NOVA IMS Information Management School

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Master Degree Program in

Data Science and Advanced Analytics

Where to place Airbnb?

Identifying Alternative Locations For Accommodations In Lisbon through Fuzzy Analytical Hierarchy Process

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Project Work

presented as partial requirement for obtaining a Master's Degree in Data Science and Advanced Analytics

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledged the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, July 2024

ABSTRACT

Gentrification is a current issue faced by many cities due to the increased influx of tourists, often driven by platforms like Airbnb. This phenomenon poses a significant challenge, as neighborhoods, especially historic centers, are losing their unique character to accommodate tourists. This research focuses on the city of Lisbon and, following a thorough literature review and an exploratory analysis of the city's current situation, aims to identify alternative locations for local accommodations (LAs) outside the historic center to replace some of the existing units in these areas. By combining Fuzzy Analytical Hierarchy Process (FAHP) and Geographic Information Systems (GIS) techniques, multiple criteria influencing tourists' choice of accommodations were evaluated and integrated into a final suitability map, highlighting potential new locations for LAs across various parishes in Lisbon. Therefore, this research suggests a strategic approach to redistributing local accommodations throughout Lisbon, aiming to preserve the historic identity of the city's neighborhoods while promoting sustainable urban development.

KEYWORDS

Airbnb; Tourism; Local Accommodation; Fuzzy Analytical Hierarchy Process; Geographic Information Systems

Sustainable Development Goals (SDG):

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LIST OF ABBREVIATIONS AND ACRONYMS

LA	Local Accommodation
AHP	Analytical Hierarchy Process
GIS	Geographical Information Systems
MCDA	Multi-criteria Decision Analysis
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
HAS	Hotel Advisory System
DEA	Data Envelopment Analysis
MCDM	Multi-criteria Decision Models
ANP	Analytical Network Process
OWA	Ordered Weighted Average
FAHP	Fuzzy Analytical Hierarchy Process
KNN	K-Nearest Neighbors
TFN	Triangular Fuzzy Number
CR	Consistency Ratio
CI	Consistency Index
RI	Random Index

1. INTRODUCTION

1.1. MOTIVATION

One of the major challenges facing contemporary Portugal stems from the escalating influx of tourists to the country, resulting in heightened demand for local accommodations (LAs). Owing to this surge, there has been a notable upswing in the number of LA establishments, particularly in the historic centers of major Portuguese cities (Lestegás et al., 2019). This trend had several consequences for these municipalities. On one hand, the tourism industry had some positive impacts, such as a great impulse to the Portuguese economy, as well as the proximity to other cultures and the rehabilitation of some buildings previously abandoned or in decadent conditions. On the other hand, it had several negative consequences, namely the process of gentrification. Residents are losing their right to the city and the neighborhoods' distinctive character is being diminished to other cultures (Fernandes, 2019).

1.2. OBJECTIVES AND METHODOLOGY

Since 2008, when Airbnb was founded, these problems regarding the historical centers of several cities in the world, many times holding more tourists than locals, have been a rising global concern (Franco & Santos, 2021). Previous studies have explored policies aimed at tackling this issue, including the creation of "areas of contention", in which no new LA can be registered, under certain conditions (Torkington & Perdigão Ribeiro, 2020). However, so far there have not been any effective alternatives to counteract the gentrification problem and thereby safeguard the essence of these cities. Hence, this study aims to investigate viable alternatives for accommodating the growing influx of tourists in Lisbon, answering the following research question: How can we identify alternative locations for local accommodation in Lisbon to mitigate gentrification and preserve cultural heritage? To achieve this, the study also aims to address the following research questions:

1. How has the number of opening LA units in Lisbon changed over the past decade and what factors have influenced these trends?
2. Which criteria have the most significant impact on the selection of a LA unit by tourists?
3. Which parishes in Lisbon have the potential for implementing new LAs as alternatives to the historic center?
4. How do the suitability scores of parishes for the implementation of new LAs correlate with the existing number of units in those areas?

The first step of this research involves preprocessing the data that will be used, namely local accommodation's data. Then, an analysis of the data over time will be conducted, using both data visualization tools and geospatial techniques. These analyses will provide insights, which will later contribute to the formulation of future recommendations to address the research questions. The next step consists of applying Fuzzy logic with Analytical Hierarchy Process

(FAHP), using Geographical Information Systems (GIS), and being the very first task of this phase to define the criteria that will be considered. After the application of these techniques, the output will consist of the several possible neighborhoods that should be considered as alternative locations for the implementation of LAs, considering the defined criteria.

In conclusion, this research provides a comprehensive analysis and set of recommendations regarding the evolution of local accommodation in Lisbon. The results detailed in this thesis offer valuable insights into the current state of LAs and potential solutions for mitigating gentrification. This analysis could contribute to the guidance of urban planners and policymakers in making informed decisions regarding LA placement, leading to sustainable development in Lisbon while preserving the character of its historic center.

This thesis follows the following structure: **2.** Literature Review contains a background of the topic under study and discusses previously developed related works; **Research Context & Data** describes the city being studied and offers an exploratory analysis of the existing local accommodation units; **Methodology** outlines the research steps, starting with the definition of the chosen criteria, followed by the steps of Fuzzy AHP to determine their importance, and finally presenting the created layers for the criteria; **Results and Discussion** presents and discusses the FAHP results, including the obtained criteria weights and the final suitability map, and also the answers to the proposed research questions; **Conclusions** provide a summary and final assessment of the research conducted throughout this study; and **Limitations and Future Works** outlines the limitations encountered in this study and suggests potential ideas for future research.

2. LITERATURE REVIEW

2.1. BACKGROUND

Portugal has won the "Europe's Leading Destination" title at the World Travel Awards for the second consecutive year in 2023, having also won it from 2017 to 2019, while Lisbon won the "Europe's Leading City Destination" award in 2023, having also achieved other categories' awards since 2009 (*World Travel Awards*, 2023). Hence, the Portuguese capital is seen as a top destination, renowned for its cultural, recreational and professional offerings, as well as its gastronomy, climate and safety (Brandelli Ribeiro, 2017). Therefore, tourism in Portugal has been increasing exponentially.

Tourism plays a crucial role in Portugal's economy, serving as the main source of national income (*O Turismo Em Portugal: Factos e Números*, 2023). In fact, the tourist is seen as the ideal citizen who carries capital (Patrício, 2019). With the increase in the influx of tourists coming to the city, the number of short-term rentals also had to grow. This growth has several consequences, one of them being the increase in house prices and rental, which is something that is occurring in several cities, such as Athens, Milan, Barcelona and Los Angeles, aside from Lisbon (Amore et al., 2022; Franco & Santos, 2021; Garcia-López et al., 2020; Koster et al., 2021). Perić et al. (2022) conducted a study examining the impact of tourism and local accommodation on housing prices across 27 European Union countries, analyzing data spanning from 2005 to 2018 and came to the conclusion that these factors increase significantly housing prices, not only in tourist areas, but throughout the country, due to a spillover effect. In fact, in August 2022, Lisbon was the most expensive city in Southern Europe to buy a house, reaching a mean value of 4,817€ per squared meter (*Lisboa Ultrapassa Madrid, Barcelona e Milão Como Cidade Mais Cara Do Sul Da Europa (Com Áudio)*, 2023).

Tourists are drawn to authentic local experiences, leading them to prefer staying in the historic areas of Lisbon, where the short-term rental market is heavily focused. In these neighborhoods, and extending into middle and lower-class residential areas, like Mouraria-Arroios, there are hardly any hotels. On the other hand, hotels are predominantly located in tertiary, financial and office centers, emphasizing proximity to specific amenities, such as airports or entertainment parks. As a result, in a first phase, short-term rentals came to fill this lack of hotels (Barata-Salgueiro, 2017). However, this dynamic causes residents to contend with tourists and other temporary city visitors, with higher economic power, as they compete for access to a restricted supply of local housing (Lestegás et al., 2019).

This competition for housing access has had various consequences. On one hand, it has contributed to the revitalization of previously depopulated areas, due to the intense presence of visitors, many of them tourists. This resulted in the direct or indirect displacement of residents, to make way for new tourist apartments (Barata-Salgueiro, 2017). On the other hand, short-term rentals have also come to give use to vacant houses. According to a study performed in 2016 concerning the city of Lisbon, before being converted into short-term

rental accommodations, 59% of the real estate properties were unoccupied (Gonçalves Pereira, 2017). However, this suggests that about 40% of the remaining properties were for housing, which shows a meaningful loss of local population, at the expense of tourist occupation. This also may be alarming for tourism itself, since tourists seek a true experience as a local (Lopes et al., 2019).

There has been a growing interest in foreign investment in the hospitality market in Portugal, namely the purchase of hotels and local accommodation facilities (Barata-Salgueiro, 2017). Besides foreign individuals finding the real estate prices in Portugal affordable, they are also incentivized by the government to invest in it (Lestegás et al., 2018).

Technology platforms such as Airbnb facilitate the process of renting out real estate properties for tourism. The problem with this platform is that it is not regulated, so, along with other factors, such as policies released, it can lead to a social and territorial imbalance (Brandelli Ribeiro, 2017). The growth of tourism in the historic centers of European cities is progressively disrupting the daily lives of residents (García, 2012) and transforming these centers into commodities for cultural consumption (Gotham, 2005a). Grassroots movements supporting the right to the city and affordable housing have emerged in Lisbon, striving for changes in policies. Although locals protested the surge of Airbnb in Lisbon, they also understand its importance for the city's economy (Lestegás et al., 2018).

Besides the obvious advantages brought by tourism growth, the city is facing substantial challenges arising from the excessive tourism, which is leading to the continuous increase of inequalities, making it impossible for individuals from low to middle-classes to live in the center of Lisbon due to the escalating high housing prices (Barata-Salgueiro, 2017). In an attempt to solve these problems, the government has been releasing several laws. In the table below (Table 2.1), there are presented the main consequences of tourism in Lisbon, grouped into three categories – sociocultural, urban and economic (Brandelli Ribeiro, 2017).

Table 2.1 - Consequences of tourism growth in Lisbon.

Context	Positive Consequences	Negative Consequences
Sociocultural	- Territorial pride - Proximity to other cultures - Cultural offer - Local communities strengthen	- Gentrification - Conflicts of coexistence - Mischaracterization - Fake authenticity - Loss of local businesses
Urban	- Buildings' rehabilitation - Requalification of public spaces - Encouraging heritage conservation - Infrastructure investment - More dynamic in the city - More investments	- Increased population - Overcrowding on public transportation - Urban landscape modification - Loss of residential character - Ambiental impacts - Increased waste - Increased noise - Increased number of hotels and LA - Pedestrian traffic
Economic	- Increase in employment - Increase in revenue - Foreign investments - Increase in several sectors - Resident population growth - GDP growth	- Low wages - Inflation in the cost of living - Real estate speculation - Low housing supply - Tourism as the main economic activity

2.2. IMPLEMENTED LAWS

Following the 2010 bailout and Troika intervention, urban revitalization policies shifted toward attracting foreign investors and tourists. Airbnb's rise in Lisbon intensified international competition in the housing market, resulting in a significant increase in property values in key tourist areas. From 2011 to 2020, there was a surge in the number of apartments listed in Lisbon from 20 to nearly 17.000, with 90% listed on Airbnb. Tourism was then seen by the Economy Minister as the best way to bring the Portuguese economy back on the right

track. However, it had several consequences. While owners of several properties in Lisbon profited from Airbnb, low-income and elderly residents faced real estate pressure, leading to a considerable number being evicted from their homes (Amore et al., 2022).

In 2012, Portugal launched the Golden Visa Program, designed to attract foreign capital to the country and stimulate economic growth. This initiative allows non-European Union citizens to obtain Portuguese residency by making qualified investments in the country, particularly in the real estate market (*Golden Visa De Portugal: O Guia Definitivo De 2023 | Get Golden Visa*, 2023). Additionally, the new urban lease law was introduced in 2012, providing more flexibility to landlords and tenants in stipulating urban rental contracts. This law also facilitated rehabilitation works and simplified the process of eviction (*NRAU - Apresentação Do NRAU - Lei 31/2012*, 2021).

In 2014, a law was released that allowed individuals to obtain a license for renting their properties online, without incurring any fees. This marked the beginning of the surge in the number of short-term rentals, especially in Lisbon and Porto. Concerns soon emerged about rising rents and house prices, partly due to the increase in the number of local accommodation units (Franco & Santos, 2021; S. M. Páscoa Ferreira, 2022). In an attempt to prevent the excessive occupation from jeopardizing the sustainability of the tourist destination, in 2016, it was implemented a tourist tax, charging 1€ per night (with a limit of 7 consecutive nights) and per guest (over 13 years old) (Brandelli Ribeiro, 2017).

Later, in 2018 the government enacted a new law (Lei nº 62/2018), giving municipalities and property owners in a building a say in determining the eligibility of properties for short-term rentals. In order to preserve the social character of the neighborhoods, there were also created “containment areas”, in which limits regarding the number of local accommodation establishments can be imposed, it can be suspended for a maximum of one year the authorization of new registrations, the town hall has to approve the opening of new short-term rentals and one landlord can only have a maximum of 7 local accommodation establishments. However, these rules only applied to new listings (Artigo 15.o-A - Áreas de Contenção - Lei No 62/2018 de 22-08-2018 - BDJUR, 2018; New Alojamento Local Rules Come into Effect - The Portugal News, 2018).

In 2023, legislative changes named “Mais Habitação” suspended the issuance of new licenses across the country, with some exceptions for interior regions and autonomous regions. Regarding the already existing short-term rental establishments, they will be reviewed in the year 2030, when they can be renewed for another 5 years. The new register for local accommodation has a duration of 5 years and can only be renewed with the approval of the city council. Besides this, inactive establishments for a period of 2 months will be cancelled (Lei Mais Habitação, 2023).

2.3. GENTRIFICATION

The term “gentrification” emerged in 1964 when a sociologist, Ruth Glass, noticed some changes in certain neighborhoods in London. She observed the influx of wealthier and better-educated individuals into previously working-class areas. These individuals bought and renovated old stables and houses, leading to the transformation of the neighborhood’s character and the consequent displacement of existing residents (Glass & Centre for Urban Studies Report. London: MacGibbon & Kee, 1964).

Gotham (2005) proposes a definition for the concept of gentrification, that states it is a process of urban transformation that involves the displacement of low-income residents and the influx of affluent newcomers in a neighborhood. It is also seen as a result of global and local forces that include the restructuring of the real estate industry, the promotion of tourism, state policies and consumer preferences. Besides this, it is a source of social and spatial conflicts that arise from the competing interests of residents, businesses, developers and tourists over the use and meaning of urban space.

Smith (1996) proposed the Rent Gap Theory, which consists of the disparity between the current rent of a property and its potential rent level. According to him, gentrification initiates when the rent gap is substantial enough to incentivize investment. The rent gap grows as neighborhood deterioration continues.

The rehabilitation that has been happening in historic centers of several cities, along with the surge of local lodging is contributing to the emergence of the phenomenon of gentrification, since properties’ values increase (García, 2012), and thus families with lower incomes are displaced.

There is another term related to gentrification, that is touristification. These concepts are both seen as opportunities and as negative (S. M. Páscoa Ferreira, 2022). According to Troitiño Vinuesa & Troitiño Torralba (2016), touristification is usually seen with a negative connotation and it is considered to be the submission of the neighborhoods to the demands of the tourism sector. The touristification of Lisbon’s historic center was boosted by public policies benefiting the liberalization of the real estate market, urban rehabilitation and the attraction of foreign investors. These policies, however, have been leading to the spatial displacement of local communities, particularly those belonging to the working classes with the lowest economic power. This led to the loss of their right to the city and a diminishing of its cultural and historical identity (Nofre & Sequera, 2019).

2.4. FUTURE CONSIDERATIONS

The document “Estratégia Turismo 2027” foresees a tourism growth in Portugal of 4% per year, reaching 80 million overnight stays per year (Brandelli Ribeiro, 2017), which means that Portugal needs to adopt new measures to prevent the worsening of the previously identified problems.

It is necessary to adapt the land use planning, in order to find a balance between tourism development and locals' life quality, keeping the residents in their historic neighborhoods, creating a society that is open to diversity, while being socially inclusive (Barata-Salgueiro, 2017; Lopes et al., 2019; Nofre & Sequera, 2019).

Pedro Martins Ribeiro da Fonseca (2018) concluded that Airbnb housing resembles rental options in the lower-tier accommodation segment, suggesting that users are sensitive to pricing. Thus, it is suggested scattering tourist accommodation away from the city center, given the lower real estate values in these areas, and therefore creating an opportunity to develop affordable lodging options. This measure would also benefit these areas, since local accommodations have the capability of bringing tourism into neighborhoods where it was sparse (Paolo Russo & Quaglieri Domínguez, 2014), which contributes to the increase of consumption in commercial and service establishments in these areas. This is the main idea in the development of this thesis. However, there is a new challenge implied, which is to improve and speed the access from these areas to the center of the city.

2.5. RELATED WORK

This section examines key studies in location selection methodologies in several contexts, including insights into the challenges and solutions involved in these works. There hasn't yet been developed any work finding locations for short-term rentals in Lisbon, however, the approach that will be followed will be based on techniques used to cover other subjects. The studies that will be referenced encompass a range of methodologies, including Fuzzy logic, Multi-criteria Decision Analysis (MCDA) methods, such as Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Geographical Information Systems (GIS). It is common to all the works analyzed the emphasis on the importance of systematic decision-making in site selection.

In a prior study, Ngai & Wat (2003) developed an expert system, HAS (Hotel Advisory System) using Fuzzy logic to assist tourists in their hotel selection process. This system incorporates 3 primary factors - price, facilities and food type – to assess the alignment between customers' expectations and the actual offerings of the various hotels. By employing Fuzzy logic, HAS is able to handle subjectivity, a pivotal aspect when considering individuals' preferences and opinions. Upon evaluation, the system generates an ordered list of hotels tailored to the specific user, facilitating an informed decision-making process.

Ballis (2003) conducted a multicriteria analysis using both AHP and experts' judgments to identify suitable locations for the development of an airport on a Greek island. After establishing the main criteria to consider when choosing the site for an airport, some restrictions regarding the island's characteristics were identified, and then the Analytical Hierarchy Process was applied, as well as the engineering judgment of the study-team. AHP is a decision-making method, that reduces complex problems into hierarchies of criteria and alternatives, making use of pairwise comparisons to determine the relative importance

between factors and assist in making informed decisions. The aim of this research was to identify if engineering judgment and AHP lead to the same decision, which was proven to be true.

Chou et al. (2008) developed a Fuzzy Multi-Criteria Decision-Making (MCDM) model, combining Fuzzy set theory, hierarchical structure analysis, ideal and anti-ideal and AHP, that is able to select a location for a tourist hotel in Taiwan, which could be helpful for tourist hotel managers and investors. The ideal and anti-ideal concepts represent, respectively, the best and worst possible outcomes, being the ideal point a point at which all criteria are optimized. One disadvantage of AHP comes from its inability to properly address the inherent ambiguity and imprecision involved in the mapping of the decision-maker's perception to exact values, thus the Fuzzy set theory, combined with linguistic value concept, is used to counteract this issue. The same approach (AHP with Fuzzy logic) was applied by Vahidnia et al. (2009) to select the optimum location for the construction of a hospital in Tehran, with the addition of GIS. Several studies have shown effectiveness in using GIS in site selection problems. Its combination with MCDM methods is especially beneficial in ill-structured or semi-structured problems, where specifications, alternatives and results are not fully and reliably known by decision-makers. That is the case of site selection problems, due to the conflicting character of the various factors taken into consideration. Thus, the authors started by constructing geographical databases, creating one layer for each factor to have in consideration for the resolution of the problem. After visualizing the maps, some locations were selected as possible ones, and then traditional AHP was employed. Regarding the pairwise comparison matrices comparing alternatives with each criterion and the criteria with the main goal, the evaluation regarding the alternatives was made based on the GIS analysis' outcomes, and the assessment at the criteria level was based on an expert's own experience. Then, the fuzziness was introduced, and new pairwise comparison matrices according to this method were developed. In the end, to each location is assigned a number, concerning its priority as the problem solution.

The literature also explores alternative approaches. AHP combined with Fuzzy set theory and TOPSIS was employed to identify the criteria that influence tourists' destination choices (Hsu et al., 2009), resulting in a ranking assigned to each criterion. Due to the fact that AHP requires making pairwise comparisons, which translates into a tedious process, as an alternative the authors of this research applied instead the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to evaluate the alternatives. This technique is based on the notion that the best alternative should have the shortest distance from the ideal solution and the farthest from the negative-ideal solution, considering the Euclidean geometrical distance. As main advantages of this method are its mathematical simplicity and large flexibility in the definition of the choice set. Thus, the final approach followed implied using fuzzy logic to measure the preference of alternatives assessed by respondents, resulting in crisp numbers and then applying TOPSIS to final rank the destinations. Another study used AHP and Data Envelopment Analysis (DEA) to determine the optimal site for a railway station in a northeast

Iranian city (Mohajeri & Amin, 2010). DEA is a method used to assess the relative efficiency of a set of entities by comparing their input-output relationships. In this study, AHP priority weights were defined and used as multiple outputs applied to a DEA model, that found the optimum location for a railway station.

Further, GIS-based MCDM was applied to evaluate solar farm locations in south-eastern Spain (Sánchez-Lozano et al., 2013), using AHP and TOPSIS. In a first phase, the possible areas for the installation of photovoltaic plants were established, considering restrictions and impediments for its construction, resulting in a layer with these suitable areas. Then, these suitable sites were evaluated, using AHP to establish the importance of each criterion, and then TOPSIS to evaluate the alternatives. Once again, the TOPSIS method was chosen due to the fact that it does not require an evaluation made by an expert for each alternative. These methods are combined with GIS, which contributes to the ease of the task, since a practical observation of the criteria is possible. One limitation of this work is the lack of qualitative factors that could have an impact on the solution provided. Still on the same subject, GIS combined with AHP was used to identify suitable sites for organic farming in Uttarakhand (Mishra et al., 2015). Criteria maps were created using GIS, followed by their weights' determination, through AHP, and then the suitability map was created by weighted overlay.

In 2015, Guo & Zhao utilized the Fuzzy TOPSIS approach to select the optimum location for an electric vehicle charging station in Changping, Beijing. To determine the possible location alternatives, a group of experts was formed. They provided the linguistic ratings judgments for the criteria, as well as their weights, which allowed to apply fuzzy TOPSIS, resulting in a ranking of the alternatives. Additionally, Ghorbanzadeh et al. (2019) integrated GIS-based MCDA with the Analytical Network Process (ANP) to suggest potential areas for nature-based tourism in East Azerbaijan Province, Iran. The authors created GIS datasets from relevant factors, then ANP was used to obtain their weights, which were aggregated using the Ordered Weighted Average (OWA) method, resulting in a map displaying the locations with high potential for nature-based tourism. The ANP is an extension of the AHP, that is capable of handling more complex decision structures, involving feedback and interdependencies between elements. The OWA is an aggregation method that aggregates weights into a single result, being able to include priorities in this process, which allows for certain values to have more importance in the outcome.

These studies collectively demonstrate the diversity of methods employed in location-based decision-making and provide valuable insights into the challenges and opportunities associated with various approaches. The table below (Table 2.2) synthetizes these works, presenting their purpose and the methodologies used.

Table 2.2 - Summary of related works.

