ANALYSIS AND PREDICTION OF AIRSPACE AVAILABILITY FOR URBAN AIR MOBILITY OPERATIONS IN THE SAO PAULO METROPOLITAN REGION

João Vitor Turchetti Ribeiro*, Mayara Condé Rocha Murça
Aeronautics Institute of Technology

* joaojvtr@ita.br

PAPER ID: SIT207

ABSTRACT

Urban Air Mobility (UAM) is an emerging form of transportation that is expected to introduce novel flight networks into already busy and complex airspace surrounding major cities and metropolitan regions. This paper studies the dynamics of urban airspace use by conventional aircraft over the Sao Paulo metropolitan region in order to identify and predict which airspace volumes are least constrained and best accessible for future UAM flights. Using historical flight tracking data, clustering analysis is first performed to identify departure and arrival trajectory patterns flown by conventional traffic at the two major airports – Sao Paulo/Guarulhos International airport and Sao Paulo/Congonhas airport. We then create a probabilistic model of the spatiotemporal distribution of air traffic under known meteorological conditions, which enables the prediction of active procedures, their spatial confidence regions and the resulting airspace availability for UAM in response to dynamic operational factors. The data-based approach allowed for a high-fidelity characterization of the Sao Paulo urban airspace use patterns as well as for accurate predictions of the available airspace for UAM, bringing novel insights and capabilities in support of dynamic and efficient urban airspace management.

Keywords: Urban Air Mobility, Air Traffic Management, Clustering, Probabilistic Model.

ACKNOWLEDGEMENTS

The authors thank Atech, an Embraer group's company, and the National Council for Scientific and Technological Development (CNPq) for the support.

1. INTRODUCTION

Everyday, millions of people around the world have the basic need of moving around metropolises due to various reasons – commuting to work, going to the airport, visiting a relative etc. – some of them traveling dozens of kilometers through clogged roads to reach their destination and spending more time than desired. A research performed by the Brazilian Institute of Public Opinion and Statistics (Ibope et al., 2014) estimated that, in Sao Paulo, the average citizen spends up to 167 minutes daily in road traffic while commuting. The problem of urban mobility is not new, and many systems have been proposed as alternatives to classic road transportation, such as subway and surface railways, electric light buses and others. Moving around *above* the city, through the air, is an idea that has always existed in popular imaginary, but the only way to do it nowadays is by helicopter, which is inaccessible for most part of the population. Emerging Urban Air Mobility (UAM) is a new concept that is coming to fulfill the gap of urban air transportation, and has the potential of reducing costs of commuting through the air and reducing road congestion.

UAM is based on Electric Vertical Takeoff and Landing vehicles (eVTOL), a novel type of aircraft that has been developed by different companies for the last few years. A 74 billion dollar UAM market is expected to rise in the next decade, with up to 23,000 eVTOL vehicles operating globally (EmbraerX et al., 2019). The importance of this new urban mobility system is highlighted by the heavy road traffic currently observed in many big metropolises and by the increasing need of people for faster mobility0. Hence, the introduction and development of UAM may lead to great benefits, especially in the scope of personal time management (FAA, 2020).

UAM is expected to introduce new complex flight networks in low-altitude airspace over big cities, especially below 3,000 feet Above Ground Level (AGL) (Vascik et al., 2019). Hence, re-architecting the urban airspace will be essential to provide a safe environment in which these novel operations can harmoniously cohabit with current flights. This challenge brings a new level of complexity considering that the urban airspace is already structured in an adequate and manageable fashion, which is well-perceived as safe by the population in general.

Currently, the airspace over cities is designed to procedurally segregate aircraft, assuring proper vertical and lateral separation at all times. In large metropolitan regions served by multiple airports, such as Sao Paulo, the problem of organizing traffic becomes even more complex, since it is necessary to prevent conflicts between the active procedures of multiple closely located airports. This usually translates into longer arrival and departure procedures for each airport, which ultimately leads to delays and lower fuel efficiency. Hence, the addition of new vehicles, UAM for instance, to these already busy types of airspace becomes a problem, which is the central theme of this paper.

