Universidade Federal da Paraíba

Centro de Tecnologia

PROGRAMA DE PÓS-GRADUAÇÃO EM ENGENHARIA CIVIL E AMBIENTAL

–DOUTORADO –

IMPACTO DE VARIÁVEIS DA FORMA URBANA E DA TEMPERATURA DE SUPERFÍCIE NAS CONDIÇÕES CARDIORRESPIRATÓRIAS DE MORADORES EM ÁREAS DO MUNICÍPIO DE JOÃO PESSOA

Por

Alinny Dantas Avelino

Tese de Doutorado apresentada à Universidade Federal da Paraíba para obtenção do grau de Doutor

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RESUMO

As complexas interações entre a forma urbana e o ambiente térmico urbano são um dos principais fatores que contribuem para os problemas de saúde, sociais, econômicos e ambientais causados pela urbanização. Esta tese tem como objetivo estudar a relação entre temperatura superficial e variáveis de forma do ambiente urbano e o número de mortes cardiorrespiratórias entre moradores de áreas do município de João Pessoa entre 2013 e 2019. A ocupação urbana desordenada está associada a cenários urbanos de risco. O efeito desta ocupação na saúde cardiorrespiratória é um problema complexo que precisa ser avaliado em múltiplos níveis, mas a maior parte das pesquisas que tratam de ambiente construído e térmico foca em situações extremas ou na variabilidade da temperatura. Este estudo investiga as correlações entre fatores de urbanização como uso do solo, número de andares dos edifícios e presença de áreas verdes e taxas de mortalidade cardiorrespiratória na área. Imagens do satélite Landsat 8 foram utilizadas para aquisição da temperatura superficial (Ts) de bairros específicos da cidade. Os registros sanitários oficiais e os mapas das cidades foram obtidos junto aos órgãos reguladores sanitários oficiais de João Pessoa. As plataformas QGis e R foram utilizados para desenvolver mapas de densidade da ocorrência de mortes, análise de vizinho mais próximo, correlação de Pearson e modelos de regressão entre os dados de temperatura de superfície e forma urbana e as mortes ocorridas em João Pessoa por causas cardiorrespiratórias entre 2013 e 2019. O estudo revela uma correlação positiva entre temperaturas superficiais mais elevadas e taxas aumentadas de mortes cardiorrespiratórias. A análise de vizinho mais próximo observa que há uma relação de cluster entre a localização das mortes no município. Além disso, constatou-se que aspectos da forma urbana, nomeadamente a presença de áreas comerciais e áreas de uso misto, afetam significativamente as taxas de mortalidade, especialmente entre as populações mais idosas. Os espaços verdes não mostraram um impacto estatisticamente significativo na mitigação destes resultados em várias escalas de análise. Estas conclusões destacam as implicações críticas do desenho urbano e do uso do solo na saúde pública, particularmente face às alterações climáticas. É necessária uma abordagem integrada no planejamento urbano que considere os impactos na saúde da forma urbana e das temperaturas da superfície. Um simples aumento de áreas verdes pode não ser suficiente; é crucial avaliar a distribuição de lotes entender como diferentes elementos urbanos interagem para afetar a saúde dos

moradores, uma vez que mudanças como a integração de lotes comerciais ou mistos pode afetar positivamente a saúde e longevidade dos residentes. Dessa forma, destaca-se a necessidade de mais investigação para solidificar estas observações e explorar os mecanismos subjacentes a estas relações.

PALAVRAS-CHAVE: forma urbana, temperatura superficial, mortes cardiorrespiratórias, planejamento urbano, saúde pública.

ABSTRACT

Complex interactions between urban form and the urban thermal environment are one of the main factors that contribute to the health-related, social, economic, and environmental problems caused by urbanization. This thesis aims to study the relationship between surface temperature and form variables of the urban environment and the number of cardiorespiratory deaths among residents of 10 neighborhoods of João Pessoa between 2013 and 2019. Disordered urban occupation is associated with risky urban scenarios. The effect of this occupation on cardiorespiratory health is a complex problem that needs to be evaluated at multiple levels, but most research dealing with the built and thermal environment focuses on extreme situations or temperature variability. This study investigates the correlations between urbanization factors such as land use, building height, and the presence of green areas and cardiorespiratory mortality rates in the area. Landsat 8 satellite images were used to obtain surface temperature (Ts) of specific neighborhoods in the city. Official health records and city maps were obtained from the official health regulatory agencies in João Pessoa. The QGis and R platforms were used to develop death density maps, nearest neighbor analysis, Pearson correlation, and regression models between surface temperature and urban form data and deaths in João Pessoa from cardiorespiratory causes between 2013 and 2019. The study reveals a positive correlation between higher surface temperatures and increased rates of cardiorespiratory deaths. Nearest neighbor analysis shows that there is a cluster relationship between the location of deaths in the area. Additionally, it was found that aspects of urban form, particularly the presence of commercial areas and mixed-use areas, significantly affect mortality rates, especially among older populations. Green spaces did not show a statistically significant impact in mitigating these outcomes at various scales of analysis. These findings underscore the critical implications of urban design and land use in public health, particularly in the face of climate change. An integrated approach to urban planning that considers the health impacts of urban form and surface temperatures is necessary. Simply increasing green areas may not be enough; it is crucial to assess lot distribution and understand how different urban elements interact to affect residents' health, as changes like integrating commercial or mixed-use lots may positively affect residents' health and longevity. Thus, there is a need for further research to solidify these observations and explore the mechanisms underlying this relationship.

KEYWORDS: urban form, surface temperature, cardiorespiratory deaths, urban planning, public health.

SUMMARY

LIST OF ABBREVIATIONS

LST – Land Surface Temperature

ICD – International Classification of Diseases

QGIS – Quantum GIS

AIC – Akaike Information Criterion

IC – Confidence Interval

OSM – Open Street Map

TIRS – Thermal Infrared Sensor

OLI - Operational Land Imager

NVDI - Normalized Difference Vegetation Index

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1 INTRODUCTION

Climate change is becoming an emergency in different locations, and temperatures are rising across the globe. Anthropogenic actions associated with land use already contribute to large disasters and heat islands caused by climate change (Jacobi; Sulaiman, 2016). Consequently, cities and urban areas are increasingly recognized as strategic arenas for climate change action (Broto, 2017).

João Pessoa, located in Brazil's tropical northeast, experiences high temperatures year-round. The effect of climate change, which is also associated with higher temperatures, is being combined with the growth in verticalization, which provides less ventilation (Palusci; Cecere, 2022; Ng, 2008; Chow, 2004), which has made areas of João Pessoa behave as heat islands. It is, therefore, critical to understand its causes and consequences to develop effective strategies to prevent and reduce heat-associated risks.

The potential implications of climate change on health must be given special attention. Some of the identified health impacts of climate change include increased frequency and severity of illnesses such as asthma, allergies, low birth weight, heat-related illnesses, and even mental health problems (Kemper; Etzel, 2020). However, the effect of climate change on cardiorespiratory health is a complex problem that needs to be addressed at multiple levels, which includes urbanization issues.

Urbanization and its impacts on human health are complex and vary according to the specific characteristics of each city and region. João Pessoa has experienced significant urban growth in recent decades, impacting several aspects of its urban form and the quality of life of its inhabitants. Industrial growth, population density, and greater use of vehicles are noted alongside the city's verticalization.

Urbanization has significantly changed city structure and spatial forms (Teknologi; Muslim; Koesmaryono, 2016). The verticalization and proximity of buildings in urban centers in hot climates such as João Pessoa cause a decrease in the average wind speed due to the increase in urban roughness (Ferreira; Cardoso, 2014). The reduction on average wind speed increases the temperature inside these buildings. Urban densification and different forms of use and coverage of the soil can be related to the processes of change occurring in the urban climate system.

Jacobi and Sulaiman (2016) state that the form and occupation of land in disordered occupation are associated with the urban risk scenarios raised in this research. Regarding the climate change and heat issues concerning João Pessoa, urban areas' form exacerbates this situation. Urbanization usually results in a significant increase in surface temperatures (Ts), which contributes to the overheating of the air in urban areas (Kuttler, 2008).

Surface temperature is one component of a region's temperature and can be measured over wider regions via satellite. It is also a determinant as it affects urban thermal comfort. According to the United States Geological Survey (USGS), the satellite Landsat 8, among other important variables, infers the Earth's surface temperature.

Urban morphology refers to the physical form of a city, including the layout of buildings, road patterns, land use, and green spaces (Lau, 2011). Studies have shown that a city's urban morphology can affect air dispersion (Edussuriya; Chan; Ye, 2011; Hang *et al.,* 2012; Li; Tsang; Edwards, 2011) induce urban heat islands (Siu; Hart, 2012; Wong, P. *et al.,* 2016), cause health problems (Ng; Cheng, 2012; Wong, P. *et al*., 2016), and influence energy consumption (Wong, N. *et al*., 2011). Urban morphology can also affect the quality of urban life and the pleasure of living, leading to overcrowding, congestion, air pollution, and lack of green spaces (Lai *et al.,* 2018).

Urban morphology includes several variables that may influence the population's health, such as land use, roads, and proximity of buildings. The characteristics that create the morphology of a city frequently contribute to urbanization issues that may stem from them. The evolution of research and risk assessment methods and the increase in the volume of data grounds an increase in the number of links between health and the environment

In 2019, 18.6 million cardiovascular and 4.1 million respiratory disease deaths occurred globally (Prüss-Ustün *et al*., 2016). João Pessoa recorded 34,930 deaths between 2013 and 2019, 13,608 of which were caused by cardiovascular and respiratory diseases (DataSUS website, 2024). Some of these deaths could have been avoided.

Lifestyle choices have often been associated with cardiovascular and respiratory diseases of different natures. 23% of global deaths and 26% of deaths among children under five are caused by modifiable environmental factors (Prüss-Ustün *et al.,* 2016).

Urban areas' form exacerbates these unnecessary deaths. Lack of urban planning and the absence of green areas in the city may cause a rapid shift in energy balance and consequent intensification of heat islands (Teknologi; Muslim; Koesmaryono, 2016). They can contribute to poor air quality, magnify the impacts of extreme heat events, and put people's health at higher risk (United States Environmental Protection Agency, 2021). The resultant health effects include diseases communicated by vectors, water, and food and non-communicable diseases, especially cardiovascular, cerebrovascular, and respiratory illnesses (Hobbhahn *et al.,* 2019).

In addition, there are increasing concerns about the physical and mental health consequences of climate change, especially for vulnerable populations such as children, older people, the sick, and marginalized groups (Andrade, 2021; Wang Q. *et al.,* 2018).

Despite these connections between urbanization, temperature, and health, most scientific research focuses on whether certain deaths stem from extreme heat or temperature variability (Ma, Zhou; Chen, 2020; Khatana; Werner; Groeneveld, 2022). However, the effect of climate change on cardiovascular health is a complex problem that needs to be addressed at multiple levels.

The consequence of this urbanization-caused changes is an urban form that has been increasingly pointed out as causing diseases across the planet (Choe *et al.,* 2018; Chum; O'Campo; Matheson, 2015; Dzhambov *et al.,* 2018; Ebisu *et al*., 2016; Engemann *et al.,* 2019; Madzia *et al*., 2019; Ramezankhani *et al*., 2018). Furthermore, the available research did not provide any studies relating to surface temperature, urban form, and diseases as intended by this research.

One of the main factors contributing to the health-related, social, economic, and environmental problems caused by urbanization is the complex interactions between the urban form and the urban thermal environment.

The main goal of this research was to examine the relationship between surface temperature and form variables of the urban environment and the number of cardiorespiratory deaths among residents of areas in João Pessoa. It combines remote sensing with death data provided by the city's authorities to identify critical points. It shows a relationship between land use and death rate that may provide the city with a new view on city land usage, motivating the city to consider mixed-use areas as a way to keep its population healthy in the future.

1.1 Objective

<u>*Main objective:*</u>

Study the relationship between surface temperature, the urban environment variables, and the number of cardiorespiratory deaths in neighborhoods of João Pessoa.

<u>*Specific Objectives:*</u>

a) Analyze the literature on the relationship between urbanization factors and health issues;

b) Study the relationship between surface temperature and the number of cardiorespiratory deaths in neighborhoods in the city of João Pessoa;
c) Analyze the relationship between urban form characteristics and the number of cardiorespiratory deaths in neighborhoods in João Pessoa.

1.2 Thesis's structure

The first chapter of this thesis builds the basis for the work by presenting an introduction to the topic, the objectives and hypotheses evaluated, the structure of the work, and the general methodology applied.

The second chapter deals with an exploratory review of the literature, seeking to identify the gaps that exist in the study of the relationship between diseases and urban form. It highlights the need for advancement in research regarding the study of this form with the advancement of the climate problem.

The third chapter locates and describes the analyzed area's climate and land characteristics. It also highlights the urbanization process and the consequences on the neighborhoods in this research.

The fourth chapter proposes the methodology to be applied to this research. It explains the acquisition process for the disease, form, and temperature variables. It also describes the processing procedure for the maps generated on QGIS and the statistical tests and analyses performed.

The fifth chapter presents the results of this research in the same order that the methodology proposes. It shows the relationship between temperature and death occurrences in João Pessoa and the model built using the form variables collected as independent variables to the death occurrence as the dependent variable.

The final chapter of the thesis will combine information on the context, motivation, and purpose of the previous chapters with suggestions for future work presenting this thesis's conclusions.

1.3 Hypothesis

This research hypothesizes that aspects of urban form are linked to the incidence of cardiorespiratory disorders in João Pessoa. It further suggests that characteristics of urban form influence temperature variation within the city. Additionally, the study posits that the surface temperature in João Pessoa reflects the incidence of cardiorespiratory diseases, indicating a strong correlation between urban form, temperature, and health outcomes.

2 LITERATURE REVIEW

This chapter has five subsections. The first shows the results of extensive exploratory research conducted to identify the issue to be explored in the thesis. The second discusses temperature and its variables. The third gives specifications in surface temperature as this research's primary variable. Subsection four discusses urban form, and the fifth is cardiovascular disease.

2.1 Exploratory research

A World Health Organization (WHO) report published in 2016 concluded that environmental risks represent a significant fraction of the global disease burden (Prüss-Üstün *et al.,* 2016). Environmental impacts on health are unequal across the life course and gender, but low- and middle-income countries have the highest share of environmental disease, and evidence of the quantitative links between health and the environment has increased.

This chapter presents a systematic survey of articles that relate one or more diseases to one or more environmental risk factors. The purpose of this research is to find out what diseases may be influenced by environmental urbanization factors. Moreover, it identifies what factors have been found in the literature as related to diseases and what the nature of these relationships between disease and urbanization factors is.

A search was performed in the Scopus database using seven words related to urbanization (urbanization, Urban development, environment, pollution, deforestation, urban density, and contamination) combined with the word "disease" and four others related to it (illness, disorder, infection, health). A total of 200,931 articles were found. Criteria of elimination were applied to remove any articles related to animals that were not written in English, Portuguese, or French and articles that were not reviewed by peers. There was also an applied rule for inclusion: the paper had to correlate a disease to an urbanization factor and be published from 2014 to 2019. Figure 1 synthesizes the process of exclusion and inclusion of the papers and the number of papers kept after each intervention.

