

Geospatial analysis of the relationship between urban structure, vegetation, population and surface temperature in the Cuiabá-Várzea Grande-MT conurbation

Análise geoespacial da relação entre a estrutura urbana e da vegetação, populacional e de temperatura de superfície na conurbação Cuiabá-Várzea Grande-MT

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Abstract

The urbanization process does not occur in a synchronized way, which could result in differences of urban areas depending on various socioeconomic factors. The implications of such differences can result in long-term consequences for the local urban context. This study proposes a descriptive model to characterize the Cuiabá-Várzea Grande (Mato Grosso State) conurbation, considering its building structure, vegetation cover, land surface temperature, population, and topography. To accomplish this, spectral indices derived from remote sensing data, related to built-up areas, vegetation, and land surface temperature were employed, along with terrain elevation and population information from census data. The model, based on cluster analysis, allowed the identification of three units which explain the urban distribution of the conurbation: two strongly associated with the building structure (more or less densely built up) and a third one with mainly vegetation cover, generally located at the edges of the study area. These characteristics are reflected in land surface temperature, which is lower in the unit with a higher presence of green cover and higher in the area with dense constructions and scarce vegetation. The unit encompassing the central regions has open areas that could be used for more efficient uses, such as commercial, residential, or social activities. The proposed model demonstrates the potential to improve the

management of the urban development in the area under study.

Keywords:

Remote sensing, Green areas, Urban planning, Data mining.

Resumo

O processo de urbanização não ocorre de forma sincronizada, o que pode gerar diferenças na formação das áreas urbanas, dependendo de diversos fatores de natureza socioeconômica. As implicações dessa formação podem resultar em desdobramentos permanentes para o contexto urbano local. Neste trabalho, propõe-se um modelo descritivo para caracterizar a conurbação Cuiabá–Várzea Grande (MT), considerando seus aspectos de edificação, cobertura vegetal, temperatura de superfície, população e relevo. Para isso, foram empregados índices espectrais obtidos por sensoriamento remoto, referentes às áreas edificadas, vegetadas e à temperatura de superfície, bem como dados de elevação do terreno e de população em nível de setor censitário. O modelo, baseado em análise de agrupamento, permitiu a identificação de três grupos que explicam a distribuição urbana da conurbação: dois fortemente relacionados à estrutura das edificações, um mais adensado e outro menos, e um terceiro representativo de áreas com maior cobertura vegetal, geralmente localizado nas margens da área estudada. Essas características refletem-se na temperatura de superfície urbana, sendo menor no grupo com maior presença de áreas verdes e mais elevada no grupo com edificações mais adensadas e vegetação escassa. O grupo característico das regiões centrais permite identificar a presença de áreas abertas, que podem ser destinadas a usos mais eficientes, como atividades comerciais, habitacionais ou de socialização. O modelo proposto apresenta potencial para subsidiar uma gestão mais eficiente do desenvolvimento urbano da área analisada.

Palavras-chave:

Sensoriamento remoto, Áreas verdes, Planejamento urbano, Mineração de dados.

I. INTRODUCTION

Brazil has experienced a significant expansion of its urban areas, although with a progressive slowdown in the growth rate. Between 1985 and 2023, the national urban territory increased by 2.4 million ha, reflecting the structural changes in land use and occupation that affect directly the socio-environmental dynamics of cities (MAPBIOMAS, 2024). In Mato Grosso State, this process is expressed in a striking way, with the urban area increase from 58,418 ha in 1985 to 138,009 ha in 2023, an evidence of important changes in land use and cover in urban space, even at more moderate rates in recent years.

This urban expansion occurred in parallel with a significant demographic growth. Between 1991 and 2022, the Brazilian population grew from 146.9 million to over 203 million inhabitants, an increase of approximately 38% (IBGE, 2010, 2022). In Mato Grosso State, the population increase was even more pronounced, jumping from a little over 2 million to 3.6 million inhabitants in the same period, an increase of

approximately 81%. The combination of population growth and urban expansion poses complex challenges to urban management, especially with regard to the sustainability of cities and the mitigation of environmental phenomena, such as Urban Heat Islands (UHI), whose increase is directly associated with the replacement of vegetation covered areas by buildings and impermeable surfaces (Oke, 1982; Arnfield, 2003; Wei et al., 2024).

In the context of the conurbation between Cuiabá and Várzea Grande (Mato Grosso State - MT), these processes are even more relevant (Marandola et al., 2011; Visconti; Santos, 2014). The articulation between the two urban centers promotes spatial densification that aggravate the effects of urban transformations (Dupont et al., 2010), requiring a more refined analysis that must consider not only the distribution of built-up areas, but also the remaining vegetation cover, the surface thermal patterns and the population structure. Recent studies highlight the importance of intra-urban analysis, such as the census sector, as they allow the identification of spatial inequalities with higher precision, supporting improved and more effective public policies (Pereira; Schwanen; Banister, 2017).

Despite the growing volume of studies on the impacts of urbanization on urban environmental dynamics, investigations that integrate, on an intra-urban scale, multiple structural and environmental parameters, such as vegetation, urban structure, surface temperature and population data, through data mining techniques, applied to the Brazilian context, are still limited. There are no studies in the national literature referring to the Cuiabá-Várzea Grande conurbation from an integrated perspective, especially at a census scale. This work is therefore justified by the need to improve the understanding of how urban and environmental patterns are organized in this urban area, to support more effective urban planning and management strategies. The main contribution of this study consists on the application of a descriptive model based on spectral indices and socio-spatial data, to understand the physical and structural aspects that characterize the Cuiabá-Várzea Grande (MT) conurbation. In this frame, the analysis of the built-up area, the distribution of green areas, the effects of this arrangement on the surface temperature (which influences the well-being of the population) and the distribution of the population in these areas are relevant.

Based on a methodological approach such as that one of Kebede et al. (2022), demonstrating the effectiveness on the use of spectral indices to extract impervious surfaces in complex urban environments, our study applies a descriptive analysis based on data mining to characterize the Cuiabá-Várzea Grande conurbation. This approach combine population census data with parameters derived from remote sensing data (NDVI – Normalized Difference Vegetation Index; TST – Surface Temperature; NDBI – Normalized Difference Built-up Index; BRBA – Band Ratio for Built-up Area; and BAEI – Built-up Area Extraction Index) to describe the

structural, vegetation, thermal and population configurations at the census scale. Thus, the objective of this work is to describe, on a census scale, the urban conurbation Cuiabá–Várzea Grande (MT) emphasizing its structural and environmental configurations, addressing the urbanized area, vegetation cover, surface temperature and population distribution, with a descriptive analysis based on data mining.

