XXI SITRAER
2024 | Air Transportation Symposium

AIRPORT ATTRACTIVENESS FOR REGIONAL AIR TRANSPORT: A COMPARATIVE ANALYSIS IN NORTHEASTERN BRAZIL

Bárbara Alves*, Giovanna Ronzani, Evandro José da Silva, Mauro Caetano
Aeronautics Institute or Technology (ITA)

*** Corresponding author e-mail address**: barbarabmap@ita.br

PAPER ID: SIT892475

ABSTRACT

The study of airport attractiveness is necessary for understanding passenger preferences and improving airport competitiveness, which in turn drives regional economic development. This research provides a comparative analysis of three airports in Northeastern Brazil: Recife, Campina Grande, and João Pessoa. Employing the Multinomial Logit Model (MNL), the study evaluates key determinants of airport attractiveness, including connectivity, infrastructure, and regional influence. The results demonstrate that Recife Airport stands out as the most attractive due to its extensive network of national and international routes and superior infrastructure. This finding underscores the importance of connectivity and infrastructure in enhancing airport attractiveness, aligning with established theoretical frameworks. The empirical evidence presented not only validates existing theories but also offers practical insights for airport management and policymaking. The study contributes to the broader literature on airport attractiveness by providing a comprehensive analysis that highlights the critical factors influencing passenger choices and regional hub dynamics.

Keywords: catchment area, attractiveness, hub airports, MNL model

1. INTRODUCTION

Airport attractiveness is a critical topic in transportation research, significantly impacting passenger choices, airport competitiveness, and regional economic development. Understanding what makes an airport attractive is essential for optimizing its operations, improving passenger satisfaction, and fostering regional growth.

With the implementation of new regional flights by Azul and Gol since 2019, access to these tourist destinations, such as Jericoacoara in Ceará and Porto Seguro in Bahia, has become feasible. This has brought new investments to the region and consequently expanded local businesses. Tourism is an important source of revenue for many cities, and air connectivity is essential for its growth. Efficient airports attract both domestic and international tourists, who spend money on hotels, restaurants, shops, and local attractions, promoting a cycle of economic growth.

The significance of airport attractiveness has been underscored by numerous studies, such as those by Coelho and Silva et al. (2021), Seabra et al. (2020) and Zhou et al. (2018) which emphasize the importance of connectivity and infrastructure. These studies have demonstrated that airports with a higher number of direct routes, superior facilities, and better services tend to attract more passengers. In Brazil, some studies were developed using big data from mobile phone networks, like de Paula et al. (2019). In this paper a study was developed with the aim of predicting passenger movement and determining the catchment areas for potential airports, utilizing an Origin-Destination Matrix (OD Matrix) for demand forecasting.

The study of airport catchment areas is a widely explored subject in the global literature. In an increasingly dynamic and competitive scenario, understanding the airport catchment area becomes fundamental for the effective management of these airport infrastructures, also to understand passengers' preferences, whether traveling by air or by land, where they are heading, and for what purpose. However, much of the existing research is centered on major international airports or those in developed regions, leaving a gap in understanding the dynamics at play in regional airports in developing countries. This study aims to address this gap by focusing on the unique context of Northeastern Brazil.

The relevance of this study extends to both theoretical and practical domains. Theoretically, it provides empirical validation and extension of existing frameworks on airport attractiveness, contributing to a more nuanced understanding of the interplay between connectivity, infrastructure, and regional dynamics. Practically, the findings offer valuable insights for airport managers and policymakers, guiding strategic decisions to enhance airport competitiveness and support regional development. Addressing these theoretical gaps and providing actionable insights underscores the importance of this research in advancing both academic and practical knowledge in the field of airport attractiveness.

This study is divided into 4 sections. First, we briefly discuss about the importance of the study of airports attractiveness and the benefits that the expansion of the airport can bring to the region (Section 2). Soon after, the econometric methodology used for the development of the research is presented (Section 3). Section 4 presents the results and brief conclusions. Finally, Section 5 brings the main conclusions and what future works can be done.

2. AIRPORT ATTRACTIVENESS AND ECONOMIC GROWTH

Many studies, such as Lieshout (2012), Oliveira et al. (2020), Seabra et al. (2020) and Gibbon and Wu (2021), have been conducted with the aim of finding patterns in people's movement, whether by means of transportation such as land, air, or water modes. Studies focused on mobility transportation dynamics aim to understand how individuals travel within and between regions. These studies analyze various factors influencing travel behavior, including socioeconomic variables,

infrastructure availability, and regional connectivity. By examining these patterns, researchers can identify trends, predict future transportation needs, and develop strategies to improve transportation systems. This knowledge is crucial for urban planning, reducing congestion, enhancing public transit systems, and promoting sustainable development. Additionally, understanding mobility patterns can help in the efficient allocation of resources and in the creation of policies that better serve the public's transportation needs.

