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BLUE-GREEN INFRASTRUCTURE DISTRIBUTION IN PIAUÍ, BRAZIL

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Resumo

A distribuição da infraestrutura verde-azul no Piauí, Brasil. Estudos sobre infraestrutura verde-azul (IVA) ainda são incipientes no Brasil. Como o seu acesso e seus benefícios podem não ser bem distribuídos pela população, é importante avaliar a distribuição da IVA para dar base ao planejamento territorial e ambiental. Isso é especialmente verdade para estados menos urbanizados e menos desenvolvidos, como o Piauí. Desta forma, o objetivo deste estudo foi avaliar parâmetros de urbanização, socioeconômicos e da IVA nos municípios do Piauí. Uma avaliação quantitativa foi realizada por meio de análise estatística descritiva e de correlação, e de visualização espacial de dados considerando população absoluta, densidade demográfica, área construída relativa, e área construída por habitante como parâmetros de urbanização; renda per capita, pobreza, e índices de desigualdade de GINI e de desenvolvimento humano como parâmetros socioeconômicos; e cobertura florestal relativa, cobertura florestal por habitante, cobertura da IVA relativa, e cobertura da IVA por habitante como parâmetros de IVA. Correlações fortes foram encontradas entre IVA e urbanização, enquanto correlações importantes, porém fracas, foram encontradas entre IVA e variáveis socioeconômicas. Municípios com mais IVA são menos urbanizados e têm piores condições socioeconômicas. Resultados indicam que os processos de urbanização dos municípios do Piauí precisam garantir espaços abertos para a IVA urbana, assim buscando justiça ambiental e o acesso e os benefícios da IVA para todos.
Palavras-chave: aspectos socioeconômicos, cobertura florestal, justiça ambiental, serviços ecossistêmicos, urbanização.

Abstract

Studies of blue-green infrastructure (BGI) are still incipient in Brazil. Since its access and benefits may not be well-distributed among the population, it is important to evaluate BGI distribution to base territorial and environmental planning. This is especially true for less urbanized and developed states, like Piauí. Thus, this study aimed to assess urbanization, socioeconomic and BGI parameters in Piauí municipalities. We conducted a quantitative assessment through descriptive and correlation statistical analysis and spatial data visualization considering absolute population, population density, relative built area, and built area per inhabitant as urbanization parameters; per capita income, poverty, GINI inequality, and human development indexes as socioeconomic parameters; and relative forest area, forest area per inhabitant, relative BGI area, and BGI area per inhabitant as BGI parameters. Strong correlations were found between BGI and urbanization, while important but weak correlations were found between BGI and socioeconomic variables. Municipalities with more BGI are less urbanized and have worse socioeconomic conditions. Results reinforce that the urbanization processes of Piauí municipalities need to ensure open spaces for urban BGI, therefore pursuing environmental justice and BGI access and benefits for all.
Keywords: ecosystem services, environmental justice, forest cover, socioeconomic aspects, urbanization.

INTRODUCTION

The blue-green infrastructure (BGI) is an interconnected network of natural and semi-natural areas which aims to conserve biodiversity and generate a wide range of ecosystem services (SILVA; WHEELER, 2017; PAULEIT *et al.*, 2017). BGI includes blue elements, such as rivers, ponds, lakes, lagoons, floodplains, and wetlands; and green elements, like forests, other non-forest ecosystems (e.g. savannas, grasslands etc.), and even urban green spaces, lawns, and isolated trees. These elements provide many benefits to people including carbon storage and climate regulation; soil protection and erosion control; water safety; disaster risk reduction; air and noise pollution attenuation; and overall social well-being and physical and mental health (FOOD AND AGRICULTURE ORGANIZATION – FAO, 2016; YING *et al.*, 2021). BGI is, therefore, a counterpoint to grey infrastructure as a nature-based solution to address societal problems.

