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# SPATIAL STATISTICS MODELING OF AIRCRAFT NOISE COMPLAINTS

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## ABSTRACT

This study employed spatial statistical modeling to analyze the distribution of aircraft noise complaints around São Paulo's Congonhas Airport, validating a detailed geographic approach for this phenomenon. The methodology followed three main steps, including the construction of a spatial weight matrix (1575 cells of 0.5km×0.5km), followed by Exploratory Spatial Data Analysis (ESDA). This analysis revealed a strong and statistically significant positive spatial autocorrelation in complaints, with a Global Moran's I of 0.565 indicating the geographic clustering of incidents (hotspots). Although Ordinary Least Squares (OLS) regression was globally significant (F=37.5909, $p<0.0001$), its low explanatory power (R2 of 0.177752) reinforces the inadequacy of non-spatial models and suggests the existence of unmodeled factors. The identified determinants include residential land use, presence within specific noise contour zones (e.g., 65dB,70dB), and proximity to landing routes. The main research limitation lies, however, in the exclusion of socioeconomic and perceptual variables, which are known to influence complaint behavior, due to the unavailability of data at the cell level. To make the study more comprehensive and in-depth, it is recommended that future investigations incorporate spatial regression models and a broader spectrum of variables, such as socioeconomic, biological, climatic, and psychological data, aimed at enhancing predictive power and the integral understanding of the annoyance phenomenon.

Keywords: Aircraft Noise, Spatial Statistics, Urban Areas, Spatial Autocorrelation, Noise Complaints, Geographical Information Systems (GIS).

## GENERATIVE AI USAGE STATEMENT

The authors declare that the use of generative AI tools was restricted to technical support activities, without compromising the originality, analysis, and conclusions presented in the work. All information obtained through these resources was carefully evaluated and integrated into the study, ensuring methodological rigor and academic integrity. Consensus was used for automated research, enhancing the search for references related to the study topics, and Google Gemini was used to review the text.

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# SPATIAL STATISTICS MODELING OF AIRCRAFT NOISE COMPLAINTS

## 1. INTRODUCTION

The issue of aircraft noise has evolved from a consideration for onboard comfort to a complex environmental and social concern. Assessing aeronautical noise impact involves more than acoustic measurements alone. Perceived annoyance, which translates into a subjective response, is shaped by various non-acoustic factors, including social, economic, cultural, psychological, and environmental aspects. This implies that the spatial distribution of aircraft noise complaints does not always align with sound exposure intensity maps. Such variability and the subjective nature of complaints complicate their effective interpretation and management.

Analysis of documentation produced by civil aviation regulatory bodies addressing aircraft noise impacts on people reveals a historical concern with this topic. Early studies primarily focused on enhancing passenger and crew comfort (until the 1950s) but later broadened their scope to encompass the social impact of noise. Scientific research indicates that aircraft noise complaints are not always direct manifestations of annoyance solely caused by aircraft operations, due to the presence of other urban noise sources and the inherent subjective nature of noise perception.

To better understand the inconsistency in noise complaints, a more thorough analysis of noise complaint datasets from communities near airports is crucial. This analysis should directly correlate these complaints with actual air operations. This analysis must account for the essentially spatial nature of airborne noise, whose intensity and impact vary geographically due to noise source locations (airports and flight paths), urban environmental characteristics, and the distribution of complainants, for example.

Conventional statistical models, such as Ordinary Least Squares (OLS) regression, prove limited. They typically do not consider spatial dependence (where neighboring areas mutually influence each other) or spatial heterogeneity (where relationships vary geographically). This gap can lead to incomplete or biased analyses. Recognizing this need, this study proposes the use of spatial statistical modeling to better understand the geographical patterns and the factors influencing aircraft noise complaints.