Understanding how passengers choose an airport within a catchment area is necessary for airport management and planning. The catchment area size is influenced by various factors such as the airport's location, services, accessibility, and competition from nearby airports. Lieshout (2012) propose a methodology to identify the factors that determine a passenger to choose an airport and thus measure the size of the area of influence of that same airport. The study considered the mode of transport that the passenger uses to the departure airport, the purpose of the trip, whether it will be for leisure or work, and the destination. Some trips are made via connections, at hub airports, so this observation was also considered when applying the MNL model. The model shows how these factors change depending on the reason and destination of the trip over time. Furthermore, it is possible to estimate the area of influence if the airport undergoes changes to its infrastructure and the services it offers. The study was conducted at Amsterdam Schiphol Airport, and the findings indicate that the airport's attractiveness is significantly influenced by the destination. The expansion of airports to the south and southeast of Schiphol has reduced both the size of its catchment area and the market shares within it. This attractiveness study is not only a tool for airport management, to understand its area of influence, to understand its competitive strength in the interior regions, but to influence airlines to bring new destinations there.

Gibbons and Wu (2021) provide new evidence that the rapid growth of air transport infrastructure in China throughout the 2000s significantly boosted industrial output, productivity, and GDP, based on data from individual firms and counties. It was reached three main conclusions. First, improved access due to reduced landside distance resulting from the construction of new airports leads to higher industrial productivity. Secondly, most of the variation in air transport access generated by the construction of new airports comes from the reduction in landside travel times, so the main gains for manufacturing come from reduced landside costs. This highlights an obvious but previously overlooked point that the accessibility of airports on the landside is the key factor that should guide airport location decisions. Although, the third conclusion it was that there were no clear effects of the GDP in the service sector, which contradicts common assumptions and some previous evidence regarding the role of air transport in business transactions in finance and other services in developed countries.

One of the main factors for choosing the air mode over other modes is the cost-benefit factor. If there is the possibility of a passenger traveling in a short period of time at an affordable price, there is a high probability that they will choose to travel by airplane. Low Cost Carriers (LCC) bring this benefit to the passenger. Pantazis and Liefner (2006) examine how LCCs influence the passenger catchment areas of established international airports, focusing on Hanover Airport, Germany. The authors used an empirical approach based on a passenger survey conducted at Hanover Airport throughout 2003 and included interviews with 15,177 passengers, of which 9.5% were LCC passengers, specifically Hapag Lloyd Express (HLX). It is concluded that the entry of LCCs at Hanover Airport resulted in an overall increase in passenger volume in 2003. Total air traffic grew by 6.2%, while traffic to European destinations increased by 9.2%, reflecting the positive impact of LCCs that only serve European destinations. Consequently, with this growth in air traffic, there was an increase in the airport's catchment area. LCC passengers are also more likely to choose Hanover Airport for reasons such as cheaper prices and exclusive offers only available at that airport.

Zhou et al. (2018) use two methodologies to determine the capture of airports in a region of Australia. The first involved creating an area of influence using Thiessen polygons, ensuring that people in an airport's area of influence are closer to that airport than any other, and the second methodology defines areas of influence based on a radius 2.5 hours of driving. Lieshout (2012) use

MNL (Multinomial logistic) model to identify which variables are influential when a passenger chooses an airport to travel to. This model is widely used to probability models for discrete response.

The Multinomial Logit Model (MNL) has been widely utilized in the analysis of transportation and airport attractiveness due to its ability to handle multiple choice alternatives and model passenger preferences effectively. Lieshout (2012) have demonstrated its robustness in capturing the impact of connectivity, infrastructure, and service quality on airport choice, by incorporating variables such as route availability, frequency of flights, and passenger convenience. The MNL model provides a comprehensive framework for understanding the determinants of airport catchment areas. Therefore, this model was applied in this paper to evaluate the attractiveness of some airports in the Brazilian Northeast.

3. METHODS

The measurement of catchment area of airports has been made using the Euclidian distance from cities within a catchment radius of 90km, the number of airlines present at each airport and the number of domestic destinations offered by each of them. The literature shows that airports have their catchment area reduced with the presence of other airports close to them, which offer similar destinations. The difference in expanding the catchment area is the presence of more distant destinations. However, low cost carriers (LCC) attract more passengers than traditional carriers due to low fares, meaning airports can also expand their catchment area with the presence of more LCC (Lieshout, 2012; Pantazis and Liefner, 2006).

