MODELING AIRPORT CATCHMENT AREAS

Using a Spatial Analysis Approach

Abstract

The airport catchment area is the geographic area from which an airport can reasonably expect to draw commercial air service passengers. The purpose of this interdisciplinary research is to estimate airport catchment areas using a spatial analysis method for informed airport management. In order to ensure the comprehensiveness and reliability of the research, we chose to analyze the catchment areas for five airports of different sizes and in different geographic locations in the United States. The Huff model, which is usually used in marketing, economics, and retail research, was adopted in this study. We applied this model in airport catchment analysis for the selected airports, with consideration of ground transportation distance and airport attractiveness. We identified the best distance factors and parameters for modeling purposes. The results provided reliable information for the selected five airports to estimate their catchment areas. In addition, the model can provide a good reference for other airport catchment analysis studies about the effectiveness of the Huff model in prediction.

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INTRODUCTION

The Airport Cooperative Research Program defined "an airport catchment area, or air service area, as a geographic area surrounding an airport where it can reasonably expect to draw passenger traffic" (Transportation Research Board [TRB], n.d.). It is defined by several factors, including geographical and access considerations, as well as the proximity of alternative aviation facilities (TRB, n.d.). The estimation of an airport's catchment area is usually based on the passenger's driving distance and the distances to competing airports in the region (TRB, n.d.). Airport catchment area is one of the important concepts in airport master planning and operations. It informs the airport and other stakeholders such as the airlines about locations from which potential travelers are likely to commute to the airport to start their trips. It allows for better-informed route planning by airlines and facilitates location-based business development.

In existing research, there is no single method to estimate the airport catchment area. Many studies have used a single parameter, such as driving distance, driving time, or distance to competing airports to estimate the airport catchment area (Baltazar & Silva, 2018; Zhou et al., 2018). In 2020, Carmen Huber and colleagues published a paper that highlighted probabilistic approaches, which do not assume that individuals choose an airport solely based on proximity but estimate the likelihood that a population would use one or more airports for travel (Huber et al., 2020). In this study, the Huff model was introduced to analyze airport catchment areas. The Huff model is a spatial analysis method for forecasting the probability of a consumer visiting a location. Based on the Huff model, the probability that someone would use an airport is defined largely by two main factors: distance to each surrounding airport, and a measure of attractiveness of the selected airport compared to each surrounding airport, such as available flights or traveler volume.

The previous research adopted the Huff model in airport catchment analysis for a selected airport. To expand upon their research, our study examines the effectiveness of a spatial analysis method (the Huff model) in airport catchment area estimation. In order to ensure the comprehensiveness and reliability of the research, we chose to analyze the catchment areas for five airports of

different sizes and in different geographic locations in the United States. At the end of this project, we hope the results will provide reliable management information for the selected airports and a good reference for other airport catchment analysis studies.

METHODOLOGY

To establish theoretical airport catchment areas, we utilized ArcGIS Pro to build the Huff model for the selected airports. We opted to evaluate the catchment areas for five airports in the United States of various sizes and geographic locations in order to ensure the research's comprehensiveness and reliability:

- Boston Logan International Airport (BOS, large hub, Eastern/New England region)
- Dallas Love Field Airport (DAL, medium hub, Southwest region, Southwest Airlines hub)
- Ontario International Airport (ONT, medium hub, Western-Pacific region, panel member affiliated)
- Akron-Canton Airport (CAK, small hub, Great Lakes region, panel member affiliated)
- Jacksonville Albert J. Ellis Airport (OAJ, nonhub primary airport, Southern region, panel member affiliated)

The Huff model was chosen for this study because it is a well-established spatial analysis theory, commonly used in business analysis, which predicts the likelihood of a consumer visiting a site as a function of its distance, attractiveness, and the relative attractiveness of alternatives. The results were calculated based on the census block group (CBG), the smallest geographical unit used by the U.S. Census Bureau. The probability of each targeted airport j at census block i (Pij) is generated from the classical formulation of a Huff model (Huff, 1963):

$$P_{ij} = \frac{\frac{S_j}{T_{ij}^a}}{\sum_{j=1}^{n} \frac{S_j}{T_{ij}^a}}$$

With:

Pij: Probability of a consumer at point i traveling to retail location j

Sj: Measure of the attractiveness of store j

Tij: Travel distance from the consumer at point i to location j

a = An exponent applied to distance, so the probability of distant sites is dampened

We calculated the probability of customers in each census block using the selected airport in this research (Pij), and we used driving distance as the travel distance between census blocks and the target airport (Tij). Attractiveness is expressed as one number that combines all the factors that make a center attractive. We use enplanement data to generate the attractiveness (Sj), which is passenger (enplanement) and cargo data extracted from the Air Carrier Activity Information System (ACAIS), a database that contains revenue passenger boarding and all-cargo data (Federal Aviation Administration, 2022). The assumption is that a larger airport might have more flight options and better ticket prices to attract more potential travelers, which will have an impact on the attractiveness of the target airports. We applied this method to analyze airport catchment areas for the selected airports in this study, taking into account travel distance and airport attractiveness. With the consideration of size difference between the selected airports, we tried multiple distance cutoffs for each target airport to test the effectiveness of the model. These distance cutoffs reflected the maximum distance a consumer would travel to the airport (Huber et al., 2020). The distance from census block (i) to target airport (j) was measured using driving distance in miles. The number of potential customers was estimated by the population data acquired from the 2020 Census of the United States.

The theory of distance decay states that the distance between two locales increases as the amount of activities between them decreases. In the Huff model, the exponent applied to distance represents the distance impact on the customer's decision to utilize the target airport. A smaller exponent indicates that distance has a lower impact on people's airport choices and is typically used for items or services that are not readily available, whereas a bigger exponent indicates the opposite. In this study, the same distance decay exponent (a) would be considered for each distance cutoff, with exponents of −1.5 and −2. After comparing model results, we will detect how the distance factor impacts the performance

and effectiveness of the Huff model for airports of different regions and sizes.

We applied the Huff model with a variety of input estimates (distance cutoffs and distance decay exponents) and evaluated the validity of the results qualitatively. We estimated the distance cutoffs for the selected airports based on the size and population capacity of each airport.

HUFF MODEL RESULT: AKRON-CANTON AIRPORT

Akron-Canton Airport is a small hub. Its enplanement data is relatively low and there are two competing airports in the surrounding area, Pittsburgh International Airport (PIT) and Cleveland-Hopkins International Airport (CLE); these are big airports that are likely to draw potential passengers away. The Huff model results for Akron-Canton Airport with different parameters are shown in Figure 1. The blue dots signify airports in close proximity to the target airports, while the "airport label" shows the airports we selected. The census blocks with darker red color suggest that passenger flow from the census block to the target airport is more likely, which means the target airport has higher attractiveness to consumers. We settled on two-level driving distance cutoffs due to the airport's relatively big size and busy passenger activity. CAK is a small hub with surrounding airports; we assume consumers won't drive more than two hours to depart from this target airport. Therefore, the distance cutoffs of Akron-Canton Airport are set to 60 and 100 miles.

Figures 1.A and 1.B show the Huff model for under 60 miles distance cutoff with distance decay exponents 1.5 and 2, and Figures 1.C and 1.D calculate the Huff model in a two-level distance exponent but with the same 100 miles distance cutoffs. We studied the impact of the distance exponent on the passenger flow possibility using the same distance layer. When the distance decay exponent increases, a wider variety of census blocks have a higher chance of using the CAK airport, which can reach over 40%. Furthermore, when the distance exponent is increased, census blocks that are close to the chosen airport will raise the likelihood of attractiveness to roughly 60%. Even though raising the

distance decay exponent may weaken passengers' desire to travel to the selected airport, the results show that increasing the distance decay exponent will stimulate activity between the census block and the CAK airport (Figures 1.A and 1.B). The potential difficulty is that the likelihood of using the airport may interact with other parameters, and different combinations will affect the Huff model's performance.

When two-level distance cutoffs are compared, the most noticeable difference is that smaller distance cutoffs result in a greater range of census blocks having a higher probability of using the selected airport; census blocks at 60 miles cutoff have a probability of using CAK of over 40%, which is higher than census blocks at 100 miles cutoff. The possible cause is that the 100-mile cutoff includes one more neighboring airport than the 60-mile cutoff, thereby scattering travelers away from the target airport and reducing the possibility of customers visiting the chosen airport. Therefore, those who lived in census tracts near other major airports were less likely to fly out of CAK (Figures 1.A and 1.C).