The purpose of this work is to offer a data-based approach for modeling the current patterns of urban airspace use by traditional aviation in order to identify and predict the airspace volumes that are least constrained and therefore best accessible for UAM flights. We select as case study the Sao Paulo's urban airspace, the largest metropolitan region in Latin America. Nevertheless, the methodology proposed in section 3. is designed to be generally applicable in any other desired context.

2. RELATED LITERATURE

The topic of urban airspace design and management for integration of emerging UAM operations has been subject of numerous studies. Different authors have addressed the matter using different techniques, from geometric approaches supported on published procedures and topographic data, to flight trajectory data analytics based on the application of machine learning algorithms on Automatic Dependent Surveillance-Broadcast (ADS-B) data.

Vascik et al. (2019) developed a geometric framework that used only static, publicly available information, evaluated in multiple scenarios. The authors defined four ConOps scenarios and studied seven airspace constructs, as terrain clearance, airports airspace clearance, special flight rules areas, and others. Then, geometrically combining all constructs, they were able to estimate the airspace availability for UAM under their specific hypotheses and scenarios.

Regarding data-driven approaches, most of them resort to flight tracking data gathered from ADS-B networks or similar (Vascik & Hansman, 2019), (Murça, 2021), (Vascik & Hansman, 2019), (Eerland et al., 2016), (Eerland et al., 2017), (Murça et al., 2018), (Gariel et al., 2011), (Eckstein, 2009), (Olive & Morio, 2018), (Murça et al., 2020), (Olive et al., 2021).

Vascik & Hansman (2019) addressed the urban airspace availability analysis problem using a statistical approach. The authors used Airport Surface Detection Equipment - Model X (ASDE-X) data rather than ADS-B in order to gather not only commercial flight data, but also rotary-wing and general aviation flight data. They suggested the application of containment boundaries around multiple observed trajectories of traffic departing and arriving at some of the largest airports in the U.S. Then, they clustered the flight trajectories and mapped volumes of airspace around each cluster centroid that were occupied by a certain percentile of the flights of interest.

Murça (2021) addressed the problem of identifying available volumes of urban airspace for UAM operations using ADS-B data of arriving and departing traffic at Congonhas airport, the most central airport in Sao Paulo, Brazil. The author also analyzed the impact of adopting different lateral separation buffers (ATC-assumed minimum lateral separation) to procedurally separate UAM from conventional traffic, and the differences between integrating UAM dynamically or statically. The author found that using a reduced lateral separation criterion increased airspace availability by up to 87%.

Gaussian-based probabilistic models have been used to study the air traffic behavior. Eerland et al. (2016) investigated the dispersion of flight trajectories using Gaussian Processes; a similar objective to Vascik & Hansman (2019). Eerland et al. (2017) used the same model to quantify the air traffic complexity inside an specific airspace volume, aiming to provide a comprehensive map to improve the visualization of the airspace complexity. Both authors performed flight trajectory clustering using DBSCAN prior to inputting its results in the probabilistic model.

Addressing the matter of flight trajectory clustering, several authors have tried different techniques to properly identify spatial and/or temporal patterns from flight tracking data. Hierarchical algorithms, for example, use the distance between the observed points of a dataset to build the clusters and have been explored by Rehm (2010) and Delahaye et al. (2017). These algorithms may be useful to identify trajectory clusters within small datasets, since it is easy to implement. Some of them are biased to globular clusters and hence not suitable for flight trajectory analysis, while others do not work well with noise (Carvalho et al., 2021). This may be a problem in airspace characterized by the occurrence of too many holding patterns or ATC vectoring.

