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MAPPING REGIONAL SUSTAINABILITY: an esg-based index for road infrastructure

MAPEAMENTO DA SUSTENTABILIDADE REGIONAL: um índice baseado em esg para infraestrutura rodoviária

MAPEO DE LA SOSTENIBILIDAD REGIONAL: un índice basado en ESG para infraestructura vial

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Abstract: Highways are essential drivers of local development and community change but ignoring social and environmental factors in their planning cand operation can exacerbate inequalities and lead to environment. Environmental, Social, and Governance (ESG) actions can drive changes in current practices within the road infrastructure sector, when considering local social, economic, and environmental factors. This paper aims to bridge this gap by proposing a Sustainability Index (SI) tailored for road infrastructure contexts, offering a practical and replicable approach to ESG considerations using freely available census and remote

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sensing data. The SI, computed as a geometric mean of eleven socio-economic and environmental indicators, ranges from 0.00 to 0.56 across the analyzed area. Spatial autocorrelation analysis reveals statistically significant clustering (Global Moran's I = 0.40; z-score = 16.7126; p < 0.0001), while multivariate clustering highlights vegetation cover (R^2 = 0.752), carbon sequestration (R^2 = 0.718), and built-up area (R^2 = 0.665) as the most influential variables. Spatial patterns for urban centers in the South-Central and Amazon Regional Complex highlight significant local sustainability disparities, underscoring the need for regionally targeted ESG strategies. This framework improves analysis of socio-environmental dynamics near major highways, offering a practical tool for decision-making in data-limited regions.

Keywords: Socioeconomic Indicators, Environmental Indicators, Spatial Statistics, Machine Learning.

Resumo: As rodovias são importantes vetores de desenvolvimento local e transformação das comunidades; contudo, a negligência de fatores sociais e ambientais em seu planejamento e operação pode agravar desigualdades e gerar impactos negativos ao meio ambiente. A incorporação de práticas no campo Ambiental, Social e de Governança (ESG) pode promover mudanças nas abordagens atuais do setor de infraestrutura rodoviária, ao considerar aspectos sociais, econômicos e ambientais em escala local. Este artigo busca preencher essa lacuna ao propor um Índice de Sustentabilidade (IS) específico para o contexto rodoviário, oferecendo uma abordagem prática e replicável para a incorporação de critérios ESG, com base em dados censitários e de sensoriamento remoto de acesso livre. O IS, calculado como a média geométrica de onze indicadores socioeconômicos e ambientais, varia de 0,00 a 0,56 na área analisada. A análise de autocorrelação espacial revela a existência de agrupamentos estatisticamente significativos (Índice de Moran Global = 0,40; z-score = 16,7126; p < 0,0001), enquanto a análise de agrupamento multivariado aponta a cobertura vegetal (R^2 = 0,752), o sequestro de carbono (R^2 = 0,718) e a área construída (R^2 = 0,665) como as variáveis mais influentes. Os padrões espaciais observados em centros urbanos do Complexo Regional Centro-Sul e Amazônico evidenciam disparidades locais relevantes de sustentabilidade, destacando a necessidade de estratégias ESG direcionadas regionalmente. O framework proposto aprimora a análise das dinâmicas socioambientais no entorno de rodovias, oferecendo uma ferramenta prática para a tomada de decisão em regiões com escassez de dados.

Palavras-chave: Indicadores Socioeconômicos, Indicadores Ambientais, Esta-

Author Contributions
AGLS: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review editing. MRG: Conceptualization, Funding acquisition, Methodology,Project administration, Resources, Supervision, Writing – review editing. LATB: Conceptualization, Funding acquisition, Methodology,Project administration, Resources, Supervision, Writing – review editing.

Conflict Declaration
Nothing to declare.

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tísticas Espaciais, Aprendizado de Máquina.

Resumen: Las carreteras son impulsores esenciales del desarrollo local y de la transformación de las comunidades; sin embargo, ignorar los factores sociales y ambientales en su planificación y operación puede exacerbar las desigualdades y generar impactos ambientales. Las acciones de Gobernanza, Social y Ambiental (ESG, por sus siglas en inglés) pueden promover cambios en las prácticas actuales del sector de la infraestructura vial cuando se consideran los factores sociales, económicos y ambientales locales. Este artículo busca contribuir a abordar esta limitación mediante la propuesta de un Índice de Sostenibilidad (IS) adaptado a contextos de infraestructura vial, ofreciendo un enfoque práctico y replicable para la incorporación de consideraciones ESG mediante datos censales y de teledetección disponibles gratuitamente. El IS, calculado como la media geométrica de once indicadores socioeconómicos y ambientales, varía entre 0,00 y 0,56 en el área analizada. El análisis de autocorrelación espacial revela una agrupación estadísticamente significativa (I de Moran Global = 0,40; puntuación z = 16,7126; $p < 0,0001$), mientras que el análisis de agrupamiento multivariante destaca la cobertura vegetal ($R^2 = 0,752$), el secuestro de carbono ($R^2 = 0,718$) y el área construida ($R^2 = 0,665$) como las variables de mayor influencia. Los patrones espaciales de los centros urbanos del Complejo Regional Centro-Sur y Amazónico evidencian importantes disparidades locales de sostenibilidad, lo que pone de manifiesto la necesidad de estrategias ESG orientadas a las características de cada región. Este marco contribuye a mejorar el análisis de las dinámicas socioambientales en las proximidades de las principales carreteras y ofrece una herramienta práctica para la toma de decisiones en regiones con disponibilidad limitada de datos.

Palabras clave: Indicadores Socioeconómicos, Indicadores Ambientales, Estadísticas Espaciales, Aprendizaje Automático.

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1 INTRODUCTION

Urban growth is a complex and multifaceted process that depends on planning, local infrastructure, public policies, and community participation (Wang; Jin, 2023). However, some factors can act as catalysts for this process, such as local topography, the presence of reserves and parks, urban sprawl, and, notably, the presence of highways (Freiria; Sousa, 2024; González-gonzález; Nogués, 2019; Li; Wang; Li, 2023).

Beyond major urban centers, it is also essential to understand the growth and sustainability patterns of small municipalities located in remote areas highly influenced by the presence of highways (Afukaar *et al.*, 2019). Transport investments are crucial in shaping social equity in rural areas, creating lasting effects that unfold over time (González-gonzález; Nogués, 2019). In particular, the construction and operation of roads in these locations may be associated with poverty reduction and economic growth (Asher; Novosad, 2020; Cascetta *et al.*, 2020; Lu *et al.*, 2023). The presence of highways plays a fundamental role in local development, whether in terms of household income (Lu et al., 2023), urban growth mechanisms (Nadoushan, 2022), induction of occupation patterns (Barros; Andrade; Júnior, 2022), or travel time savings and resulting monetary gains (Condeço-melhorado *et al.*, 2014). Studies in developing countries have also demonstrated the regional development impacts of highway infrastructure (Rathee; Sadhukhan, 2025).

Although the role of highways in local development is widely recognized, neglecting contextual issues in planning, implementation, and operation can contribute to catalyzing habitat destruction, overexploitation of resources, pollution, community fragmentation, worsening inequalities, and the emergence of vulnerabilities (Thacker *et al.*, 2018). Despite the protagonism of rural transport in promoting social and economic cohesion among communities, it remains relatively underexplored and warrants further investigation to fully understand its impacts and potential improvements (González-gonzález; Nogués, 2019). Thus, understanding the local social-environmental context is crucial for proposing solutions that mitigate related impacts and effectively align with the Sustainable Development Goals (SDG), promoting balanced and sustainable development (Pfaff *et al.*, 2018).

