Spatial methodologies for visualizing social inequalities in metropolitan areas

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November 11, 2020
Project, City and Processes Permanent Forum

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Outline

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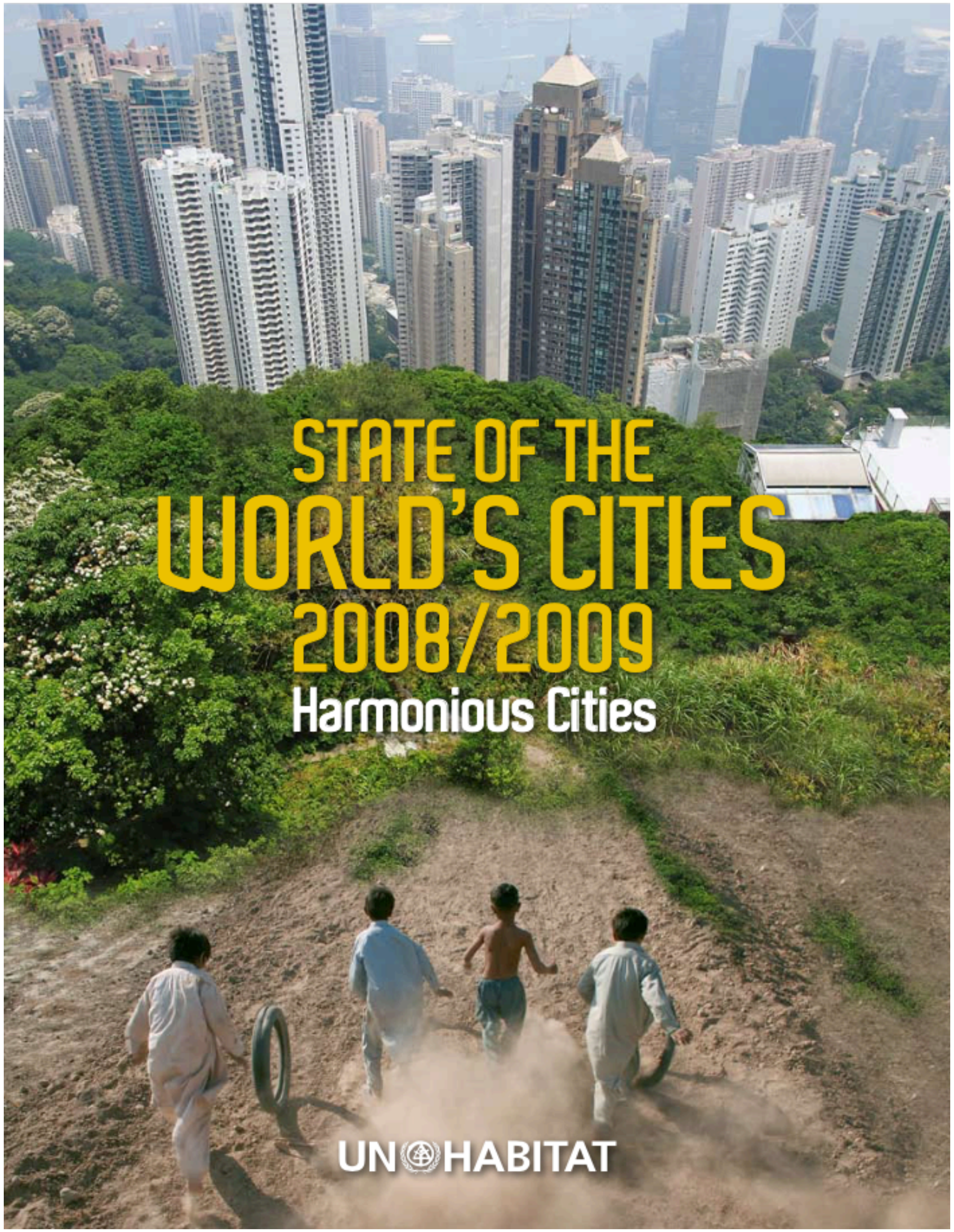
Objective

- Discuss spatial methodologies to better visualize socioeconomic inequalities within metropolitan areas
- Not viable with traditional measures of inequality
- We applied this methodology to investigate the complex structure of segregation in the Metropolitan Region of Goiânia (RMG), Brazil

Motivation

- United Nations reports about the state of the world's cities generated reactions from Brazilian politicians
  - UN studies indicated high levels of economic inequality in several cities in Brazil

- Politicians did not take advantage of this debate to better understand inequality and segregation
  - This would have been more helpful to implement adequate public policies for urban planning