However, there is evidence that BGI access and its benefits are not well-distributed across the population, with those in more urbanized areas and in worse socioeconomic conditions being the most negatively affected (FAO, 2016; MORATO *et al.*, 2018; REZENDE *et al.*, 2018; ARANTES *et al.*, 2021). People’s right to nature is called environmental justice, which occurs when the BGI is equally distributed without any kind of discrimination (SILVA *et al.*, 2018).

Research on environmental justice has been increasingly conducted, but gaps still exist, mostly in developing countries (YING *et al.*, 2021). Moreover, environmental injustice seems more direct in the Global North, for example with a high positive correlation between vegetation cover and both education and income parameters in the United States (NESBITT *et al.*, 2019). Yet it is not as straightforward in the Global South. Hetrick *et al.* (2013) found, for instance, less forest cover in the more urbanized higher-income city center of Altamira, Pará, Brazil, and more forest cover in its less urbanized lower-income surroundings. The same pattern was discovered by Arantes *et al.* (2021) in the city of São Paulo, where native vegetation remnants, in general, are more present in lower-income peripheral areas, while public urban green spaces specifically, which have better infrastructure, accessibility, and safety, are found in higher-income areas closer to the more urbanized city center. Thus, people with worse socioeconomic conditions might live closer to the BGI but have less access to it at the same time.

This may be due to the urbanization patterns of Brazilian cities, which intensified with the industrialization policies of the first half of the 20th century (CRUZ, 2018). Urbanization starts in city centers that concentrate people and greater life conditions, with better infrastructure, public services, employment, and income. However, these centers are initially occupied through deforestation, without territorial or environmental planning, limiting the available space for the BGI (ARANTES *et al.*, 2021). Urban sprawl comes later, advancing closer to the native vegetation remnants of the peripheral areas, usually with irregular occupations and constructions, in addition to limitations on the city center's benefits (CRUZ, 2018; ARANTES *et al.*, 2021). The BGI is then planned and implemented, if at all, mainly at the city centers using the often few open spaces left (ARANTES *et al.*, 2021). City centers and other higher-income areas tend to receive higher investments in BGI, favoring the population with already better socioeconomic conditions. Furthermore, when BGI is implemented in lower-income areas, it may cause environmental gentrification, which is when an area gains value and higher-income people's interest by receiving investments in public urban green spaces, displacing or excluding the lower-income population (SILVA *et al.*, 2018).

Considering these topics, the Brazilian State of Piauí appears as an area of interest to investigate possible relations between the distribution of the BGI and urbanization and socioeconomic conditions. Piauí is the state with the highest proportion of forest cover outside the Amazon Biome (77,12%) while having the lowest proportion of water surface (0,30%) in the country (MAPBIOMAS, 2022). It has one of the smallest urban population together with one of the lowest per capita income (INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA – IBGE, 2016). Moreover, it is one of the less-researched states of Brazil. Understanding these relations is important to subsidize territorial and environmental planning, aiming at environmental justice so all people are benefited from the BGI. Thus, the objective of this study was to assess urbanization, socioeconomic and BGI parameters for the 224 municipalities of Piauí.

MATERIAL AND METHODS

Piauí is one of the nine states of the Brazilian Northeast Region (Figure 1). It has an area of 251,755.48 km², approximately 2.95% of the country's size, with 0.19% of built area (FUNDAÇÃO BRASILEIRA PARA O DESENVOLVIMENTO SUSTENTÁVEL – FBDS, 2022; IBGE, 2022). Piauí is located within the Cerrado and Caatinga Biomes, with 52.81% and 47.19% of the state's area, respectively (IBGE, 2019). The state is fully inserted in the Parnaíba hydrogeographic region, mainly composed of intermittent rivers (LIMA, 2017). Its population is estimated at 3,289,290 inhabitants in 2021, 1.54% of the country's population, with 65.77% considered urban residents, and an average population density of 13.06 inhabitants per km² (IBGE, 2022). Its average per capita income in 2021 was BRL 837.00, the 23rd among the 27 Brazilian states (Brazil's average per capita income was BRL 1,439.00) (IBGE, 2022). Piauí's proportion of people vulnerable to poverty is 58.13%, the 3rd most vulnerable state (Brazil's poverty index is 32.56%); its GINI inequality index is 0.610, the 13th less equal state (almost the same as Brazil's 0.600); and its Human Development Index (HDI) is 0.646, the 4th less developed state (Brazil's HDI is 0.765) (IBGE, 2016).