II. MATERIAL AND METHODS

The descriptive model from the Cuiabá–Várzea Grande (MT) conurbation, developed in this study, was constructed from the integration of spectral indices related to the configurations of urbanized areas, the characteristics of vegetation cover and surface temperature during the winter and summer seasons, in addition to the digital elevation model and census data on population density. These variables were pre-processed to remove inconsistencies and standardize the data. Then, a cluster analysis algorithm was applied, with the objective to classify the census data into groups with patterns of internal similarity, allowing the identification of different spatial configurations within the conurbation under study.

Study area and period

The study area of this work corresponds to the urbanized portion of the Cuiabá–Várzea Grande conurbation (MT), located within the Paraguay River Basin. This area covers approximately 446 km² and is home to a population of 932,385 inhabitants, according to data from the 2022 Demographic Census (IBGE, 2022) (Figure 1).

As for the time frame, spectral and surface temperature images for the winter (mid-year) and summer (end of the year) of 2023 were preliminarily selected. The choice of these dates considered the availability of satellite images with the lowest possible percentage of cloud cover, to guarantee the quality of the analyses.

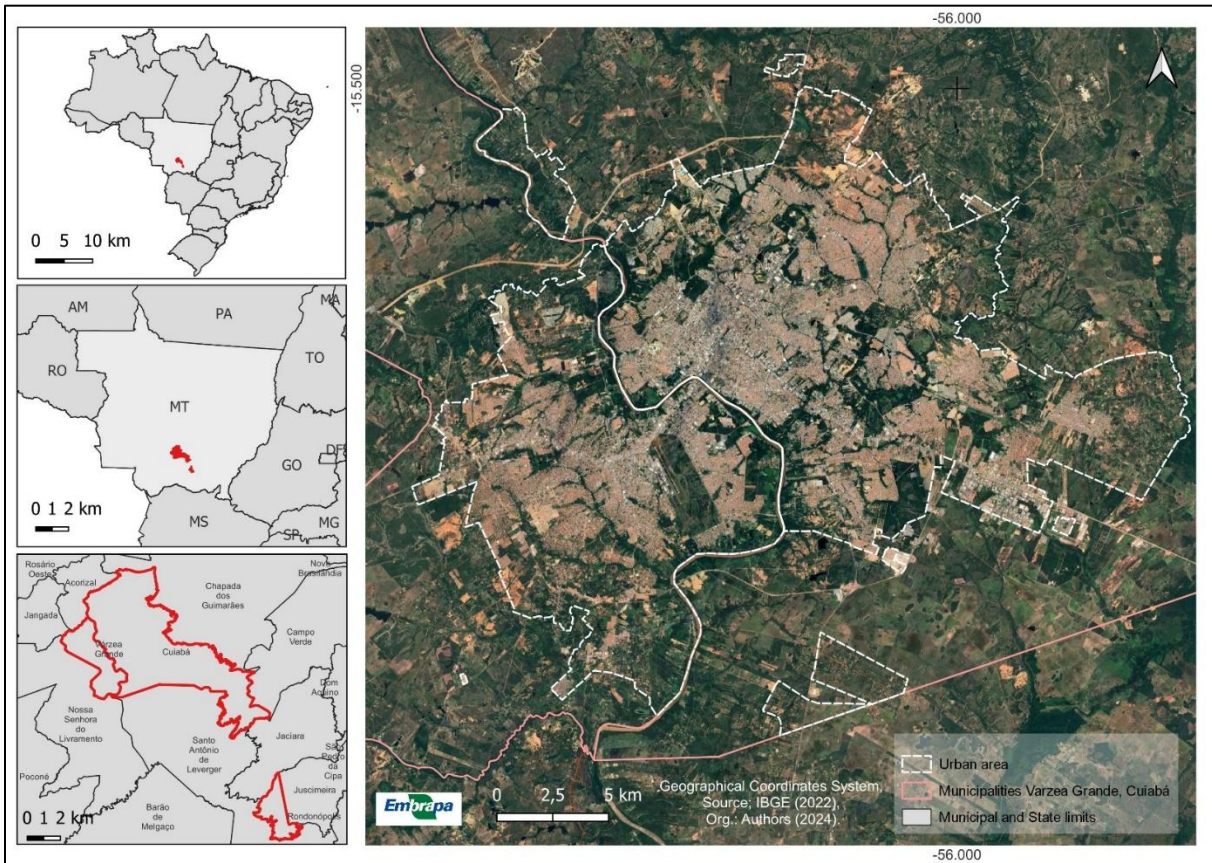


Figure 1 – Localization of area undre study. Source: Elaboration by authors (2025).

Database

Spectral data from the TIRS/Landsat 8-9 and MSI/Sentinel-2A satellites were used to calculate the surface temperature and spectral indices, respectively. Table 1 shows the selected bands of the respective satellites and Table 2 presents the equations used to calculate the parameters derived from these bands.

Table 1 – Configuration of remote sensor data to determine the parameters of spectral data.

Data	Satellite/Sensor	Band	Spectral range (nm)
• 04/07/2023 (winter)	Landsat/TIRS-2	Thermal infrared (B10)	10.800
• 27/12/2023 (summer)			
• 04/08/2023 (winter)	Sentinel-2A/MSI	Green (B3)	559
• 31/01/2024 (summer)		Red (B4)	665
		Near infrared (NIR) (B8)	833
		Short wave infrared 1 (SWIR1) (B11)	1.610,4
		Long wave infrared 2 (SWIR2) (B12)	2.185,7

Source: Elaboration by authors (2025).

Table 2 – Parameters extracted from remote sensors to determine spectral profiles.

Characteristic	Parameter	Equation	Nr.	Source
Temperature	TST (°C)	$((B10 * 0,00341802) + 149) - 273.15$	(1)	EROS (2020)
Constructions	UI	$(B11 - B8)/(B11 + B8)$	(2)	Kawamura et al. (1996)
	NDBI	$(B12 - B8)/(B12 + B8)$	(3)	Zha et al. (2003)

	NBI	$(B4 * B12)/B8$	(4)	Jieli et al. (2010)
	BRBA	$B4/B12$	(5)	Waqar et al. (2012)
	NBAI	$((B12 - B11)/B3)/((B12 + B11)/B3)$	(6)	Waqar et al. (2012)
	MBI	$((B11 * B4) - (B8^2))/(B4 + B8 + B11)$	(7)	Ali et al. (2021)
	BAEI	$(B4 * 0,3)/(B3 + B11)$	(8)	Bouzekri et al (2015)
Vegetation	NDVI	$(B8 - B4)/(B8 + B4)$	(9)	Rouse et al. (1973)

Source: Elaboration by authors (2025).