Sustainability increasingly assumes a pivotal role in developing corporate practices, particularly within industries with substantial environmental and social impacts, such as the road infrastructure sector. This evolution in expectations and responsibilities has prompted companies to incorporate sustainable practices into their strategic frameworks to address the increasing demands for enhanced social responsibility (Antolín-lópez; Delgado-ceballos; Montiel, 2016). In this context, Environmental, Social, and Governance (ESG) actions have become widely recognized as essential for assessing organizational performance and sustainability, significantly influencing investment decisions (Santos; Pereira, 2022; Qi; Wang; Gao, 2023).

Despite the significant attention given to ESG initiatives in the road infrastructure sector in recent years, challenges persist in developing effective ESG indicators and policies (Qi; Wang; Gao, 2023). Notably, the social pillar of sustainability has not received as much emphasis as the economic and environmental aspects, hindering attempts to implement social governance and effectively assess the impact of decisions on communities (Okte; Boakye; Behrend, 2024). Part of the complexity lies in considering context-specific variables,

often overlooked in generalized analyses (International Organization for Standardization, 2019; Thacker *et al.*, 2018). The absence of clear and quantifiable social impact metrics, especially in the road infrastructure sector, leads to challenges in evaluating and incorporating these aspects into sustainability strategies. The analytical gap hinders a comprehensive understanding of the social effects and the ability to develop ESG policies and practices suited to local needs, emphasizing the importance of methodologies to develop indicators of potential social impacts (United Nations Environment Programme, 2020). These indicators can provide essential information about the social impact of road infrastructure activities and operations, contributing to built social inventories.

Thus, integrating social sustainability assessment frameworks is essential in infrastructure projects, as it incorporates social equity, stakeholder engagement, and local impact considerations into decision-making, especially under uncertain conditions (Sierra; Yepes; Pellicer, 2017). Composite indices (CI) have been developed globally to measure and compare performance across diverse dimensions, offering valuable insights for decision-making (Kaba; Assaf, 2019). In the field of road infrastructure, some examples include the Road Safety Index (RSI) (Gitelman; Doveh; Hakkert, 2010), which aggregates traffic and safety indicators to guide improvements in road safety policies, and the Road Financing Priority Index (RFPI) (Kaba; Assaf, 2019), which combines technical, economic, social, and environmental indicators to prioritize road construction and maintenance projects. Although valuable, such indices face limitations, mainly due to the lack of reliable and up-to-date data in certain regions.

In Brazil, the largest and most influential country in Latin America, there is a research gap regarding the relationship between ESG practices and the practical actions implemented for sustainable development. Empirical evidence has established this relationship, underscoring the need for improved indicators to assess social and environmental impacts (Hluszko *et al.*, 2024). Consequently, national and regional transport planners face a significant challenge in identifying the key indicators that drive the infrastructure planning process (Magalhães, 2016), preventing a comprehensive understanding of the inherent complexity. Therefore, it is crucial to apply tools that enable multiple-scale analyses and assess the fundamentally spatial nature of socio-environmental phenomena.

Multivariate spatial analysis, geostatistics, and machine learning techniques are emerging as suitable tools to support informed decision-making, assisting in recognizing spatial relationships (Rathee; Sadhukhan, 2025; Silva; Torres, 2021; Wang *et al.*, 2023; Yue *et al.*, 2024). Specifically, the spatial correlation of indicators is effective in describing and visualizing spatial distributions, identifying patterns, and locating outlier areas. This approach is particularly beneficial when access to quality data for subsidy evaluation is limited. Furthermore, the spatial correlation helps refine the analyses enabled by the existing data, supporting the design and implementation of more targeted and efficient interventions (Mangukiya; Sklarew, 2023) by identifying social hotspots where a social issue or risk is likely to occur (United Nations Environment Programme, 2020), as also demonstrated in spatial analyses of regional highway impacts in developing regions (Rathee; Sadhukhan, 2025).

Thus, the primary research questions of this study are: i) how can existing socio-economic-environmental dynamics data gaps within the road infrastructure sector be effectively addressed? ii) how can existing data

support decision-making? In this context, this paper proposes a method based on spatial statistics to define a Sustainability Index (SI), whose main features are: i) use of free and nationally available data, ensuring replicability; ii) analysis of social and environmental variables aligned with the SDG; iii) multivariate analysis of social and environmental aspects with spatial association. The findings may motivate planners to investigate a low-cost approach that enhances decision-making processes and effectively supports sustainable practices in the road infrastructure sector, grounded in transdisciplinary sustainability concepts.

2 METHOD

2.1 Study Area

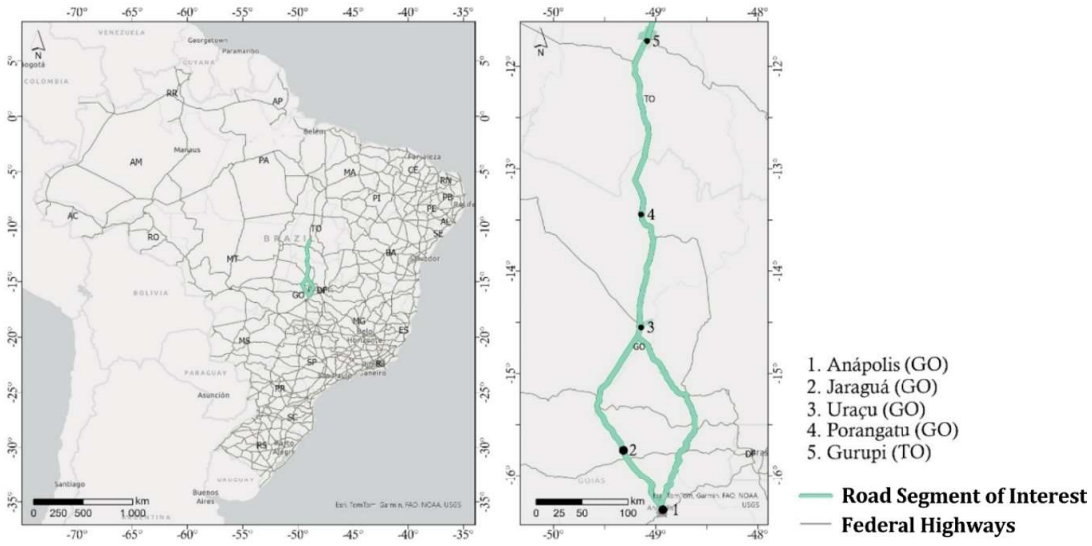
The significance of choosing the South-Central and Amazon Regional Complex relies on its biodiversity and essential role in carbon and hydrological cycles (Pfaff *et al.*, 2018). This region comprises small municipalities whose dynamics are heavily influenced by road infrastructure, shaping local ecosystems and social development. Consequently, combining the influence of the road infrastructure with social, economic, and environmental aspects is strategic for planning and implementing targeted interventions. The study area currently hosts the country's largest contracted road infrastructure project, which involves the duplication of 622 km of highways with a substantial impact on the surrounding area. Thus, considering the protagonism and potential implications of the local infrastructure development, the SI might provide valuable insights for the current and future projects, especially regarding the alignment with the SDG.

