1	82.4%	191,184.6	92.2%	79,192.4	97.2%	270,399.1	95.8%
1300	17.5	83.2%	69,207.6	96.4%	19,629.7	97.6%	88,854.8	97.3%
1400	9.3	83.6%	27,812.5	98.1%	33,419.6	98.3%	61,241.3	98.3%
1500	22.2	84.7%	5,078.4	98.4%	12,496.8	98.6%	17,597.4	98.5%
1600	40.2	86.7%	8,511.9	98.9%	15,235.8	98.9%	23,787.9	98.9%
1700	21.1	87.7%	5,197.4	99.3%	10,123.7	99.1%	15,342.2	99.2%
1800	41.3	89.7%	2,393.1	99.4%	10,285.0	99.4%	12,719.3	99.4%
1900	59.6	92.5%	1,328.6	99.5%	11,822.8	99.6%	13,211.0	99.6%
2000	30.6	94.0%	278.9	99.5%	4,089.5	99.7%	4,399.0	99.7%
2100	6.1	94.3%	3,991.5	99.7%	2,650.4	99.8%	6,647.9	99.8%
2200	18.9	95.2%	347.0	99.8%	966.8	99.8%	1,332.7	99.8%
2300	16.6	96.0%	2,785.5	99.9%	2,669.3	99.9%	5,471.4	99.9%
2400	34.7	97.7%	447.3	100.0%	4,383.5	100.0%	4,865.5	100.0%
2500	15.2	98.4%	431.6	100.0%	473.2	100.0%	920.0	100.0%
2600	22.5	99.5%	141.5	100.0%	1,335.7	100.0%	1,499.7	100.0%
2700	7.6	99.9%	39.5	100.0%	32.1	100.0%	79.2	100.0%
2800	2.7	100.0%	1.2	100.0%	2.7	100.0%	6.5	100.0%

3.2.3 Pharma Transport

This section briefly reports on the author's work published in the following journal article: Bridgelall, Raj. "Unlocking Drone Potential in the Pharma Supply Chain: A Hybrid Machine Learning and GIS Approach." *Standards*, 3(3):283-296. DOI:10.3390/standards3030021, August 2023.

This section delves into the burgeoning issue of supply chain disruptions in the pharmaceutical industry, exacerbated by increasing urban congestion. The study found a need for more reliable, faster, and secure methods of transporting medical products, especially given the increased frequency of weather events and traffic congestion. There is a growing demand for pharmaceutical products due to population growth, increased life expectancy, and a rise in chronic and age-related diseases. Consequently, the objective of this study was to enhance the reliability of the pharmaceutical supply chain and thereby improve healthcare outcomes.

The literature review revealed three primary application areas: 1) deliveries to areas with limited accessibility such as oil rigs, ships, and remote communities, 2) rapid delivery of emergency medical items like antidotes, resuscitation equipment, and human transplant organs, and 3) same-day or same-hour delivery of packages and food in congested urban environments. There has been a lack of research focusing on "middle-mile" deliveries, i.e., transportation between hubs, which is the focus of this study.

This research utilized the data-driven analytical workflow developed in the previous study (Figure 3.15) to identify metropolitan areas where drone services can yield the most significant initial benefits. Figure 3.19 shows the results of the cluster analysis. Figure 3.20 shows the ranked distribution among the MSAs that moved more than 90% of pharmaceuticals by weight. The top 9 MSAs are in four U.S. regions, namely Los Angeles (California), Houston (Texas), Northeast (New York, New Jersey, Pennsylvania), and Southeast (Florida, Georgia). The four regions highlighted collectively moved 41.6% of the weight of all pharmaceuticals transported in the contiguous United States (CONUS).

Figure 3.21 shows the distribution of truckload equivalents of pharmaceuticals moved within consecutive 100-mile distance bands among those top 9 MSAs. Analysis of the data found that cargo drones capable of traveling at least 400 miles can transport 68.2% of the pharmaceutical truckload equivalent moved by all modes among the target MSAs. Therefore, cargo drones operating within the four regions with a robust range of 400 miles can move 41.6% × 68.2% = 28.4% of all pharmaceutical truckload equivalent moved in the CONUS.