For Brazil, de Paula et al. (2019) seeks to estimate the demand potential of airports using socioeconomic variables from the regions where existing or new airports are located, assuming that all airports are connected by a network. The model considers that the demand is divided into two distinct groups: "primary demand," which consists of people who are closer to the airport, and "secondary demand," which includes people who do not have flight services and need to travel to the nearest airport to board flights. The airport of Barreiras in Bahia, in the northeastern of Brazil, was projected to have 229,000 passengers in one scenario, but this number dropped by 19% to 187,000 passengers, with the inclusion of the airports in Bom Jesus da Lapa-BA, Guanambi-BA, and Irecê-BA. The airport of Chapecó, located in the state of Santa Catarina, south of Brazil, experienced a drop in passenger movement by 33% with the introduction of seven new airports in the region. The model acts as an effective tool for assessing airport networks and understanding the competitive dynamics within the system.

The biggest airport in the state of Pernambuco is the International Airport Recife/Guararapes – Gilberto Freyre, located on the coast of the state, in the far east. The state of Pernambuco also has other 10 aerodromes, located in the municipalities of Araripina, Arcoverde, Santa Magalhães, Garanhuns, Pesqueira, Petrolina, Caruaru, Salgueiro and Fernando de Noronha. The international airport of Petrolina, Senador Nilo Coelho, is the second biggest airport in Pernambuco, located 720km away from the airport Gilberto Freyre.

Paraíba is another state in Brazil, which borders Pernambuco, and has 10 public aerodromes, two of which are larger: João Pessoa's airport, the state capital, and Campina Grande's airport, in the interior of the state. The other aerodromes are in the cities of Catolé do Rocha, Conceição, Itaporanga, Cuité, Monteiro, Cajazeiras, Sousa and Patos.

The airports of Recife, João Pessoa and Campina Grande were concessioned to the Spanish company AENA, in 2020, undergoing several internal changes, such as expansion of the passenger terminal, expansion of the aircraft apron, adaptation of flight visual systems, to work with o Instrumentation Flight Rules, IFR, implementation of the Runway End Safety Area (RESA), among others (ANAC, 2024). Since then, these airports were capable of expand new routes, including international destinations.

The proposed methodology seeks to estimate the catchment area of Recife, João Pessoa and Campina Grande's airports using the MNL model, utilizing the airport characteristics that were found to be relevant according to the literature and analyze the impacts that each one has on the other.

Table 1 - Airports of João Pessoa, Campina Grande and Recife (AENA, 2024; Hórus, 2024)

Name	*Municipality*	*ICAO*	*Passengers 2022 (thousand)*	*Aircraft 2022 (thousand)*
Internacional Airport of João Pessoa - Presidente Castro Pinto	João Pessoa	SBJP	1,230	9.17
Airport of Campina Grande – Presidente João Suassuna	Campina Grande	SBKG	130.67	1.86
Internacional Airport of Recife/Guararapes - Gilberto Freyre	Recife	SBRF	8,630	71.84

Table 1 indicates the airports that are covered in this study, the municipality in which they are located, their respective ICAO (International Civil Aviation Organization) codes, and their total movement of passengers and aircraft in the year of 2022 (Hórus, 2024).

