How to assess the feasibility of sUAS applications in urban environment: geodemographic analysis of 3D urban space

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Abstract— **The rapid growth of small Unmanned Aerial System (sUAS) in urban areas has garnered greater interest in its application in urban space. As a first step to assess the feasibility of sUAS and UAM in urban areas, the authors utilize a diverse set of urban airspace use data to model the interaction of urban dwellers and the 3D airspace. With the anticipated utilization of sUAS in urban airspace, a multi-dimensional understanding of such space is essential. In doing so, it is necessary to integrate and analyze two important elements that constitutes an urban environment: people (or human behavior) and man-made structures. In this study, highly urbanized areas – San Francisco, CA was analyzed for their urban space characteristics by considering both the daytime and nighttime population with the 3D geospatial information. We aim to evaluate the temporal variations of such interactions and geofence in populated urban regions. Regionalization is conducted using SKATER algorithms for clustering purpose. The outcomes have several unique information that can benefit drone delivery target area identification, landing location identification, demand prediction.**

Keywords-sUAS; Geodemographic Analysis; Spatial Clustering; UTM

I. INTRODUCTION

The anticipated proliferation of small Unmanned Aerial System (sUAS) in urban areas has generated greater interest in its application in urban space. Although vehicle technology related to sUAS has made considerable progress over the decade, wider adoption of drone use is still in the process. Recently, several aviation authorities have put efforts to develop UAS traffic management technologies that enable safe and efficient UAS operations at lower altitudes in various operational environments, including urban areas [1-3]. The NASA Safe Autonomous Flight Environment for the Last 50 Feet (SAFE50) project is conducting an advanced conceptual design study to enable safe and efficient UAS operations in low-altitude high-density urban environments with a high degree of automation [4]. However, there are several areas that need to be researched and streamlined to overcome the current stagnation related to the legal, economical, and safety, to name a few. Such socio-economical discussion should take into account not only economic feasibility, but also acceptability of risks in achieving safety and efficiency, based on the characteristics of *urban space*.

The conventional usage of the term urban space in research domain has been limited to land transportation, economic development, and urban design. Since the use of sUAS is expected to be active in urban airspace, a multidimensional understanding of urban space is essential. Therefore, it is necessary to integrate and analyze two important elements that constitutes an urban environment: man-made structures and people. The urban drone use is particularly challenging since a good amount of the airspace is already occupied with manmade structures and terrains. In such environment, there is no argument that safety of people and surrounding structures are top priority, including privacy protection. Unlike remote or rural areas, urban areas are filled with densely located man-made structures of varying heights, leaving limited space both for land and air users. The distribution of such structures presents a fundamental difference in the geometry of open. We identify spaces occupied by buildings as permanently blocked and focus on unblocked, vacant space when analyzing urban space characteristics. In addition, populated regions in urban environment can be interpreted in two different ways: where potential demand is concentrated and where the risk of conflict between land/air users and non-involved person can be maximal.

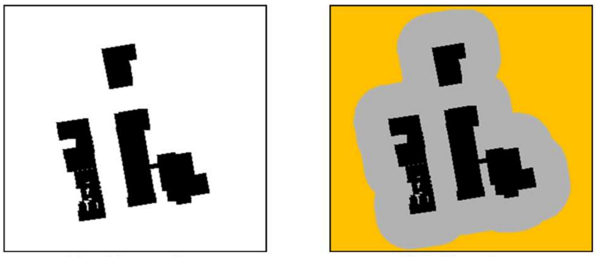
In this paper, we aim to identify areas with high economic feasibility and areas with high collision risk for populations and buildings through regionalization using SKATER (Spatial

K'luster Analysis by Tree Edge Removal) considering both available airspace and population that can be operated in the urban space.

II. REGIONALIZATION USING SKATER

A. 3D geospatial information and population dataset

The 3D geospatial characteristics of San Francisco is sourced from the open data portals [5], which contain the footprint and height information of 3D building structures. Since this study focuses on small UAV applications in lower altitude (under 400 feet), one can identify the obstacle-free airspace by taking the volume of 3D structures off the airspace boundary. There is another factor to consider for sUAS applications in addition to the spatial obstacles. It is conventional to impose minimum safety margin of virtual buffer around the obstacles, or geofence, for safety and privacy purpose [6]. In regard to the San Francisco included in the study, such safety margin is not specified by the U.S. government. However, most countries require the minimum of 30 meter geofence space for drones to stay out of, and the same standard is applied in our analysis [7-9]. In Fig. 1, the effect of geofence is projected in 2D, where static obstacles are shown in black and the geofenced area is shown in gray. Note the effect of geofence to reduce the available area shown in yellow. In this study, the available airspace is evaluated in both categories of the raw obstacle-free available airspace (A_0) and the available airspace with geofence of 30 meters (A_{30}). Computing the 3D geofence around the predefined geometry was carried out by Minkowski sum of a disk and a geometry.



(a) : without geofence (b) : with geofence

Fig. 1 2D projection of the effect of geofence.