Building on this context, to deepen the understanding of the spatial distribution of noise complaints from airport operations, this study proposes an exploratory analysis applying statistical techniques to:

(a) Identify Spatial Patterns: Map and locate clusters (hotspots) and anomalies (outliers) in noise complaints, indicating areas of greater or lesser sensitivity or impact that may extend beyond typical noise contours.
(b) Assess Spatial Autocorrelation: Verify the existence and type of spatial autocorrelation in noise complaints, to determine if the intensity of complaints in one locality is statistically related to that in its neighboring areas.
(c) Compare Regression Models: Develop and compare spatial regression models with the OLS model, aiming to demonstrate how spatial models better explain variance and incorporate the spatial structure of complaint data.

The spatial modeling utilizes data from São Paulo's Congonhas Airport (CGH, SBSP)[1], Brazil.

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[1] The IATA and ICAO codes for São Paulo's Congonhas Airport, respectively.

## 2. SPATIAL ANALYSIS OF NOISE COMPLAINTS

Concerns regarding aircraft noise have been present since the beginning of air operations, but their motivations have changed with advancements in aircraft technology and the growth of commercial aviation. In the early days of air operations, concerns about aircraft noise stemmed from the need to improve travel comfort for passengers and crew, as noise was widely considered a major disadvantage of air transport (Haskin, 1930; Edgerton, 1932). Later, until the mid-1950s, due to scarce commercial aircraft operations and the relatively small and quiet propeller-driven commercial aircraft, aircraft noise was seen as a problem confined to neighborhoods adjacent to runway ends (Fidell, Mestre, 2020). In response to these issues, the Bureau of Standards initiated studies in cooperation with the Aeronautics Branch of the Department of Commerce[2] for aircraft noise reduction (US, 1932).

It was only from 1950 onwards, with the jet era and a significant increase in air traffic, that government bodies began investigating the negative impacts of aircraft noise on people, exemplified by the work of Rosenblith & Stevens (1953), a consultancy report for the Wright Air Development Center, Air Research and Development Command, United States Air Force. This report dedicates a chapter to exploring the complex relationship between noise and human behavior, questioning not only if noise affects behavior, but how and what type of noise affects which behavior. The document emphasizes the importance of noise complaints as a direct manifestation of observable behavior, revealing the perception of an undesirable sound and the extent of annoyance caused. The chapter details how annoyance is a multidimensional concept, shaped by sound intensity, pitch, and modulation, as well as contextual and attitudinal factors, and how complaints frequently arise from this perception of discomfort or interference with daily activities, even without immediate physiological effects beyond hearing. By considering complaints as a crucial behavior, the study underscores the need for rigorous analyses that capture the complexity of noise impact, moving beyond simple acoustic measurements to understand human responses to this phenomenon.

In 1976, the first comprehensive U.S. aviation noise reduction policy, called the Aviation Noise Abatement Policy, was issued. It defined the aircraft noise problem and characterized aircraft noise exposure from DNL 65 to 75 decibels (dBA) in residential areas as "significant" and DNL 75 dBA or more as "severe," relating these noise exposure levels to previous interpretations of expected community actions based on case studies (US, 2022). The document indicates an evaluation of community reaction to aircraft noise exposure with interpretations of Noise Exposure Forecast (NEF[3]) values, demonstrating concern for predicting noise complaints (Table 1).

**Table 1:** NEF values interpretation

| NEF Values | Description |
|---|---|
| Less than NEF 30 | Essentially no complaints expected; noise may interfere with community activities. |
| NEF 30 to NEF 40 | Individuals may complain; group action possible. |
| Greater than NEF 40 | A repeated vigorous complaints expected; group action probable. |

Source: US (1976)

Starting in the 1980s, noise control laws began to be published. In the USA, the FAA published Part 150, Airport Noise Compatibility Planning, issued on January 18, 1985, while in Brazil, Law No. 7.565, the Brazilian Aeronautics Code, was published in 1986, and later detailed (in 2011) in Brazilian Civil Aviation Regulation (RBAC) No. 161, which establishes Aerodrome Noise Zoning Plans. Concurrently with the new aircraft noise regulations (1980s), the most recent phase of aircraft noise monitoring improvements occurred, with the development of a single

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[2] The Aeronautics Branch of the Department of Commerce was the first federal agency in the United States focused on regulating civil aviation.