Many authors have used density-based clustering algorithms, such as DBSCAN (Gariel et al., 2011), (Liu et al., 2017), (Murça et al., 2018), (Murça et al., 2020), (Murça, 2021), (Eerland et al., 2016), (Olive & Morio, 2018), (Olive et al., 2021). DBSCAN works well with noise and outliers and is not limited to globular shapes, being able to discover trajectory clusters of any form. In a busy environment as a metroplex‘s terminal area (TMA), tactical air traffic flow management may generate non-conforming trajectory behavior typically regarded as noise (ATC vectoring, holding patterns, go around procedures and so on). The algorithm can also deliver satisfactory results without the need for the user to inform the number of clusters beforehand. Thus, it is safe to assume that DBSCAN is a powerful tool for flight trajectory data analytics.

Review of the literature shows that, while several studies have succeeded to identify spatial and temporal patterns from flight trajectory data, few have attempted to leverage that knowledge to predict the traffic behavior. That line of research is where this paper builds itself upon, aiming to propose data-driven models to identify and predict urban airspace availability for UAM operations, based on a comprehensive set of external features that are found to impact the air traffic distribution.

3. METHODOLOGY

We developed a data-driven approach to identify and predict urban airspace availability for UAM operations. The methodology is based on gathering flight tracking data and properly processing it, performing a trajectory clustering analysis to identify traffic patterns, then estimating a probabilistic model to forecast spatial confidence regions for the traffic patterns and the resulting airspace availability, which are displayed using map visualizations. The methodology is summarized in Figure 1 and detailed in this section.

3.1. Region of interest

Our study case is the Sao Paulo metropolitan region, especially the urban airspace surrounding Congonhas (CGH) and Guarulhos (GRU), hence our Region of Interest (ROI) is a part of the Sao Paulo TMA. Also, since UAM is expected to fly at low altitudes – between 400 ft and 1,500 ft AGL (EmbraerX, 2020), and maximum 3,000 ft AGL (Vascik et al., 2019) – we define 3,000 ft as the superior limit of the ROI, which corresponds to an altitude a little higher than 5,500 ft MSL (above Mean Sea Level) for Sao Paulo.

3.2. Data

The emergence of ADS-B turned incredibly large amounts of flight tracking data easily accessible to air traffic managers, flight planners, researchers and others. ADS-B is a surveillance technology incorporated into regular transponder units in which an aircraft automatically broadcasts its navigation data (speed, altitude, heading etc) in regular intervals. This work uses ADS-B data gathered inside the Sao Paulo TMA to map arrival and departure flows at CGH and GRU and understand the behavior of commercial air traffic inside the urban airspace.

In this work, we relied on flight tracking data from the OpenSky Network (Schäfer et al., 2014) gathered for the whole month of November 2019 using the OpenSky's REST API. The database consists of almost 1 million observations, corresponding to approximately 15,000 flights. It contains, among other attributes, information about aircraft callsigns, destination and origin airports and, most importantly, trajectory data (latitude, longitude and altitude) for each timestamp. The acquisition rate is about 6 per minute.

Data preprocessing was conducted to filter the observations inside the terminal area: all trajectory observations not further than 40 nautical miles from the airport of operation and not higher than 19,500 feet were filtered, and to eliminate flights with incomplete or noisy trajectory data based on sanity checks. Figure 2 presents a visualization of the filtered flight tracking data, separately for CGH and GRU, respectively.

In addition, each object (line) of that dataset is a single observation of some flight at a single timestamp, but, before clustering, it was necessary to change its structure. We restructured the dataset to represent each flight with a single line, given by a time series of trajectory data (latitude, longitude and altitude). Moreover, as each different flight had a different number of observations inside the terminal area, it was necessary to resample the trajectory data to represent each object with the same number of attributes, making the dataset suitable for the clustering step.

The probabilistic model needs meteorological and other external inputs in order to learn how air traffic is distributed depending upon weather and different airport runway configurations. We used meteorological information to forecast active runway configurations and procedures. The meteorological data were obtained from historical METAR messages for CGH and GRU, which are available via REDEMET's API (Redemet, 2022). METARs are standardized messages issued by local aviation authorities to inform aircraft of an airport's actual meteorological situation, including wind and visibility characteristics. Being fed with this information, the probabilistic model is capable of learning the spatial distribution of traffic given the meteorological condition.

