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THEMATIC SECTION | AIR TRANSPORTATION SYSTEMS: INFRASTRUCTURE, OPERATIONS, AND ENVIRONMENTAL INTEGRATION

Spatial and Statistical Patterns of Aircraft Noise Complaints

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ABSTRACT

This study proposes and applies an integrated geospatial and statistical approach to investigate the spatial distribution of aircraft noise complaints (2021–2023) near Congonhas Airport (CGH). The methodology comprised four stages: (1) developing a multivariate theoretical framework; (2) collecting and integrating operational and territorial data; (3) spatial modeling using Geographic Information System (GIS) tools; and (4) multiscale statistical analysis incorporating Ordinary Least Squares (OLS) regression and spatial autocorrelation (Moran's I = 0.565). Results reveal that 70% of complaints fall outside the noise contours established by the airport's Specific Noise Zoning Plan, highlighting significant regulatory limitations. Additionally, 87% of complaints originated from residential areas directly under landing and takeoff trajectories. Statistical modeling identified the most influential variables as the presence within 65- and 70-dB zones, inclusion in landing routes, total built-up area, maximum building height, and distance to the runway. The study offers a replicable conceptual and methodological framework for urban airports, with applications in airport noise management, public policy development, acoustic zoning revision, and environmentally sensitive urban planning. This approach is particularly relevant for airport managers, regulatory agencies, and professionals in geotechnologies and urban sustainability.

Keywords: Aircraft noise; Spatial analysis; Noise complaints; Urban planning; CGH Airport.

INTRODUCTION

Among the various challenges facing air operations are the impacts of airports on the land area they occupy. The noise and air pollution from arriving and departing aircraft affect both the local population and the environment (flora and fauna), proportionally to the intensity of operations. Consequently, airports with higher aircraft traffic face the establishment of institutional limits on traffic volume to meet prescribed noise and/or air pollution quotas (daily and annual), which in turn generates effects on the airport's profitability (Janic 2009) and its entire performance system (Zografos *et al.* 2013).

Major global air hubs increasingly face the challenge of balancing growing traffic demand with societal calls for reduced environmental impact on surrounding communities. This tension is amplified in airports located within urban perimeters, demanding greater regulatory coordination among all involved stakeholders. Despite rising concerns about air quality, noise impact remains the most significant environmental issue (Visser *et al.* 2008), as the sound of air turbines triggers instant irritation (Kasioumi 2021).

Noise assessment presents a complex, multidisciplinary challenge, drawing upon fields such as acoustics, physiology, sociology, psychology, and statistics (Kang 2007). Furthermore, the perception of noise annoyance is not solely determined by acoustic properties.

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A range of social, economic, cultural, and attitudinal factors also contribute to individual judgments regarding acceptable noise levels. As a result, spatial distribution patterns of noise complaints from aircraft operations in the vicinity of airports around the world show that the distribution of annoyance does not always follow the intensity of noise exposure corridors that are modeled, monitored, or expected (*e.g.*, Collette 2011, Fidell *et al.* 2012, Morrell *et al.* 1997).

Noise annoyance is a subjective reaction to sound, influenced by numerous non-acoustic factors, including psychological, social, demographic, biological, and environmental processes (Schultz 1978). Individual sensitivity, attitudes, behaviors, and contextual elements like neighborhood and culture also play a role (Kang 2007). While acoustics are important, understanding noise annoyance requires considering a wider range of variables. Noise complaints are outward expressions of annoyance, typically filed when noise significantly impacts quality of life. However, not everyone who experiences annoyance complains, due to factors like lack of awareness or varying tolerance thresholds.

Spatial analysis of noise complaints is instrumental in discerning how environmental and operational elements impact noise propagation and perception, thereby facilitating the identification of hotspots and the prioritization of mitigation. This study comprehensively examines the spatial factors influencing aircraft noise annoyance, underscoring the critical role of geostatistical methods in modeling spatial dependence. Through this investigation, the research aims to elucidate the intricate relationship between spatial characteristics and noise perception, ultimately fostering more effective noise abatement strategies.

Within this framework, this paper proposes to investigate the spatial attributes associated with noise complaints in the vicinity of São Paulo–Congonhas Airport (CGH), in Brazil.

Spatial factors and the distribution of aircraft noise complaints

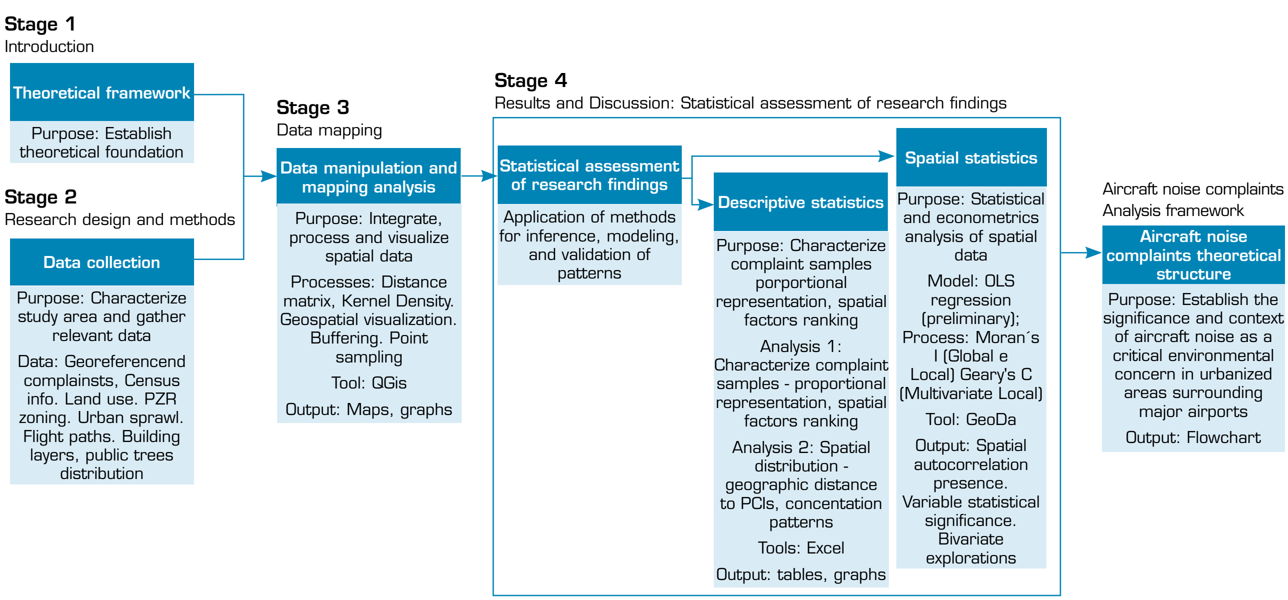
Spatial analysis is crucial for understanding noise complaints as it reveals hidden patterns and their correlation with environmental and operational factors. This study investigates how the following factors influence the frequency and distribution of complaints.