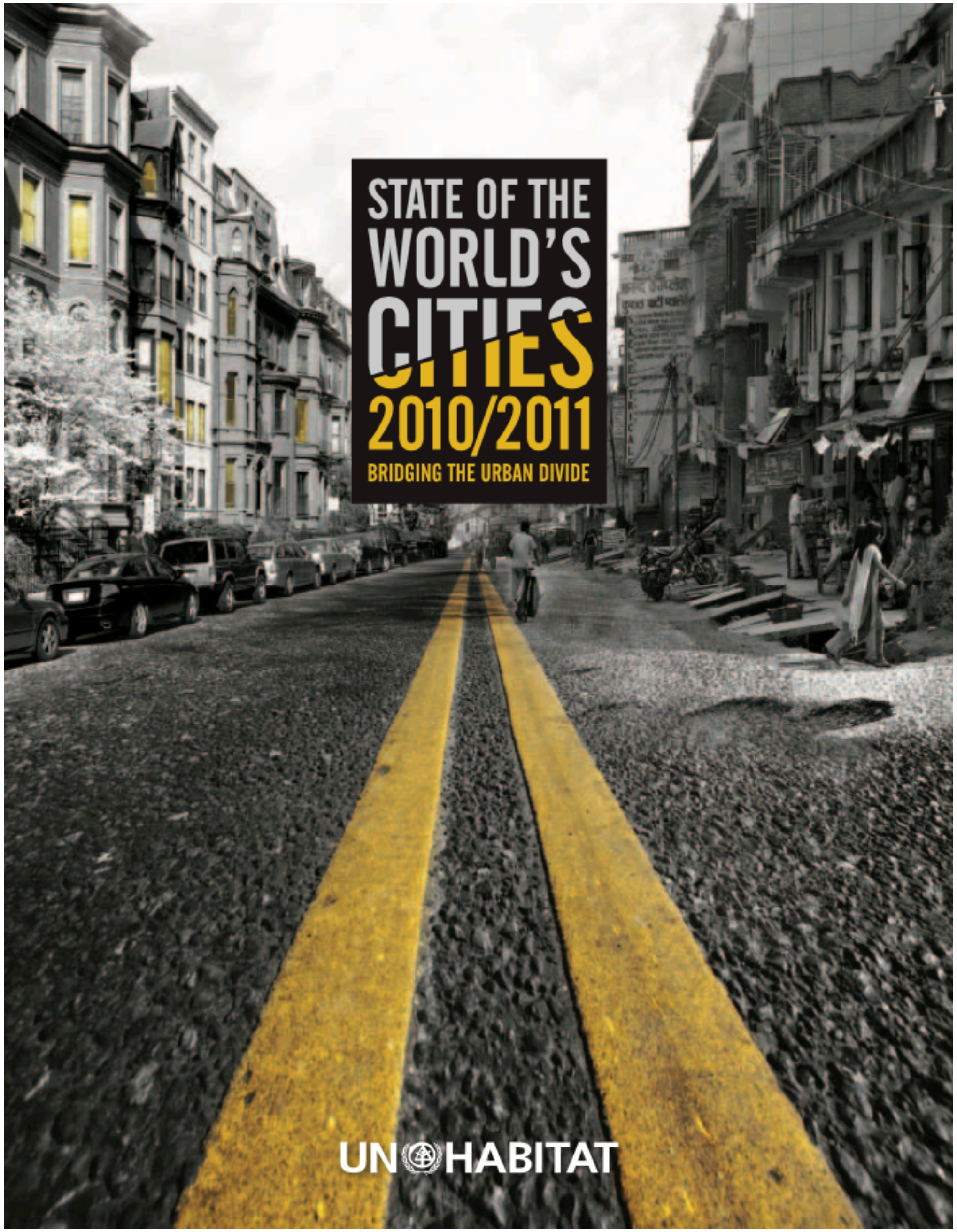
Source: UN-Habitat, 2008.

UN-Habitat, 2008/2009

- Among 19 cities analyzed in Latin America and the Caribbean, these cities had extremely high inequality
  - Gini coefficient above 0.60
  - Goiânia, Brasília, Belo Horizonte, Fortaleza, São Paulo, Bogotá
- The Goiânia mayor Iris Rezende Machado (2005–2010) reacted
  - The UN did not utilize an appropriate methodology
  - Goiânia doesn't have "slums"

http://www.jornaldiariodonorte.com.br/noticias/goiania-cidade-das-desigualdades-2803

Source: UN-Habitat, 2008, p.68.



Source: UN-Habitat, 2010.

UN-Habitat, 2010/2011

- Among 24 cities analyzed in Latin America and the Caribbean
- Goiânia had the highest inequality
- Gini coefficient = 0.65 (2005 data)

Source: UN-Habitat, 2010, p.193.