We did a quantitative assessment of the BGI and its relation to urbanization and socioeconomic conditions in the 224 municipalities of Piauí. Microsoft Excel 365 software was used for data curation and visualization, IBM SPSS Statistics 25 for statistical analysis, and QGIS 3.16.11 for data spatialization and map elaboration.

The dependent variables selected as BGI parameters were the proportion of forest area relative to municipality area, absolute forest area per inhabitant (i.e. forest index), the proportion of BGI area relative to municipality area, and absolute BGI area per inhabitant (i.e. BGI index), presented in Table 1. Here, BGI consists of forests, other non-forest native ecosystems, and water covers. We decided to also consider forest cover separately from BGI since there is evidence that human health and well-being are positively affected more by forests than other vegetation types (REID *et al.*, 2017).

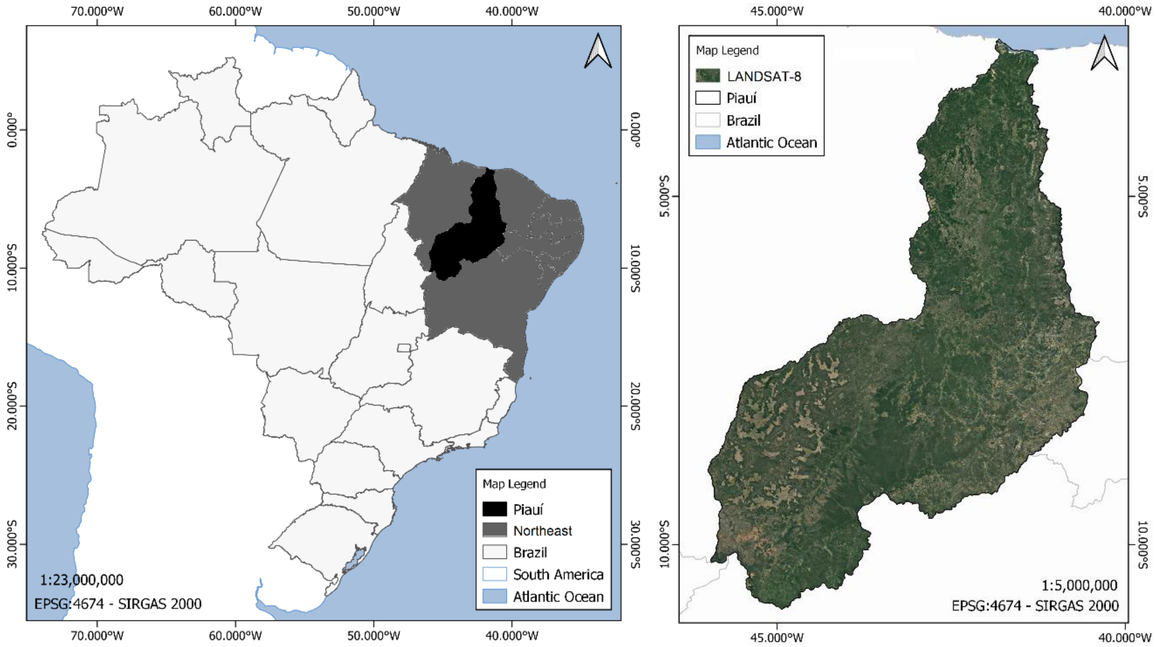

Figure 1. Geographic location of Piauí State, Brazil.
Figura 1. Localização geográfica do estado do Piauí, Brasil.

Table 1. List of collected and calculated data for the study area.
Tabela 1. Lista dos dados levantados e calculados para a área de estudo.