The population data was sourced from 2016 ESRI demographic datasets [10], which contains both the daytime and nighttime population per census tract. Daytime population is defined as the total number of residents and workers present during normal business hours. Nighttime population refers to residential population. The daytime and nighttime population were estimated from the decennial census, American Community Survey (ACS), and business data from Infogroup.

Note that the spatial dataset is vectorized while the population data is available in census tract. Since the resolution of two data sources differs, spatial availability were aggregated to be measured in census tract. To normalize variances, airspace availability are measured as percentage available ($A_k = \frac{amount\ of\ available\ airspace\ considering\ size\ k\ of\ geofencing}{3D\ volume\ of\ a\ census\ tract\ up\ to\ 120\quad AGL}$) and population is measured as population density per census tract ($\rho = \frac{population\ of\ a\ census\ tract}{area\ of\ a\ census\ tract}$).

B. Regionalization with SKATER

Regionalization was carried out using SKATER proposed by Assuncao et al. in 2006 [11]. SKATER is a partitioning technique that incorporates the geospatial contiguity using graph structure to generate clusters of regions of similar characteristics. SKATER first creates undirected weighted graph $G(V, E)$based on the node adjacency, where V is the set of nodes and E is the set of edges. Given $G(V, E)$, edge weight $w: E \to R^+$ is defined with the dissimilarity of two connected nodes. Minimum Spanning Tree (MST) is then obtained by pruning edges to minimize the sum of dissimilarities over all nodes through Prim's algorithm [12]. Finally, the MST is partitioned into the set of sub-trees (cluster) that minimizes within-cluster sum of squares. In our analysis, the V is the set of census tracts and E is established based on the rook neighborhood. The populations density ρ and airspace availablility A_0 and A_{30} are used as weights to define the weight function w.

III. CASE STUDY ANALYSIS

In preparation for new users in the air, in-depth analysis of urban environment in San Francisco, CA is conducted.

A. Airspace and Population Characterists of San Francisco

The city of San Francisco is located at latitude 37.77 and longitude -122.42, spanning about 119.46km^2 as shown in Fig. 2. According to U.S. Census Department data from 2010, San Francisco is the fifth most densely populated County [13]. In addition, the estimated nighttime and daytime population in 2016 from Esri demographics were 844,577 and 1,018,741 respectively.

Among the 176,366 building structures included, the majority of tall buildings are located in the Financial District. Once excluding those regions, the majority of San Francisco is characterized by loosely distributed low-rise buildings with green space. The citywide raw airspace availability A_0 is 96.71%, which essentially captures the amount of open airspace to human perception up to 400 feet to reduce to 89.71% with 30m geofence. In Fig. 2, the blocked airspace is illustrated before (shown in black) and after (shown in red) 30m geofence application at 15m. At 15m altitude, a large portion of buildings is already removed compared to Fig 2 (a), except for the northeast corner of the city. One can also observe that geofence significantly reduces the airspace availability near North Beach

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and Market Street area, and such reduction is not evenly distributed across the city.

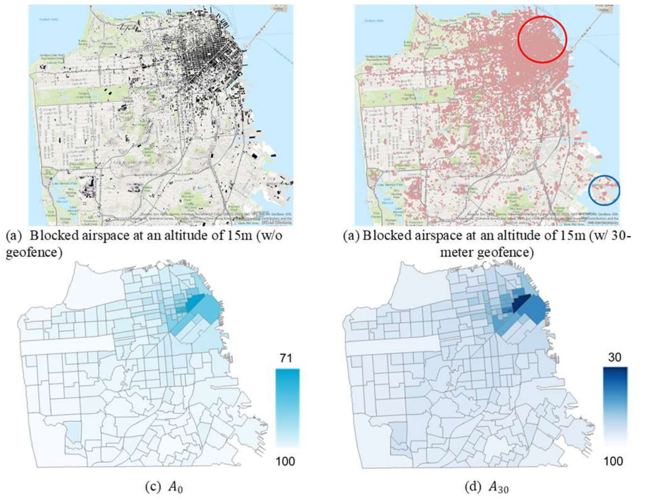

Fig. 2 Several maps of airspace availability in San Francisco. (a): Blocked airspace at an altitude of 15-meter without geofence, (b): Blocked airspace at an altitude of 15m with 30-merter geofence, (c):Thematic map of A_0, (b): Thematic map of A_{30}

B. *Regionalization of San Francisco*

To define the geospatial boundaries of similar characteristics both in airspace and population, SKATER is applied to the four combinations of airspace availability and population density. The number of regions, or clusters, was chosen to achieve high similarity in the cluster as well as high dissimilarity among the clusters using jump index technique. Regionalization results of the San Francisco with respect to population density and urban airspace availability is shown in Fig. 3.

We first notice that 7 regions were identified from the regionalization process with respect to daytime population density(ρ_D) and raw airspace availability (A_0). Overall, several regions were identified, biased towards the north-eastern Embarcadero. The inner sunset downtown area, whose population density was very high compared to the surroundings, was identified as region 6. Even if geofence is applied, one can observe that regionalization results with or without geofence is very similar in daytime.