Sources	Purpose	Methods
(Ngai & Wat, 2003)	Develop an expert system for hotel selection	Fuzzy logic
(Ballis, 2003)	Site selection for a new airport in Greece	AHP
(Chou et al., 2008)	Site selection for a hotel in Taiwan	Fuzzy logic + AHP
(Vahidnia et al., 2009)	Site selection for a hospital in Tehran, Iran	GIS + Fuzzy logic + AHP
(Hsu et al., 2009)	Identify the criteria that influence tourists' destination choices	Fuzzy logic + AHP + TOPSIS
(Mohajeri & Amin, 2010)	Site selection for a railway station in Iran	AHP + DEA
(Sánchez-Lozano et al., 2013)	Evaluate solar farm locations in Spain	GIS + AHP + TOPSIS
(Mishra et al., 2015)	Site selection for organic farming in Uttarakhand	GIS + AHP
(Guo & Zhao, 2015)	Site selection for an electric vehicle charging station in Changping	Fuzzy logic + TOPSIS
(Ghorbanzadeh et al., 2019)	Site selection for nature-based tourism in East Azerbaijan Province	GIS + ANP + OWA

While methodologies like DEA and TOPSIS have proven effective in specific decision-making contexts, their application within this context may present some limitations. DEA is mainly used to assess the relative efficiency of entities based on their input-output relationships, thus it may not be directly applicable to the problem in study. Likewise, while TOPSIS has shown to be effective in several decision-making problems, it relies on establishing an ideal and anti-ideal solution, which might be challenging and not realistic, since there is not one single ideal location for a local accommodation, and its definition would be subjective. Regarding ANP and OWA, they are advanced decision-making methods capable of handling complex decision structures and aggregating weights, which introduces some complexity that may not be necessary for the relatively straightforward problem of identifying alternative locations for LA establishments in Lisbon, where the focus is mainly on spatial analysis and criteria prioritization.

Therefore, the methodologies chosen for this thesis are Fuzzy logic, AHP and GIS. Fuzzy logic accommodates the uncertainties in decision-making, AHP facilitates comprehensive decision hierarchies and GIS enables spatial analysis, crucial for location-based research. This hybrid approach is believed to be well-suited for addressing the multi-faceted challenges posed by gentrification in the context of alternative accommodation in Lisbon.

3. RESEARCH CONTEXT & DATA

The challenge that is being faced in this thesis can be seen as a site selection problem, which involves two stages, being the first one the screening of the study area, in which the candidate locations are selected. The second phase consists of the evaluation, where the alternatives are assessed and the most suitable locations are identified (N.-B. Chang et al., 2008). In order to perform the first step, an exploratory analysis is made regarding the study area, the city of Lisbon, the capital of Portugal, known for its rich history, stunning architecture and diverse cultural offerings, some of the reasons why the city has been attracting more and more tourists from all over the world. Covering an area of approximately 100 km^2 and home to 545,142 inhabitants, the municipality of Lisbon is divided into 24 parishes (Figure 3.1), each with its own distinct character and heritage (*INE - Indicadores*, 2021).

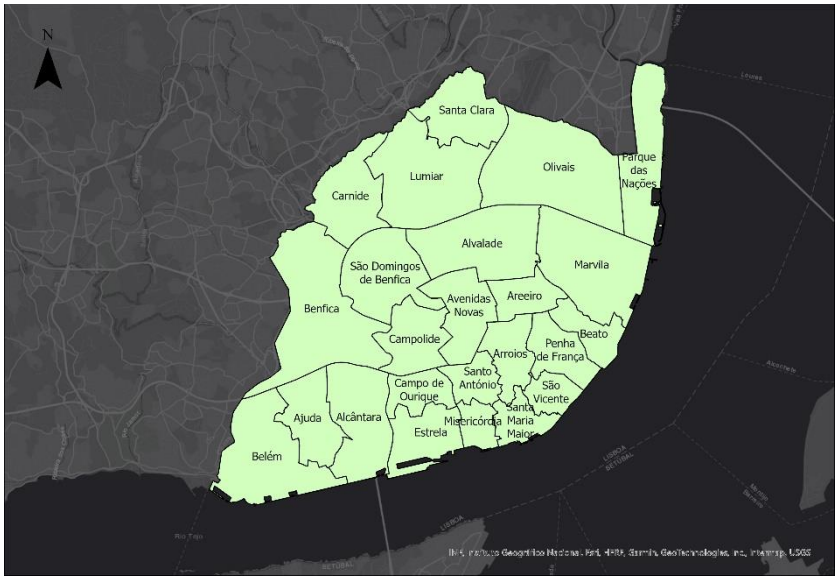

Figure 3.1 – Lisbon's parishes.

The historical center of the city is composed of the parishes Santa Maria Maior, Misericórdia and São Vicente. In order to obtain some relevant insights regarding the presence of LA within the study area, two datasets were used, that will be described in the next sections.

3.1. LOCAL ACCOMMODATION DATASET

The first dataset regards all LA establishments in Portugal. This data was retrieved from the Turismo de Portugal website[1], which had the last actualization on February 26, 2024. It contains information mainly regarding LA locations, thus it will be used to observe their distribution within the city of Lisbon and their evolution throughout the years. Below is a table containing the most relevant features from this dataset, which has a total of 40 variables, followed by a brief description (Table 3.1).

[1] https://dadosabertos.turismodeportugal.pt/

Table 3.1 - LA metadata.

Column	Description	Data Type
X	GPS coordinate (longitude)	Float
Y	GPS coordinate (latitude)	Float
OBJECTID	Listing ID	Int
DataAberturaPublico	Listing opening date	Object
Freguesia	Listing parish	Object
Concelho	Listing municipality	Object
Total Observations	113622	

The first step involved dropping the columns that would not be used, followed by filtering the establishments to those located in the city of Lisbon, using the "Concelho" variable, which resulted in a smaller dataset containing 19311 rows and 7 columns. From the relevant features previously described, there were no missing values nor duplicated observations. Within the preprocessing phase, the feature "DataAberturaPublico" was converted to a datetime format.

3.2. AIRBNB DATASET

This dataset regarding Airbnb listings was obtained from the website Inside Airbnb[2], which data was last updated on December 17, 2023. It only contains information regarding Airbnb establishments in the district of Lisbon, however, it has more specific data than the LA dataset, such as the listings' characteristics. Thus, it will be used to perform a more detailed analysis, with the disadvantage of not englobing other types of LA. The dataset has a total of 18 variables, which can be seen on Table 3.2, alongside a brief description of them.

[2] http://insideairbnb.com/

Table 3.2 - Airbnb metadata.

Column	Description	Data Type
id	Listing ID	Int
name	Listing name	Object
host_id	Host ID	Int
host_name	Host name	Object
neighbourhood_group	Listing municipality	Object
neighbourhood	Listing parish	Object
latitude	GPS coordinate	Float
longitude	GPS coordinate	Float
room_type	Type of room	Object
price	Price per night	Float
minimum_nights	Minimum stay	Int
number_of_reviews	Number of reviews	Int
last_review	Date of last review	Object
reviews_per_month	Number of reviews per month	Float
calculated_host_listings_count	Host's number of listings	Int
availability_365	Number of days the listing is available for rent	Int
number_of_reviews_ltm	Number of reviews in the last twelve months	Int
license	Listing license	Object
Total Observations	22751	

The initial step was to filter the data to focus solely on the municipality of Lisbon, using the "neighbourhood_group" feature. During the exploration process, we identified typing errors in some of the neighborhood names, which were subsequently corrected. Following this, "last_review" was converted into a datetime format for consistency.

Next, we checked for missing data and duplicates. While no duplicate rows were found, four variables contained missing values. These included "price", with 775 missing values, "license" with 825, and "last_review" and "reviews_per_month", both with 1832 missing values each. Since the "license" variable was not pertinent for further analysis, its missing values were disregarded. Concerning the missing values in "last_review" and "reviews_per_month" columns, some analysis revealed that these missing data corresponded to listings lacking any reviews, thus it makes sense that these fields remain missing. This conclusion was drawn by

examining the variables “number_of_reviews” and “number_of_reviews_ltm”, where all values were zero for these observations.

For the “price” variable, the missing values were filled using the KNN (K-Nearest Neighbors) Imputer method, employing 5 neighbors to estimate the missing values. This approach was chosen due to its ability to impute missing values by considering similar instances. In this context, employing 5 neighbors allowed for the estimation of missing prices by considering the prices of the 5 nearest listings, thereby maintaining the integrity of the dataset, while minimizing bias.

Furthermore, while observing the values for the “price” column, it was noted that some values appeared to be exorbitant. Notably, the maximum value for the “price” variable was recorded as 15000€, which initially seemed unrealistically high. However, further investigation revealed that this value corresponds to the most expensive Airbnb listing in Lisbon, which is located in Marvila. This finding underscores the importance of thoroughly examining outlier values before making assumptions about their validity, as they may represent unique or exceptional cases within the dataset.

Additionally, the “name” feature underwent further analysis, as it contained information regarding several fields of the listings. Consequently, from this column, five additional columns were created to extract and separate this information. These new columns include:

1. “listing_name”: This column contains the actual name of the listing.
2. “rating”: This column stores the rating of the listing.
3. “n_bedrooms”: It contains the number of bedrooms in the listing.
4. “n_beds”: This column indicates the number of beds in the listing.
5. “n_baths”: It holds the number of bathrooms in the listing.

Since some listings did not contain information for all of these fields, the columns that lacked corresponding data were filled with “None”. This process ensures that the dataset is properly structured and that relevant information is extracted and organized for further analysis.

The final dataset after treatment, and ready for the exploratory analysis, ended up having 15611 observations and 23 variables.

3.3. EXPLORATORY ANALYSIS

The initial focus of this analysis was on illustrating the distribution of LA establishments in Lisbon. The first map, a point map, (Figure 3.2) was designed to visualize the locations of these establishments. However, due to the high density of points, it was challenging to discern the quantity of LA establishments in each area. To address this issue, a second map was created, a choropleth map (Figure 3.3). This map provides a clearer understanding of the distribution by shading different areas of Lisbon based on the density of LA establishments. Darker colors correspond to higher values, indicating a greater number of LA establishments in that parish.

Additionally, the map includes a legend that delineates the interval of the number of LA establishments represented by each tone of color, further aiding interpretation.

All maps produced were generated using the Folium library in Python, which is used to create interactive web maps. For the second map, additional information was integrated to enhance clarity. A GeoJSON file containing the boundaries of Lisbon's parishes was incorporated and merged with the LA dataset. This GeoJSON file was obtained from ArcGIS Hub and was last updated on February 27, 2024. This allowed for the display of parish names alongside the choropleth map, providing viewers with a more comprehensive view of the data.

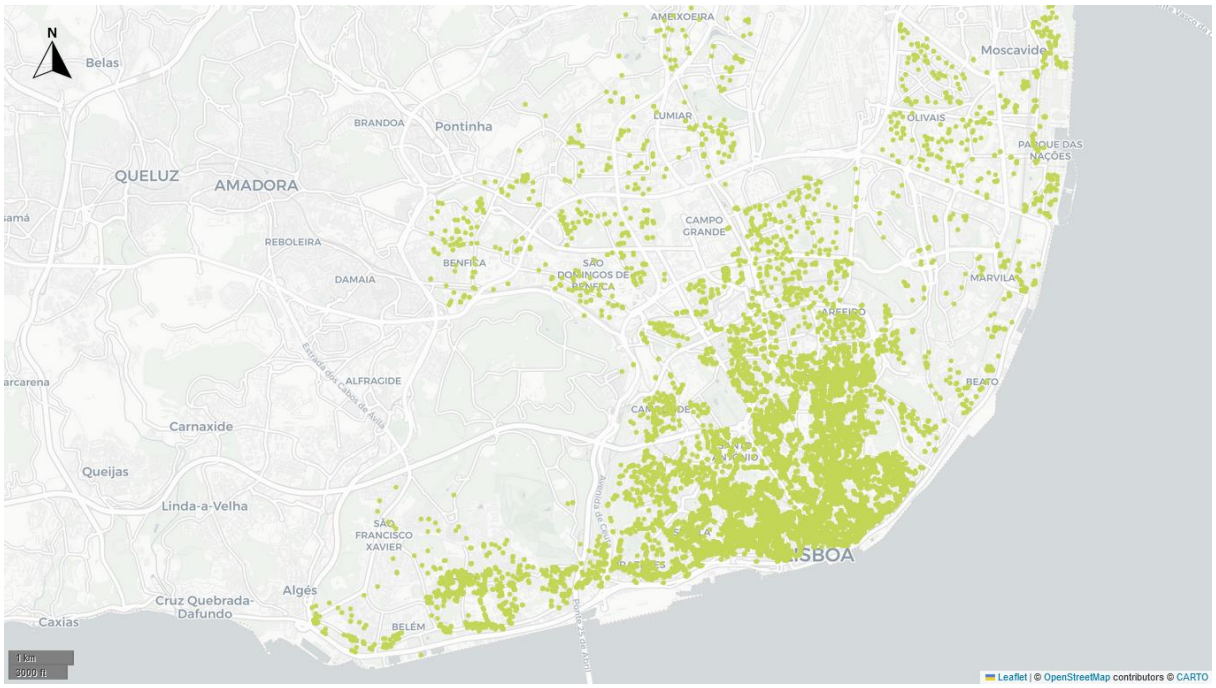

Figure 3.2 - Point map with the distribution of LA.

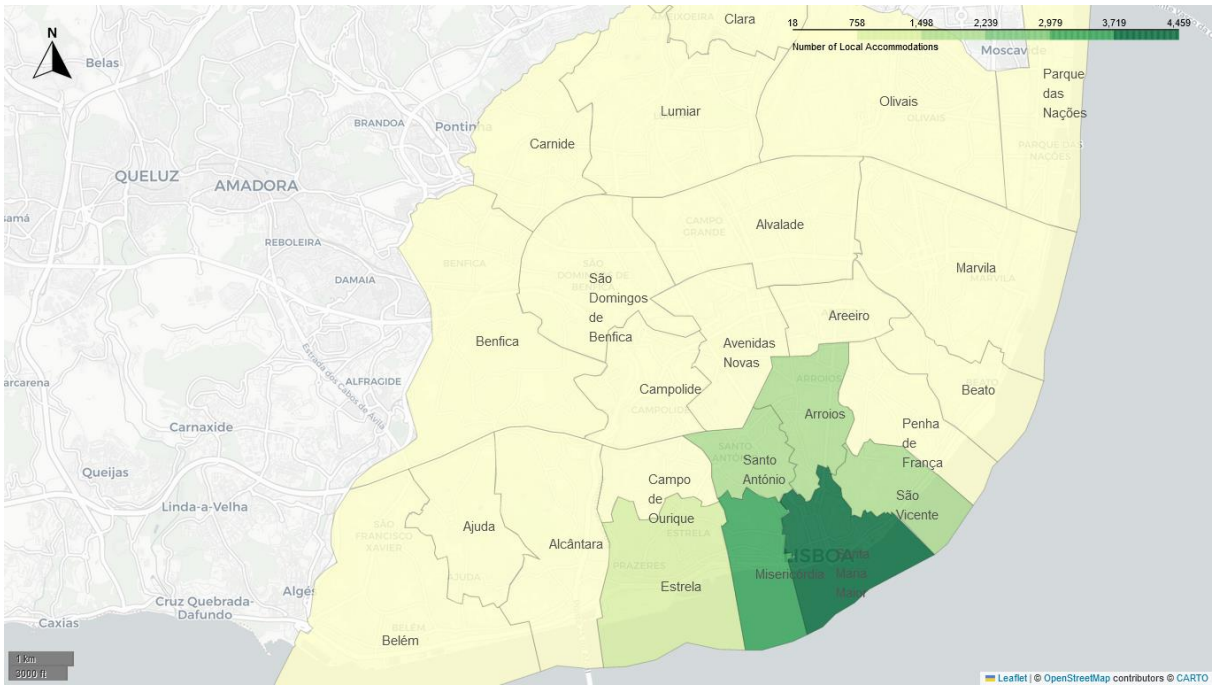

Figure 3.3 - Choropleth map with the distribution of LA.

From Figure 3.2 and Figure 3.3, one can observe that, as expected, the parishes with the highest number of local accommodations are the ones corresponding to the historic center of the city.

With the aim of analyzing the number of new LA establishments that opened over the last years, a bar chart was made (Figure 3.4), using the “DataAberturaPublico” feature.

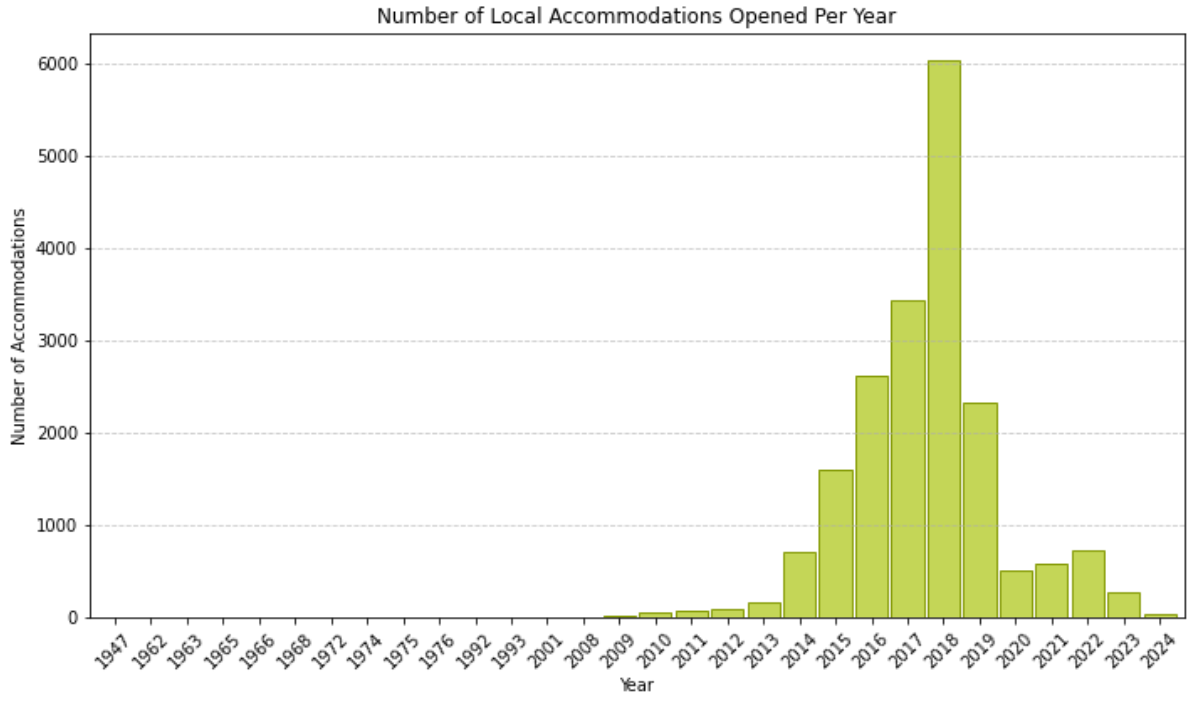

Figure 3.4 - LA openings over time.

From Figure 3.4, it can be seen that local accommodation establishments in Lisbon initially emerged in 2008/2009 with the inception of platforms like Airbnb, having a more pronounced growth from 2014 onwards. Notably, the period between 2016 and 2018 marked a significant surge, with approximately 6000 new LA establishments opening in 2018 alone. This growth aligns with Portugal's recognition as a leading tourist destination, as mentioned in section 2.1, experiencing an exponential increase in tourism since then. However, regulatory interventions and shifts in government policies have influenced the trajectory of LA establishment openings, leading to a significant decline in new establishments in 2019 to less than 2500, followed by a further decrease in 2020 to approximately 500 new LA openings. In 2023 there was another significant decrease of more than half of new units opening compared to the previous year. These decreases reflect the efforts to address the challenges posed by the rapid expansion of LA units.

Still regarding the evolution of LA units, a time-series map was generated to illustrate the geographical distribution of LA units that opened over the past years, starting from 2008, since as observed in Figure 3.4, that was the year when these establishments began to open. The "TimestampedGeoJson" data format was used for this purpose. For each year, spanning from 2008 to 2024, a map was generated and saved as an image to ease interpretation. These images can be found in Appendix A, Figures 1 to 17.

In addition to drawing conclusions about the number of units opened in each year, also obtained from Figure 3.4 - LA openings over time., these maps provide insights into the specific locations where LA establishments have emerged. Notably, the maps reveal a trend starting from 2021, wherein the number of LA units opening in the historic center decreased, with more units opening in areas surrounding them. These observations suggest a shifting pattern in the spatial distribution of LA units, which may indicate a potential response to regulatory interventions aimed at controlling the negative impact of the elevated number of LA units.

Moving to the Airbnb data, the first analysis made involved examining trends in listing prices across different parishes within the study area. A choropleth map was generated to visualize the average prices of listings in each parish, with colors indicating relative price levels. In Figure 3.5, it is evident that Marvila stands out as the parish with the highest mean price, significantly surpassing others. This could be attributed to the fact that Marvila hosts the most expensive Airbnb listing in Lisbon. Additionally, Parque das Nações and Santo António exhibit relatively higher prices compared to other parishes. Surprisingly, the highest-priced areas are not the historical center, although they still command higher rates than many other regions.

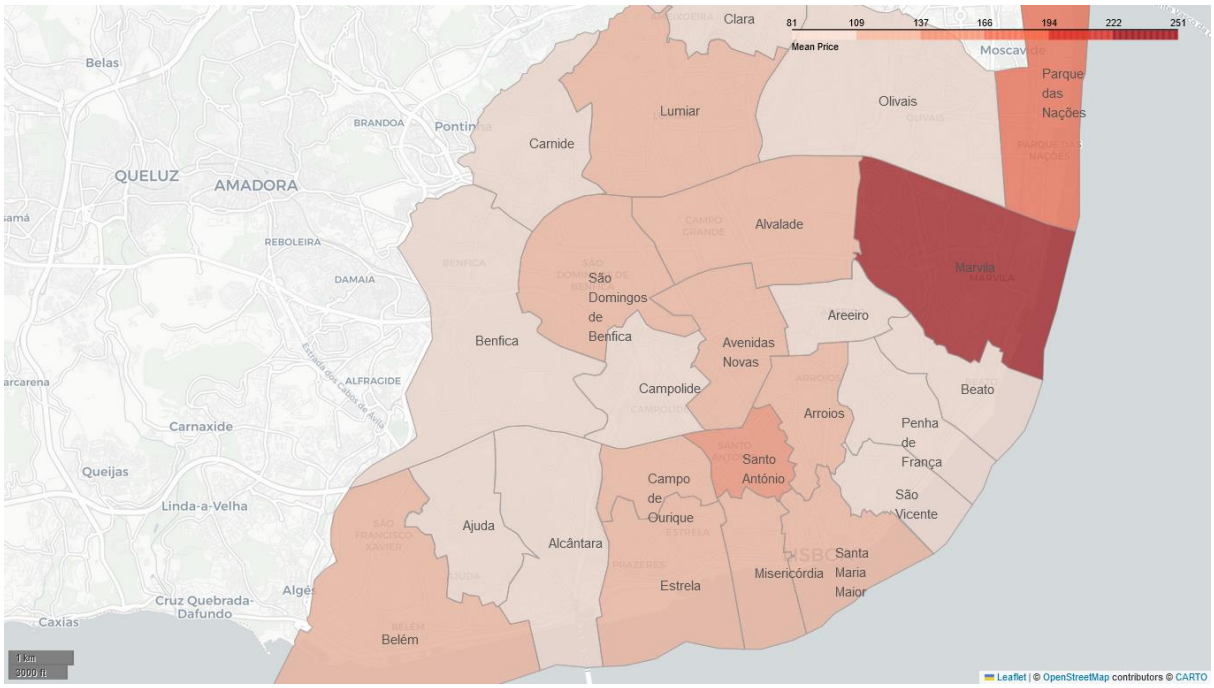

Figure 3.5 - Choropleth map with Airbnb listings' mean prices per parish.

