University of São Paulo
"Luiz de Queiroz" College of Agriculture

The role of the urban forest and climate change

Gustavo Torquatro Oliva

Thesis presented to obtain the degree of Doctor in Science. Area: Forest Resources. Option in: Conservation of Natural Ecosystems

Piracicaba
2024

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Environment Management

The role of urban forest and climate change

versão revisada de acordo com a Resolução CoPGr 6018 de 2011

Advisor:
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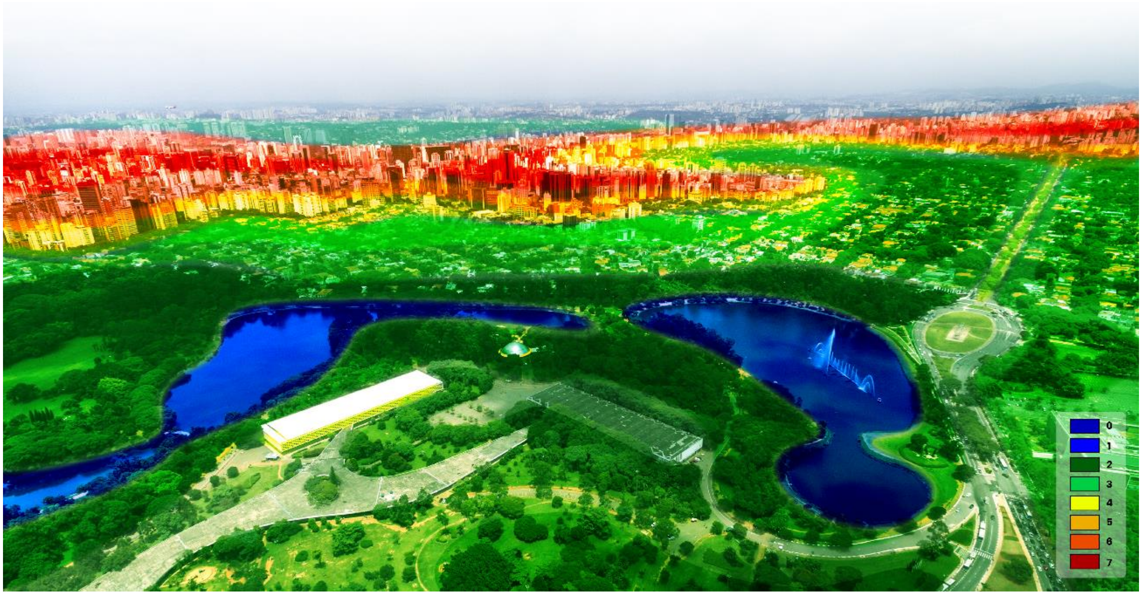
1. Floresta urbana 2. Ilhas de calor urbano 3. Soluções baseadas na natureza 4. Índice de Vegetação Melhorado 5. Mudanças climáticas 6. Modelo de regressão múltipla I. Título

DEDICATÓRIA



Overview of Ibirapuera Park represented with Urban Heat Islands in the Sao Paulo, City

I dedicated my dissertation work to my family, especially to my mom and my dad, Maria Aparecida and Odair, who have always loved me unconditionally and whose great examples have taught me to believe in my dreams.

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EPÍGRAFE

“La paura di essere te stesso è la tua peggiore malatia.” Gustavo Oliva

SUMMARY

RESUMO

O papel da floresta urbana e as mudanças climáticas

O papel da floresta urbana é extremamente importante nas grandes cidades, dada a sua vulnerabilidade às alterações climáticas. Estas zonas verdes urbanas desempenham um papel crucial na promoção de uma melhor qualidade do ar e na redução dos efeitos de ilha de calor. Em São Paulo, os modelos selecionados indicam que para o arrefecimento de 0,5°C na temperatura média urbana de São Paulo, seriam necessários incrementos de 17,50 e 22,56 pontos percentuais, (p.p), em torno de 20 p.p para as estações chuvosa e seca, respectivamente. E Piracicaba, os modelos selecionados (R^2 em torno de 60%) indicam que para o arrefecimento de 0,5°C na temperatura média urbana de Piracicaba, seriam necessários incrementos de 25,4 e 9,3 pontos percentuais, (p.p) para as estações chuvosa e seca, respectivamente. Para a variável umidade relativa, foram obtidos modelos em função de cobertura arbórea e outras variáveis relativas ao uso do solo com coeficientes de determinação em torno de 65% para ambas as estações. Esses resultados constituem-se em informações imprescindíveis para a implantação de políticas de arborização urbana. Incrementos dessa magnitude podem ser obtidos pela arborização de vias (ainda não arborizadas), aumento de número de árvores em vias já arborizadas e implementação de novos espaços verdes.

Palavras-chave: Floresta urbana, Ilhas de calor urbano, Soluções baseadas na natureza, Índice de vegetação melhorado, Mudanças climáticas, Modelo de regressão múltipla

ABSTRACT

The role of urban forest and climate change

The role of the urban forest is extremely important in large cities, given their vulnerability to climate change. These urban green areas play a crucial role in promoting better air quality and reducing heat island effects. In São Paulo, the selected models indicate that in order to cool the average urban temperature of São Paulo by 0.5°C, increases of 17.50 and 22.56 percent points (p.p) would be needed, around 20 p.p for the rainy and dry seasons, respectively. In Piracicaba, the selected models (R^2 around 60%) indicate that to cool the average urban temperature in Piracicaba by 0.5°C, increases of 25.4 and 9.3 percent points (p.p) would be needed for the rainy and dry seasons, respectively. For the relative humidity variable, models were obtained as a function of tree cover and other variables relating to land use with coefficients of determination of around 65% for both seasons. These results constitute essential information for implementing urban afforestation policies. Increases of this magnitude can be achieved by afforesting roads (not yet afforested), increasing the number of trees on roads that are already afforested and implementing new green spaces.

Keywords: Urban forest, Urban heat islands, Nature-based solutions, Enhanced vegetation index, Climate change, Multiple regression model

1. INTRODUCTION

The role of urban forests is extremely important in large cities, given their vulnerability to climate change. These urban green areas play a crucial role in promoting better air quality and reducing heat island effects. In addition, the urban forest performs many well-known environmental services: (improving air quality, health, real estate valuation, and as a mitigator against climate change and extreme weather events (BOUDET et al., 2020).

The diversity of São Paulo's urban tissue is highly heterogeneous, reflecting the complexities of a megacity that faces significant environmental, social, and economic challenges (LOMBARDO, 1985). An important phenomenon that has been observed is green gentrification, which results in the expulsion of the most vulnerable populations from wooded areas of the city (GOULD and LEWIS, 2016). It is essential to highlight the considerable impact of sugarcane activity on deforestation in Piracicaba. The continuous expansion of sugarcane plantations has contributed to the degradation of local ecosystems, raising concerns about environmental sustainability and the loss of natural habitats (FEARNSIDE, 2016). Deforestation in the city of Piracicaba is closely linked to this sugarcane cultivation activity, representing a significant challenge for the preservation of biodiversity and protection of the local environment.

The process of urbanization directly interferes with the atmosphere, altering the local climate, referred to as the urban climate. In other words, the city interferes with the built environment, with emphasis on the local scale. In metropolises, changes in the atmosphere become exacerbated and have an influence on the regional scale. The meteorological conditions of the air are strongly modified, creating a local climate type, known as the urban climate.

The different urban compartmentalization causes differences, interfering with thermal comfort and its consequences for urban planning. It is known that climate is the set of atmospheric conditions specific to a place, consisting of the quantity and frequency of rain, humidity, temperature, winds, etc., and whose complex action influences the existence of the beings subjected to it. A location’s climate is affected by its latitude, terrain, and altitude, as well as nearby bodies of water and their currents.

The quality of urban life depends, among other variables, on the climate, maintaining a two-way relationship, since the climate determines the adaptation of buildings and urban structures to the climatic context, which ends up influencing microclimatic conditions.

The first concerns about urban climate arose before the Industrial Revolution in the West. The oldest trace of the urban climate can be found in London in the 17th century. XVII, with Evelyn – 1661. In 1818, chemist Howard, in his book on climate in London, describes air contamination and the occurrence of higher temperatures in the city than its surroundings.

In 1927, in Vienna, data were obtained that served as the basis for creating an urban temperature map. After World War II, there was rapid growth in metropolitan areas and increased industrialization. From then on, studies on urban climate intensified, making the contamination of the city's atmosphere evident.

The number of studies on that theme becomes widespread in Europe and then in North America. With the environmental crisis at the end of the 1960s, studies pointed to the first syntheses. In Brazil, urban climate studies began with Carlos Augusto de Figueiredo Monteiro in 1970. The increasingly rich topic in detailed analyses emphasized the meteorological level, with truly geographic perspectives being limited.

From the comparison between the city and the surrounding countryside, the following fundamental facts emerged: 1) cities modify the climate through surface changes; 2) cities produce an increase in heat, complemented by changes in ventilation, humidity, and even precipitation, which tend to be more pronounced.

Currently, urban climate is one of the most consolidated fields of climatology and its results can be applied to other areas of knowledge. Urban climate is an example of unintended climate change and is one of the most relevant climate problems today. The city is a living laboratory in which one can experiment with the complex mechanisms triggered by human action on the climate: the changes that occur as a consequence of these actions and the influences that such changes can have on society.

It is in metropolises that environmental problems generally reach greater magnitude, with concentrations of pollutants in the air and water, and degradation of the soil and subsoil, as a result of the intensive use of the territory by urban activities. In urban environmental analysis, it is also necessary to consider three-dimensional space (horizontal and vertical planes), including air space, soil and underground. Environmental problems need to be addressed at different scales.

On a metropolitan scale, the effects of temperature variations are significant, as considering the "heat island" phenomenon there is a 10°C gradient between the surrounding rural area and the São Paulo metropolis (LOMBARDO, 1985). Nature Based- Solutions are alternatives to minimize the Urban Heat Island: through green roofs, the use of materials with a high solar reflectance index, increased soil permeability (vertical gardens, installation of lakes, and water mirrors.

The implementation of green infrastructure in cities can be an NBS, focusing on medium and large afforestation. Green infrastructure can be defined as the open spaces fundamental to the ecological functioning of the area that contributes to the preservation of natural ecosystems, wildlife, air, and water quality, and consequently the quality of life of the inhabitants. Parks, forests, squares, community gardens, and other forms of public or private natural landscapes make up Green Infrastructure. In cities, green infrastructure includes urban afforestation and green roofs (AMATO – LOURENÇO et al., 2016).

Urban heat mitigation is an increasingly urgent concern given the challenges posed by urbanization and global warming. In many cities, disorderly growth and urban expansion have contributed to the formation of heat islands, where temperatures can be significantly higher than in surrounding areas. Microclimate models play a crucial role in understanding these complex heat patterns and identifying critical areas that require intervention. By analyzing factors such as urban density, land use patterns, vegetation distribution, and topographic features, these models offer valuable insights for sustainable urban planning and the implementation of solutions adapted to local conditions.

One of the main advantages of microclimate models is the ability to simulate hypothetical scenarios and evaluate the impact of different heat mitigation strategies. This allows urban planners and policymakers to make informed and effective decisions to promote urban cooling. From implementing green roofs and permeable walls to planning wind corridors and creating shaded areas, solutions based on microclimate models can be adapted to the specific needs of each region, maximizing their effectiveness and long-term sustainability.

Furthermore, by involving local communities and stakeholders in the planning process, microclimate models can promote awareness of urban heat challenges and encourage active participation in the search for innovative solutions. By transforming complex data into accessible and actionable information, these models play a key role in building more resilient, healthy, and livable cities for all their residents. Therefore, the adoption and continuous improvement of microclimate models represent an essential approach to addressing urban heat challenges and creating more sustainable and inclusive urban environments for the future.

Research on tree-scale microclimate models with the goal of reducing urban average temperatures by 1°C represents a significant advance in the field of urban heat mitigation. By focusing specifically on this scale, researchers can better understand how trees and urban vegetation influence the local microclimate and, therefore, contribute to reducing temperatures in urban areas.

These models allow a detailed analysis of shading patterns, evapotranspiration, evaporative cooling effects and air flows around trees, crucial factors for understanding the impact of wooded areas on the urban environment. By incorporating data on vegetation density, type of tree species, spatial distribution and other relevant factors, models can more accurately predict the benefits that trees provide in terms of heat reduction.

This approach not only provides valuable information for urban planners and environmental managers, but also highlights the importance of urban vegetation as an effective climate change adaptation strategy. In addition to reducing local temperatures, trees and vegetation also offer a range of other benefits, such as improving air quality, reducing urban noise, promoting biodiversity, and increasing the emotional and mental well-being of urban residents.

By involving the local community in the planning and implementation process of these models, it is possible to create a sense of shared responsibility in relation to the conservation and expansion of urban green areas. This not only strengthens social bonds and community cohesion, but also promotes a culture of sustainability and resilience in cities.

Ultimately, the research and implementation of tree-scale microclimate models to reduce average urban temperatures not only directly addresses the challenges of urban heat, but also contributes to building greener, healthier and more livable cities for present and future generations. future ones. This approach exemplifies the power of science and community collaboration in creating innovative solutions to the complex environmental problems facing urban areas around the world.

This doctoral thesis is structured in 2 chapters, the first of which is a case study for São Paulo (SP), the country's largest city. The general objective was the role of forested urban areas in adapting to climate change. Using regression models, the research aimed to predict the amount (% of total area) of vegetation cover needed to reduce the average temperature by 0.5°C in the urban areas of the municipality of São Paulo. The study's conclusions provide a solid scientific basis for the efficient implementation of urban afforestation policies.

The second chapter focused on a medium-sized city in the interior of São Paulo, Piracicaba (SP). The aim of this chapter was to create a microclimate model, a linear model, to estimate average relative temperature and humidity as a function of variables relating to land cover and EVI (Enhanced Vegetation Index).

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CHAPTER I. GREENNESS MODELS APPLIED TO MITIGATE HEAT URBAN ISLAND IN THE MEGACITY OF SOUTH AMERICA, SÃO PAULO CITY, BRAZIL

Abstract

It is important to note that Brazil is home to a remarkable biological diversity, with the Atlantic Forest being one of the biomes under threat. Around 24% of the country's total Atlantic Forest is present in Brazilian territory, 13% of which is concentrated in the state of São Paulo, with 40% in the city of São Paulo, covering an area of more than 1,500 km². The city of São Paulo is a megacity; these figures indicate the importance of the Atlantic Forest biome in the urban context of São Paulo. Extreme heatwaves, intense rainfall and forest fires are increasingly recurrent. São Paulo's urban climate is a product of the intense emission of pollutants in industries, the intense flow of vehicles, the lack of afforestation, the excessive imperviousness surface and the types of materials used in construction that absorb high rates of thermal radiation. The main objective of this work was to create a (multiple) linear regression model to predict average temperature as a function of tree cover in the urban area of the municipality of São Paulo (% of area), with the aim of estimating the increase in tree cover needed to cool the average urban temperature by 0.5°C. The models were selected for both seasons using the stepwise method. In order to verify the relationship between the variables air temperature (°C) and LST (Land Surface Temperature) and a set of candidate predictor variables related to land use and EVI (Enhanced Vegetation Index). The microclimate variables were obtained from 28 weather stations located in different sub-prefectures of the city of São Paulo, during the Jan-Mar and Jun-Aug quarters, in the 2019-2023 period. The selected models, for the rainy (R^2 = 64.14%) and dry (R^2 = 78.99%) seasons, respectively, indicate that in order to cool the average urban temperature in São Paulo by 0.5°C, increases of 17.50 and 22.56 percent points (p.p) would be needed, around 20 p.p. for the rainy and dry seasons, respectively. These results are essential information for implementing urban afforestation policies. Increases of this magnitude can be obtained by afforesting roads (which are not yet afforested), increasing the number of trees on roads that are already afforested, and implementing new green spaces.

1. Introduction

The urban forest plays a fundamental role in cities, and its beneficial effects are already well known: improving air quality (VOS et al., 2013), reducing heat islands (MOHAJERANI; et al., 2017), intercepting rainwater to minimize flooding (ASADIAN; WEILER, 2009), increasing biodiversity in its surroundings (THRELFALL et al., 2017), associated with the mental health of the urban population (BEYER et al., 2014), real estate valuation and aesthetics in properties (LUTTIK, 2000) and as a mitigator against climate change and extreme weather events (BOUDET et al., 2020).

MILLER (1997) already defined urban forests as the sum of the woody vegetation in the urban perimeter, considering the vegetation contained even in rural areas. The intensified process of urbanization leads to the phenomenon known as the "urban heat island" (UHI), which is marked by an increase in temperature within urban areas concerning neighboring regions, as pointed out by (LOMBARDO, 1985) in his study in the municipality of São Paulo.

According to CONTOIS and OKE (1978), a city's climate is an excellent indicator of the quality of urban life. The urbanization process already alters this microclimate in a very peculiar way, turning it into an atmosphere and microclimate that differs according to the use and occupation of the land (e.g., type of buildings, roof tiles, amount of vegetation, soil permeability).

In times of climate change and extreme weather events, Nature-Based Solutions (NBS) have gained importance and have been employed as actions for the protection, sustainable environmental management, and restoration of natural or modified ecosystems, which address society's challenges in an effective and adaptive way, while simultaneously providing benefits to human well-being and biodiversity (IUCN, 2016). According to (LAFORTEZZA; SANESI, 2020), although the idea of Nature-Based Solutions (NBS) is gaining increasing consensus among researchers and policymakers around the world, there is still a need to formalize its role and potential in relation to the various factors and mechanisms that underpin the process of sustainable urbanization so that decision-makers can make the best decisions in the face of often scarce resources and priorities.

The importance of trees in providing these ecosystem services is essential because of future and current climate change scenarios. For this reason, evaluating the ecosystem services provided by urban afforestation and constantly monitoring them are essential to promote environmental sustainability and urban resilience in the face of climate change. Recent studies show a trend toward an increase in extreme events such as droughts (HAO et al., 2018), extreme heat waves (VOGEL et al., 2019), intense precipitation (THACKERAY et al., 2022), and windstorms (ZHANG; SUN; CHEN, 2021). The urban climate of Sao Paulo is a product of the intense emission of pollutants in industries, the intense flow of vehicles, the lack of trees, the excessive surface area of pavement, and the types of materials used in construction that absorb high rates of thermal radiation (LOMBARDO, 1985).

Recently, microclimate-modeling studies in urban forests have been crucial to understanding and mitigating the effects of climate change in urban areas. Multiple studies highlight the significant influence of vegetation on climate control (ZHOU et al., 2022; WU et al., 2015; WOODWARD; MCKEE, 1991; ARNETH, 2015; LOMBARDO, 1985; SILVA, 2012; OLIVA, 2016; MARTINI, 2016; AMORIM, 2017). Recent advances in microclimate modeling have explored the integration of high-resolution remote sensing data, allowing for a more detailed representation of microclimate patterns in vegetated urban areas. However, there is a considerable gap in the application of microclimate models using vegetation indices, particularly in tropical regions such as Brazil. The lack of adaptation of existing models, derived from studies in temperate regions, compromises the accuracy of forecasts for Brazilian cities, making it essential to develop models adapted to the tropical reality.