Overall, when bigger distance cutoffs and distance decay exponents are applied, travelers who are closer to the airport are more likely to use the selected airport, and the likelihood of travel to the target airport increases. The supplied parameters resulted in a wide range of outcomes. The combination of a 60-mile distance cutoff and a distance exponent of –1.5 has the highest probability of customers using the airport, with a 60% average probability. If the catchment area is larger, customers are more likely to go to the selected airport, which has larger distance cutoffs and a larger distance decay exponent.

We can only discuss the details of the data analysis results of the CAK airport due to content constraints. We used the same analysis procedure for other airports and received similar results, indicating that the Huff model is useful in estimating an airport catchment area. For Figures 2–5, we chose the Huff model that can best perform the estimated airport catchment areas as examples.

Due to the selected airports' relatively large size and high passenger traffic, we decided on two-level driving distance cutoffs. The distance cutoffs of Boston Logan International Airport and Dallas Love Field Airport are
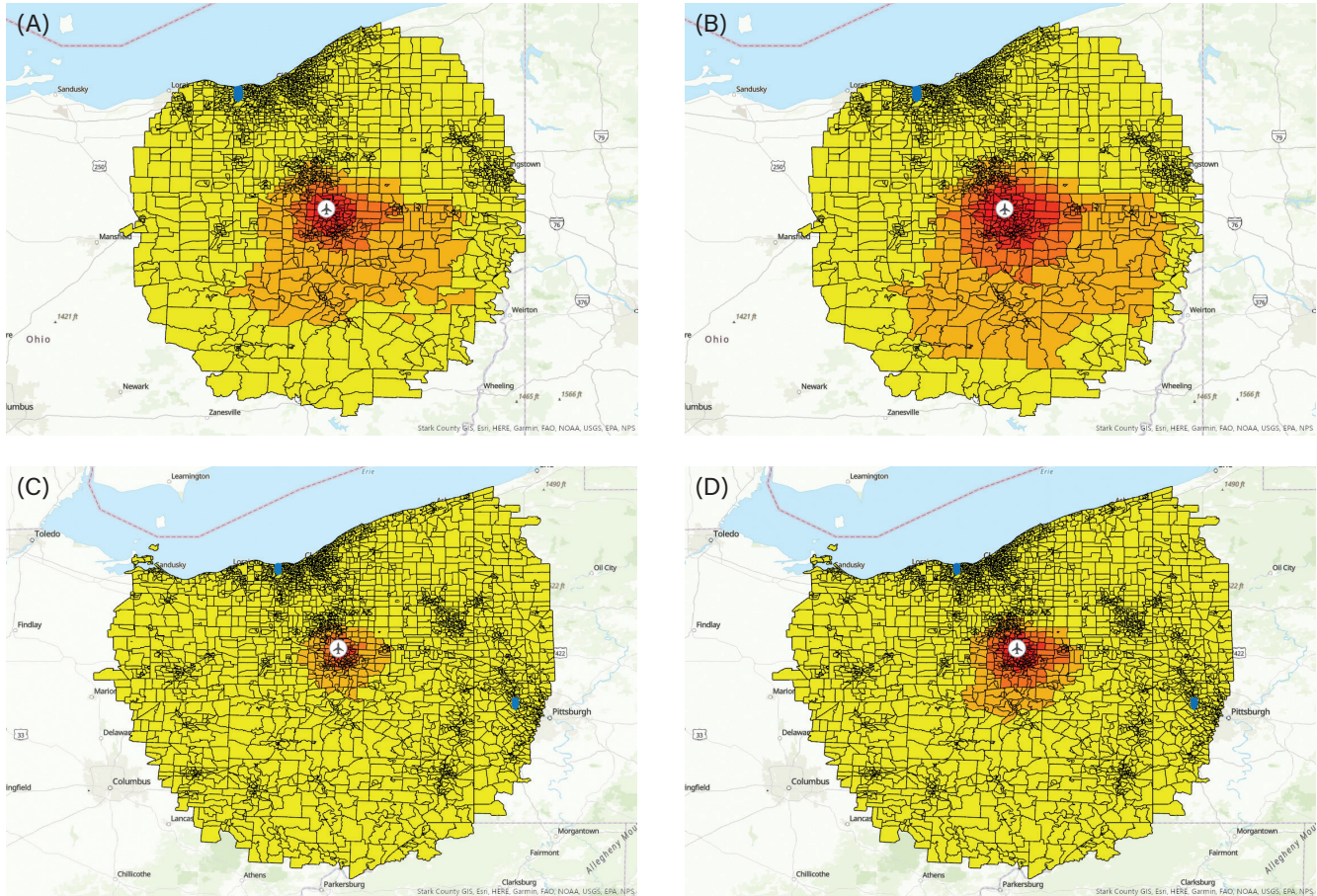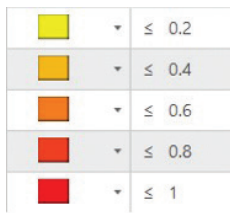
FIGURE 1. The Huff Model results for Akron Canton Airport with variance combination based on two parameters: distance decay exponents and distance cutoffs.