- Flight paths: The configuration of runways and operational procedures fundamentally determines flight paths, defining how and where noise impacts surrounding communities (Boucsein *et al.* 2017). Beyond runway orientation, factors such as prevailing wind conditions, air traffic volume, aircraft types, and operational procedures (*e.g.*, departure and arrival routes) contribute to the complexity of flight paths and the distribution of associated noise.
- Runway distance: Airport proximity is a key factor in noise annoyance, with noise exposure decreasing with distance. Takeoff is the loudest phase (ICAO 2023), making the runway the primary noise source and takeoff the most significant part of the landing and takeoff cycle due to the aircraft using full power. Accurate location data for complaints and their relation to runways is crucial for effective noise management and defining noise impact.
- Noise zoning: Required by Brazilian regulations (RBAC 161), Noise Zoning Plans (NZPs) map aeronautical noise impact using DNL (day-night average sound levels). While a standard metric, DNL has limitations in predicting annoyance due to non-acoustic factors (Fidell and Mestre 2020). Studies of Los Angeles airports (Oliveira 2024, Southgate 2007) show complaints often originate outside NZP boundaries, suggesting potential inadequacies in zoning or planning and the need for further investigation and adjustments.
- Predominant land use: With respect to airports, land use planning, also referred to as spatial or urban planning, is probably the most effective instrument in the strategic range (Visser *et al.* 2008). Research into aircraft noise annoyance has predominantly concentrated on residential land use (Fidell and Mestre 2020), suggesting a correlation between residential land use and elevated complaint rates. However, the relationship between land use and noise complaints is likely more complex. Commercial, industrial, and recreational uses may also be significantly impacted by aircraft noise, and their occupants may exhibit different tolerance levels and complaint behaviors.
- Height of buildings: The height of buildings significantly affects the propagation of aircraft noise. Within the urban morphology, buildings are elements that act as reflecting surfaces and modify sound pressure levels according to their exposure to noise (Flores Castillo *et al*. 2018). Taller structures can exacerbate noise levels by acting as acoustic barriers that prevent the natural sound dispersion, causing sound waves to reflect between building facades, which can amplify noise in certain areas. Conversely, lower buildings can provide some degree of acoustic shielding, reducing noise impact on the opposite side.

• Population density: Traditional noise contour maps, while indicating noise levels, do not directly correlate with impacted population density or the total nuisance caused (Elliff *et al.* 2021). Nonetheless, population density is crucial for understanding aircraft noise impact, as effective impact is contingent upon population spatial distribution (Visser *et al.* 2008). Consequently, the observed correlation between population density and the frequency of noise complaints requires the inclusion of population distribution as a key variable in community noise nuisance assessments.
• Tree density: Evergreen trees effectively reduce ground run-up noise. However, urban trees offer limited mitigation of elevated aircraft noise due to high-frequency sound penetration, low sound absorption, impractical density needs, and seasonal variations (Zaporozhets *et al.* 2011). In certain conditions, urban trees can even increase aircraft noise by approximately 10 dB (Schäffera *et al.* 2020). Consequently, a preliminary assessment of urban tree coverage within the study area is essential to inform subsequent in-depth investigations into afforestation characteristics and their relationship with noise complaints.

Research design and methods

This study adopted a systematic and spatially oriented methodology to analyze aircraft noise complaints filed in the vicinity of CGH. By integrating geospatial analyses and statistical methods, the approach aimed to ensure robust and comprehensive results. This study employed of a four-stage approach specifically designed to address both spatial and contextual factors influencing noise complaints (Fig. 1).



Source: Elaborated by the authors.

Figure 1. The four-stage methodological approach for assessing the impact of the spatial distribution of aircraft noise complaints in this work.

• Stage 1: Theoretical framework. This stage aimed to establish a robust theoretical foundation, guided by existing knowledge. A thorough literature review was conducted to identify key spatial factors influencing noise perception and to develop a theoretical framework for understanding noise complaint patterns. This framework provided critical insights into potential drivers, shaping subsequent analyses.
• Stage 2: Data collection. This stage focused on gathering relevant data from various reliable sources to support the spatial and statistical analysis. Table 1 summarizes the primary data sources and their reference years. The collected data encompassed georeferenced noise complaints, census information, land use maps, and zoning regulations. These datasets were crucial for defining spatial factors relevant to the study objectives, ensuring a comprehensive analysis of the factors influencing noise complaints. Data source selection prioritized relevance as well as the availability of reliable and up-to-date information.

Table 1. 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. Source: Elaborated by the authors.

A total of 303 noise complaints were analyzed and categorized by year and decibel level (Table 2).

Table 2. Complaints classified according to the noise level curves.

Year	2021	2022	2023	Total
< 65 dB	18	169	24	211
65 dB	6	49	9	64
70 dB	0	11	15	26
75 dB	0	1	1	2
Total	24	230	49	303

Source: Infraero (2022; 2023), adapted by the authors.

For this analysis, we calculated the geodesic distance from each complaint point to the center of the primary runway (17R-35L). The runway's center point (at latitude –23.6275 and longitude –46.6558) was determined as the midpoint between its two geographic endpoints. The Haversine formula was then used to calculate the geodesic distances from each complaint point to this runway center, accounting for the Earth's curvature (Movable Type Scripts, accessed January 27, 2025). These distances were subsequently integrated into our statistical and spatial analyses.