The dataset comprises 5648 hosts. To ascertain whether these individuals are likely to be involved in property rental businesses on platforms like Airbnb, we examined the number of listings each host possesses. A bar chart was generated to visualize the distribution of hosts based on the number of listings they have (Figure 3.6). Hosts that have more than 10 listings were grouped into the same category, since they can be seen as potential business owners. It was revealed that 3631 hosts possess only one listing, and 222 have more than 10 listings. Notably, the host with the highest number of rental properties has 258 listings. This analysis suggests that a significant proportion of hosts potentially have only individual or occasional property rental activity. However, a notable minority manages more extensive portfolios, with some hosts overseeing a considerable amount of listings.

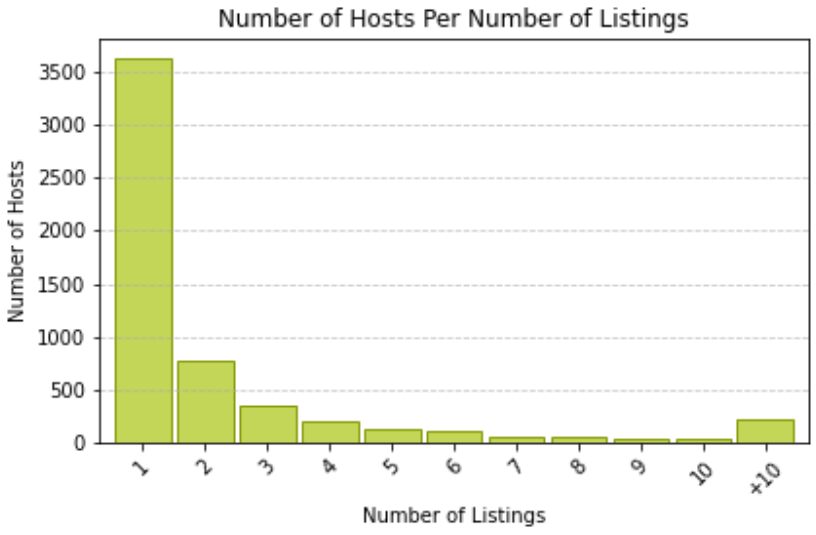

Figure 3.6 - Number of hosts per number of listings.

Afterwards, an analysis was made regarding the “minimum_nights” variable, in order to discern the prevalence of short and long-term rentals within the Airbnb platform. Short-term rentals were defined as those with a maximum of 29 nights as minimum stay, while listings with longer minimum stay requirements were categorized as long-term rentals. The analysis revealed a significantly higher number of listings corresponding to short-term rentals, totaling 14955, compared to long-term rentals, which comprised only 656 listings. Figure 3.7 (a) shows that the majority of short-term rentals have minimum night requirements ranging from 1 to 5, while Figure 3.7 (b) depicts that for long-term rentals, the majority of listings have minimum nights lower than 50.

It is essential to acknowledge that housing policies in many cities can be restrictive towards short-term rentals, aiming to safeguard housing availability for residents. This regulatory landscape may have contributed to the observed distribution, with a prominent portion of listings falling under the long-term rental category. The presence of both short and long-term rental options reflects the complex interplay between market dynamics and the diverse needs of Airbnb users.

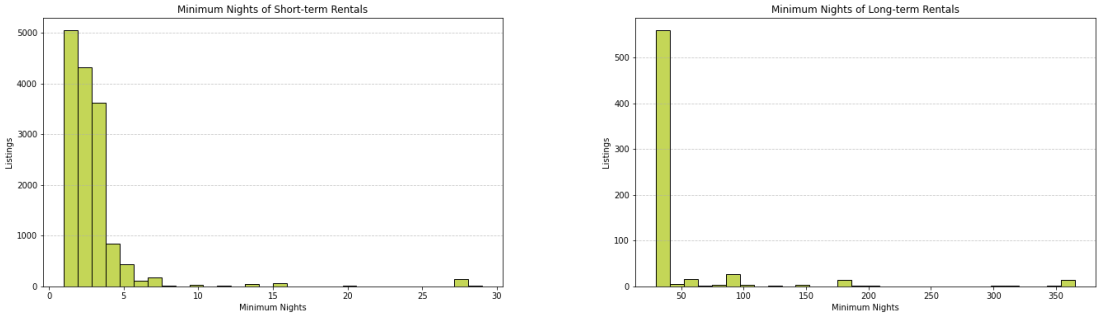

Figure 3.7 - Minimum nights of short (a) and long-term rentals (b).

The next variable examined was “number_of_reviews_ltm”, providing insights into the occupancy rates of listings. A low occupation rate may suggest potential underutilization of the property, prompting consideration for cancellation. However, it is crucial to acknowledge that long-term rentals typically accumulate fewer reviews within the period of a year.

Upon closer examination, it was found that among listings with zero or one review in the last 12 months, 12 had the maximum minimum stay requirement of 365 nights. This finding aligns with expectations, since properties with a year-long minimum stay may naturally accrue minimal reviews. Furthermore, it can be seen in Figure 3.8 the distribution of the listings based on the number of reviews received in the last 12 months. It can be noted a total of 6029 listings having fewer than 5 reviews during that period.

Distinguishing between short and long-term rentals is crucial, as the significance of review counts varies between the two. Figure 3.9 (b) depicts the scarcity of long-term rental listings with a high number of reviews in the past year, contrasting with the wider range of review counts observed in short-term rental listings in Figure 3.9 (a). However, it is notable that many

short-term listings have very few reviews, suggesting potential grounds for removal from Airbnb, particularly if located in the historical center of the city.

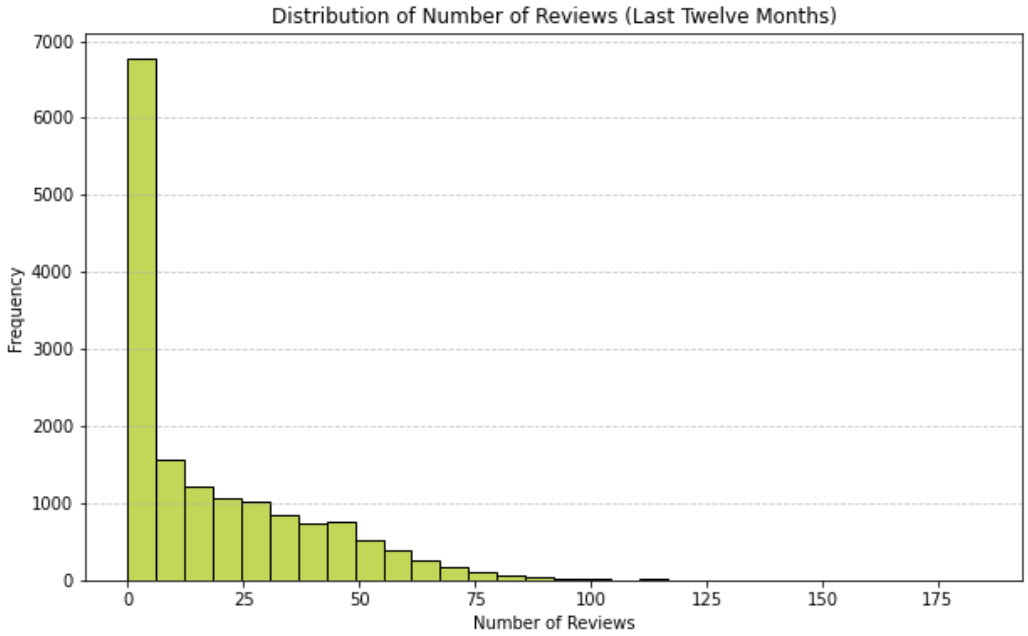

Figure 3.8 - Listings number of reviews in the last 12 months.

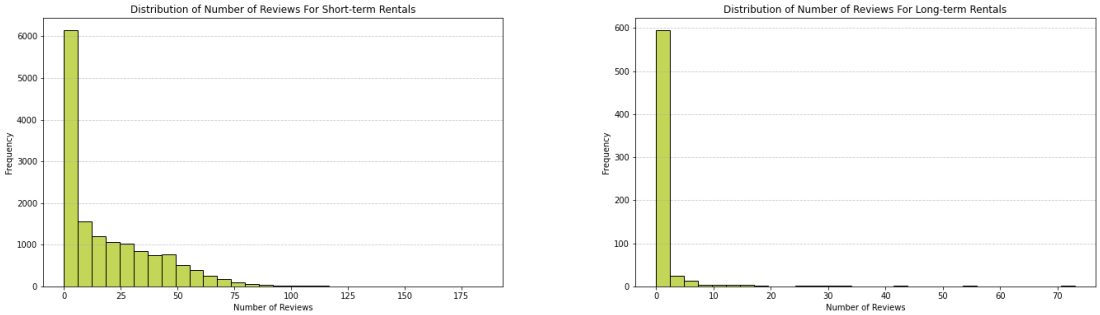

Figure 3.9 - Listings number of reviews in the last 12 months for short (a) and long-term rentals (b).

Regarding the listings' ratings, it was observed that 502 listings have ratings below 4, indicating poor satisfaction from the users. The distribution of these lower-rated listings can be visualized on the map in Figure 3.10, revealing a concentration in the city center. Given this concentration, it is advisable to consider removing listings in this area to mitigate the proliferation of LAs and improve the overall quality of accommodations available.

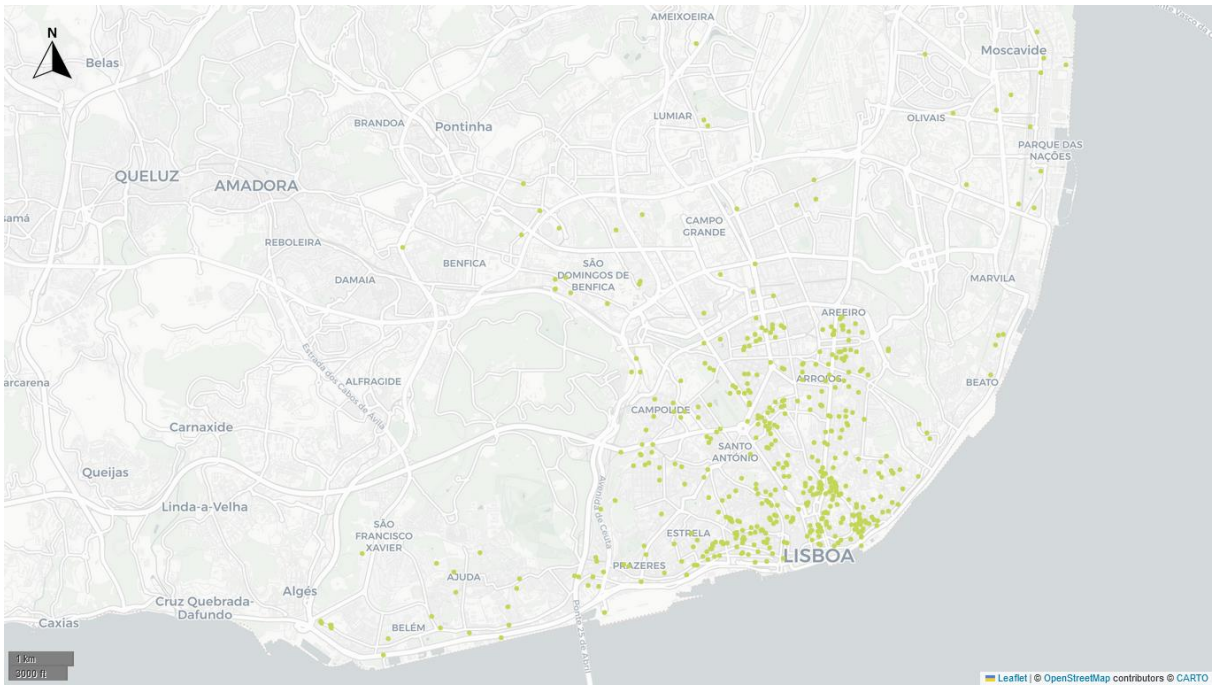

Figure 3.10 - Lisbon map with the listings with lower ratings.

Furthermore, the map in Figure 3.11 illustrates the distribution of new listings, showing a substantial number of properties opening in Lisbon's historic center. This influx of new listings demands careful monitoring to ensure sustainable growth and to prevent over-saturation in these areas.

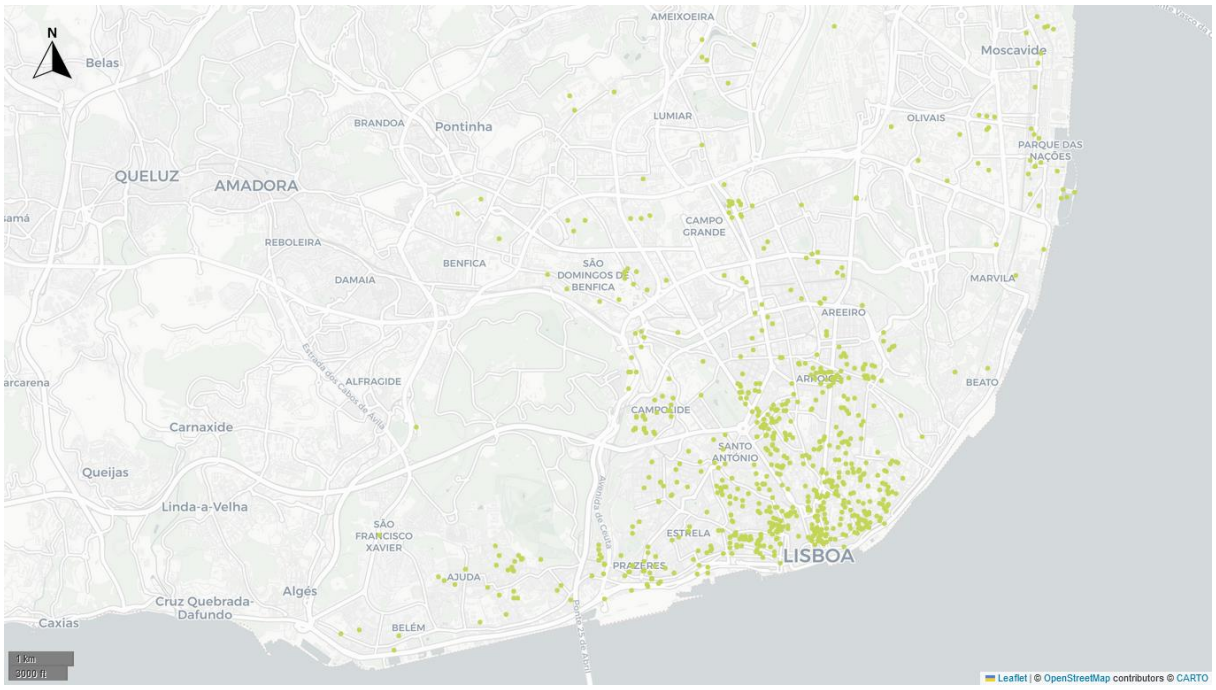

Figure 3.11 - Lisbon map showing new listings.

In conclusion, the exploratory analysis of local accommodation (LA) establishments and Airbnb listings within the city of Lisbon has provided valuable insights into their distribution,

evolution, and characteristics. Through comprehensive data exploration and visualization techniques, we have observed the concentration of LA establishments primarily within the historic center of Lisbon, reflecting its popularity among tourists. Additionally, trends in the opening of new LA units over the years have been identified, highlighting periods of significant growth followed by regulatory interventions that led to declines in new establishments.

Furthermore, the analysis of Airbnb listings revealed interesting patterns regarding pricing, host distribution, and rental durations. Notably, the presence of both short and long-term rental options underscores the complex dynamics shaping the city's accommodation landscape. Challenges such as potential over-saturation in certain areas, low satisfaction ratings, and the need for sustainable growth have been identified.

This analysis has provided a solid foundation for defining restricted areas for the application of the next techniques. By understanding the current distribution and characteristics of local accommodation establishments and Airbnb listings in Lisbon, we have identified areas that are already heavily saturated with tourist accommodations, particularly the historic center. These areas, marked by high densities of establishments, potential overpricing, and lower satisfaction ratings, can be designated as restricted zones for further development.

4. METHODOLOGY

We are dealing with a multi-criteria decision-making (MCDM) problem, in which the final solution will include some suggestions for locations for the implementation of new LA establishments, as a replacement for some of the already existing units located in the historic center of Lisbon. The methodology that will be pursued starts by selecting the criteria that will be considered and collecting the necessary data, followed by the calculation of their weights through Fuzzy AHP. Then, the data regarding the criteria is prepared into layers using GIS, and finally, the outcomes are combined and, through the GIS tool of overlay, a final map is generated, in which areas that would benefit from more LA establishments are visible (Figure 4.1).

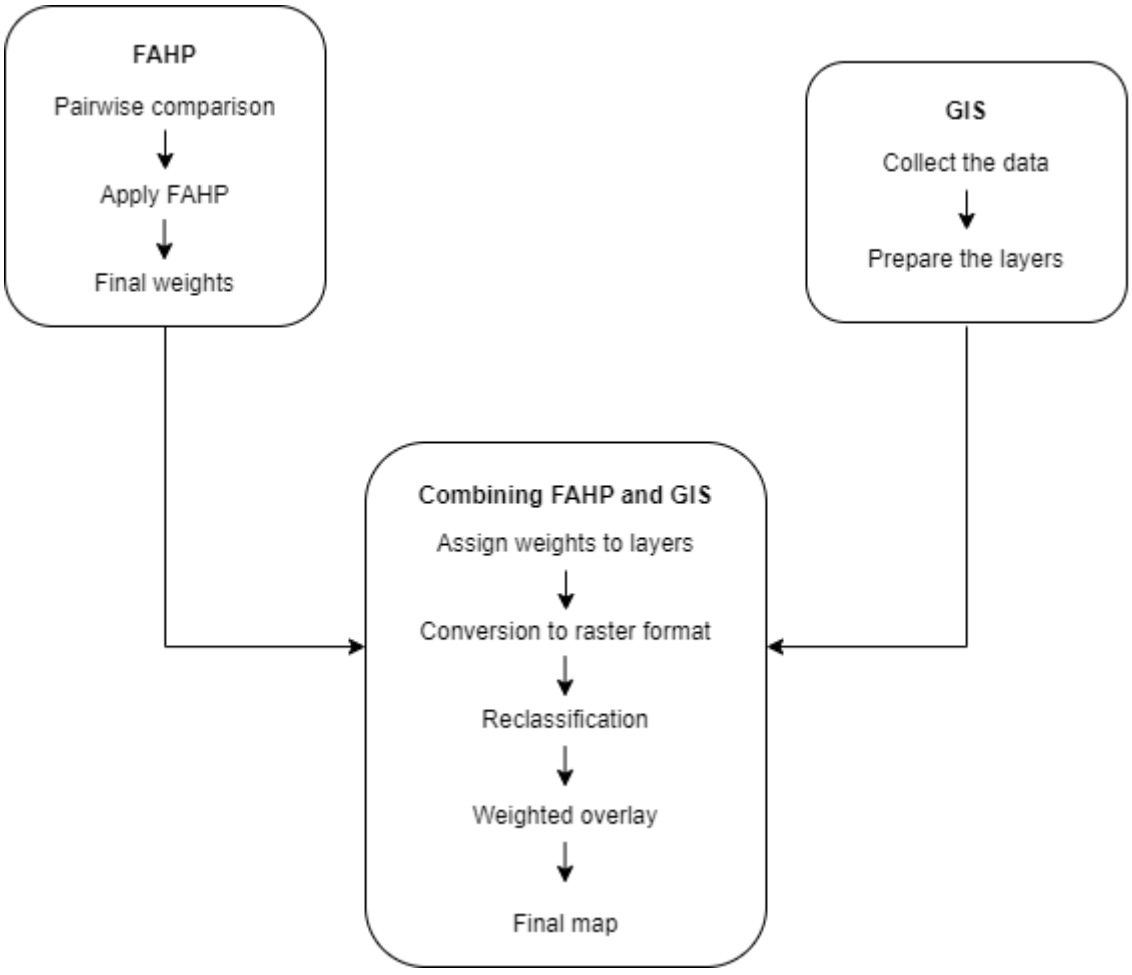

Figure 4.1 - Methodology's diagram.

4.1. DEFINING THE CRITERIA

When choosing the criteria, a table was constructed compiling the factors used in previous research, alongside the study objectives (Table 4.1). These studies related to either tourist accommodations or housing selection. Additionally, it is worth noting that when numerous criteria were involved, only the most pertinent to the problem were included.

Table 4.1 - Comparison of the applied criteria in previous studies.

Reference	Goal	Criteria applied
(Chou et al., 2008)	Site selection for an international tourist hotel	- Proximity to public facilities - Distance to existing competitors - Public security - Natural resources characteristic - Nearby rest facilities - Distance to airport or freeway - Distance to downtown area - Distance to tourism scenic spots - Parking area - Convenience of airport or freeway communication - Extensiveness of traffic routes - Convenience of traffic to tourism scenic spots - Indoor leisure facilities - Diversity of restaurants in the hotel - Amalgamation with local culture - Outside leisure facilities area - Convenience of obtaining nearby land - Quality of manpower - Land cost - Regulation restrictions
(Sohrabi et al., 2012)	Identify the most significant criteria in hotel selection	- Promenade and comfort (near recreational places, in city-center neighborhood, …) - Security and protection - Network services - Pleasure (good view, green spaces, …) - Hotel staff and their services - News and recreational information - Cleanliness and room comfort

		- Expenditure - Room facilities - Car parking
(Alam, 2018)	Optimal accommodation site selection	- Market - Office - Road - Park - Beach - Hospital - University - School - Playground - Airport - Police station
(Mahdi & Esztergár-Kiss, 2021)	Recommendation of lodging options for tourists	- Place rating - Cost per room - Distance from the center - Breakfast included - Level of security - Free cancellation
(Fang et al., 2022)	Site selection of affordable housing	- Park landscape greenspace - Rail transit - Bus stop - Industrial park - Educational facility - Cultural and sports facility - Medical facility - Spatial agglomerations

Based on the literature and the available data, the final criteria were selected and are listed below. These criteria represent common factors that tourists typically consider when choosing a LA.

C1 - Proximity to public transportation hubs (metro stations, bus stops);

C2 - Proximity to the airport;

C3 - Proximity to tourist attractions (museums, parks, viewpoints, cultural sites);

C4 - Proximity to amenities (restaurants, cafes, supermarkets);

C5 - Proximity to police stations;

C6 - Proximity to healthcare facilities and pharmacies;

C7 - Accommodation price.

4.2. ANALYTICAL HIERARCHY PROCESS

The Analytical Hierarchy Process, proposed by Saaty (1980), stands as a cornerstone tool used by decision-makers when faced with a multi-criteria decision problem (Vaidya & Kumar, 2006). It is a methodology that simplifies complex decisions by breaking them into a series of pairwise comparisons between alternatives. This technique is helpful when handling options with intangible attributes, and suits particularly well problems where the best alternative has to be chosen. The main advantage of AHP is that it is easy to integrate with different techniques, such as Linear Programming and Fuzzy Logic, enhancing its applicability across diverse decision-making domains (Vaidya & Kumar, 2006).

However, one disadvantage of this technique is that it may not be efficient and may lead to inaccurate results when uncertainty is involved. To mitigate this challenge, some researchers have combined AHP with Fuzzy Logic (Vahidnia et al., 2008).

4.3. FUZZY AHP

Fuzzy logic, in contrast to classical logical systems, seeks to replicate the imprecision and ambiguity that play a role in the human ability to make rational decisions, being able to handle inexact and vague information (Ngai & Wat, 2003). It was developed by Zadeh (1988) to handle problems where the classes lack sharp boundaries. It allows decision-makers to express their judgments using interval values, achieved by transforming crisp judgments into fuzzy ones. When integrated with AHP, despite its computational demands, it effectively captures human appraisal of uncertainty in complex MCDM problems (Erensal et al., 2006).