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Source: UN-Habitat, 2016.

UN-Habitat, 2016

- Among 32 cities analyzed in Latin America and the Caribbean
- Goiânia had the second highest inequality
  - Gini coefficient = 0.65 (2005 data)
- Brasília and Curitiba had the highest inequality
  - Gini coefficient = 0.67 (2009 data)
- Considering all other 153 cities in 74 countries, only 9 cities in South Africa had higher inequality than Goiânia
  - Gini coefficients from 0.67 to 0.75 (2005 data)

Source: UN-Habitat, 2016, p.206–207.

The politician reacted again

- In July 2016, in one of his letters announcing the end of his political career, Machado wrote
  - Goiânia doesn't coexist with "slums" ("Goiânia não convive com favelas")
  - Goiânia is the only one that doesn't coexist with a lack of treated water ("[Goiânia é a] única que não convive com a falta de água tratada")

- At the end of 2016, Machado ran for mayor and was elected for the 2017–2020 mandate

Source: http://www.dm.com.br/politica/2016/07/iris-diz-em-carta-que-nao-sera-candidato-a-prefeito-de-goiania.html.

Goiânia in 2010

- Goiânia had 423,297 occupied households
  - 1,066 households (0.25%) were situated in seven irregular communities ("aglomerados subnormais")
  - 92.97% of households had a regular water supply

- Studies that utilize global indicators do not allow us to understand complex spatial inequalities within a metropolitan area

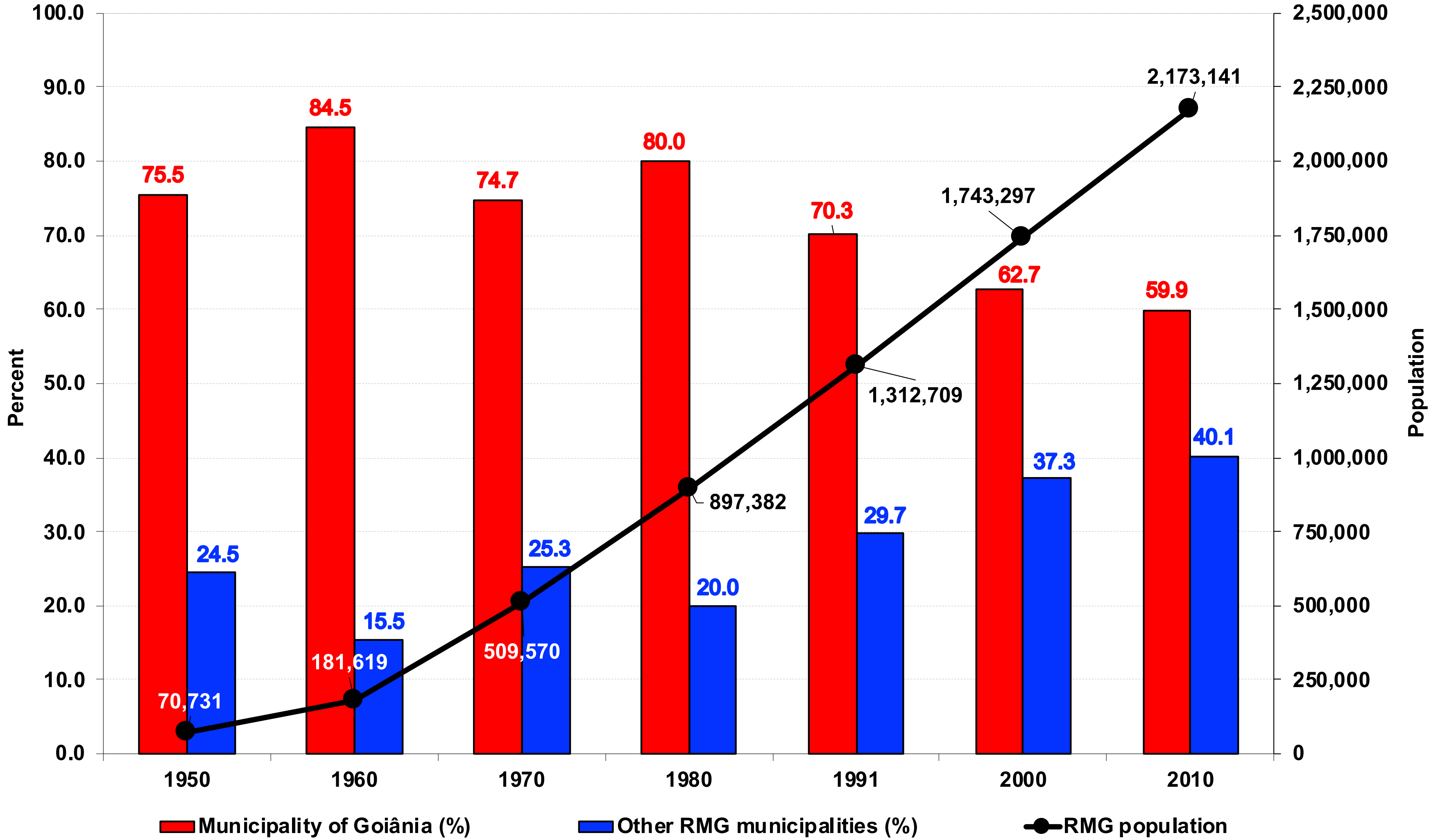
Source: 2010 Brazilian Demographic Census.