- Stage 3: Data manipulation and mapping analysis. Spatial data were integrated and analyzed using Quantum Geographic Information System (QGIS). Tools such as distance matrix, kernel density estimation, and geospatial visualization were used to identify patterns in complaint distribution and their relationship to spatial factors. Data on urban sprawl, flight paths, noise zoning, and complaints were georeferenced and integrated. The estimated 10-m accuracy of complaint points is sufficient for the block-scale analysis (average 106-m block face size), enabling identification of complaint trends and clusters relative to noise contours.
- Stage 4: Statistical analysis methodologies and results. Two primary statistical analysis methodologies were employed in this study:
  a. Descriptive statistics involved two distinct analyses. The first characterized noise complaint samples by aggregating mapped data to quantify the proportional representation of each variable, thereby establishing a preliminary ranking of spatial factors based on observed characteristics. The second analysis focused on the spatial distribution of complaints, measuring geographical distances from complaint locations to key points (*e.g.*, the runway centerline and the calculated center of gravity of all complaints) to identify spatial concentration patterns.
  b. Spatial statistics is formally defined as the statistical and econometric analysis performed on datasets that incorporate positional coordinates, commonly referred to as spatial data (Yamagata and Seya 2020). Nearby observations in such data are often highly correlated, making it essential for any adequate statistical analysis to account for these spatial interdependencies (Kent and Mardia 2022). The spatial weight matrix was built in QGIS, and the GeoDa software was utilized to ascertain the presence of spatial autocorrelation. This process was executed through an exploratory spatial data analysis, specifically employing Local Indicators of Spatial Association (LISA). This analytical approach facilitated the verification of the statistical significance for all variables under consideration and, furthermore, enabled the development of a comprehensive series of bivariate explorations across multiple variables.

DATA MAPPING

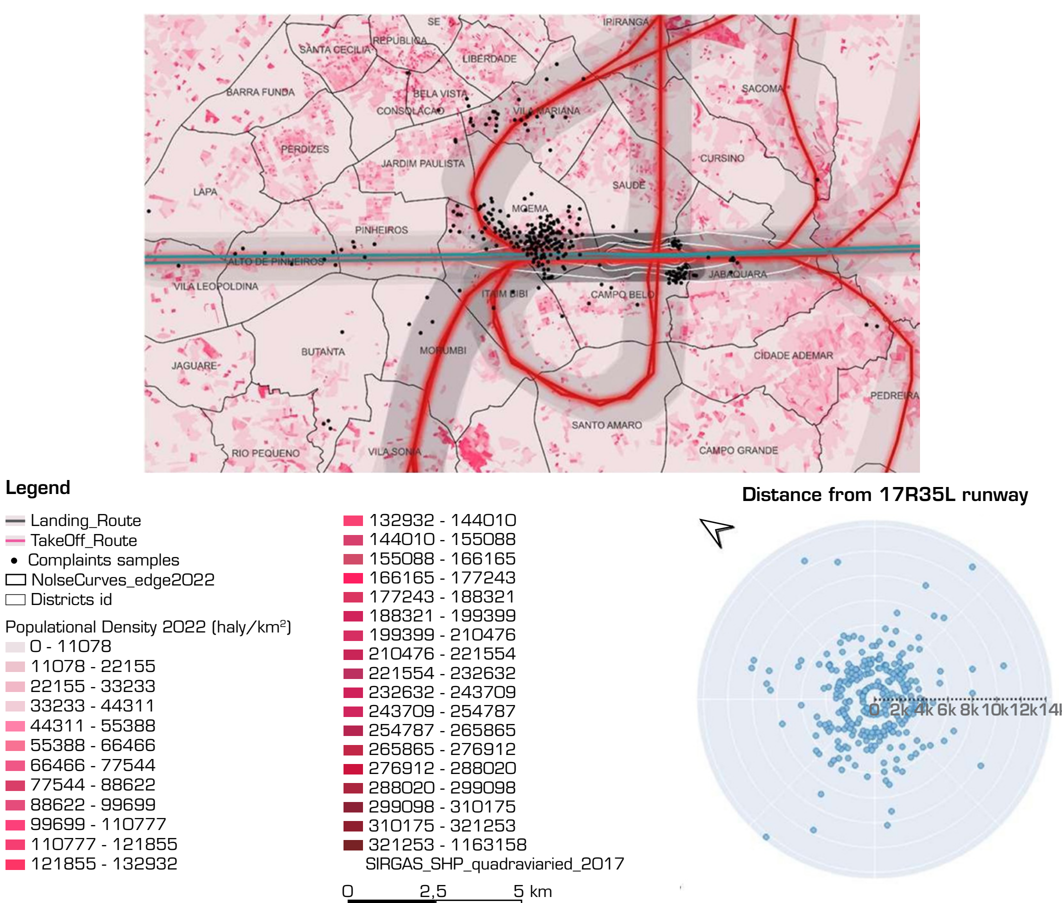
The São Paulo–Congonhas Airport (CGH)

In Brazil, the regulation of aircraft noise was initiated by the 1986 Brazilian Civil Aviation Code, which later established NZPs through Brazilian Civil Aviation Regulation (RBAC 161/2011). Despite this broader regulatory framework, Congonhas Airport, which served as Brazil's busiest passenger airport from its founding in 1936 until 2009, had its inaugural noise plan approved as early as 1984 (Heleno 2010). This plan has since undergone updates by Infraero in 2003, 2014, 2019, and 2022. Noise data collection commenced in 2010 (ANAC 2011), while complaint data are systematically derived from the airport's Annual Aeronautical Noise Reports, which were compiled by Infraero from 2021 to March 2023 and subsequently by Aena in March 2024.

São Paulo–CGH Airport requires particular attention in noise management due to its status as Brazil's second busiest airport by aircraft movements—234,689 in 2024, behind Guarulhos airport's 389,344 (DECEA 2025)—and its surrounding highly densified urban environment, which exacerbates noise impact challenges.

Geospatial analysis

Spatial analysis (Fig. 2, left) utilized flight path modeling data from the National Civil Aviation Agency (ANAC 2011), georeferenced in QGIS. Complaint points (Infraero 2023) and noise contour lines from the CGH NZP (Infraero 2022) underwent the same procedure. These layers were then overlaid with population density distribution data from the 2022 Census (IBGE 2022), calculated in QGIS from total population and census sector areas.