Several extensions of Fuzzy AHP have been developed since the proposal of Van Laarhoven & Pedrycz (1983), which presented a fuzzy version of Saaty's pairwise comparison method. In 1978, Saaty proposed a method for measuring the relativity of fuzziness by structuring a system hierarchically in a multiple objective framework (Saaty, 1978). Later, Buckley (1985) extended Saaty's hierarchical analysis, so that participants were allowed to use fuzzy ratios instead of crisp values when expressing a judgment. In 1996, Chang introduced a new approach for dealing with fuzzy AHP, which makes use of triangular fuzzy numbers and the extent analysis method (Chang, 1996). The computations for this approach are relatively simpler than other approaches, thus this will be the one followed in this thesis.

4.3.1. Pairwise comparison matrices

The first task is to perform the pairwise comparison between the criteria. To that end, a survey was conducted with a sample of 15 people that are used to travel and stay in local accommodation establishments. It should be noted that having a small sample is not critical and is very common in MCDM problems. Using the AHP scale ranging from 1 to 9 proposed by

Saaty (1980), the participants were asked to express their opinion regarding the level of importance between each pair of criteria. This scale is presented in Table 4.2 and translates verbal assessments into levels of preference: equally important (1), moderately more important (3), much more important (5), very much more important (7), and absolutely more important (9). Intermediate values between these are used to distinguish similar alternatives. To represent inverse relationships, reciprocals of these numbers are used.

Appendix B contains the questions forming the survey. For each pair of criteria, two questions were made. The respondent is only asked to answer one of them. In case he believes the first criterion to be the most important, only the first question should be answered, otherwise the second question should be answered. If the criteria are considered equally important, it is not relevant which question is answered, and the response should be 1. This approach allows to assess which criterion the participant considers most important and to what extent. All of the questions followed this structure, ensuring that every pair of criteria was evaluated.

After the definition of the pairwise comparison matrices for each participant, their elements are normalized, and criteria weights are obtained. One of the most used methods is the Mean of Normalized Columns, in which the elements in each column are summed and then each element in the matrix is divided by the sum of the corresponding column, generating a new normalized pairwise comparison matrix. Then, for each criterion (row), the normalized values are averaged, resulting in the estimated weights (Azevêdo et al., 2017).

The consistency ratio (CR) can then be calculated. It is a measure to assess the consistency of judgments made during the pairwise comparisons. To ensure reliability, it must be below 0.1, and if that condition is met, the participants' responses can be used (Saaty, 1980). The CR is determined through the application of formulas (4.1) and (4.2):

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{4.1}$$

$$CR = \frac{CI}{RI} \tag{4.2}$$

Where CI is the consistency index, $\lambda_{\max}$ is the highest eigenvalue of the pairwise comparison matrix, n is the number of rows in the matrix, and RI is the random index, which is the consistency index of a randomly generated reciprocal matrix.

To obtain the highest eigenvalue, the weighted sum is divided by the criteria weights, for each row, and then the obtained values are averaged. Regarding the random index, Saaty attributed values to it, according to the order of the matrix (n). In this case, n is 7, which has a corresponding RI value of 1.32.

4.3.2. Chang's fuzzy extent analysis

Step 1: Obtain the fuzzy evaluation matrix.

After having checked the consistency ratio, the pairwise comparison matrices are converted into fuzzy numbers, employing the triangular fuzzy number (TFN) approach. A triangular fuzzy number is denoted by (l, m, u), where l, m and u represent the lower, mean and upper numbers of TFN, respectively. The membership function of a TFN ranges from 0 to 1 and is represented by equation (4.3) and Figure 4.2.

$$\mu M(x) = \begin{cases} \dfrac{x}{m-1} - \dfrac{1}{m-1}, & x \in [l, m], \\ \dfrac{x}{m-u} - \dfrac{u}{m-u}, & x \in [m, u], \\ 0, & otherwise. \end{cases} \tag{4.3}$$

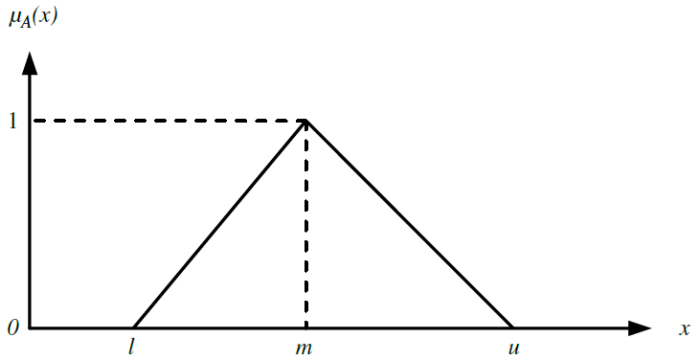

Figure 4.2 - Triangular Fuzzy Number (Chang, 1996).

The levels of preference were converted into fuzzy triangular numbers, based on Table 4.2 and Figure 4.3.

Table 4.2 - Definition of AHP terms, AHP scale, triangular fuzzy numbers and the reciprocal triangular fuzzy numbers.

Linguistic terms	AHP scale	TFN	Reciprocal TFN
Equally important	1	(1, 1, 1)	(1, 1, 1)
Moderately more important	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Much more important	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Very much more important	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Absolutely more important	9	(9, 9, 9)	(1/9, 1/9, 1/9)
Intermediate values	2	(1, 2, 3)	(1/3, 1/2, 1)
	4	(3, 4, 5)	(1/5, 1/4, 1/3)
	6	(5, 6, 7)	(1/7, 1/6, 1/5)
	8	(7, 8, 9)	(1/9, 1/8, 1/7)

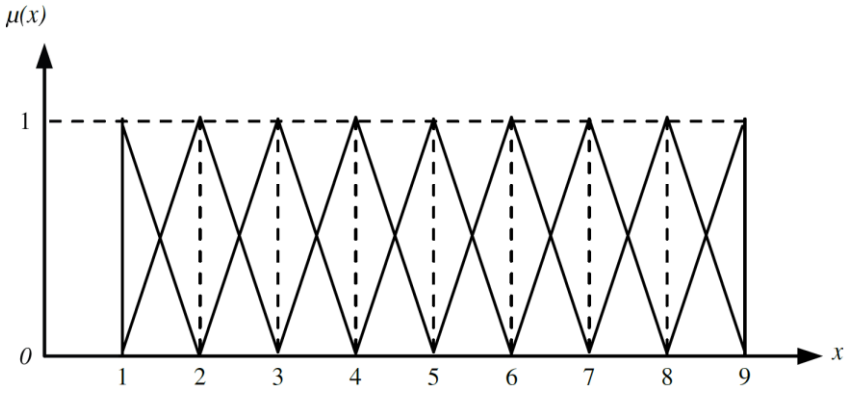

Figure 4.3 - TFN corresponding to the linguistic terms (Vahidnia et al., 2009).

After converting the pairwise comparison matrices into fuzzy numbers, the equations (4.4) to (4.6) are applied to obtain a single matrix (Mahdi & Esztergár-Kiss, 2021).

$$l_{ij} = min_{k=1,2,\dots,k}(l_{ijk}), \tag{4.4}$$

$$m_{ij} = \sqrt[k]{\prod_{k=1}^{k} m_{ijk}}, \tag{4.5}$$

$$u_{ij} = max_{k=1,2,\dots,k}(u_{ijk}), \tag{4.6}$$

Where i and j represent the participant k's relative importance assigned to each criterion.

Step 2: Calculate the values of fuzzy synthetic extent.

Let X = {x_1, x_2,…, x_n} and G = {g_1, g_2,…, g_m} denote the object set and the goal set, respectively. According to Chang's extent analysis, for each object, the extent analysis is performed for each goal, obtaining m extent analysis values for each object:

$$M_{gi}^{1}, M_{gi}^{2}, \dots, M_{gi}^{m}, \qquad i = 1, 2, \dots, n, \tag{4.7}$$

Where M_{gi}^{j} (j = 1, 2,…, m) are triangular fuzzy numbers.

Then, the value of fuzzy synthetic extent with respect to the i-th object is defined as:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \odot \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1}, \tag{4.8}$$

Where:

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j\right), \tag{4.9}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i\right), \tag{4.10}$$

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right), \tag{4.11}$$

$$S_i = \left(\sum_{j=1}^{m} l_j \odot \sum_{i=1}^{n} l_i, \sum_{j=1}^{m} m_j \odot \sum_{i=1}^{n} m_i, \sum_{j=1}^{m} u_j \odot \sum_{i=1}^{n} u_i\right). \tag{4.12}$$

Where ⊙ denotes the extended multiplication of two fuzzy numbers.

Step 3: Determine the degree of possibility of two fuzzy numbers.

Given two fuzzy numbers, the degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$, is defined as:

$$V(M_1 \geq M_2) = \sup_{y \geq x}\left[min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right], \tag{4.13}$$

Which can be expressed as:

$$V(M_1 \geq M_2) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = \begin{cases} 1, & if\ m_1 \geq m_2, \\ \dfrac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)}, & otherwise. \end{cases} \tag{4.14}$$

Figure 4.4 illustrates $V(M_2 \geq M_1)$, for the case $m_2 < l_1 < u_2 < m_1$, in which d is the highest intersection point D between μ_{M_1} and μ_{M_2}.

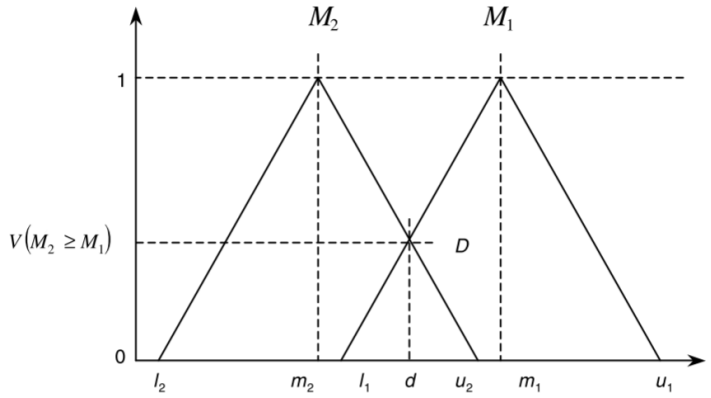

Figure 4.4 - The degree of possibility of $M_1 \geq M_2$ (Chang, 1996).

In order to compare M_1 and M_2, we need both the values of $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$.

Step 4: Determine the weight vector.

The degree of possibility for a convex fuzzy number to be bigger than k convex fuzzy numbers $M_i = (i = 1, 2, \dots, k)$ can de determined as:

$$V(M \geq M_1, M_2, \dots, M_k) = V[(M \geq M_1)\ and\ (M \geq M_2)\ and \dots and\ (M \geq M_k)] \\ = \min V(M \geq M_i), i = 1,2, \dots, k \quad (4.15)$$

If we assume that $d'(A_i) = \min V(S_i \geq S_k)$, for k = 1, 2,..., n; k ≠ i, then the weight value is given by:

$$W' = \left(d'(A_1), d'(A_2), \dots, d'(A_n)\right)^T, \quad (4.16)$$

Where A_i (i = 1, 2,..., n) are n elements.

Step 5: Obtain the final weights for each criterion.

The final weights are obtained via normalization, and are given by:

$$W = \left(d(A_1), d(A_2), \dots, d(A_n)\right)^T \quad (4.17)$$

Given two triangular fuzzy numbers $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$, their arithmetic operations are the following:

1. $(l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2)$,

2. $(l_1, m_1, u_1) \odot (l_2, m_2, u_2) = (l_1\, l_2, m_1\, m_2, u_1\, u_2)$,

3. $(\lambda, \lambda, \lambda) \odot (l_1, m_1, u_1) = (\lambda l_1, \lambda m_1, \lambda u_1)$,

4. $(l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right)$

4.4. GEOGRAPHIC INFORMATION SYSTEMS

The first step regarding the implementation of GIS involves acquiring data, followed by performing the necessary treatment and the creation of layers for each defined criterion. After having the layers created, the weights obtained from FAHP are assigned to each layer, which will then be overlayed, resulting in a final map showing the most suitable zones for the implementation of new LA units. The GIS software that will be used for data manipulation and visualization is ArcGIS Pro, one of the most widely used software in the industry.

4.4.1. Data acquisition

A comprehensive search was undertaken to gather the most recent and reliable data regarding the criteria defined in section 4.1. In the table below (Table 4.3), it is possible to see the sources from which the data was retrieved, as well as their format.

Table 4.3 - Geographical data acquisition.

Criteria	Data Description	Data Format	Source
Proximity to public transportation hubs	Metro station locations	GeoJSON	Lisboa Aberta[3]
	Bus stop locations	GeoJSON	dados.gov
Proximity to the airport	Airport location	JSON	Câmara Municipal Lisboa[4]
Proximity to tourist attractions	Museum locations	GeoJSON	Lisboa Aberta
	Park locations	GeoJSON	Lisboa Aberta
	Viewpoint locations	GeoJSON	Lisboa Aberta
	Cultural sites	GeoJSON	Lisboa Aberta
Proximity to amenities	Restaurant/cafe/market locations	GeoJSON	Lisboa Aberta
Proximity to police stations	Police station locations	GeoJSON	Câmara Municipal Lisboa
Proximity to healthcare facilities and pharmacies	Healthcare facility locations	GeoJSON	Lisboa Aberta
	Private hospital locations	GeoJSON	Lisboa Aberta
	Public hospital locations	GeoJSON	Lisboa Aberta
	Pharmacy locations	GeoJSON	Lisboa Abera
Accommodation price	Accommodation prices per parish	Quantitative	Inside Airbnb[5]

4.4.2. Layers creation

For each criterion, a vector layer was created. For the criteria representing proximity to specific points, a point layer was initially obtained for each criterion, followed by the creation of Service Areas around each point. To do so, a network for walking time was established, which served as the cost metric for the analysis. This approach allowed to determine the areas reachable within specific walking times from each point, providing a clear visualization based on walking distance.

[3] https://lisboaaberta.cm-lisboa.pt/index.php/pt/

[4] https://www.lisboa.pt/

[5] http://insideairbnb.com/lisbon/

Regarding the criterion concerning accommodation prices, data from the Airbnb dataset, previously used in the exploratory analysis, was utilized. The mean price for each BGRI[6] division was calculated, and the layer corresponding to this criterion was represented by a choropleth map. This process is further explained below, alongside the criteria layers.

4.4.2.1. Proximity to public transportation hubs

This criterion encompasses 2 data files, one regarding bus stops and the other concerning metro stations. It was created a layer for each data file, which were then merged into a single one. Using a custom travel mode where the cost was defined as walking time, service areas were generated with cutoffs of 5, 10 and 20 minutes. These specific cutoffs were chosen to represent varying levels of pedestrian accessibility, namely immediate, moderate and extended but reasonable access, respectively. Higher walking times were not considered, as they would exceed typical pedestrian travel preferences.

The obtained layer depicting the proximity to public transportation hubs based on walking time was then obtained (Figure 4.5).

Figure 4.5 - Proximity to public transportation hubs layer.

It can be seen that transportation hubs are somewhat dispersed throughout the city, however with some exceptions. These include the location of Monsanto Park, the area along the river including Beato and Marvila, and near the border between Carnide and Lumiar. To what

[6] Geographic Information Reference Base contains the smallest geographical unit used for detailed statistical data collection and analysis in Portugal.

concerns the parish Marvila, it is a recent emerging zone with a growing commercial presence. Despite this economic growth, this area could benefit from more transportation options to support its expanding commerce and accommodate the needs of residents and visitors alike.

4.4.2.2. Proximity to the airport

This layer was made the same way as the previous one, with the difference that this criterion was represented by a single file, and the Service Area only incorporated 2 cutoffs of 5 and 10 minutes (it is the exception, all the other layers' Service Areas have 3 cutoffs of 5, 10 and 20 minutes), since the surroundings of the airport isn't walkable (Figure 4.6).

Figure 4.6 - Proximity to the airport layer.

This is a very specific criterion due to its singular location near the city's limits, thus only being close to very few zones, and accessible just by car, bus or subway. However, this criterion received the lowest weight, therefore it will have a low impact on the final suitability map.

4.4.2.3. Proximity to tourist attractions

The criterion of proximity to tourist attractions was derived from four distinct data files encompassing museums, parks, viewpoints and other cultural sites. Each file was imported into ArcGIS as a separate layer. The objective was to consolidate these layers into a single one, to then create the Service Areas. However, a challenge arose as the park data was in polygon format and it is not possible to create Service Areas around polygons in ArcGIS. Thus, this layer was turned into a point layer, using the Polygon to Line tool, which creates lines from the polygons' boundaries, followed by the application of the Generate Points Along Lines tool,

that creates points along lines within specific intervals. The intervals used were of 200 meters, which could represent the entrances of the parks. Then, this layer was merged with the remaining ones and the Service Areas were finally created (Figure 4.7).

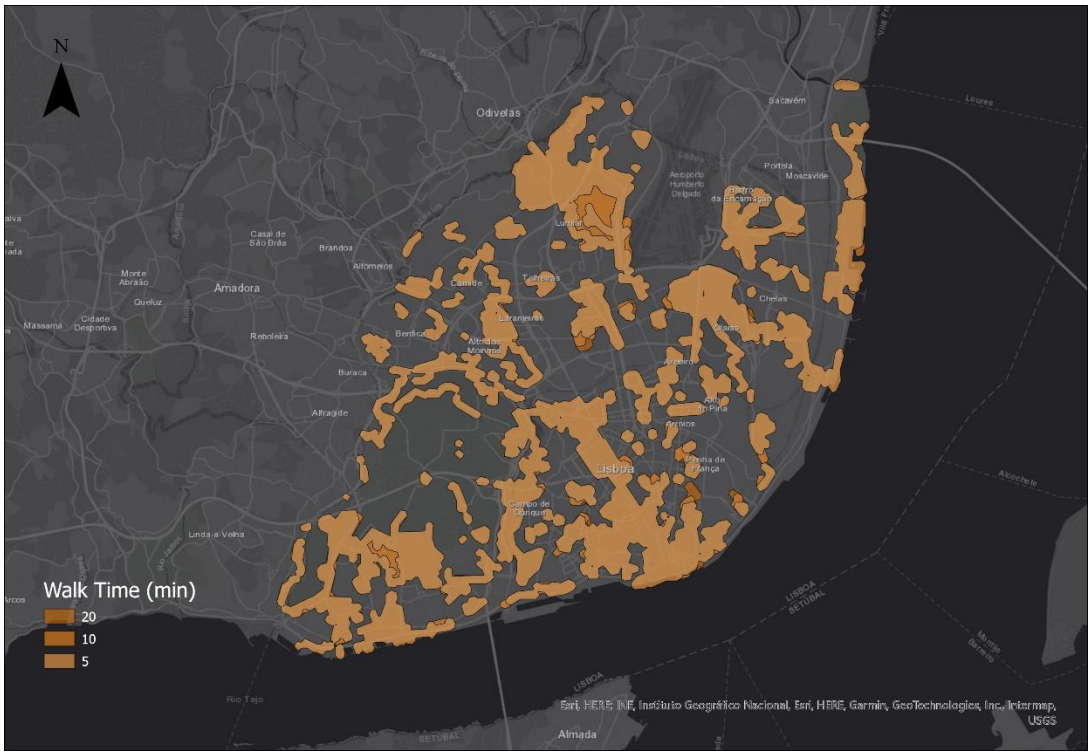

Figure 4.7 - Proximity to tourist attractions layer.

Figure 4.7 highlights a more significant zone regarding the high distance from tourist attractions, corresponding to the airport's location, as expected. Despite the main tourist attractions being more concentrated in the city center and in Belém parish, there are plenty of points of interest scattered throughout the city that can attract tourists.

4.4.2.4. Proximity to amenities

Regarding the amenities, this data was contained all in the same file, thus this process was very straightforward. The data was imported to the software to a new layer and the Service Areas were created, resulting in the map in Figure 4.8.

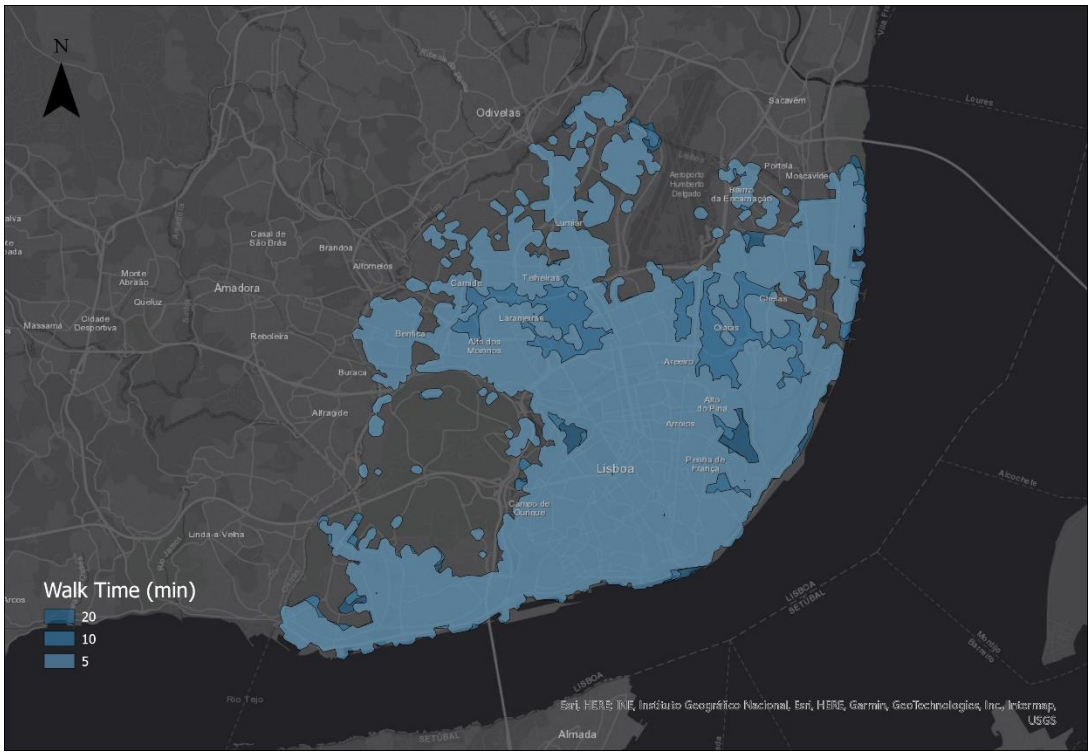

Figure 4.8 - Proximity to amenities layer.

From Figure 4.8, it is observable that amenities, such as restaurants, cafes and supermarkets are densely dispersed throughout the city. However, there is one zone that lacks these establishments, notably the north zone of Parque das Nações, mainly due to its undeveloped nature. Additionally, two other areas stand out, corresponding to the Monsanto Park and the airport, which is understandable given their nature.

4.4.2.5. Proximity to police stations

Following the same approach as the previous criterion, the proximity to police stations layer was also created (Figure 4.9).

