A Generative Adversarial Network Framework for Vertiport Location: A Case Study in Toronto

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Abstract

Urban Air Mobility (UAM) is an avation-based urban transportation that enables time-efficient passenger and cargo movement within complex low-altitude urban airspace. Vertiports are the ground infrastructes of this novel transporation system. Choosing the best location for vertiports in a city is one of the main challenges in developing this system. Previous studies have suggested different methods to solve this problem. This study takes the strengths of several existing methods and integrates them with a deep learning approach called Generative Modeling to propose a new framework for optimal vertiport placement. The core component of the proposed framework is the conditional Generative Adversarial Network (GAN), which learns complex and implicit spatial relationships between different factors and identifies highly suitable areas for vertiport construction. Subsequently, the refined suitability map created by the GAN is combined with the DBSCAN clustering technique to group feasible sites, and the resulting candidates have been optimized using a Location-Allocation model to choose the best locations with maximum service coverage and minimum travel time to Toronto airports. The results show that the proposed method can successfully integrate the UAM system with the existing transportation network and support the development of an integrated and interconnected urban transportation system. Furthermore, the identification of existing now-closed airport infrastructure as a viable vertiport location indicates that the results are coherent and aligned with real-world conditions.

1. Introduction

Nowadays, with the growing urban population and the resulting increase in ground traffic congestion, carbon emissions have become a global concern. In this regard, various initiatives have been targeted to reduce carbon emissions by 90% by 2050 through innovative solutions for carbon-neutral urban transportation (Conrad et al., 2024). Urban Air Mobility (UAM), as a subset of Advanced Air Mobility (AAM), is one of the proposed options. UAM enables the transportation of both passengers and cargo in low-altitude urban airspace (below 400 feet or 122m) using electric vertical take-off and landing (eVTOL) aircrafts, which enables time-efficient travel in congested, obstacle-rich urban environments (Fontaine, 2023).

Vertiports are the ground infrastructure or the connection point between the UAM and the ground (Brunelli et al., 2023). Finding suitable locations for vertiports is one of the main challenges in implementing UAM, because it directly affects the accessibility and attractiveness of this new urban transport system. According to previous studies, a wide range of factors or constraints, including safety, accessibility, integration with multimodal transportation systems, as well as environmental, social, and economic considerations, must be taken into account in vertiport placement. Therefore, it is highly recommended to build vertiports in locations with high potential demand, such as areas with high population density and income; areas near Points of Interest, such as city centres, office and commercial buildings and tourist attractions; and areas identified as Hotspots through travel pattern analysis.

Additionally, the integration and interconnectivity of this novel transportation system with existing urban transportation systems are key to the success of UAM. In this regard, using existing resources, such as multimodal transportation hubs, helipads, airports, train and metro stations, and bus terminals, as vertiports, not only enables the construction of an integrated transportation system but also leads to reduced costs and complexity while facilitating regulatory approval processes. On the other hand, in terms of noise from UAM aircraft, vertiport interchange transport nodes are considered suitable locations for vertiport placement (Brunelli et al., 2023).

Many algorithms have been developed in the literature for vertiport location planning, including optimization-based methods, spatial or GIS-based analyses, and clustering techniques. In optimization-based approaches, the main objective is to find the optimal solution for a cost function. For vertiport placement, this usually means minimizing travel time. Methods such as integer programming, the p-hub location problem, and machine learning are often used in these scenarios. GIS-based methods often use rule-based overlay of different factors, where the results depend on user-set weights. Clustering-based methods, such as K-means and DBSCAN, aim to find the best locations by calculating the geometric centers of the data points, but they do not directly account for environmental or contextual constraints.

The vertiport placement problem is mathematically NP-hard because of the complex environment of the cities and numerous factors influencing the identification of optimal sites. Therefore, the proposed algorithm is expected to find the best locations without subjective bias, follow physical and practical logics, and be efficient in terms of computational cost.