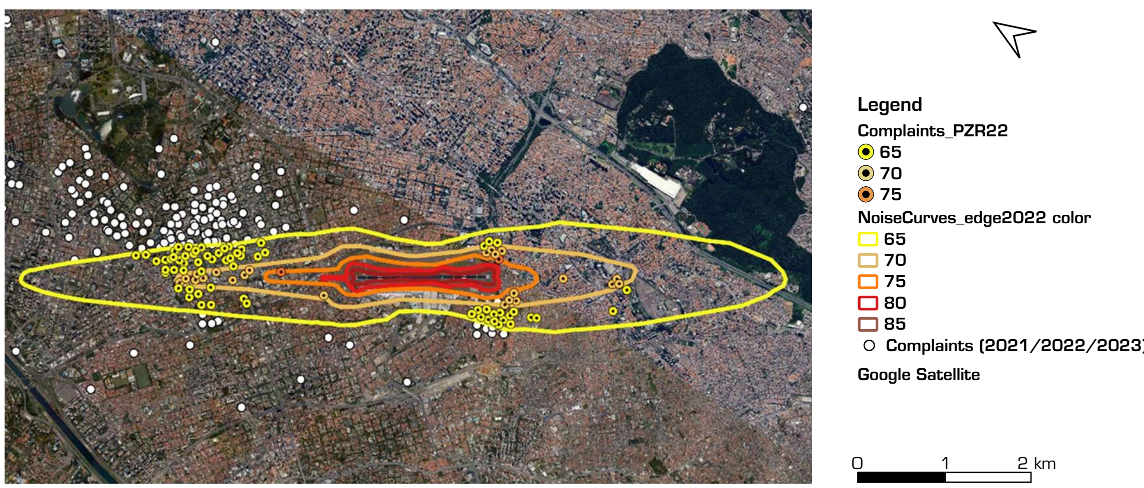
Source: Elaborated by the authors (in QGis).

Figure 2. Spatial distribution of aircraft noise complaints in relation to population density and flight paths (left); distance-based analysis of aircraft noise complaints (right).

Figure 2 (left) reveals a strong correlation between noise complaints and flight paths, with the eastbound takeoff trajectory accounting for approximately 67% of all complaints. A 1-km buffer generated around these paths (using the MMQGis plugin and aligning with the NZP's contour) shows that 83.1% of complaints originated within this projected area. The map also highlights a disproportionately high 70% of total complaints stemming from low-density residential areas (up to 20 hab·km^{-2}).

Figure 2 (right) presents the results of a distance matrix operation, which measured complaint point distances to the runway 17R-35L midpoint, established as the airport's central reference. This analysis reveals that a significant 49.2% of complaints originated between 2 and 4 km from the runway, with an additional 21.1% within the 4–6 km range.

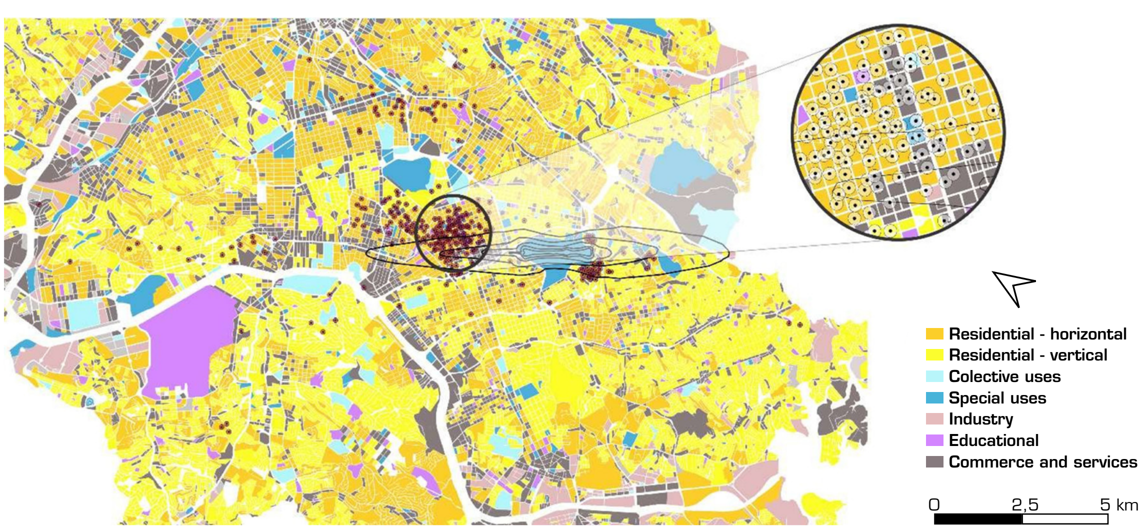
The location of the origin of complaints in relation to the noise contours was also verified (Fig. 3). Only 30% of complaints were within the noise zone established by the 2022 NZP. Of this amount, most (69.5%) were in the 65 dB noise zone, with smaller percentages in the 70 dB (28.2%) and 75 dB (2.3%) noise zones.



Source: Elaborated by the authors (in QGis).

Figure 3. Spatial distribution of aircraft noise complaints in relation to the 2022 NZP.

Regarding land use, Fig. 4 presents a spatial distribution of predominant land use and noise complaints around CGH. The map highlights the significant prevalence of residential land use (yellow and orange tones) within the blocks where noise complaints originate.



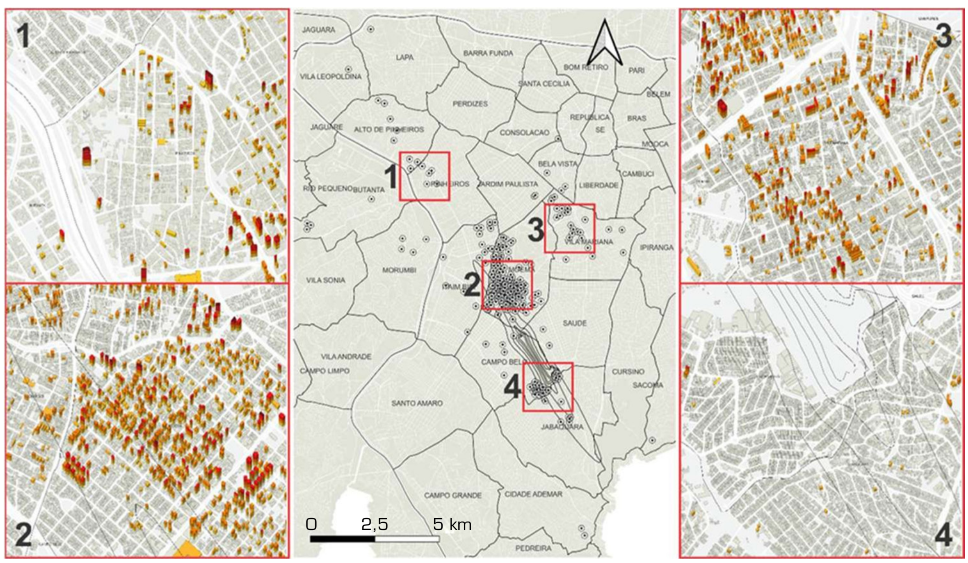
Source: Elaborated by the authors (in QGis).