100 and 200 miles, and the Ontario International Airport and Jacksonville Albert J. Ellis Airport distance cutoffs are 60 and 100 miles, respectively. The Huff model has high performance in estimating these airport catchment areas. After comparing the Huff model findings from the 5 selected airports (Figures 2–5), we discovered there are numerous airports in Boston, most of them are in close proximity to the target airport, and the census block around the nearby airport has a low probability of using the target airport. Then we discovered that, despite the fact that driving distances are roughly equal, travelers choose airports that are closer to them. The 60-mile Huff

model of Jacksonville Albert J. Ellis Airport can also reflect this result. The catchment area for Dallas Love Field Airport is similarly 200 miles, and the Huff model map shows that passengers from the east are more likely than those from the west to use that airport. Furthermore, we located a few airports in the east-west direction near Ontario International Airport with a 60-mile distance cutoff, but there is very little chance of passengers visiting these airports. Therefore, the Huff model is effective in estimating the airport catchment area, and these insights help with providing reliable information for airports and aid in their management.
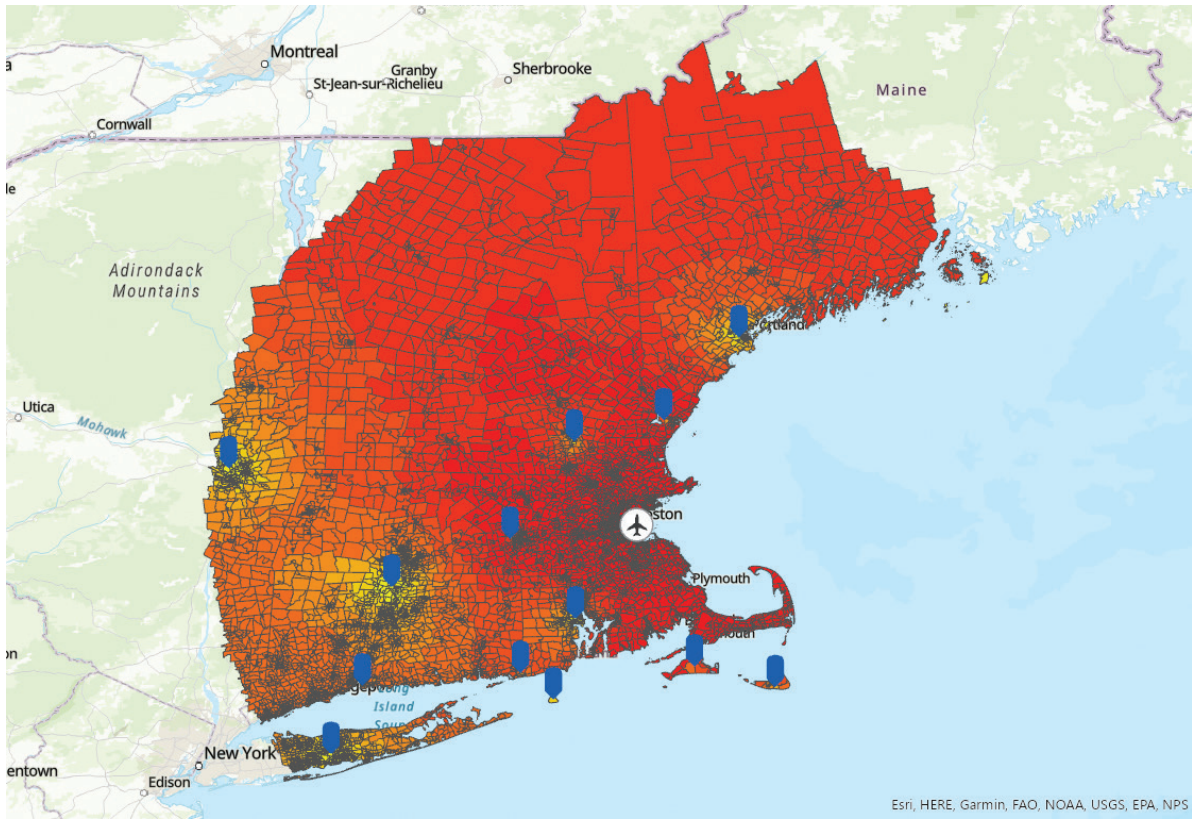
FIGURE 2. 200-mile Huff model of Boston Logan International Airport with distance exponent –1.5.
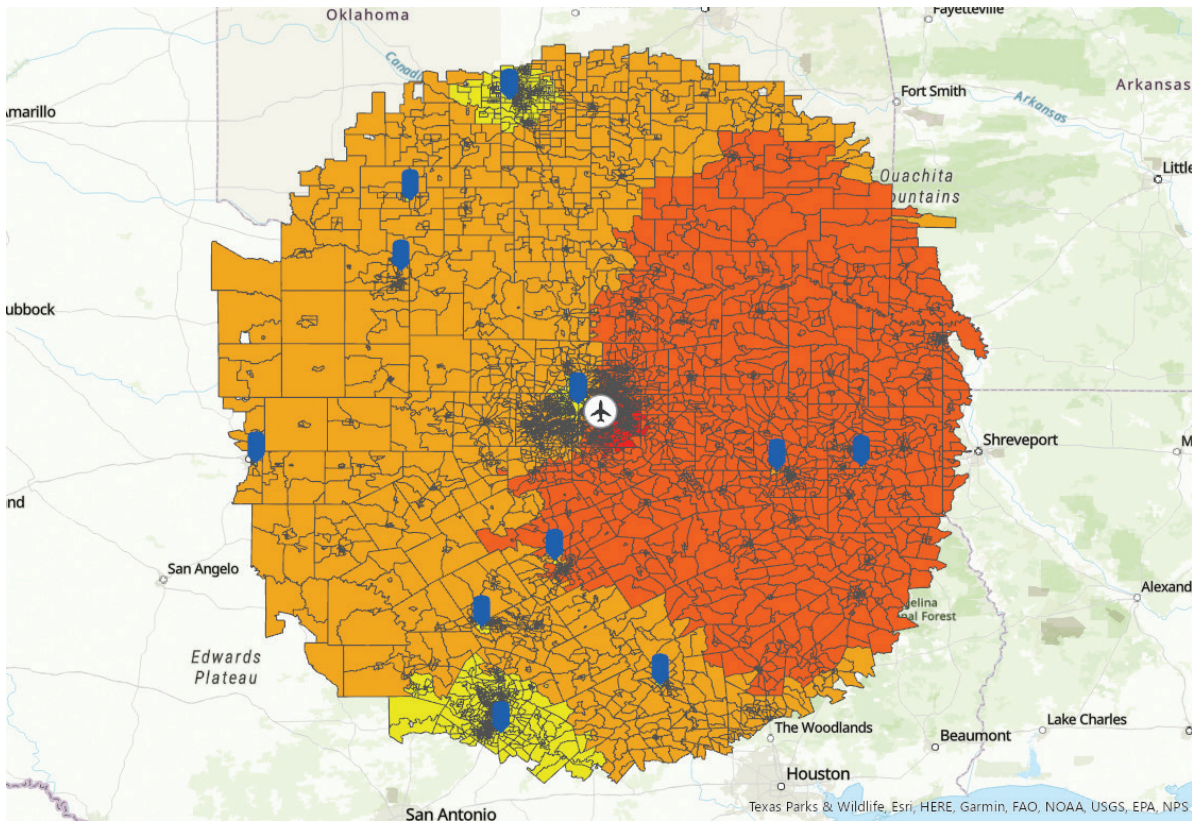