Controversy

- How is it possible that Goiânia
  – Is one of the most unequal cities in the word?
  – Does not have “slums”?
  – Provides adequate public infrastructure to its population?

- Goiânia is not an isolated municipality
  – It is integrated with neighboring municipalities
  – “Slums” are not the only segregated spaces
  – We need to analyze several indicators and variations within the metropolitan region

RMG population, 1950–2010



Source: 1950–2010 Brazilian Demographic Censuses.

Data

- 2010 Brazilian Demographic Census (IBGE 2010)
  - Aggregated data by 2,889 RMG census tracts
- Spatial distribution of socioeconomic indicators throughout census tracts
  - Household income per capita
  - Education (percentage literate)
  - Color/race (percentage white)
  - Households with regular water supply
  - Households with daily garbage collection service
  - Households with regular sewer system

Methods

- We characterize spatial segregation patterns

- In the analysis of spatial association, we recognize that people are not randomly distributed over space

- Neighboring areas tend to be more similar to each other than areas situated a greater distance apart

Moran's I

- Moran's I statistic is the most commonly used indicator of global spatial autocorrelation (Anselin 2018)
  - It is the result of a comparison between a specific spatial variable and its corresponding spatially lagged variable
- The lagged variable is the characteristic of the neighboring census tracts for each one of the analyzed census tracts
  - Neighboring areas are defined as all areas sharing a border (queen contiguity)

Hypothesis testing

- Moran's I is based on a null hypothesis of spatial randomness
  - Each value is equally likely to occur at any location

- This indicator tests if people and households with specific characteristics are randomly distributed throughout RMG census tracts
  - If people and households with specific characteristics are concentrated in certain census tracts ($p<0.05$), the null hypothesis of spatial randomness is rejected

Local spatial autocorrelation

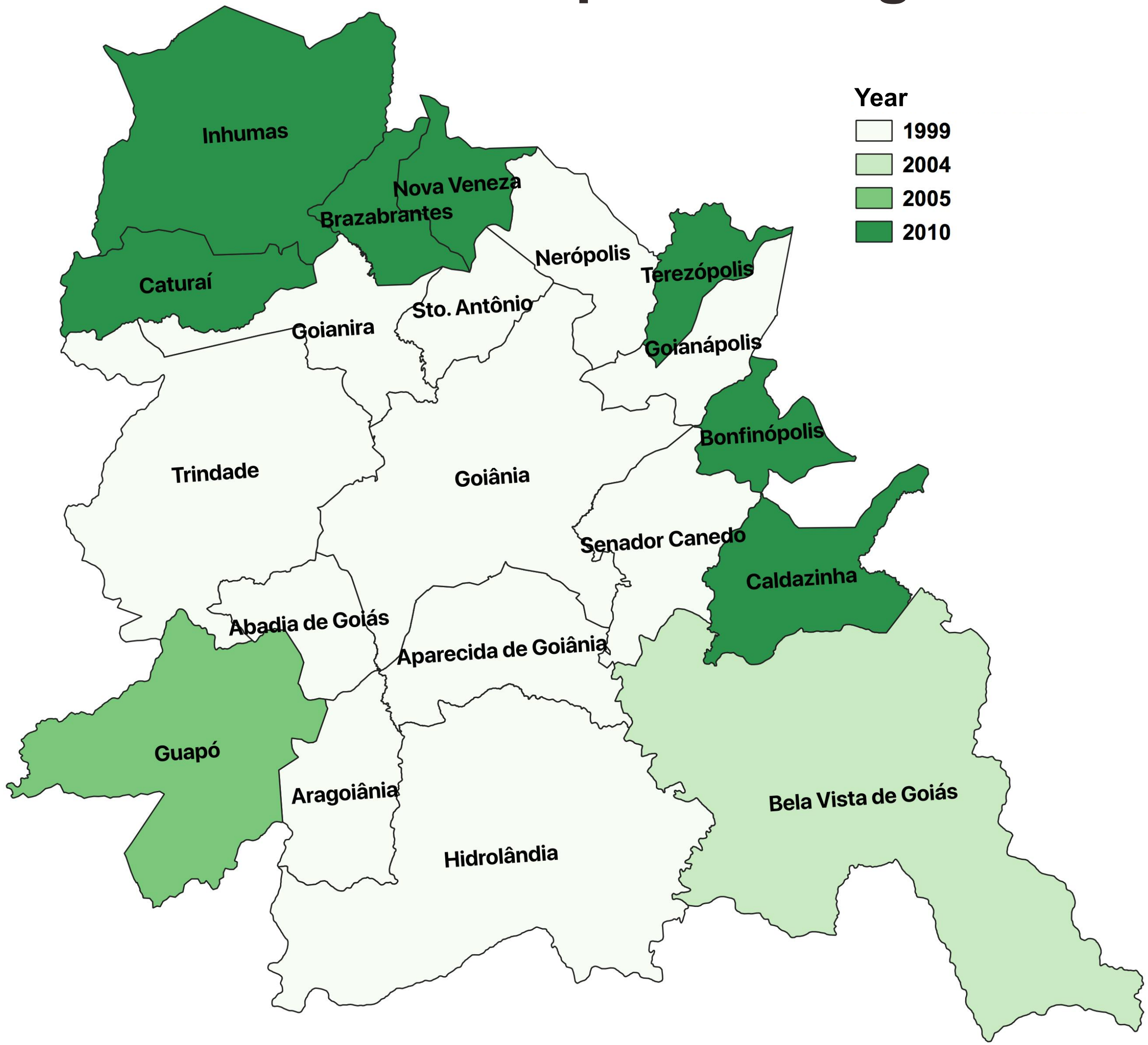
- The local indicator of spatial association (LISA) identifies spatial clusters and spatial outliers
  - LISA allows for the decomposition of global indicators into the contribution of each individual area (Anselin 1995, 2019)
  - LISA was estimated in GeoDa
    - https://spatial.uchicago.edu/geoda
  - Maps were formatted in QGIS
    - https://qgis.org
- LISA classifies areas considering information about indicators of surrounding areas