Figure 4. Complaints versus predominant land use.

To provide a more detailed analysis, the Dataplotly plugin was used in QGIS to quantify and organize the data. The results indicate that over 87% of complaints primarily originate from residential areas, with high-rise residential buildings accounting for 52.7% of these. Furthermore, 62.4% of complaints are concentrated in areas with low building density (less than 50,000 m² per block).

To identify the correlation between complaints and building height, a 2.5D vector visualization was employed in QGIS, with a custom style for classifying buildings in 20 m intervals. Height data was sourced from GeoSampa's building layers database (2017). Buildings up to 20 m are depicted in gray in Fig. 5, while taller buildings are depicted with progressively darker shades.

Figure 5 also highlights four areas to enhance the 3D visualization of buildings in blocks with high complaint concentration. The Moema district concentrates 54.8% of the complaint records, which also has the tallest buildings closest to the complaint points, with a maximum height of 100 m under this condition. The areas show notable spatial variability in building height.

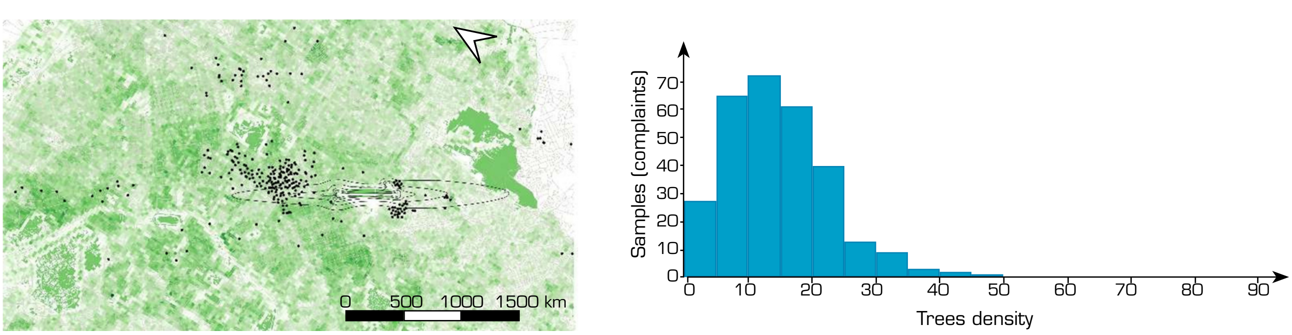


Source: Elaborated by the authors (in QGis).

Figure 5. Building heights in four high-complaint zones.

The green density analysis was performed by generating a raster image through kernel density estimation of street tree distribution data sourced from GeoSampa (2017). The density image (Fig. 6, left) represents tree density within 100 × 100 m pixel cells, with a minimum of 3.2 and a maximum of 90.7 trees per pixel within the study area.

The Point Sampling tool plugin was utilized to establish a correlation between complaint points and the raster image. The resulting graph is presented on the right side of Fig. 6. The graph reveals that nearly three-quarters of the complaints (74.2%) originate from areas with lower tree density (up to 19 trees per 10,000 m²).



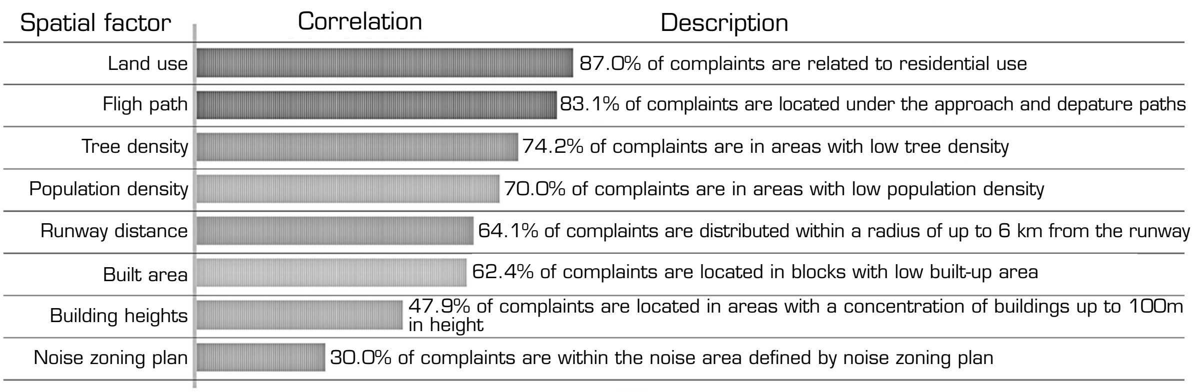
Source: Elaborated by the authors (in QGis).

Figure 6. Spatial distribution of complaints compared to tree density (left) and the corresponding numerical correlation (right).

RESULTS AND DISCUSSION

Ranking of spatial factors based on observed sample characteristics

The mapping conducted enabled the extraction of data and information regarding the spatial characteristics of the geographic area surrounding CGH, where aircraft noise complaint points are distributed. Spatial factors were ranked according to the pattern found in the majority of complaint points, resulting in the graph presented in Fig. 7.



Source: Elaborated by the authors.

Figure 7. Spatial factors ranking for the observed sample characteristics.

Figure 7 illustrates the most significant spatial factors associated with aircraft noise complaints:

- Residential land use: 87.0% of complaints are linked to residential areas, highlighting their primary vulnerability.
- Flight paths: 83.1% of complaints occur directly under approach and departure trajectories, underscoring the need for optimized flight paths to reduce community noise impact.
- Noise Zoning Plan (NZP) contours: Notably, 70% of complaints originate from areas outside traditional "close-in" noise contours. However, the highest complaint concentration is still within 6 km of the airport, suggesting current noise exposure models may need refinement.
- Building height: While not a significant overall factor, high-end (39.2%) and mid-range (39.3%) buildings are most commonly associated with complaints, possibly indicating a link to socioeconomic conditions.
- Tree density, population density, and built area: These variables show a negative correlation with noise complaints, suggesting that areas with lower densities of these features and less built-up environments are more prone to complaints.
- Runway distance: The number of complaints generally increases as proximity to the airport decreases.