The acronyms refer to the following parameters: *Surface Temperature (TST)*; *Urban Index (UI)*; *Normalized Difference Built-up Index (NDBI)*; *New Built-up Index (NBI)*; *Band Ratio for Build-up Area (BRBA)*; *Normalized Built-up Area Index (NBAI)*; *Modified Build-up Index (MBI)*; *Build-up Area Extraction Index (BAEI)* e; *Normalized Difference Vegetation Index (NDVI)*.

The indices related to the characteristics of built-up areas were used by Kebede et al. (2022) to assess their effectiveness to identify impervious surfaces during the rainy season in Ethiopia. These authors concluded that, although all indices showed high similarity in results, those based on the shortwave infrared band (B11 and B12 bands of Sentinel-2A MSI) presented a higher performance compared to the others.

In the present study, the parameters related to built-up areas were calculated exclusively for the date of 04/08/2023, considering the low probability of significant changes in the urban configuration between that date and the period represented by the summer image. On the other hand, the vegetation indices and surface temperature were obtained for the two periods analyzed (winter and summer).

In addition to the parameters derived from remote sensing data, a database referring to the resident population by census sector, according to the 2022 Demographic Census (IBGE, 2022), and a digital elevation model (Copernicus GLO-30; 30 m resolution) were incorporated to integrate the information on the altimetry variation and the position of the census sectors in relation to the Cuiabá River, which is the border between the Cuiabá and Várzea Grande municipalities.

Except for the population variable, whose absolute total per sector was considered, the other parameters were summarized using the median (more robust due to outliers) of the spatial distribution from each census sector and the standard deviation to represent its degree of homogeneity.

Descriptive model

The database preprocessing stage began eliminating attributes with low informational contribution. One of the strategies commonly adopted for this purpose is the exclusion of attributes that are highly correlated with each other, to avoid redundancy and reduce the dimensionality of the data set (Han et al., 2012). For this purpose, the Pearson correlation coefficient between the attributes was calculated, resulting in a correlation matrix (Appendix 1), from which variables with a high correlation ($r \geq 0.90$) with any others were eliminated.

As a result of this procedure, the medians and spatial standard deviations of the BRBA (winter), BAEI (winter), NDBI (winter) and NDVI (summer) indices were maintained, in addition to surface temperatures

(winter and summer) and the total population by census sector.

According to Kebede et al. (2022), the BRBA index is effective to detect circulation routes (streets and roads) and uncovered areas, while the BAEI, although also sensitive to roads, has a higher capacity for the detection of buildings. The NDBI, on the other hand, allows to distinguish built-up areas from non-built-up areas. However, each of these indexes has specific limitations: the BRBA tends to confuse vegetated areas with built-up areas; the BAEI, built-up areas with uncovered areas; and the NDBI, exposed soil with built-up areas.

Once the attribute selection stage was completed, atypical values (outliers) were removed, defined as census tracts whose aggregate values differed substantially from the pattern observed in the set. To this end, the interquartile range method was applied, which considers as outliers (O+) the records whose values exceed, either upwards or downwards, the limits defined by:

$$O_+ = \begin{cases} > Q3 + 1,5 * (Q3 - Q1) \\ < Q1 - 1,5 * (Q3 - Q1) \end{cases} \quad (1)$$

where Q1 and Q3 are the percentiles 25% and 75%, respectively.

The descriptive model was generated with the K-Means algorithm (James et al., 2023), an algorithm that seeks to optimize the problem by minimizing the following equation

$$\min_{C, \{m_k\}_1^K} \sum_{k=1}^K N_k \sum_{C(i)=k} \|x_i - m_k\|^2 \quad (2)$$

by assigning, for each record (i) of N observations, the group (C) with the smallest Euclidean distance (i.e., inertia)

$$C(i) = \operatorname{argmin}_{1 \leq k \leq K} \|x_i - m_k\|^2 \quad (3)$$

between the attribute (x) of record (i) and the mean value (mk) of group C, a process that is repeated iteratively until the minimization stabilizes or a predetermined stop criterion is reached (e.g., number of repetitions). A fundamental step in the application of K-Means is the prior definition of the K group numbers, the choice of which depends on the application context and therefore it is not a generalizable parameter (Ahmed et al., 2020; James et al., 2023). For this analysis, the "elbow rule" was adopted as the criterion, which consists of selecting the lowest value of K that results in the greatest relative reduction in inertia compared to the single grouping (K=1), before the curve stabilizes. Despite being a simple technique, the choice is based on the fact that excessive increases in KKK tend to generate unbalanced groups, impairing the generalization capacity of the model (Fränti;

Sieranoja, 2018). Based on this criterion, the formation of three groups (K=3) was defined, considered the most appropriate to represent the internal similarities and distinctions between the census sectors (Figure 2).

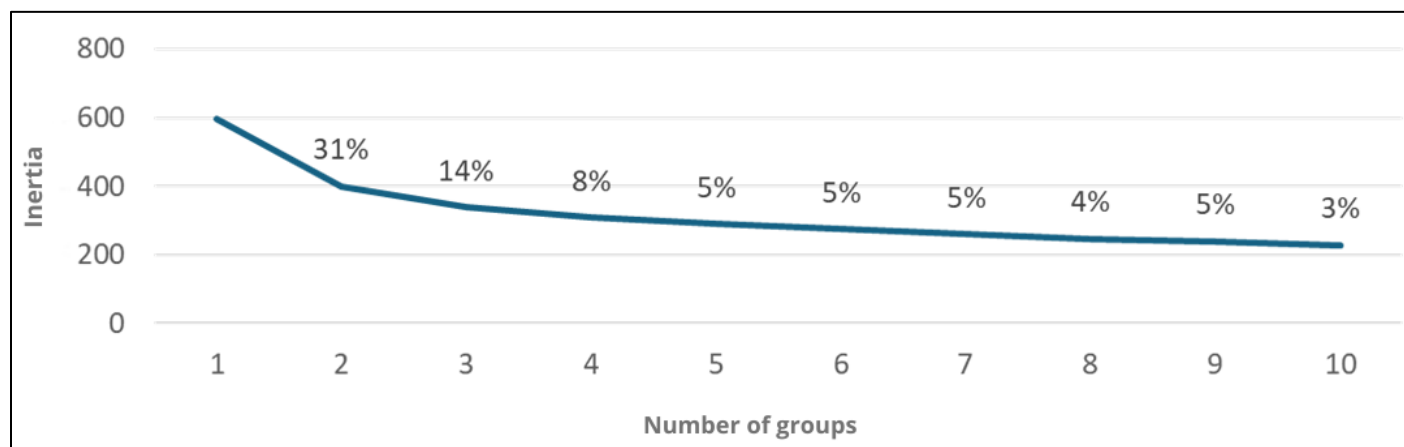


Figure 2 – Inertia variation as a function of the variation in the number of descriptive groups (K). The percentages close to the line show the relative reduction of inertia in relation to K-1. Source: Elaboration by authors (2025).