Spatial clusters and outliers

- **Spatial clusters**
  - Areas with <u>high</u> levels of a specific indicator surrounded by areas with <u>high</u> levels for that indicator (**high-high**)
  - Areas with <u>low</u> levels of a specific indicator surrounded by areas with <u>low</u> levels for that indicator (**low-low**)

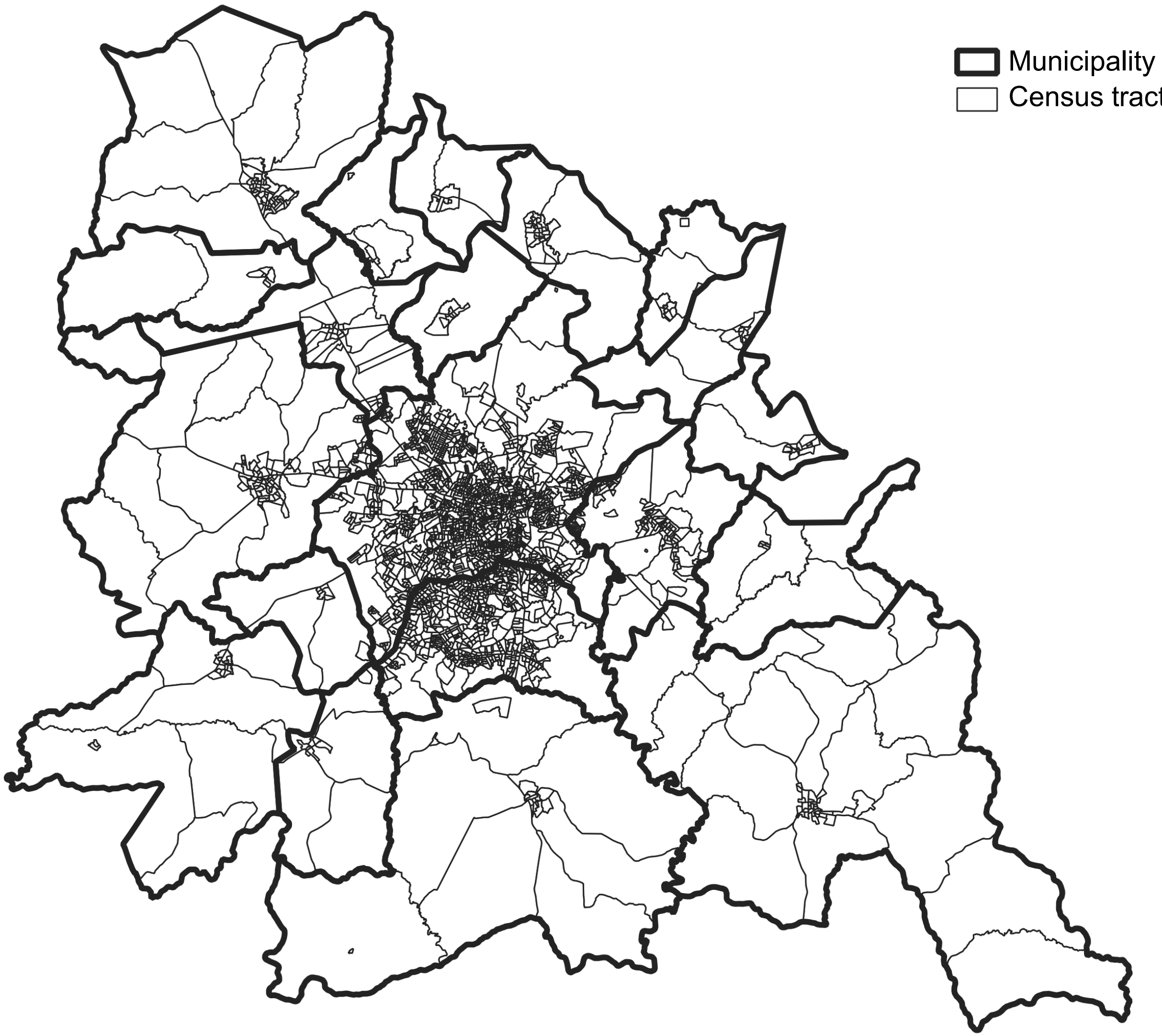
- **Spatial outliers**
  - Areas with <u>high</u> levels of a specific indicator surrounded by areas with <u>low</u> levels for that indicator (**high-low**)
  - Areas with <u>low</u> levels of a specific indicator surrounded by areas with <u>high</u> levels for that indicator (**low-high**)