Gaps remain in the microclimate modeling of Brazilian urban forests due to the scarcity of detailed climate data and the heterogeneity of urban conditions. The integration of high-resolution remote sensing data, the accurate collection of field data, and the validation of models are areas that need investment and attention in Brazilian research. In this study, an innovative multiple regression model was developed for the city of São Paulo, with the aim of predicting the amount of increase in current tree cover that would reduce the average urban temperature by 0.5°C. This study used a 5-year time series of daily microclimate data (2019-2023), and integrated data from a vegetation index obtained by high-resolution remote sensing, with the collaboration of experts in different fields. Investing in studies adapted to Brazil's climatic conditions and urban networks is fundamental to improving urban and environmental management. The collection of data with high spatial resolution and the development of specific models for tropical regions are crucial to support public policies on urban afforestation. This multidisciplinary approach not only enriches the understanding of the effects of vegetation on urban temperature, but also offers valuable guidelines for creating healthier and more sustainable urban environments.

It is important to note that Brazil is home to a remarkable biological diversity, with the Atlantic Forest being one of the biomes under threat. Around 24% of the country's total Atlantic Forest is present in Brazilian territory, 13% of which is concentrated in São Paulo State. In addition, approximately 40% of this amount is located in the city of São Paulo, covering an area of more than 1,500 km², according to SVMA (2023) - São Paulo's Municipal Secretary for Greenery and the Environment. These values indicate the importance of the Atlantic Forest biome within São Paulo's urban context.

Currently, the ideal amount of trees needed to mitigate excessive heat in specific urban areas has yet to be determined. This is particularly crucial in the face of climate change and the water and energy supply crises that many cities are facing. A viable approach would be to develop a climate model based on data from geographic information systems, taking into account both tree density and population density, to justify changes in urban structures. The aim would be to improve the well-being of urban residents.

The hypotheses of this study were: H1) models based on urban land use classes and other auxiliary variables: EVI (Enhanced Vegetation Index) and LST (Land Surface Temperature), obtained from satellite images, are capable of predicting the average urban temperature of cities in tropical regions; H2) The cooling rates of the average urban temperature as a function of the percentage of tree cover decrease as this percentage increases.

In this context, this research focused on analyzing the role of urban wooded areas in adapting to climate change. Using regression models, the research aimed to predict the amount of vegetation cover needed to reduce the average temperature by 0,5°C in the urban areas of the municipality of São Paulo. The conclusions of the study can provide a solid basis for informing public policies that promote a more robust green infrastructure in the city.

2. Material and Method

2.1Area of study

The city of São Paulo is located in the southeast of the state of São Paulo, at 23º 32' S and 46º 37' W, with an altitude of 860 meters, a territorial extension of 1,521 km² and a Cwa-type climate, according to the Köeppen climate classification (CEPAGRI, 2023a), characterized as high altitude tropical climate, with a rainy summer and dry winter. The average temperature of the hottest month is above 22°C, reaching an average maximum of 28°C and an annual average of 20.7°C (CEPAGRI, 2023 b). The city has around 22 million inhabitants in its metropolitan region and almost 12 million in the city, according to the last Brazilian census (IBGE, 2022).

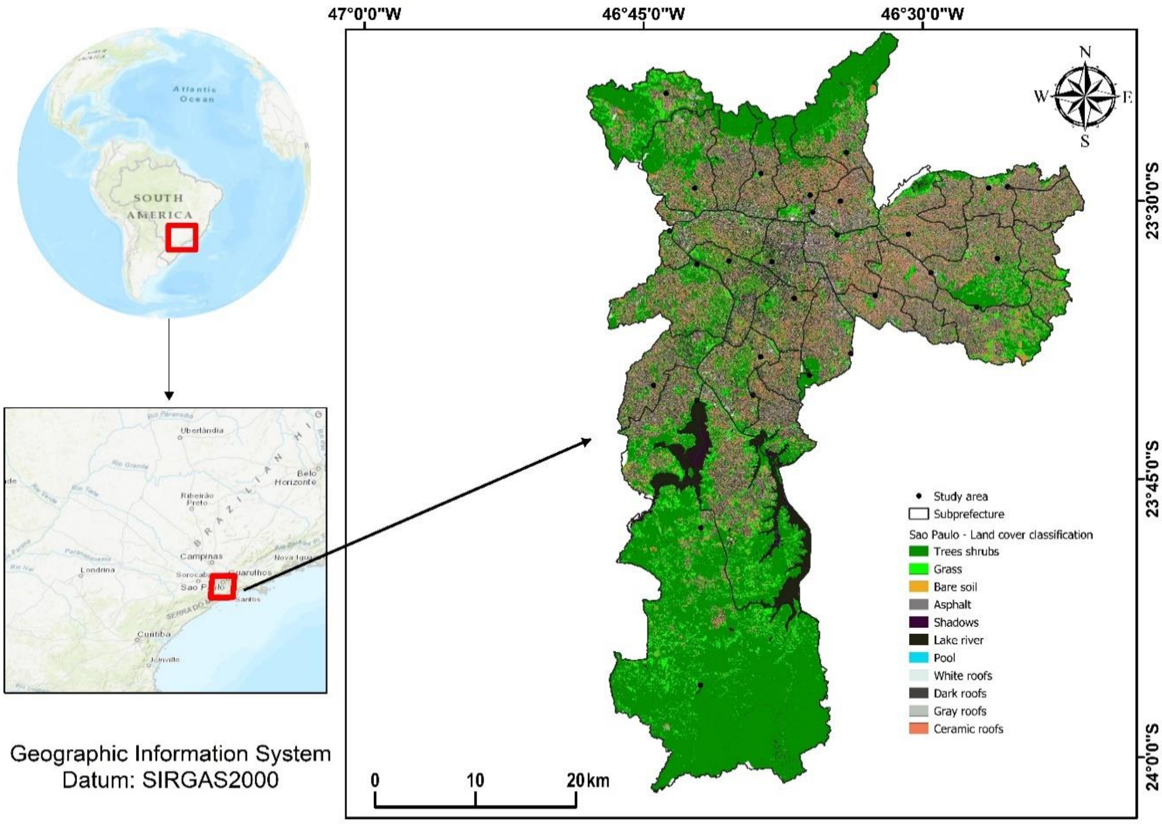


Figure 1: Study area including 28 weather stations in the urban are of São Paulo city, São Paulo, Brazil. (Prepared by the author).

The original biome where the São Paulo City is located is the Brazilian Atlantic Forest. The research area (Figure 1) includes the network of weather stations available in the city of São Paulo/SP. With a long historical series, the city has the station of the Institute of Astronomy, Geophysics, and Atmospheric Sciences of the University of São Paulo (IAG-USP)/Água Funda, World Meteorological Organization (WMO), (GIVONI, 1989), which has been in operation since 1933, and INMET (National Institute of Meteorology), which has been operating since 1943, WMO Standard. The others ones are from the Emergency Management Center (CGE); from 2010 onwards, there were already some measurement records.

2.2. Microclimatic data

The data was obtained from 28 official weather stations spread across the five regions mentioned above over five years in the rainy and dry seasons of (2019-2023), reference period was chosen due to greater availability of climate data and satellite images, in the municipality of São Paulo/SP. The variables are air temperature (°C) and air relative humidity (%) - (Tmed, URmed, Tmin, URmin, Tmax, URmax, T range, UR range). All the stations are 1.5 meters above the ground, as recommended by (Oke, 2006), according to the WMO Standard (GIVONI, 1989).

In this study, the daily data corresponding to the quarter (January, February, and March) and the quarter (June, July, and August) for both stations were selected, using the quarterly daily averages of the variables of interest (average temperature, minimum temperature, maximum temperature, average, minimum and maximum relative humidity) to run the multivariate regression models.

2.3 Urban land use, satellite data and volumetry

2.3.1 High-resolution multispectral images

The supervised classification of São Paulo's urban tissue was carried out using Quantum GIS 3.30 software, using the trainer and auditor, and 200 samples were taken from each class. These are shown below tree cover, shrubs/grass, bare soil, asphalt, shadows, lake river, pool, white roofs, dark roofs, gray roofs, and ceramic roofs, the percentages of the total area of the urban fabric for the above-mentioned classes were obtained.

High-resolution images containing bands in the near-infrared were used. For this, a product derived from images from the CBERS 4A satellites (2-meter resolution), with spectral resolution-near-infrared ranging up to 900 nanometers, and LandSat 8 (15-meter resolution, panchromatic band) and Planet (3-meter resolution) was used to extract vegetation EVI index (Enhanced Vegetation Index) and Land Surface Temperature (LST) for the years 2019 to 2023.

The Enhanced Vegetation Index (EVI) is a vegetation index that is used to monitor the health and vigor of vegetation on the Earth's surface. It is particularly useful for monitoring areas with dense vegetation cover, such as forests or croplands. The formula for EVI was developed to improve upon the Normalized Difference Vegetation Index (NDVI) by correcting for atmospheric influences and soil backgrounds. The formula for EVI is as follows:

$$EVI = 2.5 * ((NIR – RED) / ((NIR) + (C1 * RED) – (C2 * BLUE) + L))$$

Where:

NIR = Near Infrared band reflectance

RED = Red band reflectance

BLUE = Blue band reflectance

G = Gain factor (default value: 2.5)

L = Canopy background adjustment (default value: 1.0)

C1 = Coefficient of aerosol resistance for the red band (default value: 6.0)

C2 = Coefficient of aerosol resistance for the blue band (default value: 7.5)

The values of coefficients G, L, C1, and C2 can vary depending on the sensor and the specific conditions of the study. These default values are commonly used but may be adjusted for specific applications.

The EVI formula attempts to correct for atmospheric influences, canopy background effects, and the differential scattering of light in the blue band. It produces values that range from -1 to 1, with higher values indicating denser and healthier vegetation.

Table 1: Period of satellite image collection to obtain mean values of the variables EVI (Enhanced Vegetation Index) and LST (Land Surface Temperature) to be used in the proposed regression models.

Satellite	Variable	Year	Season	Collection Dates
Planet (3 m resolution)	EVI	2019	Rainy	01/27, 02/24 and 03/23
			Dry	06/30, 07/23 and 08/08
		2020	Rainy	01/21, 02/16 and 03/14
			Dry	06/13, 07/21 and 08/26
		2021	Rainy	01/25, 02/18 and 03/23
			Dry	06/26, 07/19 and 08/18
		2022	Rainy	01/19, 02/21 and 03/30
			Dry	06/23, 07/23 and 08/27
		2023	Rainy	01/27, 02/26 and 03/29
			Dry	06/26, 07/23 and 08/18
LandSat 8 (15 m res.)	LST	2019	Rainy	01/21, 02/22 and 03/26
			Dry	06/30, 07/26 and 08/17
		2020	Rainy	01/30, 02/25 and 03/28
			Dry	06/16, 07/18 and 08/03
		2021	Rainy	01/26, 02/27 and 03/15
			Dry	06/03, 07/21 and 08/22
		2022	Rainy	01/21, 02/14 and 03/18
			Dry	06/30, 07/24 and 08/01
		2023	Rainy	01/16, 02/09 and 03/21
			Dry	06/25, 07/27 and 08/04

A land use map was generated from the high-resolution satellite images, which were subjected to supervised classification. Radar diagram were built for 5 of the 28 stations studied (500 m buffers): Pinheiros, Sé, Marsilac, Itaim Paulista, and IAG/USP. These stations were chosen because they have very different land uses, with tree cover ranging from 5 to 82%.

The radar diagram illustrates the distribution of land use, in the categories of tree cover, asphalt and built space, in each of the 16 circular sectors defined by the cardinal, collateral and sub-collateral points of each wind rose (N, NNE, NE, ENE, E, ESSE, SE, SSE, S, SSW, SW, WSW, W, WNW, NW and NNW). (APPLEQUIST, 2012). The radar diagram were constructed using the package *ggplot* of the language and environment for statistical computing, R version 4.3.1 (R Core Team, 2023). The five radar diagram were superimposed on the land use map at the locations corresponding to each of the five seasons mentioned above.

2.3.2. Satellite data and volumetry

The maps generated for the Land Surface Temperature (LST), for both stations, were in Quantum GIS 3.30 software, complemented by Luca Congedo, processing from raster to vector, using the pixel value for temperature (LST) in (°C). To obtain the LST maps, map algebra was performed in QGIS, where the LSTs were averaged over 5 years (2019-2023) and the arithmetic mean was obtained for mapping.

The volumetry was generated using shapefiles of the buildings, available on GEOSAMPA, which show the area and height of each building. As well as the road network, the shapefiles of the streets were used and a buffer (radius of influence) of 10 meters was processed. The total length of the roads was determined, which multiplied by the width of the buffer resulted in the road area itself. With regard to the tree cover present on road of Sao Paulo network, this was extracted using general supervised classification, which resulted in land use mapping, respectively.

2.4 Statistical methods

2.4.1 Descriptive exploratory analysis (Box plot)

To visualize the characteristics of the probability distributions of each of the variables, especially asymmetry, dispersion, and the presence of outliers, box and whiskers plots were constructed.

2.4.2 Multiple regression models

Multiple regression models (Eq.1) were adjusted to represent the relationship between the response variables of interest and the candidate predictor variables.

$$Yi = \beta 0 + \beta 1 * X1i + \beta 2 * X2i \ldots + \beta j * Xik \ldots \beta k * Xki + \varepsilon i \quad (Eq.1)$$

In equation 1, Yi corresponds to the value of the response variable at station i (I= 1, i=2, i=3, ..., i=28). β0 is the model intercept; β1... βj ... βk are the angular parameters corresponding to each predictor variable. Xki is the value of predictor variable j at station i (i=1, 2, ... 28) and K is the number of candidate predictor variables. εi is the random error associated with each observation Yi.

The response variables of interest are Tmin, Tmed, Tmax, Trange and LST. For each response variable, a model was fitted for the dry season and another for the rainy season. For the rainy season, the microclimate response variables (Temperature and LST) correspond to the averages for the January, February and March quarter (JFM) and for the dry season the averages correspond to the June, July, and August quarter (JJA). For both seasons, the daily data for the respective quarters over a five-year period (2019-2023) was taken into account.

Predictor variables related to land use were used (tree cover, lawn, exposed soil, asphalt, shade, swimming pool, light tile, dark tile, gray tile, ceramic tile, built space (BS), Vegetation Index (EVI), Volumetrics and Urban Forest Index (UFI). For each model, the predictor variables that remained in the model were selected by the Stepwise method (Miler, A. 2002), using the Akaike criterion (AKAIKE, 1976) with tolerance limits of 0.15 for entry and 0.10 for remaining in the model. The REG procedure (PROC REG) of the SAS/STAT® statistical software (SAS Inst. Inc., 2020) was used with the "STEPWISE" option as the method of selection of the best predictors.

2.4.3 Nonlinear models

To test the hypothesis that the cooling rates of the average urban temperature as a function of the percentage of tree cover decrease as the cover increases (H2), non-linear models were also fitted to represent the relationship between the average temperature and tree cover.

(H2), non-linear models were also fitted to represent the relationship between average temperature and tree cover in both seasons. Three types of decline models were tested for each season (Table 2): exponential decline, harmonic decline and hyperbolic decline (BATES and WATTS, 1989; SEBER and WILD, 1989).

Table 2: Candidate nonlinear models tested to represent the relationship between daily mean temperature (Tmean, °C) and tree cover (TC, %), in periods of both rainy (Jan-Mar) and dry seasons in urban area of Sao Paulo, SP, Brazil. Meteorological data from 28 weather stations (2019-2023).

Nonlinear model	**Model equation**
Exponential decline	$Tmean_{ij} = \beta_{0j} * exp\ (-TC_i/\beta_{1j}) + \varepsilon_{ij}$
Harmonic decline	$Tmean_{ij} = \beta_{0j}/(1 + TC_i/\beta_{1j}) + \varepsilon_{ij}$
Hyperbolic decline	$Tmean_{ij} = \beta_{0j}\ (1 + \beta_{2j} * TC_i/\beta_{1j})^{(-1/\beta_{2j})} + \varepsilon_{ij}$

*Tmean*ij* is the daily mean temperature of the station *i* *(i=1,2,…28)* in the season j; TC_i is the tree cover in the station *i*, *i=(1, 2, 3…28)*; β_{0j}, β_{1j} and β_{2j} are model parameters corresponding to the rainy and dry seasons *(j=1,2)*.

In the models presented in Table 2, $Tmean_{ij}$ (°C) is the daily mean air temperature (response variable) of the station *i (i=1,2,…28)* calculated in the season *j*, *j=(JFM, JJA)*, during the period 2019-2023; *TCi* (%) is the tree cover in the 500m buffer corresponding to the station *i (i=1,2,…28);* β_{0j} is the model intercept, and β_{1j} and β_{2j} are the shape model parameters for the season j and ε_{ij} the random error associated to each $Tmean_{ij}$ observation. The nonlinear models were fited using the NLIN Procedure (Proc NLIN) of the statistical software SAS/STAT (SAS Inst. Inc., 2020).

2.5 Mapping of predicted mean temperature

The mean temperature values predicted corresponding to each meteorological station (28), obtained from the selected models for each season (rainy and dry) where used to produce maps using kernel-barrier interpolation (GRIBOV, 2011).

3. Results and Discussion

3.1 Land use obtained by supervisor classification and vegetation index

The supervised classification of the image of the municipality of Sao Paulo/SP obtained a kappa index of 96.97%, showing excellent accuracy. This result makes it possible to use quantified cover data and relate it to microclimate data later (Figure 2).

The city of São Paulo has a high degree of variability in tree cover between the sub-prefectures (5-85%; Figures 2 and 4). It can be seen that the concentration of tree cover is more pronounced in the North (Cantareira Region), South (Parelheiros Region) and some expressive fragments in the East Zone of the city (Parque do Carmo) and in the center-south region (Ibirapuera Park) (Figure 2). The municipality of São Paulo is a heterogeneous city, being a megacity, with great heterogeneity in relation to land use and occupation, Local Climate Zones (LCZs) defined by STEWART and OKE, (2012).