However, this trend reverses within a 2-km radius, implying that other factors, such as specific land uses, may mitigate noise complaints in these closest areas.

Statistical analysis of spatial distribution of complaints

Statistical and graphical analyses examined noise complaint distances relative to two key points: the main runway centerline (17R-35L) and the calculated center of gravity for all complaints. The analysis calculated the mean, median, and standard deviation of these distances, visualized through tables and graphs. The dataset comprised georeferenced complaint coordinates linked to their corresponding noise levels (dB).

Specifically, Euclidean distances were calculated from each georeferenced complaint to both the runway centerline and the center of gravity of all complaints. Mean, median, and standard deviation quantified the central tendency and dispersion of these distances.

Table 3 reveals that most noise complaints are concentrated near the runway centerline, with a mean distance of 3.58 km and a median of 2.89 km. This spatial pattern strongly suggests that aircraft landing and takeoff operations are the primary sources of noise.

Table 3. Results of statistical distances.

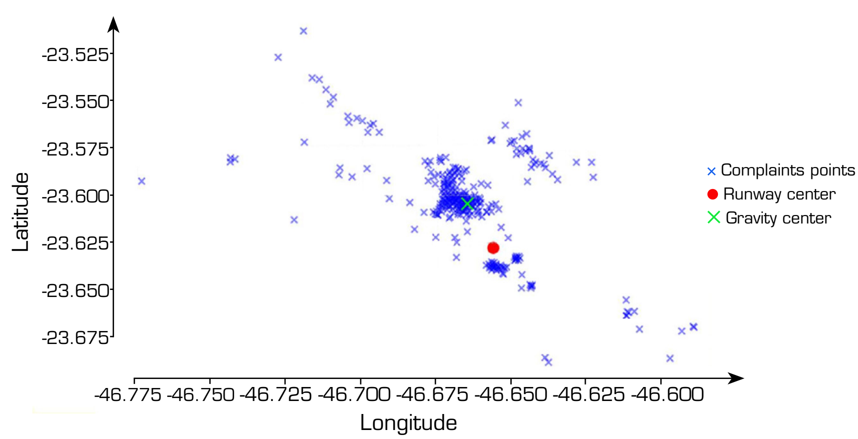
Analysis deviation (km)	Mean distance (km)	Median distance (km)	Standard
Distance from complaints to the center of runway 17R-35L	3.58	2.89	2.20
Center of gravity of complaints	2.39	1.46	2.39

Source: Elaborated by the authors.

Significant dispersion is indicated by standard deviation values of 2.20 km (relative to the runway centerline) and 2.39 km (relative to the center of gravity). The greater variability near the center of gravity suggests that while complaints cluster, noise impacts extend to more distant areas. This dispersion likely stems from factors such as flight paths, sound reflection from the built environment, and local topography.

The runway centerline (17R-35L) was set at latitude (Y): –23.6275 and longitude (X): –46.6558. The center of gravity of complaints was calculated from the arithmetic mean of latitude and longitude coordinates for all 303 valid complaint points, resulting in latitude (Y): –23.6041 and longitude (X): –46.6645.

To find the distance between the complaints' center of gravity and the runway centerline, conversion factors transformed the geographic coordinate differences (degrees) into a linear distance in kilometers. Given that 1° of latitude equals approximately 111 km, and adjusting for longitude using the average latitude [klon = 111 · cos(average latitude)], the distance between these two points is 2.74 km (Fig. 8).



Source: Elaborated by the authors.

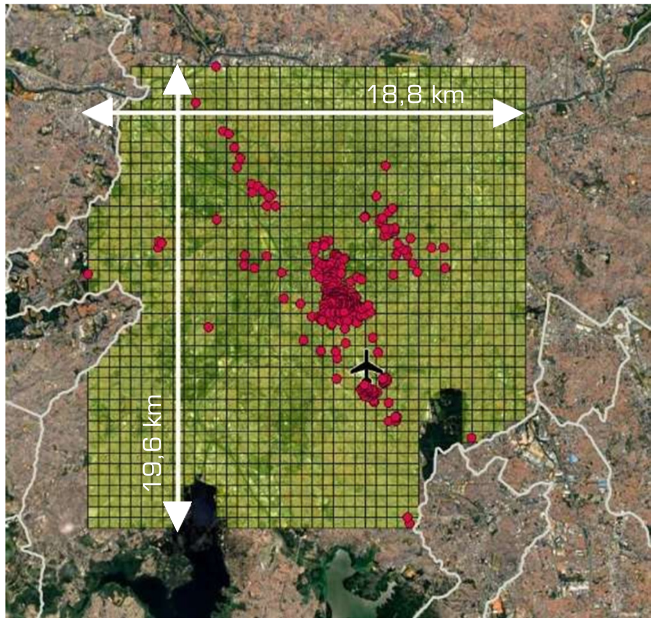
Figure 8. Distances to runway center with gravity center.

Figure 8 illustrates the spatial distribution of aircraft noise complaints around CGH. A significant concentration of complaints appears near the runway's centerline, emphasizing the direct influence of landing and takeoff operations on perceived noise annoyance. However, many complaints are dispersed in more distant areas, suggesting the acoustic impact extends beyond the immediate vicinity of the runway, potentially linked to flight trajectories and local sound propagation.

The center of gravity of complaints (green marker) is situated northwest of the runway center (red marker). This positional asymmetry points to operational influences from factors such as preferential flight paths, land use, and prevailing atmospheric conditions. This displacement further underscores the need to review existing acoustic zoning contours and implement mitigation strategies informed by spatial evidence.

Spatial autocorrelation analysis

The spatial autocorrelation analysis process commences with the construction of the spatial matrix, which is developed based on the comprehensive distribution of samples within the municipal boundaries of São Paulo. This matrix comprises a total of 1,575 cells, each measuring 0.5 × 0.5 km, collectively covering an area of 412.5 km² (Fig. 9).



Source: Elaborated by the authors (in QGis).

Figure 9. Spatial matrix showing complaint distribution (red).

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.

Table 4. OLS Regression model data report.