Figure 1 – Literature review process

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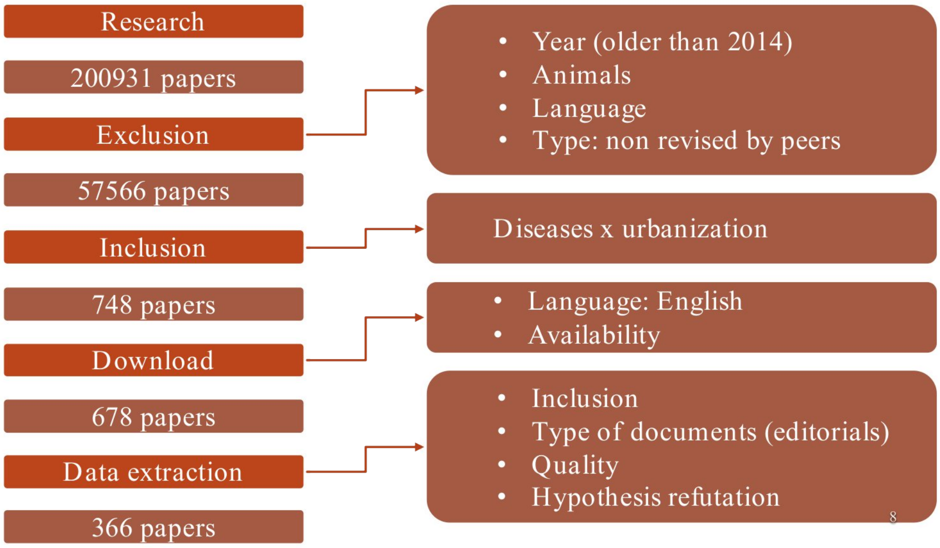
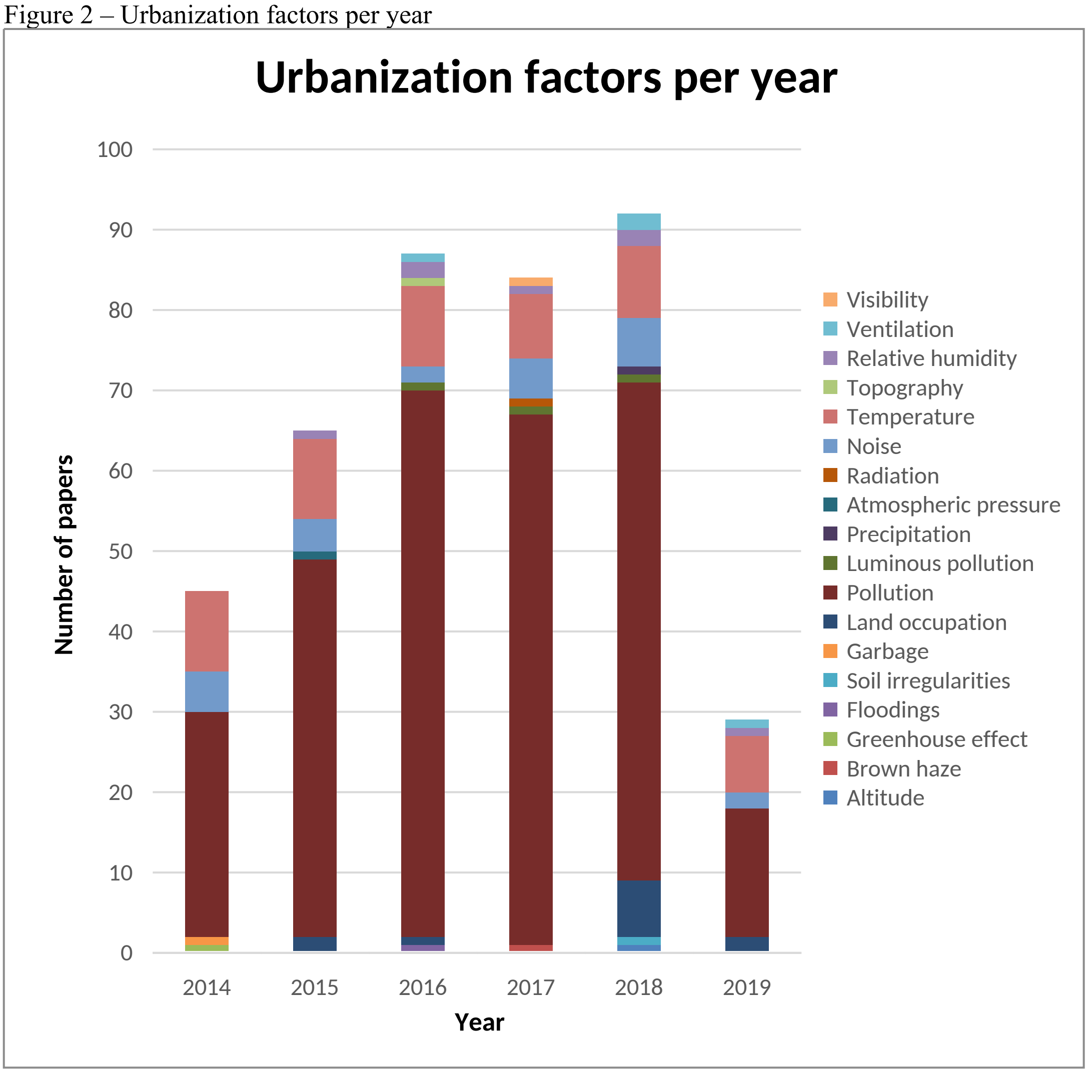


Source: Author

Figure 2 – Urbanization factors per year



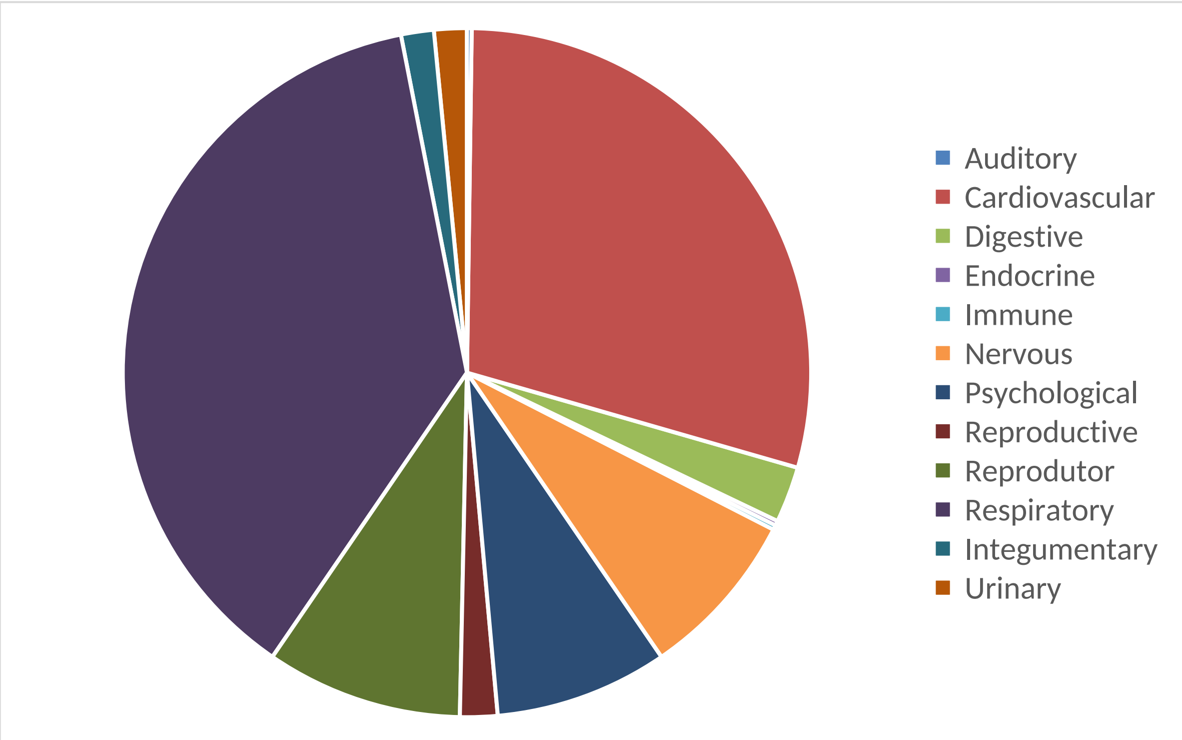
Source: Author

Figure 2 shows the organization factors studied by year. Pollution is the most analyzed issue, as it appears in many articles every year, mainly causing heart disease. The second factor most heavily studied is temperature. These results do not discriminate specific temperature variables as there are many (air temperature, radiation temperature, humid bulb temperature, land surface temperature, etc.). Soil occupation is one of the least studied urbanization factors in this research.

A relationship has been identified between land use and the occurrence of reproductive system diseases (Ren, 2016) and mental illnesses such as depression and anxiety (Dzhambov *et al*., 2018b; Engemann *et al*., 2018; Madzia *et al*., 2019; Chum; O'Campo, 2015; Bezold, 2018), but the literature still does not provide a link between cardiorespiratory diseases and urban form.

Figure 3 shows the systems most affected by the research. The respiratory system is the most affected, followed by the cardiovascular system and then the reproductive system. This picture does not represent any papers related to death that affect the whole body and cannot be restricted to one system. It also removes from the results any diseases, such as diabetes, which do not affect only one specific system.

Figure 3 – Affected body system's



Source: Author

Observing land use, Choe *et al.* (2018) used logistic regression to estimate the association between residential distance to green and blue spaces and gestational diabetes mellitus, gestational hypertension, and preeclampsia. The authors haven't found any evidence that being close to green spaces has an impact on these diseases.

Chum, O'Campo, and Matheson (2015) used multilevel logistic and multinomial logistic regressions to analyze the association between land use and sleep duration/problems in Toronto, Canada. The authors found positive associations between sleep problems/duration and commercial, residential, and industrial land use. They attributed this to noise and traffic. They also investigated green areas, but no relationship was found.

Pelgrims *et al*. (2021) evaluated the association of long-term exposure to air pollution, noise, surrounding green at different scales, and building morphology with several dimensions of mental health in Brussels. The authors found that air pollution was positively associated with higher odds of depressive disorders, but no association was found between the presence of green areas, noise, building morphology, and mental health.

On the other hand, Ebisu *et al.* (2016) used a linear mixed effects model and a logistic mixed effects model to identify associations between low birth weight and three land uses: urban space, urban open space, and green space in 250m buffers. The authors found protective associations between green space and improvements in both birth outcomes.

Engemann *et al*. (2019) linked higher green space exposure during childhood to a lower risk of various psychiatric disorders later in life. The authors created square areas around children's residences from age 0 to 10 measuring 210m by 210m, 330 by 330 m, 570 by 570 m, or 930 by 930 m and used Landsat to identify green areas. The correlation was only found on the 210 m-by-210 m distance.

Madzia *et al*. (2019) found a positive association between exposure to residential greenspace and reduced youth's problematic internal and external behaviors.

2.2 Temperature

The general term temperature describes the thermal state of a physical system. It is defined as the average measure of the kinetic energy of molecules in a system (Sullivan; Spencer, 2022; Cliffe, 1962). There are several types of temperature, and the exploratory research did not specify which temperature appears in the articles analyzed, so they may refer to one or more of these: air temperature, surface temperature, which leads to land surface temperature, radiation temperature, and atmospheric temperature.

Air temperature is the conventional measure of ambient temperature at a given location. It is influenced by solar radiation, humidity, and atmospheric pressure. Studies (Gao *et al*., 2015; Guo *et al.,* 2018; Lavigne *et al*., 2014; Ngo; Horton, 2016; Ponjoan *et al.,* 2017; X. Wang *et al*., 2015) have investigated the relationship between air temperature and extreme weather events, such as heatwaves.

Land surface temperature refers to the temperature of the earth's surface layer (Kumar, R.; Kumar, A., 2020; Abidin *et al.,* 2021). It varies depending on factors such as incident solar radiation, soil moisture, and vegetation cover (Liming *et al.* 2020). Radiation temperature is a measure of a body's temperature. It is determined by the rate of electromagnetic radiation emitted by the body (Rutgers, 1958).

Atmospheric temperature refers to the measure of the air's hotness or coldness, determined by the heat flow between bodies until thermal equilibrium is reached (Ahmad *et al.* 2022). It varies with altitude and is influenced by solar radiation, convection, and greenhouse gas concentrations.

Canopy temperature is the air temperature measured at the ground level of a tree canopy, including the tree's leaves, flowers, and fruit (Alonzo *et al.,* 2021). Canopy density, porosity, and vegetation type in urban aggregated green infrastructure influence cooling and humidifying effects (Wei *et al*., 2021). Therefore, Monitoring canopy temperature can help assess the effectiveness of urban greening initiatives in mitigating heat stress and improving urban microclimates.

Indoor temperature refers to the combination of radiations received through a building's roof and walls. These surfaces absorb and retain heat, contributing to elevated temperatures in urban areas (Ponni; Baskar, 2015). Indoor temperature is influenced by factors such as building design, insulation, HVAC systems, and occupant behavior. Maintaining comfortable indoor temperatures is essential for human health, productivity, and energy efficiency in urban environments (Salthammer; Morrison, 2022; Tong *et al.,* 2018).

According to forecasts by the Ministry of Science and Technology, the increase in average air temperature throughout Brazil of 3 to 6°C in the year 2100 compared to the end of the 20th century is one of the implications that will impact human beings (INCT for climate change, 2010).

Global warming is an intensifying problem that is generating unrest in society. A deterioration of baseline symptoms in cardiomyopathy patients from the Mayo Clinic was observed while experiencing a temperature change (Bois; Malenfant; Wahl Jean-Christophe; Danis, 2014).

Some research indicates that temperature variability can impact cardiovascular morbidity. However, some peer-reviewed work found no statistically significant links between heat and cardiovascular morbidity (Centers for Disease Control and Prevention, 2020).

In New England, research found that a rise in mean air temperature of 1°C was associated with variability in death rates related to cardiovascular diseases. The same paper shows that the increase in standard deviations of the average temperature increases mortality rates (Shi *et al.,* 2015).

In Mashhad (Iran), a strong positive association was found between the maximum air temperature obtained in the city and cardiovascular disease mortality (Baaghideh; Mayvaneh, 2017). These data show that high temperatures may increase the risk of cardiovascular deaths. However, they do not relate to how they influence cardiovascular and respiratory health outcomes over time.

Researchers in Dongguan, a subtropical city in China, pointed out the need to evaluate how increases in moderate temperatures contribute to temperature-related deaths. They found that exposure to non-optimal temperatures, either higher or lower, increased the risk of respiratory morbidity, and moderate heat contributed to most temperature-related respiratory morbidities (Zhao *et al*., 2019). In contrast, exposure to cold temperatures is associated with an increased risk of cardiovascular disease admission in four hospitals in Thai Nguyen Province analyzed between 2008 and 2012 (Giang *et al*., 2014).

In contrast, exposure to cold temperatures is associated with an increased risk of CVD admission in four hospitals in Thai Nguyen Province analyzed between 2008 and 2012 (Giang *et al*., 2014).