Code	**Variable**	**Unit of measure**	**Parameter**
id1	Geocode	Number	-
id2	Municipality name	Name	-
area.km²	Municipality area in km²	km²	-
area.m²	Municipality area in m²	m²	-
population	Population	Number of inhabitants	Urbanization
pop.density	Population density	N. inhabitants/km²	Urbanization
built	Built area	m²	-
built%	Built area per municipality area	%	Urbanization
built.index	Built area per inhabitant	m²/n. inhabitants	Urbanization
income	Average per capita income	BRL	Socioeconomic
poverty	Poverty vulnerability	%	Socioeconomic
GINI	GINI inequality index	0 low – 1 high	Socioeconomic
HDI	Human development index	0 low – 1 high	Socioeconomic
forest	Forest area	m²	-
forest%	Forest area per municipality area	%	BGI
forest.index	Forest area per inhabitant	m²/n. inhabitants	BGI
BGI	BGI area	m²	-
BGI%	BGI area per municipality area	%	BGI
BGI.index	BGI area per inhabitant	m²/n. inhabitants	BGI

Legend: km² = square kilometers; m² = square meters; n. = number; % = percentage; BRL = Brazilian Real; HDI = human development index; BGI = blue-green infrastructure.

The following independent variables were selected (Table 1): population, population density, proportion of built area relative to municipality area, and built area per inhabitant (i.e. built area index) as urbanization parameters; and average per capita income, proportion of the population vulnerable to poverty, GINI inequality index, and human development index (HDI) as socioeconomic parameters.

These variables were selected to represent urbanization, socioeconomic status, and BGI based on scientific literature. Data on the municipalities' total area and population were collected from the Brazilian Institute for Geography and Statistics (IBGE, 2022), land cover from the Brazilian Foundation for Sustainable Development (FBDS, 2022), and socioeconomic conditions from the National Survey by Household Sample (IBGE, 2016).

We applied statistical descriptive analysis of minimum, maximum, mean, and standard deviation values for all parameters, as well as bivariate non-parametric correlations with the application of Spearman's and Kendall's coefficients (Equations 1 and 2), both considered robust and efficient statistic methods (CROUX; DEHON, 2010). Correlation coefficients were interpreted considering Table 2 (KOZAK, 2009).

$$\text{Equation 1. } r_s = 1 - 6 * \frac{\sum d_i^2}{n(n^2-1)}$$

where: r_s = Spearman's rho; d_i = difference between the ranks of two parameters; n = number of alternatives.

$$\text{Equation 2. } \tau = \frac{[(\text{concordant})-(\text{discordant})]}{0.5*\text{n}*(\text{n}-1)}$$

where: τ = Kendall's tau; concordant = number of concordant pairs; discordant = number of discordant pairs; n = number of pairs.

Table 2. Interpretation of correlation coefficients values (adapted from Kozak (2009)).
Tabela 2. Interpretação dos valores dos coeficientes de correlação (adaptado de Kozak (2009)).

Positive values	**Meaning**	**Negative values**	**Meaning**
0.00 – 0.20	Non-important correlation	-1.00 – -0.70	Very strong correlation
0.20 – 0.50	Weak correlation	-0.70 – -0.50	Strong correlation
0.50 – 0.70	Strong correlation	-0.50 – -0.20	Weak correlation
0.70 – 1.00	Very strong correlation	-0.20 – 0.00	Non-important correlation

Moreover, all data were attributed to a vector file of Piauí municipalities in QGIS. We elaborated maps considering five classes of equal number of units (quantiles) to visualize differences between data distribution.

RESULTS

The statistical descriptive analysis for the urbanization, socioeconomic, and BGI parameters for the 224 municipalities of Piauí is presented in Table 3. The municipalities vary greatly both in size and population, thus the selection of relative-valued parameters, instead of absolute variables, was appropriate for the assessment. Santo Antônio dos Milagres is the smallest municipality, with 33.17 km², and Uruçuí the biggest, with 8,405.41 km². Miguel Leão is the municipality with the smallest population, of 1,253 inhabitants, while Teresina, the state's capital, has the biggest, with 814,230 inhabitants. Santa Filomena has the lowest population density, with 1.15 inhabitants per km², and Teresina has the highest, with 585.34 inhab./km². About 15% of the municipalities (33) had no built area (0.00%; 0.00 m²/inhab.), while Teresina had the highest proportion of built area (11.52%) and Colônia do Gurguéia had the highest built index (507.94 m²/inhab.).