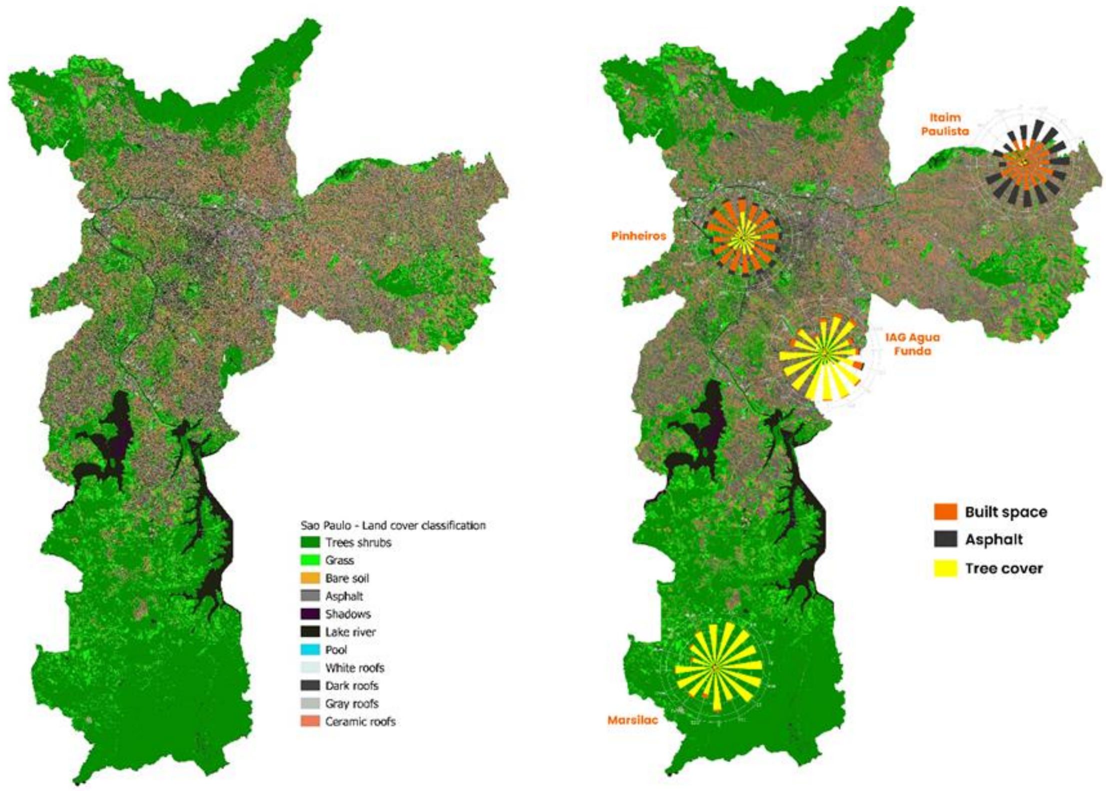


Figure 2: Land Use of Sao Paulo (SP), Brazil, obtained by supervised classification using CBERS 4A satellite image, Set-2020. Radar diagram corresponding to the distributions of the main land use classes (asphalt, built space, and tree cover) for each one of five selected weather stations (IAG, Itaim Paulista, Marsilac, Pinheiros, and Se), are shown in B): Each wind rose displays the percentage of the urban area occupied by asphalt, built space, and tree cover for each of the 16 sectors of the corresponding 500 m buffer.

Among the 28 points studied, the following LCZs were found using this classification, adapted by FERREIRA (2019): Dense Trees: (Marsilac, IAG/Agua funda, Capela do Socorro, M'Boi Mirim and São Mateus); Compact low-rise: (Itaim Paulista, Vila Prudente, Ipiranga, Perus, Penha, Campo Limpo, Freguesia do O, Itaquera, Sé, Cidade Ademar, Santo Amaro, Vila Maria/Vila Guilherme, Vila Mariana, Mirante de Santana, Tremembe, Pirituba, Butantã, Pinheiros, and Large low rise (São Miguel Paulista, Vila Formosa, Mooca, and Santana).

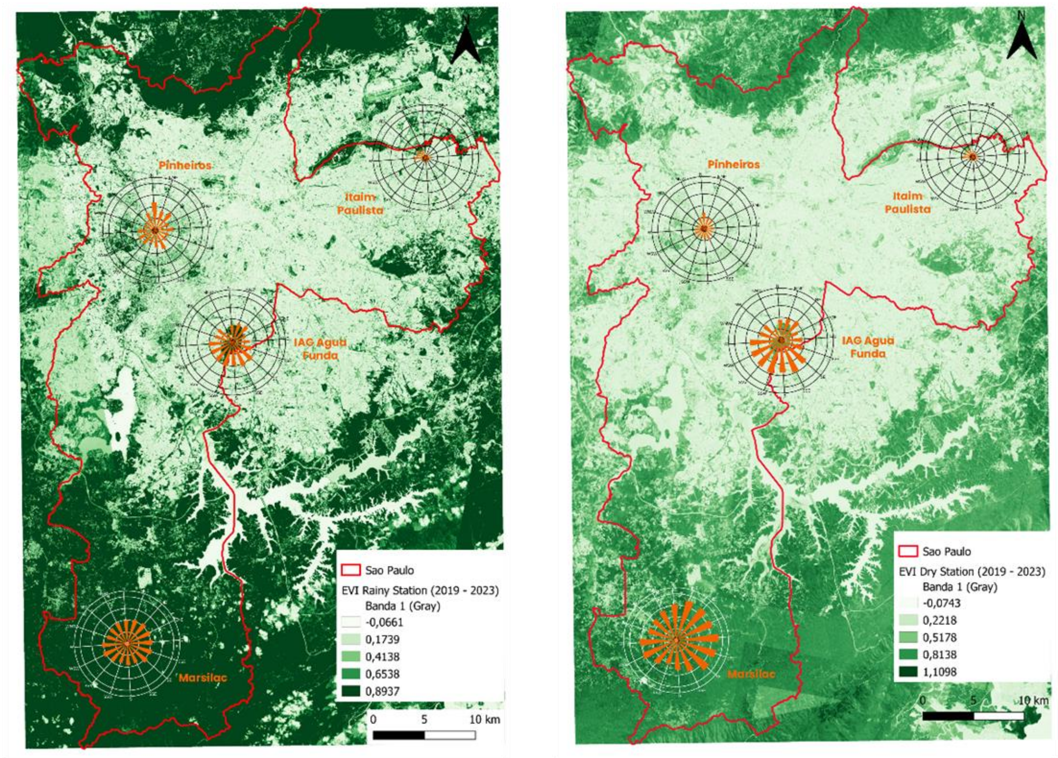


Figure 3: Mean Enhanced Vegetation Index (EVI) of Sao Paulo urban area. Data obtained by the satellite Planet (3 m resolution) collected at 15 dates, during the rainy period (Jan-March) of each year from 2019-2023.

Among the sample areas studied, the subprefectures of Parelheiros (Marsilac Station) and Ipiranga Subprefecture (IAG AGUA Funda) had the highest (%) tree cover (81.9% and 76.8%), respectively. In the stations' areas of influence: The stations with a prevalence of low coverage were mostly concentrated in the East Zone sub-prefectures: Vila Formosa, São Miguel Paulista, Itaim Paulista, Penha, and Vila Prudente (between 5 and 10%; Figures 3 and Figure 2B).

3.2 Characterization of the input data

The distribution of tree cover values between the stations (500 m buffer) is highly asymmetrical to the right due to the extremely high tree cover values of the Marsilac and IAG/Agua Funda stations, which are discrepant from the others (Figures 4, 5 and 6). The distribution of built-up space (%) has the opposite characteristics: it is asymmetrical to the left, with discrepant points with low percentages of built-up space at the aforementioned stations. The percentage of asphalt has a relatively symmetrical distribution, with the following stations standing out: Vila Formosa, Vila Prudente, Itaim Paulista and São Miguel Paulista (East Zone).

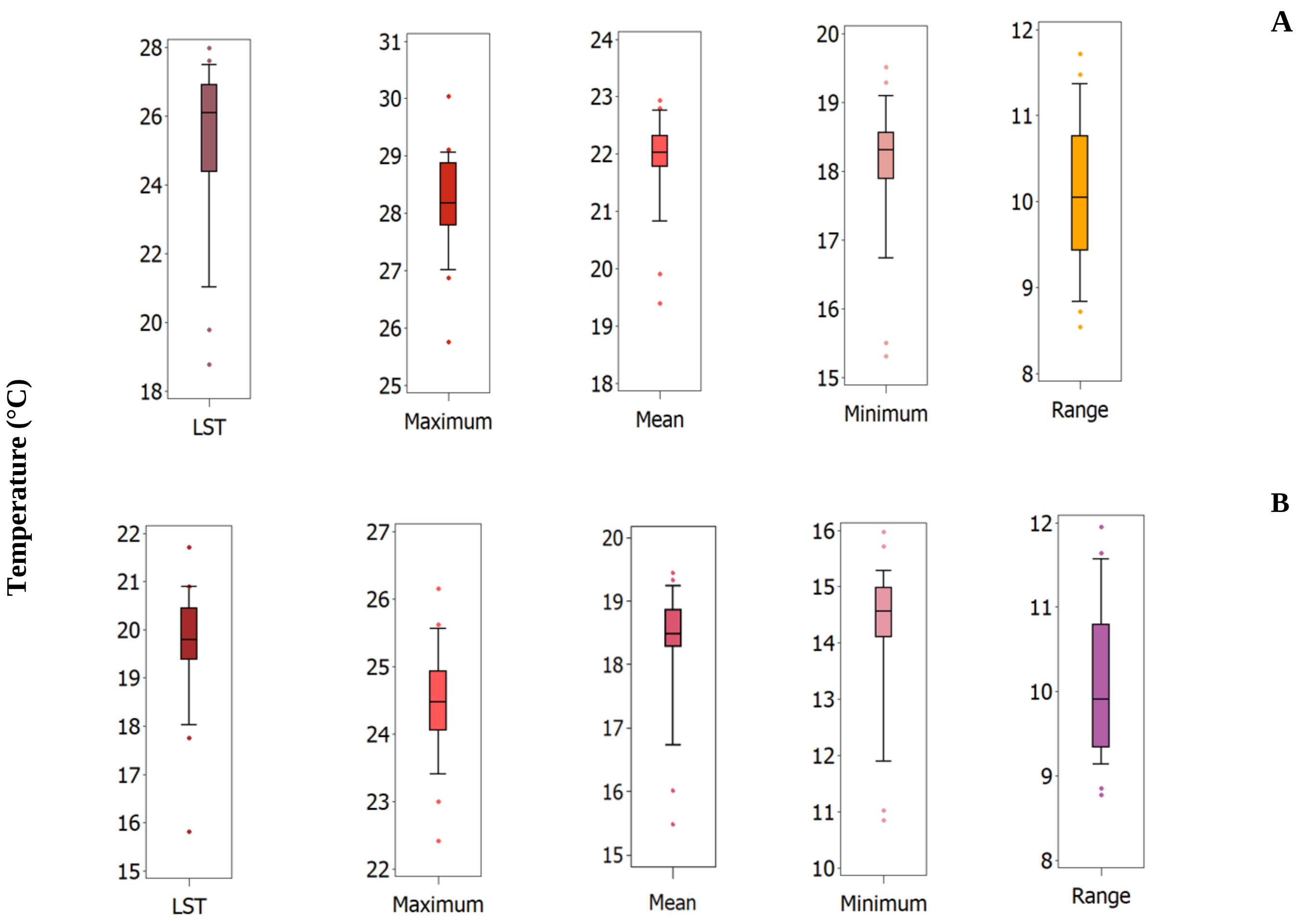


Figure 4: Box and whiskers plots of LST, maximum, mean, minimum and range temperature from 28 weather stations in São Paulo, Brazil. Statistics calculated using data from JFM trimester (rainy season) and JJA (dry season) from 2019 to 2023. The bottom and top edges of the box are located at the 25th and 75th percentiles. The center horizontal line is drawn at the median (50th percentile). The vertical lines, or whiskers, extends from the box as far as the data extend, to a distance at most 1.5 interquartile ranges.

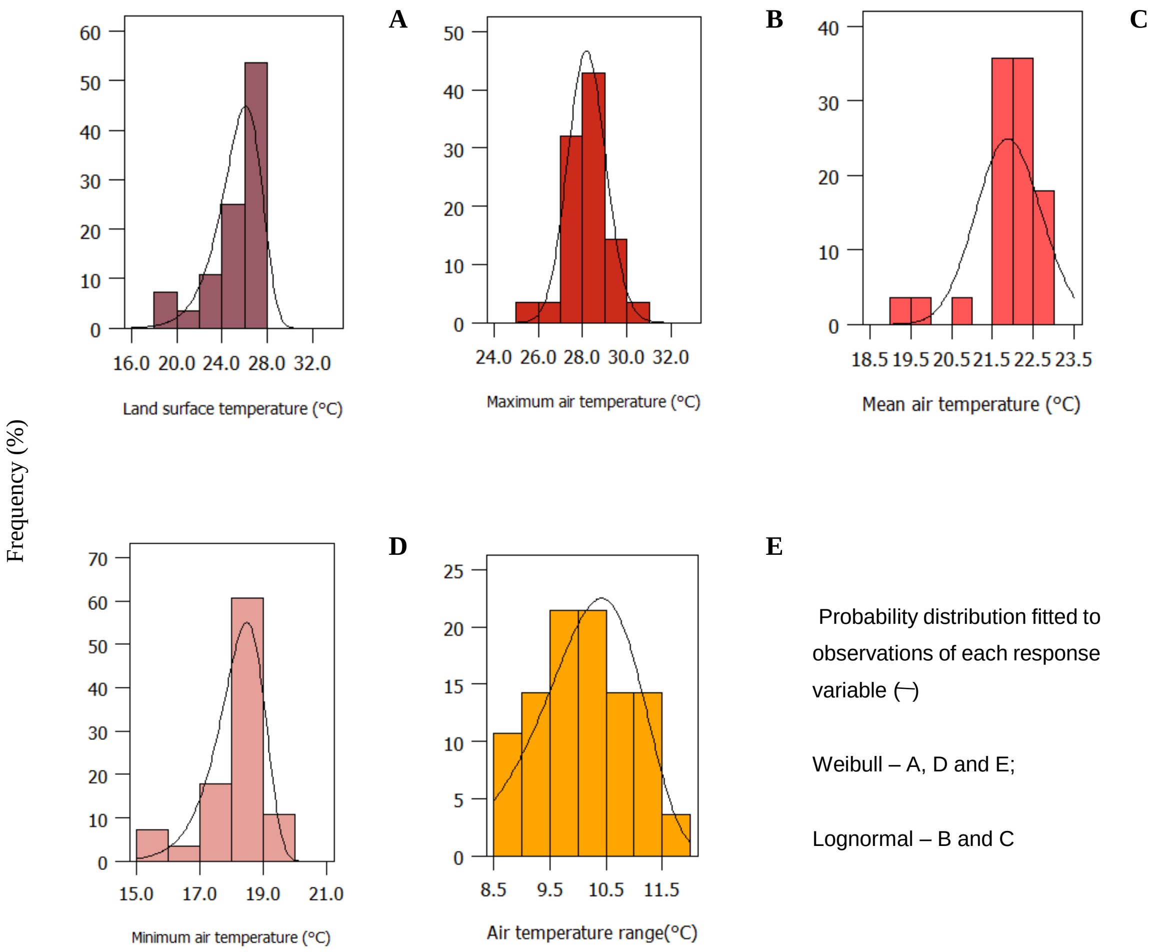


Figure 5: Histogram of LST, maximum, mean, minimum and range temperature from 28 weather stations in São Paulo, Brazil. Statistics were calculated using data from JFM trimester (rainy season) from 2019 to 2023.

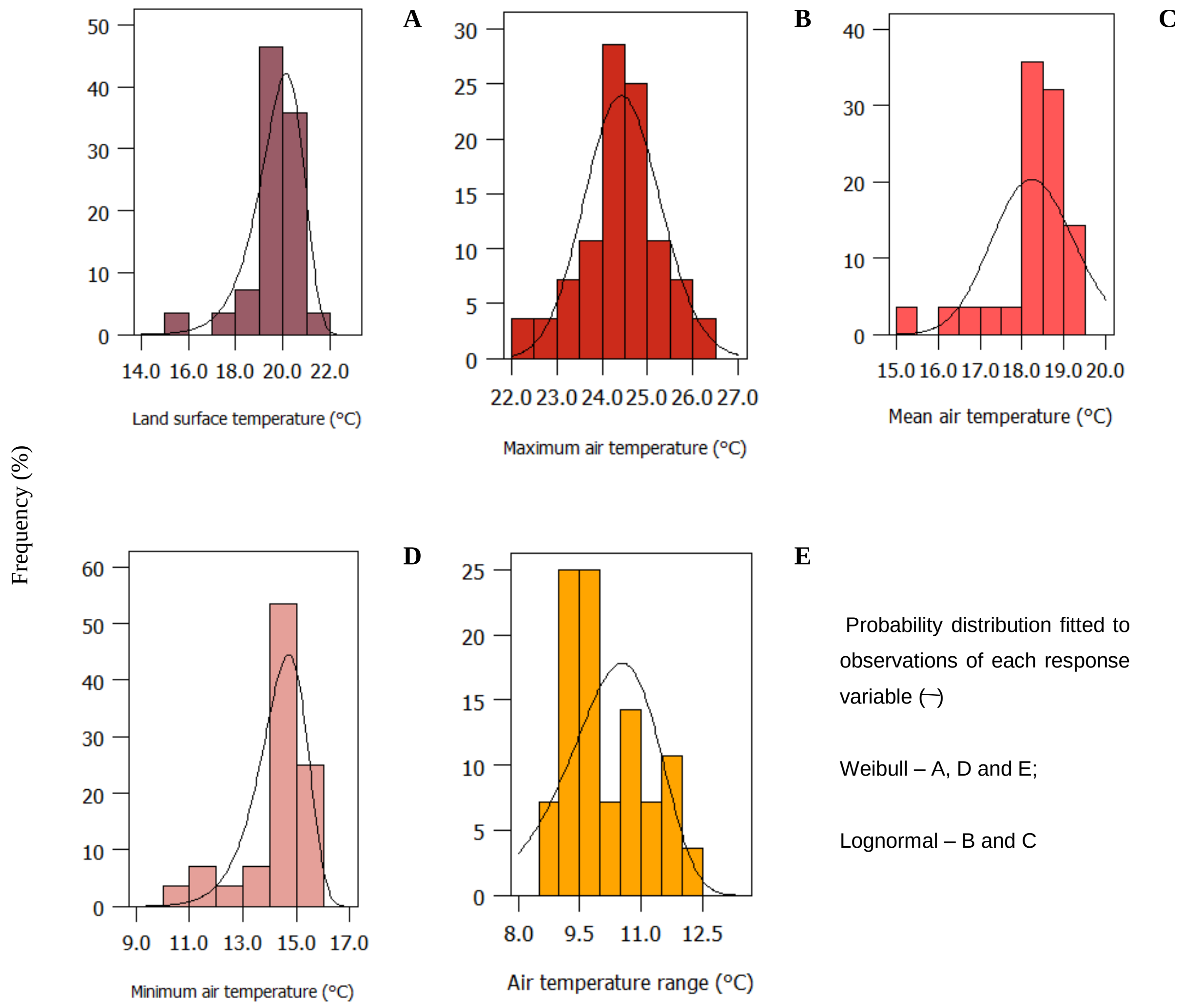


Figure 6: Histogram of LST, maximum, mean, minimum and range temperature from 28 weather stations in São Paulo, Brazil. Statistics were calculated using data from JJA trimester (dry season) from 2019 to 2023.

The stations shown below reflect the great diversity of land use in the urban area of São Paulo (Figures 3 and 7). The IAG and Marsilac stations had the greatest tree cover compared to the others. The predominance of tree cover at the IAG station is greater in the quadrants: Southeast - (IV), Southwest (III). At Marsilac Station, the predominance is in the east quadrants (I and IV).

Itaim Paulista station, on the other hand, has an almost complete predominance of built-up space and asphalt, with a percentage of around 5% tree cover. The eastern quadrants (I and IV) have a higher concentration of asphalt surfaces and built-up space. Sé station shows the same behavior as Itaim, only with a higher percentage of tree cover, around 15%, and asphalt surface and built space predominating in the northwest quadrant (II).

At Pinheiros station, there is a homogeneity of coverage, well distributed, with all quadrants well distributed.