According to research conducted in China, Australia, India, and Spain, temperature-related cardiorespiratory mortality increases during overtime periods, using punctual data over a time period (Shen *et al*., 2021; Achebak; Devolder; Ballester, 2019; Lu *et al*., 2021)

Although some studies have shown that temperature variability over time affects mortality, research has yet to determine whether microclimate temperature variability influences it (Shi *et al*., 2015).

In this direction, 5896 participants' lung function was analyzed in the Northeastern U.S. Researchers used remote sensing to acquire temperature averages for their addresses from 2000 to 2011. The results indicate that lung function differed by temperature in the cohort. Researchers suggest behavioral changes on warm days may explain these differences (Rice *et al.,* 2019).

2.3 Surface temperature

Some studies suggest that there is a significant positive correlation between air temperature and land surface temperature, particularly during certain seasons, land cover types, and times of day (Al-Ruzouq *et al*., 2022; Cao *et al*., 2021; Gallo *et al*., 2011; Hill, 2013; Liu *et al*., 2022; Mutiibwa *et al*., 2015; Shen; Leptoukh, 2011; Sheng *et al*., 2017; Zhang *et al*., 2022).

In mountainous regions, the strongest correlations occur during late summer and fall and the weakest during winter and early spring (Mutiibwa *et al*., 2015). Vegetated areas have higher correlation coefficients than water and impervious surfaces (Sheng *et al.,* 2017).

In complex terrains, LST can serve as a valuable proxy for predicting near-surface air temperature (Tair) due to the scarcity of meteorological stations (Mutiibwa *et al*., 2015). Within cities, air temperature exhibits firm spatial heterogeneity with significant positive correlations with LST, especially in cloudy conditions that tend to reduce the differences and variability in the relationship between LST and air temperature when compared to clear-sky conditions (Cao *et al.,* 2021; Gallo *et al.,* 2011).

2.4 Urban Form

Urban form is a complex and dynamic concept encompassing the physical layout, structure, and design of urban spaces, their functionality, and the socioeconomic processes they encapsulate.

Urban form is influenced by social and economic processes, with innovation, diffusion, and constructional activity playing critical roles in shaping the arrangement of forms within cities, as well as regional variations in these activities affecting the character of different towns (Crooks; Pfoser; Lamprianidis, 2015; Wentz *et al*., 2018)

Urban form has a profound impact on sustainability and livability, influencing transportation systems, access to work and life opportunities, housing availability, and overall regional prosperity (Grosso, 1998). Marzukhi *et al*. (2020) examined depression and anxiety and their relationship with density and land use. The authors found that the mix and accessibility of land uses generated less stress and anxiety in residents.

Understanding the elements of urban form, such as structure, plot, building, block, and street pattern, is crucial for assessing urban areas' development potential and sustainability. No relationship was found between building height and health.

2.5 Cardiovascular and respiratory disease

Cardiovascular diseases are a group of multifactorial disorders affecting the heart and blood vessels caused by genetic and environmental factors (Davidson, 1994; Kathiresan; Srivastava, 2012; Kalayinia *et al.,* 2020). Known environmental issues are ambient air pollution and metal exposure. It includes diseases such as coronary artery disease, cardiac dysrhythmias, congestive heart failure, and myocardial infarction, among others (Kathiresan; Srivastava, 2012; Kalayinia *et al.,* 2020). They negatively affect the body and, when developed, may affect the blood circulation to the kidneys and the brain and result in death. Cardiovascular diseases are the leading house of death globally (Flora; Nayak, 2019).

Respiratory diseases are a group of disorders affecting the airways and lungs, including a wide range of superior (nose, larynx, and trachea) and inferior (lungs) conditions such as asthma, chronic obstructive pulmonary disease, acute respiratory infections, tuberculosis, lung cancer, bronchitis, and pneumonia (GBD chronic respiratory disease collaborators, 2017; Ferkol; Schraufnagel; 2014). These diseases can cause symptoms such as cough, shortness of breath, and difficulty breathing, which may lead to reduced function and socioeconomic impacts. Like cardiovascular diseases, respiratory diseases are multifactorial, and the leading causes are viruses and bacteria that badly interact with the superior respiratory tract (Zhang *et al.,* 2020; Dowell *et al.,* 1996).

The exploratory phase of this research delved into the relationship between urban factors and diseases. When properly discussing respiratory and cardiovascular diseases, most of the relationships were with pollution, a manmade known problem, especially regarding the respiratory system. Land use and the cardiovascular system were only associated by Choe *et al.* (2018) as they evaluated the impact of blue and green spaces presence on pregnant women's hypertension, amongst other health outcomes. The authors could not find a relationship between green presence and this outcome.

Most studies relating temperature and cardiorespiratory diseases have it associated with another factor. For instance, Lin *et al.* (2017) associated short-term exposure to high temperatures with Kawasaki disease. However, the purpose of their study included pollution that ended up not having any link to Kawasaki disease, according to the authors. Sherbakov *et al.* (2018) used distributed lag nonlinear models to find diseases that affect the entire body were associated with higher temperatures and heat waves, among ischemic stroke.

Li *et al.* (2014) found a linear relationship between respiratory symptoms in asthmatic children and the air temperature in China. Wang *et al.* (2015) found data that extreme temperatures, both high and low, increased the susceptibility to hypertensive disease and ischemic heart disease. Qiu *et al.* (2015) focused on temperature variability and found that more significant temperature variation increased the risk of asthma exacerbation.

In Brazil, Zhao *et al.* (2019) identified that a temperature variability of 5 °C was associated with the risk of ischemic heart disease, particularly in men and in older age groups.

Table 1 - Relationship between diseases and urban factors

Urban factor	Cardiovascular	Respiratory
Garbage		1
Pollution	133	208
Noise	7	3
Temperature	7	12
Topography		1
Relative humidity		2
Land use	1	
Ventilation		1
Total finds	148	228

Source: author

3 CHARACTERISTICS OF THE STUDY AREA

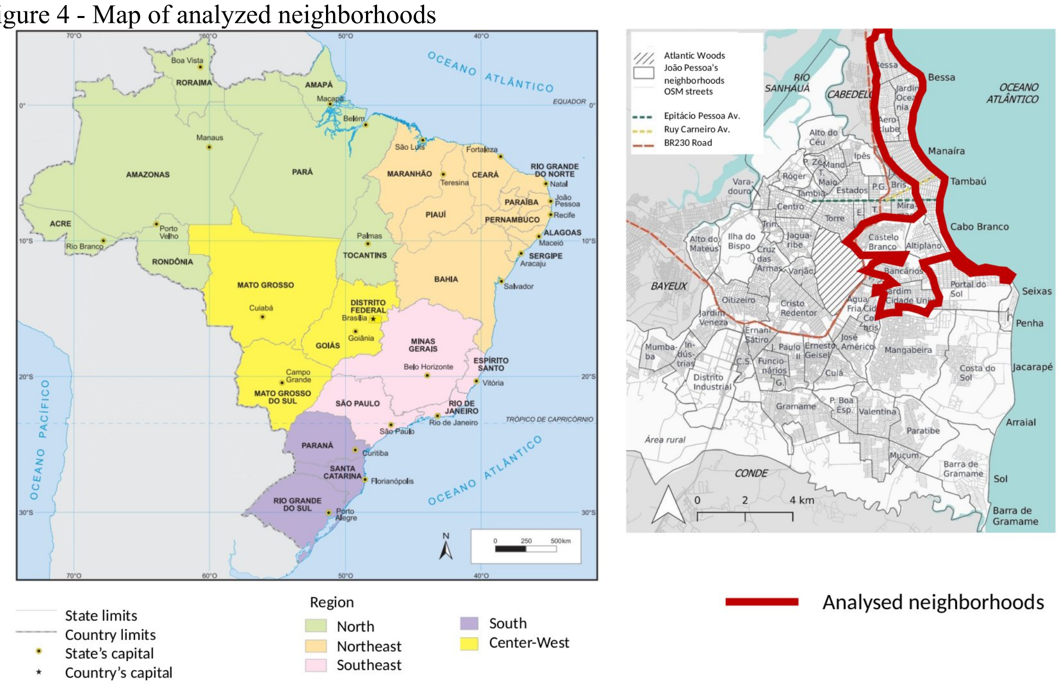
João Pessoa, the coastal capital of Paraiba, a northeastern state in Brazil, serves as both a regional epicenter and a thriving urban nucleus (Instituto Brasileiro de Geografia e Estatística, 2018). The city has a population numbering 825,796 individuals, encompassing a land area of 211.29 km², resulting in a gross population density of 3,908.35 inhabitants per square kilometer. Under the Köppen and Geiger classification, João Pessoa experiences a tropical savanna climate marked by dry-winter conditions, where the mean temperature averages around 25.8 °C, and annual rainfall registers at 1,019 mm.

João Pessoa is located in a tropical savanna climate with dry-winter conditions, by Köppen e Geiger climate classification. The average air temperature is 25.8 °C, and the average rainfall is 1019 mm. This urban landscape is distinguished by a varied topography, encompassing plains and gentle hills, and it also contains a rich diversity of ecosystems, including mangroves, coastal dunes (restingas), and forests. These geographical facets play a pivotal role in the region's ecology and the well-being of its inhabitants. Moreover, João Pessoa has witnessed significant economic growth in recent decades, with sectors such as tourism, commerce, services, and industry contributing substantially to its economy.

In this context, environmental preservation has emerged as a pressing concern for the city, prompting measures to safeguard its natural resources, promote sustainability, and address environmental challenges. Examples include beach closures in areas prone to erosion, contentious beach expansion projects, and a constitutional provision that restricts the construction of high-rise buildings along the coastline of coastal cities.

The area also portrays different socioeconomic and morphological portions of the city. Factors such as topography, wind, and proximity to the ocean influence the climate, diversifying the sample to represent the city's population and form accurately. Figure 4 highlights the neighborhoods chosen for this research. They were chosen to represent different urban forms without presenting significant socioeconomic differences.

Figure 4 - Map of analyzed neighborhoods



Source: adapted from IBGE website (2024) and Donegan e Alves (2022)

The neighborhoods to be analyzed in this thesis are Bessa, Jardim Oceania, Manaíra, Aeroclube, Cabo Branco, Tambaú, Altiplano, Castelo Branco, Cidade Universitária and Bancários.

Bessa is a primarily residential neighborhood expanding in the eastern part of João Pessoa. It is known for its coastal location and proximity to beaches. Despite being mostly residential, it features a growing number of commercial establishments, including a mix of high-rise apartment buildings, condominiums, and single-family homes. Along the main avenues are shopping centers, supermarkets, restaurants, and cafes catering to residents' daily needs.

Next to Bessa, Jardim Oceania is also predominantly residential with limited commercial activity. Single-family homes, townhouses, and low-rise apartment buildings characterize it.

Manaíra is known for its nightlife and Manaíra, where there are upscale hotels and beachfront properties for tourists. It encompasses a diverse mix of residential and commercial buildings, including high-rise condominiums, luxury apartments, and single-family homes. The neighborhood is known for Manaíra Shopping, one of the largest shopping centers in João Pessoa, which offers a wide range of retail stores, restaurants, cinemas, and entertainment venues.

Aeroclube is primarily a residential neighborhood with limited commercial activity. Single-family homes, townhouses, and mid-rise apartment buildings characterize it.

Cabo Branco is primarily residential. Cabo Branco and its waterfront promenade are popular leisure and recreation commercial spots. Castelo Branco is a residential neighborhood with a mix of housing options. It features single-family homes, townhouses, and low-rise apartment buildings. The neighborhood offers a quiet living environment with tree-lined streets and green spaces. While some commercial establishments, such as local shops and cafes, serve the community, the area is primarily residential.

Altiplano is predominantly residential, with some clubs, associations, and performance establishments. The neighborhood varies between very high-average and low-density areas (Filipeia website).

For all these neighborhoods, until 2019, João Pessoa documented its mortality data using the International Classification of Diseases, 10th edition (ICD 10). Consequently, this research encompasses all illnesses falling under the purview of chapters 10 and 11 of the ICD 10. The ICD is a global system that assigns unique codes to over 55,000 diseases worldwide. This classification system facilitates statistical analysis and maintains records of individuals' illnesses and mortalities.

Notably, the ICD 10 underwent an update, transitioning to the ICD 11 in 2019, with its implementation commencing in 2022 (ICD website, 2022). Each chapter within these classifications corresponds to a distinct category of diseases. In this transition, diseases related to the circulatory system, formerly housed in Chapter 10 of the ICD 10, have been relocated to Chapter 11 in the ICD 11. Similarly, previously situated in Chapter 11, respiratory diseases are now categorized under Chapter 12 urban forms without presenting significant socioeconomic differences.

4 MATERIALS AND METHODS

This chapter presents the methodology to be applied to this research. It explains the acquisition process to the disease, urban form and temperature variables. It also describes the processing procedure of the maps generated on Qgis and the statistical tests and analysis performed.

4.1 Surface Temperature

Surface temperature was chosen as a climate variable because it may be acquired spatially distributed and analyzed through satellites for large areas. Satellite images were acquired from the United States Geological Survey (USGS) website from Landsat 8 between 2013 and 2019. These images are freely available on the USGS website. Images came from a Thermal Infrared Sensor (TIRS) that captures radiance from the surface. Landsat 8 began registering the necessary bands (images) to calculate the surface temperature in 2013.

Table 2 shows temperature, humidity, and precipitation information for the days the images were acquired. João Pessoa has one climate station in the city and one in the airport, but since the airport is in the metropolitan region, only data from the station in the city was used. Most images were obtained between November and December when the temperature was high and precipitation was low in João Pessoa. The exception was made for 2018 and 2014 due to the lack of cloud-free images.