Average per capita income varies between BRL 141.79 in Assunção do Piauí and 757.57 in Teresina; where 37.83% are vulnerable to poverty, against 85.39% in Madero. The GINI inequality index is 0.431 in São José do Piauí and 0.797 in Isaías Coelho; and the HDI vary between 0.485 in São Francisco de Assis do Piauí and 0.751 in Teresina.

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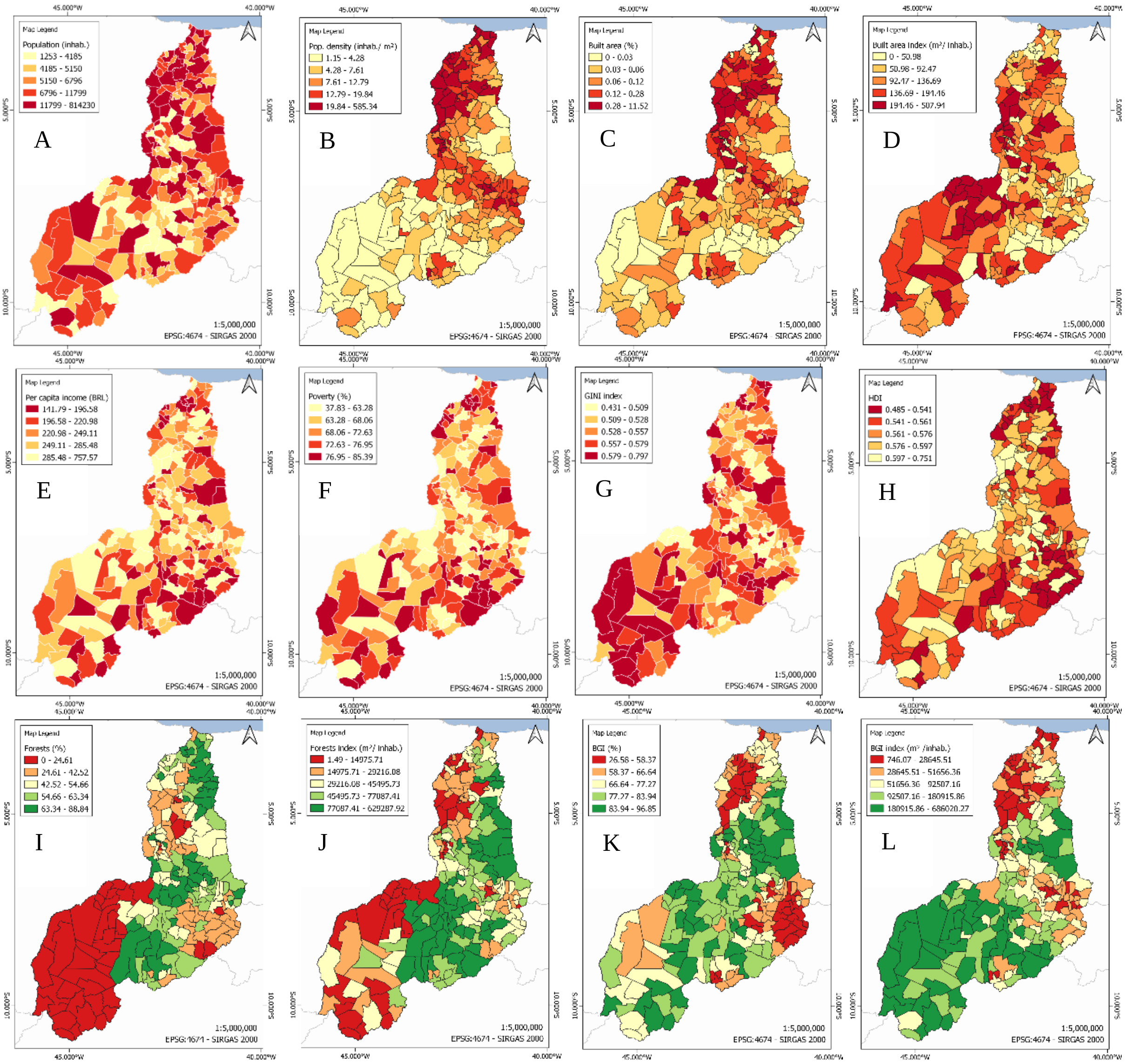
In addition to the highest built index, Colônia do Gurguéia has both the lowest proportion of forest and forest index (0.00%; 1.49 m²/inhab.), even though its BGI relative area and index are high (83.09%; 59,257.99 m²/inhab.), due to being in the Caatinga, a non-forest ecosystem. Água Branca has the lowest proportion of BGI area (26.58%) and Teresina has the lowest BGI index (746.07 m²/inhab.). Guaribas has the highest forest relative area and index (88.84%; 629,287.92 m²/inhab.), and BGI relative area and index (96.85%; 686,020.27 m²/inhab.).