The above findings are significant for supply chain managers, policymakers, and the medical community at large. They represent the largest mode shift opportunities that can demonstrate early societal benefits. Consider the integration of cargo drones into existing urban transportation networks to alleviate supply chain disruptions. Planners can standardize the workflow and scale it for applicability in other regions and for other types of high-value commodities vulnerable to supply chain disruptions. In summary, this study offers valuable insights into leveraging emerging technologies to improve the resilience and efficiency of the pharmaceutical supply chain, which has broader implications for urban systems planning.

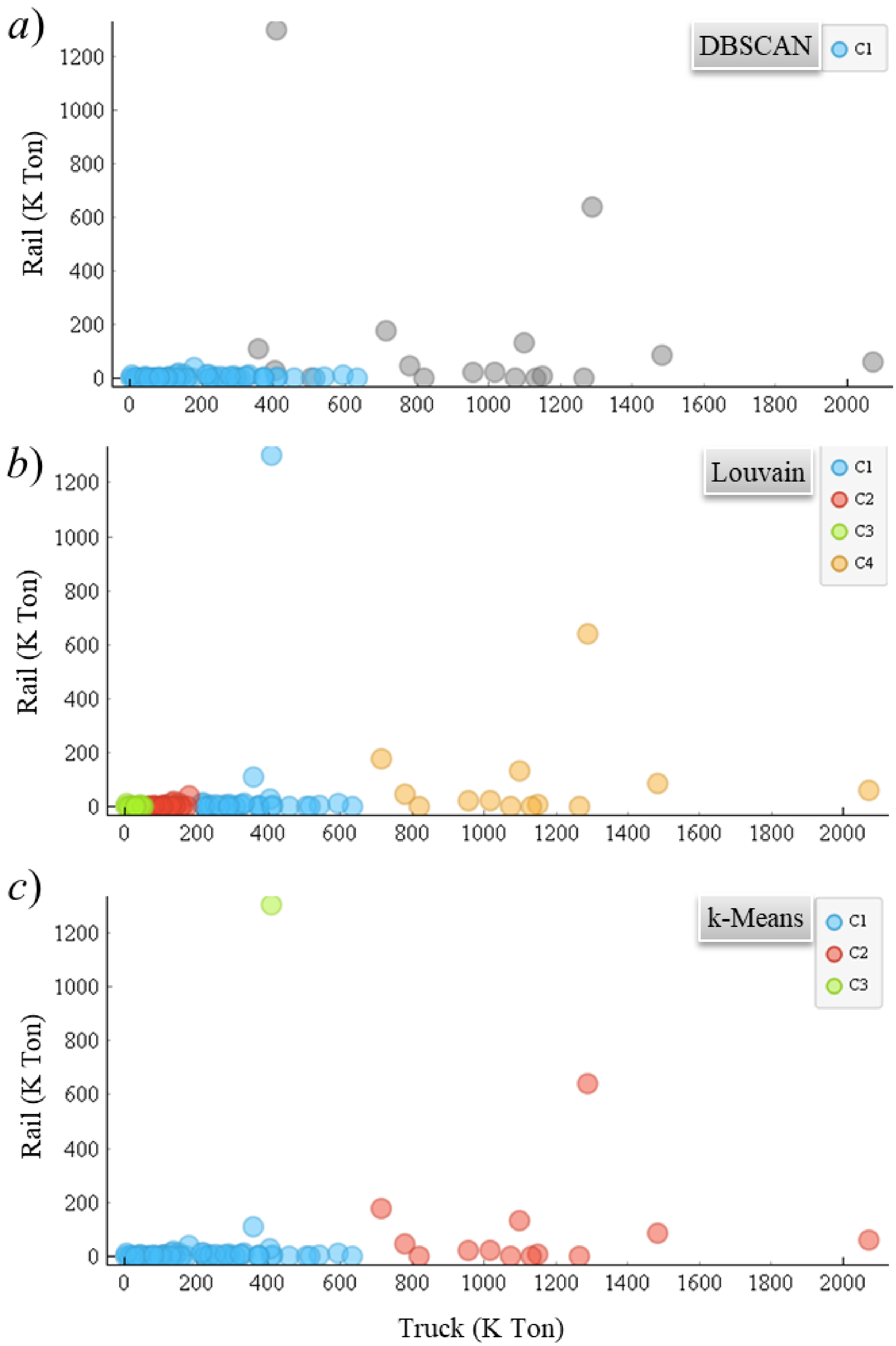

Figure 3.19 Outlier MSA identification by a) DBSCAN, b) Louvain, and c) k-means clustering methods