Table 2 – Climate information for the image date

Date received	Max. Registered temperature	Min. Registered temperature	Max. relative Humidity	Max. precipitation (24h)
03/12/2013	31.5	24.4	57.0	0.0
26/04/2014	32.1	23.7	57.0	0.0
23/11/2015	31.6	25.0	51.0	0.0
25/11/2016	32.4	25.3	66.0	0.0
30/12/2017	32.4	26.6	67.0	0.0
27/08/2018	30.2	20.9	62.0	0.4
04/12/2019	32.5	24.1	63.0	0.0

Source: INMET website

The images were obtained in level 1 pre-processing. Radiance was calculated using images from bands 10 and 11 as shown in Equation 1 (United States Geological Survey, 2024).

$$L_\lambda = M_L Q_{cal} + A_L \qquad \text{Equation 1}$$

where:

L_λ = Top of atmosphere radiance (W/(m^2*sr*mm))

M_L = Band-specific multiplicative rescaling factor from the metadata

Q_{cal} = Quantized and calibrated standard product pixel values

A_L = Band-specific additive rescaling factor from the metadata

Landsat 8-TIRS radiance data is made available with digital number according to radiometric resolution which need to be converted to top of atmosphere level 1 radiance. The radiance was then converted to brightness temperature using Equation 2 (United States Geological Survey, 2024).

$$T = \frac{K_2}{ln\left(\frac{K_1}{L_\lambda} + 1\right)} \qquad \text{Equation 2}$$

where:

L_λ = Top of atmosphere radiance (W/(m^2*srad*mm))

K_1 = Band-specific thermal conversion constant from the metadata

T = Top of atmosphere brightness temperature (K)

K_2 = Band-specific thermal conversion constant from the metadata

Images from Bands 4 and 5 from the Operational Land Imager (OLI) sensor were then used to calculate the Normalized Difference Vegetation Index (NVDI), which identifies areas on the map with higher vegetation cover. Vegetation cover influences on land emissivity which is why this information was later used to calculate emissivity using Equation 3. The average and the difference between emissivity on bands 11 and 10 were used in the next step.

$$LSE = \varepsilon_S\left(1 - \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2\right) + \varepsilon_V\left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \qquad \text{Equation 3}$$

where:

LSE = Land surface emissivity

ε_S = Band-specific land emissivity

$NDVI$ = Normalized Difference Vegetation Index

$NDVI_{min}$ = Minimum normalized Difference Vegetation Index

$NDVI_{max}$ = Maximum normalized Difference Vegetation Index

ε_V = Band-specific vegetation emissivity

All the indexes mentioned above are used to calculate the surface temperature through equation 4 (Jiménez-Muñoz, Sobrino, Skoković, Mattar, & Cristóbal, 2014):

$$T_{sup} = T_{b10} + 1{,}378\,(T_{b10} - T_{b11}) + 0{,}183\,(T_{b10} - T_{b11})^2 - 0{,}268 + (54{,}3 - 2{,}238\omega)\,(1 - \varepsilon) + (-\,129{,}2 + 16{,}4\omega)\,\Delta\varepsilon \quad \text{Equation 4}$$

Where:

T_{b10} = brightness temperature of the band 10 image

T_{b11} = brightness temperature of the band 11 image

ω = total vapor in the atmosphere

ε = surface emissivity average

$\Delta\varepsilon$ = emissivity difference between the bands.

4.2 Urban form data

The free software QGIS version 2.18.2 (Quantum GIS) was used to process and make the data available. This software is widely used in scientific research and is freely accessible. It allows for the creation of maps for the studied neighborhoods, as well as the visualization, editing, and analysis of georeferenced data (Gouveia, 2011).

The official lot division map by blocks, in layer form, compatible with QGIS, is available on the Filipeia portal (Filipeia website, 2024), and the free software Google Earth was used to demarcate the lots and areas of each of the neighborhoods in this study. Filipeia is the official digital atlas of João Pessoa, in which the city offers a collection of maps and geographical data to the citizens. For each lot, the number of floors, type of land use, and presence of green area were obtained through the block map with a satellite map.

The *OpenLayers* Plugin provided by QGIS was used to visualize Bing Maps' satellite imagery and its association with the lot map. This process involved overlaying the satellite map with the lot layer and creating a layer classifying the number of building floors. Data collection for this new layer was conducted through observation using the Google Street View tool on Google Earth, enabling the visualization of each lot to count the building floors and see the land use. In locu validation was conducted, when necessary, in situations and points of construction, and when the Street View map was outdated.

Every piece of information in the lot was categorized as a number so that it could be statistically analyzed in the next stage. Table 3 explains the characterization used for each variable. It shows the variable inserted in the software, the number used to represent it since the software cannot make regressions with string data, and what each number represents.

Table 3 – Variable characteristics and software representation

Variable	Number	Representation
Number of floors	Any	0 means no construction, any other number represents the proper number of floors in the building
Land use	1	Underutilized or parking
	2	Residential
	3	Commercial
	4	Mixed (residential and commercial)
	5	Square
Green area	1	Presence
	2	Absence

Source: author

4.3 Disease data

Information regarding cardiovascular and respiratory fatalities spanning from 2013 to 2019 was sourced from João Pessoa's official health regulatory bodies. This data is mandatorily sent from private and public hospitals and health bodies to the health secretary that contains and manages it. The analysis, purposefully excluding the timeframe of the COVID-19 pandemic, encompassed deaths attributed to chapters 10 and 11 of the ICD-10 framework. This data set comprised crucial details including the deceased's address, age, year of passing, health coverage status, reason for mortality, gender, racial background, place of demise, and health insurance particulars. Each individual dataset was represented on the map as a point, marked at the corresponding address location.

For the temperature comparison, using an Epanechnikov Kernel function, free software with open-source code called QGis, the density of deaths was calculated and computed on the map. Geodensities are most often calculated using this method. The Kernel function used to create the map is represented by the following equation in which the x's represent each point of the map, K is the kernel density, and h represents the bandwidth:

$$\hat{f}(x;h) := \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \quad \text{Equation 4}$$

Where:

x - each point of the map

K - kernel density

h – bandwidth

n – number of points

4.4 Nearest Neighbor analysis

A Nearest Neighbor analysis of the death data was performed to evaluate the spatial distribution of deaths in the study area. The analysis produced key indicators, including the Nearest Neighbor index and Z-score.

4.5 Data analysis

For each point representing a death, a buffer of 50, 100 and 150 diameter meters were created. In each of these areas, data from the lots was imported as statistical descriptive variables. The number of pavements in each building was incorporated in the area through minimum, maximum, range, sum, average, median and error. The land use was turned into 5 binary variables to express subtilized lot, residential lot, commercial lot, mixed use lot or square and the presence of green area was also considered a binary variable. All the variables used in the research are detailed in Table 4.

Table 4 - Variables considered in the research

Identifier	Variable	Type	Categories (when applied)
fid	identifier	quantitative	
ADDRESS	address	text	
ANO	Year of death	Quantitative	
IDADE	Age	Quantitative	
SEXO	sex	binary	
RACACOR	Declared race	Categorical	
ESTCIV	Marital status	Categorical	1 – Single; 2 – Married; 3 – Widowed; 4 – Divorced 9 – not applied.
BAIRES	Neighborhood	Categorical	
CAUSABAS	Death cause	Categorical	
NUMPOINTS	Number of deaths nearby	Quantitative	
pavimentos	Number of pavements (minimum in the area)	Quantitative	
paviment_1	Number of pavements (maximum in the area)	Quantitative	
paviment_2	Number of pavements (range in the area)	Quantitative	
paviment_3	Number of pavements (sum in the area)	Quantitative	
paviment_4	Number of pavements (area's average)	Quantitative	

paviment_5	Number of pavements (area's median)	Quantitative	
paviment_6	Number of pavements (standard deviation)	Quantitative	
solo_1_max	Presence of Underutilized or parking	binary	0 - not present
solo_2_max	Presence of Residential area	binary	0 - not present
solo_3_max	Presence of Commercial area	binary	0 - not present
solo_4_max	Presence of Mixed-use area	binary	0 - not present
solo_5_max	Presence of Square	binary	0 - not present
verde_max_2	Presence of Green area	binary	0 - not present
NUMPOINTS60	Number of deaths nearby (60+)	quantitative	

Source: author

4.6 Statistical Analysis

The temperature and kernel death maps processed by QGis were the input data for this analysis as it integrates with another free, open-source platform called R Project. This integration uses data pixel by pixel to develop the statistics between maps. A Pearson correlation was tested to understand the correlation between the heat and death maps. The maps and data were also qualitatively compared and quantitatively analyzed.

Descriptive data analysis was carried out from measures of central tendency to understand their variability and error. Box plot graphs were built for comparative analysis of the variables studied. Statistical tests were used to analyze the significant differences between the variables investigated.

4.7 Mathematical models

For each of the distances considered, two regression models were created. Before the regression model, a correlation analysis was conducted to explore potential relationships among pavement variables since they all came from the number of pavements in the original lot. This analysis aimed to identify correlations that might influence model construction. Since the dependent variable countable, two probability distributions, Poisson and negative binomial, were considered. The super disposition of data that the Poisson distribution presented due to the number of deaths being a countable variable eliminated the possibility to use as the distribution for this analysis. Therefore, the negative binomial distribution, which exhibited a better fit, was selected to represent the impact of morphological variables on cardiorespiratory deaths.

A stepwise backward variable selection procedure was applied to construct the regression model. One variable was systematically removed at each step until the Akaike

Information Criterion (AIC) value increased. Models with fewer variables and greater explanatory power, as indicated by the AIC, were preferred.

The final model, chosen based on the stepwise method and AIC, included specific variables. These variables were assessed for their impact on cardiorespiratory deaths in the study area, providing effect estimates, confidence intervals, z-scores, and p-values. The same analysis was performed using all death as the dependent variable and only deaths of people over the age of 60 as the dependent variable.

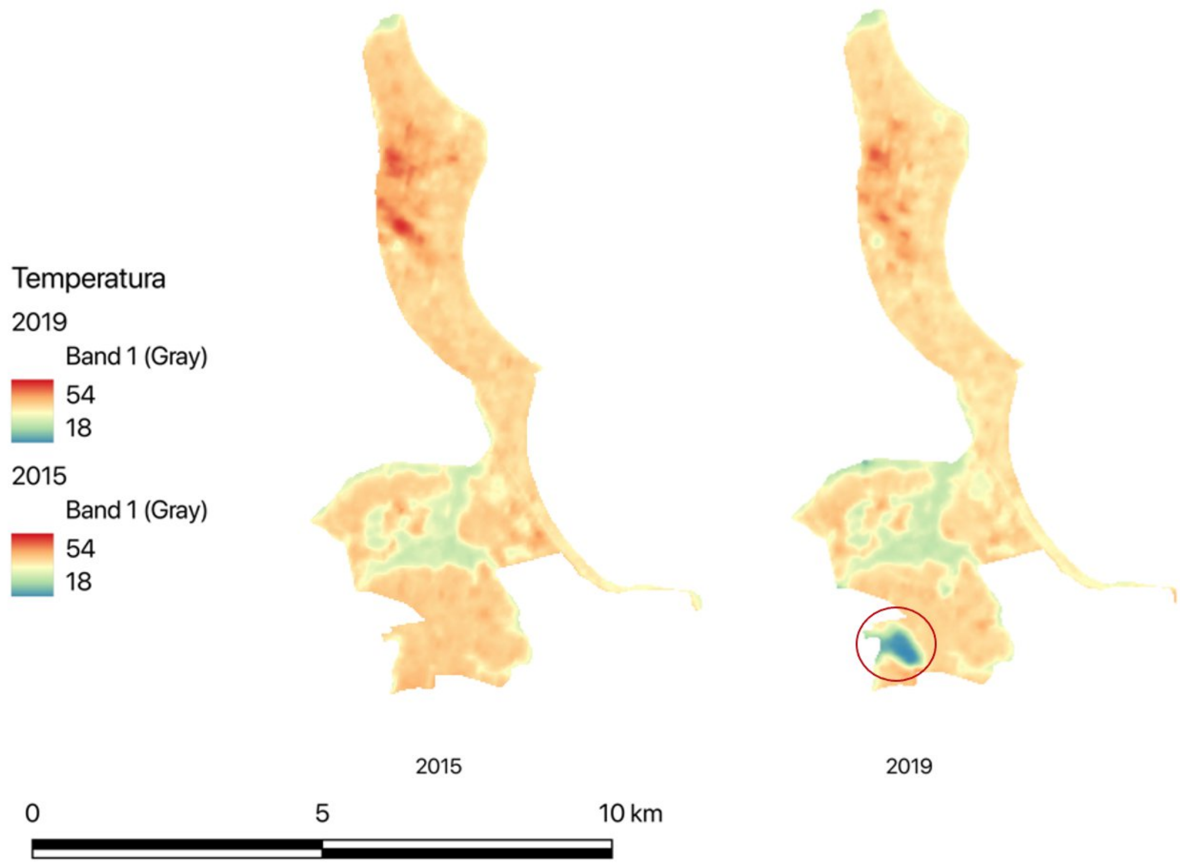
5 RESULTS AND DISCUSSIONS

In this chapter, we present the results from the data analysis, highlighting the key findings and insights crucial for understanding the studied phenomenon. Additionally, it delves into the interpretation and implications of the results presented earlier, exploring their significance in the context of the broader research framework and addressing any limitations or unexpected findings.

5.1 Surface Temperature

Examples of the surface temperature maps are displayed in Figure 5. The maps illustrate the surface temperature on the specified dates chosen in each year. João Pessoa's surface temperature varies from 23 to 54 ºC. On satellite images of 2017 and 2019, the circled areas where the temperature was below 23 ºC were obscured by clouds. These areas were not considered in the research. Even with such limited parameters, it was not possible to obtain all images without clouds during the research period due to the city's location in a typically cloudy region.

Figure 5 - Surface temperature maps of the neighborhoods of João Pessoa in 2015 and 2019



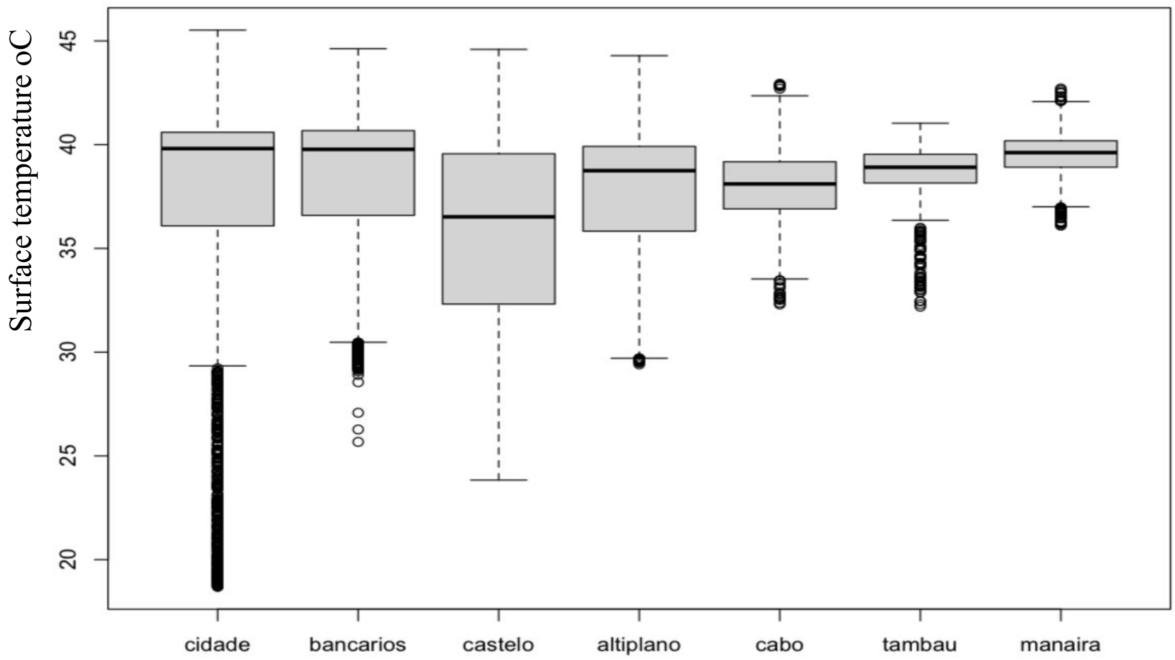
Source: author

Red areas present the highest temperatures, but as the color changes towards blue, the temperatures are lower. Across all the maps, a cooler area appears in the south of the studied neighborhoods between Castelo Branco and Bancários.