The selected urban centers (Figure 1) comprehend 4 (four) municipalities in Goias (Anápolis, Jaraguá, Uruaçu, and Porangatu) and 1 (one) in Tocantins (Gurupi), intersected by BR-080 and BR-153 federal highways, and represent key population density hubs within the analyzed road segment.

2.2 Sustainability Index

The development of the SI comprehends the selection of socio-economic and environmental indicators, followed by data collection for urban centers in a Brazilian municipality within the South-Central and Amazon Regional Complex, identification of patterns through spatial neighborhood relationships, and validation by a machine learning cluster analysis.

Figure 1 – Localization of Study Area.



2.2.1 Socio-economic and environmental indicators

Considering the limited data availability in developing countries, particularly within small and medium-sized municipalities, the indicators prioritize those for which data is accessible, ensuring consistent analysis and replication for other regions facing similar challenges.

Figure 2 illustrates the 11 (eleven) indicators, 7 (seven) representing the socio-economic dimensions, and 4 (four) representing the environmental dimensions, as well as their relationships with the SDG: Income (IIn), Literacy (Ili), Income/Gender Equity (IEq), Water (IWa), Sanitation (ISa), Electricity (IEl), Population Density (IDen), Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-Up Index (NDBI), and the Carbon Sequestration Index (CO_2flux). The data processing and indicator calculation were implemented using the ArcGIS Pro software.

The socio-economic indicators, derived from the 2010 Brazilian Demographic Census conducted by the Brazilian Institute of Geography and Statistics (IBGE), represent the most up-to-date data available at the census tract level, providing the highest spatial detail for intra-urban analysis. The indicators and their corresponding units and descriptions are summarized in Table 1. The values for each indicator were normalized to a scale ranging from 0 to 1, where 0 represents the most negative quality (e.g., lower literacy rates in the study area) and 1 represents the most favorable quality (e.g., higher literacy rates in the study area). The normalization process was essential to harmonize indicators with different units, such as percentages, absolute values, and densities, enabling meaningful comparisons and integrated analysis across the study area. Normalization also ensures a local comparison, highlighting the different patterns within the study area.

Figure 2 – Sustainability Index composition.

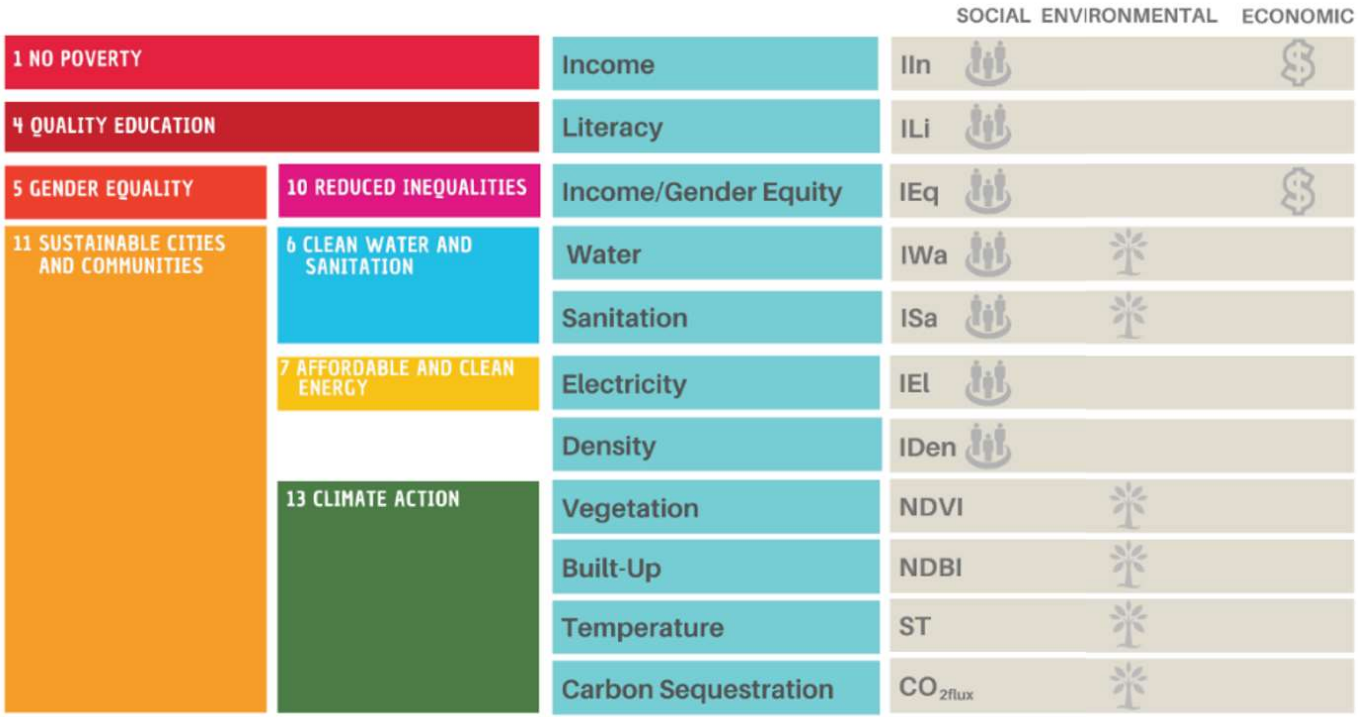


Table 1 – Socio-economic Indicators

Indicator	Description	Unit before normalization
Literacy (ILi)	Percentage of literate individuals within the total population in each tract.	Percentage (%)
Income/Gender Equity (IEq)	Ratio of female to male income, indicating gender equity in income.	Percentage (%)
Water Supply (IWa)	Percentage of households with access to piped water supply.	Percentage (%)
Sanitation (ISa)	Percentage of households with access to adequate sewage systems.	Percentage (%)
Electricity Access (IEI)	Percentage of households with access to electricity.	Percentage (%)
Income (IIn)	Average household income per census tract.	Brazilian Real (BRL)
Population Density (IDen)	Total population divided by tract area (inhabitants per square kilometer).	Inhabitants/km^2

Source: Authors' elaboration.

The environmental indicators for the study area comprehend images acquired on April 23, 2010, by the TM sensor of the Landsat 5 satellite at points 68, 69, 70, and 71 of line 222. Although more recent primary

data is available for environmental indicators, data from 2010 was used to maintain a consistent framework and ensure that the environmental information aligns effectively with the available socio-economic data. The data acquisition was carried out using the Google Earth Engine platform.

The surface reflectance data are from Collection 2, Level 2. In this collection, the LEDAPS system is used to estimate surface reflectance from the data obtained by the sensor (Masek *et al.*, 2006). Based on the reflectance data, the average values for the Normalized Difference Vegetation Index (NDVI) (Rouse *et al.*, 1973), the Normalized Difference Built-Up Index (NDBI) (Zha; Gao; Ni, 2003), and the Carbon Sequestration Index (CO2flux) (Amaral *et al.*, 2021; Gamon; Penuelas; Field, 1992; Rahman *et al.*, 2000) were calculated for each census tract.