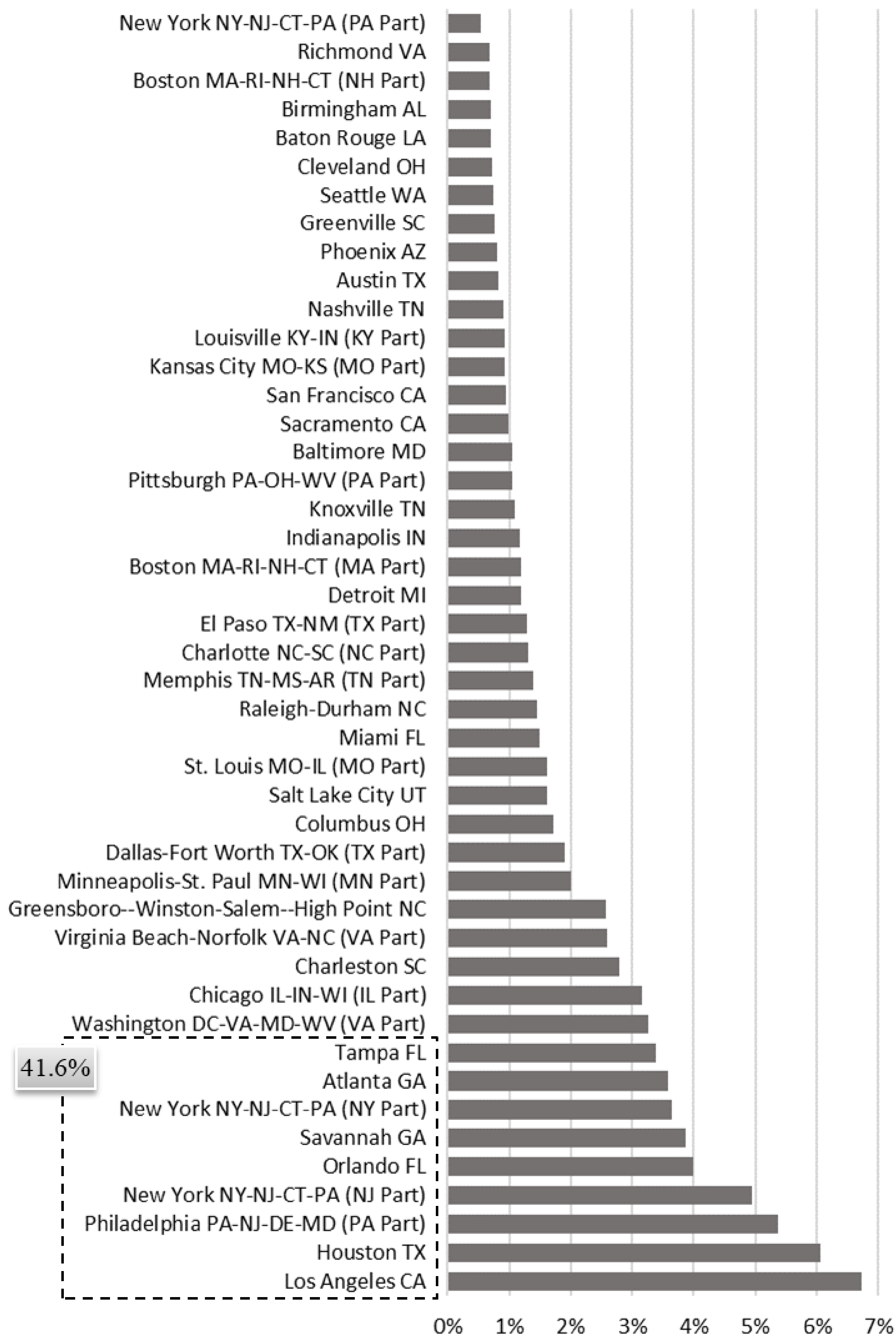

Figure 3.20 Ranked distribution of pharmaceutical weight moved by air, truck, and rail