Description	Independent variable	Coefficient	Standard Error	t-Statistic	p-Value
Number of trees in public spaces	r_trees	0.000559	0.000245001	2.2841	0.02250
Area within the 65dB zone	r_65db	0.000675	0.000130	5.20240	0.00000
Area within the landing route projection	r_landing	0.000004	0.000000	5.94460	0.00000
Total built area	r_Acont	0.000001	0.000000	4.55530	0.00001
Maximum building height	r_hmax	0.000105	0.000044	2.37210	0.01775
Residential area	r_red	–0.000060	0.000009	–6.65840	0.00000
Distance from the runway centerline	r_Distrun	–0.000040	0.000010	–3.98140	0.00007
Number of census tracts	r_setcens	0.033039	0.010602	3.11540	0.00183
Area within the 70-dB zone	r_70db	0.000006	0.000002	2.52120	0.01175

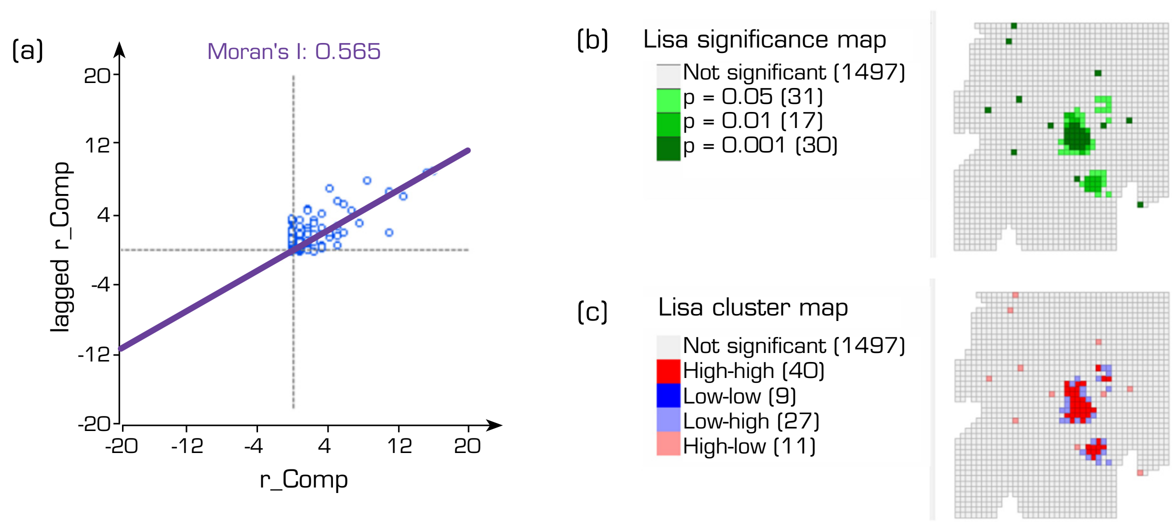
Model Statistics: $R^2 = 0.1778$ | $F(9, 1565) = 37.5909$ | $p < 0.00001$ | AIC = 4687.5. Source: Elaborated by the authors.

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

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 various subsets and combinations derived from a broader pool of potential independent variables. 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 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.

Test statistics used to verify the existence of spatial autocorrelation for the grid cells (r_Comp variable), known as Global Indicators of Spatial Association (GISA), are presented in Fig. 10a. Concurrently, measures pertaining to the specific locations where spatial autocorrelation occurs, termed LISA, are depicted in maps (b) and (c).



Source: Elaborated by the authors (in GeoDa).

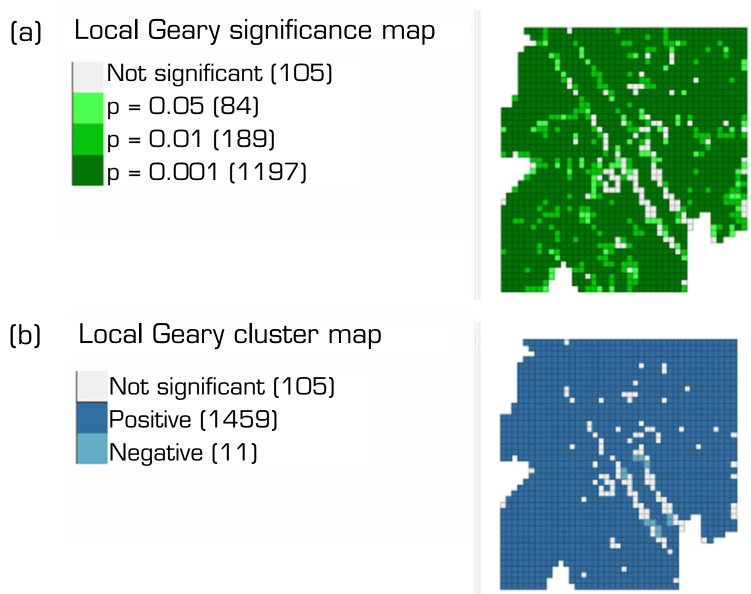
Figure 10. (a) GISA: Moran's I for complaint data; (b) LISA for complaint data: significance; (c) LISA for complaint data: clusters.

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 ($p < 0.001$).

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 Fig. 11 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.

This strong underlying spatial structure in r_Comp underscores the unsuitability of non-spatial models, such as OLS regression, which fail to account for the interdependence among geographical observations. This is further evidenced by the OLS regression report, in which the global statistical significance, as indicated by the F-statistic, is 37.5909 with a p-value of less than 0.0001.



Source: Elaborated by the authors (in GeoDa).

Figure 11. Multivariate Local Geary: significance (a) and clusters (b).

This implies that the set of independent variables collectively possesses explanatory power over r_Comp. However, an R-squared value of 0.177752 indicates that approximately 17.8% of the variance in r_Comp is accounted for by the included variables. This value, while not uncommon in studies involving complex datasets, suggests the presence of other factors or relationships not captured by the current model.