Regionalization results for the nighttime population density (ρ_N) and airspace availability identified 6 regions. Despite the fact that the census tract in the Financial District, which is shown in red, has a very low population density, regionalization result is shown to preserve spatial contiguity as a region 3. As geofence is applied, one can see a slight change in the regional boundaries near the northeast corner of San Francisco. But at nighttime as well, the overall regionalization results are very similar.

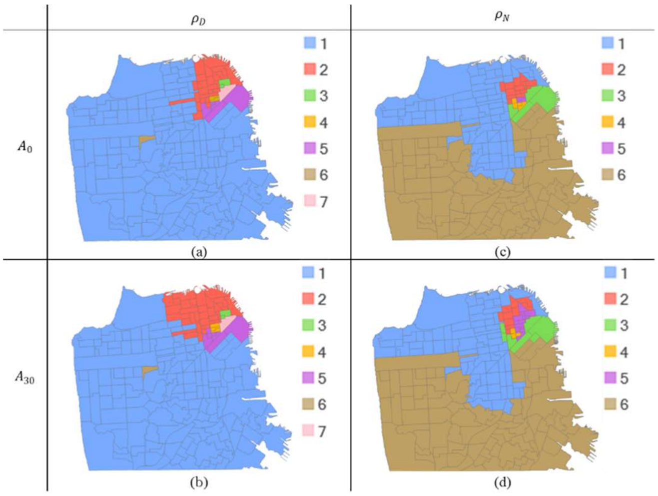

Fig. 3 Regionalization results of the San Francisco with respect to population density and urban airspace availability

To further understand the regionalization results, quadrant map of each region regarding population density and airspace availability is shown in Fig. 4. According to Breunig et al (2018), population density of urban area is classified into 3 categories: low (1,564/km^2), medium (6,629/km^2), and high (32,880/km^2) by following LandScanTM Global Population Database [14]. Black vertically dotted line refers high population density. (see Fig. 4)

One can observe that dotted lines make up quadrants. Through quadrant plots, four different forms of regions are identified: High–High, Low–Low, Low–High, and High–Low. These four forms correspond one-to-one with the four quadrants. High-High (or Low-Low) classified region implies that the locations show high (or low) values of the both airspace availability and population density. On the other hand, Low-High (or High-Low) classified region implies that the locations show low (or high) values of the population density and high (or low) values of the airspace availability.

In general, the regions identified as a result of regionalization in north eastern San Francisco are generally High-High classified regions during the daytime. In High-High classified regions, potential demand can be concentrated in those regions due to the high exposed population. Furthermore, one can expect relatively high airspace capacity for UAS. Taken together, one can expect a high-added value business model of UAS applications in there.

Since the Financial District in daytime with geofence has significantly low airspace availability (cluster 7 in Fig.3&4 (c)), one can expect the number of UASs that can be operated is very limited. Since balancing potential demand and capacity is crucial in High-Low classified region, efficient traffic flow management is needed. Furthermore, the risks to safety, urban canyons, and privacy should be considered due to its low airspace availability. In this sense, we could argue that High-Low classified region should consider not only efficient traffic flow management but also the risk due to the geospatial complexity for UAS applications.

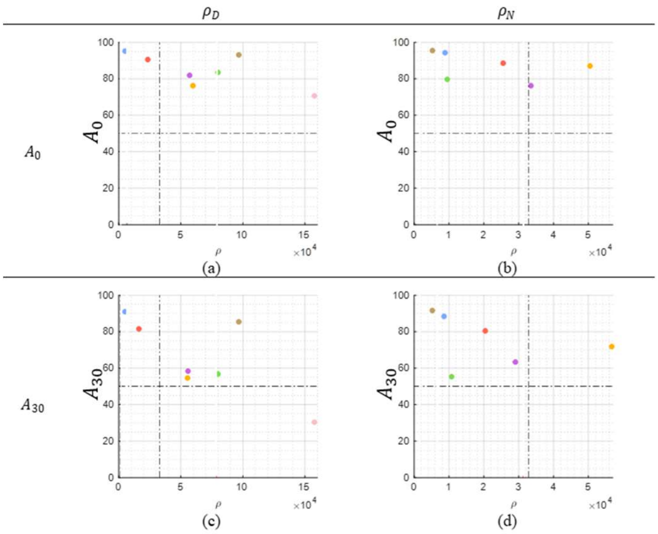

Fig. 4 Quadrant plots of regionalization results.

IV. CONCLUSION AND FUTURE STUDY

In this study, we applied spatial clustering to identify feasibility of sUAS in a highly built-up urban environment. A case study of a San Francisco provided further insights into the economic feasibility and safety to risk in a real 3-D environment. Regionalization results show that population risk and geospatial complexity are much higher in the north east corner than in other regions. However, considering the daytime population density, it can be seen that the region can be expected to create high value-added industries.

In future study, we apply our method to various metropolitan cities to propose a framework for assessing risk and economic feasibility according to the characteristics of the city. For this, we extend our approach to assess risk to population and spatial connectivity of airspace. Our approach also has the potential to produce useful information to design drone delivery target area identification, landing location identification, demand prediction.

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