This study introduces a hybrid approach based on a Generative Adversarial Network (GAN) model. Since UAM can reduce travel time by about 25% for long-distance commutes and 50% for short-distance commutes in crowded cities, it is therefore considered suitable for time-sensitive transports, such as

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medicine delivery, emergency response, and airport access (Zhao et al., 2025). Therefore, this study aims to optimize vertiport placement to improve and accelerate access to Toronto's airports, which are among the busiest in the world.

The remainder of the paper is organized as follows: Section 2 introduces methodology. Section 3 incorporates the results. Finally, the conclusions and future directions are presented in Section 4.

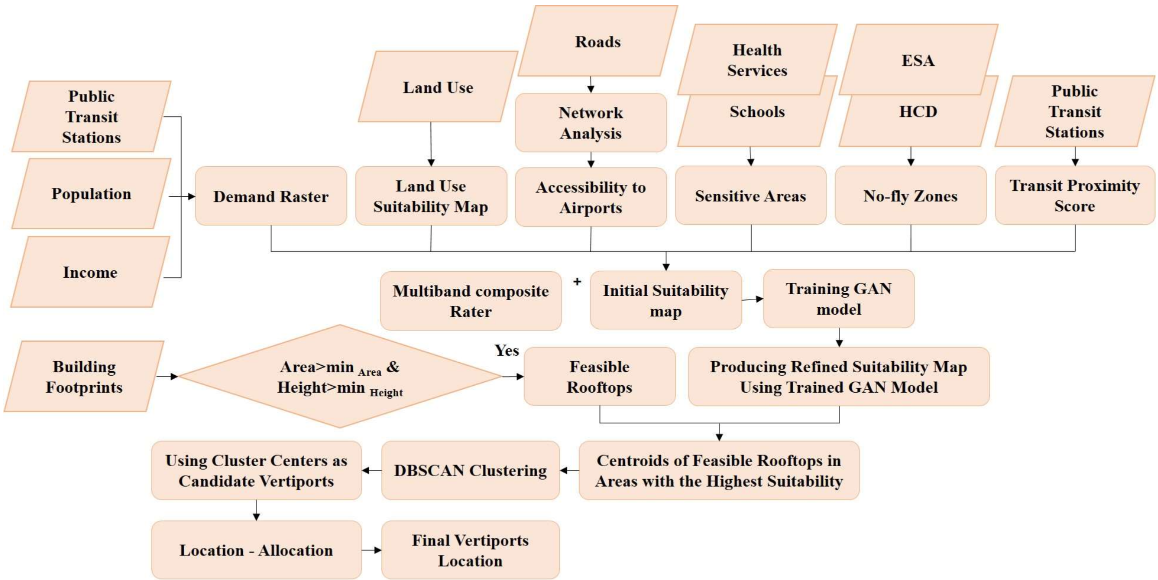

Figure 1. Flowchart of the proposed methodology

2. Case Study

In this study, the City of Toronto, Ontario, Canada (43°39′09″N, 79°22′54″W) was selected as a case study to identify the optimal locations for constructing vertiports to facilitate access to the Toronto Pearson International Airport and Billy Bishop Toronto City Airport. A variety of spatial datasets were collected and processed to generate the input layers required for the analysis. These datasets were primarily derived from open-source platforms and represent key factors influencing the suitability of locations for UAM ground infrastructure. The selected factors encompass demand-related variables, including population density and average income, as well as land use characteristics, no-fly restrictions, and transportation infrastructure such as public transit and road networks.

Socioeconomic data, including population density and average income at the census tract level for 2025, were obtained from Simply Analytics[1]. Information on land use, no-fly zones, and building characteristics was sourced from the City of Toronto’s Open Data Portal[2]. Specifically, the “Zoning Area” layer of the “Zoning By-law” dataset and were used to analyze land use patterns. Based on the data dictionary, the “GEN_ZONE” attribute classifies land into categories such as residential, commercial, open space, and other uses.

No-fly zones were determined by integrating multiple datasets, including locations of health services (“Wellbeing Youth - Health Services”) and educational facilities (“School Locations - All Types”), along with designated “Environmentally Significant Areas” and “Heritage Conservation Districts.” In addition, the “3D Massing” dataset was utilized to extract building footprint and height information, providing detailed three-dimensional representations of urban structures across the Greater Toronto Area.