[3] The NEF (Noise Exposure Forecast) value quantifies aircraft noise exposure at a specific location by summing daily noise energy with a nighttime penalty, forming contours based on aircraft type, operations, flight paths, and time (US, 1976).

complex system integrating data from noise monitors, flight records, meteorological information, and public complaints (Zaporozhets *et al*, 2011).

Since then, aircraft noise policies, regulations, and monitoring methodologies have been continuously updated and refined to address technological advancements and the growth of air traffic. Documents and methods developed from the 1980s onwards directly or indirectly incorporate noise complaints as a factor in aviation impact management. The volume of complaints received by an airport constitutes one criterion that can be utilized to assess the effectiveness of aircraft noise reduction during airport operations (Zaporozhets *et al*, 2011).

While regulations do not always mandate a globally standardized approach to complaint collection or management, they do establish frameworks that rely upon or are influenced by these complaints. The lack of standardization in complaint data collection stems from the subjective nature of individual responses to aircraft noise, which vary substantially according to local contexts (US, 1976). This implies that local contexts (e.g., environmental and social factors such as climate, lifestyles, community concerns) can influence how noise is perceived. Some studies assert that the subjectivity characterizing complaints may render them inadequate indicators of the full extent of noise effects on a population (Fields & Hall, 1987; FICON, 1992), as not all annoyance results in a formal complaint, nor is every complaint solely attributable to aircraft movement.

Traditional statistical models face significant challenges when analyzing the complex spatial nature of noise complaints. They often cannot properly account for spatial relationships like spatial dependence, where complaints in one area are directly influenced by those in neighboring areas. Furthermore, they struggle with spatial heterogeneity, which reflects the varying impact and sensitivity of noise across different communities. This fundamental limitation, given that noise complaints are inherently interconnected rather than isolated, can lead to biased, ineffective, or incomplete analytical results.

Spatial statistical modeling, conversely, examines datasets that integrate positional coordinates, generally termed spatial data (Yamagata & Seya; 2020). These datasets often exhibit strong correlations, thereby rendering the application of spatial statistical methods indispensable for analyses requiring consideration of such spatial interdependencies (Kent & Mardia, 2022). This analytical framework enables the verification of a range of conditions, notably including the statistical significance for all variables pertinent to the study.

Spatial autocorrelation describes how data points in a given area relate to their neighbors. It's primarily categorized into positive spatial autocorrelation, where nearby data show similar trends (aligning with Tobler's (1970) First Law of Geography that "near things are more related than distant things"), and negative spatial autocorrelation, where neighboring data exhibit notable differences, often seen in competitive scenarios like crop distribution without thinning.

Exploratory Spatial Data Analysis (ESDA), which extends traditional data analysis to identify spatial patterns, encompasses methodologies such as LISA (Local Indicators of Spatial Association). While Global Indicators of Spatial Association (GISA) assess the overall presence of spatial autocorrelation in noise data, LISA specifically pinpoints where this correlation manifests, thereby revealing "hot spots" (concentrations of high noise complaints) and "cool spots" (concentrations of lower values), in addition to spatial outliers (Yamagata & Seya; 2020).

Given that aircraft noise propagates and impacts communities in a distinctly spatial manner—influenced by factors such as flight paths, airport proximity, prevalent land use, and urban morphology—its inherent characteristics exhibit significant spatial interdependencies. Analyzing these through local spatial autocorrelation is crucial for pinpointing precise areas experiencing concentrated noise issues and for comprehending variations in community impact and sensitivity. Consequently, this detailed geographic analysis is essential for effectively evaluating noise complaint occurrences, thereby facilitating the development of more targeted and efficient mitigation strategies aimed at enhancing urban quality of life.

## 3. METHODOLOGY

### 3.1 Study Area

São Paulo Airport's first noise plan was approved in 1984 (Heleno, 2010), with subsequent updates carried out by Infraero in 2003, 2014, 2019, and 2022. Noise data collection has been ongoing since 2010 (ANAC, 2011). Complaint monitoring, derived from Annual Aeronautical Noise Reports, was compiled by Infraero from 2021 to March 2023, and subsequently, from March 2024 onwards, it has been conducted by Aena (Cavion, Bandeira, 2024).