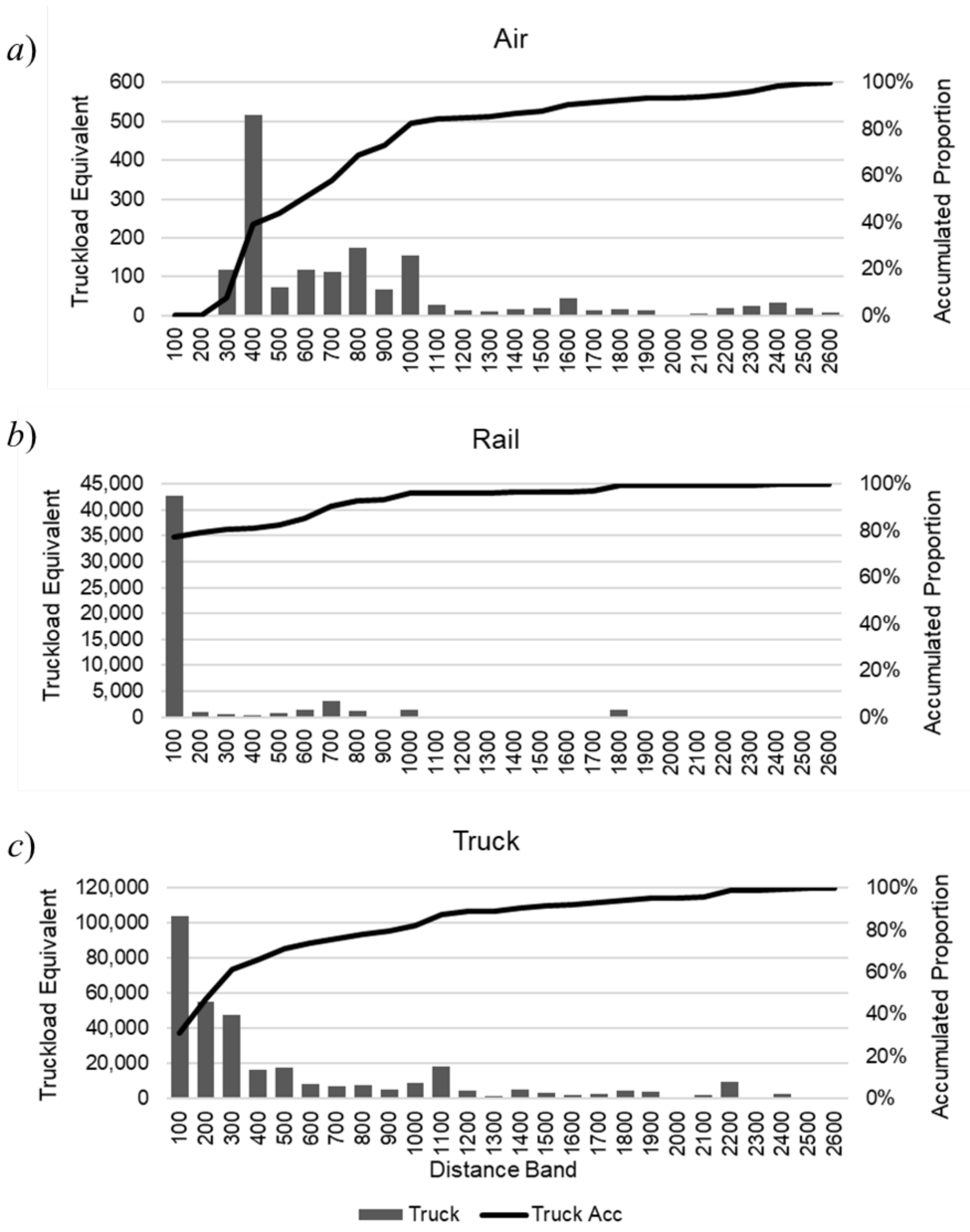

Figure 3.21 Distance band distribution for the top 9 MSAs by a) air, b) rail, and c) truck

4. LIMITATIONS

While this report provides a comprehensive analysis of Advanced Air Mobility (AAM) with a focus on regulatory frameworks, market forecasts, and various applications, several limitations should be noted:

Data Scope: The data used in this study primarily focuses on the U.S. market, which may not be directly applicable to other regions with differing economic, regulatory, and technological landscapes.