The NDVI, proposed by Rouse et al. (Rouse *et al.*, 1973), is calculated through Equation 1, where NIR is the near-infrared monochrome reflectance, characterized by band 4, and Red is the red monochromatic reflectance, characterized by band 3.

$$\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \tag{1}$$

The NDBI, based on built-up areas spectral response characteristic, is expressed by Equation 2 (Zha; Gao; Ni, 2003), where SWIR represents the surface reflectance in the shortwave infrared spectral band (band 5), and NIR is the surface reflectance in the near-infrared spectral band (band 4).

$$\text{NDBI} = \frac{\text{SWIR} - \text{NIR}}{\text{SWIR} + \text{NIR}} \tag{2}$$

The different performances of vegetation in atmospheric carbon sequestration were estimated using Equation 3 (Amaral *et al.*, 2021; Gamon; Penuelas; Field, 1992; Rahman *et al.*, 2000), where Blue represents the surface reflectance in the blue spectral band (band 1), and Green is the surface reflectance in the green spectral band (band 2).

$$CO_{2_{flux}} = \text{NDVI} \times \frac{\frac{\text{Blue} - \text{Green}}{\text{Blue} + \text{Green}} + 1}{2} \tag{3}$$

Surface temperature, calculated in Celsius degrees, was derived from thermal infrared bands and other auxiliary data (Masek *et al.*, 2006) requiring only band 6 rescaling.

For the NDVI, NDBI, CO_2flux indicators, 0 corresponds to the least favorable environmental condition (e.g., lowest vegetation cover, highest built-up presence, lowest CO_2flux, and highest ST), and 1 represents the most favorable condition.

The proposed SI was obtained by aggregating the 11 indicators using the geometric mean, as shown in Equation 4.

$$SI = \sqrt[11]{IIn \cdot ILi \cdot IEq \cdot IWa \cdot ISa \cdot IEl \cdot IDen \cdot NDVI \cdot NDBI \cdot CO_{2_{flux}} \cdot ST} \tag{4}$$

By guaranteeing proportional contributions from all indicators, this method prevents higher values in

some variables from compensating for lower values in others. The use of the geometric mean in sustainability assessment literature is well-documented (e.g., (Laslett; Urmee, 2020; Shmelev; Shmeleva, 2025), showcasing its effectiveness in providing a true reflection of overall performance and aligning well with the multidimensional nature of sustainability frameworks.

2.2.2 Spatial neighborhood relationship

The nonlinear dynamics and spatial relationships among socioeconomic and environmental indicators and the low inter-variable correlations hinder the applicability of conventional multivariate techniques (e.g., Principal Components Analysis), which typically rely on linear assumptions. Thus, as such methods may inadequately capture sustainability assessments' intricate synergies, potentially leading to oversimplified conclusions, this study proposes to address sustainability's complexity considering its spatial nature through a spatially explicit approach.

First, the Global Moran's I statistic was used to determine whether the phenomenon exhibited spatial patterns across the study area. Subsequently, the Local Moran's I was applied to highlight specific locations where these patterns occurred (Anselin, 1995).

The output of the global analysis includes five parameters: Global Moran's I, Expected Index, Variance, z-score, and p-value. Moran's I is the calculated value that measures the degree of spatial autocorrelation in the dataset. The Expected Index represents the value of Moran's I under the null hypothesis of spatial randomness; variance quantifies the variability of Moran's I; z-score indicates how many standard deviations the observed Moran's I deviates from the expected value, serving as a measure of statistical significance; and, finally, the p-value, associated with the z-score, is used to test the null hypothesis of no spatial autocorrelation. Together, these parameters enable a comprehensive interpretation of spatial patterns within the data.

The Local Moran's Index (Anselin, 1995) was calculated for each census tract using Equation5, where *zi* is the difference between the SI in sector i and the mean value of the SI, *zj* is the difference between the SI in sector j and the mean value of the SI, and *wij* is the weight or degree of spatial connectivity between sectors i and j, according to their established relationship.

$$I_i = \frac{z_i \sum_{j=1}^{n} w_{ij} z_j}{\sum_{j=1}^{n} z_j^2} \tag{5}$$

The spatial neighborhood relationship established was based on sharing a boundary or a node. Spatial weights are standardized, ensuring that the relative impact of each neighbor is proportional to the total number of neighbors. Results were considered statistically significant at a 95% confidence level.

2.2.3 Machine learning cluster analysis

A multivariate clustering method based on machine learning used as a complementary tool, provides cross-validation and a complementary perspective, considering the absence of comparable studies for the local context.

Simultaneous patterns among all indicators were identified based on similarities and differences through the multivariate k-means clustering method (Jain, 2010), supporting the proposed SI results and enhancing their validation. The unsupervised classification algorithm provides natural clusters derived from the data series, facilitating the analysis of the relationships between variables associated with various socio-environmental characteristics.

The k-means clustering algorithm employed Euclidean Distance to measure dissimilarity among observations. This choice is particularly suitable for the normalized dataset used in this study. The results were qualitatively evaluated to ensure their coherence and interpretability within the context of sustainability analysis. R^2 values were calculated to determine the contribution of each variable to the clustering results.

3 RESULTS

Figure 3 presents the box plot graphs of the socio-economic and environmental indicators, where considerable disparities can be observed. Some infrastructure indicators, such as IEl and IWa, show high medians and relatively narrow distributions, indicating good coverage and access. In contrast, indicators like IIn and IEq show low medians associated with greater variability, highlighting significant inequalities. Outliers in many indicators suggest that regions with extreme conditions need specific attention.

Figure 3 – Box plot of the SI indicators.

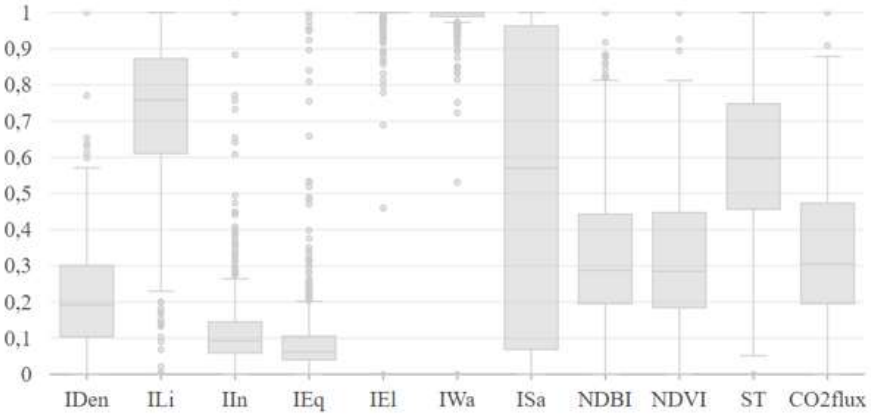


Figure 4 presents the spatial distribution of Population Density (IDen), Literacy (ILi), Income (IIn), Income/Gender Equity (IEq), Electricity (IEl), Water (Iwa), and Sanitation (ISa) indicators. Table 2 summarizes the key statistics that drive the following discussions.

Figure 4 – Spatial distribution of Population Density (IDen), Literacy (ILi), Income (IIn), Income/Gender Equity (IEq), Electricity (IEl), Water (Iwa) and Sanitation (ISa) indicators.