The complaint records utilized in this research pertain to data from 2021 (24 complaints), 2022 (340 complaints), and between January and March 2023 (49 complaints), totaling 303 records received by Infraero (2023)[4]. After standardizing the variable set for the municipality of São Paulo, data points located in neighboring municipalities (6 from 2021 and 3 from 2022) were excluded, resulting in 294 remaining records.

### 3.2 The spatial weight matrix

The spatial weight matrix is a convenient and easy-to-understand tool for addressing spatial autocorrelation among data (Yamagata & Seya, 2020). For this reason, the process commences with the construction of the spatial matrix, which is developed based on the comprehensive distribution of samples of complaint geographic points within the municipal boundaries of São Paulo. This matrix comprises a total of 1575 cells, each measuring 0.5km x 0.5km, collectively covering an area of 412.5 km$^2$ (Figure 1). Cells located over uninhabitable urban areas, such as water bodies, were excluded, adhering to the political boundaries of the city of São Paulo.

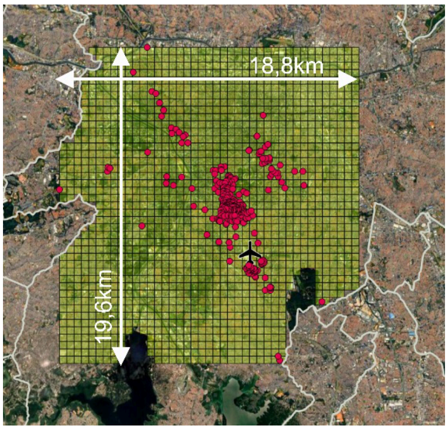

**Figure 1.** Spatial matrix with complaints distribution (red).

The construction of the spatial matrix and the measurement of variables per cell were performed using QGIS, based on data obtained from the following sources (Table 2):

**Table 2.** Data collection sources.

| Source | Data (reference year) |
|---|---|
| ANAC (2011) | Modeling landing and takeoff routes (2010) |
| IBGE (2022) | Resident population (2022), census sector area (2022), urban sprawl (2004 - 2019) |
| Infraero (2022) | Noise Curves of Specific Noise Zoning Plan (2022) |
| Infraero (2023) | Distribution of complaints (2021, 2022, Jan-Mar of 2023) |
| PMSP (2025*) | Districts, buildings, trees, predominant land use (all 2017) |

* Year of data collection from the website.

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[4] The significant increase in complaints during 2022 can be attributed to the resumption of air operations in the post-COVID period. From April 2023 onward, noise monitoring became the responsibility of Aena, which took over management of São Paulo Airport.

The spatial weight matrix (W) typology, generated using GeoDa software, employed the 'queen' contiguity convention to define the relationship type among the matrix cells. The dependent variable was the layer representing the geographic locations of noise complaint samples (r_Comp). The 'queen' contiguity convention stipulates that two spatial units are considered neighbors if they share any common boundary, whether an edge or merely a vertex (Almeida, 2012). This choice was motivated by the matrix's ability to represent a more comprehensive spatial structure in dense urban areas. Unlike distance-based matrices, which may introduce artificial connectivity across heterogeneous zones, the *queen* criterion captures both edge and vertex adjacencies, preserving the topological integrity of spatial interactions. This approach is particularly suitable for urban lattice grids, enhancing the detection of spatial clusters and improving the reliability of local indicators such as LISA (Anselin *et al.*, 2006).

## 3.3 Study Variables

The study tested a set of 27 variables within the model, organized under seven categories: noise complaint (total samples, density), air operation (landing routes, takeoff routes, distance to runway centerline), PEZR noise zones (area by noise exposure of 65, 70, 75, 80, and 85 dB), vegetation (total and density of public trees), buildings (total, maximum and average height, number of floors, built area), census data (population, census tracts, households, and densities of m²/population, m²/household, population/household), and land use (residential, commercial, others). Each variable was measured to individually characterize the 1575 cells of the matrix.