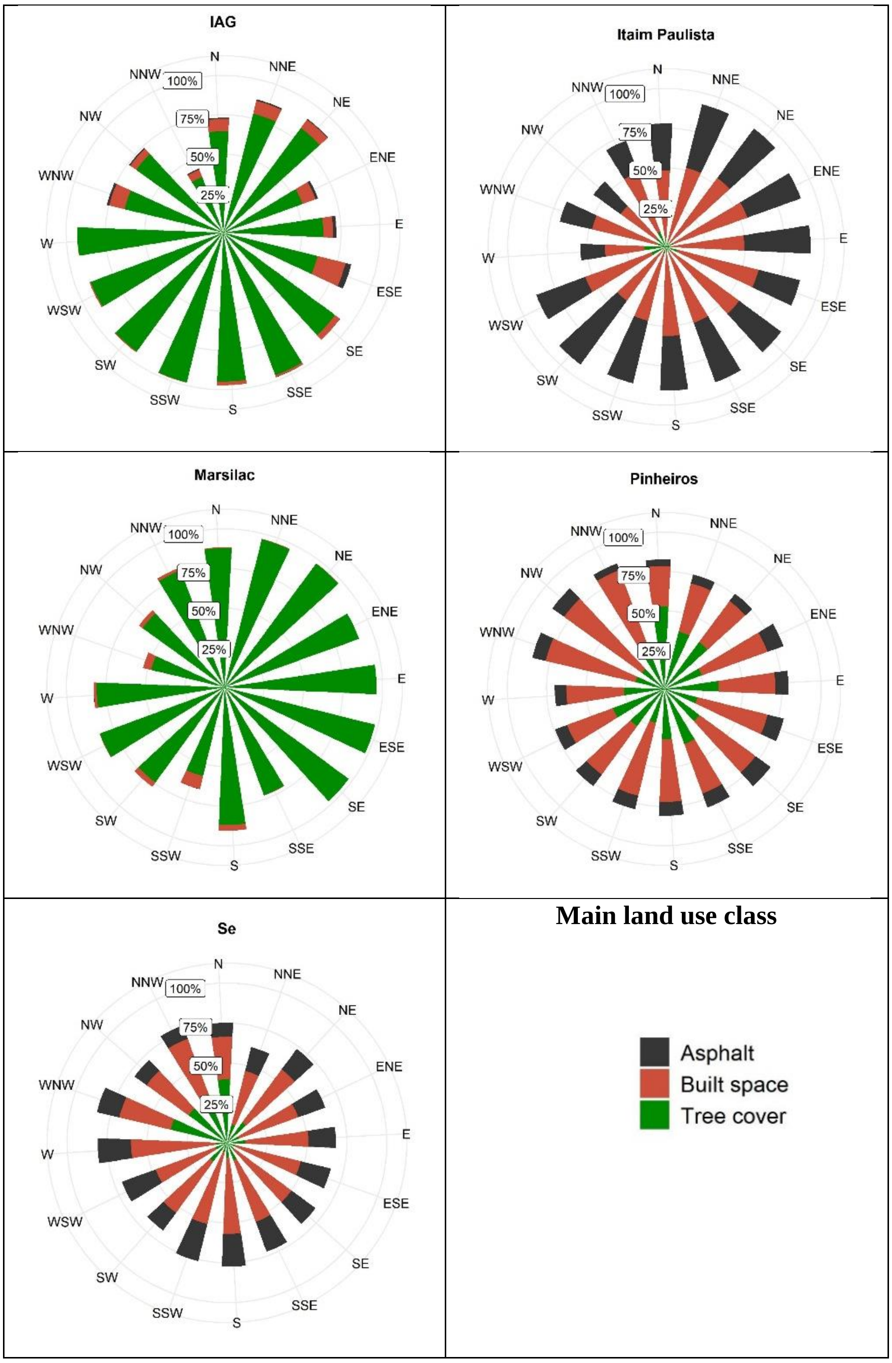


Figure 7: Radar diagram corresponding to the distributions of the main land use classes (asphalt, built space, and tree cover) for each one of five selected weather stations: IAG, Itaim Paulista, Marsilac, Pinheiros, and Se. Each wind rose displays the percentage of the urban area of Sao Paulo (SP), Brazil, occupied by asphalt, built space, and tree cover for each of the 16 sectors of the corresponding 500 m buffer

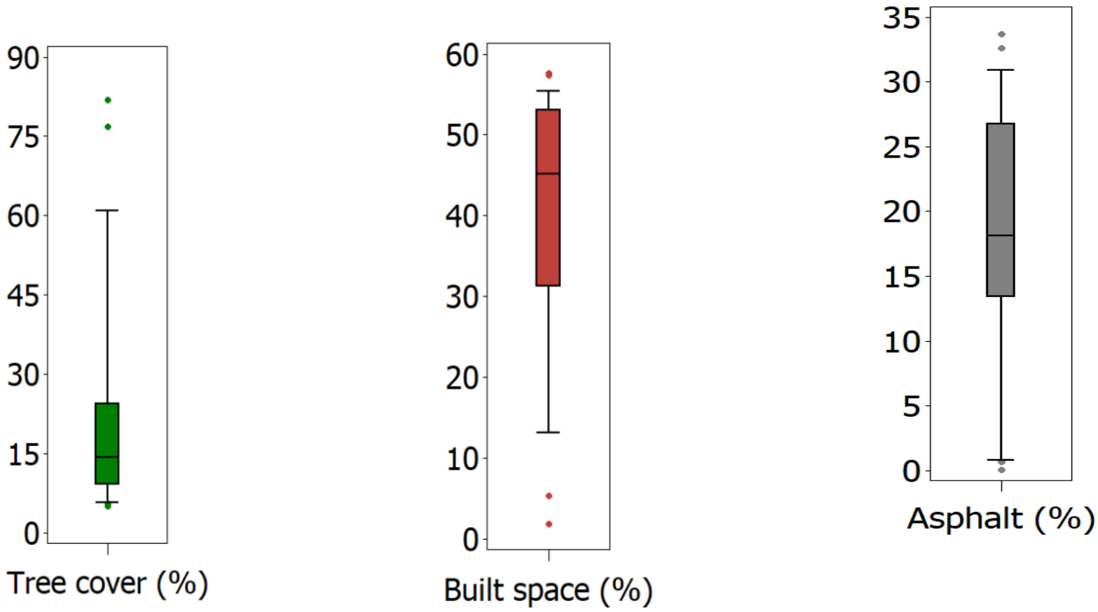


Figure 8: Box and whiskers plots for percent of the urban area occupied by Asphalt (%), Tree cover ($) and Built Space in São Paulo, Brazil. The bottom and top edges of the box are located at the 25th and 75th percentiles. The center horizontal line is drawn at the median (50th percentile). The vertical lines, or whiskers, extends from the box as far as the data extend, to a distance at most 1.5 interquartile ranges.

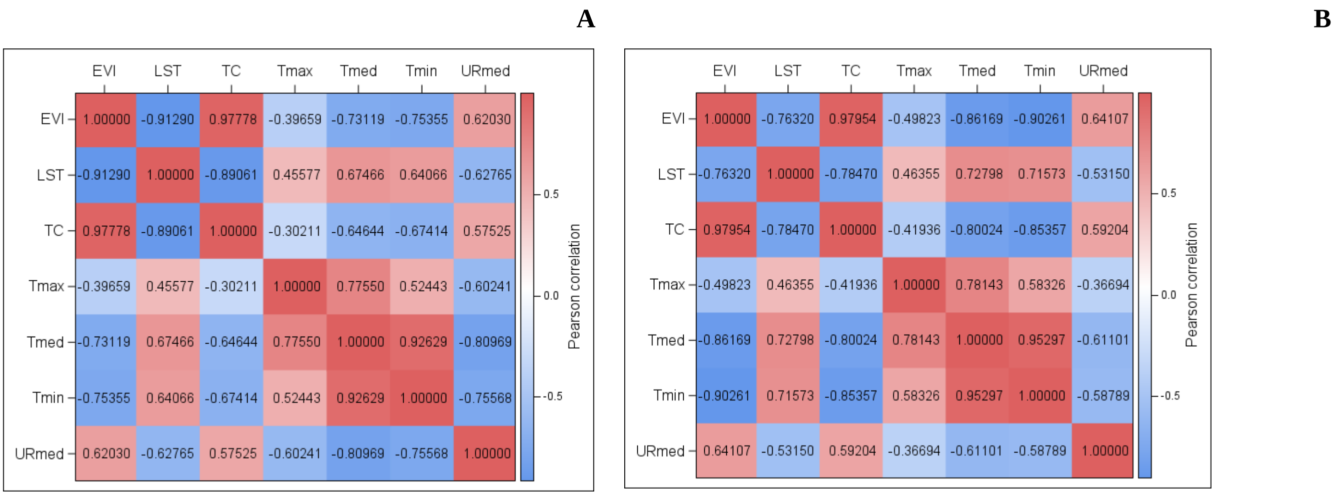


Figure 9: Matrix Correlations between pairs of model input variables: enhanced vegetation index (EVI), land surface temperature (LST, °C), tree cover (TC, %) maximum temperature (Tmax, °C), mean temperature (Tmed, °C), minimum temperature (Tmin, °C), and air mean relative humidity (URmed, %) in the urban area of Sao Paulo (SP), Brazil. A) Rainy season and B) Dry season.

The highest correlations were found between the following pairs of variables: (EVI vs TC, Tmean vs Tmin, EVI vs LST, LST vs TC, and Tmean vs URmean, for the rainy season. For the dry season, EVI vs TC, and Tmean vs Tmin showed the highest correlations, while the next highest were: EVI vs Tmin, EVI vs Tmean, and TC vs Tmin. Correlations with LST ranged from 0.53 to 078, with the highest correlation for TC vs LST (-0.78).

3.3 Analysis of similarity among stations

The analysis of the similarity between stations resulted in a classification similar to that obtained by (STEWART and OKE, 2012) who defined the LCZs (Figure 10).

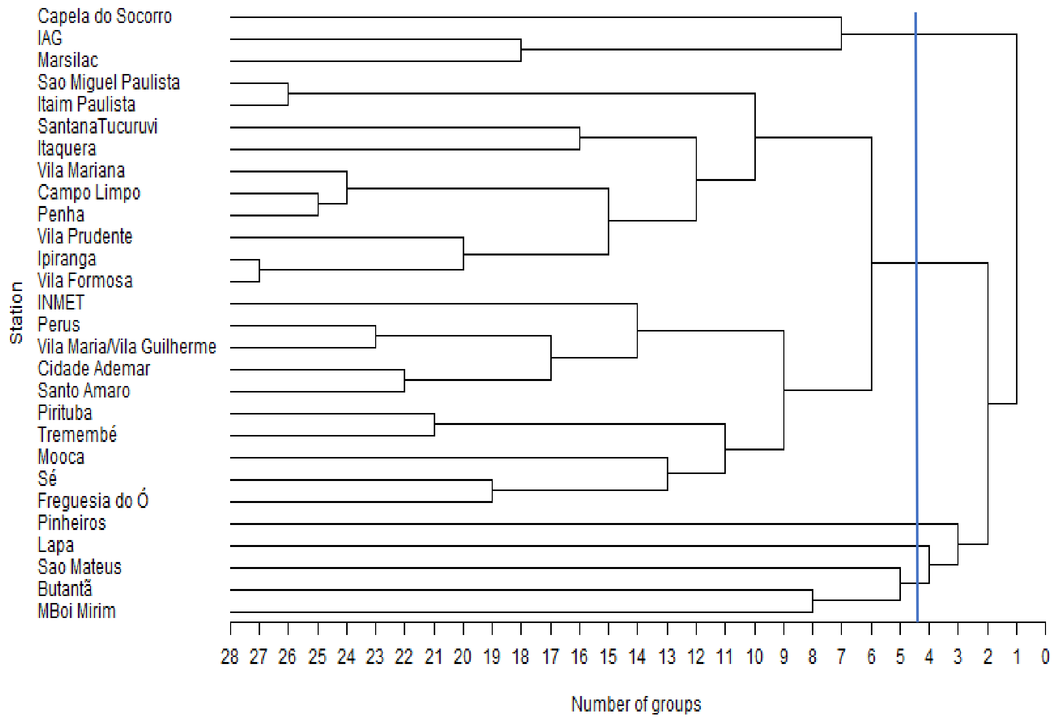


Figure 10: Similarity among the 28 sub-municipality of Sao Paulo (SP), Brazil – regarding the main use land variables (asphalt, tree cover, and built space) expressed as the respective percent of total urban area of Sao Paulo (SP).

Table 3: Group of meteorological stations of urban Sao Paulo area derived from cluster analysis. The groups were formed based on the main variables related to land use (asphalt, tree cover, and built space) with respective mean air temperature and mean tree cover.

Group	Meteorological Stations	Mean Air Temperature (°C)		Mean Tree Cover (%)
		Rainy Season	Dry Season	
I	IAG, Marsilac and Capela do Socorro	20.42°C	16.08	73.22
II	INMET, Vila Mariana, Sé, Perus, Freguesia do Ó, SantanaTucuruvi, Pirituba, Vila Prudente, Vila Maria/Vila Guilherme, Cidade Ademar, Ipiranga, Santo Amaro, Campo Limpo, Vila Formosa, Mooca, Sao Miguel Paulista, Itaquera, Itaim Paulista, Penha, Tremembé	22.18	18.67	8.92
III	Pinheiros, Butantã, Sao Mateus, Lapa and MBoi Mirim	21.73	18.17	33.63

Cluster analysis based on the main variables of land use and occupation revealed the presence of three homogeneous groups with peculiar characteristics in relation to the percentage of tree cover and average air temperature (Table 3). These groups are similar to those defined by (STEWART and OKE, 2012), namely, dense trees (DT), compact low-rise (CLR), large low-rise (LLR).

It can be seen that the average temperatures of group I, in both seasons, are lower than those of groups II and III, around 1.5°C and 2.3°C, respectively, which is consistent with its high tree cover (73.22%). The difference between average temperatures II and III in both seasons is around 0.5°C.

3.4 Linear regression Models

For each variable, there are two adjusted models: 1) the best model selected by the stepwise method and 2) a model that only predicts tree cover. In the best model, we have all the variables that significantly influence each response variable, for example, average temperature. The model with only tree cover as a predictor is an operational model, which allows us to estimate the increase in tree cover needed to cool an amount of x (°C) in the average urban temperature.

In this study, our main focus is to study the impact of tree cover on average temperature. In the best-fit model for average temperature in both seasons, the predictors selected were EVI (Enhanced Vegetation Index) and tree cover (%). We chose to keep EVI in the operational model because this predictor can be expressed as a function of tree cover, and these two predictors are highly correlated (R^2=0.95). Despite this high correlation, the inclusion of EVI in the model contributes significantly to explaining the variability of the average temperature ($p<0.01$).

The fact that EVI contributes to the explanation of average temperature in addition to tree cover is because in order to decide whether or not EVI remains in the model, the correlation of EVI with the residuals of the model that only has cover as a predictor is calculated; if this correlation is significant, EVI remains in the model.

Table 4: Estimated parameter and respective standard errors of selected models adjusted to represent the relationship between the response variables maximum, mean, and minimum relative humidity (URmax, URmean, and URmin) and their corresponding predictor variables. Data from Jan-Mar (Rainy Season) of the period between 2019 and 2023 of Sao Paulo urban area, SP, Brazil.

Response variable	Parameter	Estimate	Standard error	P value	Determination coeficiente (R^2)
Tmean	**Intercept**	**22.9471**	**0.1843**	**< 0.0001**	**0.6414**
	tree cover	**0.0571**	**0.0209**	**0.0115**	**.**
	EVI	**-9.0193**	**2.2851**	**0.0006**	**.**
Tmean	Intercept	22.4494	0.1679	<0.0001	**0.4179**
	tree cover	-0.0237	0.0055	0.0002	
Tmin	Intercept	19.3937	0.2221	< 0.0001	0.6572
	tree cover	0.0644	0.0252	0.0172	.
	EVI	-10.5850	2.7532	0.0007	.
Tmax	Intercept	28.3000	0.1400	.	.
T_range	Intercept	5.0590	1.5476	0.0032	0.4141
	tree cover	0.0586	0.0160	0.0012	.
	grass	0.0892	0.0394	0.0327	.
	built space	0.0686	0.0234	0.0072	.
LST	Intercept	27.6908	0.4987	< 0.0001	0.9226
	asphalt	0.0583	0.0136	0.0003	.
	EVI	-4.3665	0.8908	< 0.0001	.
	volumetry	-0.3042	0.0745	0.0005	.
	light roof	0.3252	0.1325	0.0225	.
EVI	**Intercept**	**0.0552**	**0.0115**	**< 0.0001**	**0.956**
	tree cover	**0.0090**	**0.0004**	**< 0.0001**	**.**

When tree cover is increased by one percentage point (p.p), the average temperature decreases by an amount equivalent to the coefficient of the cover variable in the model ($\beta 1$ in equation 1). It can be seen that for all the models where the response variable is temperature, the coefficient of the coverage predictor is negative, indicating that these variables are inversely proportional.The models for the other variables, with the exception of average temperature, could be the subject of further study in future research in which it is possible to calculate how much tree cover is needed to reduce the maximum or minimum temperature by 1°C.

Table 5: Estimated parameter and respective standard errors of selected models adjusted to represent the relationship between the response variables maximum, mean, and minimum relative humidity (URmax, URmean, and URmin) and their corresponding predictor variables. Data from June-Aug (Dry Season) of the perio d between 2019 and 2023 of Sao Paulo urban area, SP, Brazil.