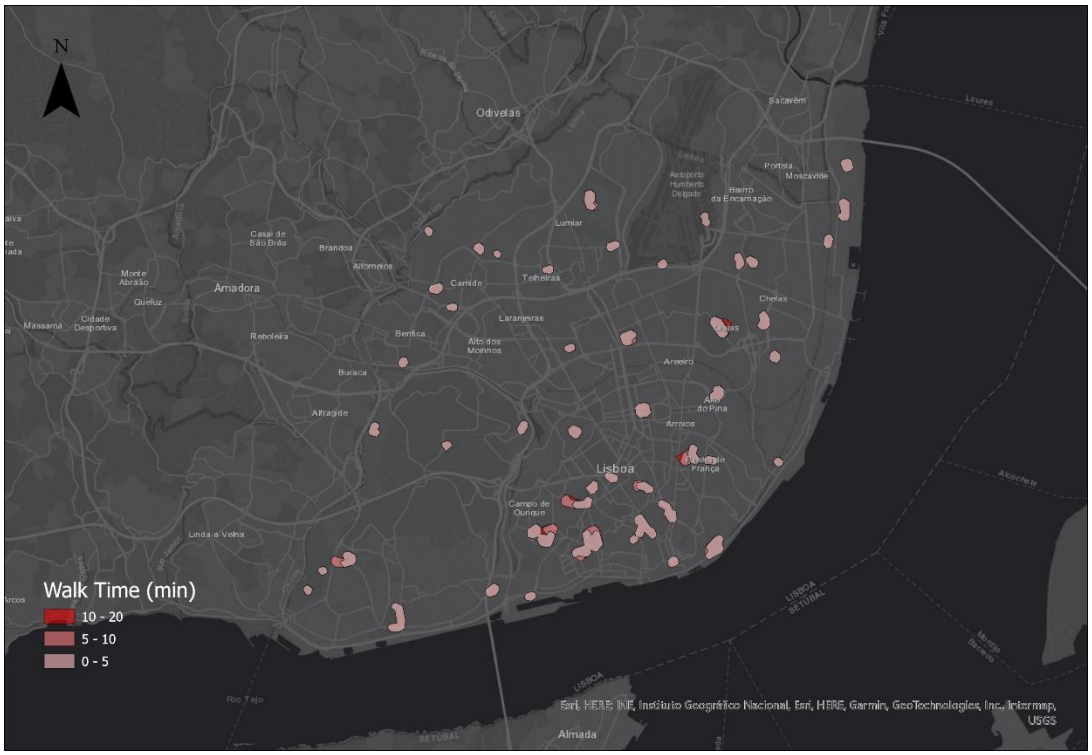

Figure 4.9 - Proximity to police stations layer.

The police stations are dispersed throughout the city, with higher concentration towards its center. This distribution can be attributed to the higher population density and commercial activity in these areas, resulting in increased demand for law enforcement services.

4.4.2.6. Proximity to healthcare facilities and pharmacies

Concerning the proximity to healthcare facilities and pharmacies, it was necessary to gather data regarding public and private hospitals, pharmacies and healthcare centers. Accordingly, these 4 files were imported to the software, assigning each to a new point layer. These layers were then merged, enabling the creation of the Service Areas (Figure 4.10).

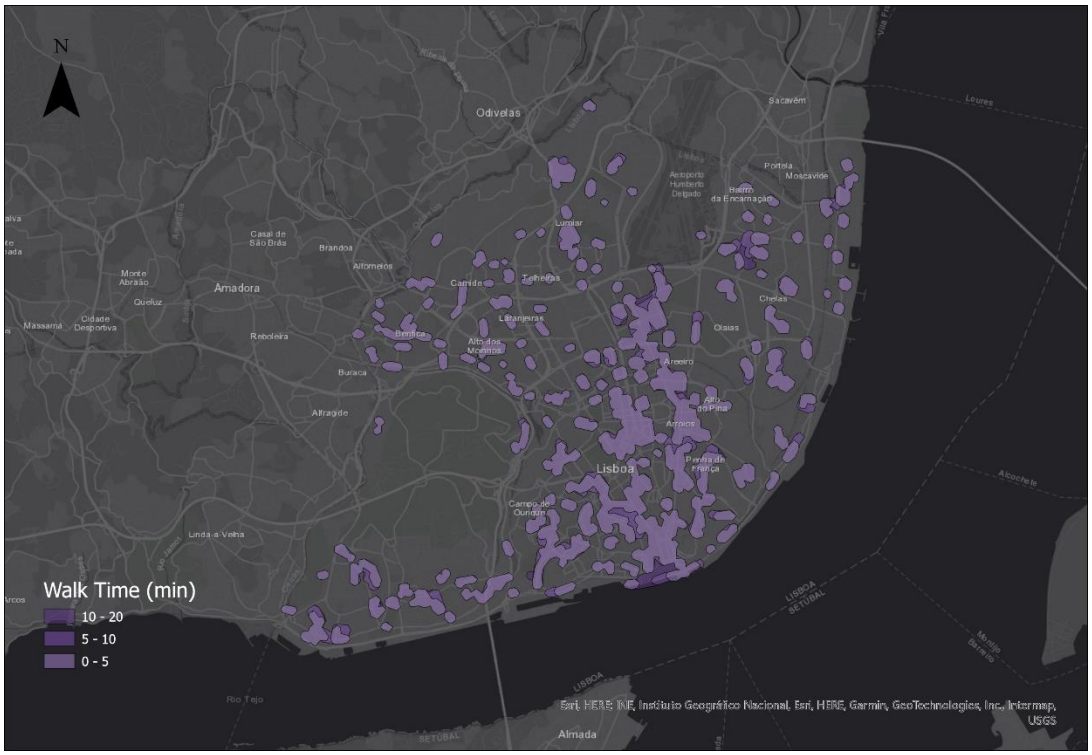

Figure 4.10 - Proximity to healthcare facilities and pharmacies layer.

There are several healthcare facilities distributed throughout the city, with some exceptions, including again Monsanto Park and the airport area.

4.4.2.7. Accommodation prices

This layer was created using information from the Airbnb listings, specifically the listings price. The mean price for each BGRI unit was calculated and then assigned graduated colors to them, based on these values. Darker colors represent areas with higher mean prices for local accommodations, while lighter colors indicate lower prices (Figure 4.11).

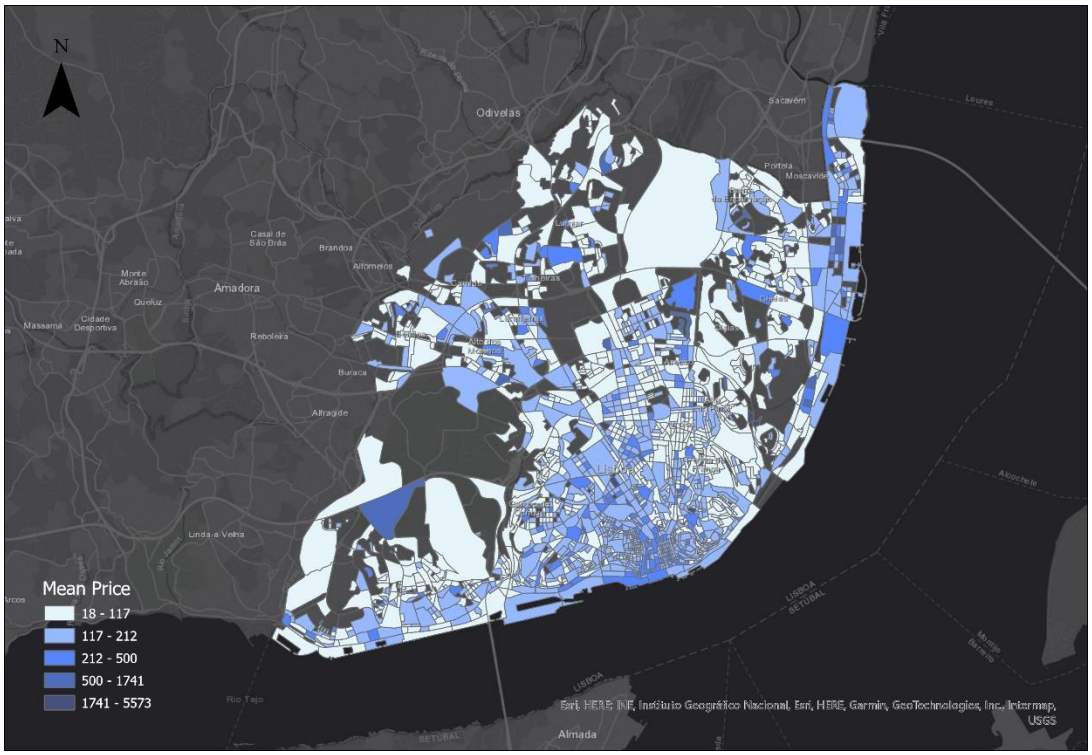

Figure 4.11 - Accommodation prices layer.

As was previously analyzed in section 3.3, accommodation prices vary across the city, with Marvila and Parque das Nações being the most expensive areas, followed by the center of the city. With the level of granularity increased, it is possible to have a more detailed understandability of the most and least expensive areas. For example, it is possible to observe certain specific zones that are expensive, and when looking at the parish level did not appear to be. Given that this criterion carries the highest weight, the most expensive areas are likely to have lower suitability scores.

4.5. GIS-FAHP COMBINATION

Finally, the results obtained from the FAHP will be combined with the criteria layers. To integrate all layers into a single analysis, they must be converted to raster format (using the Polygon to Raster tool), and the cells in each layer must be reclassified into a common scale. In this study, a scale from 1 to 5 was used, with 5 representing the most favorable conditions and 1 the least favorable ones. This process of reclassification was done through the method of Natural Breaks (Jenks), which has a purpose of identifying natural groupings within the data.

Subsequently, a weighted overlay was performed using the Raster Calculator tool. This process involves multiplying the input criteria (layers) by the weights derived from the FAHP analysis. The outcome is a suitability map that displays areas of suitability, where higher values indicate more favorable conditions.

An additional layer was created concerning the restricted areas, notably Lisbon's historic center encompassing the parishes of Misericórdia, Santa Maria Maior and São Vicente. These

areas were excluded from consideration, as the problem involves finding alterative locations to these. Besides this, another constraint is park locations and the airport, since it is not an option to have buildings in these zones.

5. RESULTS AND DISCUSSION

This chapter presents and discusses the proposed methodology. Firstly, the results of the FAHP are analyzed, as well as the steps that led to the criteria weights (section 5.1). Then, in section 5.2, the results from the combination of GIS with FAHP outcomes are displayed and a discussion is made on the final suitability map. Finally, in section 5.3, the answers to the business questions established in the Introduction are given.

5.1. FAHP RESULTS

The pairwise comparison matrices were obtained from the responses provided by the 15 participants in the survey. These matrices were used to calculate the consistency ratios for each participant, obtained from the equations (4.1) and (4.2).

Initially, only 4 out of the 15 participants achieved a consistency ratio below 0.10. Making pairwise comparisons between 7 criteria can be cognitively demanding, which may have led some participants to struggle with maintaining consistency across all comparisons. Given that only answers with a CR lower than 0.10 can be considered, the 4 consistent responses were retained and an additional 11 individuals were asked to participate in the survey. This time, extra care was taken to ensure that they fully understood their assignment. From the 4 initially consistent responses, plus the new 11 participants' responses, the final values obtained for λ_{max}, CI and CR for each participant are present in Table 5.1, in which it can be observed that 10 out of the 15 participants were able to obtain a CR below the predefined threshold. Thus, only the judgments provided by these 10 individuals will be used to apply FAHP. As was mentioned before in section 4.3.1, having a small sample size is not critical in this method.

Table 5.1 - Consistency Ratio obtained from the participants (n=7, RI=1.32).

	P1	**P2**	**P3**	**P4**	**P5**	**P6**	**P7**	**P8**	**P9**	**P10**	**P11**	**P12**	**P13**	**P14**	**P15**
$\boldsymbol{\lambda_{max}}$	7.86	8.53	7.58	8.91	8.46	8.45	7.93	7.62	7.60	7.50	7.59	7.50	7.74	7.62	7.71
CI	0.14	0.25	0.10	0.13	0.24	0.24	0.15	0.10	0.10	0.08	0.10	0.08	0.12	0.10	0.12
CR	0.11	0.19	0.08	0.09	0.18	0.18	0.12	0.08	0.08	0.06	0.07	0.06	0.09	0.08	0.09

Regarding the 15 final participants, all are Portuguese, with 10 females and 5 males. The age distribution of the participants is depicted in the pie chart below (Figure 5.1).

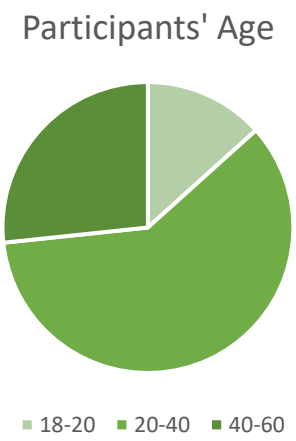

Figure 5.1 - Participants' age.

After the participants' answers have been validated, the pairwise comparison matrices of the 10 final answers are converted into fuzzy numbers, and the equations 4.4 to 4.6 are employed to obtain one single matrix (Table 5.2).

Table 5.2 - Fuzzy preference matrix.

	C1	C2	C3	C4	C5	C6	C7
C1	(1, 1, 1)	(5, 7.61, 9)	(3, 5.08, 9)	(2, 3.83, 8)	(0.25, 5.28, 9)	(0.25, 4.35, 8)	(0.25, 1.08, 6)
C2	(0.11, 0.13, 0.2)	(1, 1, 1)	(0.11, 0.22, 0.5)	(0.13, 0.18, 0.33)	(0.13, 0.65, 4)	(0.13, 0.39, 4)	(0.11, 0.14, 0.5)
C3	(0.11, 0.2, 0.33)	(2, 4.55, 9)	(1, 1, 1)	(0.17, 0.29, 0.5)	(0.17, 2.44, 8)	(0.17, 1.34, 6)	(0.13, 0.27, 4)
C4	(0.13, 0.26, 0.5)	(2, 5.59, 8)	(2, 3.42, 6)	(1, 1, 1)	(0.2, 3.8, 8)	(0.2, 3.01, 7)	(0.17, 0.33, 5)
C5	(0.11, 0.19, 4)	(0.25, 1.54, 8)	(0.13, 0.41, 6)	(0.13, 0.26, 5)	(1, 1, 1)	(0.17, 0.54, 3)	(0.11, 0.21, 7)
C6	(0.13, 0.23, 4)	(0.25, 2.56, 8)	(0.17, 0.75, 6)	(0.14, 0.33, 5)	(0.33, 1.84, 6)	(1, 1, 1)	(0.11, 0.24, 7)
C7	(0.17, 0.92, 4)	(2, 6.93, 9)	(0.25, 3.72, 7)	(0.2, 3.01, 6)	(0.14, 4.81, 9)	(0.14, 4.17, 9)	(1, 1, 1)

Using the formula (4.8), the fuzzy synthetic extent of each criterion is obtained.

$$S_1 = (11.75, 28.23, 50) \times \left(\frac{1}{240.87}, \frac{1}{94.10}, \frac{1}{30.81}\right) = (0.049, 0.300, 1.623)$$

$$S_2 = (1.71, 2.71, 10.53) \times \left(\frac{1}{240.87}, \frac{1}{94.10}, \frac{1}{30.81}\right) = (0.007, 0.029, 0.342)$$

$$S_3 = (3.74, 10.09, 28.83) \times \left(\frac{1}{240.87}, \frac{1}{94.10}, \frac{1}{30.81}\right) = (0.016, 0.107, 0.936)$$

$$S_4 = (5.69, 17.41, 35.5) \times \left(\frac{1}{240.87}, \frac{1}{94.10}, \frac{1}{30.81}\right) = (0.024, 0.185, 1.152)$$

$$S_5 = (1.89, 4.15, 34) \times \left(\frac{1}{240.87}, \frac{1}{94.10}, \frac{1}{30.81}\right) = (0.008, 0.044, 1.104)$$

$$S_6 = (2.13, 6.95, 37) \times \left(\frac{1}{240.87}, \frac{1}{94.10}, \frac{1}{30.81}\right) = (0.009, 0.074, 1.201)$$

$$S_7 = (3.9, 24.56, 45) \times \left(\frac{1}{240.87}, \frac{1}{94.10}, \frac{1}{30.81}\right) = (0.016, 0.261, 1.461)$$

The next step is to calculate the degree of possibility between the obtained fuzzy extent values (equation 4.14). Finally, it is possible to obtain the weight vector by applying equations (4.15) to (4.17). The resulting criteria weights are shown in Table 5.3.

Table 5.3 - Final criteria weights.

Criteria	Weight vector (W')	Final weight (W)
Proximity to public transportation hubs	1.000	0.171
Proximity to the airport	0.520	0.089
Proximity to tourist attractions	0.821	0.140
Proximity to amenities	0.906	0.155
Proximity to police stations	0.805	0.137
Proximity to healthcare facilities and pharmacies	0.836	0.143
Accommodation price	0.973	0.166

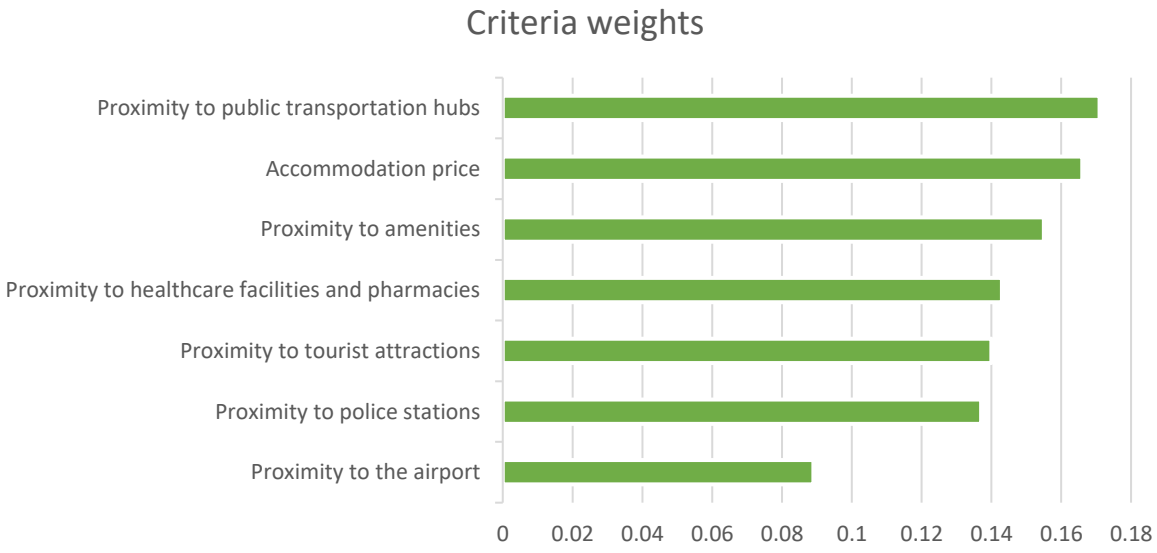

Figure 5.2 - Final criteria weights.

The results of the Fuzzy AHP show that the most influential criteria are the proximity to public transportation hubs and the accommodation price (Figure 5.2), with relatively close weights,

being them respectively 0.171 and 0.166 (Table 5.3). It would be expected that proximity to tourist attractions was one of the most weighted criteria. However, the results show that visitors tend to prioritize affordable options, as long as there is easy access to touristic points through public transportations. The proximity to the airport was the least prioritized criterion, with a weight of 0.089. This low weight can be attributed to its limited relevance when compared to other criteria that directly impact the everyday experience of tourists throughout their stay. The airport's influence is predominantly constrained to the initial and final stages of the journey. Therefore, the proximity to amenities, such as restaurants and supermarkets, is also an important factor for tourists when choosing the LA to stay in.

Although the difference was not very significant, participants valued more proximity to healthcare facilities than police stations. One possible reason for this preference could be that access to healthcare is considered a more essential and immediate need compared to the presence of police stations. The perception is that police stations primarily serve for reporting incidents rather than providing a significant sense of security. Therefore, individuals prioritize being close to healthcare facilities as it offers reassurance of readily available medical assistance in emergencies or health concerns, which is seen as more directly impactful on personal well-being.

5.2. SUITABILITY MAP

The suitability map obtained from the Raster Calculator can be seen in Figure 5.3.

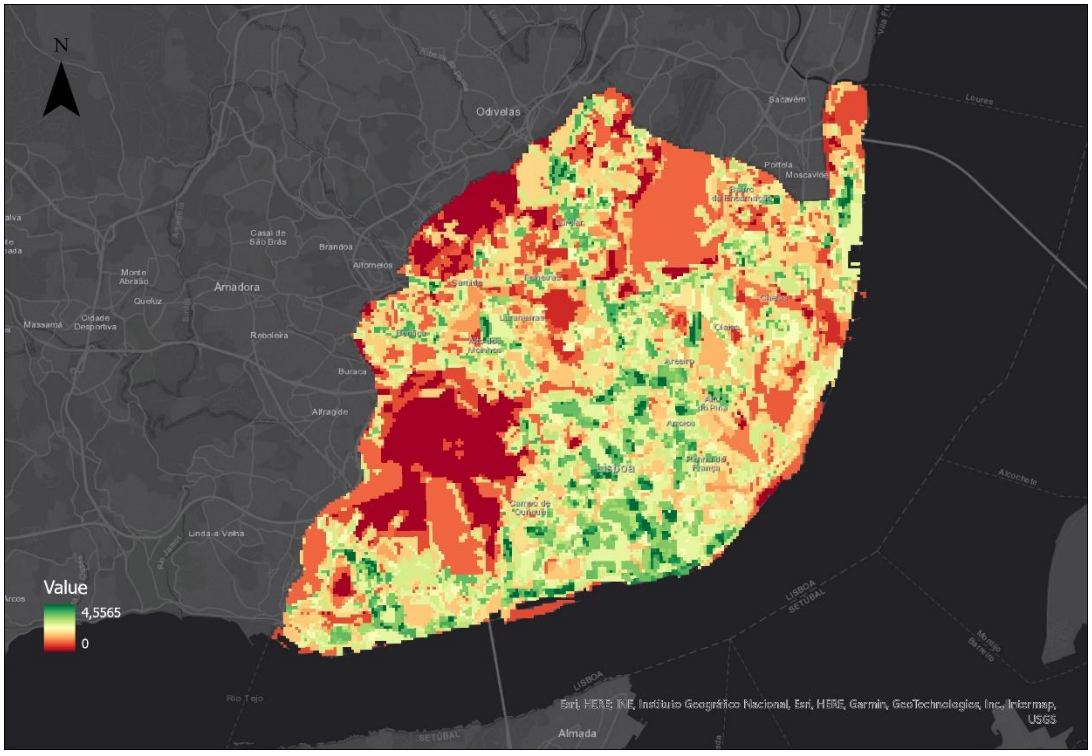

Figure 5.3 - Suitability map.

However, not all areas of the map are valid options. As previously mentioned in section 4.5, constraints are considered corresponding to Lisbon's historical center, parks and the airport. The parishes boundaries and names were added to the final map to ease interpretations (Figure 5.4).

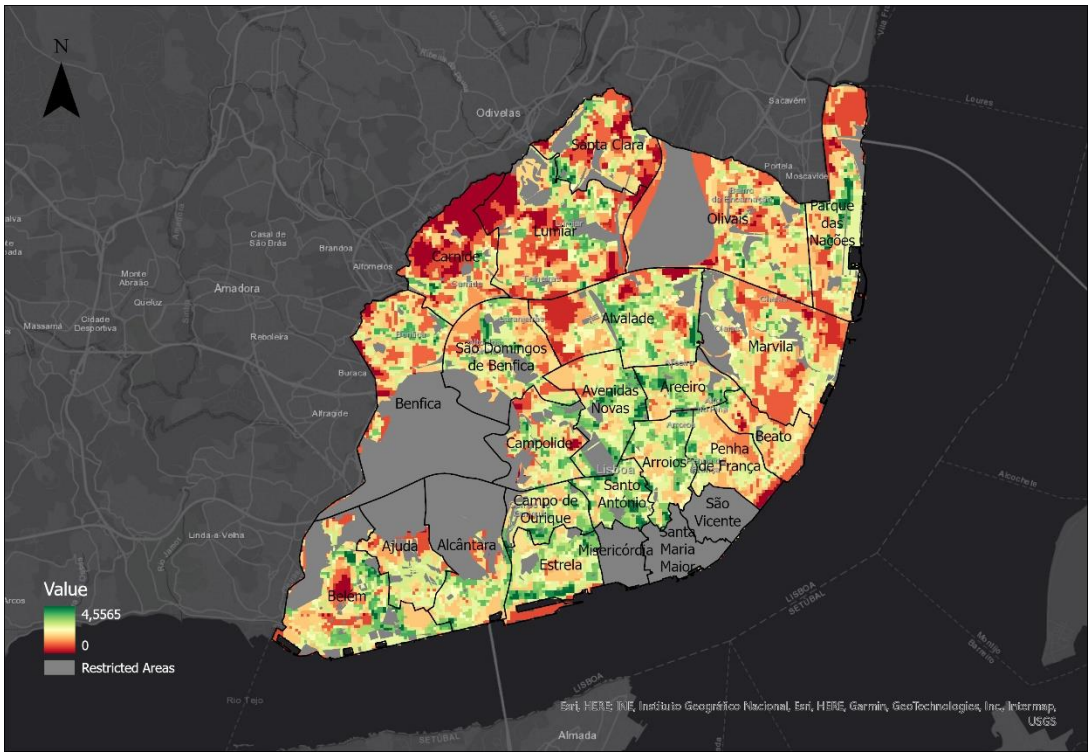

Figure 5.4 – Final suitability map with constraints and parishes boundaries.