There was little to no change in the temperatures in all the maps available; they all follow the same general pattern. As expected, the cooler areas align with dense bodies of vegetation in the city, as shown in Figure 5, except for the temperature drop near the ocean in Bessa. Higher temperatures happen in areas without significant vegetation, trees, or buildings. Vegetation should provide a decrease in LST, while buildings should provide an increase (Al Kafy *et al.,* 2021). There is a lack of research on the impact of subtilized areas in the city.

Figure 6 shows surface temperature boxplots for all seven neighborhoods from 2013 to 2019. Castelo Branco has a lower surface temperature median than others. Heat island neighborhoods show the slightest difference in surface temperatures. Castelo Branco's lowest temperatures exhibit more significant variance in the first and second quartiles than in other neighborhoods. Located near large bodies of vegetation, Castelo Branco, Bancários, and Jardim Cidade Universitária experience a reduction in surface temperature. It has been observed that fewer deaths occur in areas closest to vegetation.

Figure 6 - Box plot graphs of temperature per neighborhood



Source: author

5.2 Analysis of urban form data

Figure 7 shows the mapped lots in full and a part of it in detail. Each lot in the image was attached to a set of information pertaining to itself.

Figure 7 - Demonstration of lot map from the analyzed area.

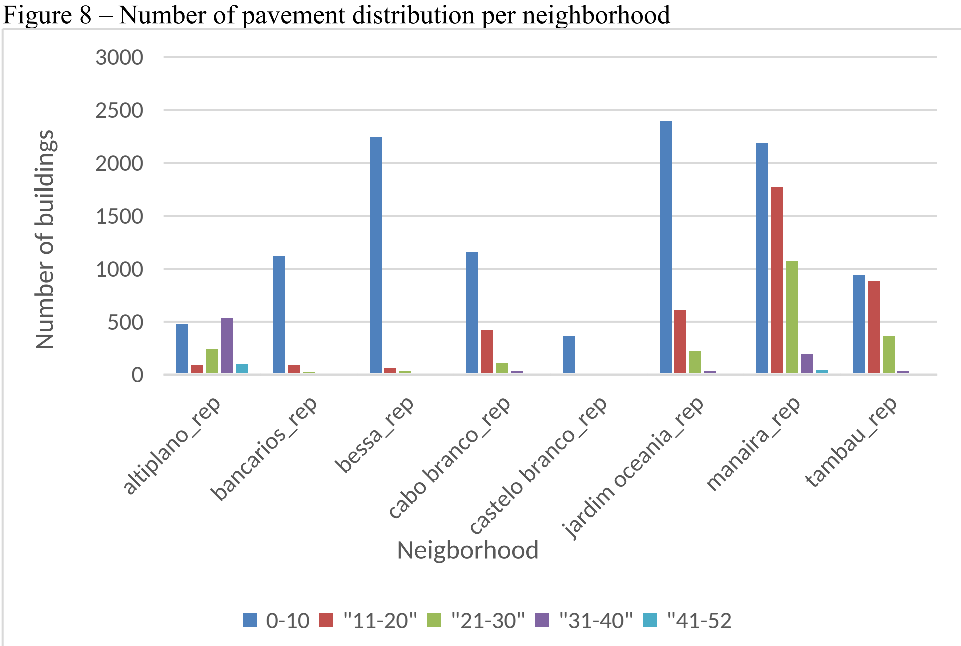
Source: author

There are 14,654 lots with a recorded number of floors. The tallest building has 52 floors. Nevertheless, the average number of floors in João Pessoa is approximately 1.22, with a median of 0 floors, indicating that most observations in João Pessoa have fewer floors. The standard deviation of 3.36 floors indicates a relatively large dispersion around the mean, and the coefficient of variation of 2.75% suggests moderate variation relative to the mean.

The interquartile range (IQR) of 1.0 floors suggests that most observations fall within this interquartile range. The most frequent value is 0 floors, which in our study indicates single-story buildings. The city has many non-occupied areas (mangroves, riverbeds, riparian forests, green areas). Some of these areas have been highlighted in Figure 4. The number of pavements distribution is depicted in Figure 8.

Bancários, Bessa, and Castelo Branco have predominantly low buildings of 0 to 10 floors. Low buildings are the majority in almost every neighborhood except for Altiplano, which has most of its buildings over 31 floors. The city's highest building, considered a tourist point nowadays, is located in this neighborhood. Following the “leopard spots” shape the temperature map shows for Manaíra, Figure 8 also shows that it has all five categories of building heights, and even though they are not equally distributed, the high building will still impact land temperature distribution.

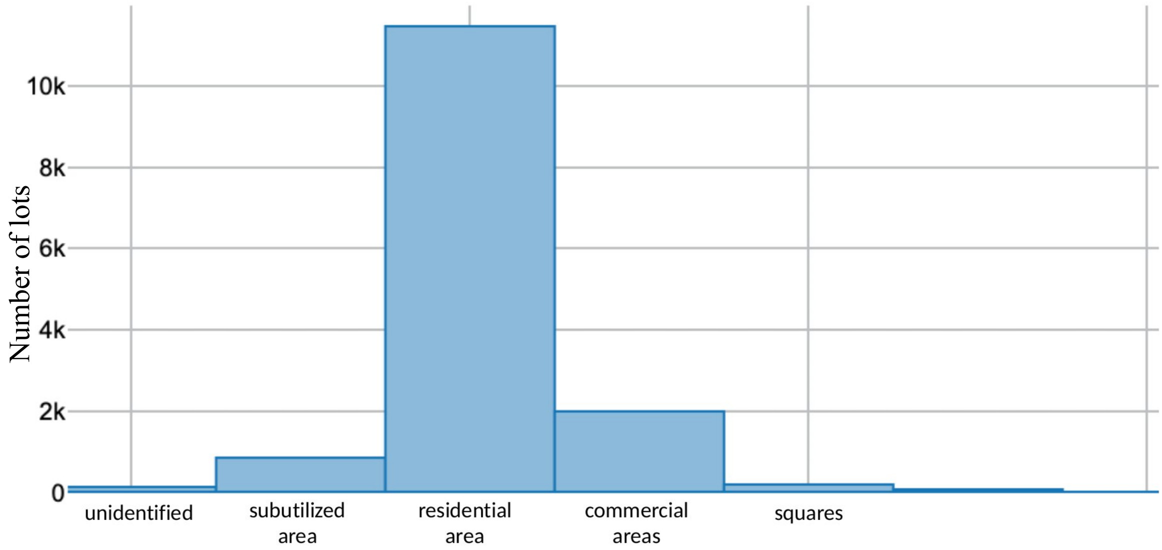
Figure 8 – Number of pavement distribution per neighborhood



Source: author

Regarding the land use variable, the most recurring value was residential use. As the variable is nominal, it is impossible to present more extensive statistics about it, but the graph representing the frequency of each type is in Figure 9. The percentage of green areas among the lots is 0.633, excluding squares and adjacent green areas. This value was obtained dividing the number of lots considered as green areas by the total number of lots.

Figure 9 - Land use in analyzed area

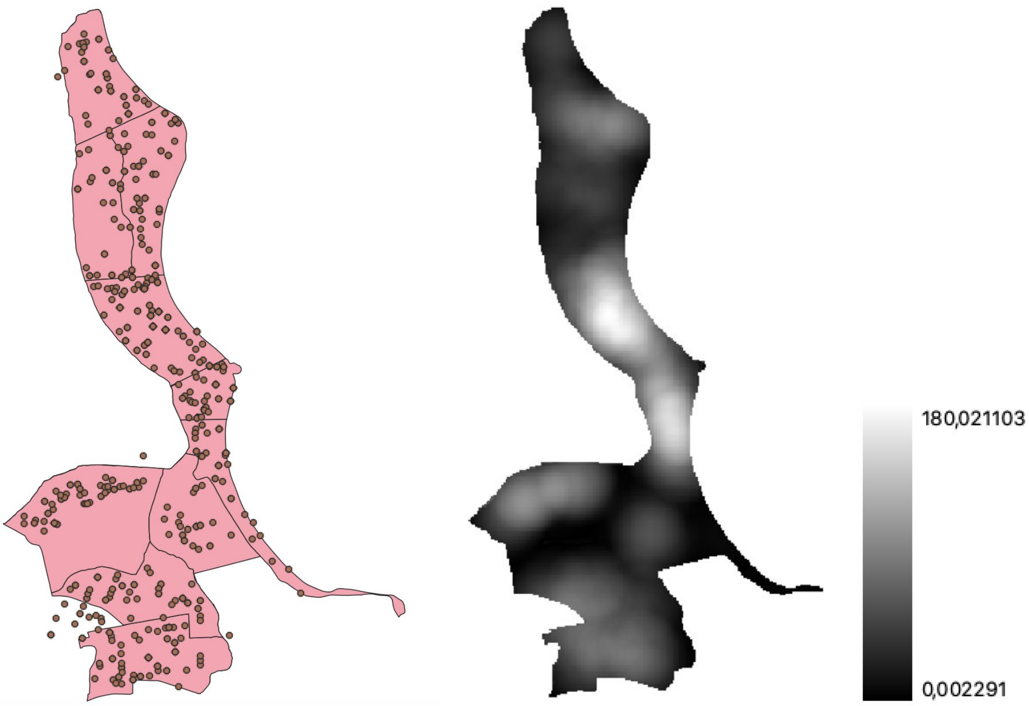


Source: author

5.3 Diseases

Figure 10 illustrates the distribution of deaths from cardiorespiratory causes between 2013 and 2019 according to housing addresses and the death density map of these values. There are 146 different diseases collected for this research. Each point in the figure represents one or more deaths at that location. The number of deaths grew a little in 2018 and 2019, the end of the analyzed period as shown in Figure 11. In most years of the research, they remained stable. The highlighted regions have fewer deaths than other areas.

Figure 10 - Points of cardiorespiratory disease occurrence and density map.

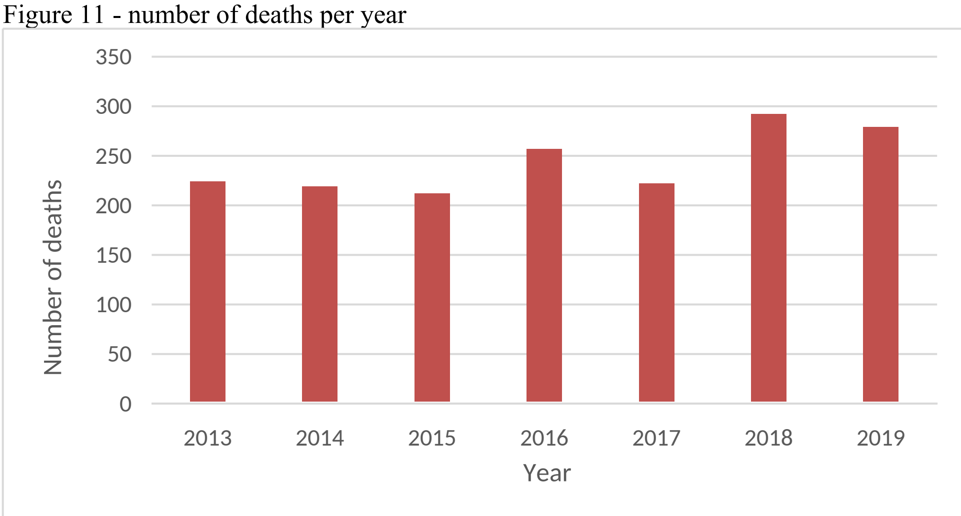


Source: author

The difference between male and female deaths is also very small as shown in Figure 12 where F represents female and M the male population divided by age. When it comes to age, though, there is a great difference. Death occurred from ages 0 to age 108. The rate increases over 60 which, in Brazil, is the age from which a person is considered an elder. The death density map incorporates both types of occurrences: cardiovascular and respiratory.

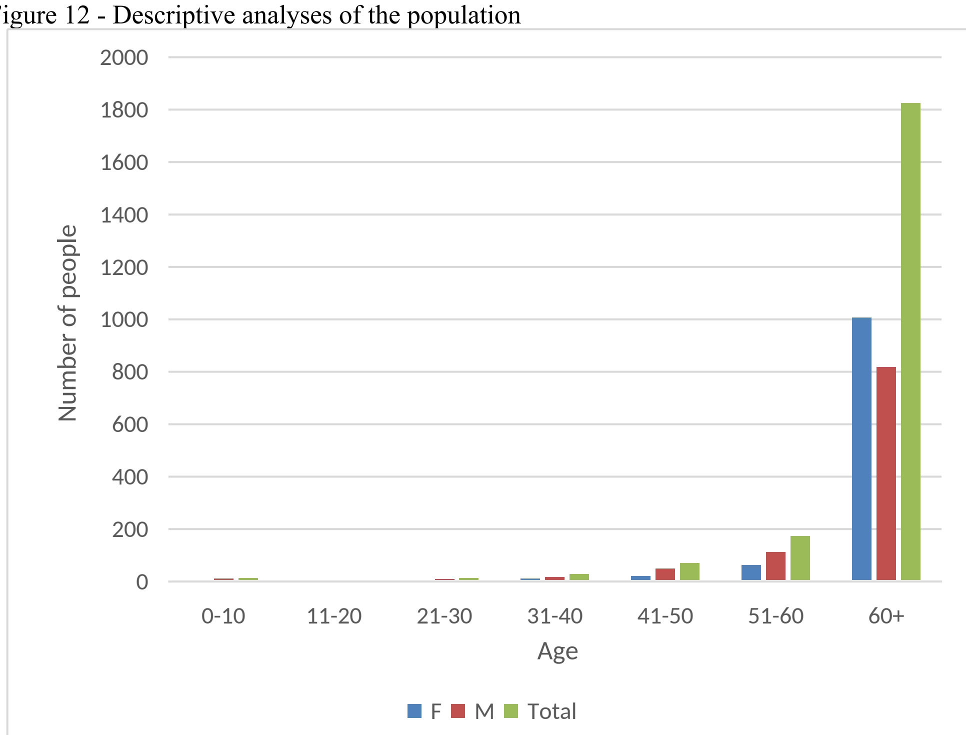
Despite Bessa registering more deaths than other neighborhoods, the elderly population is more prominent in Manaíra, Tambaú, Cabo Branco, and Castelo Branco.

Figure 11 - number of deaths per year



Source: author

Figure 12 - Descriptive analyses of the population



Source: author

The number of deaths per neighborhood is shown in Table 5. When examining death rates by neighborhood, certain figures stand out. Notably, Bessa, despite having the second-highest death rate, does not even rank among the five most populous areas. In other words, the demographic with the highest death rate is in this area, with 4.13 deaths per 100 people. Jardim Oceania is geographically adjacent to Bessa and had the fewest deaths per 100 people.