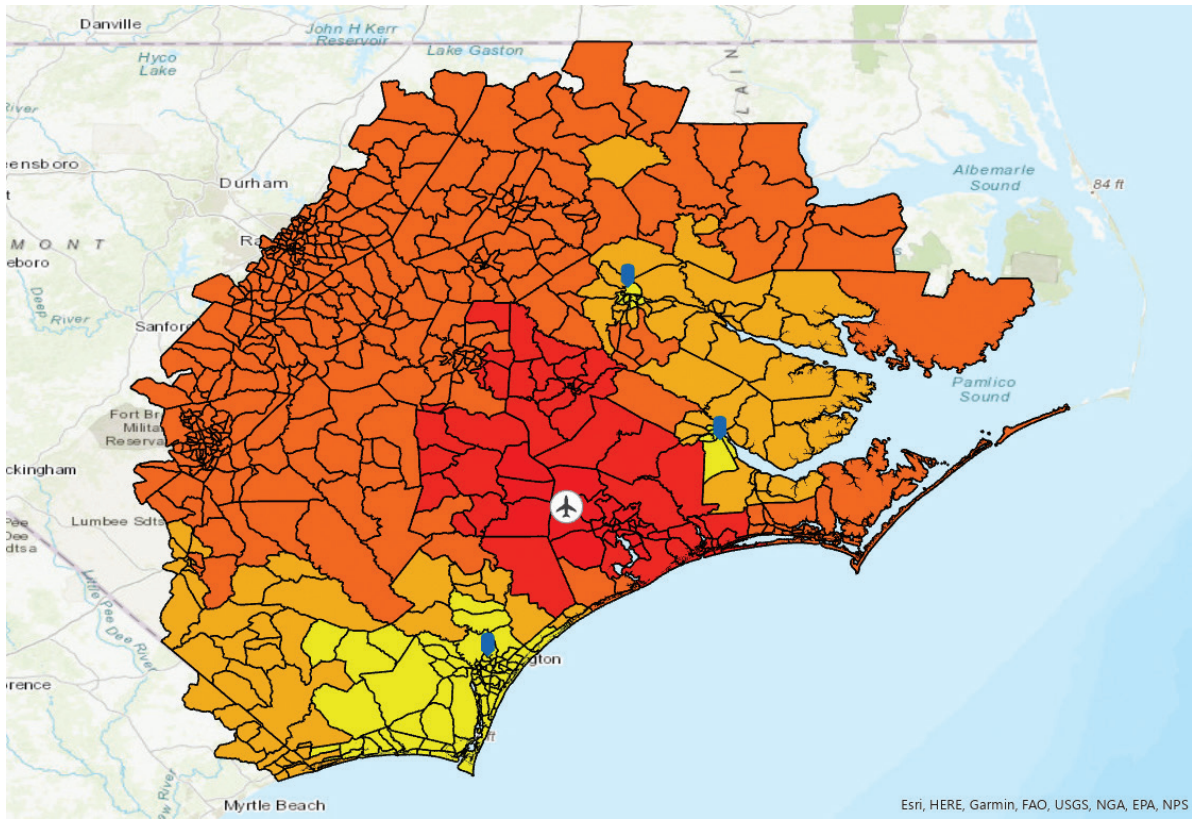**FIGURE 3.** 200-mile Huff model of Dallas Love Field Airport with distance exponent –1.5.