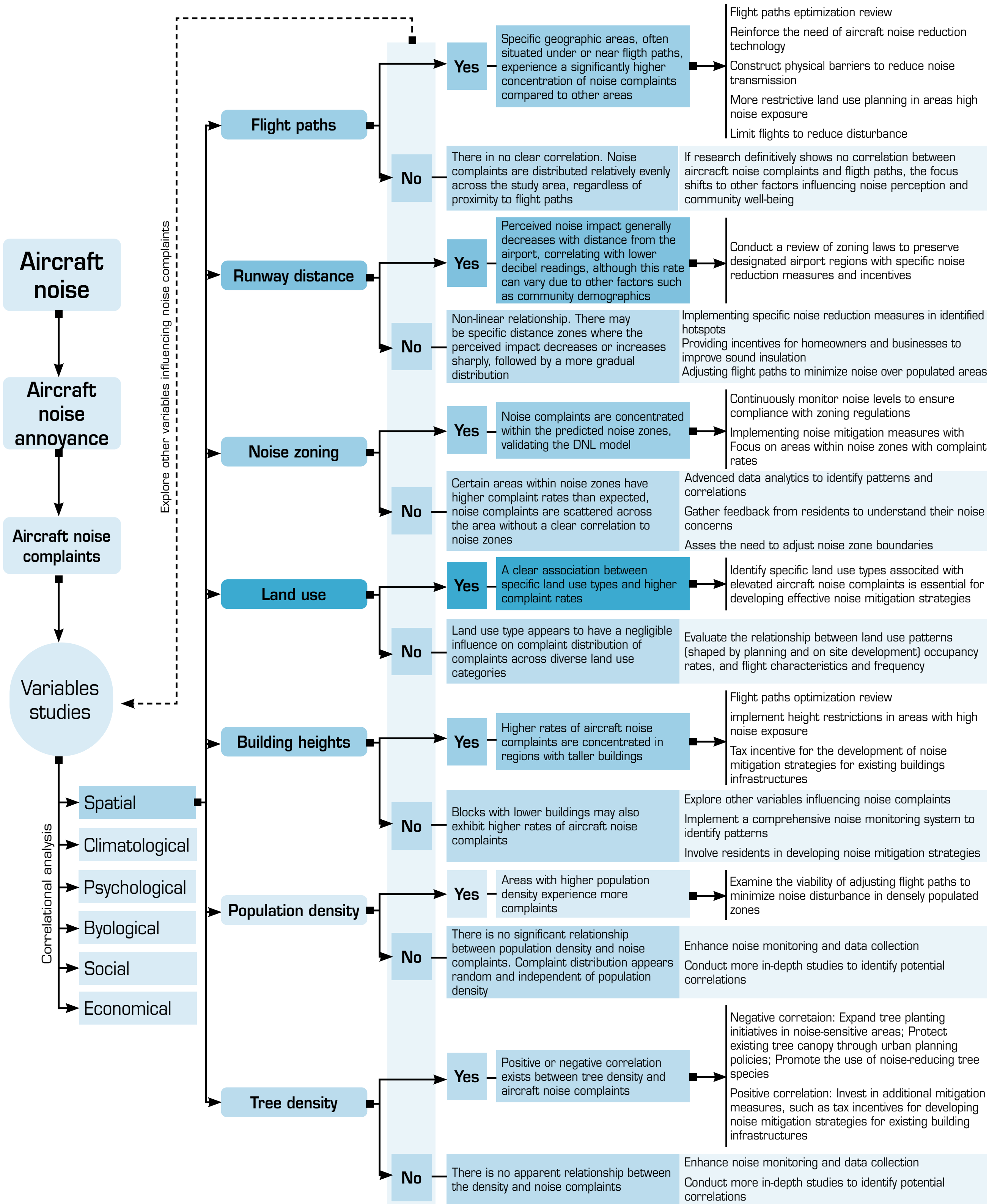
The exploratory analyses presented highlight the spatial nature of aircraft noise complaints. The strong and significant spatial autocorrelation of the r_Comp variable, evidenced by global and local indicators such as a Moran's I of 0.565 and the clustering and significance patterns from LISA and Geary maps, demonstrates that the distribution of complaints is not random but influenced by geographical proximity. This finding underscores the importance of considering spatial dependence, revealing the limitation of non-spatial models like OLS regression. Although statistically significant, OLS regression shows restricted explanatory power ($R^2 = 0.177752$) and disregards the spatial interdependence crucial for a complete understanding of the problem.

AIRCRAFT NOISE COMPLAINTS ANALYSIS FRAMEWORK

This study aimed to establish a theoretical structure for evaluating the possible relationships between spatial variables in urban settings and the distribution of aircraft noise complaints in airport vicinities. Additionally, the correlation diagram presented in Fig. 12 outlines research and decision-making pathways based on the presence or absence of correlations between variables.

The diagram depicts the placement of aircraft noise complaints within the larger context of aircraft noise area and outlines the variables that contribute to the complex interplay influencing complaint occurrence: economic, social, biological, psychological, climatological, and spatial environmental factors. Spatial factors, the focus of this study, encompass phenomena with spatial characteristics.

The diagram highlights the spatial factors analyzed for correlations with complaint occurrence, providing different paths based on whether correlations are confirmed or rejected. If a correlation is rejected, reevaluation is recommended, with consideration given to other potentially influential variables.



Source: Elaborated by the authors.

Figure 12. Correlations between aircraft noise complaints and spatial factors.

CONCLUSION

This study highlights the critical role of spatial analysis in comprehending and managing aircraft noise in areas surrounding airports. The study proposed an exploratory analysis to verify the spatial patterns of noise complaints generated over the urban area around São Paulo – CGH Airport, Brazil's second largest airport by aircraft movement.

Spatial variable mappings and three applied statistical analyses revealed a strong relationship between noise complaints and residential land use and airport approach routes. Additionally, the analysis of aircraft noise complaint distribution reveals a dual pattern of concentration which, on one hand, confirms the relationship with landing/takeoff operations, but also indicates that the acoustic impact extends beyond the immediate vicinity. This asymmetry may further suggest the influence of other factors, such as climatic conditions, on noise propagation. Notably, the statistical analysis of spatial autocorrelation demonstrated 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 factors or relationships (*e.g.*, socioeconomic data) not captured by the current model.

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 promote a more comprehensive understanding of noise annoyance, as well as support the development of territorially sensitive mitigation strategies and internationally comparable noise management policies.

CONFLICT OF INTEREST

Nothing to declare.

AUTHORS' CONTRIBUTION

Conceptualization: Cavion R; **Methodology:** Cavion R and Bandeira MCGSP; **Software:** RCavion R and Bandeira MCGSP; **Formal analysis:** Cavion R and Bandeira MCGSP; **Investigation:** Cavion R and Bandeira MCGSP; **Data Curation:** Cavion R; **Writing:** Cavion R and Bandeira MCGSP; **Supervision:** Cavion R; **Project administration:** Cavion R; **Funding acquisition:** Cavion R; **Final approval:** Cavion R.

DATA AVAILABILITY STATEMENT

The data will be available upon request.

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