Bivariate explorations involving multiple variables, conducted using GeoDa software, indicated the presence of spatial correlation among the variables presented in Table 3.

**Table 3:** Variables validated within the spatial autocorrelation model

| Variable Id | Description |
|---|---|
| r_Comp* | Aircraft noise complaints* |
| r_65db | Area within the 65dB zone |
| r_70db | Area within the 70dB zone |
| r_trees | Number of public trees |
| r_landing | Area within the landing route projection |
| r_Acont | Total built area |
| r_hmax | Maximum building height |
| r_red | Residential area |
| r_Distrun | Distance from the runway centerline |
| r_setcens | Number of census tracts |

* Dependent variable

## 3.4 Regression Modeling: Ordinary Least Squares (OLS)

Ordinary Least Squares (OLS) regression analysis, applied to the dataset discussed in this article, aimed to identify the factors influencing the dependent variable, r_Comp (number of noise complaints). The final model incorporated nine independent variables, as detailed in Table 4: r_65db, r_Acont, r_setcens, r_70db, r_landing, r_hmax, r_red, r_Distrun, and r_trees.

The selection of variables for inclusion in the model was an iterative process, involving tests of multivariate combinations within OLS regression frameworks, complemented by bivariate analyses (scatter matrices). The primary criterion for this selection was the minimization of the Akaike Information Criterion (AIC).

Regarding the interpretation of this process, the OLS model construction involved the evaluation of 702 combinations (27x27 variables) derived from a broader pool of potential independent variables (Figure 2). For each configuration, the respective AIC values were calculated. The specific set of nine variables listed was selected because it yielded the lowest AIC value among all assessed combinations. This indicates that this particular variable combination is deemed the most parsimonious and efficient in explaining the variance of the dependent variable (r_Comp), thereby optimizing the balance between model complexity and its predictive power.

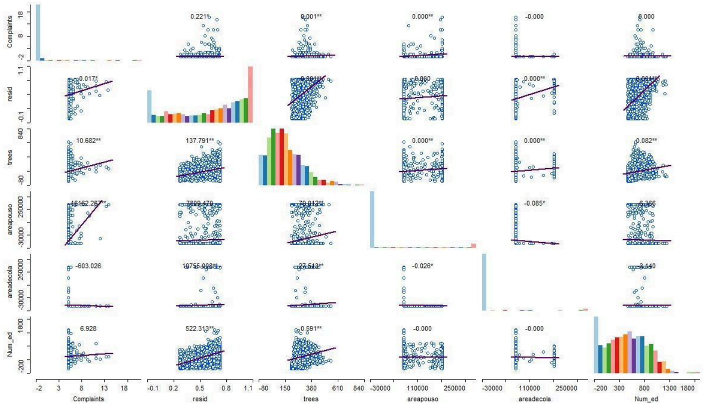

**Figure 2:** 6x6 variable evaluation resulting in 30 bivariate combinations (excerpt from the test performed in GeoDa).

Table 4 presents the results of the Ordinary Least Squares (OLS) regression model, with r_Comp as the dependent variable (number of aircraft noise complaints). Variables with $p < 0.05$ are considered statistically significant.

**Table 4:** Results of the Ordinary Least Squares (OLS) Regression Model for Aircraft Noise Complaints

| Independent Variable | Coefficient | Standard Error | t-Statistic | p-Value |
|---|---|---|---|---|
| Constant | 0.054722 | 0.12956 | 0.42233 | 0.67251 |
| r_65db | 0.000675 | 0.00013 | 5.2024 | 0 |
| r_landing | 0.000004 | 0 | 5.9446 | 0 |
| r_Acont | 0.000001 | 0 | 4.5553 | 0.00001 |
| r_hmax | 0.000105 | 0.000044 | 2.3721 | 0.01775 |
| r_red | -0.00006 | 0.000009 | -6.6584 | 0 |
| r_Distrun | -0.00004 | 0.00001 | -3.9814 | 0.00007 |
| r_trees | 0.000559 | 0.000245001 | 2.2841 | 0.02250 |
| r_setcens | 0.033039 | 0.010602 | 3.1154 | 0.00183 |
| r_70db | 0.000006 | 0.000002 | 2.5212 | 0.01175 |