FIGURE 4. 60-mile Huff model of Jacksonville Albert J. Ellis Airport with distance exponent –1.5.
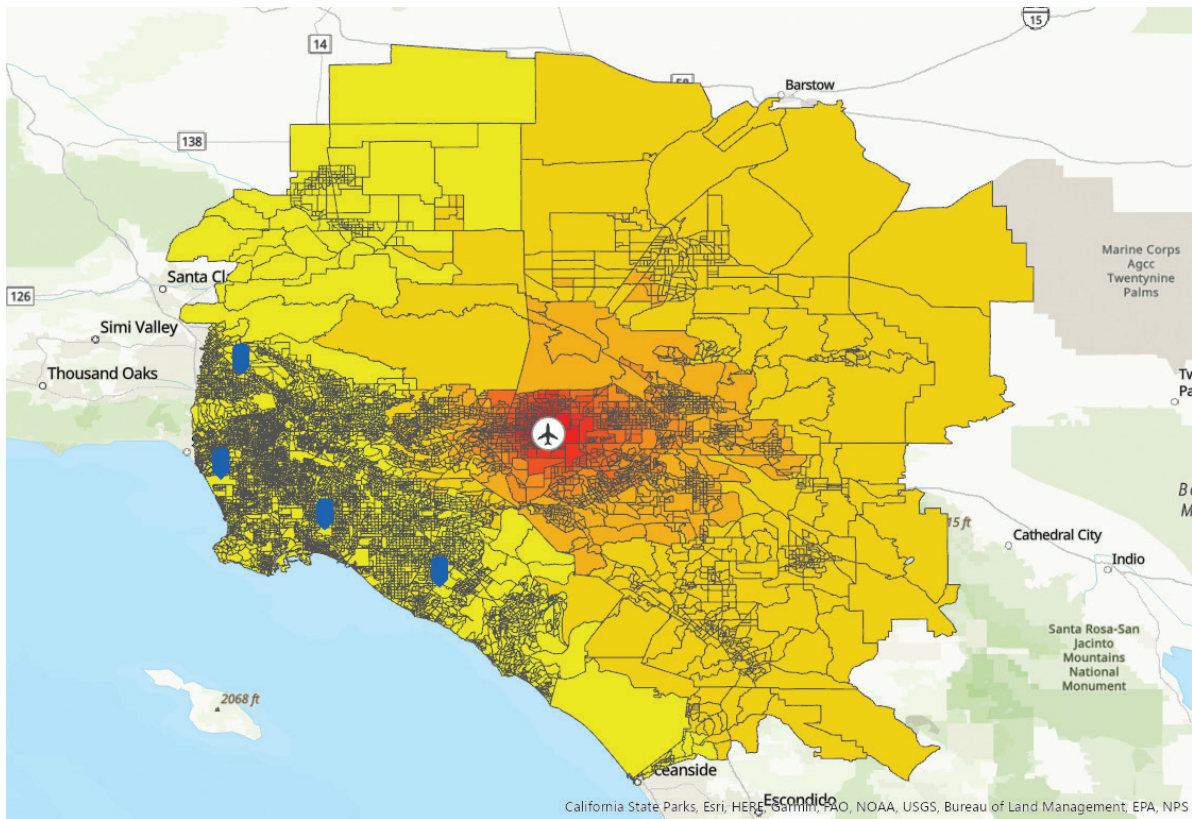

FIGURE 5. 60-mile Huff model of Ontario International Airport with distance exponent –1.5.

DISCUSSION

Only the impact of the distance element is considered in this study; nevertheless, the attractiveness of an airport is affected by other factors such as the price of a plane ticket or the number of flights available. More research may be required to examine the usefulness of the Huff model in conjunction with other parameters that will impact its performance. In this study, we also computed distance cutoffs based on the size of the airport. A more precise approach is required to determine the distance cutoff for the airport catchment region, such as real passenger movement from a given census block to the chosen airport, in order to estimate the maximum population mobility range in the surrounding area. The greater results from comparing the similarity of the estimated catchment areas can be attributed to the high similarity of the distance cutoffs. It would be preferable if we could collaborate with these five airports to apply the Huff model results to real-world operations to demonstrate the accuracy of the estimated airport catchment area. Furthermore, even though we cover varied hub sizes in this research, we may need to examine the accuracy of this approach if we want to apply it to every airport in the United States, because this project has a relatively limited sample size of airports. To utilize this method in a new airport, the distance cutoff and distance exponent must be adjusted to fit the target airport.