3.3. Trajectory clustering analysis

A trajectory clustering analysis is first performed to identify air traffic patterns in the terminal airspace. A busy TMA is typically highly structured with arrival and departure procedures

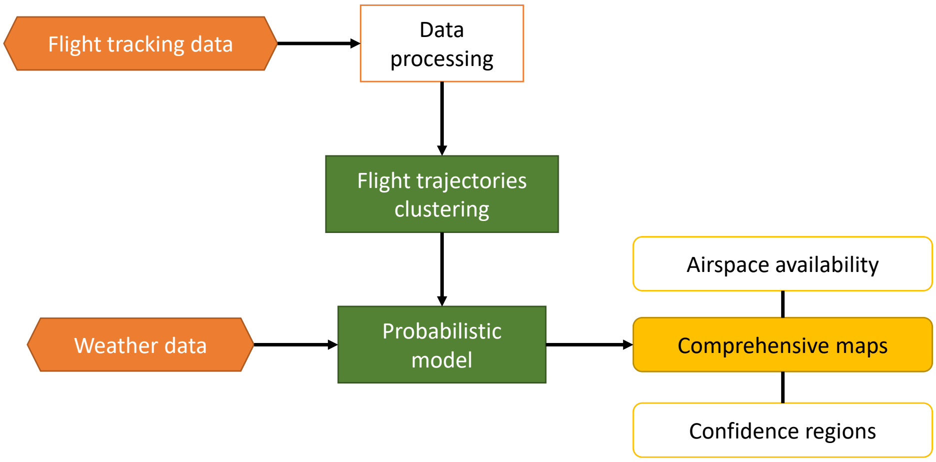


Figure 1 Summary of the methodology.

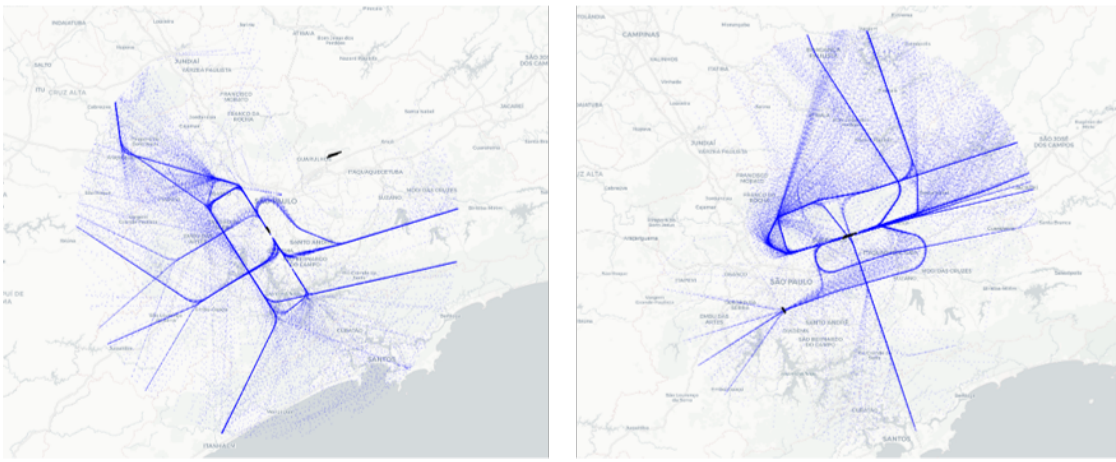


Figure 2 Filtered flight tracking data inside Sao Paulo TMA - CGH (left) and GRU (right).

that allow aircraft to transition between the airport and the en route airspace safely. The high density of operations usually makes actual trajectories subject to deviations from the planned flight procedures, since ATC vectoring, holding patterns and direct heading clearances are typically used for tactical air traffic flow management. The standard routes and the natural variability in their execution produce the core underlying patterns that we seek to identify with the trajectory clustering analysis. Yet, these ATC control actions may also create noise trajectories that deviate significantly from nominal traffic patterns.