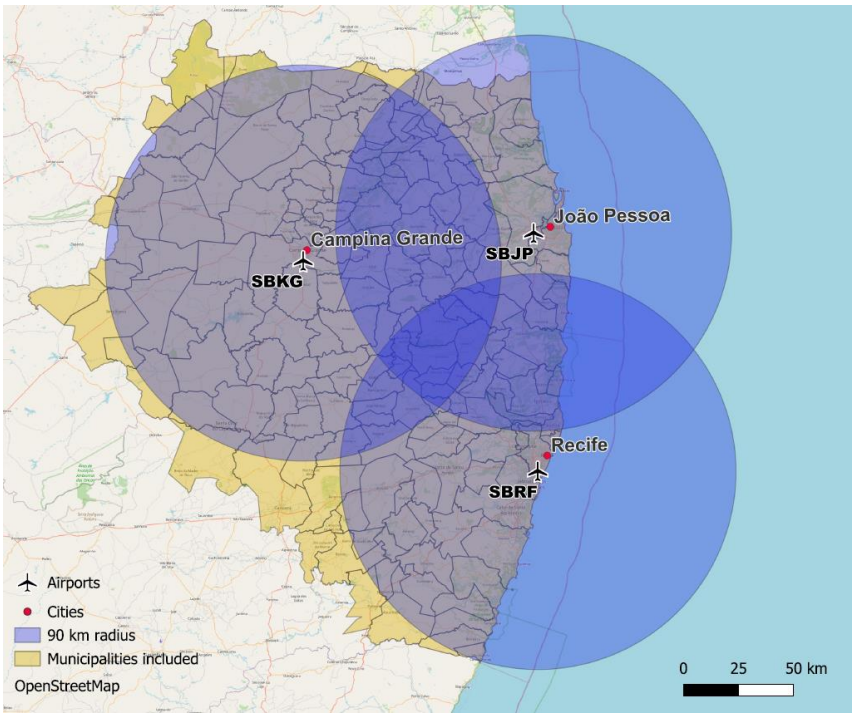


Figure 1 Municipalities included in the 90 km radius of each airport (ANAC, 2024; IBGE, 2024 – adapted by the author)

Figure 1 shows the geopositioning of airports and cities, with Recife and João Pessoa located on the coast of Pernambuco and Paraíba, respectively, and Campina Grande located in the interior of Paraíba. 90km circles were drawn around the airports, with the aim of verifying their area of influence in these regions and sees which municipalities will be included in the catchment areas. In total, 202 municipalities were selected. It is expected that the areas that had overlapping circles are cities that share the demands of airports.

The National Civil Aviation Secretariat (SAC, 2022) created an origin-destination matrix of people's movements through air and non-air transportation in Brazil, based on mobile phone data. With this database, it was possible to investigate trips made by municipalities to the airports studied in 2022, providing a detailed picture of air travel patterns. Only movements made by air were considered to ensure the analysis focuses on air travel-specific dynamics. The total number of destinations offered by the respective airports was taken from the SAC OD matrix (SAC, 2022), ensuring an accurate representation of connectivity. The number of airlines operating in these airports was collected from Hórus, a system of the National Civil Aviation Secretariat (Hórus, 2024). Additionally, data on the municipalities of Pernambuco and Paraíba were sourced from the Brazilian

Institute of Geography and Statistics (IBGE, 2024). QGIS software was utilized to identify the cities encompassed by the defined catchment areas and to generate the attractive zones of the airports, enhancing the spatial analysis of airport attractiveness.

Using these variables in the multinomial logit model (MNL Model), the probability of an airport k, between j alternatives (j=1,2,3), being chosen from someone in city i follows Equation 1 and 2.

$$P(Y = k|X) = \frac{\exp(V_k)}{\sum_{j=1}^{3} \exp(V_j)} \quad (1)$$

$$V_k = \beta_0 + \beta_1 . distance_i^k + \beta_2 . airlines_k + \beta_3 . destinations_k \quad (2)$$

Equation 1 is the probability of a person in city *i* choosing airport *k*, among the three airports studied, using as decision criteria the distance from that airport, the number of operating airlines and the number of destinations offered by the airport, as indicated by the linear utility function (Equation 2). From these equations it is expected to find the influence that the three airports have on the municipalities within the circle areas (Figure 1), and to be able to find their areas of attractiveness and evaluate the cities that are within the same area of influence for two or more airports.

4. RESULTS ANALYSIS

The study of airport attractiveness has been a subject of considerable interest in the literature. Previous works by authors such as de Paula et al. (2019), Lieshout (2012) and Coelho and Silva (2020) have laid the groundwork for understanding the critical factors influencing passenger preferences and airport competitiveness, as well as forecasting their demand, and analyzing the impact that existing airports have with the implementation of new airports in their surroundings. Teixeira and Derudder provide us with an analysis of the catchment area for airports in the New York region (USA), using prices, the passenger's distance from a city to the airport and travel time. This study builds upon these foundational theories by providing empirical evidence from a comparative analysis of the airports in Recife, Campina Grande, and João Pessoa.