Transportation infrastructure was incorporated through both public transit and road network data. Public transit data were retrieved from the “cot_geospatial7” map service available via the City’s ArcGIS REST API[3], which includes layers such as ward boundaries, Toronto Transit Commission (TTC) stops and routes, and GO Transit stations. Road network data were obtained from the GIS_OSM_Roads dataset for Toronto, sourced from OpenStreetMap through Geofabrik, providing detailed spatial information on streets, highways, and other road types[4].

3. Methodology

In this study, a deep neural network-based approach using a GAN model is proposed for constrained optimal vertiport siting. The proposed framework combines the power of GANs in learning implicit spatial patterns with the advantages of GIS analysis and clustering techniques to find the best vertiport locations. First, the data or initial suitability map for training the GAN was generated using GIS analysis. Then, the trained GAN was utilized to produce a refined suitability map. In the next step, the DBSCAN algorithm clusters candidate locations within the high-suitability areas identified by the GAN. Finally, a Location–Allocation model was implemented to select the final optimal sites for vertiport development.

The workflow of the developed algorithm is depicted in Figure 1. The entire methodology can be summarized in three steps: data

[1] https://simplyanalytics.com/data
[2] https://open.toronto.ca/
[3] https://gis.toronto.ca/arcgis/rest/services/cot_geospatial7/MapServer
[4] https://download.geofabrik.de/north-america/canada/ontario.html?utm

pre-processing and training data generation; GAN architecture and training; and post-processing and final site identification.

3.1 Data pre-processing and training data generation

GAN is a kind of deep neural network-based generative models that learns a mapping between a simple source distribution and the target probability distribution. Therefore, this supervised model requires training data. In this scenario, the training dataset was constructed as a vertiport placement suitability map, generated from spatial data layers corresponding to the key influencing factors.

The first step was data preprocessing. In this step, by reviewing previous studies and existing guidelines (Chamberlain et al., 2025; Fontaine, 2023; Ison, 2024), proximity to the existing transportation network, land use type, demand, and accessibility to Pearson and Billy Bishop airports were selected as the key factors influencing the identification of optimal vertiport locations.

To integrate UAM with the existing transportation system and generate a layer representing the proximity to the existing public transit stations, the normalized proximity score for each station was estimated using Euclidean distance from that station (d) and Equation (1). Accordingly, the closer an area is to a station, the higher its proximity score, which resulted in a higher suitability score in the initial suitability map. Figure 2 illustrates the produced proximity to public transit stations.

$$Transit\ proximity\ score = Nomamized\left(\frac{1}{1+d}\right), \quad (1)$$

Figure 2. Proximity to public transit stations

The spatial layer of land use includes the land use categories (residential, open space, utility and transportation, employment industrial, institutional, commercial residential employment, residential apartment, commercial, commercial residential) within the region boundary. To determine the suitability of each land use type for vertiport construction, a land use suitability layer was generated through weighted overlay and the Analytic Hierarchy Process (AHP) weighting method. According to the established guidelines (Chamberlain et al., 2025; Fontaine, 2023; Ison, 2024), land use types of commercial, commercial residential employment, commercial residential, employment industrial, utility and transportation, residential, residential apartment, open space, and institutional were ranked in descending order of suitability, and weights were assigned accordingly. Figure 3 illustrates the produced land use suitability layer.

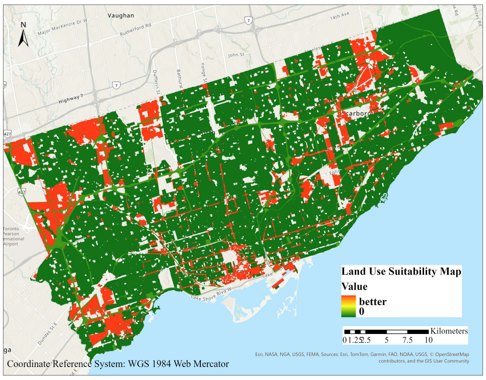

Figure 3. Land use suitability layer

Following this, the demand layer was generated. From an economic perspective, the ground structures of UAM should be built in locations with higher demand to ensure economic viability of this novel transportation system. Based on previous studies, population density (Figure 4), average income (Figure 5), and proximity to public transportation stations (Figure 2) have the greatest impact on demand. Accordingly, these layers were weighted using the AHP method, and the demand layer (Figure 6) was produced using weighted overlay of the layers. AHP is a decision-making method that combines mathematics with human judgment. In this method, decision-makers perform pairwise comparisons between criteria to define their relative importance. Then, these comparisons are combined to create a set of weights that show how much each criterion affects the final decision. Using this method, the highest weight was given to population density, followed by proximity to public transportation stations, and then income level.