Therefore, we use the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to cluster the trajectory data. DBSCAN enables the identification of the core trajectory patterns in the presence of abnormal trajectory profiles. Besides the ability to handle noise, DBSCAN deals well with non-convex clusters, does not require the number of clusters to be defined *a priori* and has been successfully used for clustering trajectory datasets in various domains.

3.4. Probabilistic air traffic model

The purpose of building a probabilistic model is to learn the spatiotemporal distribution of air traffic and to make predictions based on external inputs, such as meteorology. We model the trajectory patterns identified in the clustering phase with a Gaussian Mixture Model (GMM) (McLachlan & Basford, 1988). In other words, we assume that the spatial air traffic distribution within each cluster can be modeled with a Gaussian density and that the spatial distribution of air traffic in the TMA is given by a weighted sum of Gaussian densities. The GMM is mathematically defined as follows:

$$p(X) = \sum_{y=1}^{K} \pi_y p(X/Y = y) = \sum_{y=1}^{K} \pi_y \mathcal{N}(X; \mu_y, \Sigma_y) \quad (1)$$

X is a multivariate random variable that represents the aircraft trajectory and a specific weather condition; it results from concatenating two vectors: X_T, which contains the trajectory information, and X_W, which contains the weather information;

π are the mixture weights;

K is the number of clusters (patterns, Gaussian components);

μ is the mean vector of the Gaussian density that models the y^{th} procedure;

Σ_y is the covariance matrix of the Gaussian density that models the y^{th} procedure.

Fundamentally, Gaussian component weights cannot be individually greater than one and sum up to one:

$$0 \leq \pi_y \leq 1 \quad (2)$$

$$\sum_{y=1}^{K} \pi_y = 1 \quad (3)$$

After the model estimation, we apply it to make predictions of active procedures, their spatial traffic distribution and the resulting airspace availability given the meteorological conditions. This is accomplished by the computation of marginal and conditional densities. Eqs. 4 and 5 express the probability of occurrence of the y^{th} procedure given known weather conditions. Bayes's theorem is used to calculate that from the marginal distribution of weather conditions X_W given the y^{th} procedure, which is Gaussian with mean vector $\mu_{y,W}$ and covariance matrix $\Sigma_{y,WW}$, as in Eq. 6. This allows us to express the probability of occurrence of the y^{th} procedure given input weather conditions as in Eq. 7.

$$p(Y = y/X_W) = \frac{p(X_W/Y = y)p(Y = y)}{p(X_W)} \quad (4)$$

$$p(Y = y/X_W) = \frac{\pi_y p(X_W/Y = y)}{\sum_{i=1}^{K} \pi_i p(X_W/Y = i)} \quad (5)$$

$$X_W/Y = y \sim \mathcal{N}(\mu_{y,W}, \Sigma_{y,WW}) \quad (6)$$

$$\pi_y^* = \frac{\pi_y \mathcal{N}(X_W; \mu_{y,W}, \Sigma_{y,WW})}{\sum_{i=1}^{K} \pi_i \mathcal{N}(X_W; \mu_{i,W}, \Sigma_{i,WW})} \quad (7)$$

To model the spatial distribution of air traffic for a known weather condition, we need to compute the conditional probability distribution of aircraft trajectories X_T given input meteorological conditions X_W for the y^{th} procedure. Bishop & Nasrabadi (2006) shows that this probability distribution is Gaussian with mean vector μ_y^* and covariance matrix Σ_y^*, as expressed by Eqs. 8 to 12.

$$X_T/X_W, Y = y \sim \mathcal{N}(\mu_y*, \Sigma_y^*) \quad (8)$$

$$\mu_y^* = \mu_{y,T} + \Sigma_{y,TW}\Sigma_{y,WW}^{-1}(X_W - \mu_{y,W}) \quad (9)$$

$$\Sigma_y^* = \Sigma_{y,TT} - \Sigma_{y,TW}\Sigma_{y,WW}^{-1}\Sigma_{y,WT} \quad (10)$$

$$\Sigma_y = \begin{bmatrix} \mu_{y,W} \\ \mu_{y,T} \end{bmatrix} \quad (11)$$

$$\Sigma_y = \begin{bmatrix} \Sigma_{y,WW} & \Sigma_{y,WT} \\ \Sigma_{y,TW} & \Sigma_{y,TT} \end{bmatrix} \quad (12)$$