III. RESULTS AND DISCUSSION

The defined groups distinguish the census tracts of the Cuiabá–Várzea Grande conurbation based on characteristics derived from remote sensing data (spectral indices and surface temperature), altimetry variation and population density. Although the spectral indices related to the built-up area (BRBA, BAEI and NDBI) show distinct patterns (Figures 3.A to 3.F) among the groups regarding the density of built structures, anthropic areas and uncovered spaces, the interpretation of these patterns requires articulation with processes consolidated in the geographic literature on urbanization and its effects.

Group 1 had the lowest incidence of uncovered areas, while group 3 concentrated the highest proportions of this type of cover, and group 2 demonstrated an intermediate condition (Figure 3.A). These open areas, such as yards, parking lots, and non-developed land, may represent reserves for the expansion of the urban grid (Figure 3.A). This perspective is consistent with Angel et al. (2005), who argue that cities, especially in developing countries such as Brazil, should realistically plan their urban expansion, allocating adequate areas to accommodate projected population and urban growth. The spatial variation of the BRBA index reflects a higher homogeneity in group 1 and marked variability in group 3 (Figure 3.B), which suggests differences in land use patterns and intra-urban organization, aspects also highlighted by Angel et al. as fundamental to understand the distinct regimes of urban expansion to guide effective planning policies.

The presence of buildings captured by the BAEI index (Figure 3.C) was higher for groups 1 and 3, and group 1 being more homogeneous in the configuration of its buildings (Figure 3.D). The heterogeneity observed

in group 2 (Figure 3.C) reveals the coexistence of different types of buildings, possibly representing areas of urban transition, with a predominance of mixed uses or morphological fragmentation, as highlighted by Coelho (2015) in analyses on urban morphology and dispersed growth. This characteristic may be associated with informal occupation or the recent incorporation of peri-urban areas into the consolidated urban grid.

Finally, it was observed, from the NDBI index, that group 1 presents the largest proportion of built-up area, while group 2 concentrates the lowest values of this indicator (Figure 3.E). The high spatial heterogeneity of group 2 indicates that the reduced presence of built structures occurs in coexistence with vegetated areas (Figure 3.F), and, according to Kebede et al. (2022), the NDBI index presents spectral confusion mainly between built-up areas and bare soil. Group 3, on the other hand, exhibits a greater heterogeneity than group 1, which may be related to the presence of different building patterns, typological diversity and urban layout, which is also in line with the interpretation of the BAEI index.

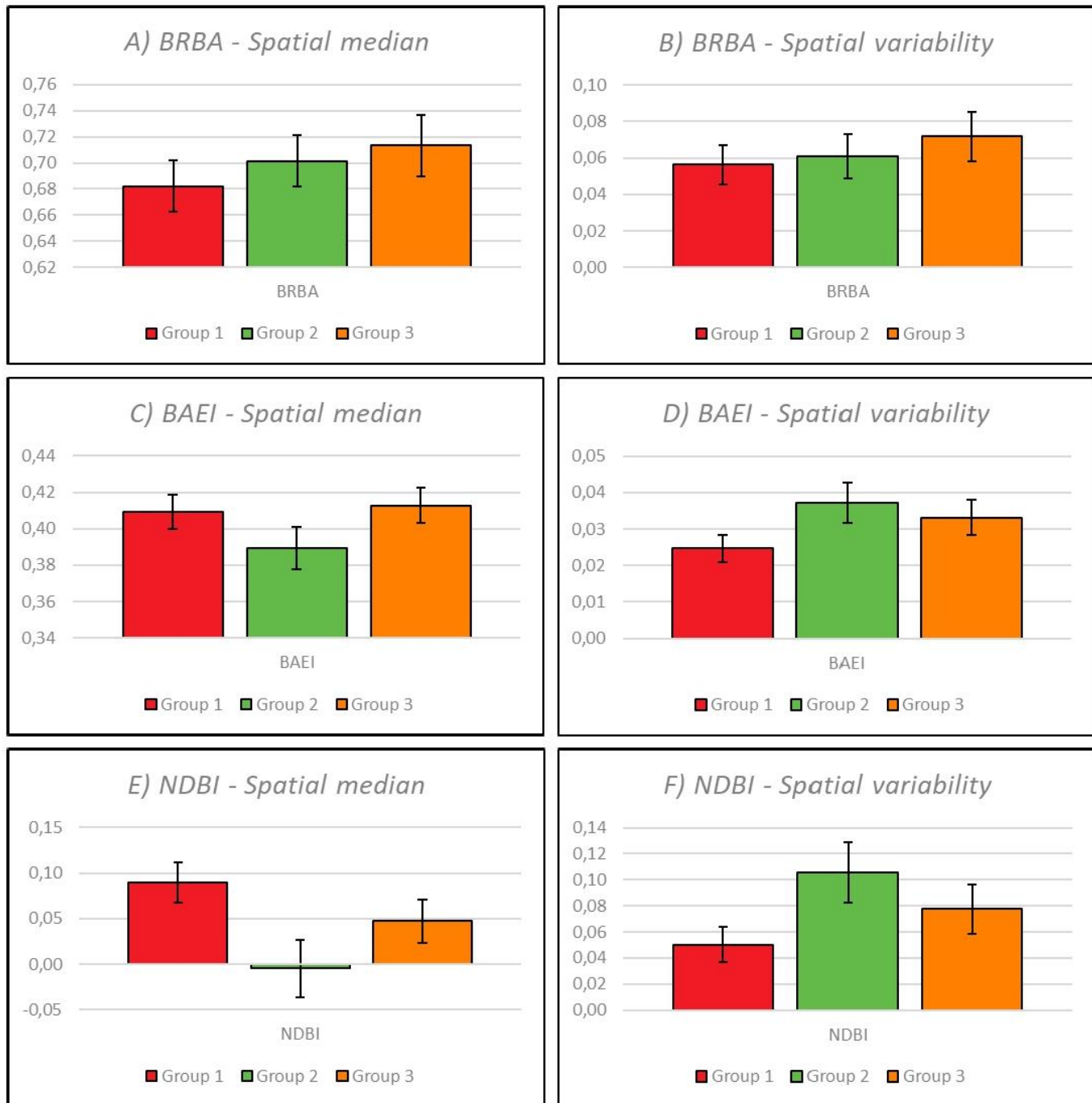


Figure 3 – Description of spectral indices from built-up area for the groups of census sectors. Source: Elaboration Prepared by the Authors (2025).