The spatial distribution of the urbanization, socioeconomic, and BGI parameters is presented in Figure 2. Through the maps, it is possible to visually evaluate possible correlations between population density, built area relative to municipality area, and the BGI index. Furthermore, it seems that average per capita income, poverty vulnerability, and HDI are correlated with each other.

Table 3. Statistical descriptive analysis (n = 224).
Tabela 3. Análise estatística descritiva (n = 224).

Variable code (unit)	**Minimum**	**Maximum**	**Mean**	**Standard deviation**
area.km² (km²)	33.1724	8,405.4144	1,123.6191	1,187.9913
population (inhab.)	1,253	814,230	13,921.25	55,469.20
pop.density (inhab./km²)	1.1541	585.3355	18.7078	47.0878
built% (%)	0.00	11.52	0.26	0.89
built.index (m²/inhab.)	0.0000	507.9390	125.0565	93.0923
income (BRL)	141.79	757.57	249.39	76.02
poverty (%)	37.83	85.39	69.47	8.29
GINI	0.4312	0.7972	0.5450	0.0454
HDI	0.4850	0.7510	0.5710	0.0401
forest% (%)	0.00	88.84	44.88	22.57
forest.index (m²/inhab.)	1.4927	629,287.9236	58,478.7201	75,794.1151
BGI% (%)	26.58	96.85	70.00	14.82
BGI.index (m²/inhab.)	746.0735	686,020.2667	120,475.1680	133,128.8687

Legend: km² = square kilometers; inhab. = number of inhabitants; pop.density = population density; built% = built area per municipality area; % = percentage; built.index = built area per inhabitant; m² = square meters; income = average per capita income; BRL = Brazilian Real; poverty = poverty vulnerability; GINI = GINI inequality index; HDI = human development index; forest% = forest area per municipality area; forest.index = forest area per inhabitant; BGI = blue-green infrastructure; BGI% = BGI area per municipality area; BGI.index = BGI area per inhabitant.



Legend: km² = square kilometers; inhab. = number of inhabitants; pop.density = population density; BRL = Brazilian Real; poverty = poverty vulnerability; HDI = human development index; BGI = blue-green infrastructure.

Figure 2. Maps of population (A), population density (B), built area per municipality area (C), built area per inhabitant (built index) (D), average per capita income (E), poverty vulnerability (F), GINI inequality index (G), human development index (HDI) (H), forest area per municipality area (I), forest area per inhabitant (forest index) (J), BGI area per municipality area (K), and BGI area per inhabitant (BGI index) (L) distribution in Piauí.