To generate a model according to Equations 1 and 2, the data was organized to be placed in GRETL. The OD matrix is divided by month, so this data was compiled to give an overview of the year 2022. Using the logit model, it is necessary to input data that estimates the probability of an airport being chosen. Therefore, this variable was estimated according to the number of trips that were made to the boarding airport, in this case one of the three airports, SBRF, SBJP and SBKG, from the cities that are within the coverage area (Figure 1). It's a binary variable, which is 1 if an airport has more trips from city *i* than the other airports, and 0 otherwise. The independent variables are "distance", "airlines" and "destinations", which is different for each airport. The SBJP have 3 airlines and 98 national destinations; the SBKG have 2 airlines and 91 national destinations; and SBRF have 6 airlines and 107 national destinations.

$$V_{ki} = 15.8523 - 0.0592064 . distance_i^k + 1.19775 . airlines - 0.159567 . destinations \quad (3)$$

According to the model generated, with the variable's "distance", "airlines" and "destinations", the Equations 3 is obtained, which is the utility function to find the probability of airport k been chosen of someone from city i.

Distance proved to be the most significant variable, with a p-value equal to 4.43e-029, far below zero. The "airline" had a p-value = 0.0013, and the "destinations" variable had a p-value = 0.0867. The coefficient of the variable "distance" is negative, suggesting that as the distance between the city and the airport increases, the less likely that airport will be chosen by someone from that city. The coefficient of "airlines" is positive, that is, the greater the number of airlines operating at the airport, the greater the probability that someone from city i go to airport k. And finally, the coefficient of

“destinations” is negative, which should not happen, since the number of destinations offered by an airport should increase its attractiveness. Therefore, the VIF test (Variance Influence Factor) was performed to identify possible collinearity between these variables. The variables “airlines” and “destinations” had a multicollinearity above 10, which indicates a collinearity problem between these two variables.

Due to the collinearity between these variables "airlines" and "destinations", two models were developed separately, only considering one of these variables together with the variable "distance".

The number of cases correctly predicted in the model was 85.15%, a high value that shows consistency in the data.

$$V_{ki} = 2.34427 - 0.0587706.\,distance_i^k + 0.581513.\,airlines \tag{4}$$

The model 2 generated from the variables “distance” and “airlines”, with positive zero beta, and negative distance coefficient, being consistent with the model initially learned, and a positive coefficient of airlines, also in accordance with expectations. The p-value obtained significant results (“distance” = 3.34e-29; “airlines” = 3.25e-11), far below zero, confirming the level of importance of theses variables for the model. The Equations 4 is the utility function to find the probability of a person in city *i* choose airport *k*, taking into consideration the travel distance to the airport and the airlines available to travel. The number of cases correctly predicted in the model was 84.4%, a little lower than the model presented previously, but still consistent.