The analysis of terrain elevation did not reveal significant differences between the medians of the defined groups, which remained close to 200 meters in average altitude (Figure 4.A). However, the spatial variation of elevation within the census tracts revealed more noticeable differences: group 1 presented a flatter topography, with an average standard deviation of approximately 2 meters, while groups 2 and 3 showed greater internal altimetry variability, between 4 and 5 meters (Figure 4.B). Despite the relatively low magnitude

of this variation, the topographic homogeneity of group 1 contributed to the distinction between more densely urbanized areas, particularly between the tracts of groups 1 and 3.

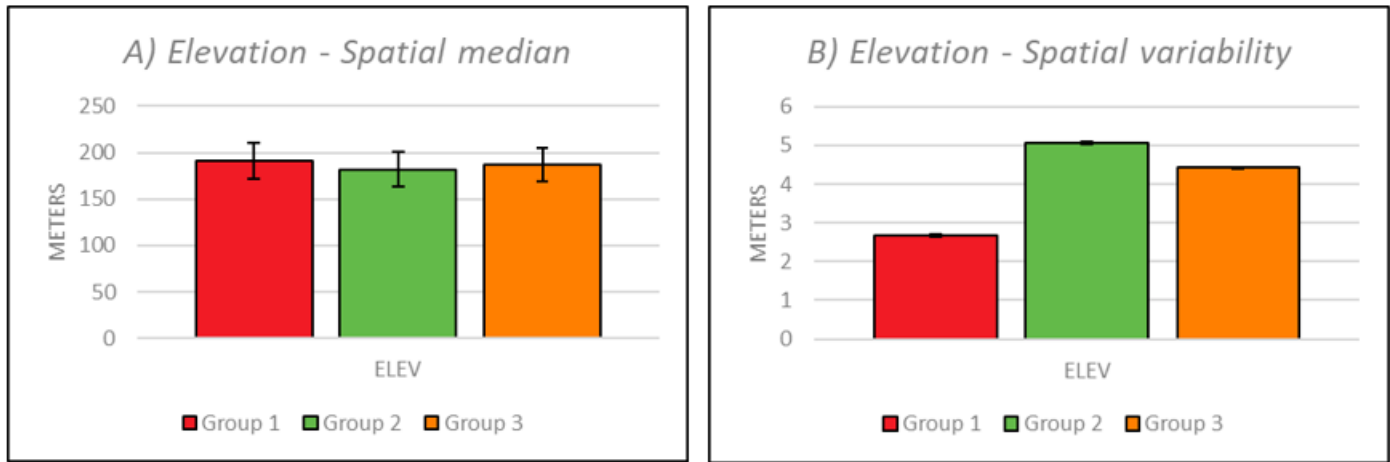


Figure 4 – Terrain elevation at different descriptive groups. Source: Elaboration by Authors (2025).

At Group 2 had a higher percentage of vegetation cover, as indicated by the median from the NDVI index, while groups 1 and 3 presented lower values, reflecting sparse or less vigorous vegetation (Figure 5.A). Considering that the NDVI expresses the photosynthetic intensity of the vegetation, the results suggest that the sectors of group 2 maintain a greater proportion of active green areas. Regarding the spatial variability of the index, group 2 also stood out for its heterogeneity, possibly resulting from the juxtaposition of buildings, open spaces and vegetation fragments in the sectors that comprise it. In contrast, group 1 showed less variability, reflecting the homogeneity of the low vegetation cover, while group 3 occupied an intermediate position (Figure 5.B).

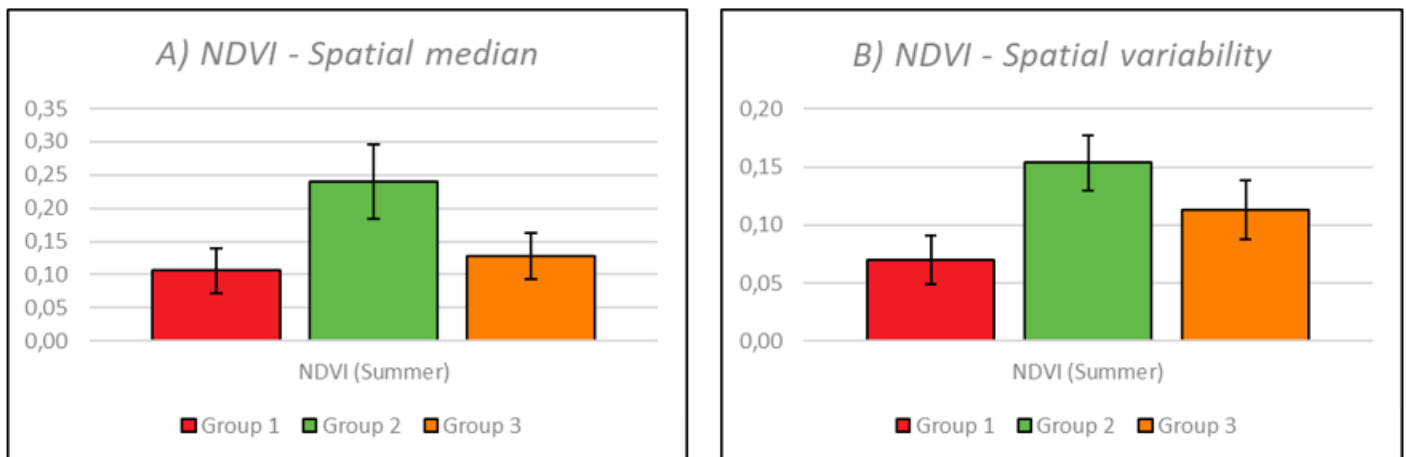


Figure 5 – Vegetation vigor measured for the summer period in the different descriptive groups. Source: Elaboration by Authors (2025).

The greater incidence of built-up areas, the densification of buildings and the reduction of green areas

increase result in an increase the surface temperature both in winter and summer. In winter, the increase occurred due to the reduction of vegetation vigor, which would contribute to attenuate surface warming. Factors related to the variation of air circulation in these sectors, which could influence temperature, were not addressed in this study and, therefore, will not be discussed. In group 2, characterized by a greater presence of green areas, an average temperature reduction of 1.65°C and 0.88°C was observed for winter, compared to groups 1 and 3, respectively (Figure 6.A). In the summer, this reduction was 1.67°C and 1.32°C (Figure 6.B), evidencing the beneficial effect of green areas for the mitigation of temperature in urban environments.