Response variable	**Parameter**	**Estimate**	**Standard ERROR**	**P value**	**Determination coefficent (R^2)**
Tmin	Intercept	16.8899	0.6703	<.0001	0.9141
	cob_arb	0.0135	0.0192	0.4896	
	sombra	0.0632	0.0202	0.0047	
	EC	-0.0232	0.0109	0.0441	
	EVI	-10.8734	2.4826	0.0002	
Tmin	Intercept	15.4112	0.1828	<.0001	0.7286
	cob_arb	-0.0499	0.006	<.0001	
Tmed	Intercept	19.3298	0.1905	<.0001	0.8227
	cob_arb	0.0376	0.0196	0.0676	
	sombra	0.0433	0.0206	0.0458	
	EVI	-10.0065	2.641	0.0009	
Tmed	Intercept	19.5627	0.1654	<.0001	**0.7899**
	cob_arb	0.0481	0.0202	0.0255	
Tmed	EVI	-11.4659	2.718	0.0003	
	Intercept	19.1048	0.1601	<.0001	**0.6404**
	cob_arb	-0.0356	0.0052	<.0001	
EVI	Intercept	0.0399	0.009	0.0001	0.9595
	cob_arb	0.0073	0.0003	<.0001	
Tmax	Intercept	25.2902	0.2536	<.0001	0.3647
	cob_arb	0.0664	0.031	0.0423	
	EVI	-11.3585	4.1673	0.0116	
Tmax	Intercept	24.8366	0.2137	<.0001	0.1759
	cob_arb	-0.0164	0.007	0.0263	
T_range	Intercept	4.1584	1.2396	0.0026	0.7119
	cob_arb	0.0811	0.0128	<.0001	
	relvado	0.0924	0.0315	0.0073	
	EC	0.0797	0.0187	0.0003	
T_range	Intercept	4.1584	1.2396	0.0026	0.7119
	cob_arb	0.0811	0.0128	<.0001	
T_range	relvado	0.0924	0.0315	0.0073	
	EC	0.0797	0.0187	0.0003	
LST_JJA	Intercept	20.6799	0.2026	<.0001	0.6158
	cob_arb	-0.0427	0.0066	<.0001	

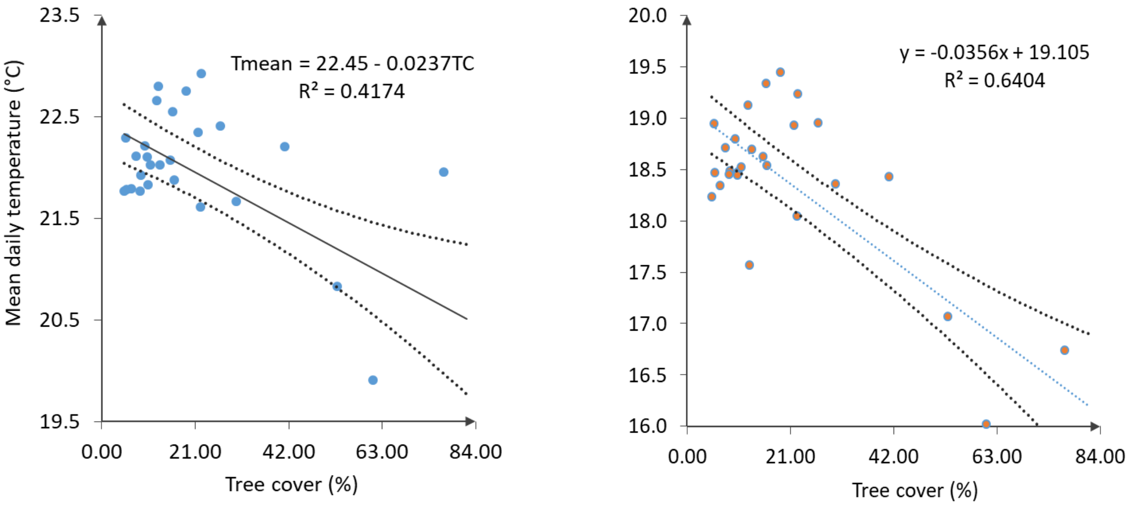


Figure 11: Linear models fitted to represent the relationship among mean temperature, and tree cover (%) for rainy and dry seasons in Sao Paulo (SP), Brazil. The inferior and superior dashed lines correspond to the lower and upper confidence limits, respectively, of the predicted means.

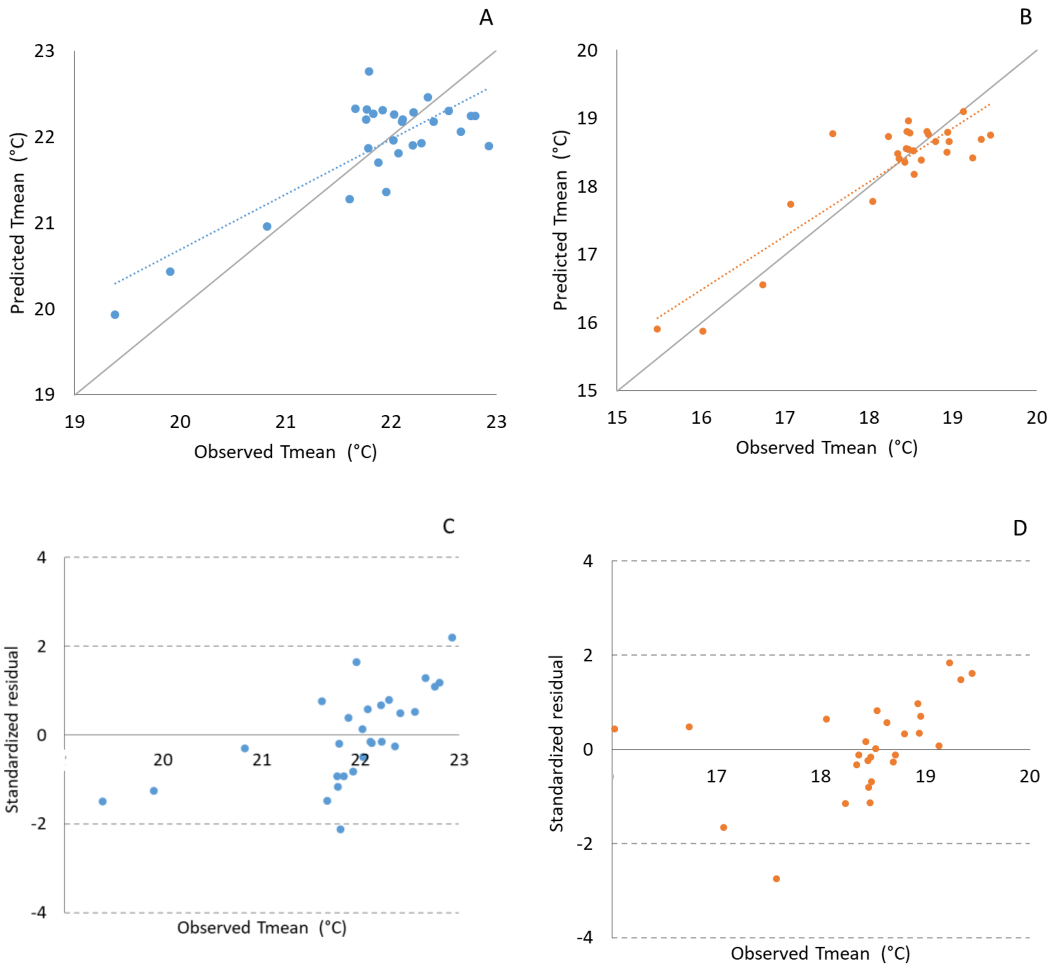


Figure 12: Graphical representation of model quality: observed versus predicted values from linear models fitted to predict mean temperature as a function of tree cover (%) and enhanced vegetation index (EVI) from rainy (A) and dry season model (B). Standardized residuals from rainy (C) and dry season model (D).

In order to check the quality of the models, it was found that the residuals were in the ranges between (-2 to 2), with more than 95% in these ranges, which demonstrates the high quality of the models. In a perfect fit, the points would be aligned along the main diagonal (continuous line - Figure 12). The closer the points are to this line, the better the quality of the model analyzed. The dotted line represents the actual relationship between the observed and predicted values. When this line is above the diagonal, it indicates that the model is overestimating the temperature, and when it is below, it is underestimating it. In both seasons, there is a tendency for the temperature to be overestimated for low coverage values and underestimated for high values. This pattern suggests a possible non-linearity in the relationship between temperature and cover, which could be explored in non-linear models in the future.

The correlation between Land Surface Temperature (LST, in °C) and tree cover (%) is more significant during the rainy season than during the dry season (see Table 4 and 5). It was observed that Land Surface Temperature (LST) during the Rainy Season, with predictors such as asphalt, EVI, volume and light tile, explains 92.26% of the variability of LST. In the Dry Season, with predictors such as tree cover, shade, light tile, dark tile and volume, the R^2 is 78.95%. Due to the higher global solar radiation in the dry season, with less cloud cover and reduced rainfall, vegetation biomass is at a low level of activity between May and September, resulting in many tree species (deciduous or semi-deciduous) dropping their leaves, which contributes to this lower correlation.

With regard to the difference between the albedos of urban surfaces and their emissivity (reflectance), it can be seen that in the rainy season, due to the greater leaf area of the vegetation, the albedo and its emissivity are lower compared to the dry season, which contributes to a greater cooling of the ground surface temperature (°C), and even the air temperature.

The predictors of the models selected to estimate the average temperature over the 5 years explained more than 50% of the variability of the response variable, with the predictors tree cover and EVI having an R^2 of 64.14%. The best buffer tested for the São Paulo study was a radius of 500 meters; other studies in tropical regions have shown that a buffer of 500 provides the best fit for multiple regression models (MARTINI, 2016).

Table 6: Estimated required tree cover increment (p.p.) for the different temperatures resulting from hypothetical decreases of 0.5°C in the current mean temperature of the São Paulo urban area during the rainy (January – March) and dry (June – August) seasons. Estimates obtained from the linear model derived from the combination of two models, referred to as new model: a) mean temperature as function of tree cover and EVI (enhanced vegetation index) and, b) EVI as function of tree cover.

		a		b	cob. Atual	nova cob	Diferenc e
Dry	**18.00**	**19.10**	**-0.04**	**22.50**	**.**	**.**	
	17.50	19.10	-0.04	22.50	45.06	22.56	
	17.00	19.10	-0.04	22.50	59.10	36.60	
	16.50	19.10	-0.04	22.50	73.15	50.65	
	16.00	19.10	-0.04	22.50	87.19	64.69	
	15.50	19.10	-0.04	22.50	101.23	78.73	
Rainy	22.00	22.45	0.14	22.50			
	21.50	22.45	0.14	22.50	40.02	17.50	
	21.00	22.45	0.14	22.50	61.09	38.57	
	20.50	22.45	0.14	22.50	82.17	59.65	
	20.00	22.45	0.14	22.50	103.25	80.73	

The relationship between EVI and tree cover has a correlation of over 95%, which justifies the use of one or the other in the models used. The city of São Paulo is very heterogeneous, with highly wooded areas, but there are also places with very sparse vegetation cover, predominantly occupied by buildings and paving, which have a low vegetation index.

Given the lack of cooling effect and evapotranspiration and shading from vegetation, these areas tend to be warmer. The effect of vegetation can vary significantly depending on several factors, including the type of vegetation, its density, height, topography, volumetry, and climatic conditions. The cooling effect provided by trees and other forms of vegetation is most significant in nearby areas, usually within a few tens of meters of where the trees are present (SHASHUA-BAR, L.; HOFFMAN, M.E., 2004). However, the exact extent of this effect can vary depending on several factors, including the size of the trees, the density of the canopy, the type of vegetation, and the local climatic conditions.

In general, the scope of the cooling effect of trees is limited to the immediate area around them. In urban spaces, where the phenomenon known as the "urban heat island" can raise local temperatures, strategic tree planting can be an effective practice to mitigate this effect by providing shaded and cooler areas.

With regard to seasonal variation, the analysis of the hottest and coldest periods (rainy and dry seasons), analyzed separately, is expected to increase the explanatory power of the variables. Models based on urban land use classes and other auxiliary variables: EVI (Enhanced Vegetation Index) and LST (Land Surface Temperature), obtained from satellite images, were able to predict the average urban temperature in cities in tropical regions.

It is expected that the cooling rates of the average urban temperature as a function of the percentage of tree cover will decrease as tree cover increases, however, given the low sample value of weather stations (n=28), it was not possible to capture the probable non-linear pattern of the relationship.

In order to preserve urban trees, it is necessary for public policies to guarantee the maintenance and development of reforestation in cities, which is fundamental for the population's quality of life (Ferreira et al., 2023). The main obligations of public policies to preserve urban trees include (1) Promoting the planting and maintenance of trees in urban areas, (2) Protecting existing trees and (3) Educating the population about the importance of urban trees. Thus, the maintenance and protection of existing trees is related to increasing the lifespan of these species, which can take years to grow and reach a leafy crown. Therefore, the evaluation of these plants should be carried out in relation to preventive and curative treatment. As Ferreira et al. (2023) proposed, as this is an urban area, treatment using vegetative endotherapy, where products are applied directly to the stems of plants, should be a viable alternative in cases of disease and pests. This would replace conventional treatments such as spraying and applying products to the soil, which are unsuitable for populated environments. Consequently, studies need to be carried out on better bioformulation using endotherapeutic treatments in urban areas to avoid eliminating plants, which goes against the proposal to cool heat islands. Endotherapy treatments are suggested by some Nature Based-Solutions (NBS) principles in relation to sustainable agricultural practices (Ferreira et al., 2023, Ferreira et al., 2022).

The study by the National Institute for Space Research (INPE) on climate change in Brazil over the last six decades reveals a significant increase in the maximum temperature in several regions. For example, in the Northeast, the average maximum temperature rose from 30.7°C in the reference period to 32.2°C between 2011 and 2020, representing a considerable increase. In addition, there have been variations in rainfall, with reductions in some areas and increases in other ones, thus affecting the occurrence of extreme weather events such as consecutive dry days and intense rainfall concentrated in a few hours of the day.

The data also highlights an increase in heatwaves across most of the country over the years analyzed, except in the South and parts of São Paulo and Mato Grosso do Sul. The number of days with heatwaves rose from seven in the reference period to 52 days between 2011 and 2020, making this the "new normal". These climate changes are already having noticeable impacts, affecting different regions in different ways. While some face increases in temperature and more frequent extreme events, others deal with changes in precipitation and periods of drought, highlighting the need to understand these transformations in order to make decisions and take adaptive actions.

One of the consequences of the intensification of the heatwaves was that in 2023 there were the 2 largest daily peaks in energy consumption in Brazil. A heatwave in Brazil caused an unprecedented increase in electricity demand, reaching a record of around 100,000 average megawatts (MW) on November 13, 2023, as recorded by the National Electric System Operator (ONS). This increase was driven by the intense heat, leading to higher electricity consumption, especially due to the intensified use of cooling appliances.

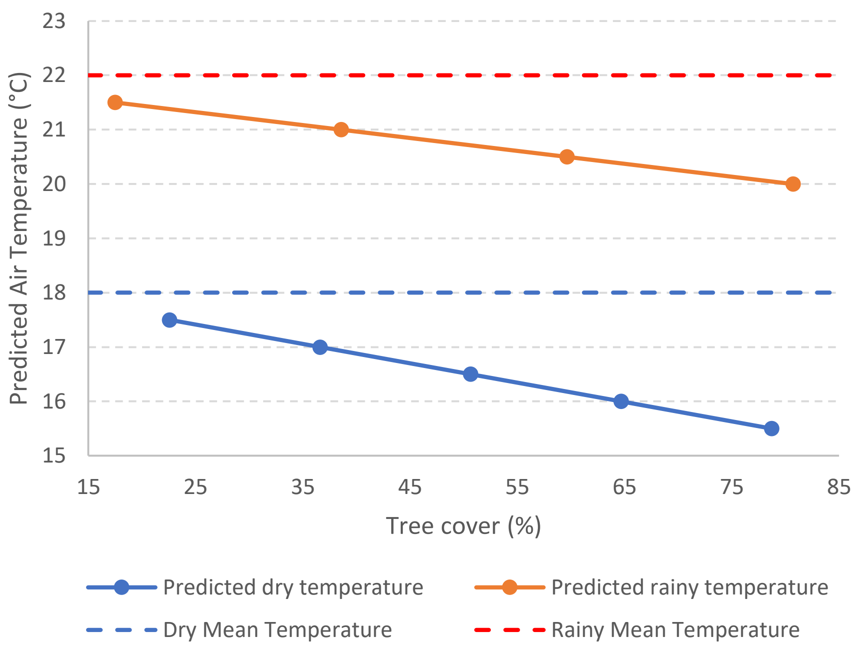


Figure 13: Estimated relationship between mean tree cover (%) and air temperature in Sao Paulo (SP, Brazil) for both seasons rainy and dry. The orange and blue dashed lines correspond to the current mean temperatures during the rainy and dry seasons, respectively. Estimates obtained from the linear model derived from the combination of two models: a) mean temperature as function of tree cover and EVI (enhanced vegetation index) and, b) EVI as function of tree cover.

3.5 Nonlinear regression models

The best nonlinear model among the tree decline models tested (Table 2) was the exponential one (Table X) for both seasons. The parameters related to model curvature (β_{21} and β_{22}) were both highly significant (Table 7, $p < 0.0001$) but their high magnitudes imply in low absolute values of the exponent of the expression $exp\ (-TC_i/\beta_{1j})$ in the exponential model (Table 2). Consequently, the model curvature is extremely smooth making the linear and nonlinear models to be almost coincident (Figure 15).

The tree cover values of the 28 points (500m-buffers) of São Paulo urban area are mostly concentrated in the 0 – 30% range (75% of the TC values), with a very few intermediate values resulting on lack of information on the influence of the TC increase on the mean temperature for intermediate values of TC. This data pattern makes difficult to capture the probable nonlinear nature of the TC influence on the mean daily temperature. To overcome such a limitation, it is necessary to use a larger number of data collection sites across the urban area to cover a high diversity of TC values with a more homogeneous distribution along the 0-100 range. Considering that 10% of the urban area of São Paulo (1521 km^2) should be included in the sample to estimate the relationship between mean temperature and tree cover, this would correspond to around 200 500m-buffer with available information on both variables.

Table 7: Parameter estimates and respective standard errors of the nonlinear models used represent the relationship between daily mean temperature (Tmean, °C) and tree cover (TC, %), in periods of both rainy (Jan-Mar) and dry seasons (Jun-Aug) in urban area of Sao Paulo, SP, Brazil. Meteorological data from 28 weather stations (2019-2023).