Finally, we can use the marginal and conditional densities to forecast active procedures and their spatial confidence regions. Eq. 13 defines the set S of procedures forecast to be active for a given probability threshold γ. Eq. 14 expresses the confidence region R_y of the spatial distribution of air traffic for a significance level α for each active procedure y.

$$S = \{y : \pi_y^* \geq \gamma\} \quad (13)$$

$$R_y = \{X_T : p(X_T/X_W, Y = y) = 1 - \alpha\} \quad (14)$$

4. RESULTS AND DISCUSSION

4.1. Identification of traffic patterns

The flight trajectory clustering analysis with DBSCAN was performed separately for each airport and type of operation – CGH departures, CGH arrivals, GRU departures and GRU arrivals – for improved clustering performance. Table 1 presents the number of clusters identified and the percentage of data noise encountered for each flow. As an example, the clusters identified for CGH departures are displayed in Figure 3.

Table 1 Clustering results.

Flow	# clusters	Noise
CGH DEP	6	10.3%
CGH ARR	5	9.6%
GRU DEP	6	12.1%
GRU ARR	6	11.3%

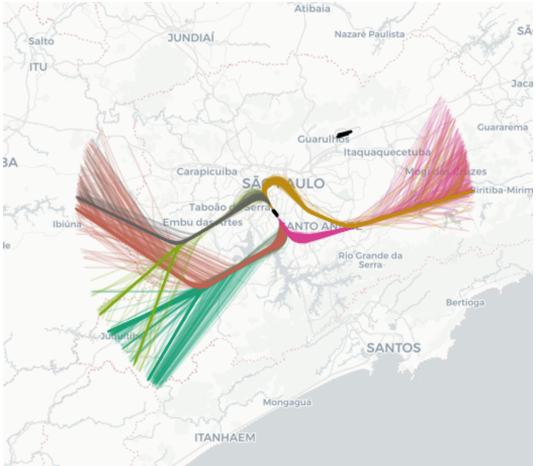


Figure 3 Clusters - CGH departures.

4.2. Air traffic spatial distribution

After the clustering analysis, a GMM was estimated for each airport and type of operation based on the traffic patterns identified. The model allowed us to examine the spatial distribution of air traffic inside each cluster. For a given altitude range, a spatial confidence region in the form of an ellipse is determined. Hence, we can find certain airspace regions where air traffic has some probability of occurring, ultimately determining a busy and unavailable portion of the urban airspace.

In this section, we present the resulting confidence regions for three levels of confidence: 90%, 95% and 99%, considering an altitude layer from Ground Level (GND) to 3,000ft AGL. In the maps displayed in Figure 4, the ellipses represent the confidence regions of each cluster for these three different confidence levels, and Figure 5 presents the results for two different altitude layers.

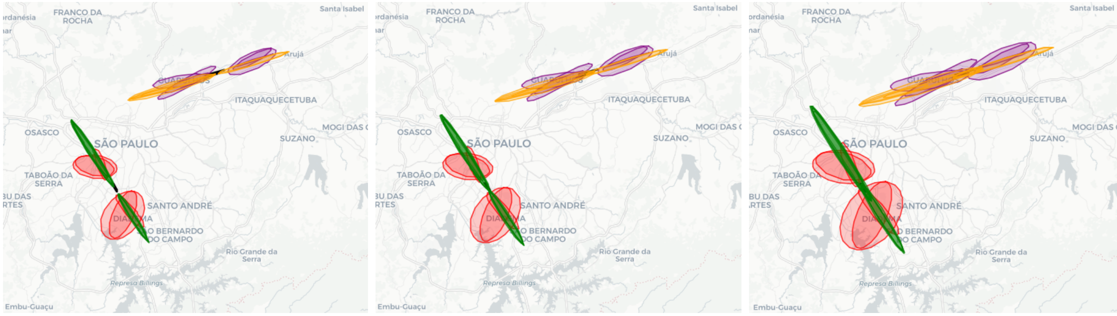
4.3. Prediction of airspace availability