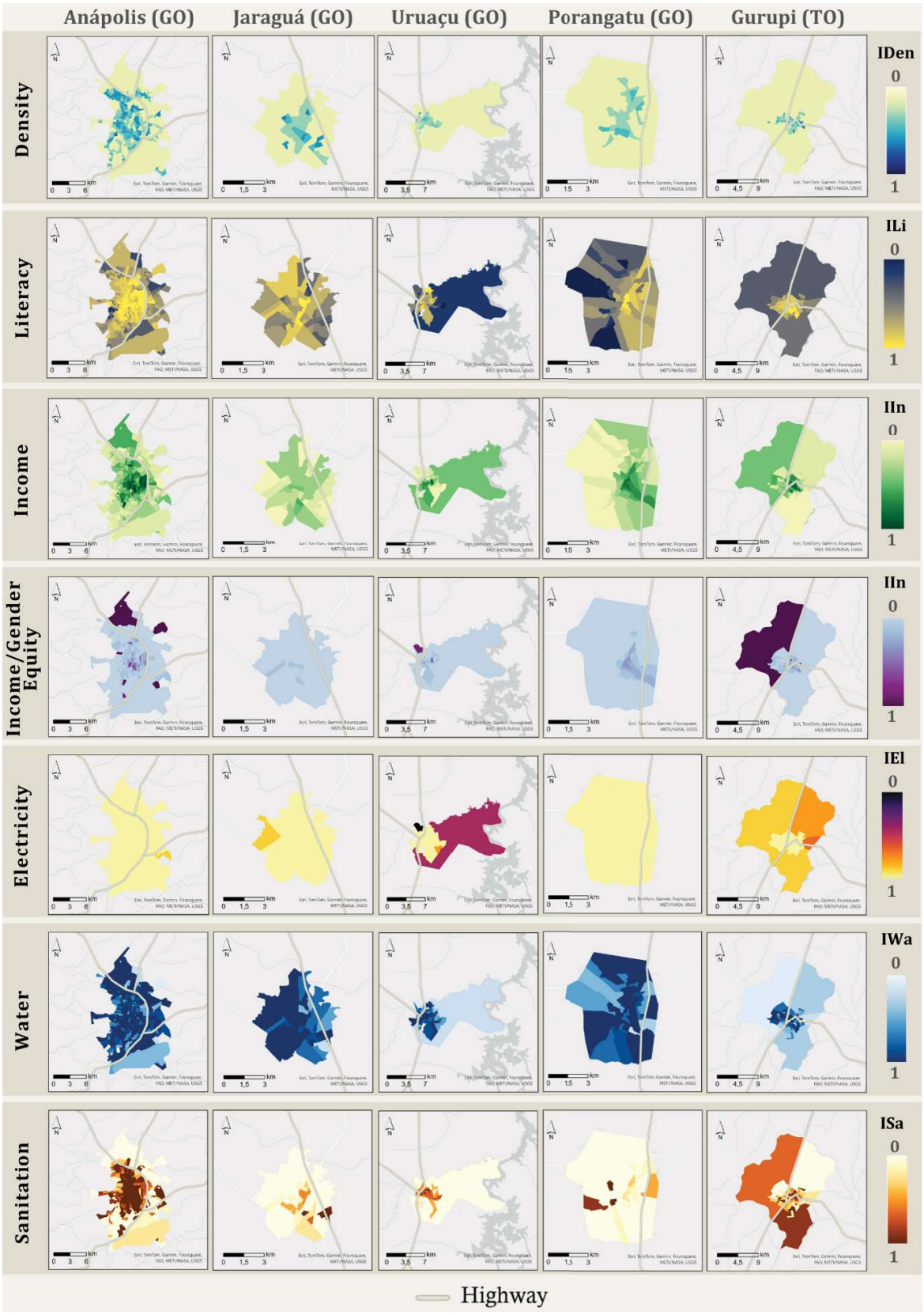


Table 2 – Statistical summary

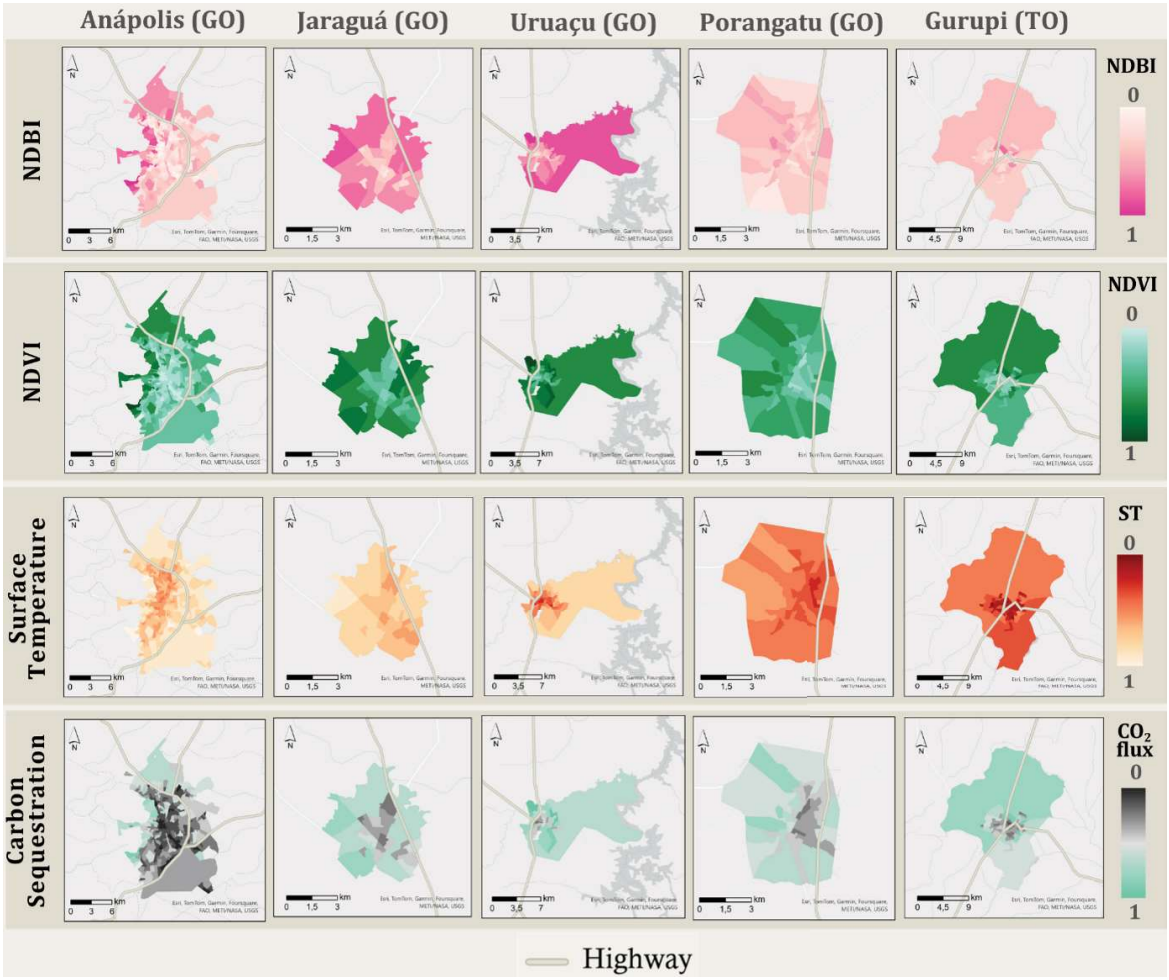
Indicator	First quartile	Mean	Third quartile	Standard Deviation
Density	0,10	0,21	0,30	0,14
Literacy	0,61	0,72	0,87	0,20
Income	0,06	0,12	0,14	0,11
Income/Gender Equity	0,04	0,10	0,11	0,14
Electricity	1,00	0,99	1,00	0,05
Water	0,99	0,99	1,00	0,05
Sanitation	0,07	0,52	0,96	0,40
NDBI	0,56	0,66	0,81	0,19
NDVI	0,18	0,33	0,45	0,19
Surface Temperature	0,25	0,42	0,54	0,21
Carbon Sequestration	0,19	0,34	0,47	0,19

Source: Authors' elaboration.