Model Statistics: $R^2 = 0.1778$ | $F(9, 1565) = 37.5909$ | $p < 0.00001$ | AIC = 4687.5

### 3.4 Exploratory Spatial Data Analysis (ESDA)

Measures (test statistics) related to verifying the existence of spatial autocorrelation for the grid cells (r_Comp variable), known as Global Indicators of Spatial Association (GISA), are presented in graph (a) of Figure 3. Concurrently, measures pertaining to the specific locations where spatial autocorrelation occurs, termed Local Indicators of Spatial Association (LISA), are depicted in maps (b) and (c).

Consequently, the analysis of the r_Comp variable reveals a strong and statistically significant spatial dependence, corroborated by both the Global Moran's I (GISA) and the LISA maps. A Moran's I value of 0.565 indicates robust positive spatial autocorrelation, signifying that locations with similar r_Comp values tend to cluster spatially.

The LISA Cluster Map delineates "High-High" clusters, which are concentrations of high r_Comp values in specific areas, thereby identifying "hot spots" of the phenomenon. Spatial outliers, specifically "Low-High" and "High-Low" classifications, are also evident, indicating instances where r_Comp values deviate significantly from those of their neighboring locations. The

LISA Significance Map statistically validates these spatial groupings, with the majority of identified clusters and outliers exhibiting high statistical significance (p < 0.001).

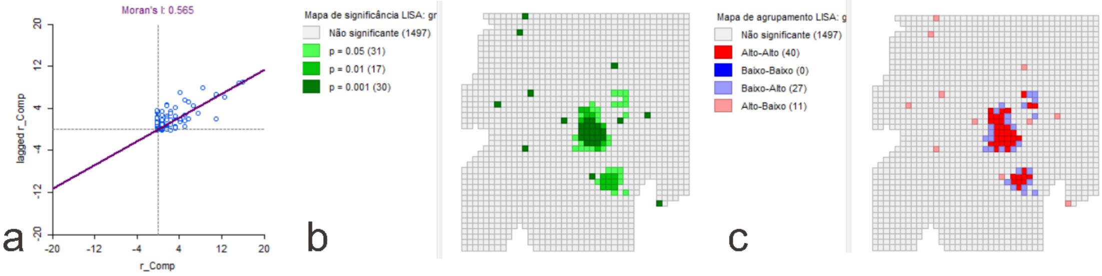

**Figure 3**. (a) GISA: Moran´s I for complaint data; (b) LISA for complaint data: significance; (c) LISA for complaint data: clusters.

While LISA analysis primarily focuses on the univariate spatial autocorrelation of the r_Comp variable, the Multivariate Local Geary's C Index illustrates the spatial correlations among all 10 variables. Map (a) of Figure 4 depicts the statistical significance analysis, while Map (b) illustrates the clustering analysis derived from the Multivariate Local Geary's C Index. Collectively, these maps enable the detection of local-level spatial autocorrelation patterns and provide both visual and quantitative evidence that the r_Comp variable exhibits strong and widespread positive spatial autocorrelation. This implies that the intensity or occurrence of r_Comp in one location is not independent of its intensity or occurrence in neighboring locations, thereby illustrating clear clusters of similar values.