Figura 2. Mapas da distribuição da população (A), densidade demográfica (B), área construída por área do município (C), área construída por habitante (índice de área construída) (D), renda média per capita (E), vulnerabilidade à pobreza (F), índice de desigualdade de GINI (G), índice de desenvolvimento humano (IDH) (H), área de cobertura florestal por área do município (I), área de cobertura florestal por habitante (índice de cobertura florestal) (J), área de infraestrutura verde-azul (IVA) por área do município (K), e área de IVA por habitante (índice de IVA) (L) no Piauí.

Of the 64 bivariate correlations performed (considering four BGI parameters as dependent variables, four urbanization parameters and four socioeconomic parameters as independent variables, and two correlation coefficients), 18 were not statistically significant, with a calculated error above 5%, and therefore were excluded from this assessment (Table 4).

Considering the remaining 46 correlations, 19 were non-important (41.30%) and 27 were important (58.70%). Two were interpreted as strong negative correlations (4.35%) and another two as very strong negative correlations (4.35%), both between BGI and urbanization parameters. They are between BGI area per municipality area and population density (r_s = -0.566); BGI area per inhabitant and built area per municipality area (r_s = -0.593); and BGI area per inhabitant and population density (r_s = -0.979; τ = -0.889). This means that municipalities with more BGI (both in relative area and per inhabitant) are the ones with less population density. Also, municipalities with a higher proportion of BGI are the ones with a lower proportion of built area.

Among BGI and socioeconomic parameters, correlations between the forest index and income (r_s = -0.351; τ = -0.241), poverty (r_s = 0.259), and HDI (r_s = -0.308; τ = -0.209); and between the BGI index and income (r_s = -0.233), poverty (r_s = 0.233), and the GINI inequality index (r_s = 0.254) were important, even though they are interpreted as weak. This indicates that municipalities with better BGI indicators have worse socioeconomic conditions.

Table 4. Statistical correlation analysis using Spearman's and Kendall's coefficients (n = 224).
Tabela 4. Análise de correlação estatística usando os coeficientes de Spearman e de Kendall (n = 224).

Predictor variables	forest%	forest.index	BGI%	BGI.index
population	r_s = 0.016 (0.812) τ = 0.011 (0.800)	r_s =-0.310 (0.000)** τ = -0.214 (0.000)**	r_s =-0.235 (0.000)** τ = -0.158 (0.001)**	r_s = -0.383 (0.000)** τ = -0.264 (0.000)**
pop.density	r_s = 0.231 (0.000)** τ = 0.149 (0.001)**	r_s =-0.484 (0.000)** τ = -0.436 (0.000)**	r_s = -0.566 (0.000)** τ = -0.387 (0.000)**	r_s = -0.979 (0.000)** τ = -0.889 (0.000)**
built%	r_s = 0.070 (0.300) τ = 0.042 (0.355)	r_s = -0.440 (0.000)** τ = -0.320 (0.000)**	r_s = -0.241 (0.000)** τ = -0.162 (0.001)**	r_s =-0.593 (0.000)** τ = -0.450 (0.000)**
built.index	r_s = -0.201 (0.003)** τ = -0.139 (0.002)**	r_s = -0.234 (0.001)** τ = -0.160 (0.001)**	r_s = 0.180 (0.007)** τ = 0.118 (0.006)**	r_s = 0.076 (0.255) τ = 0.048 (0.289)
income	r_s = -0.109 (0.105) τ = -0.070 (0.118)	r_s = -0.351 (0.000)** τ = -0.241 (0.000)**	r_s = -0.041 (0.541) τ = -0.027 (0.553)	r_s = -0.233 (0.000)** τ = -0.155 (0.001)**
poverty	r_s = 0.013 (0.845) τ = 0.006 (0.887)	r_s = 0.259 (0.000)** τ = 0.177 (0.000)**	r_s = 0.033 (0.626) τ = 0.018 (0.683)	r_s = 0.233 (0.000)** τ = 0.159 (0.000)**
GINI	r_s = -0.166 (0.013)* τ = -0.107 (0.017)*	r_s = 0.007 (0.919) τ = 0.005 (0.906)	r_s = 0.132 (0.046)* τ = 0.088 (0.050)*	r_s = 0.254 (0.000)** τ = 0.173 (0.000)**
HDI	r_s = -0.145 (0.030)* τ = -0.097 (0.031)*	r_s = -0.308 (0.000)** τ = -0.209 (0.000)**	r_s = 0.065 (0.333) τ = 0.048 (0.287)	r_s = -0.173 (0.010)** τ = -0.119 (0.008)**