CONCLUSION

Within a reasonable spatial scale, the Huff model could be used to efficiently estimate airport catchment areas at the geographic unit level. Moreover, customers are more likely to go to the selected airport, which has larger distance cutoffs and a larger distance decay exponent, if the catchment area is larger. The model provided a good reference for the effectiveness of the Huff model in prediction, and the prediction can provide trustworthy information for airports and help with their management. Airport operators can analyze the concentrated areas of passenger flow and find potential consumers using the Huff model forecast. They can develop a business and promotion strategy that will most likely utilize airport areas, or they can provide more modes of transit to encourage travelers who reside a short distance from the airport. Airports can advertise in census blocks with high passenger traffic or where customers are more likely to utilize selected airports to maintain the high probability of utilization. In addition, airports can offer discounts to encourage customers in the low probability census blocks to use the target airport. Therefore, the data has diverse parameters that can be used to estimate the airport catchment area.

FUTURE RESEARCH

We plan to compare the Huff model output with real yearly mobility patterns data from 2019 to 2021 (collected from smartphone apps using SafeGraph, with users' consent to share their location information) to evaluate the Huff model's effectiveness. SafeGraph's Patterns dataset (n.d.) includes visitor and demographic aggregations for points of interest (POIs) in the United States. This contains aggregated raw counts of visits to POIs from a panel of mobile devices, answering the questions of how often people visit, how long they stay, where they came from, where else they go, and more. We wish to analyze the aggregated, anonymized data relating to people's mobility patterns and foot traffic to businesses provided at the census block group (CBG) level to see how effective the Huff model analysis is in the airport catchment region. SafeGraph's dataset includes a breadth of information about global places. For results, we will choose the model that can best predict the airport catchment area. In addition, the five selected airports are in different parts of the United States. The next step in this research will be to examine the airports in the vicinity of each chosen airport to see if the mobility patterns data match the Huff model's predictions. We also want to discover if COVID-19 had an impact on the Huff model's prediction in 2021.

ACKNOWLEDGMENTS

REFERENCES

Baltazar, M. E., & Silva, J. (2018, July 4). *Airports catchment area size definition: A Portuguese case study*. 23rd World Conference of the Air Transport Research Society. Retrieved April 29, 2022, from https://ubibliorum.ubi.pt/handle/10400.6/9639?locale=en

Federal Aviation Administration. (2022, March 29). *Passenger boarding (enplanement) and all-cargo data for U.S. airports*. FAA. https://www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/.

How Huff model works. (n.d.). ArcGIS Pro. Retrieved April 25, 2022, from https://pro.arcgis.com/zh-cn/pro-app/latest/tool-reference/business-analyst/understanding-huff-model.htm

Huber, C., Watts, A., Grills, A., Yong, J. H. E., Morrison, S., Bowden, S., Tuite, A., Nelson, B., Cetron, M., & Khan, K. (2020, October 27). Modelling airport catchment areas to anticipate the spread of infectious diseases across land and air travel. *Spatial and Spatio-Temporal Epidemiology*. Retrieved April 25, 2022, from https://www.sciencedirect.com/science/article/abs/pii/S1877584520300587?via%3Dihub

Huff, D. L. (1963). A probabilistic analysis of shopping center trade areas. *Land Economics*, *39*(1), 81–90. https://doi.org/10.2307/3144521

Patterns: SafeGraph docs. (n.d.). SafeGraph. Retrieved April 25, 2022, from https://docs.safegraph.com/docs/monthly-patterns

Transportation Research Board (TRB). (n.d.). *Defining an air service catchment area*. Airport Cooperative Research Program. Retrieved April 29, 2022, from https://crp.trb.org/wp-content/uploads/sites/7/2016/10/E1_Tool2-DefiningAirServiceCatchmentArea.pdf

Transportation Research Board (TRB). (n.d.). *Defining your airport's catchment area*. Aligning Community Expectations with Airport Roles. Retrieved April 29, 2022, from https://crp.trb.org/acrpwebresource1/defining-your-airports-catchment-area/#:~:text=Your%20airport's%20catchment%20area%20is,proximity%20of%20alternative%20aviation%20facilities

Zhou, H., Xia, J. (C.), Luo, Q., Nikolova, G., Sun, J., Hughes, B., Kelobonye, K., Wang, H., & Falkmer, T. (2018). Investigating the impact of catchment areas of airports on estimating. *Journal of Air Transport Management*, *70*(C), 91–103. Retrieved April 29, 2022, from https://ideas.repec.org/a/eee/jaitra/v70y2018icp91-103.html