The suitability maps show the most and least suitable spots within the municipality of Lisbon for the implementation of new LA establishments, as a replacement of some of the existing in the historic center. The most suitable locations are identified with darker tones of green and have higher values (being 5 the maximum), while the least suitable zones with darker red and lower values.

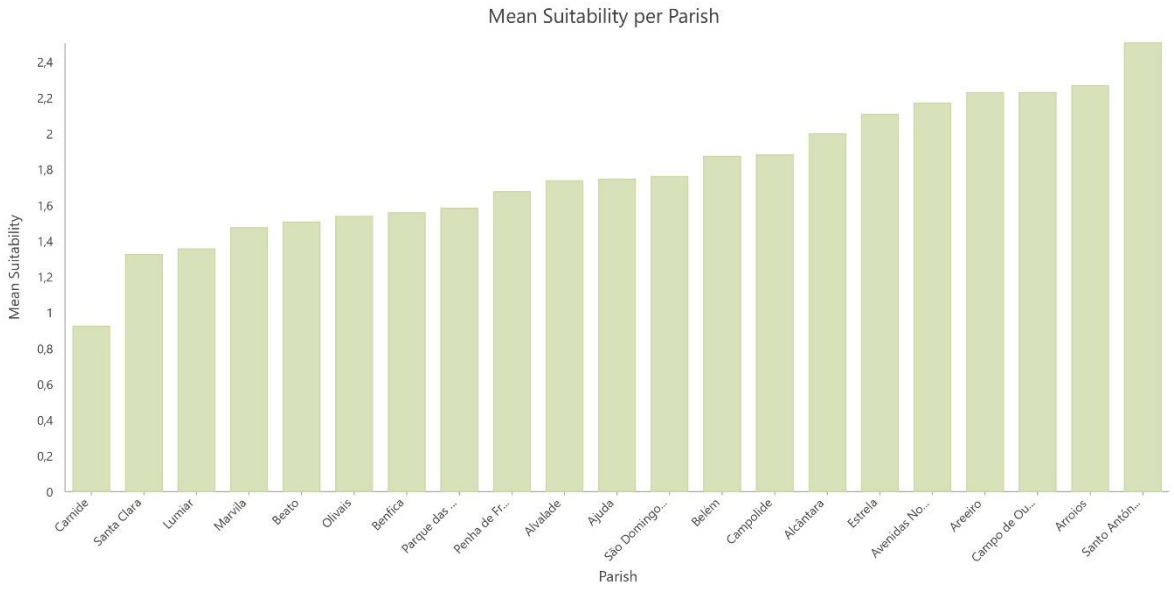

Figure 5.5 - Mean suitability per parish.

The bar chart presented in Figure 5.5 was built to understand the parishes that overall obtained higher suitability levels. It displays the mean suitability score for each parish in Lisbon, and it can be observed that the parish with the highest mean suitability score is Santo António, with a significant difference from the second highest mean value, Arroios, followed closely by Campo de Ourique and Areeiro. On the other hand, Carnide was the parish with the lowest mean suitability score, followed, with a substantial difference, by Santa Clara and Lumiar. However, it has to be noted that the analysis can not be based solely on this graphic, as it provides a generalized overview and may mask significant variations within the parishes.

From looking at Figure 5.4, it can be seen that there are several suitable areas scattered throughout the city and not confined in just one or two parishes. In fact, the majority of parishes contain both very suitable spots and less suitable spots, indicating a significant intra-parish variation. There does not seem to be a strict pattern, although the parishes surrounding the historic centre exhibit a higher suitability.

To better understand which parishes contain the most suitable spots, a stacked bar chart was produced (Figure 5.6) showing the distribution of the obtained scores per parish. For this, the suitability values were grouped into the following classes:

- 0 to 1: Not Suitable;
- 1 to 2: Less Suitable;
- 2 to 3: Neutral;
- 3 to 4: Suitable;
- 4 to 5: Highly Suitable.

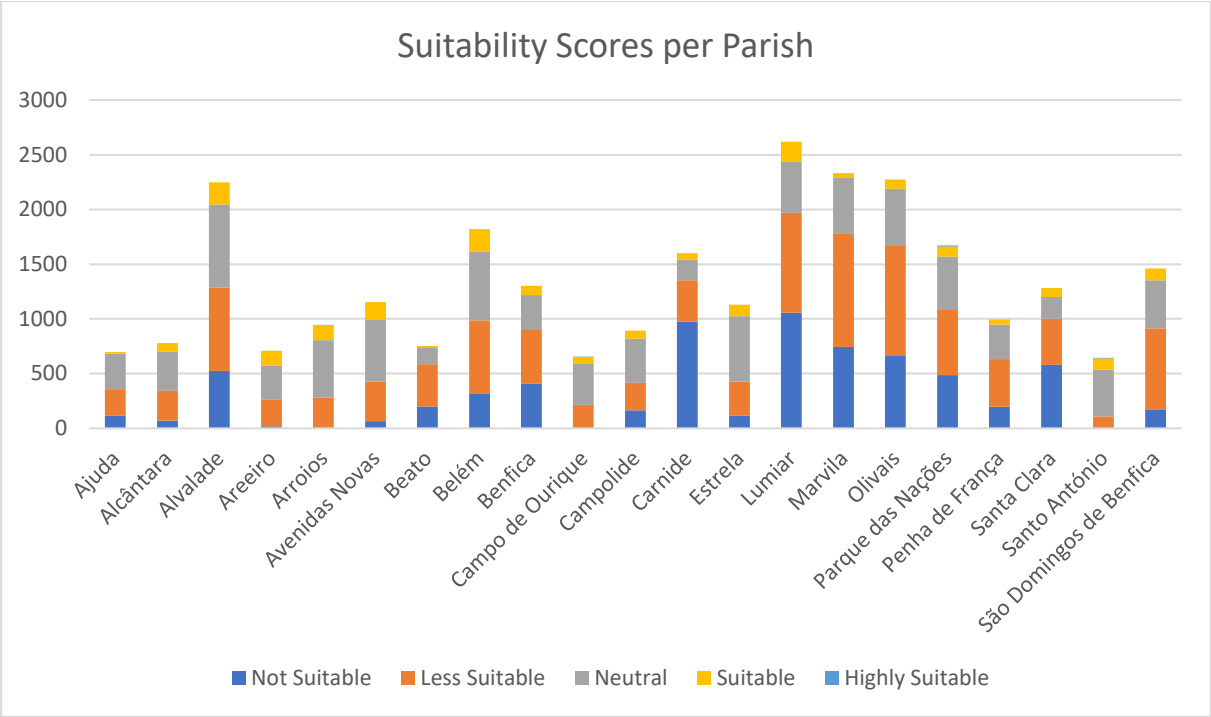

Figure 5.6 - Suitability scores per parish.

There were only very few spots that obtained a suitability value between 4 and 5. These were located within the parishes of Arroios, Belém, Campo de Ourique, Parque das Nações and Santo António, with Santo António containing the highest number of spots in the best suitability interval.

Furthermore, the “Suitable” values, although not as high as “Highly Suitable”, should also be considered as viable options. It can be observed that all parishes contain suitable spots, with Ajuda and Beato containing only a few. On the other hand, which can also be seen by looking at Figure 5.4, the parishes with the highest amount of not suitable locations are Carnide and Lumiar.

This analysis highlights that, while some parishes like Santo António and Arroios have higher overall suitability scores, there are considerable variations within each parish that need to be considered for a comprehensive understanding of suitability across Lisbon. Overall, all parishes contain certain areas in which there could be created new local accommodation units. Regarding the existing local accommodation units in the historic center, several factors such as rating and occupancy rate could be taken into consideration when deciding which ones should be closed, being then open to the locals to live in.

To gain a deeper understanding of our results, we selected the "Highly Suitable" and "Suitable" areas. This information was then combined with the existing Airbnb listings to determine if the proposed locations already have a significant number of listings. If these areas already contain a substantial number of units, adding more may not be advisable. For each highly suitable or suitable area, we calculated a ratio of the number of listings to the area size. Based

on the results, we assigned graduated colors to each zone. Darker shades of green were assigned to areas with a lower ratio, indicating a smaller number of listings relative to the area's size. Conversely, lighter shades of green were assigned to areas with a higher ratio, suggesting a higher density of listings and thus making them less recommended for new establishments. This analysis can be observed below in Figure 5.7.

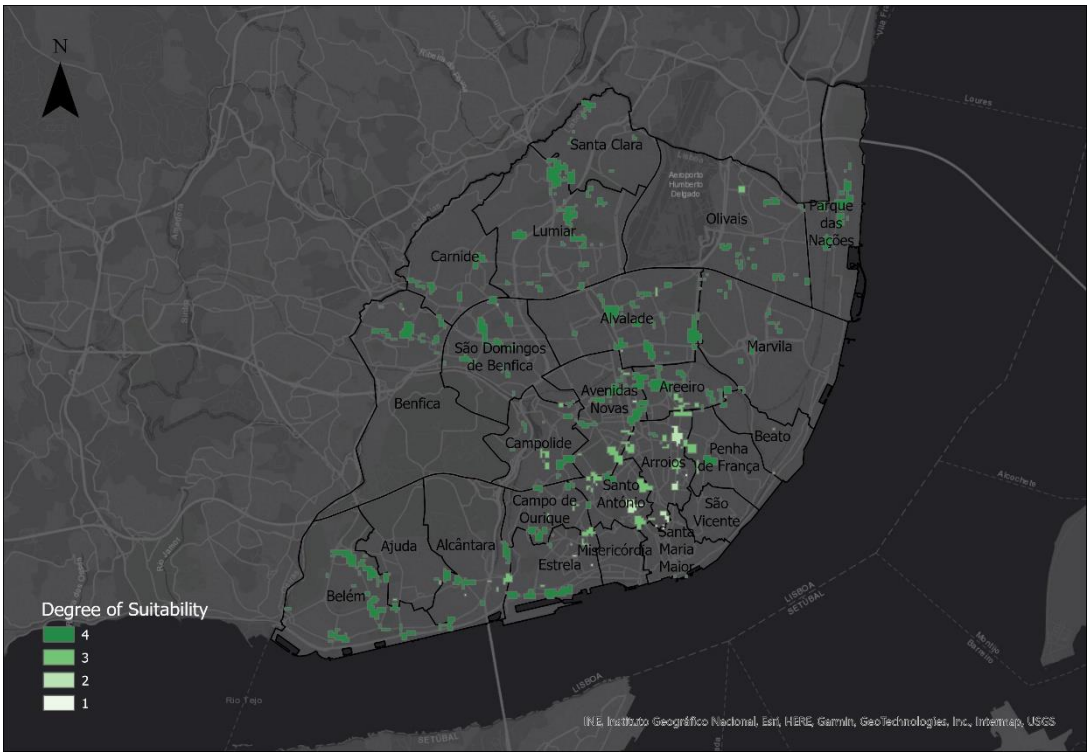

Figure 5.7 - Degree of suitability based on already existing listings.

This map uses a scale from 1 to 4, instead of the 1 to 5 scale used in previous maps, as we found that having five classes hampered the analysis. By examining the resulting map, it is evident that from the most suitable areas, the ones less recommended for the implementation of new LA units are located in more central parishes. This is expected, as these zones have the highest concentration of existing listings. Therefore, this map can be effectively used to identify the best locations for introducing new establishments.

5.3. ANSWERING THE BUSINESS QUESTIONS

In this section, objective answers to the business questions I proposed in the Introduction section are presented.

1. How has the number of opening LA units in Lisbon changed over the past decade and what factors have influenced these trends?

Over the past decade, two distinct periods can be identified. The first period saw an intensive effort to attract more tourists to the city and address the growing demand for local accommodation (LA) units due to the increasing influx of tourists. This led to a significant rise

in the number of LA units, peaking in 2017 with the highest number of new units opening. The second period began after 2017, marked by a much slower rate of new LA openings. Starting in 2019, there was a notable decrease in the number of new LAs opening in the historic center. These declines can be attributed to regulatory interventions aimed at mitigating the negative effects of the high concentration of these establishments, initially reducing the number of new LAs in general, and later creating containment areas to limit the number of LAs in specific zones.

2. Which criteria have the most significant impact on the selection of a LA unit by tourists?

The criteria that obtained the highest weights were the proximity to transportation hubs, followed by the accommodation price. This suggests that tourists tend to prioritize affordable accommodation options that are conveniently located near transportation hubs, facilitating easy access to the city's tourist attractions.

3. Which parishes in Lisbon have the potential for implementing new LAs as alternatives to the historic center?

Several parishes outside the historic center show potential for implementing new LAs. In fact, all the parishes under consideration contain suitable locations. The key question, therefore, is where the most favorable spots are situated. The parishes with the most suitable spots are Arroios, Belém, Campo de Ourique, Parque das Nações and Santo António. However, other less suitable areas should not be disregarded.

4. How do the suitability scores of parishes for the implementation of new LAs correlate with the existing number of LAs in those areas?

In a more general approach, among the five parishes containing the most suitable spots, Santo António and Arroios already have a high concentration of LAs. Consequently, these parishes should be excluded as viable options for further development. Although Estrela also has a significant number of LAs, it is fewer than in Santo António and Arroios. Thus, Estrela could be considered to some extent, allowing for a limited increase in LA units. Ultimately, the parishes that should be considered as the best alternatives to the historic center for the implementation of new units are Belém, Campo de Ourique, and Parque das Nações. By looking at Figure 5.7, the suitability of specific areas in correlation with the existing number of LA units in those areas can be more precisely determined, rather than just at the parish level.

6. CONCLUSIONS

This study aimed to identify alternative locations for local accommodations in Lisbon, rather than the historic center, to mitigate gentrification. By combining the Fuzzy-AHP method with GIS techniques we sought to address the impacts of the high influx of tourists, which has been eroding the unique character of historic neighborhoods.

Upon the identification of this current situation in Lisbon, an exploratory analysis was performed to better understand the study area. This analysis involved understanding some existing patterns regarding local accommodations in the city, revealing a concentration in the historic center, exacerbating the influx of tourists and contributing to the loss of neighborhood identity. Therefore, the main purpose of this study was to find suitable alternative locations for these accommodations, aiming to redistribute the tourism load and counteract gentrification.

Seven criteria that tourists may consider when choosing an accommodation were then defined: proximity to transportation hubs, proximity to the airport, proximity to tourist attractions, proximity to amenities, proximity to police stations, proximity to healthcare facilities and pharmacies, and accommodation prices. The weight of each criterion was calculated using FAHP, which addresses the inherent uncertainty present in multi-criteria decision-making problems. Proximity to public transportation hubs emerged as the most influential criterion, with a weight of 0.171, followed by accommodation price, with a 0.166 weight, while proximity to the airport was the least influential factor.

Using GIS techniques, the layers for each criterion were prepared and reclassified into a common scale from 1 to 5. By integrating these layers with the FAHP weights in ArcGIS Pro, a suitability map was produced, excluding restricted areas such as the historic center, airport and parks. The map values ranged from 0 to 5, categorized into five classes: “Not Suitable”, “Less Suitable”, “Neutral”, “Suitable” and “Highly Suitable”.

The main findings indicate that while all parishes have potential spots for new LAs, the most suitable areas are located in Arroios, Belém, Campo de Ourique, Parque das Nações and Santo António. However, considering the current elevated concentration of LAs in Arroios, Santo António and Estrela, with this last parish not containing as much units as the other two, it is recommended prioritizing new LA implementations in Belém, Campo de Ourique and Parque das Nações. Although other suitable areas throughout the city should also be considered. Furthermore, a map was produced containing only the “Highly Suitable” and “Suitable” spots, incorporating the number of existing Airbnb listings to indicate the degree of suitability for new units. This map could serve as a valuable tool for urban planners and policymakers, enabling them to make informed decisions to strategically distribute local accommodations, thereby preserving the historic identity of Lisbon’s neighborhoods and addressing the gentrification challenge effectively.

7. LIMITATIONS AND FUTURE WORKS

During the development of this thesis, some limitations were encountered. The first one was the insufficiency of relevant information in the local accommodations' dataset for a comprehensive exploratory analysis. Consequently, the Airbnb dataset was used for most of the analysis, which reduced the number of LAs under examination.

One of the most challenging limitations was the availability of data, since it is something out of our control. We noticed that the dataset containing the bus stops was incomplete. Additionally, we intended to include a criterion for the crime rate within the parishes, but this information was not publicly available, so this factor had to be excluded from the analysis.

Another limitation of this research was related to the difficulty in answering the survey. It is a complex questionnaire that requires the respondents' full attention to ensure consistent answers, which may have impacted the quality of the data collected.

Furthermore, the creation of service areas consumes credits if data from ArcGIS Online is used. Thus, it was not possible to use an existing network, and so we had to create our own. During its creation, the file used contained some edge features that were too small for the software to connect to other features. The solution was to remove these cases, which were few, but this still resulted in alterations to the data.

The service area of the airport was found to be very small, as it is not an accessible zone through walking. While driving time would have been a more appropriate measure, we maintained walking time as the cost for consistency with the other service area layers. However, future work should consider using driving time for such areas. Additionally, for more comprehensive analysis, future works could consider incorporating the time that it takes to get to places by public transportation.

Moreover, it would be beneficial to extend this type of study to other cities facing similar issues, such as Porto, which is also a popular tourist destination in Portugal. Additionally, in an attempt to continue contributing to the improvement of the lifestyle in Portugal, future research could focus on assessing the social and economic impacts of the proposed changes on local communities, including housing affordability and quality of life.

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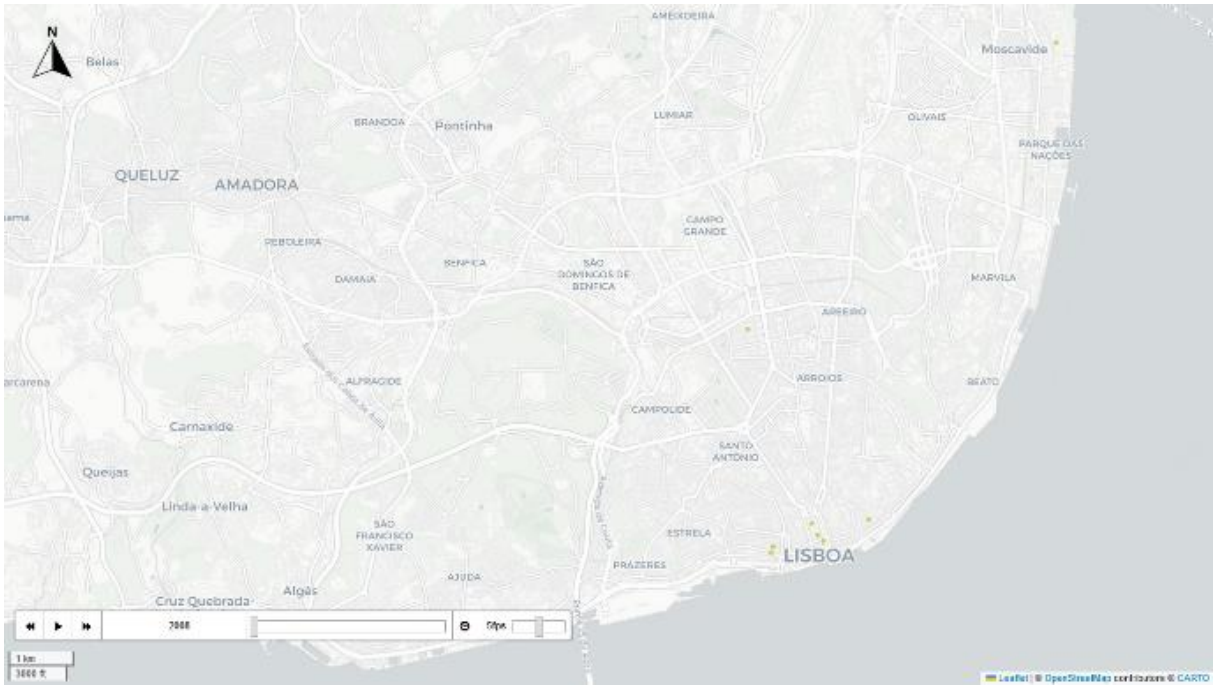
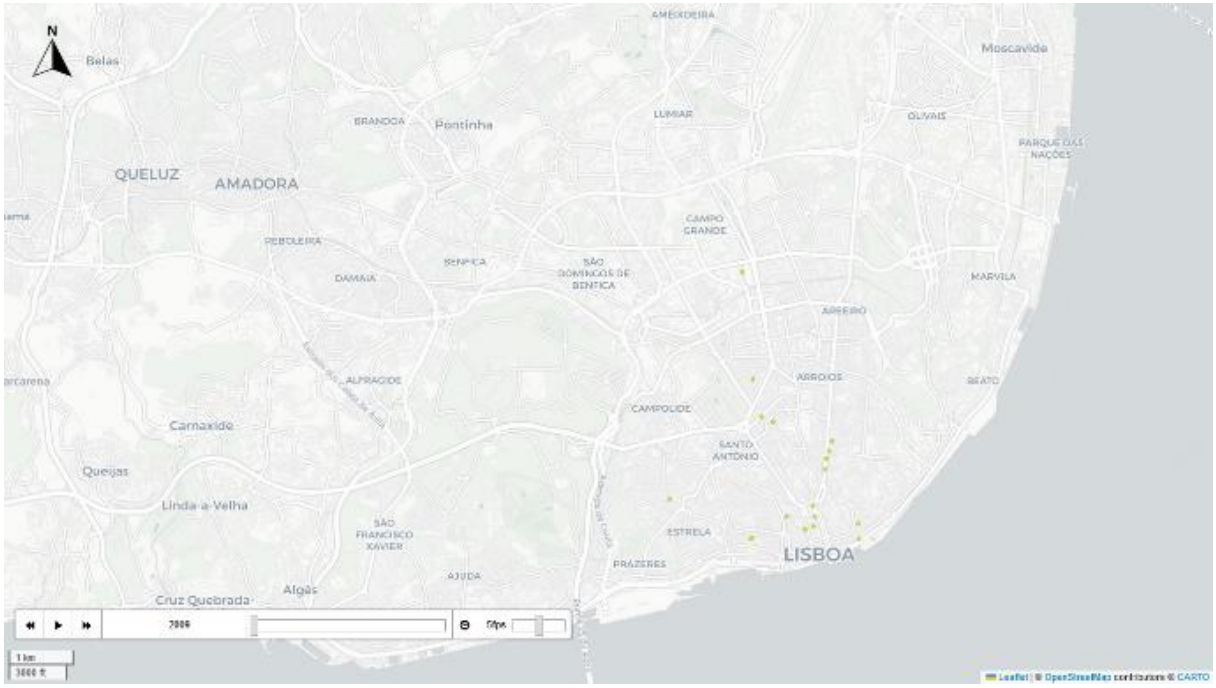
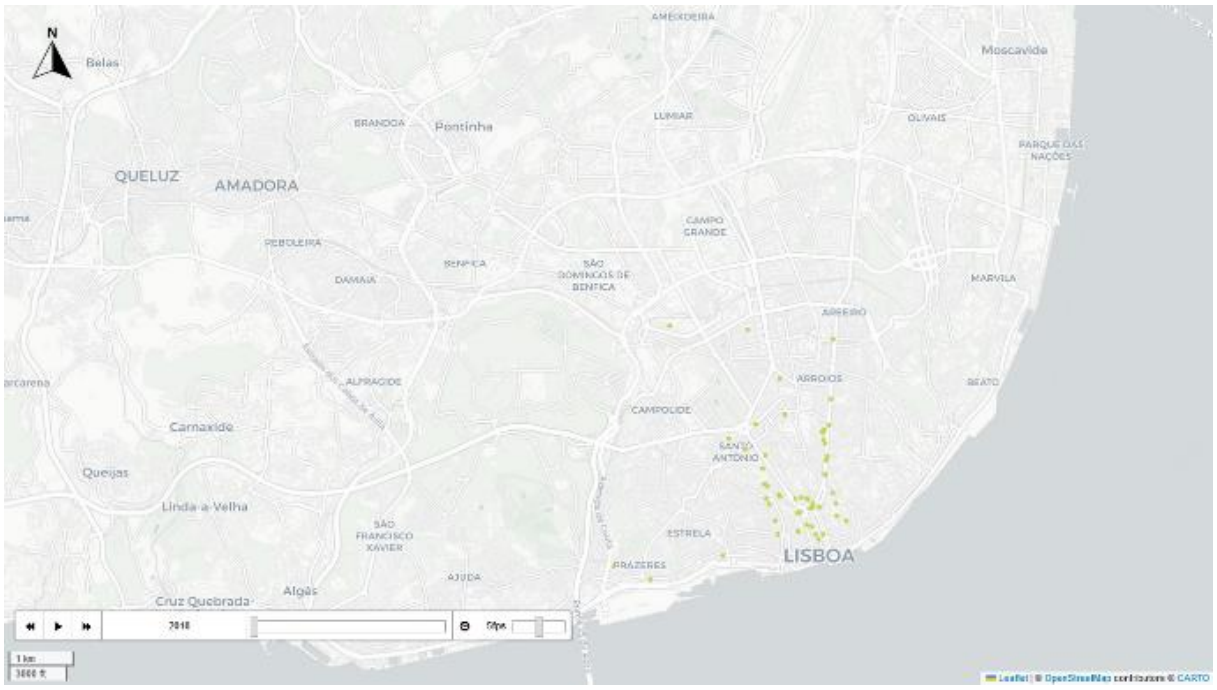
APPENDIX A