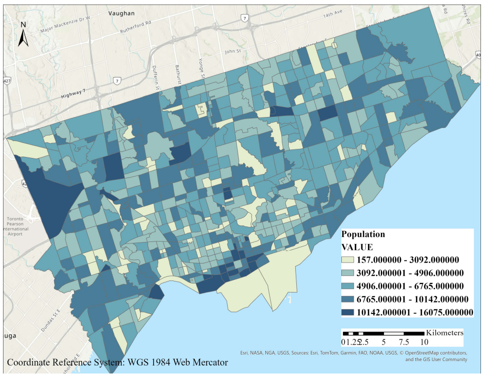

Figure 4. Population density per census tract in 2025

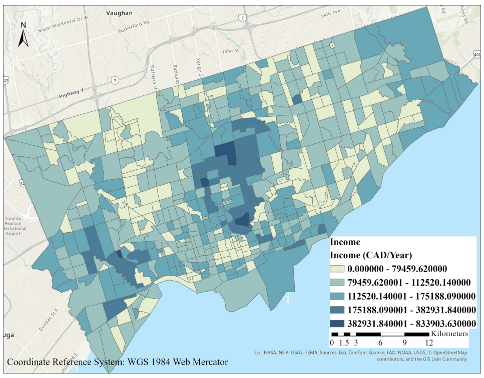

Figure 5. Average Income (CAD/Year) per census tract in 2025

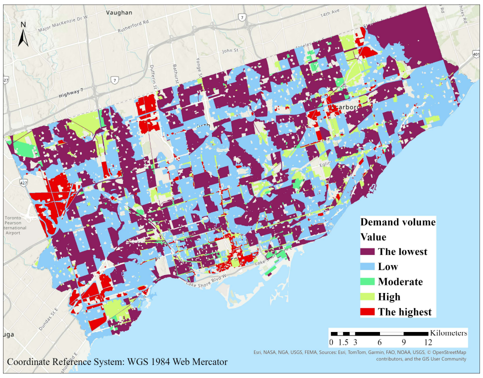

Figure 6. Demand volume layer

Next, layers representing accessibility to Pearson and Billy Bishop airports in Toronto were created. In this study, since the goal is to facilitate timely access to the airports, vertiport locations should be planned in areas where access to the airports via existing road and transit network involves higher travel time costs. To calculate the travel time cost, the road and street dataset was used to create a route network through network analysis in ArcGIS Pro. Then, using the Origin–Destination Cost Matrix, the travel time cost from census tract centres (origins) to the airports (destinations) were calculated for each origin–destination pair (without considering traffic congestion). Finally, using the Inverse Distance Weighted (IDW) interpolation technique and spatial analysis, the travel time cost to each airport were converted to raster format for the entire Toronto area. Figures 7 and 8 show the approximated travel time layer to Billy Bishop and Pearson airports.