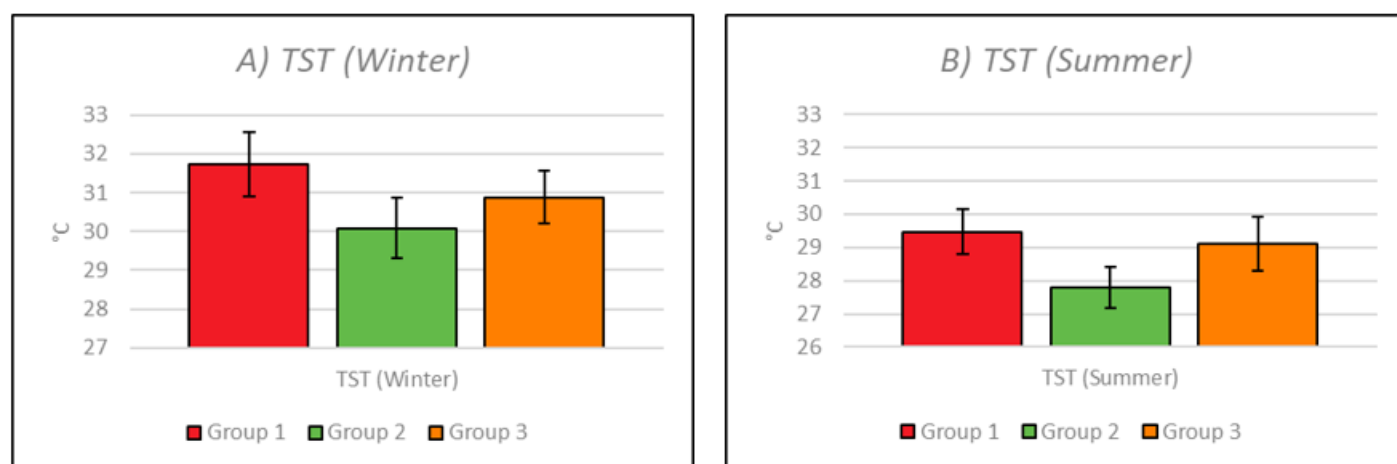


Figure 6 – Surface temperature in winter and summer for the different descriptive groups. Source: Elaboration by Authors (2025).

The number of inhabitants per sector did not show any significant distinctions between the groups, indicating that the housing occupation pattern could not be identified based on the census sectors or that such occupation was not influenced by the environmental characteristics and urban arrangement analyzed through the indexes (Figure 7).

The results obtained also raise important reflections on the environmental justice in the Cuiabá–Várzea Grande conurbation, especially when considering the distribution of the population in relation to the environmental conditions of the census tracts. Although the three defined groups have similar population densities, group 1, characterized by high building density, scarce vegetation cover, and high temperatures, is home to a significant portion of the inhabitants from the studied area. This indicates that a significant portion of the population is exposed to urbanized environments with less thermal comfort, which may imply greater risks to health and well-being. Silva (2015) pointed out the gradual increase in the average temperature from the region as a reflection of the urbanization intensification. Silva (2020) highlights that low-income populations tend to occupy areas with less urban and environmental infrastructure, evidencing territorial inequalities for the access to improved housing conditions. Therefore, it is of fundamental importance that public policies aimed

at urban planning, incorporate environmental equity criteria, prioritizing interventions in densely populated and environmentally vulnerable sectors.

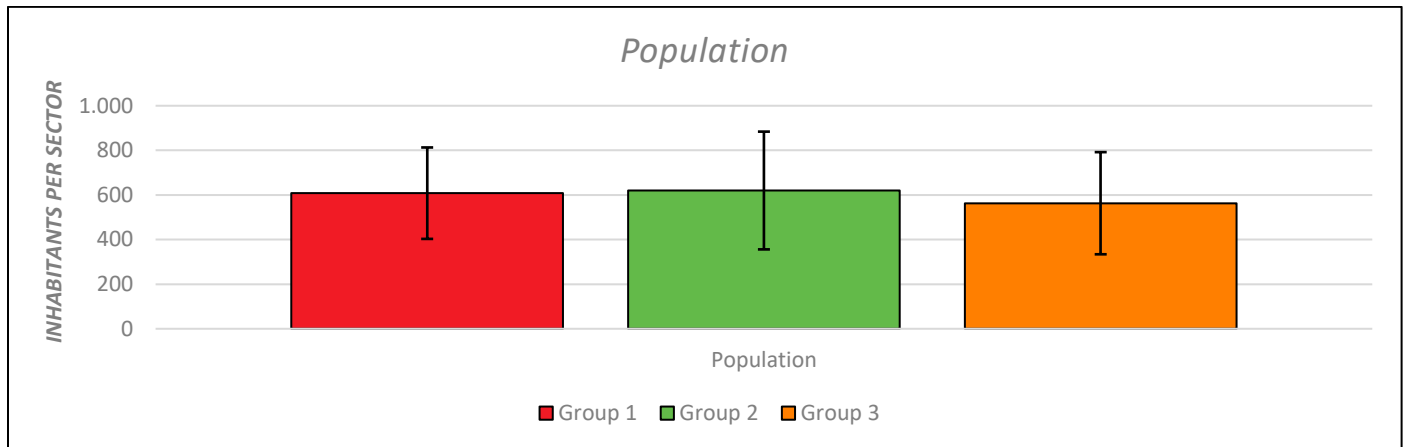


Figure 7 – Average population by census sector for the different descriptive groups. Source: Elaboration by Authors (2025).

A espacialização dos grupos indica predominância do grupo 3 nas regiões centrais dos municípios, especialmente em Cuiabá, enquanto o grupo 1 apresenta núcleos de concentração no entorno dessas áreas (Figura 8). O grupo 2, por sua vez, prevalece nas regiões periféricas da conurbação e nos setores com maior extensão territorial. A classificação dos grupos com base nas características que os definem encontra-se na Tabela 3, ao passo que a Figura 9 ilustra a distribuição espacial desses grupos sobre áreas reais da conurbação Cuiabá–Várzea Grande (MT).