Model Assumptions: The machine learning models used for predicting AAM adoption are based on certain assumptions and a fixed set of indicators. These models may not account for unexpected socio-political events or rapid technological advancements.

Regulatory Fluidity: The regulatory environment surrounding AAM is continually evolving. This report relies on the current state of regulations, which may change, rendering some conclusions obsolete.

Technological Constraints: The study assumes the technology will evolve at a certain rate, specifically in terms of range and reliability of electric vertical takeoff and landing (eVTOL) aircraft. Any deviations in technological advancements, particularly those of batteries, could affect the findings.

Market Predictions: While the report employs rigorous methodologies to forecast market demand, the actual adoption rates may vary due to factors such as consumer acceptance, safety perceptions, and unforeseen economic conditions.

Cost Estimates: The report discusses relative capital requirements for different aspects of AAM but does not provide a detailed cost-benefit analysis to provide more nuanced insights.

Limited Commodity Focus: In the analysis of cargo drones for transporting dangerous goods and pharmaceuticals, the case study limits the generalizability of the findings to other types of cargo.

Environmental Impact: Although the industry expects AAM to be more sustainable form of transport, a comprehensive environmental impact assessment, including lifecycle analyses of eVTOL aircraft, is beyond the scope of this report.

Safety Concerns: This report briefly discusses safety measures but does not provide an exhaustive analysis of the risks involved in widespread AAM adoption, particularly regarding the integration into existing air traffic management systems.

Social and Ethical Considerations: This report does not explore factors such as social acceptance, ethical considerations surrounding job displacement, and equitable access to AAM services.

Healthcare Specifics: The report outlines the potential for improving healthcare supply chains through AAM but does not examine the specific regulatory and quality control measures required in the healthcare sector.

These limitations suggest the need for future research and policy development in the field of Advanced Air Mobility.

5. CONCLUSIONS

The comprehensive view of Advanced Air Mobility (AAM) painted by this report further emphasizes its complexity and promise. Regulatory challenges continue to hinder AAM adoption. The study emphasizes that a fragmented regulatory approach across nations causes uncertainty. Indicators such as GDP and Regulatory Quality Index emerged as key predictors for AAM adoption, revealing that existing models like the Social Progress Index and land-use characteristics are less impactful. These findings affirm the need for harmonized regulations that can adapt to technological evolutions while ensuring security. Market forecasting requires a detailed and robust methodology to pinpoint potential high-demand routes. This research utilized a hybrid methodology to forecast demand within specific distance bands and identified approximately 78,000 daily passengers and 3,023 eVTOL aircraft serving viable routes. This meticulous approach could help stakeholders strategize more effectively and allocate resources with precision.

To explore opportunities in cargo logistics, this research used a three-phase data-mining and GIS algorithm to identify key markets and routes for Electric and Autonomous Aircraft (EAA). This study filled a literature gap by introducing an algorithmic approach to target prime markets, emphasizing that eight regional locations moved more than 20% of the weight of identified key commodities within a 400-mile distance band. With a case study of high-risk cargo transport, the data-mining workflow identified that cargo drones could replace 4.7 million North American semitrailer trucks for dangerous cargo, focusing on nine Metropolitan Statistical Areas where drone deployment would be most impactful. This underlines the capability of AAM technologies to not only reduce costs and ground traffic but also to enhance safety. The case study on opportunities in the pharmaceutical transport sector highlighted that cargo drones can significantly improve the pharmaceutical supply chain in congested metropolitan areas. The machine learning and GIS-based workflow identified nine metropolitan areas where drones with a 400-mile range can initially move more than 28% of the weight of all pharmaceuticals, underscoring the relevance of AAM in healthcare logistics.

In summary, the AAM landscape is teeming with challenges that range from regulatory disarray and market unpredictability to logistics and application-specific limitations. This research notably contributes to understanding these facets, offering data-driven, machine learning, and GIS-based methodologies to help navigate the complexities. For AAM to become a widespread, reliable, and efficient form of transport, an interdisciplinary and multi-stakeholder approach is essential. Future research should build upon these foundations to optimize and scale AAM technologies for global impact.

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