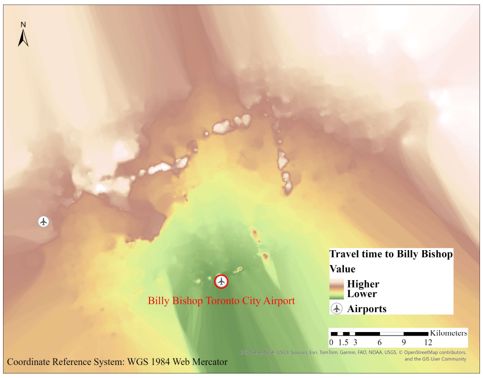

Figure 7. Travel time to Billy Bishop airport

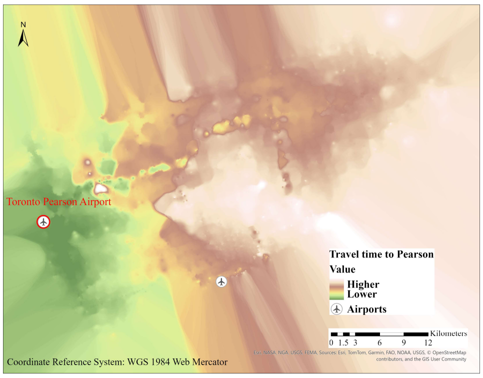

Figure 8. Travel time to Pearson airport

Based on previous studies, the construction of vertiports is prohibited in no-fly zones for social considerations. These include hospitals, medical centers, and schools (Figure 9), as well as environmental and heritage conservation areas (Figure 10). For this purpose, a spatial layer was generated using the aforementioned datasets. The produced no-fly zones layer, includes polygons related to the buffers defined around schools and healthcare service locations, as well as Environmentally Significant Areas (ESA) and Heritage Conservation Districts (HCD) areas.

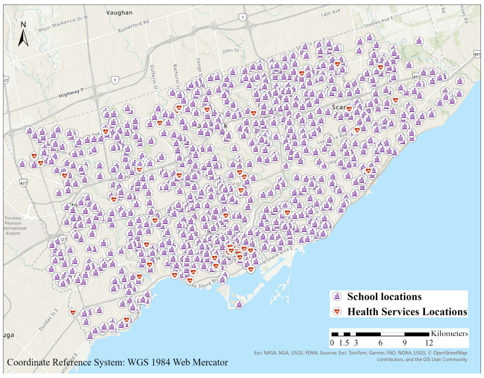

Figure 9. Schools and health services locations

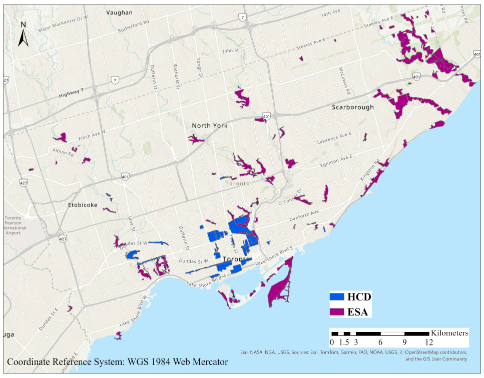

Figure 10. ESA and HCD zones

After performing the necessary pre-processing steps on the dataset, the initial suitability map, or training data required for training the GAN model, was prepared using AHP weighting and weighted overlay of the generated spatial layers. The weighting of the layers has been determined by reviewing previous studies and based on existing guidelines as well as regulations, such that the demand, land use suitability, proximity to public transportation stations, and airport accessibility layers were assigned weights from highest to lowest. Moreover, to prevent the construction of vertiports in prohibited areas, the regions in the suitability map that overlapped with the no-fly zones were removed.

3.2 GAN architecture and training

GAN is a type of deep generative model that learns to generate realistic data of any type from an unknown probability distribution using a training dataset across a variety of disciplines. GAN consists of two neural networks trained by adversarial algorithms, a Generator (G) and a Discriminator (D) (Krichen, 2023). The Generator learns to produce data that are indistinguishable from real data, while the Discriminator network learns to differentiate between them. In other words, the learning process involves minimaxing the following objective function (Equation 2) (Krichen, 2023):

$$Es\,[logD(s)] + Ev\left[log\left(1 - D\left(G(v)\right)\right)\right], \tag{2}$$

where E is the expected value, s is the real data sample, D(s) ∈ [0, 1] is the output of the Discriminator, showing the probability that s is a real data sample, and v is a random noise vector or the input of Generator for generating a synthetic data. The first term in the equation leads the Discriminator to maximize the probability of assigning the correct label to the training real data, while the second term encourages the Generator to produce synthetic samples classified as real data by the Discriminator.