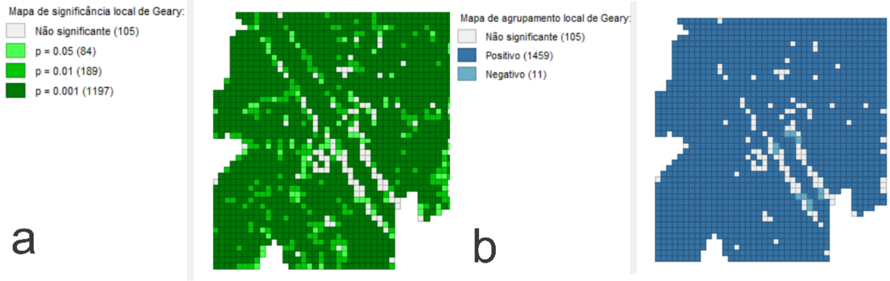

**Figure 4.** Multivariate Local Geary: significance (a) and clusters (b).

## 4. RESULTS

The pronounced underlying spatial structure in r_Comp underscores the inadequacy of non-spatial models, such as OLS regression, which fail to account for interdependencies among geographical observations. This is further substantiated by the OLS regression report, where the global statistical significance, as indicated by the F-statistic, is 37.5909 with a p-value of less than 0.0001. This implies that the set of independent variables collectively possesses explanatory power over r_Comp. However, an R-squared value of 0.177752 suggests that approximately 17.8% of the variance in r_Comp is explained by the included variables. While not uncommon in studies involving complex datasets, this value hints at the presence of other factors or relationships not captured by the current model.

The exploratory analyses presented highlight the spatial nature of aircraft noise complaints. The robust and statistically significant spatial autocorrelation of the r_Comp variable, evidenced by global and local indicators like Moran's I of 0.565 and the clustering and significance patterns from LISA and Geary maps, demonstrates that the distribution of complaints is not random but influenced by geographical proximity. This finding emphasizes the importance of considering spatial dependence, revealing the limitations of non-spatial models like OLS regression. Although statistically significant, OLS regression exhibits restricted explanatory power and disregards the crucial spatial interdependence required for a comprehensive understanding of the problem.

## 5. CONCLUSIONS

This study deepens the understanding of aircraft noise complaints as an inherently spatial phenomenon, validating the significance of a detailed geographical approach for their analysis. Acknowledging the limitations of traditional statistical models, such as OLS regression, which disregard spatial interdependence and heterogeneity, this research demonstrates how spatial modeling offers a more accurate and comprehensive representation of the problem's reality.

By applying spatial statistical techniques to data from São Paulo-Congonhas Airport, we analyzed the spatial distribution of complaints, clearly identifying clustering patterns (hotspots) and anomalies (outliers) that indicate areas of varying sensitivity and impact. Furthermore, the research confirmed the presence of robust and statistically significant spatial autocorrelation in complaints, demonstrating that annoyance intensity in one location is statistically linked to that in neighboring areas. The statistical analysis of spatial autocorrelation showed that noise complaint distribution is not random but spatially influenced. The constructed model indicates that approximately 17.8% of the variance in the spatial distribution of complaints is explained by the included variables, suggesting the presence of additional factors or relationships (e.g., socioeconomic data) not captured by the current model.

The comparison between spatial regression models and the OLS model highlighted the former's superiority in explaining observed variance and incorporating the underlying spatial structure of the data. This capability to account for geographical relationships is crucial for a complete understanding of the phenomenon. Additionally, the study successfully identified the percentage of influence and dependence among spatial factors and a set of socioeconomic and environmental variables, revealing how these elements intertwine to shape the perception of annoyance in communities. Although not included in the current model, socioeconomic and perceptual variables are known to influence noise complaint behavior. Their exclusion, due to data availability at the cell level, is a limitation to be addressed in future studies. Incorporating social indicators could enhance explanatory power and improve the understanding of non-acoustic determinants of annoyance.

Ultimately, disregarding the inherent geographical dimension of noise impedes a precise understanding of its distribution and influencing factors. Therefore, spatial modeling emerges as an essential approach to capture the complexity of the airborne noise phenomenon. Such analyses reinforce the importance of integrating complex datasets with precise noise measurements, advocating for standardized complaint recording practices. For future investigations, spatial regression models and a broader spectrum of socioeconomic, biological, climatic, and psychological variables are strongly recommended to enhance predictive capacity and foster a more comprehensive understanding of noise annoyance, as well as to guide effective and territorially sensitive solutions for harmonious coexistence.

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