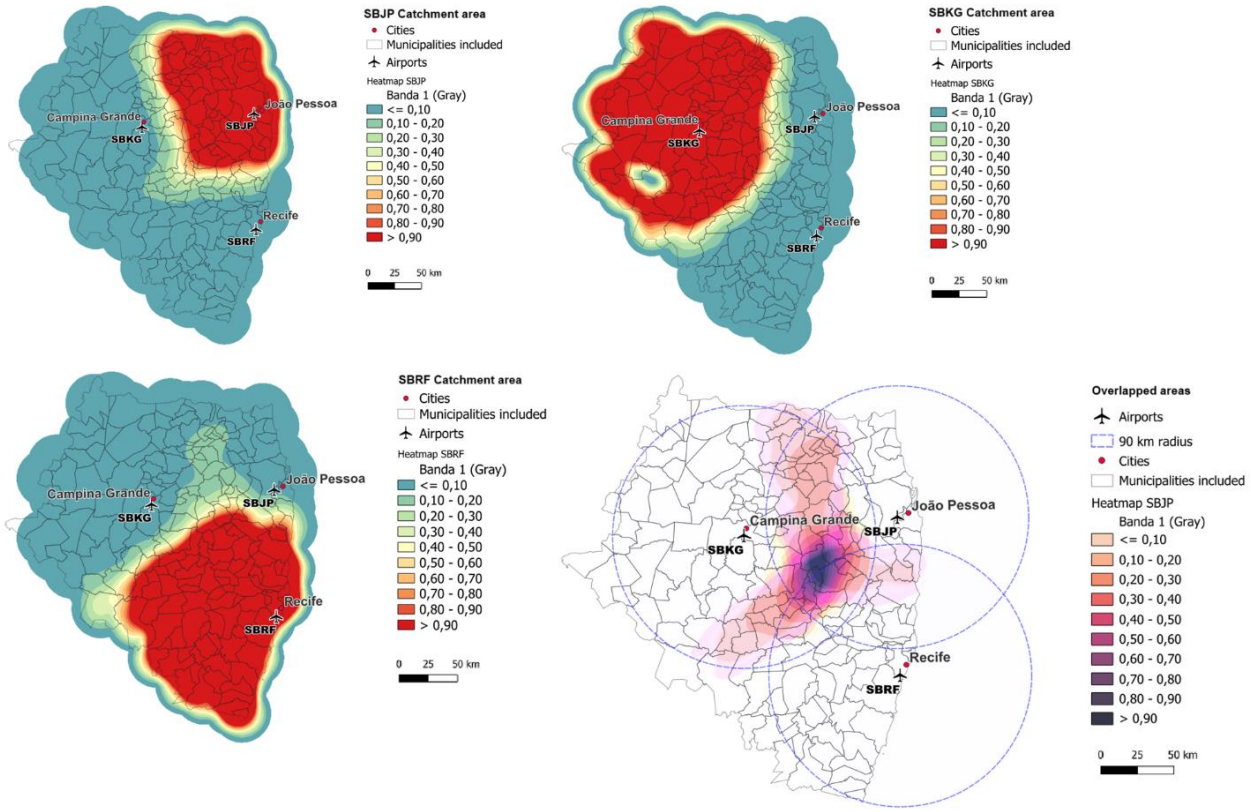


Figure 2 Catchment areas of SBJP, SBKG, SBRF (model 2)

The Figure 2 shows the catchment area of each airport separated and the overlapped areas. The maps were generated based on the probability of each city in relation to each airport, using the input data from the MNL model, where the red area indicates the cities most likely to use airport k (more than 90% probability). It’s possible to see the influence of catchment areas and how the demand at one airport can be affected due to the presence of another. Making a comparison with the 90 km radius initially drawn, it is possible to confirm the impact that the airports have on each other, with Recife airport being the most influential among the three. The overlapping area of the three areas is

located further away from the SBRF, suggesting that their area of influence reaches more distant cities, even though they are close to the SBKG and SBJP airports.

The SAC OD matrix (2022) does not include 100% of Brazilian municipalities, therefore there are cities without registered data. As a result, there are "gaps" within the area of greatest coverage due to this lack of data.

$$V_{ki} = -8{,}95117 - 0{,}0572005.\, distance_i^k + 0{,}134743.\, destinations \quad (5)$$

Equations 5 is the utility function to find the probability of each city to choose one of the airports utilizing the “distance” and “destinations” as independent variables. The p-value obtained very significant results, whit the variable with “distance” = 2.85e-29 and “destinations” = 5.46e-10, confirming the level of importance of theses variables for the model. The coefficient sign for “distance” remain negative and positive for “destinations”, which is more logical in the practical way, in other words, the greater the number of destinations offered at an airport, the greater the probability that a person from the city *i* will choose that airport. The number of cases correctly predicted in the model was 83,2%, a little lower than the model 2, but still consistent.