In this study, a conditional GAN model (Pix2Pix) in ArcGIS Pro, was utilized to learn nonlinear spatial relationships between multiple layers without explicitly defining rules, in order to generate new spatial patterns of the vertiport network that satisfy all constraints. The initial suitability map generated in the pre-processing phase, along with a multiband composite raster including layers related to demand, land use suitability, transit proximity, airports accessibility, and no-fly zones, was used as training dataset for the conditional GAN to learn generative modeling from the composite input raster to the suitability map. During training, the Generator acts as nonlinear integrator and learns to produce vertiport suitability map from the composite raster, while the Discriminator distinguishes generated maps from real suitability maps, ensuring that the generated maps follow the geographic logic. Finally, the trained conditional GAN model was implemented to generate the refined suitability map for vertiport network design.

3.3 Post-processing and final site identification

The output of the trained GAN model, or the refined suitability map, was post-processed to select the final vertiport locations. Vertiports can be constructed at ground level or on building rooftops. However, according to surveys reported in the previous literature, majority of people generally prefer elevated vertiports on rooftops, as they may reduce operational and safety conflicts (Yunus et al., 2023). Therefore, in this scenario, the goal was set to locate vertiports on building rooftops. Therefore, using the open-source buildings footprints dataset[5] and relevant guidelines, candidate buildings have been selected based on the minimum area and height required for a rooftop vertiport. Then, the candidate buildings have been further narrowed to those located in areas identified as most suitable in the refined suitability map.

Since the number of buildings located in the highest suitability areas was very large, the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) technique was applied to cluster the centroids of the selected buildings. It should be noted that the centroids of the feasible buildings were assumed to represent each building for the purpose of clustering. After clustering, the mean center of each cluster was used to identify potential vertiport locations. DBSCAN has been selected because, unlike many traditional clustering methods that rely primarily on distance metrics or require the number of clusters to be specified in advance, it is based on spatial density. This specification allows it to identify clusters of arbitrary shapes and varying sizes, making it particularly suitable for spatial data analysis in complex urban environment.
Effective DBSCAN clustering relies heavily on tuning its primary parameters known as the maximum radius of the neighbourhood around a feature and the minimum number of features per cluster. If the search distance is set too small, a region may be divided into many small, fragmented clusters, resulting in too many proposed vertiport locations that are not practical. Conversely, if it is set too large, two potentially separate vertiport locations may merge into one large, unrealistic cluster. Furthermore, the minimum number of features per cluster defines how sensitive the algorithm is toward noise. Therefore, for optimal clustering the optimal values of these parameters should be determined through sensitivity analysis.

After finding the mean centre of feasible buildings’ clusters in the most suitable areas, there were many points where candidate vertiports could be built on. Therefore, a Location-Allocation model was utilized to choose the final vertiport locations from these points, to maximize service coverage and minimize travel time to the Pearson and Billy Bishop airports.

4. Results

In this study, using the trained conditional GAN model, refined suitability maps were generated for vertiport construction to facilitate accessibility to both Pearson (Figure 11) and Billy Bishop (Figure 12) airports in Toronto. The analysis of these maps indicates that the most suitable areas are generally located in commercial and mixed-use zones, as well as in high-demand areas and near major public transport hubs. This shows that the trained GAN model produced potential maps with strong spatial coherence and realistic suitability patterns.

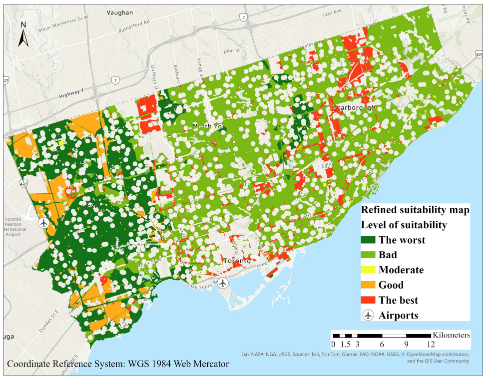

Figure 11. Refined suitability map for vertiport construction to improve access to Pearson airport.