Season	Model parameter	Parameter estimate	Standard error	95% Confidence limits		T-test p-value
				Lower limit	Upper limit	
Rainy	β_{11}	22.46	0.17	22.10	22.81	< 0.0001
	β_{21}	917.70	219.60	466.40	1369.00	0.0003
Dry	β_{12}	19.12	0.17	18.77	19.47	< 0.0001
	B_{22}	505.50	79.37	342.40	668.60	< 0.0001

β_{11} and β_{12} are the model intercepts for the rainy and dry season respectively; β_{21} and β_{22} are the parameters related to model curvature for the rainy and dry season, respectively;

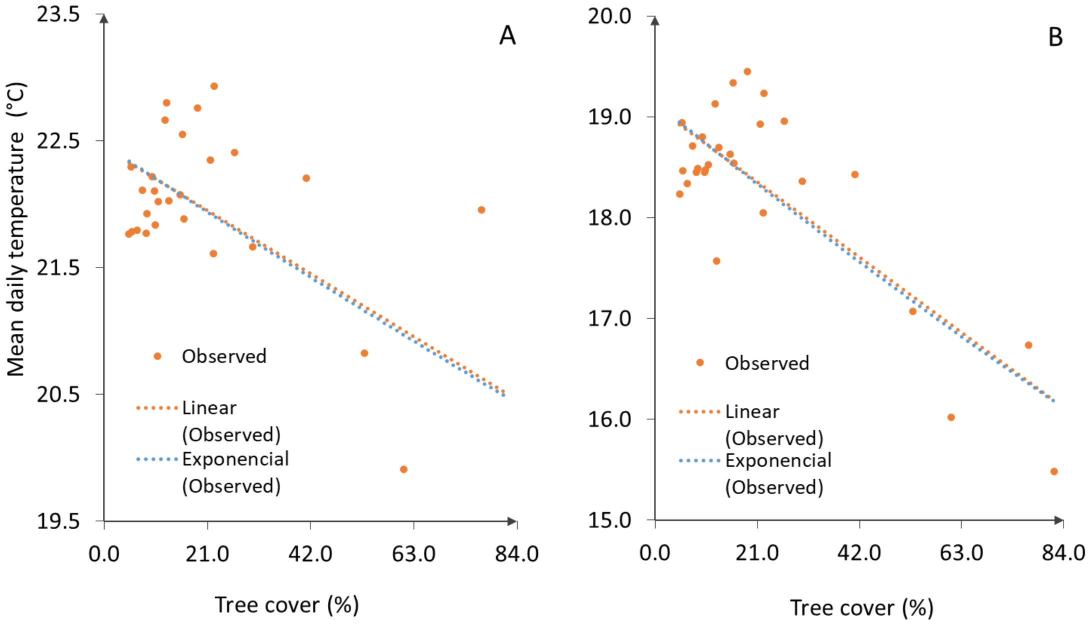
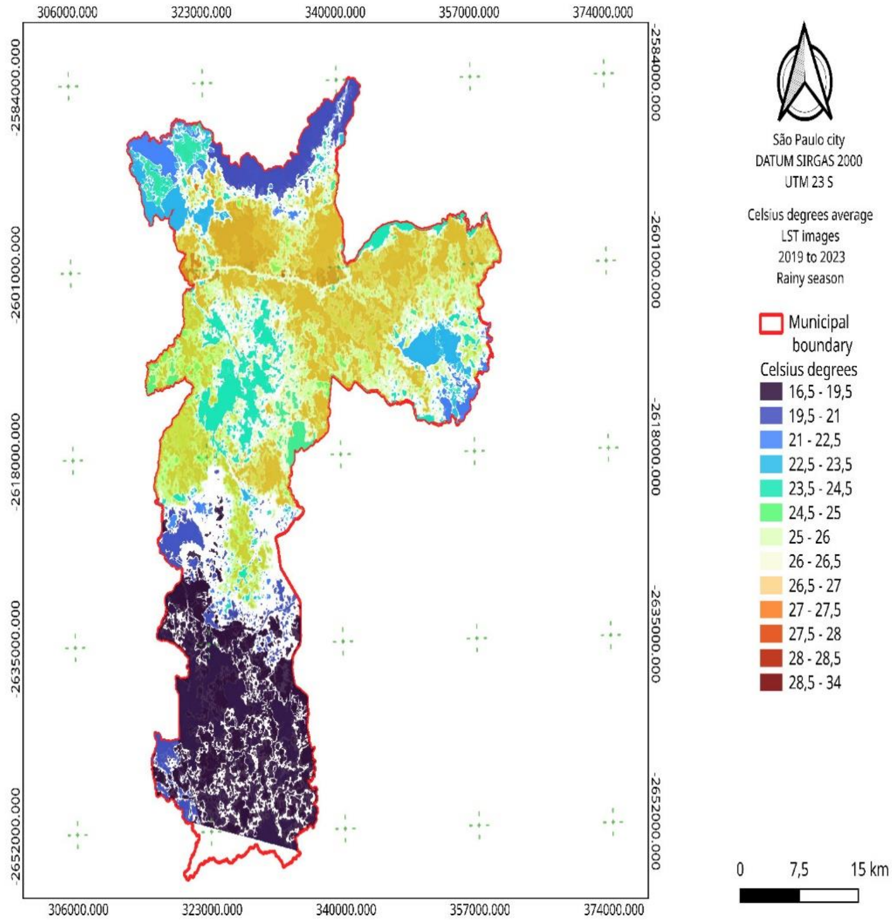
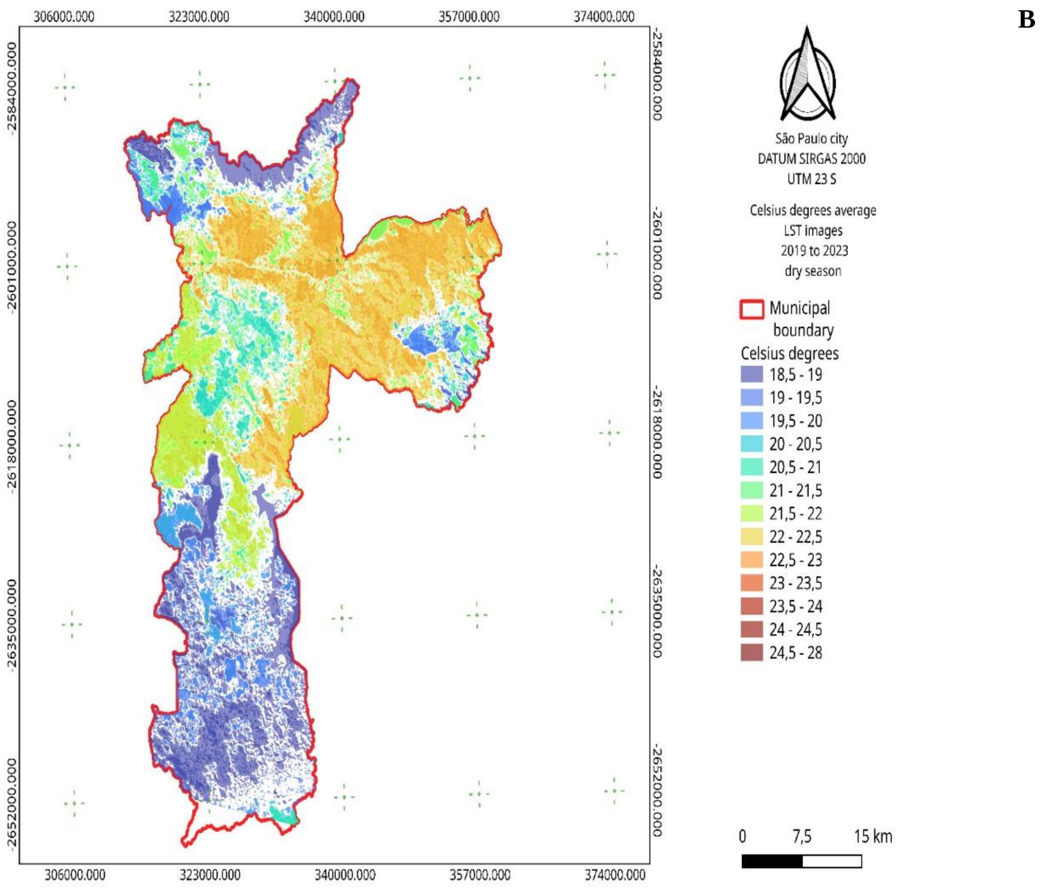


Figure 15: Linear and nonlinear models fitted to represent the relationship between daily mean temperature (Tmean, °C) and tree cover (TC, %), in periods of both rainy (Jan-Mar) and dry seasons in urban area of Sao Paulo, SP, Brazil. Meteorological data from 28 weather stations (2019-2023).

3.6 Maps of land surface temperature (LST)

A





The distribution of the LST and Tmed variables behaves in the opposite way to the tree cover variable, which is consistent with the negative correlation between these variables and tree cover: for LST, 90% in the rainy season and 80% in the dry season, for Tmed, 64% in the rainy season and 80% in the dry season (Figures 4 and 6). They show asymmetry to the left and discrepant points corresponding to the minimum average temperature values observed at Marsilac and IAG/Agua Funda in both seasons. The maximum, minimum, and range temperature variables have an approximately symmetrical distribution with outliers at the upper and lower extremes (Figure 4).

In both seasons, the buffer for which the best multiple regression models were obtained was 500 meters. The average temperature reduction rates for each 1 p.p. increase in tree cover were 0.14 and 0.04°C for the wet and dry seasons, respectively. Based on these models, the increases in cover needed to cool 0.5, 1.0, and 1.5°C in the current average temperature were estimated (Table 5). For example, in order to cool 0.5°C in the dry season, it is necessary to increase urban cover by 22.56 p.p. in the urban area of São Paulo (1521 km² or 152100 ha), which corresponds to an additional green area of 34320 ha, approximately 32,000 soccer fields. For the rainy season, the area needed would be 26613 ha (25,000 soccer fields). Considering that these area additions would only be implemented via new green parks, this would require around 10 and 14 million trees for the rainy and dry seasons, respectively. This option would be impractical, however, increases of this magnitude can be obtained by afforesting roads (which are not yet afforested), increasing the number of trees on roads that are already afforested, and implementing new green spaces.

4. Conclusion

The selected models for mean temperature estimation based on urban land use classes and other auxiliary variables present good performance, thus they provide useful information for efficient afforestation policies of cities in tropical regions.Models based on urban land use classes and other auxiliary variables: EVI (Enhanced Vegetation Index) and LST (Land Surface Temperature), obtained from satellite images, were able to predict the average urban temperature in cities in tropical regions.

It is expected that the cooling rates of the urban average temperature as a function of the percentage of tree cover will decrease as tree cover increases, however, given the low sampling value of meteorological stations (n=28), it was not possible to capture the probable non-linear pattern of the relationship. Furthermore, the Sao Paulo data pattern with few intermediate values of tree cover makes it difficult to capture the probable nonlinear nature of the tree cover's influence on the mean daily temperature. To overcome such a limitation, it is necessary to use a larger number of data collection sites across the urban area to cover a high diversity of Tree cover values with more homogeneous distribution along the 0-100 range.

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CHAPTER II. EFFECTS OF URBAN GREENNESS ON MICROCLIMATE VARIABLES IN A BACKLANDS CITY OF LATIN AMERICA

Abstract

The microclimate models developed for cities in the interior of the state of São Paulo are highly innovative and of great relevance in the face of climate change and extreme events. The city of Piracicaba stands out as a medium-sized center, with significant economic importance in the sugar-alcohol sector and in commodity investments. The preservation and expansion of green areas play a crucial role in mitigating and containing urban heat islands. The main objective of this research was to create a (multiple) linear regression model to predict average temperature as a function of tree cover (% of area), with the aim of predicting the amount of tree cover needed to reduce the average urban temperature by 0.5°C. The models were selected for both seasons using the stepwise method. In order to verify the relationship between the variables air temperature (°C), relative humidity and LST (Land Surface Temperature) and a set of candidate predictor variables related to land use and EVI (Enhanced Vegetation Index). The microclimate variables were obtained using 40 hydrothermal loggers, placed in the backyards of homes, during 40 days of collection, in both the rainy and dry seasons of the years (2015-2016). The models selected (R^2 around 60%) indicate that to cool the average urban temperature of Piracicaba by 0.5°C, increases of 25.4 and 9.3 percent points (p.p) would be needed for the rainy and dry seasons, respectively. For relative humidity, models were obtained as a function of tree cover and other variables relating to land use with coefficients of determination of around 65% for both seasons. As a relevant result of this research, the models as a function of cover make it possible to subsidize public policies for urban afforestation in São Paulo municipalities.

1. Introduction

Brazil, a country with its continental dimensions, harbors an impressive diversity of climates and ecosystems. Even within a single state, such as São Paulo, we witness various climatic conditions and natural landscapes (AB'SABER, 2003). The state of São Paulo, with an area of approximately 248,219 km², encompasses everything from the dense tropical forests of the Atlantic Forest to the vast plains of the Cerrado, displaying a wealth of biodiversity (PAULA *et al.*, 2009).

However, this natural treasure faces increasing environmental challenges due to the migration of large urban centers in search of a better quality of life. As a result, interior cities, including Piracicaba, have emerged as popular choices for many who find a better quality of life (IBGE, 2022). Nonetheless, the fast growth of these interior urban areas has driven a significant increase in deforestation resulting from uncontrolled and poorly regulated urbanization (SPAROVEK *et al.*, 2007).

Furthermore, it is crucial to highlight the considerable impact of sugarcane activity on deforestation in Piracicaba. The ongoing expansion of sugarcane plantations has contributed to the degradation of local ecosystems, raising concerns about environmental sustainability and the loss of natural habitats (FEARNSIDE, 2016). Deforestation in Piracicaba City is closely linked to this activity of sugar cane cultivation, posing a significant challenge to preserving biodiversity and protecting the local environment. Among the native species introduced in the urban tree planting in Piracicaba, notable ones include Sibipiruna (*Caesalpinia pluviosa*), known for its resistance and elegance; Pau-ferro (*Libidibia ferrea*), which offers dense and cozy shade; and genre of Ipês (*Handroanthus*), with its stunning flowers that adorn the city during spring (PIRACICABA CITY HALL, 2020).

In the last 20 years, the population of Piracicaba City has grown exponentially, around 420.000 inhabitants (IBGE, 2022). The population growth has brought significant challenges, highlighting the urgent need for more sustainable urban planning and effective measures to mitigate the negative impacts of sugarcane activity on the local environment in the face of climate change. The aim of this research was to create a microclimate model on the scale of trees in order to cool the average urban temperature of a city in the inner part of the state of São Paulo by 0.5°C to 01°C. The hypothesis of this study was: H1) hydrothermal comfort is differentiated at the different microclimate collection points in the urban mesh of Piracicaba/SP; H2) with an increase of approximately 10% of tree cover in the urban area of the municipality there is a cooling rate of 0.5 to 1.0 °C in the average air temperature.

2. Material and Method

2.1. Area of study

The study area is the city of Piracicaba (Figure 01), located between the geographical coordinates of 22°42'30"S and 47°38'01"W, with an average altitude of 554 meters. The municipality has a total area of 1,378.50 km² (IBGE, 2022) and an urban area of 233, 36 km² (IPPLAP, 2022). The total estimated population is 420.000 inhabitants (IBGE, 2022).

According to the Köppen climate classification, the climate of the municipality of Piracicaba is classified as Cwa, i.e. high altitude tropical, with average annual rainfall of 1,328 mm and average annual temperatures between 14.8°C and 28.2°C, with drought in winter (CEPAGRI, 2022).

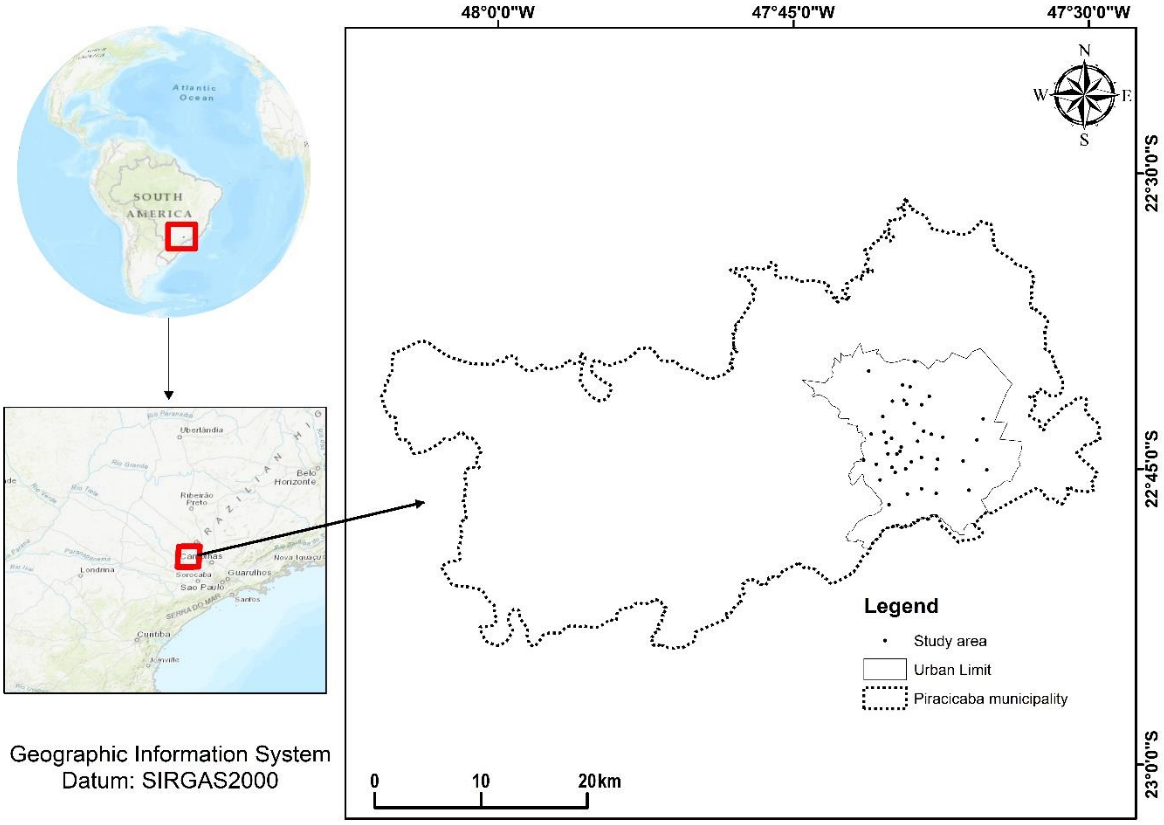

Figure 1: Study area: urban area of Piracicaba (SP), Brazil, including the location of the 36 weather stations for monitoring air temperature (°C) and relative humidity (%) (Prepared by the author).

This study covered the five distinct regions (North, South, East, West and Center) of the city of Piracicaba, in the state of São Paulo. Over a 40-day period in 2015 and 2016, a period of fieldwork collections, covering the rainy and dry seasons, a network was set up comprising 36 meteorological sensors designed to continuously record air temperature and relative humidity. Each region was equipped with approximately eight of these devices, strategically distributed in residential backyards.

2.2 Microclimatic data

The data was obtained from sensors (Therma Data Loggers) distributed across the five regions mentioned over 40 days, during the rainy and dry seasons of 2015-2016, in the municipality of Piracicaba/SP. The variables analyzed include air temperature (°C) and relative humidity (%) - (Tmed, URmed, Tmin, URmin, Tmax, URmax, T range, UR range). All the stations are located

1.5 meters above the ground, as recommended by Oke (2006), WMO standard (GIVONI, 2012). The appropriate calibrations were made using the ESALQ/USP Agrometeorological Station.

In this study, daily data was selected, excluding precipitation, for the period November to January (rainy season) and April to June 2016 (dry season) for both stations. The daily averages of this data, including average temperature, minimum temperature, maximum temperature, average relative humidity, minimum relative humidity and maximum relative humidity, were used to run the multivariate regression models.

2.3 Urban land use data

2.3.1 High-resolution multispectral images

High-resolution images from the WorldView-2 satellite were utilized (0.5 m panchromatic and 2 m multispectral), dated April 22, 2011, featuring RGB and near-infrared bands. The supervised classification was performed using MultiSpec 3.4 software, 2016 version, incorporating the following thematic classes: background, tree crown, lawn, exposed soil, asphalt, shadow, river/lake, swimming pool, light tile, dark tile, gray tile, ceramic tile, and gray floor. (OLIVA, 2016).

High-resolution images containing bands in the near-infrared were used. For this, a product derived from images from the LandSat 8 (15-meter resolution, pancromact band) was used to extract vegetation EVI index (Enhanced Vegetation Index) and Land Surface Temperature (LST) for the years 2015 and 2016.

Table 1: Period of satellite image collection to obtain secondary variables for the regression models (EVI and LST).

Satellite	Variable	Year	Season	Collection Dates
LandSat 8	LST	2015	Rainy	17-Nov 12-Dec 17-Jan
			Dry	09-Apr 12-May 28-Jun
	EVI	2016	Rainy	5-Feb
			Dry	30-Jul

2.4 Statistical methods

2.4.1 Descriptive exploratory analysis (Box plot)

To visualize the characteristics of the probability distributions of each of the variables, especially asymmetry, dispersion, and the presence of outliers, box and whiskers plots were constructed.

2.4.2 Multiple linear regression models

Multiple regression models (Eq.1) were adjusted to represent the relationship between the response variables of interest and the candidate predictor variables.

$$Yi = \beta 0 + \beta 1 * X1i + \beta 2 * X2i \ldots + \beta j * Xik \ldots \beta k * Xki + \varepsilon i \quad (1)$$

In equation 1, Yi corresponds to the value of the response variable at station i (I= 1, i=2, i=3, ..., i=36). β0 is the model intercept; β1... βj ... βk are the angular parameters corresponding to each predictor variable. Xki is the value of predictor variable j at station i (i=1, 2, ... 36) and K is the number of candidate predictor variables. εi is the random error associated with each observation Yi.