Composition of the Metropolitan Region of Goiânia



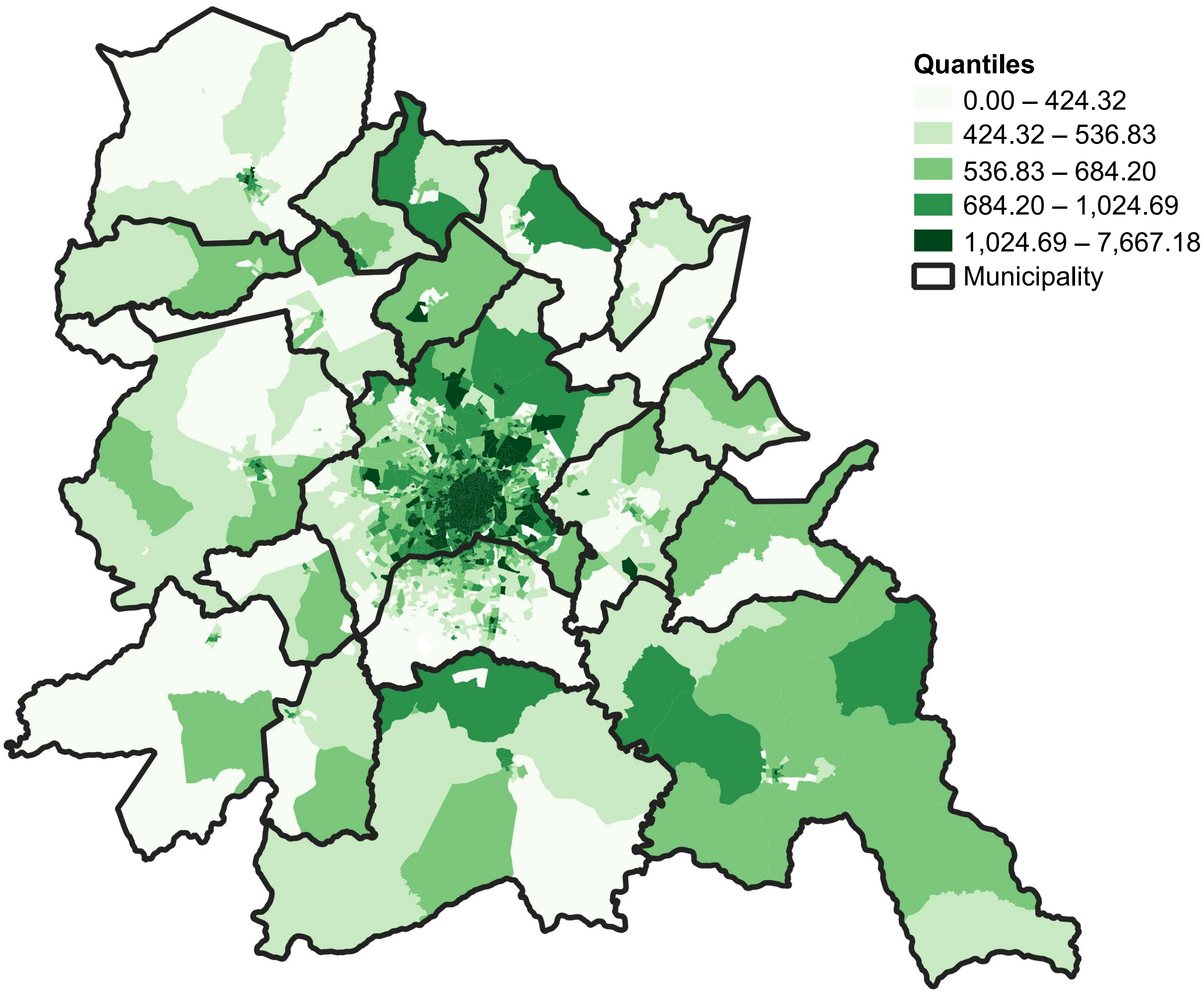
Source: Complementary laws #27 (12/30/1999), #48 (12/09/2004), #54 (05/23/2005), #78 (03/25/2010).