Once the probabilistic model was estimated, we were able to make predictions of the urban airspace availability for any meteorological condition. As an example, Figure 6 shows the results of this prediction at a level of confidence of 95% and a probability threshold of 5% for the following conditions: marginal VFR, winds coming from the southeast at 10 knots. Results for two different altitude layers are presented: below 1,500ft AGL and below 3,000ft AGL.

The confidence regions are larger for the altitude layer below 3,000ft AGL than below 1,500ft AGL, with an exception for GRU departures, which might have been caused by the quality of the flight tracking data used. Even though this conclusion needs further and deeper investigation, it is a first step towards understanding that it will be critical to properly allocate special routes and dedicate exclusive altitude layers for UAM operations, a concept already introduced by various publications and Concepts of Operations available.

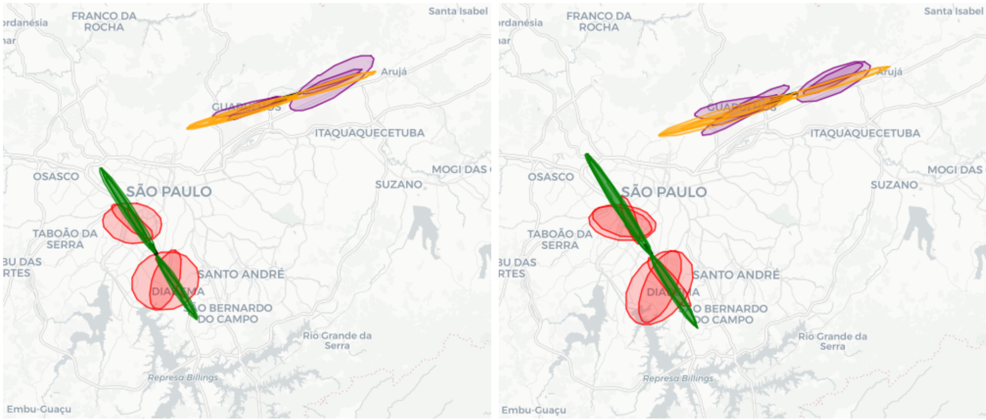
An analysis of the GMM's predictive performance was done to evaluate the quality of the model. As expressed by Eq. 13, a certain procedure is labeled as active if the probability of its occurrence is equal or greater than a threshold value γ. Thus, by testing different values for that parameter, we evaluated the sensibility and accuracy of the prediction model. The accuracy was defined by the mean of the model's success rate, measured day by day, for the test dataset (one third of the whole dataset, randomly selected). The results are displayed in Table 2.

It is evident that for a probability threshold γ of 0%, every single learned procedure would be active regardless of the input meteorological condition. By increasing the threshold to 1% and 5%, we find that the average number of predicted procedures decreases, indicating that the model is able to reasonably distinguish between active and inactive procedures and the airport runway configuration resulting from a given meteorological condition. Naturally, such prediction is not perfect, and the model's accuracy decreases with the use of higher probability thresholds. However, we observed an accuracy greater than 95% for a threshold of 5% that predicts nearly half of the patterns as active, which is very promising.



(a) Level of confidence: 90% (b) Level of confidence: 95% (c) Level of confidence: 99%

Figure 4 Confidence regions below 3,000ft AGL – CGH departures (red) and arrivals (green), and GRU departures (purple) and arrivals (orange).



(a) Below 1,500ft AGL (b) Below 3,000ft AGL

Figure 5 Confidence regions at 95% level of confidence.

Table 2 Model predictive performance results – 95% level of confidence.