The response variables of interest are Tmin, Tmed, Tmax, Trange and LST. For each response variable, a model was fitted for the dry season and another for the rainy season. For the dry season, the microclimate response variables (Temperature and LST) correspond to the averages for the 40 days of period (April-June) referring to the year 2016 and for the rainy season the averages correspond to the Nov-2015 until Feb-2016. For both seasons, the daily data for the respective 40 days for both seasons (2015-2016) was taken into account.

Predictor variables related to land use were used (tree cover, lawn, exposed soil, asphalt, shade, swimming pool, light tile, dark tile, gray tile, ceramic tile, built space (BS), Vegetation Index (EVI), and Urban Forest Index (UFI). For each model, the predictor variables that remained in the model were selected by the Stepwise method (Miler, A. 2002), using the Akaike criterion (AKAIKE, 1976) with tolerance limits of 0.15 for entry and 0.10 for remaining in the model.

The REG procedure (PROC REG) of the SAS/STAT® statistical software (SAS INST. INC., 2020) was used with the "STEPWISE" option for the predictor selection method.

2.4.3 Mapping of predicted mean temperature

The mean temperature values predicted corresponding to each meteorological station (40), obtained from the selected models for each season (rainy and dry) where used to produce maps using kernel-barrier interpolation (GRIBOV, 2011).

3. Results and Discussion

The city of Piracicaba has a much smaller range of variation in tree cover than the city of São Paulo, ranging from (1 to 53 %). The green areas in the city of Piracicaba are relatively evenly distributed, with no predominance of tree cover in any of the quadrants (Figure 2), although there is a trend towards a lower percentage of cover in the central area. The error matrix of the supervised classification showed a very acceptable Kappa index of over 80%. The distribution of main variables related to land use are relatively symmetrical for both seasons in consonance with the patters observed in the map of supervised classification (Figure 2 and 5).

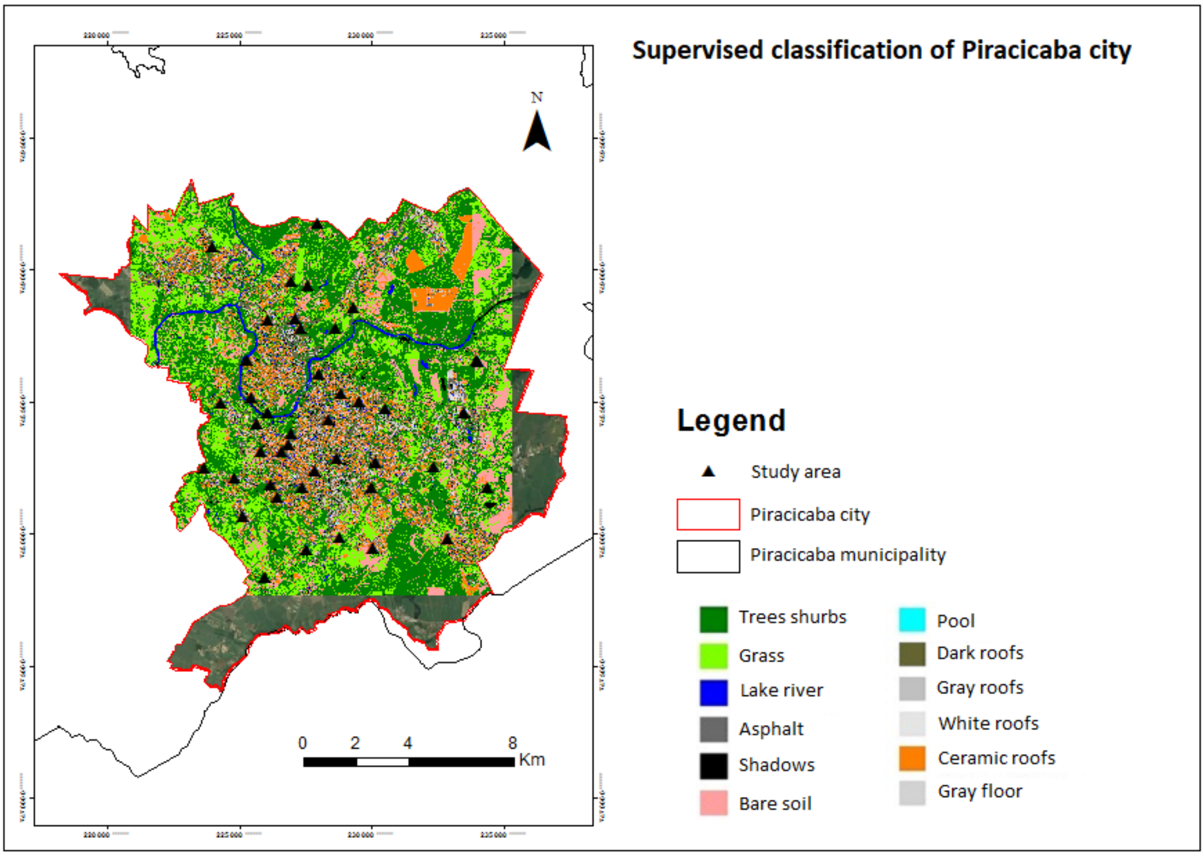

Figure 2: Classification of Piracicaba's urban network using the 2011 WorldView 2 satellite image and the areas of influence totaling 36 sensors in triangles.

3.1 Characterization of the input data

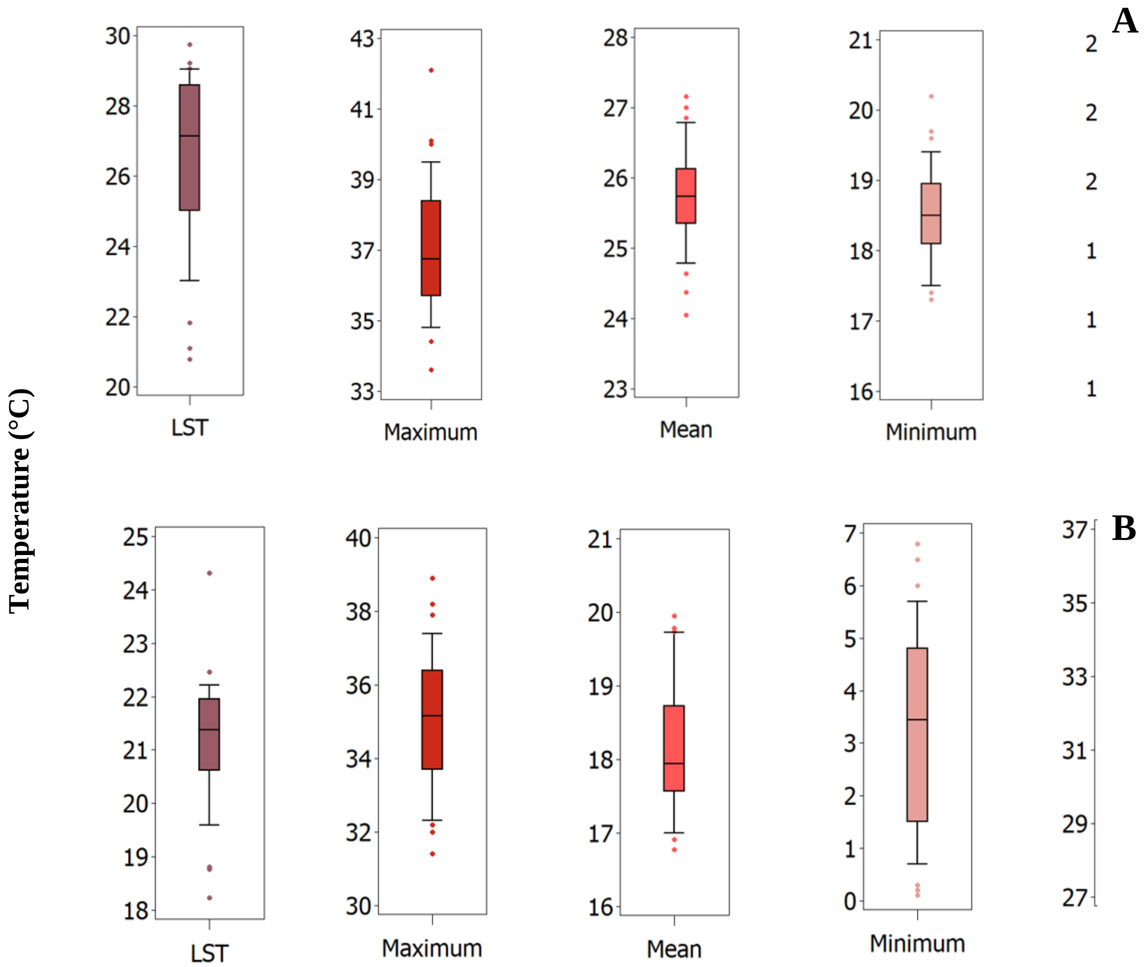

Figure 3: Box and whiskers plots of LST, maximum, mean, minimum and range temperature from 36 weather stations in Piracicaba, Brazil. Statistics calculated using data from 40 days (rainy season) and 40 days (dry season), considering only days without rain, from the years 2015 and 2016. The bottom and top edges of the box are located at the 25th and 75th percentiles. The center horizontal line is drawn at the median (50th percentile). The vertical lines, or whiskers, extends from the box as far as the data extend, to a distance at most 1.5 interquartile ranges.

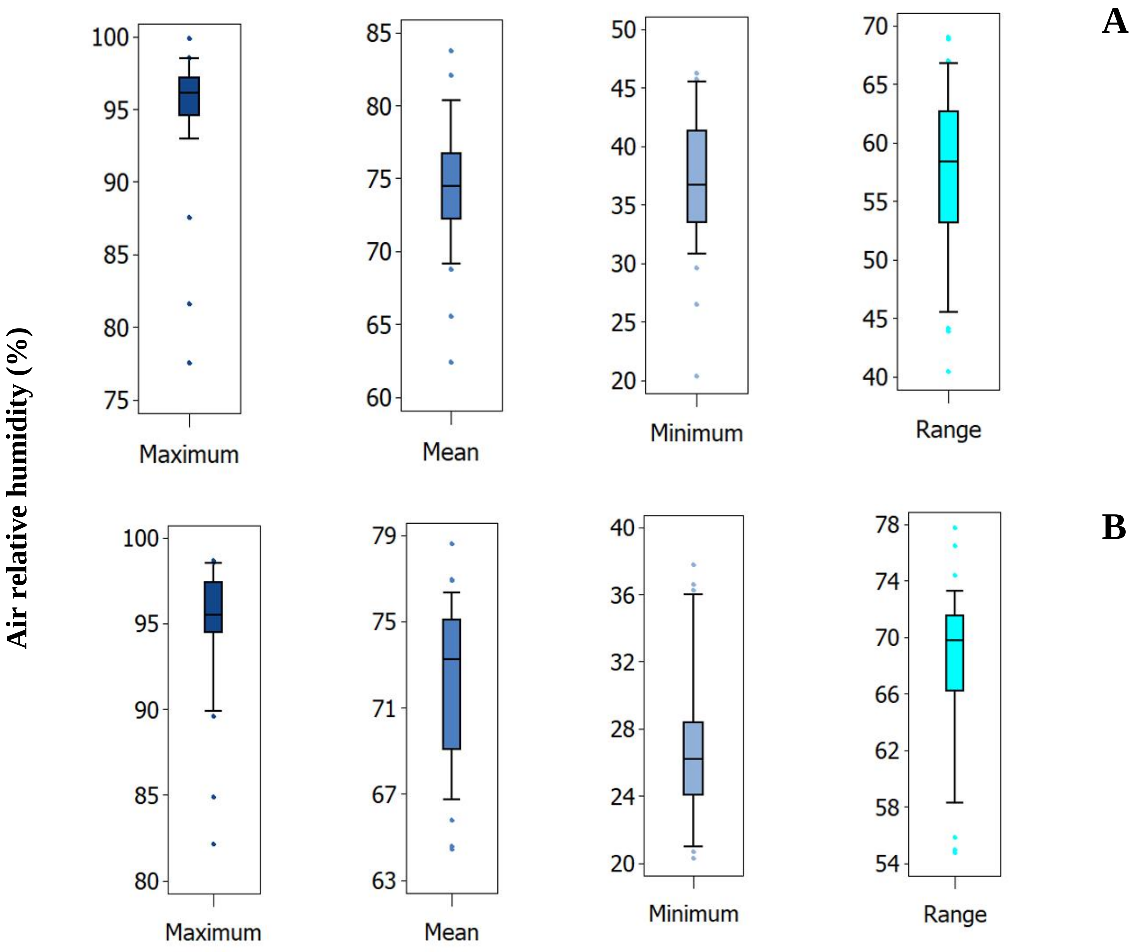

Figure 4: Box and whiskers plots of LST, maximum, mean, minimum and air relative humidity (%) from 36 weather stations in Piracicaba, Brazil. Statistics calculated using data from 40 days (rainy season) and 40 days (dry season), considering only days without rain, from the years 2015 and 2016. The bottom and top edges of the box are located at the 25th and 75th percentiles. The center horizontal line is drawn at the median (50th percentile). The vertical lines, or whiskers, extends from the box as far as the data extend, to a distance at most 1.5 interquartile ranges.

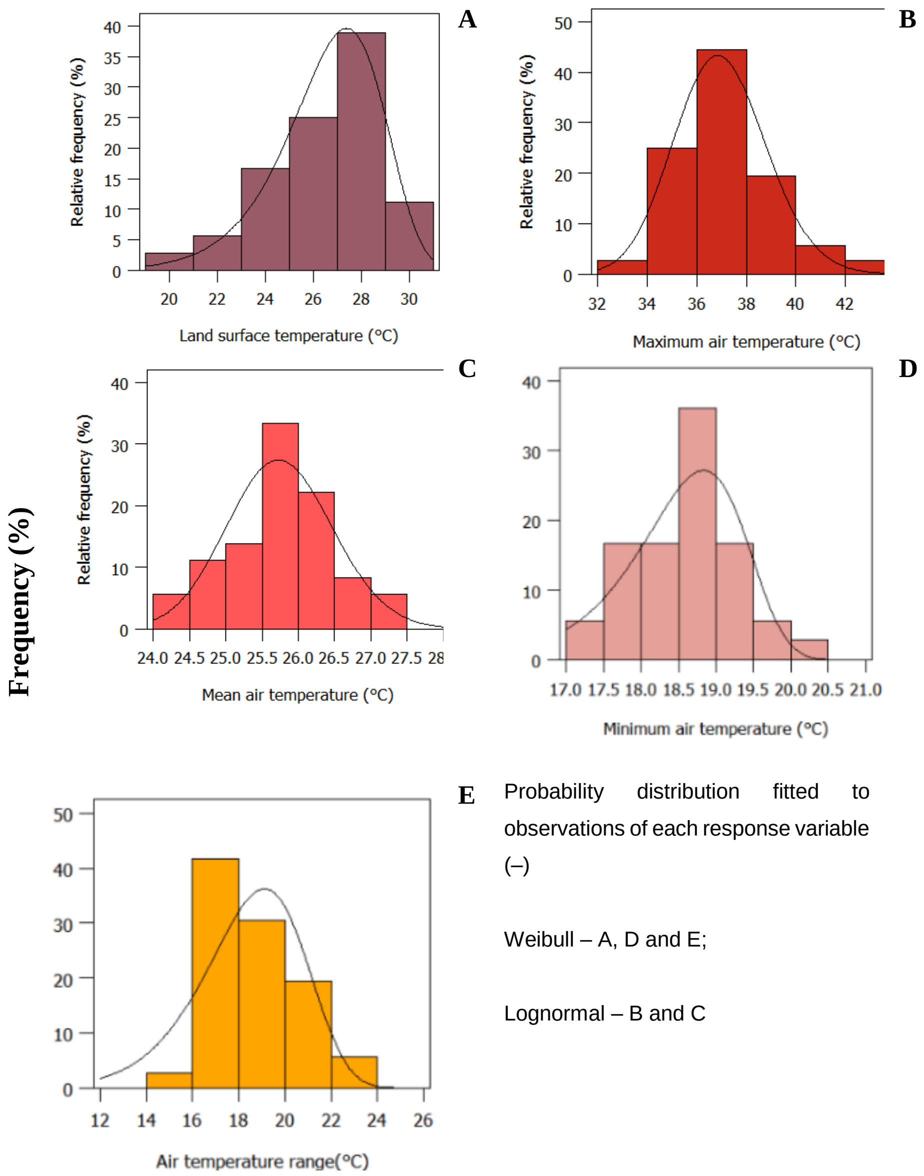

Figure 5: Histogram of LST, maximum, mean, minimum, and range temperature from 36 weather stations in Piracicaba, Brazil. Statistics were calculated using data from 40 days of the period (Nov-Feb) referring to the year 2016.

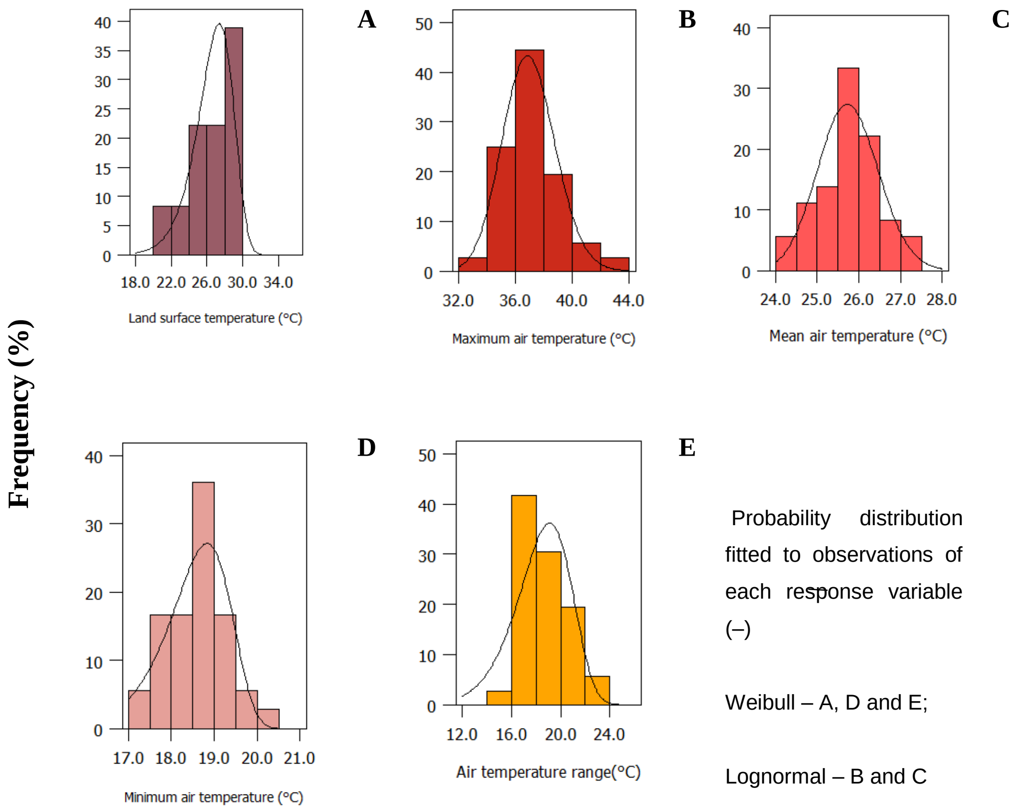

Figure 6: Histogram of LST, maximum, mean, minimum, and range temperature from 36 weather stations in Piracicaba, Brazil. Statistics were calculated using data from 40 days of the period (April-June) referring to the year 2016.