IDen indicator showed an average of 0.21 and a standard deviation of 0.14. The ILi average of 0.72 indicates a relatively high literacy level in the analyzed areas. However, lower outliers suggest that some regions still face significant challenges, with literacy rates considerably lower. The IIn reveals a wide variation, indicating potential disparities in socio-economic conditions. This variation reflects significant differences in residents' ability to meet basic needs, including infrastructure, housing, and consumption. The IIn average of approximately 0.12, combined with an asymmetric distribution with many upper outliers, illustrates these disparities. The IEq spatial distribution reveals significant gender disparities in income, with an average of 0.10, indicating that women's earnings are generally much lower than men's across most areas analyzed. The IEl showed an average of 0.99, indicating high access to electricity in the analyzed areas. The IWa high average, close to 0.99, indicates excellent water service coverage in the analyzed areas. The ISa indicates an average of 0.52, showing moderate access to sewage services in the analyzed areas.

Figure 5 presents the spatial distribution of environmental indicators NDVI, NDBI, ST, and CO_2flux.

Figure 5 – Spatial distribution of NDVI, NDBI, ST, and CO_2flux.



The NDBI average is 0.66 with a moderate variation. About 75% of the data are above 0.5, suggesting an extensive built-up area. Notably, the index was designed to detect urban areas. Still, it can also distinguish exposed soil with similar spectral responses, as observed mainly in the municipality of Porangatu. Lower values, indicating less built-up area, were classified as outliers and can be attributed to rural or regions with significantly lower urban development.

NDVI average is 0.33, with values predominantly distributed below 0.5, indicating an inverse correlation with the NDBI indicator (R^2 = 0.83). Regions with lower vegetated areas often coincide with those of higher built-up density, particularly near highways.

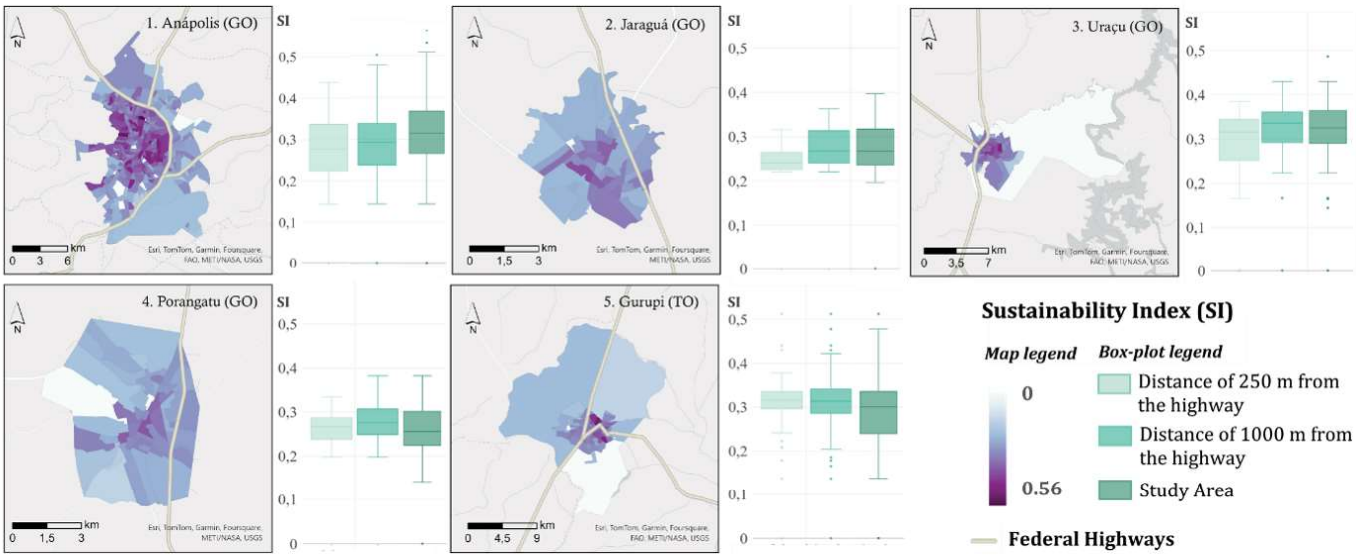
The ST has an average of 0.42 and a distribution reflecting moderate temperature variation across the analyzed areas, showing notably higher values in Gurupi and Porangatu municipalities. The CO_2flux indicator has an average of 0.35, with distribution concentrated below 0.5, indicating a generally low capacity of the landscape to remove carbon from the atmosphere.

As expected, environmental indicators related to NDVI, NDBI, and CO_2flux demonstrated a strong correlation. However, a comprehensive analysis reveals a low linear correlation within the framework for this case study, evidenced by the maximum coefficient of determination (R^2) of 0.36 observed between the

socio-economic indicators, specifically between the IIn and IEq. In this case, traditional multivariate analysis methods, such as Principal Component Analysis (PCA), are not recommended, as they assume significant correlations between variables for effective dimensionality reduction. In the context of this study, where such correlations are low, these methods may not provide helpful or accurate insights.

Figure 6 presents the spatial distribution of the SI. The SI average is 0.30, with a standard deviation of 0.09 and values ranging from 0 to 0.56. This suggests that, although some regions perform well in the evaluated dimensions, no one fully achieves sustainability according to the established criteria. The minimum value of zero indicates that there are areas with deficient performance, failing in at least one of the evaluated dimensions, reflecting a more realistic and critical assessment of the sustainability status in the assessed regions.

Figure 6 – Spatial distribution of the SI and box plots of the SI according to the distances from the highway.



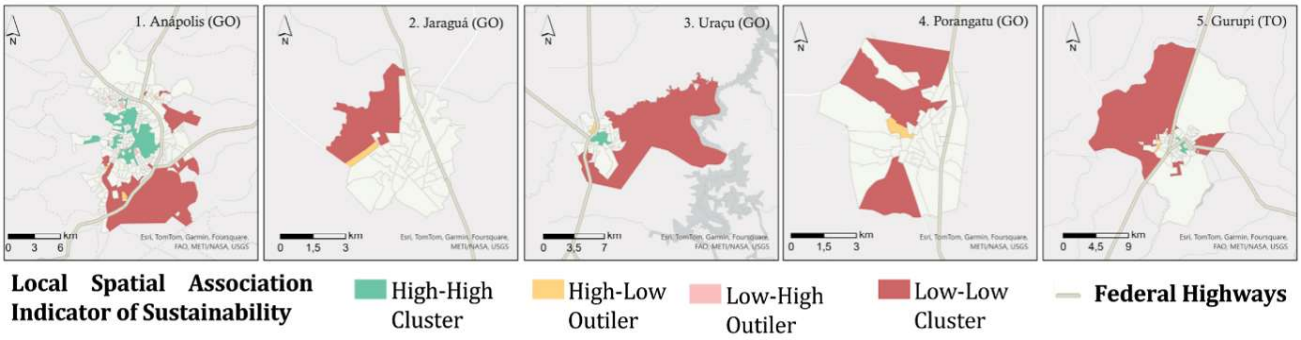
The influence of highways reveals distinct patterns of local sustainability (Figure 6). In Anápolis and Gurupi, the median SI is high, around 0.3. In Anápolis, the SI tends to decrease as the distance from the highway increases. In Gurupi, the average SI variation about the distance from the highway exhibits minimal change. However, as the distance from the highway increases, there is a noticeable rise in the variability of sustainability values, encompassing higher and lower values. In the Jaraguá and Uruaçu cities, areas within 250 meters of the highways present lower indices. In comparison, those at 1000 meters show slightly better indices, suggesting that sustainability conditions improve with greater distance from the roads. In Porangatu, the highest and lowest sustainability indices are 1000 meters from the highway, with areas within 250 meters showing similar indices to the overall values.