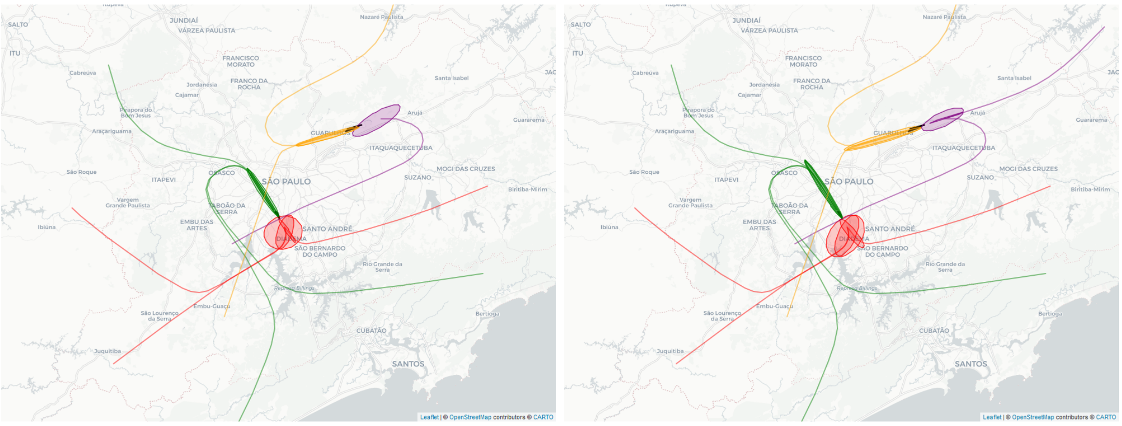
Flow	γ	# predicted active procedures (mean)	Accuracy (mean)
CGH DEP	0.00	6	100.0%
	0.01	4.7	98.0%
	0.05	3.5	96.8%
CGH ARR	0.00	5	100.0%
	0.01	3.5	98.9%
	0.05	2.7	97.8%
GRU DEP	0.00	6	100.0%
	0.01	5.1	98.8%
	0.05	3.9	98.1%
GRU ARR	0.00	6	100.0%
	0.01	4.3	98.1%
	0.05	3.2	97.4%

5. CONCLUSIONS

The application of clustering techniques followed by probabilistic analysis proved to be useful to understand multiple characteristics and the dynamics of urban airspace. Understanding how air traffic actually behaves inside urban terminal areas is of utmost importance to properly integrate UAM to existing operations.

One very evident conclusion taken from the results is that the higher the altitude the wider the dispersion of air traffic. Although this was already expected, it helps us to better understand how the TMA is actually structured, i.e. to understand at which regions – or at which distances from the airports – the traffic merges into a single path or split into many others. For example, it is notable from the maps presented that the air traffic dispersion is much wider for traffic operating at CGH than GRU.

Regardless of the airport or meteorologi-



(a) Below 1,500ft AGL **(b) Below 3,000ft AGL**

Figure 6 Example: prediction of urban airspace availability – 95% level of confidence and 5% probability threshold.

cal condition, air traffic is much more dispersed during departure than arrival. This observation is expected and coherent with the way how Instrument Flight Rules (IFR) procedures are elaborated in busy airspaces: usually, arriving aircraft supported by Instrument Landing Systems (ILS) need at least 5 to 10 NM of straight flight collinear to the runway, while departure traffic can take off and readily turn into the planned procedure. This leads us to expect that a wider region of the airspace should be unavailable for UAM on the sector dedicated for take offs.

By applying the GMM with different levels of confidence, we found that, although higher levels of confidence generated wider confidence regions, the differences in dimensions were slight. By contrast, the altitude layer where the analysis was done impacted significantly airspace availability.

Finally, our predictive model showed itself to be useful to provide better comprehension of two factors regarding airspace occupation: how widely air traffic distributes itself and how many individual procedures are being used. Since the model is capable of delivering these outputs after being fed with meteorological information, one can forecast in advance the traffic patterns most likely to be active, and hence determine the probable urban airspace availability for UAM operation. This allows for smarter and more efficient planning by both ATM agents and UAM operators.

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