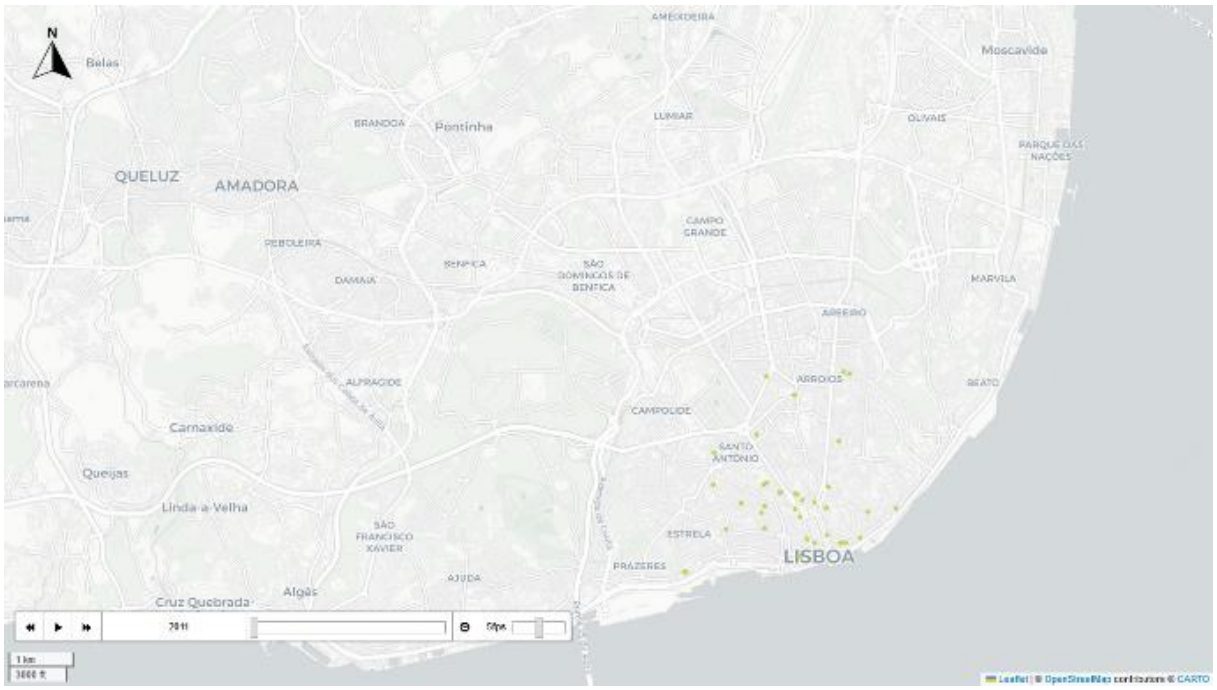
Appendix A Figure 1 - LA opening in 2008



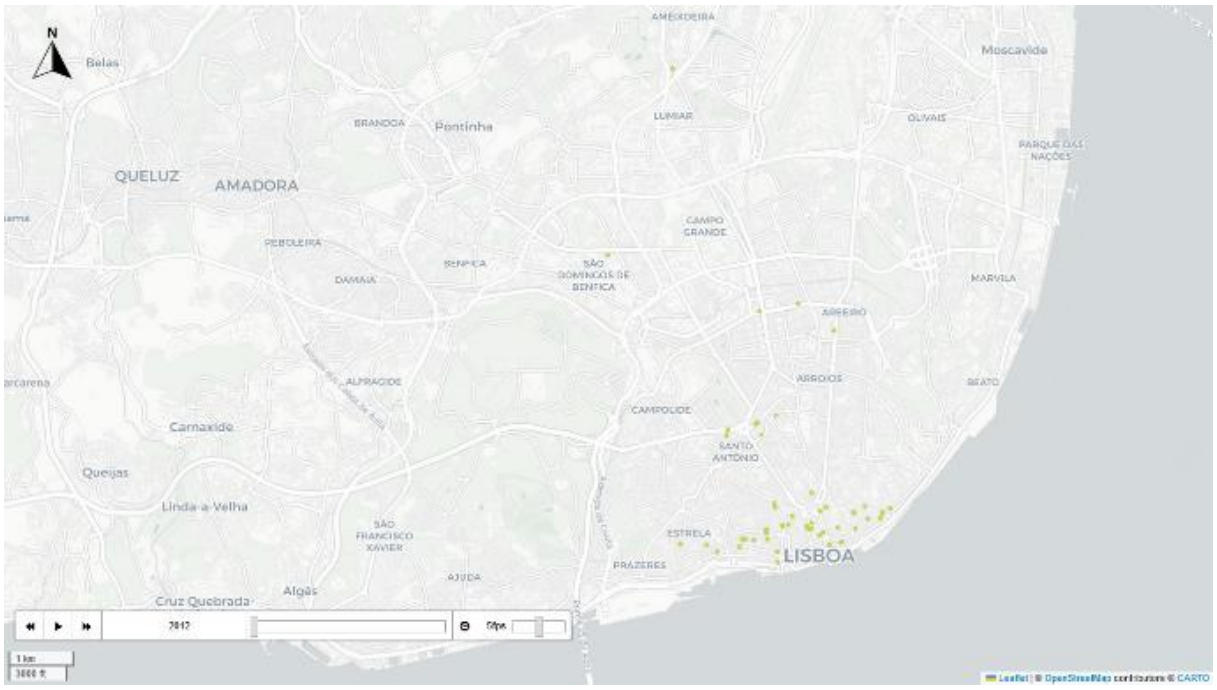
Appendix A Figure 2 - LA opening in 2009



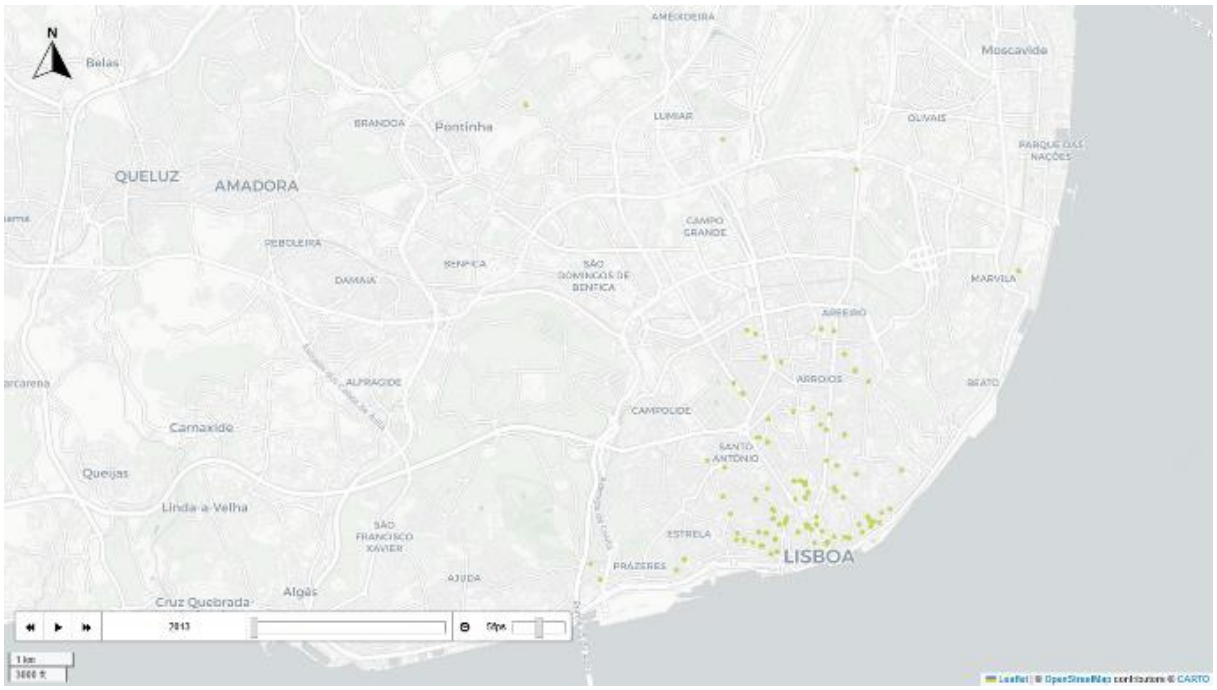
Appendix A Figure 3 - LA opening in 2010



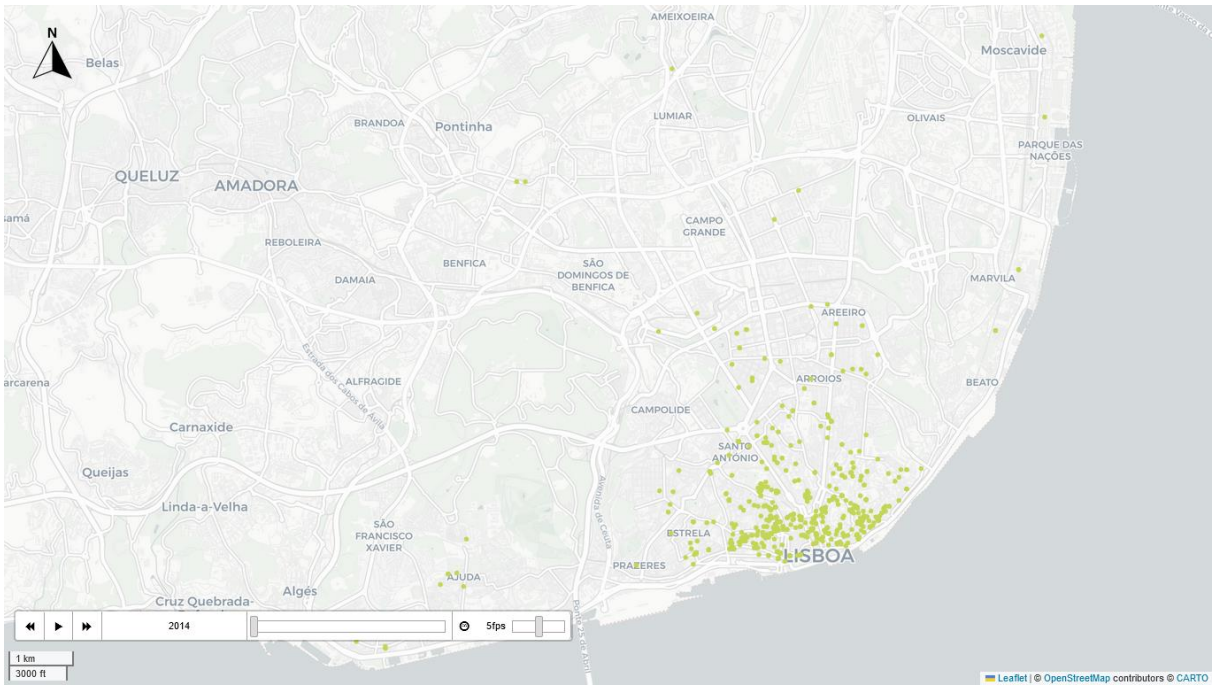
Appendix A Figure 4 - LA opening in 2011



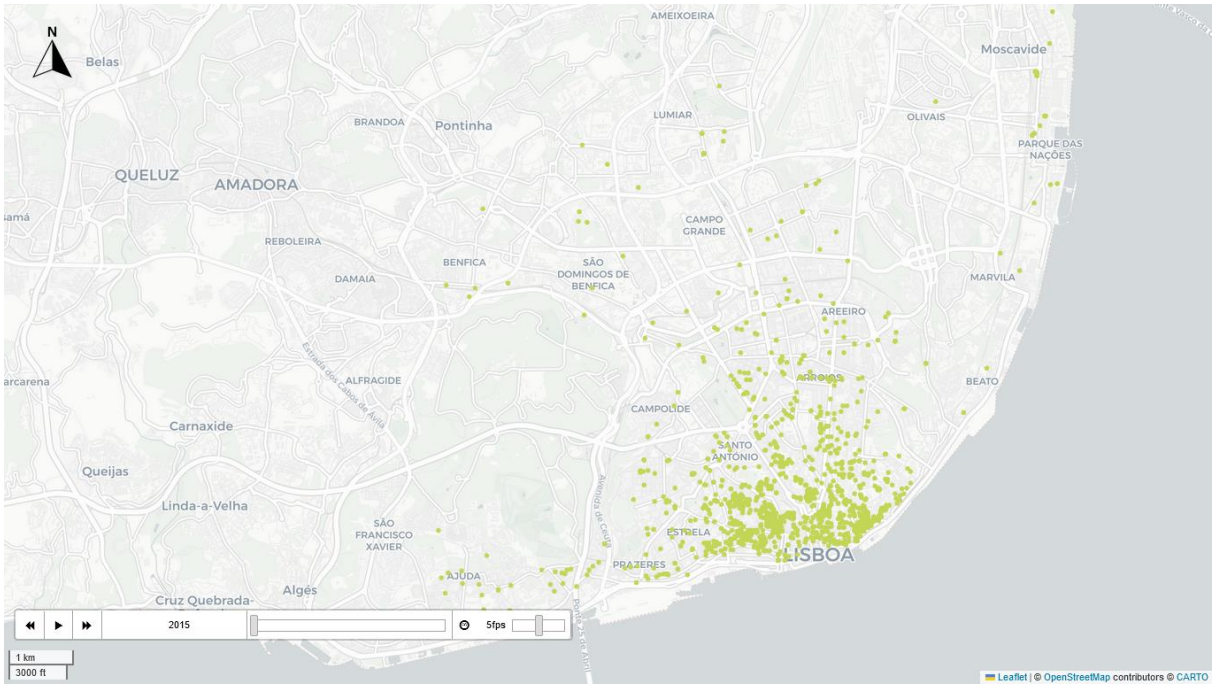
Appendix A Figure 5 - LA opening in 2012



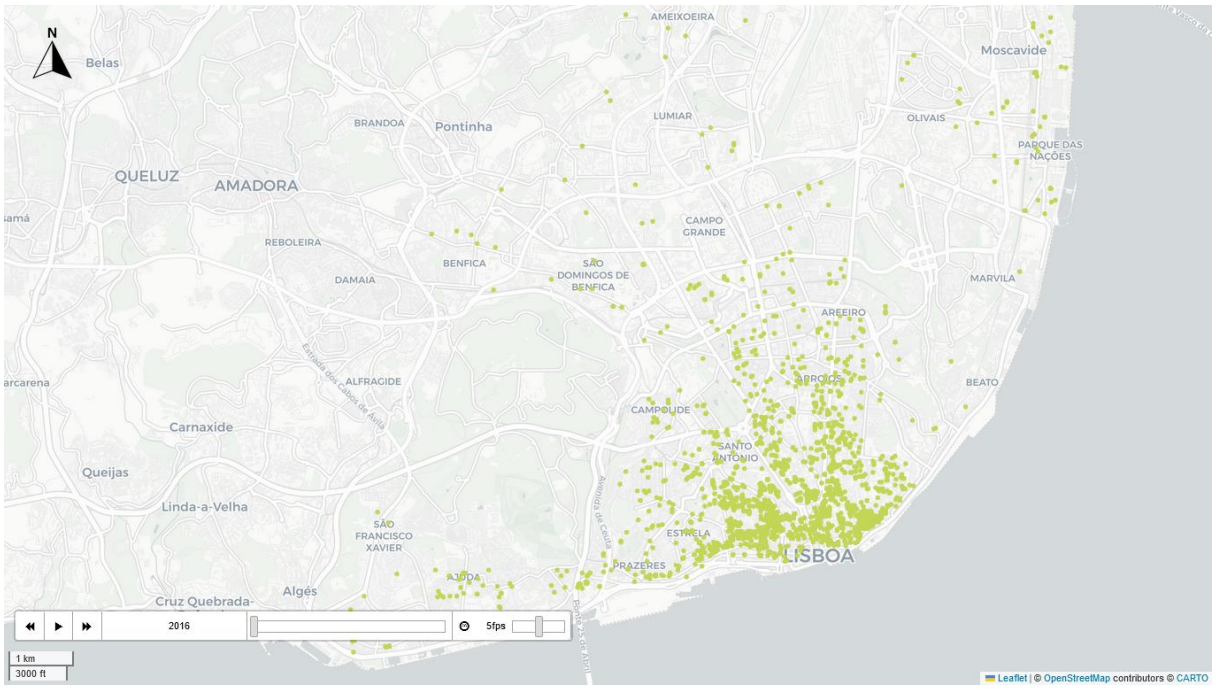
Appendix A Figure 6 - LA opening in 2013



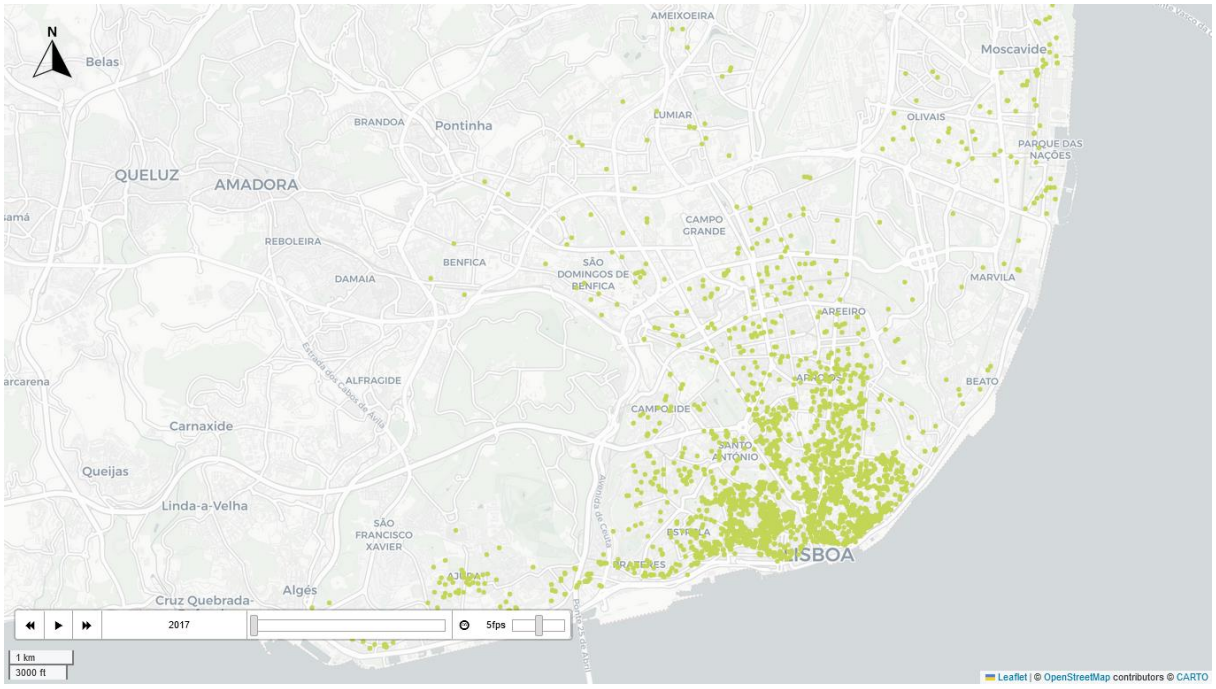
Appendix A Figure 7 - LA opening in 2014



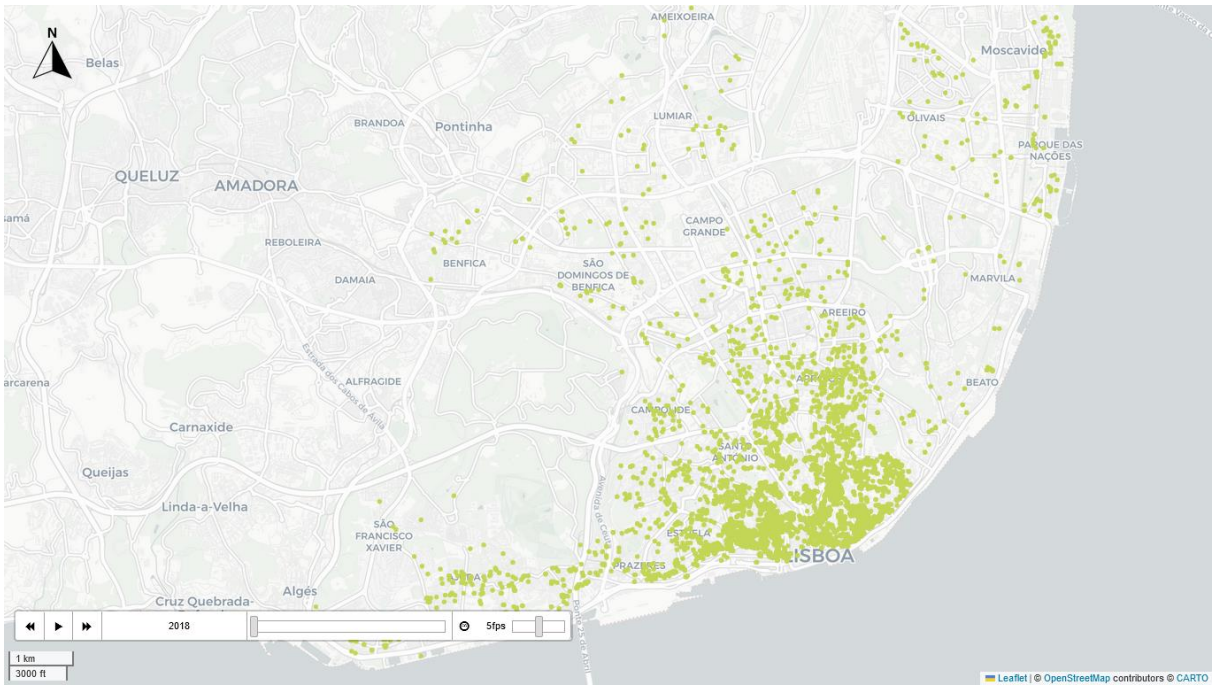
Appendix A Figure 8 - LA opening in 2015