2,889 census tracts within 20 municipalities



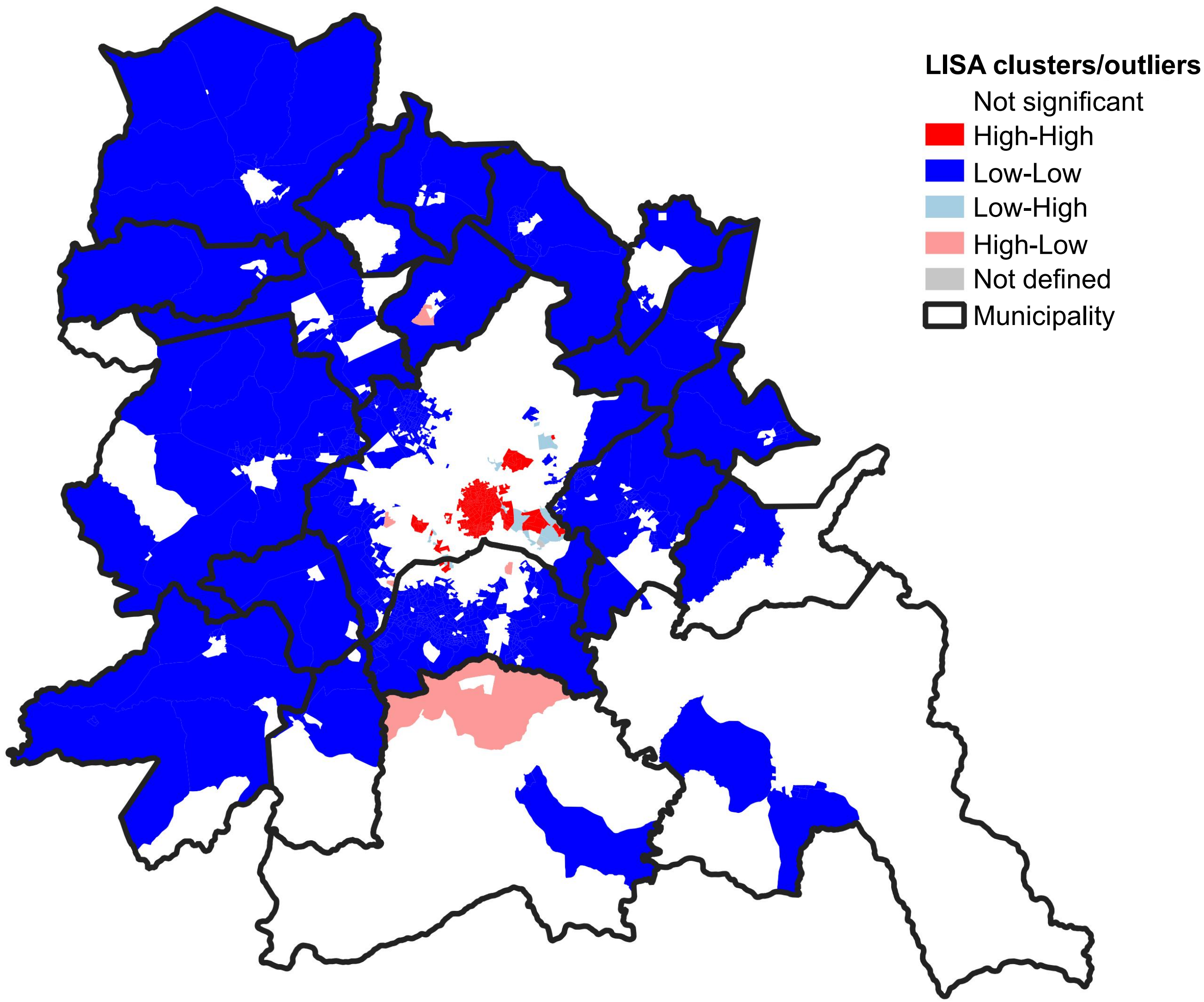
Source: 2010 Brazilian Demographic Census.