The results of the spatial autocorrelation analysis for the SI within the study area indicate a significant spatial pattern. The Global Moran's I value of 0.4023 indicates a positive spatial autocorrelation, where similar values of SI are more likely to be clustered together. The Expected Index (-0.0016) and the variance (0.0006) support the statistical reliability of the analysis. Furthermore, the high z-score (16.7126) and the corresponding

p-value ($p < 0.0001$) confirm a highly significant spatial autocorrelation. This result reinforces the existence of a clear spatial pattern. Furthermore, this conclusion aligns with the initial observations from the SI map.

SI local clusters and outliers can be identified in Figure 7, where green clusters represent areas of high sustainability and red clusters indicate areas of low sustainability. Outliers occur when there is a pronounced dissimilarity between neighboring sectors compared to the global trend; these are marked in orange for regions of high SI and pink for areas with significantly low local SI.

Figure 7 – Clusters e Outliers of SI.



The multivariate analysis of the indicators using a machine learning method corroborates the observed spatial pattern. Three patterns were identified by considering all socio-economic and environmental indicators synergistically. Figure 8a illustrates the solid spatial relationship between the clusters. Figure 8b displays the average values for each indicator within each multivariate group, highlighting the unique characteristics of each group. Additionally, the distribution of the SI by cluster in Figure 8c corroborates the previous spatial and quantitative analyses.

Figure 8 – a) Multivariate clustering mapping, considering socio-economic and environmental indicators; b) box plots of socio-economic and environmental indicators according to cluster; and c) distribution of SI by cluster.



Table 3 highlights the variables with the highest contributions to the differentiation among clusters, underscoring their relevance in shaping the grouping structure. Environmental indicators generally exhibit a more significant contribution to the differentiation of groups in the multivariate analysis, highlighting their strong relationship with local sustainability. Among these, NDVI is the most influential variable, explaining 75.2% of the observed variation. Among the socio-economic indicators, the Sanitation index (ISa) is noteworthy, accounting for 55.4% of the variation. Indicators with moderate contributions include Population Density (IDen), Literacy (ILi), and Income (IIn). On the other hand, Income/Gender Equity (IEq) explains only 6.9% of the variation, indicating its limited influence within the model. As expected, the variables with the lowest contributions are Water Supply (IWa) and Electricity (IEl) due to their minimal variability (Figure 3). Similarly, Surface Temperature (ST) suggests that this factor does not play a significant role in the local analysis context despite its notable variability.

Table 3 – R^2 Values of Variables Ranked by Contribution to Clustering Analysis

Variable	R^2
NDVI	0.752
CO_{2flux}	0.718
NDBI	0.665
Sanitation (ISa)	0.554
Population Density (IDen)	0.305
Literacy (ILi)	0.278
Income (IIn)	0.232
Income/Gender Equity (IEq)	0.069
Surface Temperature	0.052
Water Supply (IWa)	0.045
Electricity Access (IEI)	0.041

Source: Authors' elaboration.

4 DISCUSSION

4.1 Spatial Insights on Local Sustainability

It has been observed that the highway serves as an attractor of population density, as higher indicator values are evident in its vicinity, suggesting that improved accessibility and connectivity between different areas encourage population concentration in regions served by these roads. Evidence suggests that the assumption of low density as a factor in environmental resource protection may be inaccurate in specific contexts, as higher densities occupy smaller land areas per capita, thereby reducing the use of ecologically sensitive areas. Furthermore, higher population densities can help meet local urban needs (Farr, 2008) directly influencing sustainable urban practices, land use, access to services, and food production. These factors are strategic in

controlling climate change and reducing greenhouse gas emissions, as higher densities enable a reduction in per capita resource use, leading to various benefits at local, regional, and global levels.

Areas closer to highways tend to have higher literacy rates, possibly due to improved access to educational facilities and resources. In contrast, areas farther from highways may struggle with access to educational resources. The indicator's asymmetric distribution underscores the need for targeted interventions to improve literacy rates in the most affected areas, ensuring equitable access to educational services.

The relationship between income and proximity to highways is not evident, except in Anápolis and Gurupi, where accessibility and connectivity provided by highways may positively influence local economic development. Nevertheless, the absence of this correlation in other municipalities suggests that additional factors may significantly impact income distribution in these regions more than the proximity to highways.

The IEq distribution is asymmetric, with lower values being more common and higher values being outliers in only a few sectors. This gender income inequality reflects social injustices and limits economic and social development, highlighting the need for actions promoting remuneration parity and women's financial inclusion. Spatial analysis shows no significant relationship with highway proximity, suggesting that road infrastructure does not directly influence gender income equity. Additionally, the indicator showed limited performance in differentiating the groups in the multivariate analysis, demonstrating a restricted ability to explain spatial sustainability patterns. Still, the indicator can guide efforts toward achieving SDGs related to reducing local inequalities, making it valuable in sectoral planning initiatives.

The narrow IEl data distribution, with few outliers, suggests that most regions have similar access to this essential service. This uniformity reflects the effectiveness of public policies in providing widespread electricity coverage. It also underscores the crucial role of road infrastructure in delivering critical services like electricity, as spatial analysis suggests a clear relationship between highway proximity and access to electricity. The IWa data distribution is narrow, with only a few lower outliers, generally above 0.5. Spatial analysis reveals a clear relationship between highway proximity and high-water access levels, with areas near highways tending to present better infrastructure due to easier installation and maintenance of water distribution networks. However, the presence of lower outliers suggests that some places still require improvements in water access. The low variability of IEl e IWa confirms their limited influence in the multivariate analysis, contributing minimally to the explanation of spatial patterns of local sustainability.

Spatial analysis shows an evident influence of highway proximity on higher sanitation service levels. It is essential to note the significant ISa variability, as reflected by the wide data distribution and its influence on the differentiation of multivariate groups, making it a key socio-economic indicator in explaining local sustainability patterns. However, Porangatu displays a different pattern, possibly due to specific local factors that require further investigation. The relationship between the ISa and IDen suggests areas where sustainable individual solutions, like ecological septic tanks or decentralized treatment systems, could be proposed (Silva *et al.*, 2020). These sustainable solutions would improve residents' quality of life, contribute to environmental preservation, and achieve the SDGs related to clean water and sanitation.

The environmental indicators of vegetation (NDVI), carbon sequestration (CO_2flux), and built-up area (NDBI) exhibited the highest correlations among themselves and effectively explained the differentiation among

the groups in the multivariate analysis.