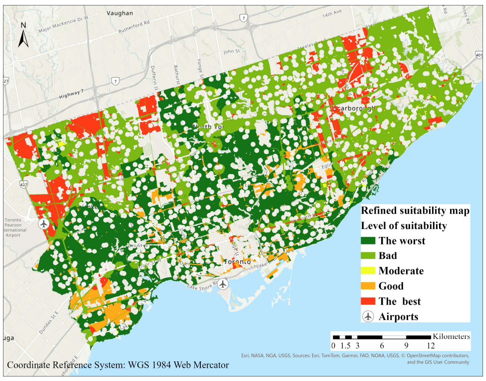

Figure 12. Refined suitability map for vertiport construction to improve access to Billy Bishop airport.

[5] https://open.toronto.ca/dataset/3d-massing/

After identifying feasible rooftops in the areas with the highest suitability and clustering them using the DBSCAN technique, the mean centers of the clusters were determined as representatives of the rooftops within each cluster. These centers are then used as service facilities in the Location-Allocation model for each airport. Six and eight points were extracted to serve Billy Bishop and Pearson airports, respectively. The implementation of the Location-Allocation optimization reduced the number of optimal sites to two for each airport, providing the best service coverage and shortest travel time. Figures 13 and 14, demonstrate the final chosen and candidate sites for vertiport construction to serve both airports in Toronto.

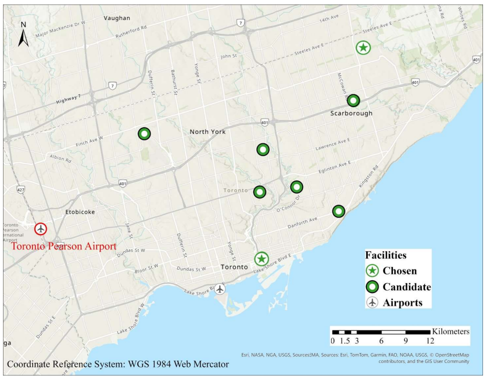

Figure 13. Final chosen and candidate sites for vertiport construction to serve Toronto Pearson Airport.

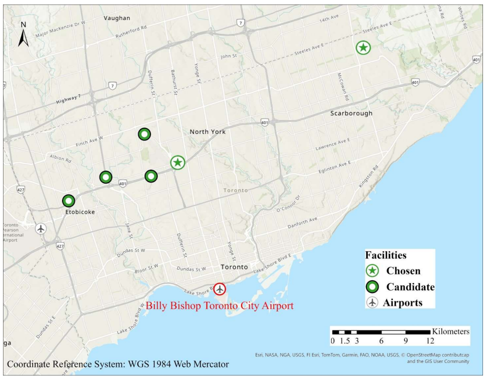

Figure 14. Final chosen and candidate sites for vertiport construction to serve Billy Bishop Toronto City Airport.

Although trips made to access airports often start from residential areas, constructing vertiports in commercial and similar zones may seem unusual. However, according to regulations and safety considerations, particularly those related to low-altitude aircraft noise, the construction of vertiports in residential areas is prohibited. On the other hand, the purpose of building these vertiports for serving Toronto airports is to offer faster travel options when regular transportation is slowed by heavy city traffic, helping passengers reach the airports on time through an integrated multimodal urban transport system. According to calculations and network analysis, 26.84% and 45.61% of the total city population can access the designated vertiport candidates using other transportation modes within 10 and 15 minutes, respectively.

Since the mean centers of each cluster are chosen as its representative, the candidate sites within the clusters corresponding to these selected centers are further examined to determine the final best locations. The result indicates that a common station in the Scarborough area was selected to serve both airports. The next facility selected as the optimal site for vertiport placement to serve Toronto Pearson Airport is located in downtown Toronto, near Subway Line 1 and Union Station, the city’s major intercity transportation hub (Figure 15). The second selected site for serving Billy Bishop Airport is also located near Subway Line 1 and Wilson Subway Station, which is geographically located close to Downsview Airport (Figure 16).