Table 5 - number of deaths per neighborhood

Neighborhood	Deaths	Population (2010)	Deaths per 100	60+ deaths	60+ population	60+ deaths per 100	Population Density (hab/ha)
Aeroclube	54	4057	1,33	43	550 (13,6%)	1,06	64.17
Jardim Oceania	91	10015	0,91	76	1223 (12,2%)	0,76	67.02
Altiplano	96	4151	2,31	76	398 (9,6%)	1,83	24,11
Cabo Branco	153	5439	2,81	127	1059 (19,5%)	2,33	57,57
Tambaú	180	6782	2,65	149	1189 (17,5%)	2,20	120,09
Cidade Universitária	208	11476	1,81	153	1050 (9,1%)	1,33	88,37
Bancários	251	8767	2,86	172	736 (8,4%)	1,96	54,18
Castelo Branco	261	12850	2,03	208	1187 (9,2%)	1,62	31,95
Bessa	294	7111	4,13	227	825 (11,6%)	3,19	46,88
Manaíra	471	19289	2,44	389	2690 (13,9%)	2,02	114,66

Source: adapted from 2010 census (IBGE)

These neighborhoods were chosen for this research because of their strong socioeconomic similarities, such as comparable access to health-related infrastructure and income distribution; therefore, social disparities among these neighborhoods do not explain the distribution of mortality rates (Ramos *et al.*, 2010). Literature suggests that areas with ethnic minorities or poor socioeconomic conditions tend to develop more issues related to temperature (Nasehi *et al.*, 2022), which does not seem to apply here, as neighborhoods with conditions, even if slightly less favorable than others (Cidade Universitária and Castelo Branco), were quite average concerning death rates.

Table 6 shows the diseases that have killed the most during the analyzed period. Acute myocardial infarction was the deadliest one. Cardiovascular diseases in the top list are acute myocardial infarction, stroke, hemorrhage or infarction and other specified cerebrovascular diseases, all with no particular causes identified by the time of death. Respiratory diseases include pneumonia, bronchopneumonia and chronic obstructive pulmonary disease with acute lower respiratory infection. The last one means an obstruction of the trachea and/or lungs.

Table 6 - Cardiorespiratory diseases that kill the most

Disease	ICD	Deaths
Acute myocardial infarction, unspecified	I21.9	387
Pneumonia, unspecified organism	J18.9	224
Stroke, not specified as hemorrhage or infarction	I64	93
Other specified cerebrovascular diseases	I67.8	80
Bronchopneumonia, unspecified organism	J18.0	80
Chronic obstructive pulmonary disease with acute lower respiratory infection	J44.0	80

Source: author

Table 7 shows the number of deaths by neighborhood per year. It shows an average of 303 deaths per year due to cardiovascular issues. The year with the most deaths during the analyzed period was 2018, and the one with fewer deaths was 2015. Data shows no tendency for growth or reduction. After 2018, there was an increase in death rates in Cabo Branco that requires following through to see if there is a growth pattern in that particular neighborhood.

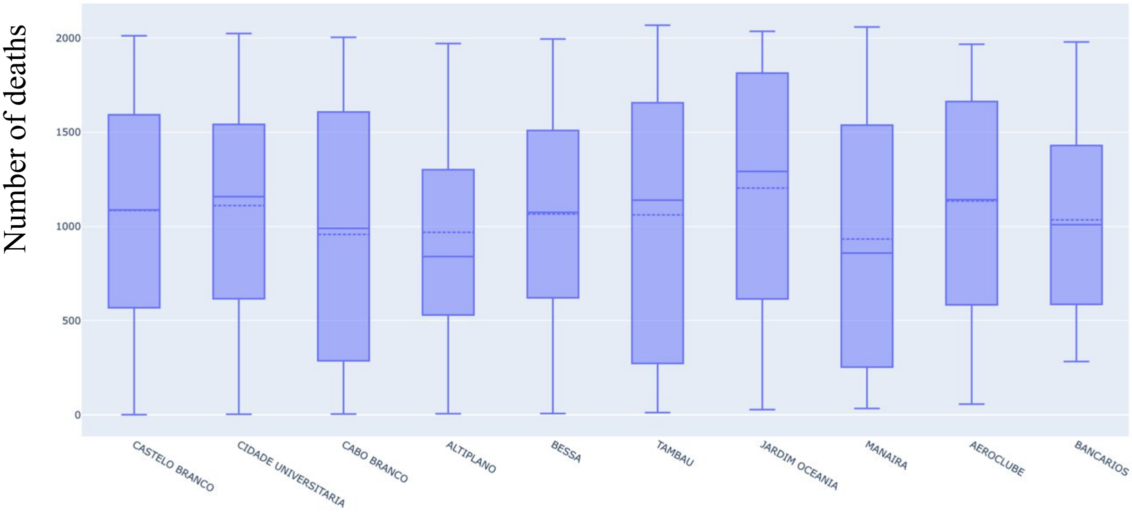
Table 7 - number of deaths by neighborhood per year

Neighborhood	2013	2014	2015	2016	2017	2018	2019	Total
Aeroclube		3	4	6	11	14	16	54
Altiplano	11	12	13	15	15	14	16	96
Bancários	41	33	30	36	34	43	38	255
Bessa	42	41	42	46	33	47	43	294
Jardim Oceania	13	7	5	6	3	5	9	48
Cabo Branco	15	23	18	19	19	30	29	153
Castelo Branco	35	46	31	38	32	47	34	263
Cidade Universitária	28	31	28	25	31	31	35	209
Manaíra	71	56	64	75	61	74	71	472
Total	277	280	271	312	276	357	348	2121

Source: author

A death boxplot is shown in Figure 13 for each of the seven neighborhoods from 2013 to 2019. Jardim Oceania has the highest average and a considerable variation, comparable to Cabo Branco, Tambaú, and Manaíra. Variations in these three neighborhoods may be due to differences in urban form since, historically, they have been dominated by one or two-story buildings. However, in recent decades, they have developed into taller buildings. All three neighborhoods have a connection to the Atlantic Ocean, which allows more robust air circulation to the east.

Figure 13 - Box plot graphs of number of deaths per neighborhood



Source: author

5.4 Statistical Analysis

The hypothesis test to evaluate the Pearson correlation between surface temperature and mortality density showed a correlation between these two variables, a 95% confidence interval (CI), and a p-value of less than 2,14e-16 < 0,05. Although the relationship is weak, data shows a statistical correlation that has yet to be found (Centers for Disease Control and Prevention, 2020; Turner *et al.*, 2012).

One possible reason for the weak correlation is the influence of confounding variables not accounted for in the analysis, such as age distribution, population density, or pre-existing health conditions. Mortality rates may be influenced by more complex interactions between environmental factors and social determinants of health (Teshale *et al.*, 2023; Chan *et al.*, 2015; Snyder-Mackler *et al.*, 2020).

Furthermore, although the correlation is weak, it highlights the importance of considering surface temperature as a contributing factor to mortality. Given the increasing frequency of extreme heat events due to climate change, even weak correlations could have significant public health implications over time, particularly in vulnerable populations.

5.5 Overall data analysis

The variation in land surface temperature (LST) presented in Manaíra resembles leopard spots. This pattern may be related to the neighborhood's form. Manaíra comprises houses with up to 2 floors and buildings with more than ten floors randomly distributed throughout the neighborhood. The buildings' height and the lots' area tend to give the neighborhood a "tall-slim" figure, which can reduce land surface temperature (Chen *et al*., 2022; Ponjoan *et al*., 2017; Zacharias; Koppe; Mücke, 2014).

The city's land use and cover create variations in LST, impacting the thermal comfort in different areas, especially over 30ºC (Wibowo; Semedi; Salleh, 2017). It is worth noticing that all the neighborhoods are situated in high-temperature areas, even the lowest points, which the literature relates to the possibility of increasing deaths by cardiovascular diseases (Baaghideh; Mayvaneh, 2017).

When we divide deaths per neighborhood, some numbers draw attention. For instance, despite having only the second-highest death rate, Bessa does not even rank among the five largest populations. In other words, 4,13 deaths per 100 people living in this area are the highest death rate demographic. Geographically, next to it, Jardim Oceania was the neighborhood with fewer deaths per 100 people.

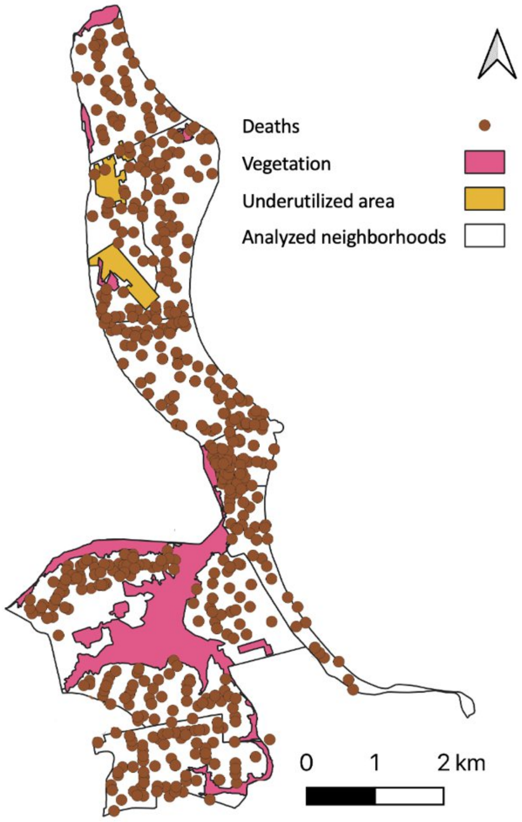
Another possible explanation would be age, as Figure 12 shows that most deaths occurred among the elderly. However, despite Bessa registering more deaths than other neighborhoods, the elderly population is much more prominent in Manaíra, Tambaú, Cabo Branco, and Castelo Branco.

Literature indicates that areas with ethnic minorities or poor socioeconomic conditions experience more local temperature problems (Nasehi *et al.,* 2022), which does not appear to be the case here since neighborhoods with conditions even if slightly less favorable than the others (Cidade Universitária and Castelo Branco) were very much average regarding death rates.

Studies in the field have shown a similar result in situations of extreme temperatures or extreme weather events (Braga; Zanobetti; Schwartz, 2002; Carmona *et al*., 2016; Aboubakri *et al*., 2019; Revich; Shaposhnikov, 2016; Casas *et al.,* 2016; Ma *et al*., 2022). Literature indicates that environmental factors significantly influence cardiovascular health (Roshan *et al*., 2022). Areas with artificial coverage, such as buildings and asphalt, tend to accumulate more heat. Areas that have forestation tend to be cooler due to the cover and humidity provided by vegetation.

There are several spots where the surface temperature has been higher or lower than the surrounding areas, indicated by red and blue, respectively, on the images. Most spots with lower surface temperatures (around 19 to 20 ºC) can be found in green areas of riparian areas or dense forests. Spots with the highest surface temperatures (up to 54 ºC) are located in large areas of the city that have not yet been developed. These areas are shown in Figure 14. Each dot in the figure represents one or more deaths. The yellow polygons represent areas of underutilized lots, and the pink polygons represent dense vegetation areas. The pink polygons represent areas of dense vegetation, while the mustard polygons represent a combination of underdeveloped areas of the city.

Figure 14 - Forest and non-built areas in the analyzed neighborhoods.



Source: author

Vegetation is critical for urban heat mitigation (Yang *et al*., 2022; Kjelgren; Montague, 1998). Keeping vegetation or creating projects that bring vegetation to underdeveloped lots in the city might help reduce spots of higher temperatures. The figure shows vegetation, underdeveloped areas, and their surroundings showing decreased mortality rates. The areas highlighted seldom have points representing deaths.

The area highlighted in yellow in Figure 14 represents a large portion of lots with no construction, characterized later in this thesis as underutilized areas, and in the temperature maps displayed in Figure 5, they appear as hotspots of the city. It has been shown that built-up and green areas have lower LST than non-urbanized areas (Ismaila, Muhammed, Adamu, 2022). According to this study, the same phenomenon occurs inside urbanized neighborhoods without construction. It creates a microclimate resembling a heat island in a populated area that emits heat to its surroundings and is more likely to increase mortality rates around it.

João Pessoa is the most extreme east point of South America and has a large portion of the studied area connected to the Atlantic Sea. It was expected that surface temperatures in the east of the city would be lower due to this large water body (Cai; Han; Chen, 2018). However, this phenomenon has only been observed in a small portion of Jardim Oceania. Other neighborhoods did not experience the same occurrence; the literature presents this as a possibility (Patriota *et al.*, 2024). The opposite occurred in a second maritime curve between Manaíra and Tambaú, where surface temperatures rose near the ocean. The impact found in the literature of being close to the coast in pregnancies (Choe *et al.*, 2018) did not translate to the proximity in this research.

Other diseases, such as anxiety, sleep dysfunctions, social functioning, and depression, were connected to land surface temperature by the literature (Mirzaei *et al.,* 2020). As most of these diseases may increase the likelihood of heart-related complications that can lead to mortality, the heat in the hottest spots can harm long-term health, increasing the risk of heart-related death. Suppose the surface temperature in a determined neighborhood is high. In that case, there is the possibility of potential risks to heart health, which will lead to an uncomfortable sleeping environment, thus creating the need to manage anxiety better.

Combining the information from Figures 6 and 13, Figure 5 shows the lowest surface temperature variation in the neighborhood. The death rate, however, exhibits the opposite pattern, suggesting a correlation between surface temperature and mortality. Figure 14 illustrates the large forest portion between Castelo Branco and Bancários. Both neighborhoods have similar death trends.

Such a correlation was tested using the Pearson correlation test yearly and the averages. 2016's surface temperature and deaths are more closely related, while 2014 has the lowest correlation index. Table x shows the correlation coefficient results for each test. All the results have a p-value under 2.2e-16, which shows the accuracy of the correlations.

Table 8 - Correlation coefficient between deaths and surface temperature

Year	Correlation coefficient
2013	0.1628494
2014	0.05620856
2015	0.1528475
2016	0.2412378
2017	0.2018928
2018	0.1838281
2019	0.2357899

Source: author

5.6 Nearest neighbor analysis

The nearest neighbor analyses conducted in the death data show a low nearest neighbor index and a high negative Z-score, indicating that the points are clustered or tend to form clusters as shown in Table 9.

Table 9 - Nearest neighbor analysis results

Observed mean distance:	7.60837340365
Expected mean distance	87.90519729912
Nearest neighbor index	0.08655203148
Number of points	1705
Z-Score	-72.1567375087

Source: author

A value significantly less than 1 indicates clustering or spatial aggregation. In other words, the points are not randomly distributed; they tend to be closer to each other than you would expect by chance. This suggests some form of spatial pattern or clustering in the data.