Generally, the higher NDVI outliers, representing areas with more significant portions of vegetation, are found in less densely populated regions further from highways, indicating that proximity to road infrastructure directly impacts the reduction of vegetated areas. Protecting and increasing vegetated areas, even in regions of developing urbanization, is crucial for maintaining biodiversity, mitigating climate change, and improving residents' quality of life. Strategies that encourage the creation and maintenance of urban parks and green corridors, as well as the adoption of sustainable construction practices, can help balance urban development with environmental preservation.

The proximity to highways notably influences the lowest CO_2flux values. This indicator provides a direct representation of landscape alterations that result in the depletion of natural vegetation, which is crucial for carbon sequestration. Identifying areas with lower carbon sequestration capacity enables targeted interventions to restore and enhance vegetation in these regions, thereby increasing their climate change mitigation potential. In this sense, areas indicated by the lowest NDBI indicator values may present opportunities for future urban development or environmental preservation policies. In contrast, areas with higher building density could focus on sustainable development strategies that incorporate green spaces and efficient infrastructure to minimize environmental impacts.

The ST variation trend aligns with the IDen, NDBI, and NDVI indicators (Figure 5), suggesting that areas with higher building density and lower vegetation cover experience higher temperatures, confirming the influence of urban development on local climate variations. This indicator identifies local variation patterns, providing a detailed view of the specific thermal dynamics. Although the temperature indicator does not perform well as a differentiator of local sustainability clusters, its ability to detect local variations is crucial for planning actions to mitigate the effects of urban heat islands. Integrating temperature data with other environmental and development indicators can guide the implementation of solutions such as expanding urban green spaces and using reflective construction materials, contributing to more sustainable and resilient urban planning.

A comprehensive analysis of each indicator is essential for formulating detailed plans within specific sectors, as previously discussed. This analysis provides valuable insights to inform targeted strategies and actions within those sectors. However, conducting a study that considers all factors synergistically becomes challenging.

Sustainability cannot be assessed through a linear framework, as it encompasses complex interactions (Laslett; Urmee, 2020) that are often not adequately captured by conventional analytical approaches, e.g., Principal Component Analysis (PCA), useful for dimensionality reduction when variables are strongly correlated. In this sense, identifying patterns and nonlinear interactions between variables is essential for a deeper and more comprehensive understanding of local sustainability.

In this study, the SI composition was designed to ensure that high values are only achieved when numerous variables perform satisfactorily. The choice of the geometric mean for the composition of the indicator incorporates the idea that each component contributes with maximization properties, enhancing benefits as their values increase. At the same time, each indicator imposes constraints, as low values adversely affect

overall sustainability performance. This reflects the multifaceted and interdependent nature of sustainability dimensions and reveals synergies that are not readily apparent. These results highlight the complexity of sustainability and the need for targeted local interventions, emphasizing the importance of a contextualized approach in planning.

Also, the SI spatial association evaluation allows identifying significantly different local clusters and their localization using a structured method. Thus, the not only aids in mapping potential sustainability hotspots but also provides insights into where targeted interventions may be most needed. The observed spatial patterns are consistent with those in the SI mapping, supporting the proposed index. Cluster 1 (green) displays the highest socio-economic indicators compared to the other groups. However, it performs less in environmental metrics, such as NDVI and CO_2flux, which implies moderate vegetation cover, limited carbon sequestration capacity, and intermediate population densities. Although this cluster encompasses several smaller sectors, limiting its coverage, the SI histogram shifts toward higher values, indicating improved overall sustainability within this group. In Cluster 2 (oranges), socio-economic indicators are generally lower.

In contrast, environmental indicators are higher, suggesting improved vegetation cover, enhanced carbon sequestration capacity, and milder temperature conditions. Regarding the SI, the distribution slightly shifts to the right, indicating that this cluster is associated with average to high SI values overall. Cluster 3 (blue) displays intermediate values for its indicators. Notably, the income (IIn) and income/gender equity (IEq) indicators reflect levels comparable to the low performance observed in Cluster 2 for these metrics. In contrast, the environmental indicators in Cluster 3 are higher than those in Cluster 1, except for ST.

One of the most notable distinctions among the clusters is the elevated population density observed in Cluster 3, which corresponds to the lowest overall performance in sustainability metrics and SI. This combination of high density and low sustainability outcomes warrants special attention, as it indicates that a larger population is directly affected by these adverse conditions, highlighting where targeted ESG actions could be most effective.

4.2 Application on road infrastructure sector

The results demonstrate that the presence of highways generally influences local sustainability levels. The spatial analysis reveals that, although low-sustainability clusters occur predominantly in areas farther from urban centers and highways, the spatial distribution of the SI does not follow a linear pattern across all municipalities. Despite better environmental indicators, such as vegetation cover, these regions present lower socio-economic indicators. Reduced access to essential services such as sanitation and potable water and lower literacy rates are identified. Population density, considered a premise of sustainability in this study, tends to be lower in these areas.

Although general patterns can be identified, it is important to note that each location exhibits unique characteristics, and understanding these particularities helps make more informed decisions. This underscores the necessity of conducting a detailed and nuanced analysis of the impact of road infrastructure on local

sustainability.

This approach can guide the road infrastructure sector in implementing sustainable practices responsive to urban communities' needs. By using socio-economic and environmental indicators to identify specific challenges and opportunities, the sector can design targeted strategies, prioritizing investments in areas with lower sustainability indices, reducing inequalities, and enhancing the quality of life. Aligning road infrastructure ESG practices with local needs and priorities promotes stakeholder trust and cooperation, leading to more sustainable and resilient urban environments.

This methodology also plays a crucial role in addressing the analytical gap in data-scarce countries, where decisions are frequently made without a solid foundational framework. In summary, combining scientific rigor and visual clarity makes the proposed method powerful for dialogue and decision-making. Stakeholders can use the generated results to identify priority areas, understand interactions between socio-economic and environmental variables, and propose informed and effective interventions, promoting more inclusive and collaborative sustainable development.

4.3 Study Limitations

This study presents a pilot framework for evaluating socio-economic and environmental aspects in small municipalities intersected by major highways. The methodology was specifically designed to address the challenges posed by limited data availability, with the potential for enhancement in scenarios where a more robust and structured database becomes accessible. Although a temporal gap in the data from the study area is acknowledged, the framework utilizes the most current information for the analyzed context. Notably, the proposed method can be reapplied as newer datasets emerge, ensuring its adaptability and long-term relevance. Its principal contribution lies in its ability to provide an in-depth assessment of local sustainability, even without reliable or up-to-date data — a significant limitation in Brazil and many other countries (Kaba; Assaf, 2019).

5 CONCLUSIONS

The following conclusions can be drawn from the discussions performed in the paper:

• Spatial analysis has proven to be an effective tool for understanding local patterns to support strategies to improve sustainability.

• Local spatial sustainability patterns identified through the Local Moran's Index revealed both clusters and outliers of high and low sustainability indexes.

• The spatial patterns highlighted areas with significant differences in local sustainability, indicating the need for targeted interventions and contributing to a better understanding of the concerns and priorities of local communities.

• Clustering machine learning technique proved to be adequate in considering the intricate relationships

among various indicators. This method deepens our understanding of the spatial distribution of local sustainability conditions and bolsters the proposed SI.

• This approach allows for a deeper understanding of socio-economic and environmental dynamics, facilitating the implementation of more effective policies and practices to achieve significant equity and environmental justice.

• The reproducible and versatile method can provide valuable insights for understanding potential impact indicators, thereby addressing current challenges in the road infrastructure sector in developing countries, particularly in the context of limited data availability.

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