Legend: forest% = forest area per municipality area; forest.index = forest area per inhabitant; BGI = blue-green infrastructure; BGI% = BGI area per municipality area; BGI.index = BGI area per inhabitant; pop.density = population density; built% = built area per municipality area; built.index = built area per inhabitant; income = average per capita income; poverty = poverty vulnerability; GINI = GINI inequality index; HDI = human development index; r_s = Spearman's coefficient; τ = Kendall's coefficient. Correlation coefficients are shown with standard error in brackets. Significance: in grey = not-significant (p-value > α-value 0.05); * = p-value ≤ α-value 0.05; ** = p-value ≤ α-value 0.01.

DISCUSSION

This study aimed at assessing urbanization, socioeconomic and BGI parameters in Piauí. The results indicated a strong negative correlation between BGI and urbanization, with more BGI in municipalities with fewer people per km² and less relative built area. These findings were compatible with those of Hetrick *et al.* (2013) and Arantes *et al.* (2021) in Brazilian cities, with more urban forests observed in less urbanized areas both in Altamira, PA (HETRICK *et al.*, 2013) and in São Paulo, SP (ARANTES *et al.*, 2021).

The relations between BGI and socioeconomic conditions found by those authors were also observed here, through important, however weak, correlations. This may have occurred due to the use of the municipality as an assessment unit, preventing the study from finding inter-municipal specificities. Therefore, we recommend that more detailed studies should be conducted in Piauí's municipalities in the future. Nevertheless, the analyzed data show negative correlations between BGI and socioeconomic development. This result possibly expresses a connection between urbanization and socioeconomic parameters, both inverse to the BGI, since cities tend to provide better living conditions.

We could not compare our results with forest cover recommendations, since they aim mostly at the urban forest specifically, while we considered the BGI as a whole. Moreover, we could not separate private from public BGI from our data, which could be important to assess people's physical access to the BGI. The World Health Organization recommends 15 m^2 of accessible urban green spaces (WHO, 2017) while, the ideal amount, would be 50 m^2 (WHO, 2010). Van den Bosch (2022) proposes the 3-30-300 rule, where every person should be able to see three trees from their home, have 30% of tree canopy cover in every neighborhood, and be at most 300 meters from a public green area. Thus, we suggest further studies in urban forestry in Piauí to make these distinctions.

The thresholds that could lead the BGI to its tipping point are not known (REYER *et al.*, 2015). For the Amazon, for example, Lovejoy and Nobre (2018) affirm that 20 to 25% of deforestation would destabilize the Biome. All of Piauí's municipalities already have a higher rate than 25% of other land covers besides the BGI, which should be a point of concern for the territorial and environmental planning of the state.

Finally, we also indicate the need to update this research when newer official socioeconomic data is available for the study area, since the data used here are relatively outdated, from 2015. Thus, relations between BGI and socioeconomic parameters may not be currently the same as the ones presented in this study.

CONCLUSIONS

- BGI covers an average of 70% of the Piauí municipalities' areas, varying from 26.58 to 96.85%, with 58,478.72 m²/inhab. on average, ranging from 746.07 to 686,020.27 m²/inhab.
- Strong negative correlation was found between BGI and urbanization, meaning that there is more BGI in less urbanized municipalities.
- Important but weak correlation was found between BGI and socioeconomic conditions when there is more BGI in municipalities with worse socioeconomic conditions. This relation should be further investigated considering inter-municipal distributions.
- Results found here reinforce that the urbanization processes of Piauí municipalities need territorial and environmental planning, ensuring open spaces for urban BGI, therefore pursuing environmental justice and BGI access and benefits for all.

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