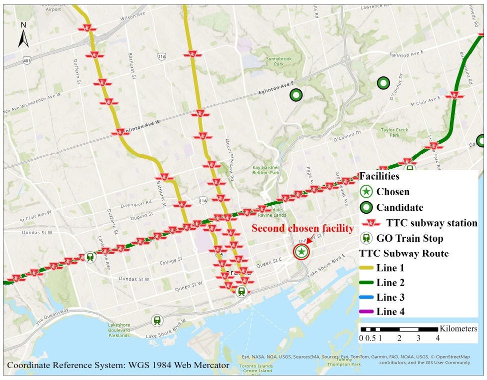

Figure 15. The second chosen facility for optimal vertiport placement to serve Toronto Pearson Airport.

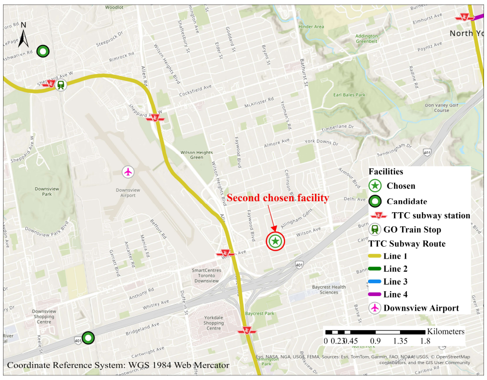

Figure 16. The second chosen facility for optimal vertiport placement to serve Billy Bishop Toronto City Airport.

5. Conclusion

With technological advancements, low-altitude Urban Air Mobility has emerged as a proposed solution for enabling fast intra-city travel. Vertiports serve as the ground infrastructure of this novel transportation system, providing access to UAM services. The geographical location of these facilities plays a critical role in the success and public acceptance of this system.

Numerous studies have been conducted in this field, employing a wide range of optimization and spatial analysis algorithms. Building upon the strengths of several of these approaches, such as GIS-based methods and clustering techniques, and integrating them with Generative Adversarial Network modelling, a trending deep learning based approach; this study proposes a novel framework for the optimal vertiport placement to improve airports accessibility in Toronto. The GAN model learns the nonlinear spatial relationships between multiple input layers without explicitly defined subjective rules and generates a refined suitability map for vertiport placement. It should be noted that this model only identifies areas with high suitability. Therefore, a combination of clustering techniques and a Location-Allocation optimization model was applied to determine the final vertiport locations with maximum service coverage and minimum travel time.

The analysis of the results demonstrates that a common station in the northeast of Toronto (Scarborough area) was chosen to serve both Billy Bishop and Pearson airports, which is more cost-effective than constructing two separate vertiports for each airport. The other chosen location for serving Pearson Airport is near downtown Toronto and a major intercity transportation hub, Union Station. This indicates that the proposed algorithm effectively integrates UAM into the existing transportation network and contributes to the development of an integrated, interconnected urban transportation system. In addition, previous studies indicate that most people prefer vertiports located in or near major transportation hubs in the city center. In terms of noise, interchange transport nodes, such as Union station, are considered ideal locations for vertiport construction.

The second identified location for vertiport construction to serve Billy Bishop Airport is situated near Wilson Subway Station and the now-closed Downsview Airport. On the one hand, the results show that the proposed algorithm can successfully integrate the UAM system with the existing transportation network. On the other hand, identifying an existing resource as a candidate vertiport can be considered a significant advantage. Previous studies (Zhao et al., 2025) emphasized the advantages of utilizing existing resources, such as airports, as vertiports, because these sites have already obtained the necessary approvals regarding security, noise, and environmental regulations.

It should be mentioned that, since the mean centers of the clusters were utilized as candidate facilities for implementing the Location-Allocation model, the identified points merely represent the potential locations within their corresponding clusters. Therefore, their geographic positions do not necessarily indicate the exact optimal sites for vertiport construction. A more detailed analysis of the areas surrounding each identified point is required to determine and select the most suitable final location.

The trained GAN model can generate a vertiport placement suitability map for any other city by using the multiband raster composed of the same spatial layers for that city as its input, which shows the scalability of the proposed algorithm. However, many factors affect the selection of the best location for vertiport construction, and this study has only considered a few of them. Therefore, for future research and to improve the proposed algorithm, it is important to include other factors, such as wind flow analysis, noise distribution, and public acceptance.

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