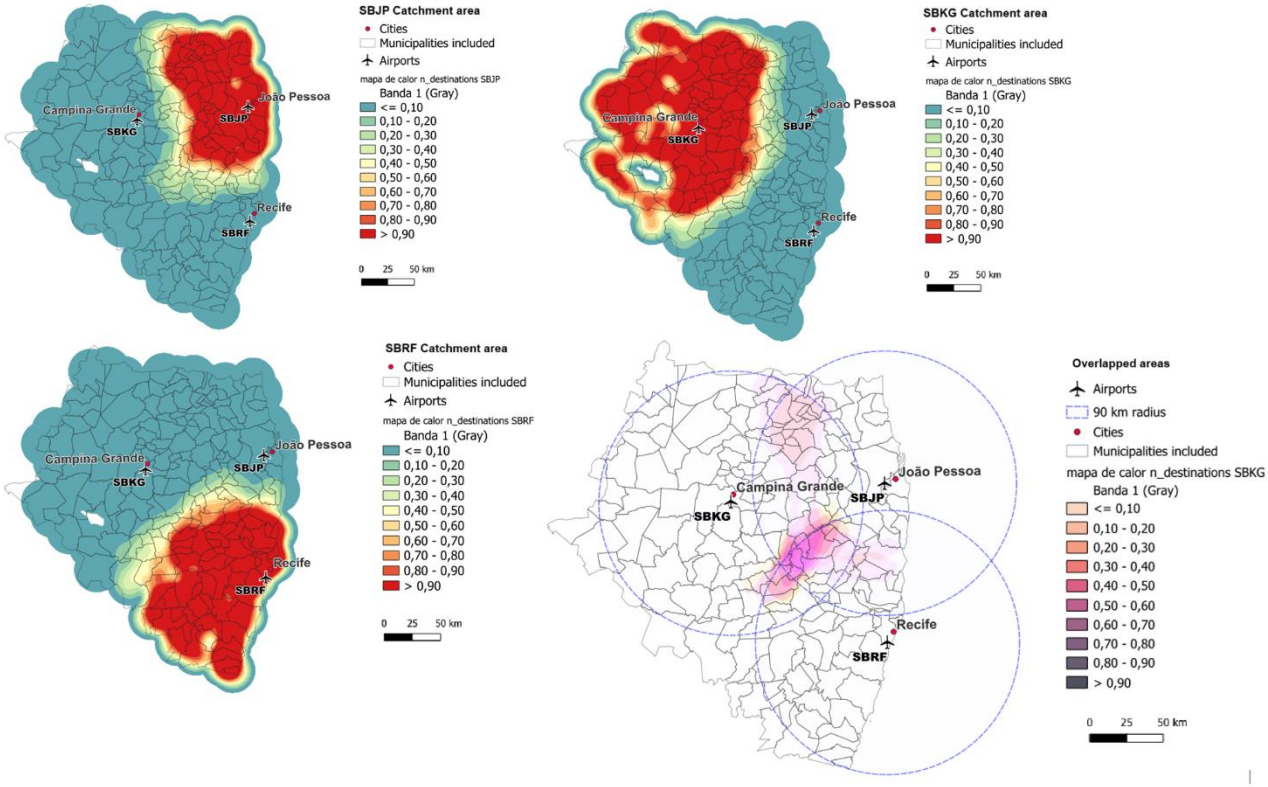


Figure 3 Catchment areas of SBJP, SBKG, SBRF (model 3)

The Figure 3 shows the catchment area of each airport generated by the MNL model utilizing “distance” and “destinations” as independent variables. Also is shown the overlapped areas of them, which indicates that the catchment area of airports has decreased, consequently reducing their overlapping areas. Despite that, Recife’s airport still has a larger catchment area and greater influence on the other two airports.

Making a comparison between model 2 and model 3, it is possible to observe that the airport catchment areas decreased, consequently the overlapping layers decreased substantially from one model to the other.

The two models achieved consistency in the database and variables and can be used equally. To choose which model to use, the ideal is to find the purpose for which the mapping is desired and which database is available. The first model has a more accessible applicability, as it only depends

on variables that do not require much effort to find. Furthermore, this model serves to evaluate the impact that a new airline can bring to the region, and in parallel with the second model, evaluate the implementation of new destinations.

De Paula et al. (2019) emphasized the importance of connectivity and infrastructure in determining an airport's attractiveness. They posited that airports with a higher number of direct routes and better facilities are more likely to attract passengers, leading to increased economic benefits for the surrounding region. Our findings align with this theory, as the Recife Airport, with its extensive network of national and international routes and superior infrastructure, was identified as the most attractive among the three airports studied.

Seabra et al. (2020) explore the role of hub-and-spoke system, suggesting that airports serving as regional hubs can extend their influence beyond their immediate geographic area, attracting passengers from neighboring regions due to better connectivity and services. This study corroborates their findings by demonstrating that Recife Airport not only serves its local population but also attracts passengers from Campina Grande and João Pessoa, highlighting its role as a key regional hub.

5. CONCLUSIONS

The analysis of the attractiveness of the airports in Recife, Campina Grande, and João Pessoa revealed significant insights based on the equations and images developed throughout the study. Recife Airport stood out as the most attractive due to its superior connectivity, with a higher number of national and international routes, as well as a larger number of airlines, causing distant cities to choose to travel further to have a more complete service.

The graphs and mathematical models used demonstrate that Recife has a wider passenger catchment area, attracting travelers not only from the city but also from surrounding regions, including Campina Grande and João Pessoa. Enhanced connectivity at Recife not only facilitates international tourism but also promotes local economic growth, driving regional development. This study reinforces existing theories on the importance of connectivity and infrastructure in determining airport attractiveness, offering empirical evidence that supports these concepts. The equations and data presented prove that passengers' choice is strongly linked to the availability of direct routes, the quantities of airlines available to travel, the distance to dislocate from the origin city and the quality of airport services.

Therefore, the analysis concludes that Recife Airport has a significant competitive advantage over the airports in Campina Grande and João Pessoa. This study provides valuable insights for airport managers and urban planners, highlighting the need to invest in infrastructure and expand flight options to increase the attractiveness and competitiveness of smaller airports.