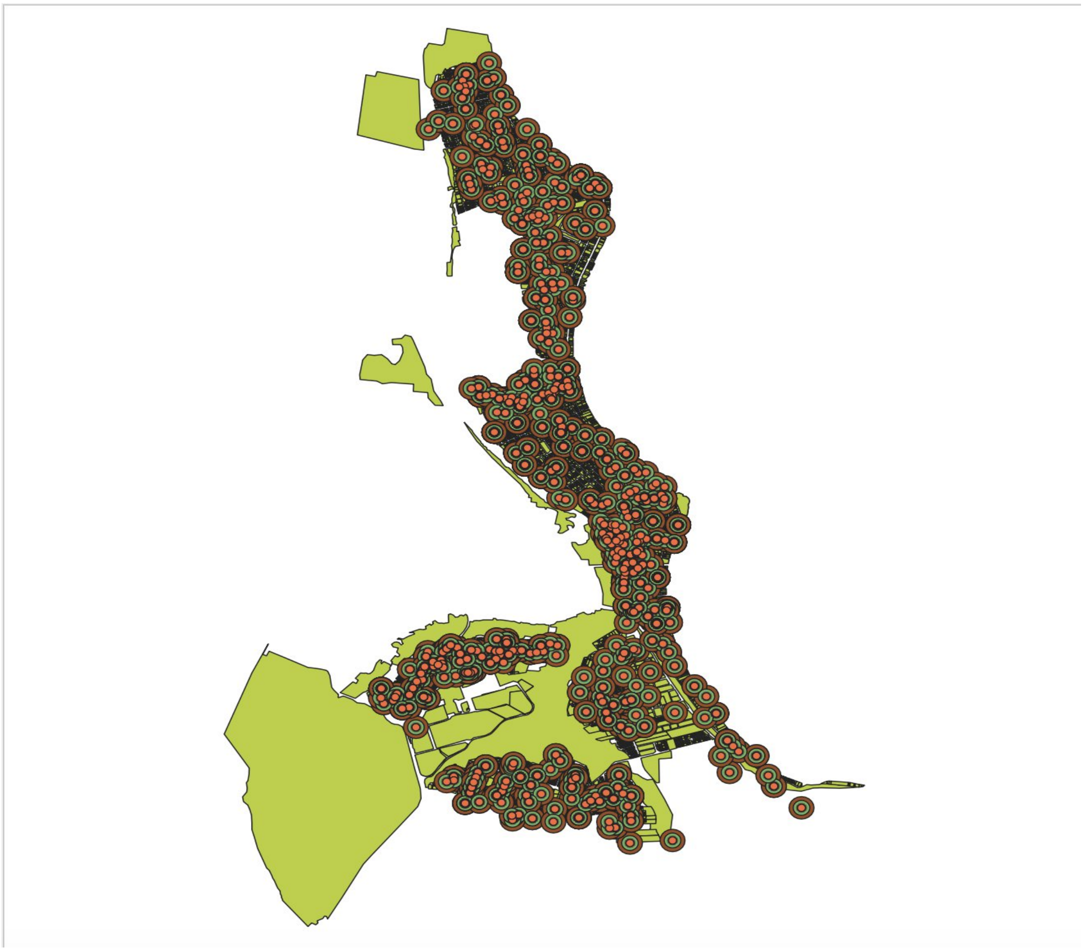
The extremely negative Z-Score indicates strong evidence against the null hypothesis of complete spatial randomness. In practical terms, this means that the data shows a highly significant spatial pattern or clustering that is unlikely to be due to random chance.

In summary, we can infer that the deaths are not randomly distributed; there is a significant spatial pattern or clustering present. Further analysis is necessary to understand the nature and causes of this spatial pattern.

5.7 Form Data analysis

For each point representing a death, buffers of 50, 100, and 150m were created. In each of these areas, data from the lots was imported. Figure 15 shows the buffers created.

Figure 15 – Buffers (50m ratio, 100m ratio, 150m ratio)



Source: author

5.7.1 Buffers of 50m

To begin the regression modeling, a correlation analysis was conducted to identify any possible correlations between the pavement variables as they were obtained from the same data.

Table 10 - Correlations between pavement variables in 50m circle

	pavimentos	pavimen t_1	pavimen t_2	pavimen t_3	pavimen t_4	pavimen t_5	pavimen t_6	pavimen t_7
pavimentos	1	0,09734882	-0,01339449	0,03202847	0,4222980	0,4466919	0,92476993	0,2761380
pavimen t_1	09734882	1	0,99385710	0,84176185	0,71255485	0,36245581	0,16631515	0,54388372
pavimen t_2	-0,01339449	0,99385710	1	0,84214161	0,66893202	0,31448116	0,06426028	0,51572399
pavimen t_3	0,03202847	0,84176185	0,84214161	1	0,79693644	0,50812610	0,15060218	0,72670188
pavimen t_4	0,4222980	0,71255485	0,66893202	0,79693644	1	0,8374956	0,5628840	0,9266168
pavimen t_5	0,4466919	0,36245581	0,31448116	0,50812610	0,8374956	1	0,6114613	0,7896354
pavimen t_6	0,92476993	0,16631515	0,06426028	0,15060218	0,5628840	0,6114613	1	0,41929957
pavimen t_7	0,2761380	0,54388372	0,51572399	0,72670188	0,9266168	0,7896354	0,41929957	1

Source: author

Table 10 shows all the correlations between the pavement variables. These correlations were evaluated to avoid multicollinearity, meaning one variable that has an effect on another would not be in the same model. Therefore, all the variables that have a correlation greater than 0,7, could not be in the same model. Table 11 shows the different combinations of variables tried.

Since we have a dependent variable in count, two distributions may be suitable to describe random variations. The Poisson distribution and the negative binomial distribution are often used to describe random variations in count-dependent variables. Noticing a better fit with the negative binomial distribution, it was used to represent the effect of morphological variables over the occurrence of cardiorespiratory deaths. The best model was selected through the AIC.

5.7.1.1 All ages

For the 50m circle considering all ages, the best model fit was numbers 7 and 8, that end up identical after the stepwise selection.

Table 11 - Variables considered in each model

Model	Variables														Final	AIC
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14		
1	x	x				x	x		x	x	x	x	x	x	7	3935.72
2	x	x					x	x	x	x	x	x	x	x	7	3939
3	x		x			x	x		x	x	x	x	x	x	7	3935.72
4	x		x				x	x	x	x	x	x	x	x	6	3938
5	x			x		x	x		x	x	x	x	x	x	6	3945
6	x			x			x	x	x	x	x	x	x	x	6	3945
7	x				x	x	x		x	x	x	x	x	x	6	3948
8	x				x		x	x	x	x	x	x	x	x	6	3948

Source: author

Table 12 illustrates the stepwise backward variable selection procedure that was employed. In this procedure, initially, 10 variables were considered, and one variable was removed at each step. Variables were removed until the AIC (Akaike Information Criterion) value increased. In this selection, models with fewer variables and greater explanatory power are considered better.

Table 12 - Stepwise selection process

Step	AIC	Number of variables	Excluded variable
Initial	3952.24	10	-
1	3950.24	9	Number of pavements (median of the area)
2	3948.39	8	Presence of residential area
3	3946.79	7	Presence of Green area
4	3945.98	6	Presence of Mixed-use area

Source: author

Table 13 shows the best model according to the stepwise method. The presence of squares is associated with an increase in the number of deaths of approximately 16%. However, the effect is not statistically significant at the conventional significance level ($p > 0.05$). This means that there is not strong evidence to suggest that the presence of this kind of parcel use affects the probability of death.

Table 13 - stepwise selected model

Variable	Effect	IC95%	z	p
Number of pavements (minimum in the area)	1.3032736	(1.09727; 1.55104)	3.055	0.00225
Number of pavements (area's average)	1.0693848	(1.03863; 1.10182)	5.144	2.69e-07
Number of pavements (area's standard deviation)	0.7221819	(0.61518; 0.84725)	-4.045	5.23e-05
Presence of Underutilized area or parking	0.8744354	(0.77959; 0.98089)	-2.296	0.02170
Presence of commercial area	1.5430436	(1.34388; 1.76961)	6.278	3.43e-10
Presence of Squares	1.1610187	(0.95669; 1.41640)	1.529	0.12624

Source: author

The number of floors is associated with an increase in the number of deaths of approximately 6%. The effect is statistically significant ($p < 0.05$), suggesting that the number of floors significantly affects the probability of deaths.

An increase in the standard deviation of the number of building floors in the area is associated with a decrease in the number of deaths by approximately 18%. The effect is statistically significant ($p < 0.05$), indicating that the standard deviation of building floors affects the probability of the incident, in this case, death.

The analysis accounted for each death individually, considering the characteristics of the immediate surroundings where the outcome occurred. In this part of the research, deaths were not treated as part of a spatial or building-height cluster. They were analyzed independently which ensures that the observed associations are reflective of individual cases and not influenced by the potential clustering of multiple deaths in high-rise buildings or areas with varying floor counts.

The presence of underutilized area is associated with a decrease in the number of deaths of approximately 13% being statistically significant ($p \approx 0.052$), suggesting that there is some evidence that the presence of underutilized area affects the probability of the incident.

The presence of a commercial area is associated with a significant increase in the number of deaths of approximately 54%. The effect is highly statistically significant ($p << 0.001$), indicating that the presence of a commercial area has a strong and positive effect on the probability of the outcome.

Some independent variables (such as the number of floors, average building height, and the presence of a commercial area) have statistically significant effects on the probability of the outcome, while others (such as the presence of squares) have effects that are not statistically significant or marginally significant. The magnitude and direction of the effects are also indicated by the estimated coefficients.

5.7.1.2 60+

The same process was conducted considering only the deaths of people aged 60+, which according to Brazilian legislation is de definition of elderly.

Table 14 shows the variables considered in each model, the same as in the models considering all ages, but in this case, the dependent variable was the deaths amongst people aged 60+. The best model, again, was number 7/8.

Table 14 - variables considered in each model

Model	Variables														Final	AIC
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14		
1	x	x				x	x		x	x	x	x	x	x	7	3840
2	x	x					x	x	x	x	x	x	x	x	7	3841
3	x		x			x	x		x	x	x	x	x	x	7	3840
4	x		x				x	x	x	x	x	x	x	x	7	3840
5	x			x		x	x		x	x	x	x	x	x	6	3845
6	x			x			x	x	x	x	x	x	x	x	6	3845

7	x	x	x	x		x	x	x	x	x	x	6	3849
8	x	x		x	x	x	x	x	x	x	x	6	3849

Source: author

Table 15 illustrates the stepwise backward variable selection procedure that was employed. Same as in with all ages, 10 variables were considered, and one variable was removed at each step, the same variables ended up in the model. The AIC, though, was higher when considering only the 60+ population.

Table 15 - stepwise selection process for 50 m and age 60+

Step	AIC	Number of variables	Excluded variable
Initial	3853.64	10	-
1	3851.64	9	Presence of residential area
2	3849.75	8	Number of pavements (median of the area)
3	3848.17	7	Presence of green area
4	3847.24	6	Presence of mixed-use area

Source: author

Table 16 shows the best model according to the stepwise method. Comparing to the same model considering all ages, the presence of squares does not have a statistically significant effect on the deaths ($p > 0.05$).

The number of floors has a statistically significant effect on the outcome ($p < 0.05$), with a stronger influence over the age of 60. Average building height significantly affects the outcome ($p < 0.05$), with a similar effect regardless of the age.

The standard deviation of building floors has a statistically significant effect on the number of deaths ($p < 0.05$), with a slightly decreased effect in over the age of 60. The presence of underutilized area is not statistically significant ($p > 0.05$) and became less significant in the second set.

The presence of a commercial area has a highly significant effect on the outcome ($p << 0.001$), with a slightly decreased effect in the second set. Overall, the comparison shows changes in the estimated effects of some variables, both in magnitude and significance, between the two sets of results.

Table 16 - stepwise selected model for 50m and age 60+

Variable	Effect	IC95%	z	p
Number of pavements (minimum in the area)	1.3852297	(1.15538; 1.66589)	3.555	0.000377
Number of pavements (area's average)	1.0755438	(1.04261; 1.11037)	5.289	1.23e-07
Number of pavements (area's standard deviation)	0.6863093	(0.57934;1.23184)	-4.388	1.14e-05
Presence of Underutilized area or parking	0.8906592	(0.78877; 1.00579)	-1.875	0.060802
Presence of commercial areas	1.5988932	(1.38090; 1.84889)	6.413	1.42e-10
Presence of Squares	1.1749633	(0.95727; 1.45058)	1.563	0.117976

Source: author

5.7.2 100m Circle

Following the same procedure, a correlation analysis was conducted to identify any possible correlations between the pavement variables as shown in table 17. Any correlation regarding the lowest parcel in the area was deemed not applicable (NA) once every area has at least one parcel with no construction on it. Therefore, from this point on in the research this variable was no longer taken into account.

Table 17 - Correlations between pavement variables in 100m circle

	pavimentos	paviment_1	paviment_2	paviment_3	paviment_4	paviment_5	paviment_6
pavimentos	1	NA	NA	NA	NA	NA	NA
paviment_1	NA	1	1	0,8150816	0,7002780	0,3097349	0,9369840
paviment_2	NA	1	1	0,8150816	0,7002780	0,3097349	0,9369840
paviment_3	NA	0,8150816	0,8150816	1	0,7021613	0,2563348	0,8605866
paviment_4	NA	0,7002780	0,7002780	0,7021613	1	0,7854260	0,8704645
paviment_5	NA	0,3097349	0,3097349	0,2563348	0,7854260	1	0,4614175
paviment_6	NA	0,9369840	0,9369840	0,8605866	0,8704645	0,4614175	1

Source: author

5.7.2.1 All ages

Table 18 shows the different combinations of variables tried.

Table 18 - variables considered in each model for 100m

Model	Variables														Final	AIC
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14		
1	x								x	x	x	x	x	x	4	4213
2		x							x	x	x	x	x	x	5	420

													6
3	x					x	x	x	x	x	x	5	420 6
4		x				x	x	x	x	x	x	4	418 4
5			x			x	x	x	x	x	x	4	421 3
6				x		x	x	x	x	x	x	5	421 0
7					x	x	x	x	x	x	x	5	420 5

Source: author

For the 100m circle considering all ages, the best model fit was model number 1. Table 19 illustrates the stepwise backward variable selection procedure that was employed. In this procedure, initially, 7 variables were considered.

Table 19 - stepwise selection process for 100m within all ages

Step	AIC	Number of variables	Excluded variable
Initial	4215.11	7	-
1	4213.3	6	Number of pavements (minimum in the area)
2	4211.4	5	Presence of Squares
3	4336.55	4	Presence of Green area

Source: author

Table 20 shows the best model according to the stepwise method.

Table 20 - stepwise selected model for 100m within all ages

Variable	Effect	IC95%	z	p
Presence of Mixed-use area	1.147988	(1.04771; 1.25802)	2.952	0.00315
Presence of Underutilized area or parking	1.210170	(1.06921; 1.36783)	3.046	0.00232
Presence of residential area	2.594675	(1.42547; 4.77477)	3.093	0.00198
Presence of commercial area	1.509868	(1.28886; 1.76566)	5.105	3.31e-07

Source: author

The presence of mixed-use areas was found to have an effect on the number of deaths, with an increase of approximately 14% in the number of deaths. This effect was statistically significant (p = 0.00315), indicating that the presence of mixed-use areas is a robust predictor of the incident.

The presence of underutilized areas was associated with an increase of approximately 21% in the number of deaths. This effect was also statistically significant (p = 0.00232), highlighting the predictive power of underutilized areas.

The presence of residential areas showed a substantial effect, with an increase of 2.6 times in the number of deaths. The presence of commercial areas had a significant effect on the outcome, with an increase of approximately 50% in the number of deaths. This effect was highly statistically significant ($p < 0,05$), indicating that the presence of commercial areas is a strong and reliable predictor of the incident.