Spatialization of descriptive groups of Cuiabá-Várzea Grande conurbation

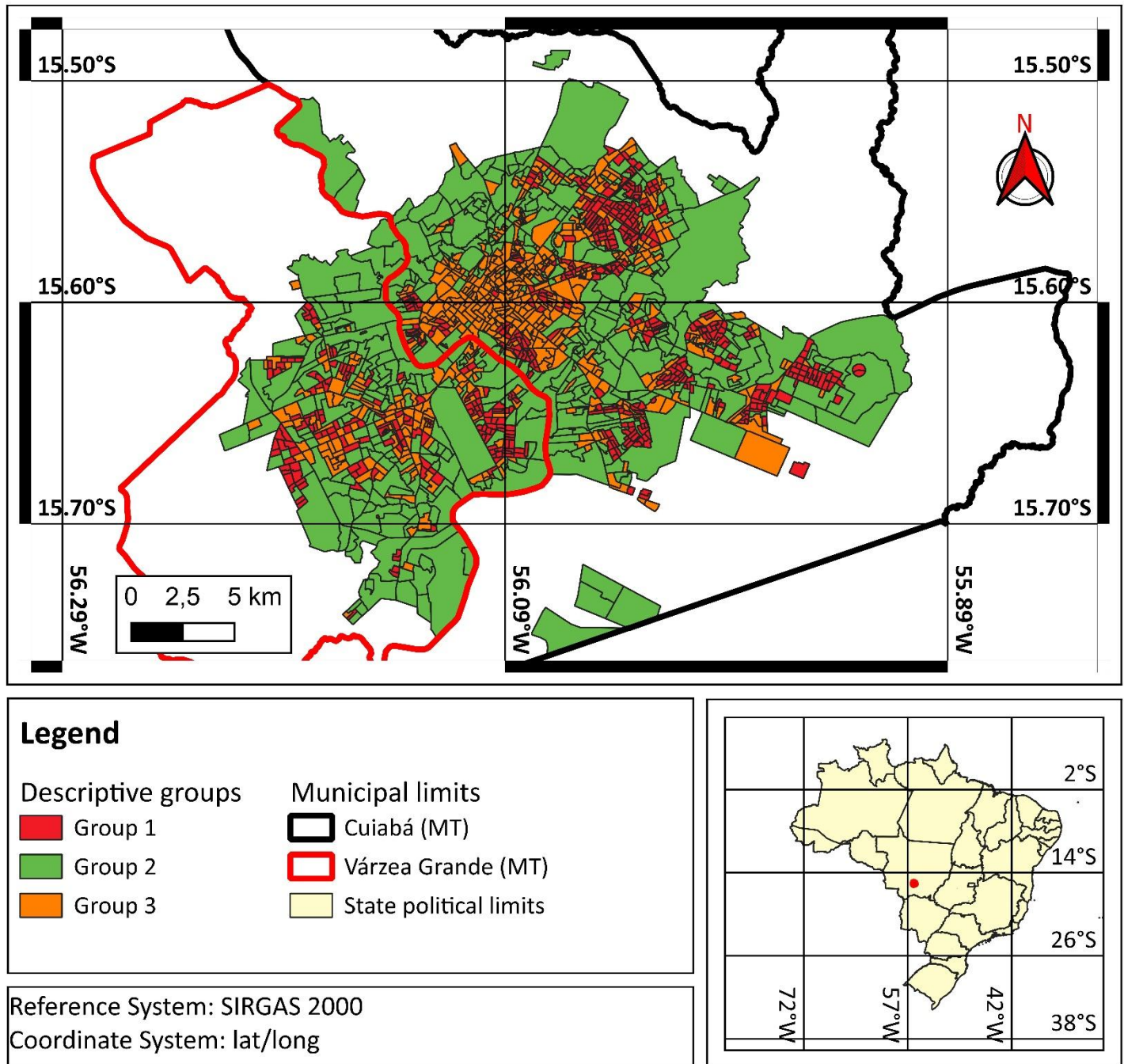


Figure 2 – Spatialization of descriptive groups of Cuiabá-Várzea Grande conurbation. Source: Elaboration by Authors (2025).

Table 3 – Labeling of different descriptive groups.

Group 1	Group 2	Group 3
Highly anthropic, with very dense arrangement of constructions. Vegetation not vigorous and homogeneous (normally little vegetation), High temperature, comparing with other groups during winter and summer. Little variation in terrain elevation. Without any pattern of population distribution.	Little anthropic, with dispersed arrangement of buildings, higher and frequent vegetation. Lower temperature regarding the other groups in winter and summer. High spatial variation in terrain elevation. No pattern of population distribution.	Highly anthropic, with more dispersed building arrangements (presence of uncovered areas). Less vigorous and homogeneous vegetation (points with more abundant vegetation). Moderate temperature in relation to other groups in winter and summer (due to air circulation?). Average spatial variation in terrain elevation No population distribution pattern.

Source: Elaboration by authors (2025).

Based on the conclusions of Silva (2015), who associates the increase of average temperature in the conurbation with the urbanization process, intensified mainly from the 1970s onwards, this analysis allows to identify areas (group 2) with lower temperatures compared to others, due to the larger presence of vegetation cover. This condition is a relevant indicator for the mitigation of the thermal feeling and promotion of well-being from the resident population.

The spatial representation of the identified groups has also had an interdisciplinary nature. The spatial distribution of areas with different temperature levels can support the development of models aimed to social monitoring and public safety. An example of this is a study by Melo (2019), who proposed a predictive model for homicide crimes based on the temperature variable. In this sense, the information generated in this study is a preliminary subsidy for planning public policies and preventive and investigative actions, as long as it is complemented by field data and empirical validations that ensure its applicability and effectiveness in the context of public safety.

In the social field, Silva (2020) proposes a reflection on the importance to promote more inclusive urban management as an instrument for improving the living conditions of the population, especially among low-income groups, who often face greater exposure to deficiencies of urban infrastructure and the negative environmental impacts associated with accelerated urbanization. In the study mentioned, the author highlights the Cristo Rei neighborhood, in Várzea Grande, as an example of local social organization led by residents. According to the model proposed in this work, this neighborhood is mostly included in areas classified as group 1 (70%) and group 3 (15%), indicating greater environmental vulnerability in terms of thermal comfort and availability of spaces for urban adaptation. Only 15% of the neighborhood corresponds to group 2, characterized by a greater presence of green areas, which limits the possibilities for urban expansion without compromising

the existing plant remains.