The theoretical insights and empirical evidence from previous studies provide a solid foundation for the current research. By applying the MNL model to the comparative analysis of the airports, this study validates and extend existing theories, offering new perspectives on regional airport dynamics and contributing valuable data-driven insights for airport management and policymaking.

While this paper provides valuable information into the catchment areas of the airports SBJP, SBKG and SBRF, there are some areas for potential improvement. Future research could incorporate additional variables such as travel time to the airport, traffic congestion, airfares and the availability of international routes, which are crucial factors that influence passenger preferences and airport choice. By expanding the scope of the analysis to include these variables, the study can offer a more comprehensive understanding of the determinants of airport attractiveness. Moreover, the methodology and findings of this research can serve as a basis for other researchers and practitioners to apply these improvements in different contexts, thereby enhancing the overall quality and applicability of airport attractiveness studies.

6. REFERENCES

AENA Brasil (2024) Available at: https://www.aenabrasil.com.br/pt/index.html

ANAC, *Agência Nacional de Aviação Civil (2024). Aeroportos Concedidos/Bloco Nordeste.* Available at: https://www.gov.br/anac/pt-br/assuntos/concessoes/aeroportos-concedidos/bloco-nordeste

ANAC, Agência Nacional de Aviação Civil (2024). Lista de aeródromos civis cadastrados. Available at: https://www.gov.br/anac/pt-br/assuntos/regulados/aerodromos/lista-de-aerodromos-civis-cadastrados

Coelho e Silva, L., Pavao, F. A., Guterres, M. X., Conde, M., Murca, R., Ribeiro Correia, A., Carvalho, M., Da, G., & Pinto Bandeira, S. (2021). *Statistical models for air transport passenger volume estimation in the Brazilian domestic market using cellular network signaling data*. https://github.com/coelhosilva/it213_research

De Paula, R. O., Silva, L. R., Vilela, M. L., & Cruz, R. O. M. (2019). Forecasting passenger movement for Brazilian airports network based on the segregation of primary and secondary demand applied to Brazilian civil aviation policies planning. *Transport Policy, 77, 23–29*. https://doi.org/10.1016/j.tranpol.2019.02.003

Gibbons, S., & Wu, W. (2021). Airports, access and local economic performance: Evidence from China. *Journal of Economic Geography, 20(4), 903–937*. https://doi.org/10.1093/JEG/LBZ021

Hórus - Módulo de Informações Gerenciais - Labtrans (2024). *Aeródromos*. Available at: https://horus.labtrans.ufsc.br/gerencial/?auth=s#Mapa/Aerodromo

IBGE, Instituto Brasileiro de Geografia e Estatística (2024). *Malha municipal dos estaod do Brasil.* Available at: https://www.ibge.gov.br/geociencias/organizacao-do-territorio/malhas-territoriais/15774-malhas.html

Lieshout, R. (2012). Measuring the size of an airport's catchment area. *Journal of Transport Geography, 25, 27–34*. https://doi.org/10.1016/j.jtrangeo.2012.07.004

SAC - National Civil Aviation Secretariat. (2022) National Aviation Plan – PAN. Available at: https://www.gov.br/participamaisbrasil/plano-aeroviario-nacional-2022

SAC - National Civil Aviation Secretariat of the Ministry of Port and Airports. (2022) Matriz Origem-Destino. Available at: https://dados.transportes.gov.br/sr/dataset/matriz-origem-destino-passageiros-base-bigdata-telefonia-movel

Seabra, F., Valente, A. M., Silva, L. R., Assis, R., Acordi, C., Marcon, A. F., & Bauer, M. M. (2020). Determinants of Brazilian international flights: The role of hub-and-spoke and infrastructure variables. *Journal of Air Transport Management, 89*. https://doi.org/10.1016/j.jairtraman.2020.101866

Pantazis, N., & Liefner, I. (2006). The impact of low-cost carriers on catchment areas of established international airports: The case of Hanover Airport, Germany. *Journal of Transport Geography, 14(4), 265–272*. https://doi.org/10.1016/j.jtrangeo.2005.05.002

Oliveira, R. P., Oliveira, A. V. M., Lohmann, G., & Bettini, H. F. A. J. (2020). The geographic concentrations of air traffic and economic development: A spatiotemporal analysis of their association and decoupling in Brazil. *Journal of Transport Geography, 87*. https://doi.org/10.1016/j.jtrangeo.2020.102792

Zhou, H., Xia, J. (Cecilia), 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 air travel demand: A case study of regional Western Australia. *Journal of Air Transport Management, 70, 91–103*. https://doi.org/10.1016/j.jairtraman.2018.05.001