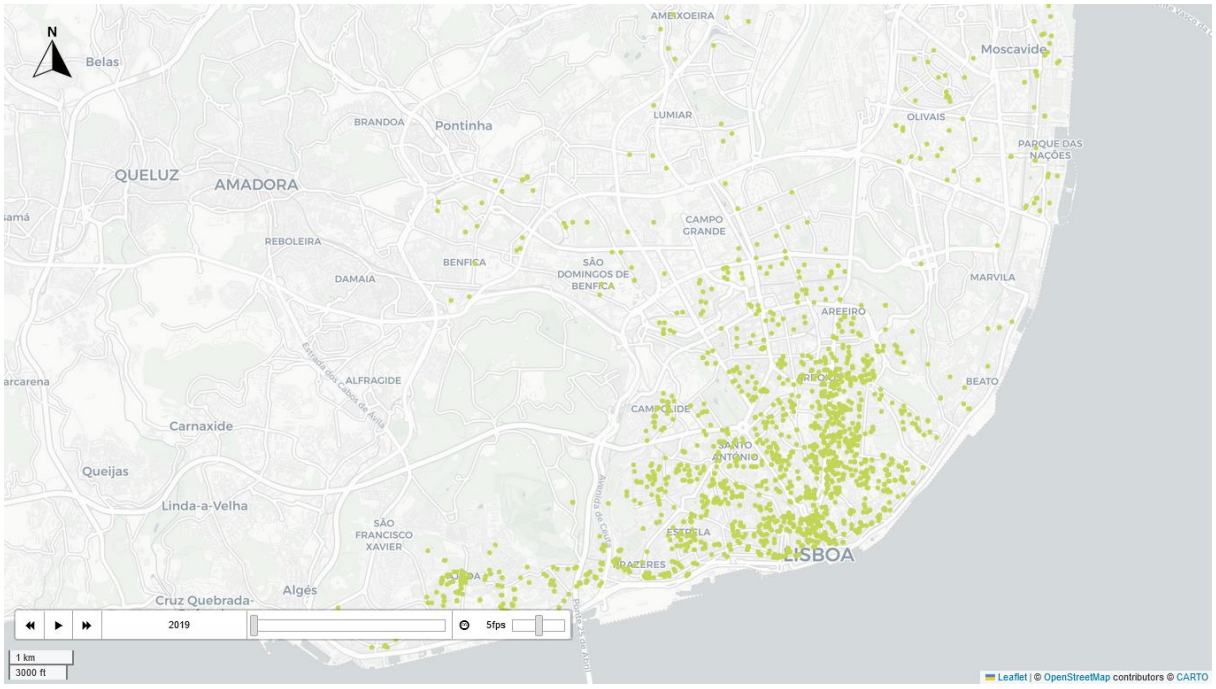
Appendix A Figure 9 - LA opening in 2016



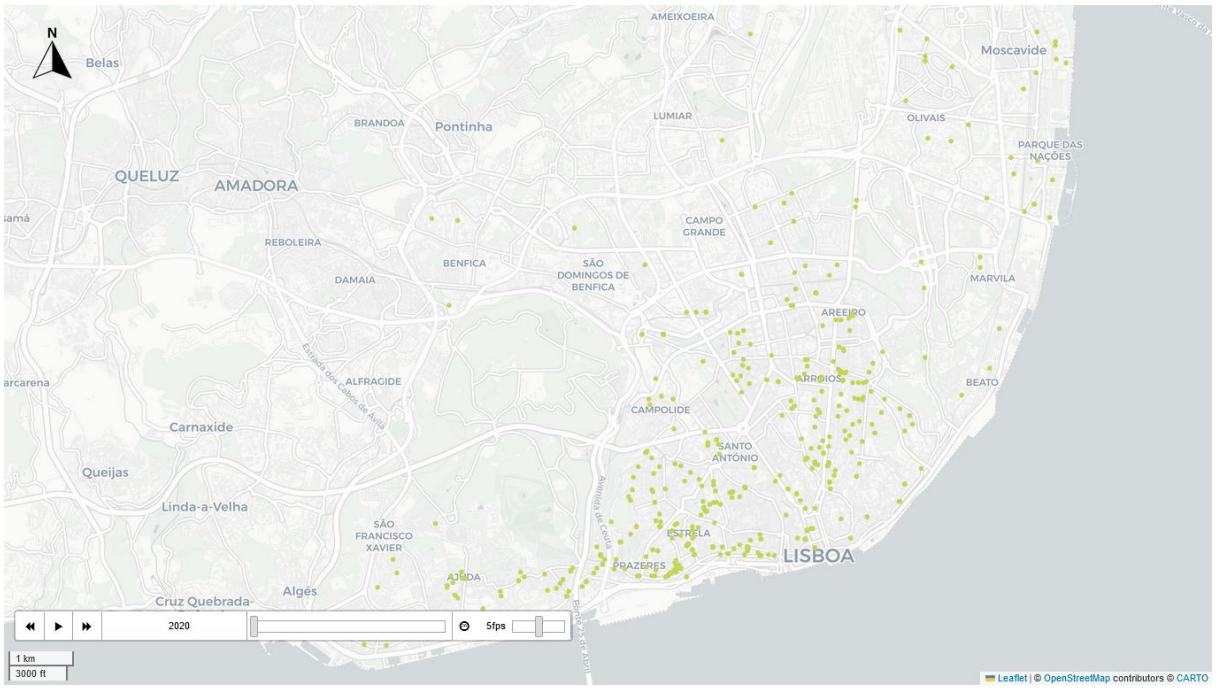
Appendix A Figure 10 - LA opening in 2017



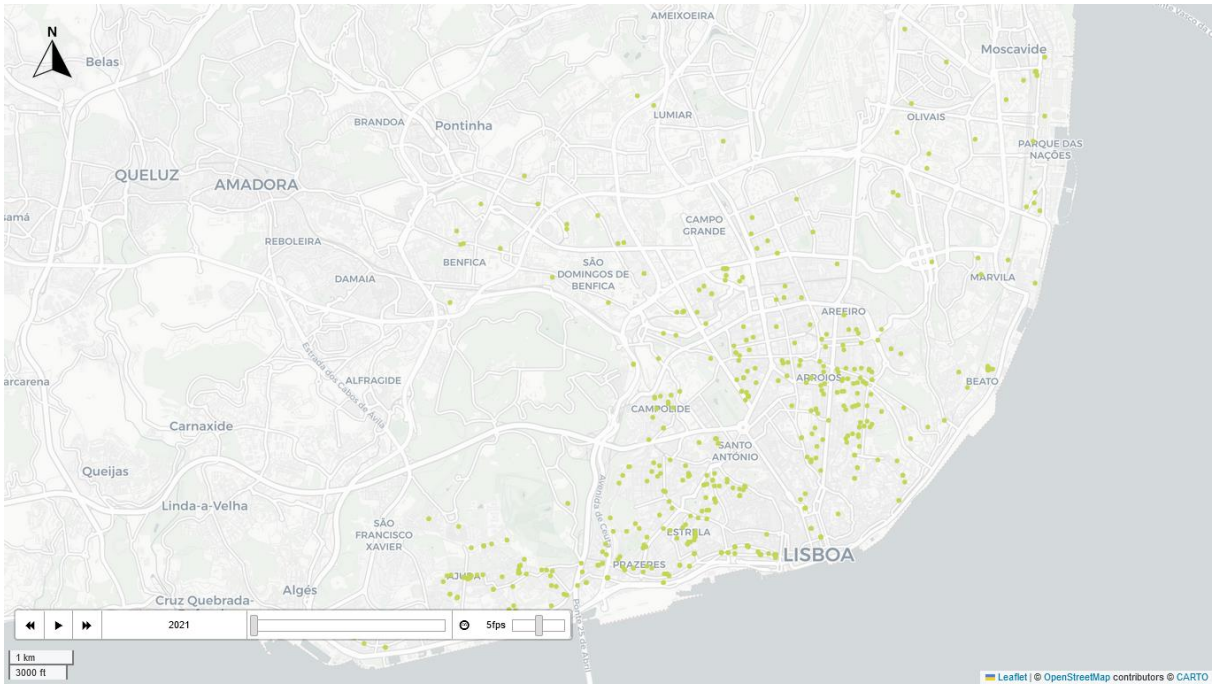
Appendix A Figure 11 - LA opening in 2018



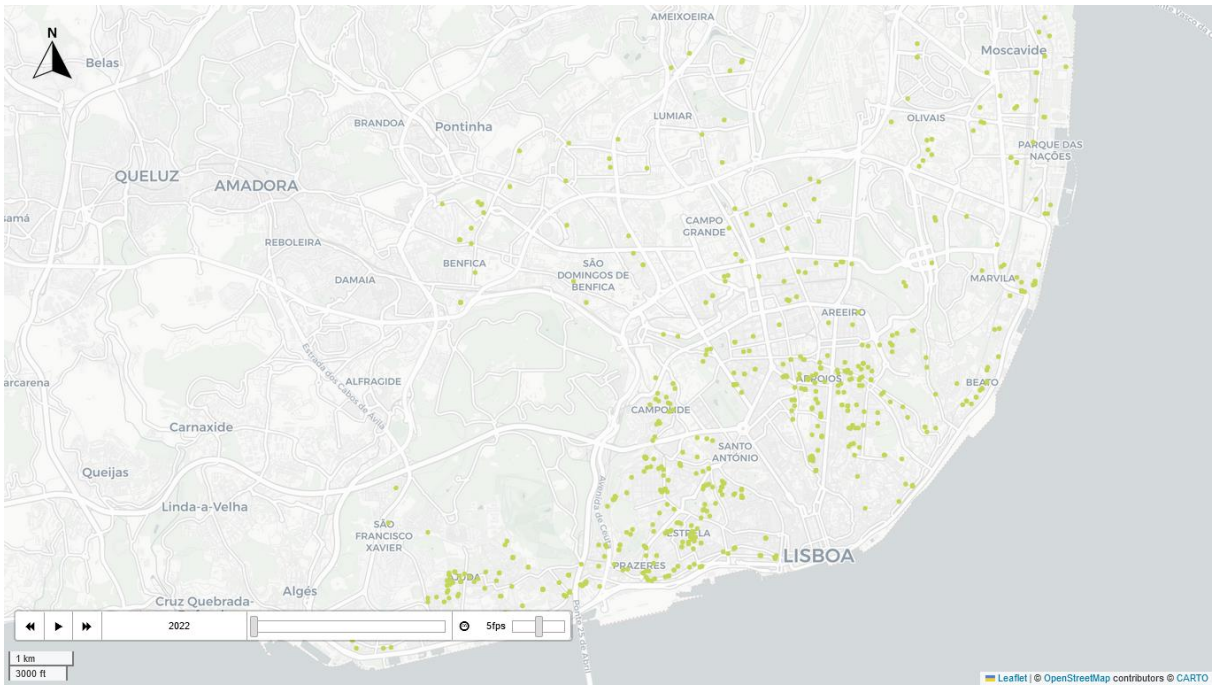
Appendix A Figure 12 - LA opening in 2019



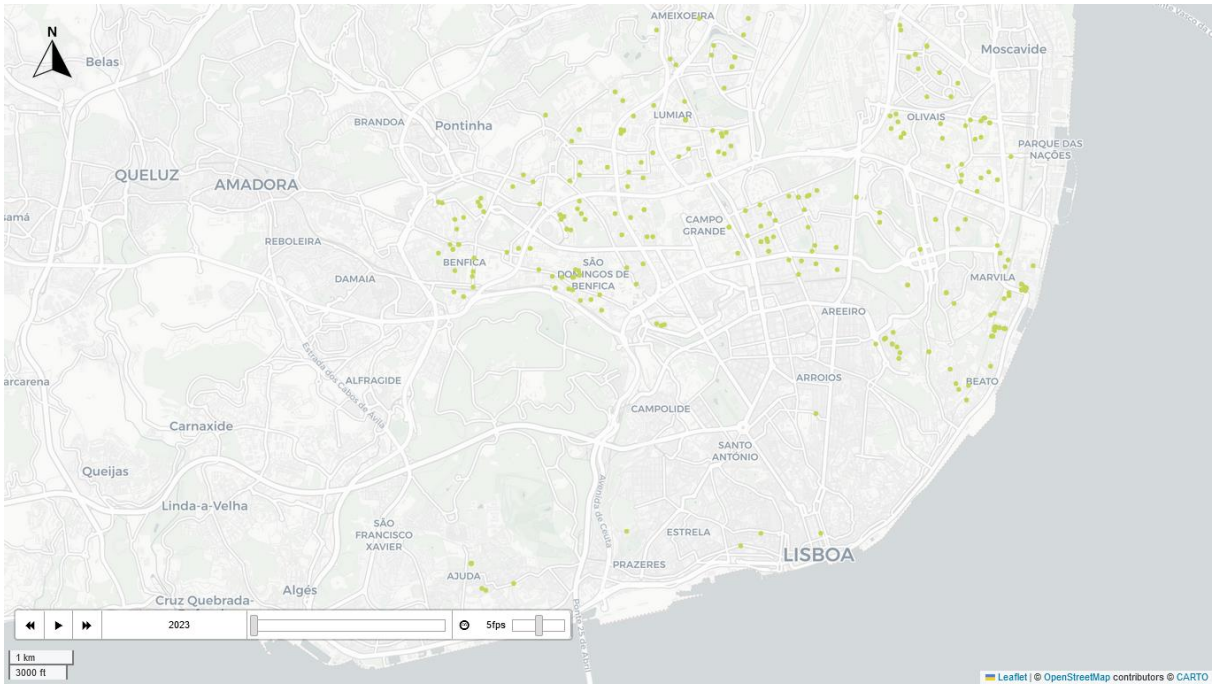
Appendix A Figure 13 - LA opening in 2020



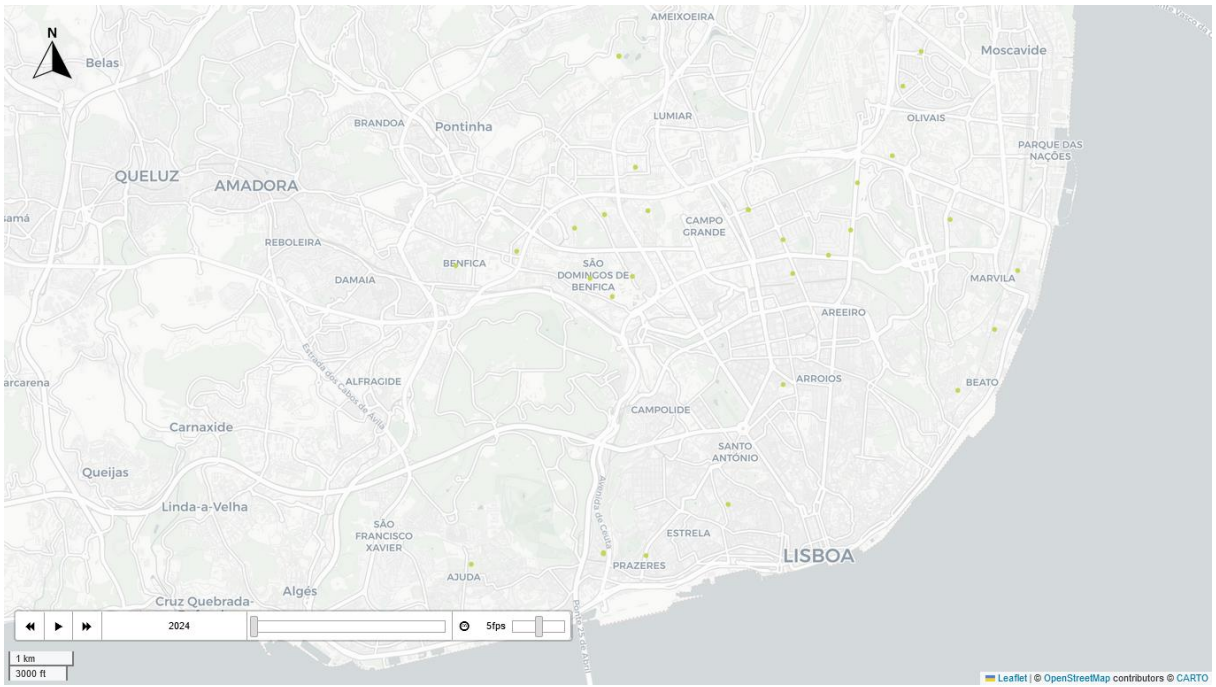
Appendix A Figure 14 - LA opening in 2021



Appendix A Figure 15 - LA opening in 2022



Appendix A Figure 16 - LA opening in 2023



Appendix A Figure 17 - LA opening in 2024

APPENDIX B - SURVEY

I am conducting this survey as part of my thesis, aimed at finding alternative locations for local accommodations in Lisbon rather than its historical center, in order to counteract the gentrification problem. Thus, the purpose of this survey is to understand the main factors that influence a tourist's choice when selecting a local accommodation to stay. Therefore, if you usually travel and stay in local accommodation establishments, such as Airbnb, I would appreciate your participation in this study, by answering this questionnaire that will only take a few minutes and is completely anonymous.

In this survey, a series of questions will be made for you to compare two criteria at a time based on your opinion when choosing the location of your accommodation in a foreign city. The scale used will be the following: equally important (1), moderately more important (3), much more important (5), very much more important (7), and absolutely more important (9). Intermediate values distinguish similar alternatives.
For each pair of criteria, you will be asked two questions. The first one will be for you to compare criterion A with criterion B and the second one will be to compare criterion B with criterion A. If you consider criterion A to be the most important, answer only the first question regarding that pair of criteria. If you consider criterion B to be more important than criterion A, do not answer the first question regarding this pair of criteria, and answer only the second one. If you consider both criteria equally relevant, you can answer only one of the questions.

Proximity to public transportation hubs VS proximity to the airport

1. How important is the proximity to public transportation hubs (metro stations, bus stops) when compared to the proximity to the airport? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

2. How important is the proximity to the airport when compared to the proximity to public transportation hubs (metro stations, bus stops)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to public transportation hubs VS proximity to tourist attractions

3. How important is the proximity to public transportation hubs (metro stations, bus stops) when compared to the proximity to tourist attractions (museums, parks, viewpoints, cultural sites)? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

4. How important is the proximity to tourist attractions (museums, parks, viewpoints, cultural sites) when compared to the proximity to public transportation hubs (metro stations, bus stops)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to public transportation hubs VS proximity to amenities

5. How important is the proximity to public transportation hubs (metro stations, bus stops) when compared to the proximity to amenities (restaurants, cafes, supermarkets)? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

6. How important is the proximity to amenities (restaurants, cafes, supermarkets) when compared to the proximity to public transportation hubs (metro stations, bus stops)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to public transportation hubs VS proximity to a police station

7. How important is the proximity to public transportation hubs (metro stations, bus stops) when compared to the proximity to a police station? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

8. How important is the proximity to a police station when compared to the proximity to public transportation hubs (metro stations, bus stops)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to public transportation hubs VS proximity to healthcare facilities/pharmacies

9. How important is the proximity to public transportation hubs (metro stations, bus stops) when compared to the proximity to healthcare facilities and pharmacies? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

10. How important is the proximity to healthcare facilities and pharmacies when compared to the proximity to public transportation hubs (metro stations, bus stops)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to public transportation hubs VS accommodation price

11. How important is the proximity to public transportation hubs (metro stations, bus stops) when compared to the accommodation price? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

12. How important is the the accommodation price when compared to the proximity to public transportation hubs (metro stations, bus stops)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to the airport VS proximity to tourist attractions

13. How important is the proximity to the airport when compared to the proximity to tourist attractions (museums, parks, viewpoints, cultural sites)? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

14. How important is the the proximity to tourist attractions (museums, parks, viewpoints, cultural sites) when compared to the proximity to the airport?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to the airport VS proximity to amenities

15. How important is the proximity to the airport when compared to the proximity to amenities (restaurants, cafes, supermarkets)? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

16. How important is the the proximity to amenities (restaurants, cafes, supermarkets) when compared to the proximity to the airport?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to the airport VS proximity to a police station

17. How important is the proximity to the airport when compared to the proximity to a police station? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

18. How important is the the proximity to a police station when compared to the proximity to the airport?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to the airport VS proximity to healthcare facilities and pharmacies

19. How important is the proximity to the airport when compared to the proximity to healthcare facilities and pharmacies? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

20. How important is the the proximity to healthcare facilities and pharmacies when compared to the proximity to the airport?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to the airport VS accommodation price

21. How important is the proximity to the airport when compared to the accommodation price? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

22. How important is the accommodation price when compared to the proximity to the airport?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to tourist attractions VS proximity to amenities

23. How important is the proximity to tourist attractions (museums, parks, viewpoints, cultural sites) when compared to the proximity to amenities (restaurants, cafes, supermarkets)? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

24. How important is the proximity to amenities (restaurants, cafes, supermarkets) when compared to the proximity to tourist attractions (museums, parks, viewpoints, cultural sites)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to tourist attractions VS proximity to a police station

25. How important is the proximity to tourist attractions (museums, parks, viewpoints, cultural sites) when compared to the proximity to a police station? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

26. How important is the proximity to a police station when compared to the proximity to tourist attractions (museums, parks, viewpoints, cultural sites)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to tourist attractions VS proximity to healthcare facilities and pharmacies

27. How important is the proximity to tourist attractions (museums, parks, viewpoints, cultural sites) when compared to the proximity to healthcare facilities and pharmacies? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

28. How important is the proximity to healthcare facilities and pharmacies when compared to the proximity to tourist attractions (museums, parks, viewpoints, cultural sites)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to tourist attractions VS accommodation price

29. How important is the proximity to tourist attractions (museums, parks, viewpoints, cultural sites) when compared to the accommodation price? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

30. How important is the accommodation price when compared to the proximity to tourist attractions (museums, parks, viewpoints, cultural sites)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to amenities VS proximity to a police station

31. How important is the proximity to amenities (restaurants, cafes, supermarkets) when compared to the proximity to a police station? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

32. How important is the proximity to a police station when compared to the proximity to amenities (restaurants, cafes, supermarkets)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to amenities VS proximity to healthcare facilities and pharmacies

33. How important is the proximity to amenities (restaurants, cafes, supermarkets,) when compared to the proximity to healthcare facilities and pharmacies? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

34. How important is the proximity to healthcare facilities and pharmacies when compared to the proximity to amenities (restaurants, cafes, supermarkets)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to amenities VS accommodation price

35. How important is the proximity to amenities (restaurants, cafes, supermarkets) when compared to the accommodation price? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

36. How important is the accommodation price when compared to the proximity to amenities (restaurants, cafes, supermarkets)?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to a police station VS proximity to healthcare facilities and pharmacies

37. How important is the proximity to a police station when compared to the proximity to healthcare facilities and pharmacies? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

38. How important is the proximity to healthcare facilities and pharmacies when compared to the proximity to a police station?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to a police station VS accommodation price

39. How important is the proximity to a police station when compared to the accommodation price? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

40. How important is the accommodation price when compared to the proximity to a police station?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

Proximity to healthcare facilities and pharmacies VS accommodation price

41. How important is the proximity to healthcare facilities and pharmacies when compared to the accommodation price? If you consider the second criterion to be more important than the first, answer only the next question.

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

42. How important is the accommodation price when compared to the proximity to healthcare facilities and pharmacies?

1	2	3	4	5	6	7	8	9

Equally important — Absolutely more important

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