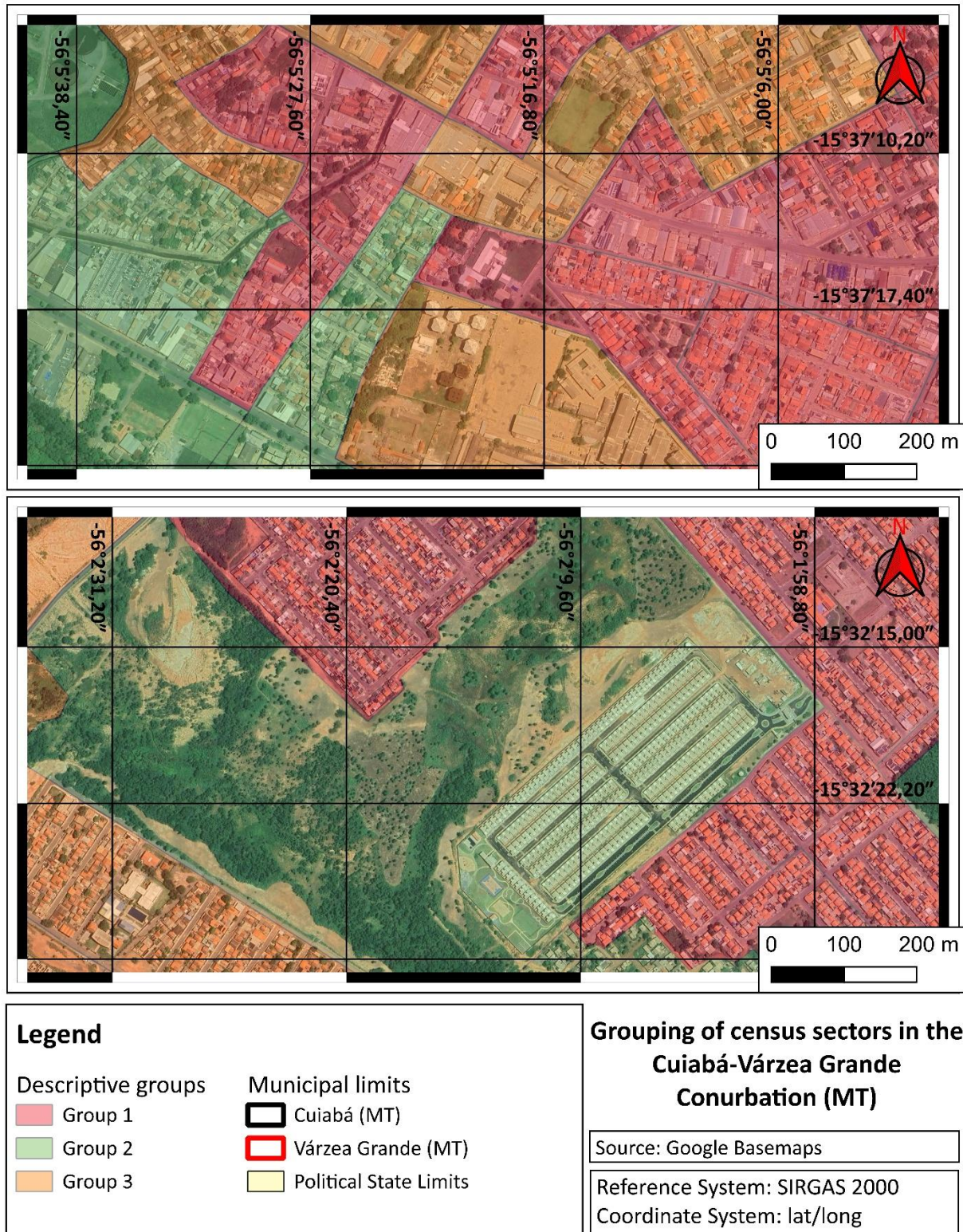


Figure 9 – Superposition of descriptive groups on satellite image Cuiabá-Várzea Grande conurbation (MT). Source: Elaboration by Authors (2025).

The analysis of group 3, identified by the proposed model, demonstrates the robustness of data, since

its delimitation coincides visually with areas of predominantly uncovered land, as shown in Figure 9. Visual validation, by superimposing the clusters on high-resolution images, confirms the accuracy of the methodology and reinforces the reliability of the results. These urban sectors may be potential targets for real estate speculation, as discussed by Oliveira and Fioravanti (2024), or represent areas underused by the government, whose qualified appropriation could expand spaces for collective use and social coexistence. These areas, if adequately planned and incorporated into the urban fabric, could contribute to the balance between urban development and environmental quality, promoting both social and ecological benefits, especially in regions with a deficit of green infrastructure.

Despite the robustness of the data used and the consistency of the results, it is important to highlight some methodological limitations of this study. The use of census tract as the analysis unit, although it offers a reasonable level of detail, it can hide important variations within urban areas. Census tracts have heterogeneous sizes and shapes, which can mask more subtle intra-urban variations, especially in densely occupied areas or those with abrupt transitions of land use and cover. Furthermore, the aggregation effect can generate distortions in the analyses, leading to interpretations that do not necessarily reflect the most refined spatial reality. Future research can explore smaller territorial units or functional divisions (such as blocks, neighborhoods or planning zones) to overcome these limitations and promote a more precise and contextualized analysis.

IV. CONCLUSION

The Cuiabá–Várzea Grande (MT) conurbation, delimited based on the census sectors that comprise it, was analyzed, considering the year 2023 and classified into three distinct groups using a descriptive model that integrated spectral indices related to the structure of the built-up area, vegetation cover, surface temperature obtained by remote sensing, and topographic and demographic information.

Group 3, which is more representative of the central regions of both municipalities, presented lower building density and a higher percentage of open areas, such as yards, parking lots, and vacant lots, which indicates a potential for expansion of the built-up area. Group 1, on the other hand, was characterized by higher building density, which limits the horizontal urban expansion. Group 2, predominant in the outskirts of the conurbation, showed a greater presence and intensity of green areas. Its high internal variability reveals a mixed urban landscape, composed of buildings, open areas and vegetation.

Surface temperatures were higher in groups with less vegetation cover. Group 2, with more green areas,

recorded average temperature reductions of 1.65°C and 0.88°C in winter, and 1.67°C and 1.32°C in summer, when compared to groups 1 and 3, respectively. These results demonstrate the climatic benefits of urban vegetation in mitigating heat islands and improving thermal comfort. Despite the physical-environmental and urban differences between the groups, population density remained close to 600 inhabitants per census tract in all cases. This pattern indicates a housing occupation that does not necessarily consider local environmental factors, such as vegetation cover or thermal comfort, and suggests that census tracts may not be the most appropriate units to represent urban spatial patterns. Therefore, it is proposed to use other units of territorial analysis, such as planning zones, neighborhoods or blocks, to support more precise and environmentally integrated urban management.

In this context, the study reveals important challenges for the promotion of a more sustainable urban planning. The accelerated and often disorderly expansion of urban areas, combined with the reduction of vegetation cover, contributes to the worsening of heat islands and the environmental vulnerability of cities. Although the model identified regions with greater climate resilience (group 2) and areas with potential for expansion (group 3), the disconnection between population distribution and local environmental conditions, highlights the urgency for more integrated public policies. It is essential that spatial planning strategies incorporate ecological criteria, promote the preservation of green areas and act to mitigate thermal impacts, contributing to more balanced, resilient and fair cities.

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