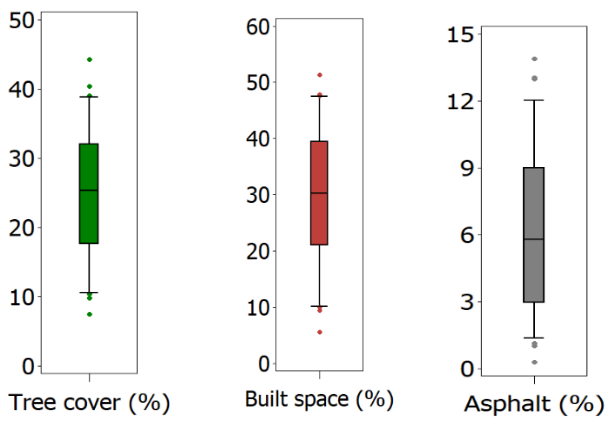

Figure 7: Box and whiskers plots for percent of the urban area occupied by), Tree cover (%) Built Space (%),and Asphalt (% in Piracicaba, Brazil. The bottom and top edges of the box are located at the 25th and 75th percentiles. The center horizontal line is drawn at the median (50th percentile). The vertical lines, or whiskers, extends from the box as far as the data extend, to a distance at most 1.5 interquartile ranges.

3.2 Fitted regression models

The buffer for which the best multiple regression models were obtained was 20 meters for the rainy season and 500 m for the dry season. The average temperature reduction rates for each 1 p.p. increase in tree cover were 0.04 and 0.08 °C for the rainy and dry seasons, respectively. Based on these models, the increase in cover needed to cool 0.5°C in the rainy season is 25.39 p.p, and in the dry season is 9.30 p.p. These increments correspond to 5925.01 (25.39*233, 36 km^2) ha and (2170.25 9.30*233, 36 km^2) ha of additional green area, respectively.

For each variable, two adjusted models were developed: one using stepwise method to select the best model, and another one employing only tree coverage as a predictor. In the optimized model, all variables that significantly influence the response variable, such as mean temperature, were included. The model based on tree coverage only serves as an operational tool to estimate the increase in tree coverage required to cool down the urban mean temperature by a certain degree.

The primary focus of this study is to examine the impact of tree coverage on mean temperature. In the best-fit model adjusted for mean temperature, in both rainy and dry seasons, the chosen predictors were the Enhanced Vegetation Index (EVI) and tree coverage percentage. The decision to retain EVI in the operational model stems from its high correlation with tree coverage ($R^2=0.95$). Despite this strong correlation, the incorporation of EVI significantly contributes to explaining variations in mean temperature ($p<0.01$).

Increasing tree coverage by one percentage point (p.p) results in a decrease in mean temperature equivalent to the coefficient of the coverage variable in the model ($\beta 1$ from equation 1). Across all models where the response variable is temperature, the predictor coefficient for coverage is negative, indicating an inverse relationship between these variables.

Table 2: Estimated parameter and respective standard errors of selected models adjusted to represent the relationship between the response variables maximum, mean, and minimum relative humidity (URmax, URmean, and URmin) and their corresponding predictor variables. Data from June-Aug (Dry Season) of the period between 2019 and 2023 of Sao Paulo urban area, SP, Brazil.

Response Variable	**Predictor variable**	**Parameter Estimate**	**Standard Error**	**p-value**	**Determination Coefficient (R^2)**
	Intercept	26.56	0.15	<.0001	**0.6301**
	tree cover	**-0.02**	**0.01**	**0.0018**	
Tmean	**EVI**	**-4.93**	**2.21**	**0.0326**	
	Intercept	**26.33**	**0.12**	**<.0001**	**0.5744**
	tree cover	**-0.04**	**0.01**	**<.0001**	
URmean	Intercept	71.56	1.09	<.0001	**0.6366**
	tree cover	0.09	0.04	0.0456	
	gray roof	-0.49	0.14	0.0016	
	EVI	28.15	14.18	0.0557	
	Intercept	71.50	0.85	<.0001	0.3894
	tree cover	0.18	0.04	<.0001	

Table 3: Estimated parameter and respective standard errors of selected models adjusted to represent the relationship between the response variables maximum, mean, and minimum relative humidity (URmax, URmean, and URmin) and their corresponding predictor variables. Data from June-Aug (Dry Season) of the period between 2019 and 2023 of Sao Paulo urban area, SP, Brazil.

Response Variable	**Predictor variable**	**Parameter Estimate**	**Standard Error**	**p-value**	**Determination Coefficient (R^2)**
	Intercept	19.5050	0.58	<.0001	0.6954
	tree cover	-0.0666	0.01	<.0001	
	shadow	0.2030	0.07	0.0065	
Tmean	light roof	-0.0036	0.03	0.9085	
	dark roof	-0.2076	0.10	0.0475	
	Intercept	19.9091	0.26	<.0001	**0.6004**
	tree cover	-0.0700	0.01	<.0001	
	Intercept	48.1473	5.24	<.0001	0.6699
	tree cover	0.3897	0.08	<.0001	
	grass	0.1970	0.06	0.0032	
URmean	exposed soil	0.52013	0.16	0.0035	
	asphalt	0.4070	0.21	0.0606	
	pool	0.2999	0.08	0.0009	
	light roof	0.3339	0.15	0.0349	

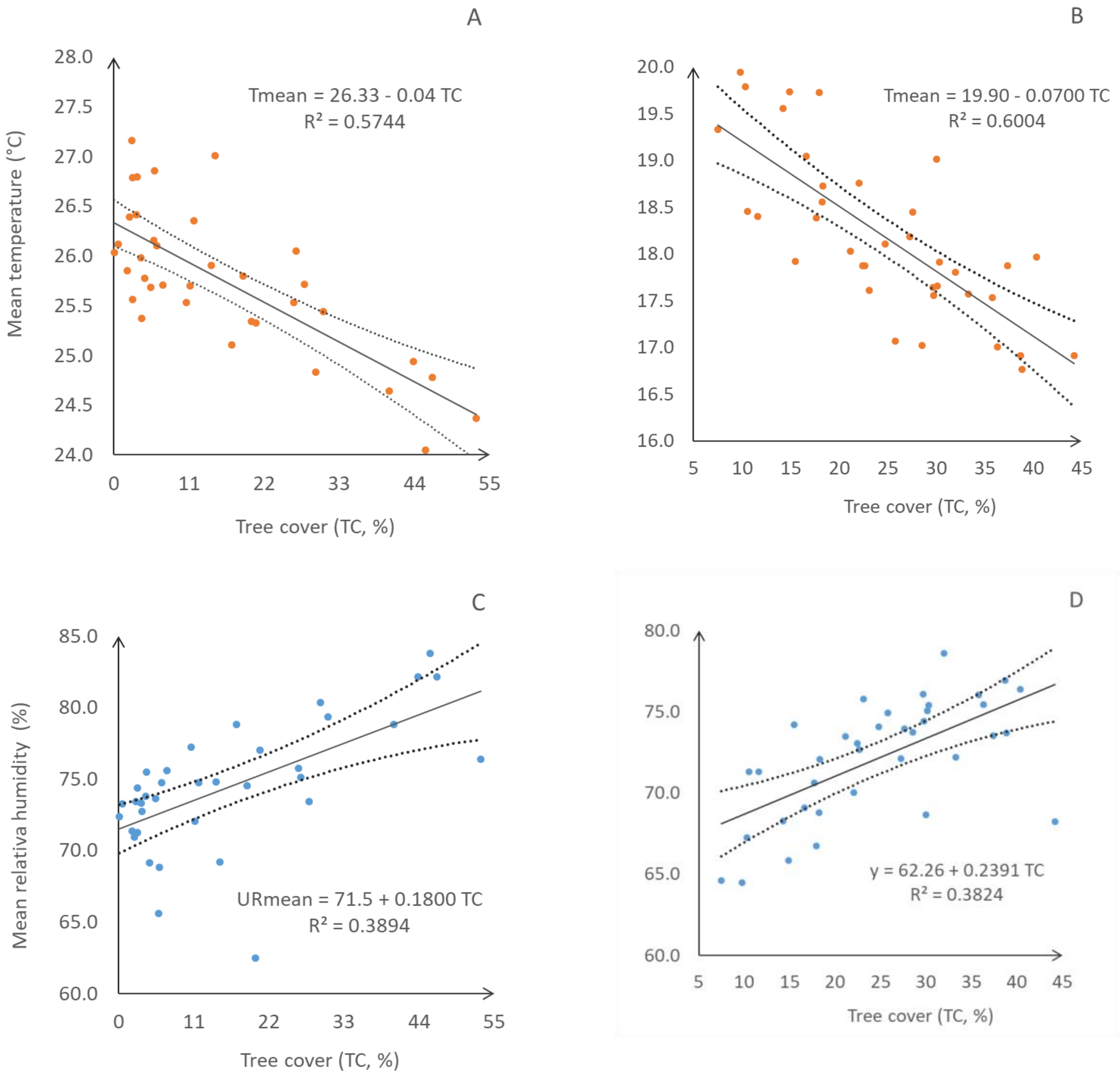

Figure 8: Linear models fitted to represent the relationship among: mean temperature and tree cover (%) for rainy (A) and dry seasons (B); mean air relative humidity (%) and tree cover (%) for rainy (C) and dry seasons (D) in Piracicaba (SP), Brazil. The inferior and superior dashed lines correspond to the lower and upper confidence limits, respectively, of the predicted means.

Model quality assessment revealed residuals predominantly within the range of (-2 to 2), with over 95% falling within this interval, indicating high model quality. In an ideal fit, data points would align along the main diagonal (continuous line - Figure 9) representing predicted versus observed values. Closer alignment to this line signifies better model quality. The dotted line represents the actual relationship between observed and predicted values. Instances where the line lies above the diagonal indicate model overestimation, while below suggests underestimation of temperature.

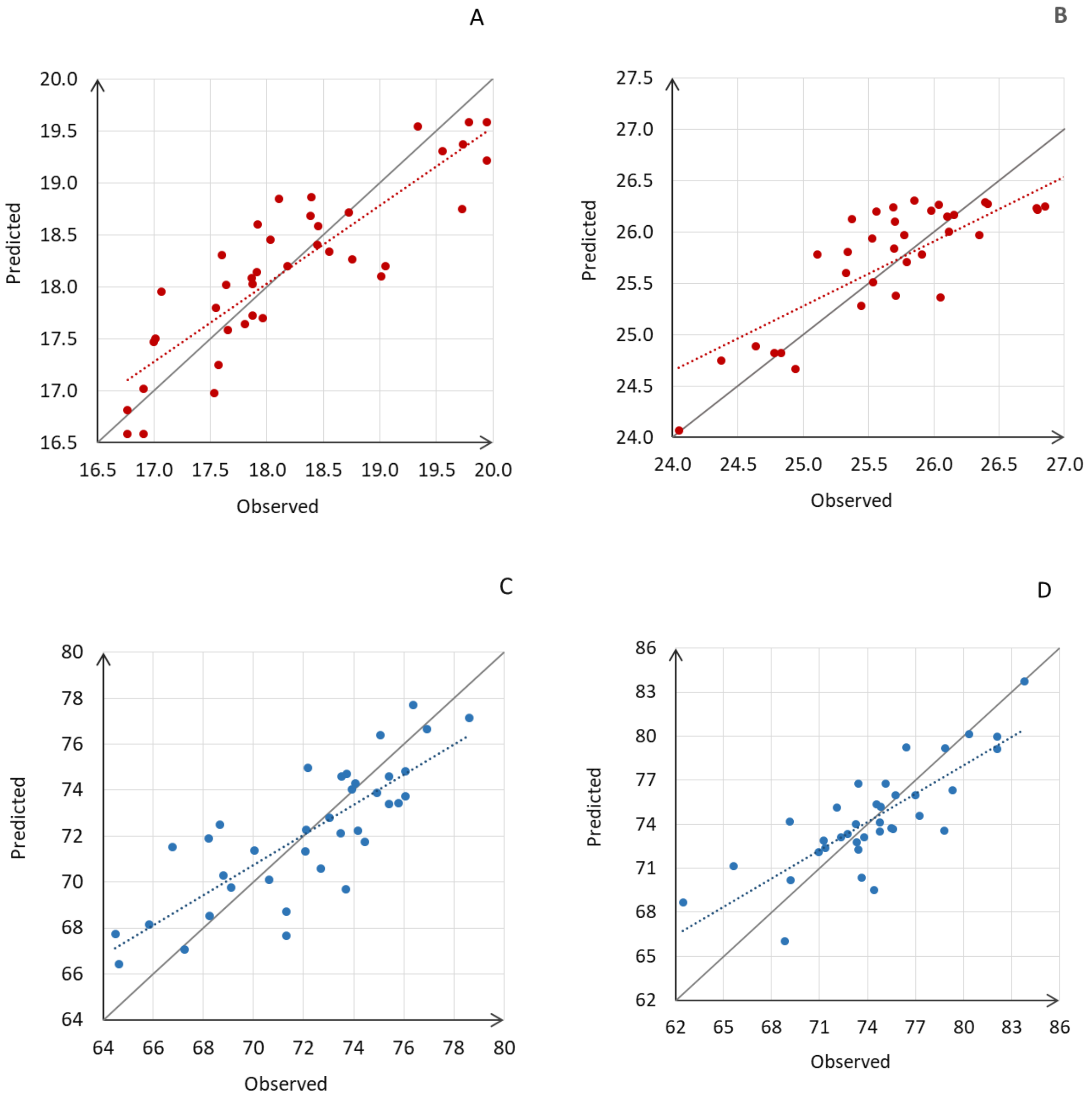

Figure 9: Graphical representation of models quality, in Piracicaba (SP, Brazil): observed versus predicted values from linear models fitted to predict mean temperature (°C; A- Rainy, B- Dry Season) and mean air relative humidity (UR; C- Rainy, D- Dry Season) as function of tree cover (%).The dashed lines, in each graphs, corresponds to the linear trend between observed and predicted values.

Both seasons display a trend: overestimation for low coverage values and underestimation for high coverage values. This pattern hints at potential nonlinearity in the temperature-coverage relationship, prompting consideration for nonlinear models in future exploration.

3.3 Maps of predicted mean land surface temperature

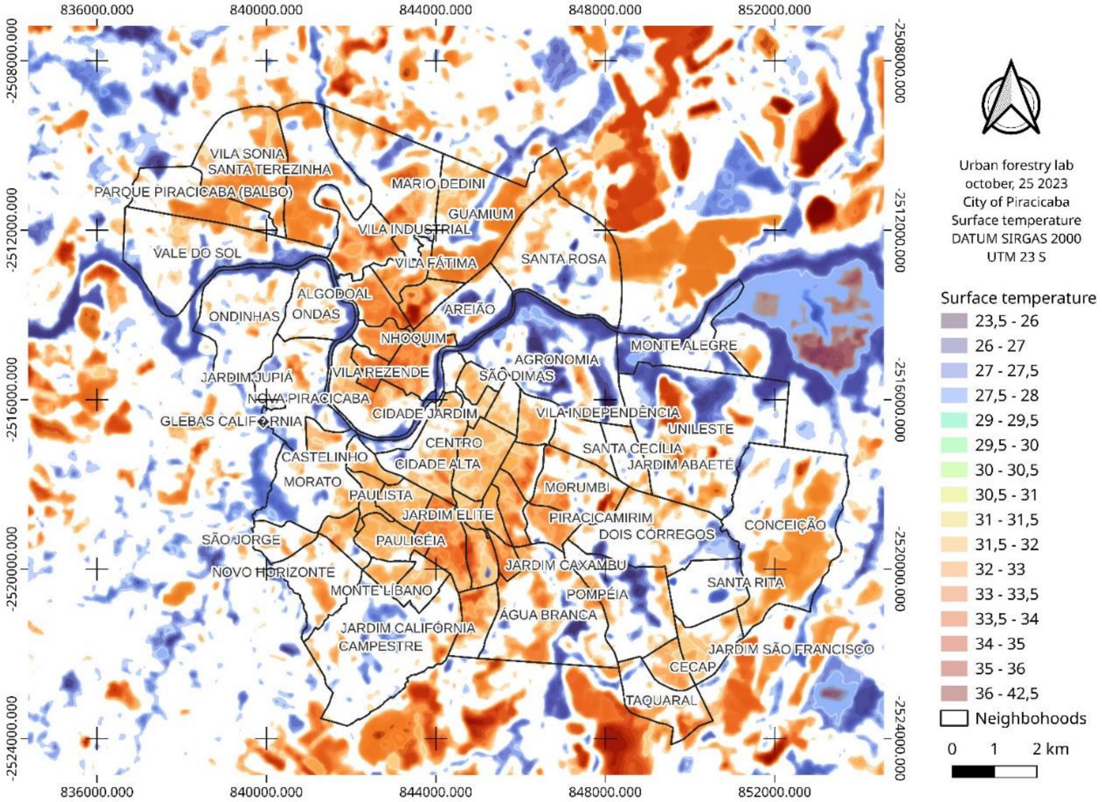

Figure 10: Spatial distribution of mean temperature surface in the urban tissue of Piracicaba,SP, Brazil.

On the map, areas that appear more reddish indicate higher temperatures. In the areas along the margins of the Piracicaba River, there is a noticeable decrease in temperature what is consistent with the high tree cover. There is a significant contrast in temperature between the reddish areas (central area, around 30°C surface temperature) and the ones along the river (22 to 23 °C). This disparity will lead to higher air temperatures in these areas where the colors tend towards red. There are many heat pockets scattered throughout the city, which should be priority areas for tree planting.

4. Conclusions

The cooling effect of tree cover in the rainy season is the double than the one of the dry season, thus increasing the environmental service generated by green areas. The models for estimating mean temperature and mean relative humidity based on urban land use classes and other auxiliary variables were adequate thus providing useful information for efficient afforestation policies of mid-sized cities in tropical regions.

The models used to estimate the average temperature based on urban land use classes and other auxiliary variables have proven to be effective, providing valuable insights for the development of efficient afforestation policies in cities located in tropical regions. Models relying on urban land use classes and supplementary variables such as the Enhanced Vegetation Index (EVI) and Land Surface Temperature (LST), obtained from satellite imagery, accurately predicted urban average temperatures in tropical city areas.

However, as observed in São Paulo, the cooling rates of urban average temperature concerning the percentage increase of tree cover were challenging to ascertain for the 36 sampled points due to the limited number of available meteorological stations. For future studies, it is recommended to utilize a 10% sampling rate of points concerning the total area of the municipality to achieve a more comprehensive representation of urban variability. Moreover, the data from Piracicaba also showed a narrow variation range (0.40), which hindered the identification of a possible nonlinear relationship between tree cover and daily mean temperature, mirroring the challenge observed in São Paulo. To overcome this limitation, it is crucial to expand the number of data collection sites across the urban area to encompass a wide range of tree cover values, distributed more uniformly across the 0 to 100% range. These recommendations are essential for subsequent studies.

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