5.7.2.2 60+

The same process was conducted considering only the deaths of people aged 60+. Table 21 shows the variables considered in each model, the same as in the models considering all ages.

Table 21 - variables considered in each model for 100m over 60+

Model	Variables														Final	AIC
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14		
1	x								x	x	x	x	x	x	4	4121
2		x							x	x	x	x	x	x	5	4113
3			x						x	x	x	x	x	x	6	4113
4				x					x	x	x	x	x	x	6	4088
5					x				x	x	x	x	x	x	4	4121
6						x			x	x	x	x	x	x	5	4116
7							x		x	x	x	x	x	x	5	4111

Source: author

For the 100m circle considering only deaths that happened with people over 60 years old, the best model fit was model number 5. Table 22 illustrates the stepwise backward variable selection procedure that was employed. In this procedure, initially, 7 variables were considered.

Table 22 - stepwise selection process for 100m over 60+

Step	AIC	Number of variables	Excluded variable
Initial	4121.56	7	-

1	4120.87	6	Presence of squares
2	4119.68	5	Presence of green areas
3	4119.42	4	Number of pavements (area's average)

Source: author

Table 23 shows the best model according to the stepwise method.

Table 23 - stepwise selected model for 100m over the age 60+

Variable	Effect	IC95%	z	p
Presence of Underutilized area or parking	1.209310	(1.06017; 1.37726)	2.855	0.004299
Presence of residential area	2.489565	(1.31896; 4.75204)	2.786	0.005343
Presence of commercial area	1.622026	(1.36846; 1.91910)	5.577	2.44e-08
Presence of mixed-use area	1.192623	(1.08227; 1.31441)	3.551	0.000383

Source: author

The presence of underutilized areas continued to be a good predictor, with an approximately 20% increase in the number of deaths. The presence of residential areas showed an effect of 2.5 times in the number of deaths. The presence of commercial areas again exhibited a significant positive effect, with an increase of approximately 62% in the number of deaths. Lastly, the presence of mixed-use areas demonstrated an effect with an increase of about 20% (p = 0.0004), highlighting their influence on the number of deaths.

5.7.3 150m circle

Following the same procedure yet again, a correlation analysis was conducted to identify any possible correlations between the pavement variables in the 150 meters distance as shown in table 24.

Table 24 - Correlations between pavement variables in 150m circle

	pavimentos	paviment_1	paviment_2	paviment_3	paviment_4	paviment_5	paviment_6
pavimentos	1	NA	NA	NA	NA	NA	NA
paviment_1	NA	1	1	0,7803346	0,7516787	0,2492466	0,9217237
paviment_2	NA	1	1	0,7803346	0,7516787	0,2492466	0,9217237
paviment_3	NA	0,7803346	0,7803346	1	0,7233818	0,2570156	0,8022496
paviment_4	NA	0,7516787	0,7516787	0,7233818	1	0,5976478	0,9259211
paviment_	NA	0,249246	0,249246	0,257015	0,597647	1	0,393527

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5		6	6	6	8		5
paviment_6	NA	0,9217237	0,9217237	0,8022496	0,9259211	0,3935275	1

Source: author

5.7.3.1 All ages

Table 25 shows the different combinations of variables tried considering 150 meters and all ages.

Table 25 - variables considered in each model for 150m within all ages

Model	Variables														Final	AIC
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14		
1		x				x			x	x	x	x	x	x	5	4517
2			x			x			x	x	x	x	x	x	5	4517
3				x		x			x	x	x	x	x	x	5	4454
4					x	x			x	x	x	x	x	x	5	4506
5						x	x		x	x	x	x	x	x	5	4509

Source: author

For the 150m circle considering all ages, the best model fit was model number 2. Table 26 illustrates the stepwise backward variable selection procedure that was employed. In this procedure, initially, 8 variables were considered.

Table 26 - stepwise selection process for 150m within all ages

Step	AIC	Number of variables	Excluded variables
Initial	4518.84	8	-
1	4517.47	7	Presence of Underutilized area or parking
2	4516.15	6	Presence of green area
3	4515.14	5	Presence of residential area

Source: author

Table 27 shows the best model according to the stepwise method. For each unit increase in the range between the highest and lowest number of floors in the buildings of the area, there is very little increase in the rate of death. The 95% confidence interval for this effect is (1.00451; 1.01242), indicating a statistically significant positive effect ($p << 0.001$). This suggests that the range of floors in the buildings of the area is a strong predictor of death.

Each increase in the median number of floors between buildings in the area is associated with a decrease of approximately 9% in the number of deaths. The 95% confidence interval for this effect is (0.86066; 0.97262), indicating a statistically significant negative effect ($p < 0.05$). This implies that more floors between buildings lead to a lower likelihood of death.

The presence of a commercial area is associated with a substantial increase of approximately 43% in the death rate. The 95% confidence interval for this effect indicates a statistically significant positive effect ($p < 0.05$). This highlights a predictive power of commercial areas on the incident.

The presence of mixed-use areas is associated with an increase of approximately 25% in the IRR. There is a statistically significant positive effect ($p << 0.001$). This underscores the substantial influence of mixed-use areas on the deaths.

The presence of squares is associated with a significant increase of approximately 22% in the number of deaths also with a statistically significant positive effect ($p << 0.001$). This emphasizes the strong predictive nature of squares with respect to deaths.

The range of floors in buildings, the presence of commercial areas, mixed-use areas, and squares all exhibit substantial positive effects on the incident. Conversely, the median number of floors between buildings has a negative impact on the deaths. These findings provide valuable insights into the factors influencing the likelihood of deaths.

Table 27 - stepwise selected model for 150m within all ages

Variable	Effect	IC95%	z	p
Range between highest and lowest number of floors in the buildings of the area	1.0084514	(1.00451; 1.01242)	4.258	2.06e-05
Median of number of floors between building in the area	0.9144211	(0.86066; 0.97262)	-2.888	0.00388
Presence of commercial area	1.4289942	(1.13946; 1.78392)	3.173	0.00151
Presence of mixed-use area	1.2561851	(1.15360; 1.36756)	5.251	1.51e-07
Presence of squares	1.2217510	(1.11137; 1.34412)	4.154	3.27e-05

Source: author

5.7.3.2 60+

The same process was conducted considering only the deaths of people aged 60+. Table 28 shows the variables considered in each model, the same as in the models considering all ages. The best model, for the 150 meters area and the elderly is model number 2.

Table 28 - variables considered in each model for 150m over 60+

Model	Variables														Fina	AIC
	V	V	V	V	V	V	V	V	V	V1	V1	V1	V1	V1	l	

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	1	2	3	4	5	6	7	8	9	0	1	2	3	4		
1		X				X			X	x	X	x	X	X	5	4400
2			X			X			X	X	X	X	X	X	5	4400
3				X		X			X	X	X	X	X	X	5	4334
4					X	X			X	X	X	X	X	X	5	4391
5						x	X		X	X	X	X	X	X	5	4393

Source: author

Table 29 illustrates the stepwise backward variable selection procedure that was employed. Same as in with all ages, it initially considered V3, V6, V9, V10, V11, V12, V13 and V14. The AIC was lower when considering only the 60+ population.

Table 29 - stepwise selection process for 150m over 60+

Step	AIC	Number of variables	Excluded variables
Initial	4401.6	8	-
3	4400.01	7	Presence of Underutilized area or parking
4	4398.45	6	Presence of green areas
	4398.13	5	Presence of residential areas

Source: author

Table 30 shows the best model according to the stepwise method. Comparing to the same model considering all ages, both with people of all ages and with the 60+ population present similar effects and statistical significances for the same set of variables. The effect estimates and significance levels are almost identical between the two tables for these variables. This consistency suggests robust findings regarding the impact of these factors on deaths.

Table 30 - stepwise selected model for 150m over the age 60+

Variable	Effect	IC95%	z	p
Range between highest and lowest number of floors in the buildings of the area	1.0090738	(1.00499; 1.01320)	4.417	1.00e-05
Median of number of floors between building in the area	0.9057045	(0.84903; 0.96673)	-3.051	0.002279
Presence of commercial area	1.4804060	(1.15638; 1.86622)	3.334	0.000856

Presence of mixed-use area	1.2899464	(1.18101; 1.40859)	5.654	1.57e-08
Presence of squares	1.2033494	(1.09098; 1.32833)	3.703	0.000213

Source: author

5.7.4 Synthesis and discussion of Form Data Findings

Literature indicates the relationship between green areas (Dzhambov *et al.,* 2018b; Ebisu *et al*., 2016b; Engemann *et al.,* 2018; Engemann *et al.,* 2019; Madzia *et al*., 2019) and mental diseases. In this research, green areas were not significant in preventing cardiorespiratory diseases. It was the only variable consistently not significant throughout the research, regardless of the size of the area analyzed (50m, 100m, or 150m) or the age of the subjects. Similarly, the literature suggests a lack of relationship between the presence of green areas and the risk of pregnancy complications (Choe *et al*., 2018).

Considering these literature findings and the results of this thesis, it is possible to consider that the presence of green areas has a much more significant psychological impact than a physiological one.

Commercial areas and areas of mixed-use were present in every model presented. Areas of mixed-use were present when the ratio started to expand (100m and 150m). They characterize areas with residential and commercial purposes (i.e., a mainly residential tall building with stores or offices on the ground floor or a house where there is also a small family-owned business).

Those areas are only sometimes adequately represented on city official maps as most of this family-owned business operate informally in Brazil. That also means that from the perspective of containing commercial areas, we can add the effects of mixed-use and commercial areas, which show a much more significant effect. Table 29 shows the combined effect. When the elderly population is discussed, proximity to commercial areas always has a more significant effect than when the general population is involved, suggesting a unique benefit to this group of being close to commercial buildings.

Table 31 - combination of effects of commercial and mixed-use areas

Distance	Age	Commercial areas effect	Mixed-use areas effect	Combined effect
50	All ages	54.30	-	54.30
50	60+	59.89	-	59.89
100	All ages	50.99	14.80	65.79
100	60+	62.20	19.26	81.46
150	All ages	42.90	25.62	68.52
150	60+	48.04	28.99	77.03

Source: author

The models needed to be more consistent in the average number of pavements, the range between taller and smaller, the sum of the building's number of pavements in the area, and any other pavement-related variable. The lack of consistency shows that the height of buildings influences in many different ways (difference between heights, actual height, maximum height).

In a closer look, the average and the standard deviation are negatively significant at 50 m, so the difference between heights reduces the number of deaths. When 150m is analyzed, the range between buildings appears in the model but with very little influence. That means it is a form trait with more meaning when closer to the subject. Ventilation might be an explanation for this trait once the difference between buildings allows for an improvement in ventilation paths.

The increasing death rate relationship in areas with proper land use, like residential and primarily commercial areas, might be related to traffic and noise. A study in Toronto (Chum; O'Campo, 2015) showed a relationship between commercial and mixed-use land use and sleep disorders that the authors considered connected to higher traffic in these areas. For this research, this influence is more prominent once people, especially those over 60, are at home, not only to sleep.

The presence of residential areas increased the number of deaths by 2.6 times. This means that being near great urbanization areas might increase the number of deaths.

Other little-explored factors regarding urbanization may be involved in explaining a small amount of these relationships. Walkability is facilitated by proximity to commercial areas and better cardiovascular health, therefore influencing the positive effect of these areas on the number of deaths. Moreover, commercial and mixed land uses tend to follow residential areas to provide public access to its products, which might justify their presence in the areas analyzed and their proximity to deaths.

Overall, land use was more significant than green areas, and there were more pavements. Land use has yet to be extensively explored as a predictor of health at the city level.

6 CONCLUSIONS AND RECOMENDATIONS

The impact of surface temperature on human health is a complex problem that requires urgent attention. To tackle this issue, it is crucial to understand the relationship between surface temperature and cardiorespiratory deaths in urban areas. This thesis found a weak correlation between these two variables by analyzing surface temperatures and cardiorespiratory death rates in the city's neighborhoods, highlighting the need for further investigation. It hasn't been possible to determine the magnitude of this impact as many factors may contribute to death, from genetics to lifestyle.

This thesis also examined form and disease data in some of João Pessoa's neighborhoods. The form data encompassed details about lots, such as the number of floors and land use. In contrast, the disease data delved into individual datasets, considering factors like age, gender, and neighborhood-specific death rates.

The analysis revealed the impacts of land use in the presence of cardiovascular and respiratory deaths in the area studied. In a 50m area, the number of floors and commercial areas significantly influenced the probability of deaths. The 100m area analysis, focusing on all ages, highlighted the impact of mixed-use areas, underutilized spaces, residential areas, and commercial areas on death rates. Similarly, the 60+ age group within the 100m circle demonstrated varying effects of these variables.

Additionally, the presence of commercial areas and mixed-use areas were all significant predictors of death, each exhibiting substantial positive effects. This analysis showcased a multifaceted exploration of the relationships between morphological variables and cardiorespiratory deaths in different spatial contexts, providing valuable insights into the factors influencing mortality rates in the studied neighborhoods.

No relationship existed between the number of deaths and the population size in each neighborhood. However, its distribution inside the neighborhood was not evaluated. Also,

Understanding the relationship between neighborhood form and cardiorespiratory health outcomes can directly impact public health interventions. This research lays the groundwork for targeted interventions and urban planning strategies to mitigate these risks and improve community well-being by identifying specific features that correlate with health risks.

It also contributes to a more comprehensive understanding of the interactions between built environments and human health. This holistic perspective is crucial for addressing contemporary challenges that require collaboration across diverse fields, such as the results of climate change.

Because João Pessoa has very specific laws that apply to its urbanization, a comparative study of cities with different morphologies but the same sociological and geographical stance may provide insights into the generalizability of these findings and help identify unique factors influencing health outcomes that only apply to João Pessoa and may be replicated in other cities.

As an integration with research that implies the impact of temperature and land use on psychiatric issues such as lack of sleep and depression, surveys with the living population might be a step in the future.

It is also critical to develop effective strategies to prevent and reduce risks associated with heat and other impacts of climate change. Such strategies must include urban planning to reduce or change underutilized areas and better distribute commercial and residential areas to improve the population's health.

As limitations, the study does not comprise the entire city. Additionally, it overlooks factors such as inner neighborhood population density, climate variables (including air temperature, pressure, and humidity), and the influence of building pavements on the number of residents per lot. Furthermore, the impact of the COVID-19 pandemic period has not been included in the research. The population data was acquired from the 2010 census and may differ from the situation in the present and also impact on the results as the disease data ranges from 2013 to 2019. Additionally, basements were disregarded for this work.

This thesis suggests the necessity of more sustainable and inclusive urban planning, focusing on what can make the city more livable and agreeable and on making the city healthy. Reducing impervious and polluting surfaces and increasing vegetation can significantly reduce the negative impacts of land use on cardiorespiratory diseases. Avoidable deaths affect individuals, families, and entire societies.

The relationship between land use, surface temperature, and cardiorespiratory diseases in João Pessoa involves an integrated view of environmental, social, and technical factors. The scientific importance lies in generating data for specific interventions; the social importance lies in improving public health and reducing inequalities; and the technical importance lies in applying evidence-based solutions to mitigate urban health impacts. The impact grows as the city grows, and the optimal point of action is early rather than later.

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