Household income per capita



Source: 2010 Brazilian Demographic Census.

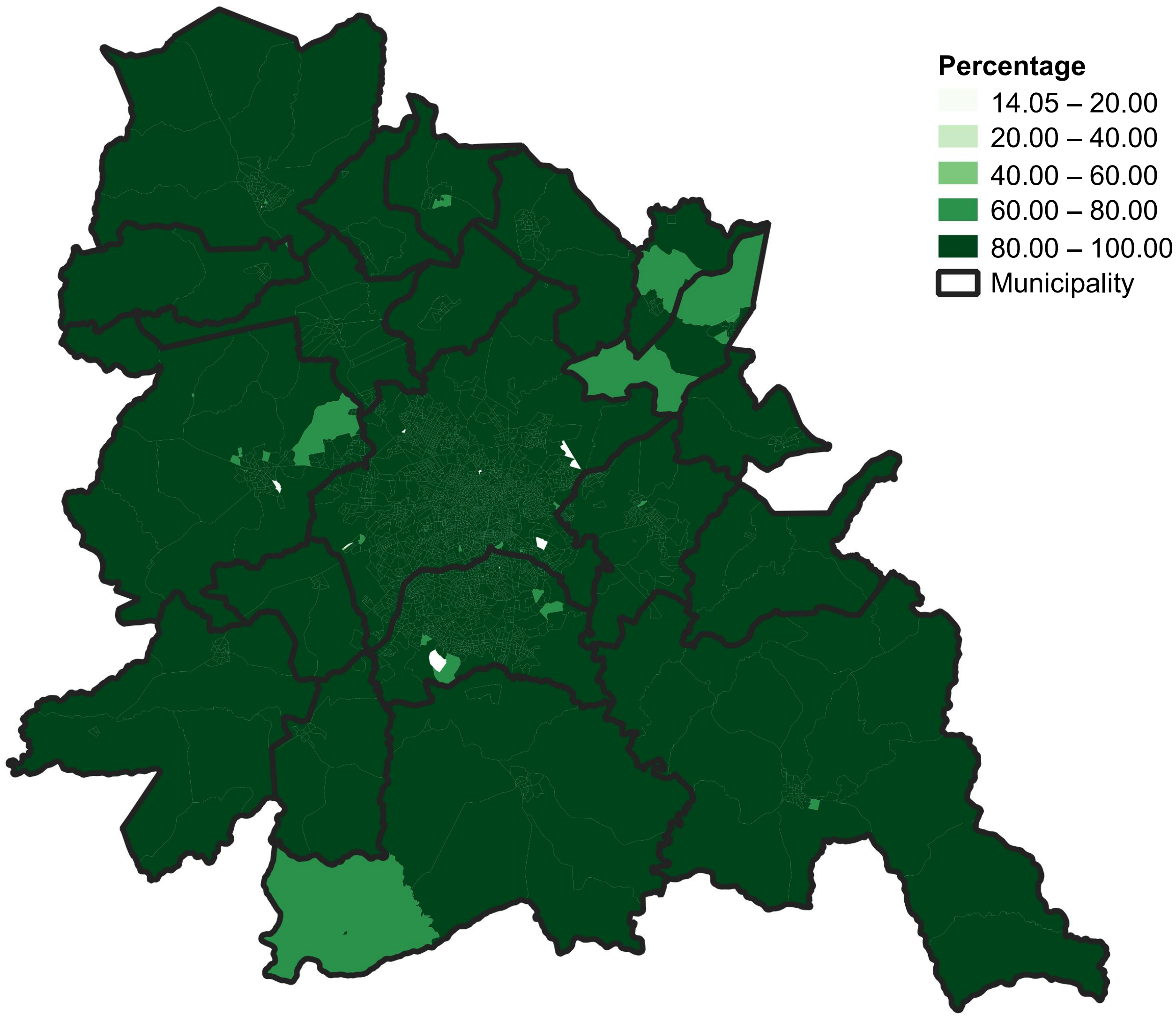
Household income per capita



Moran's I: 0.7340 (pseudo p-value: 0.001)

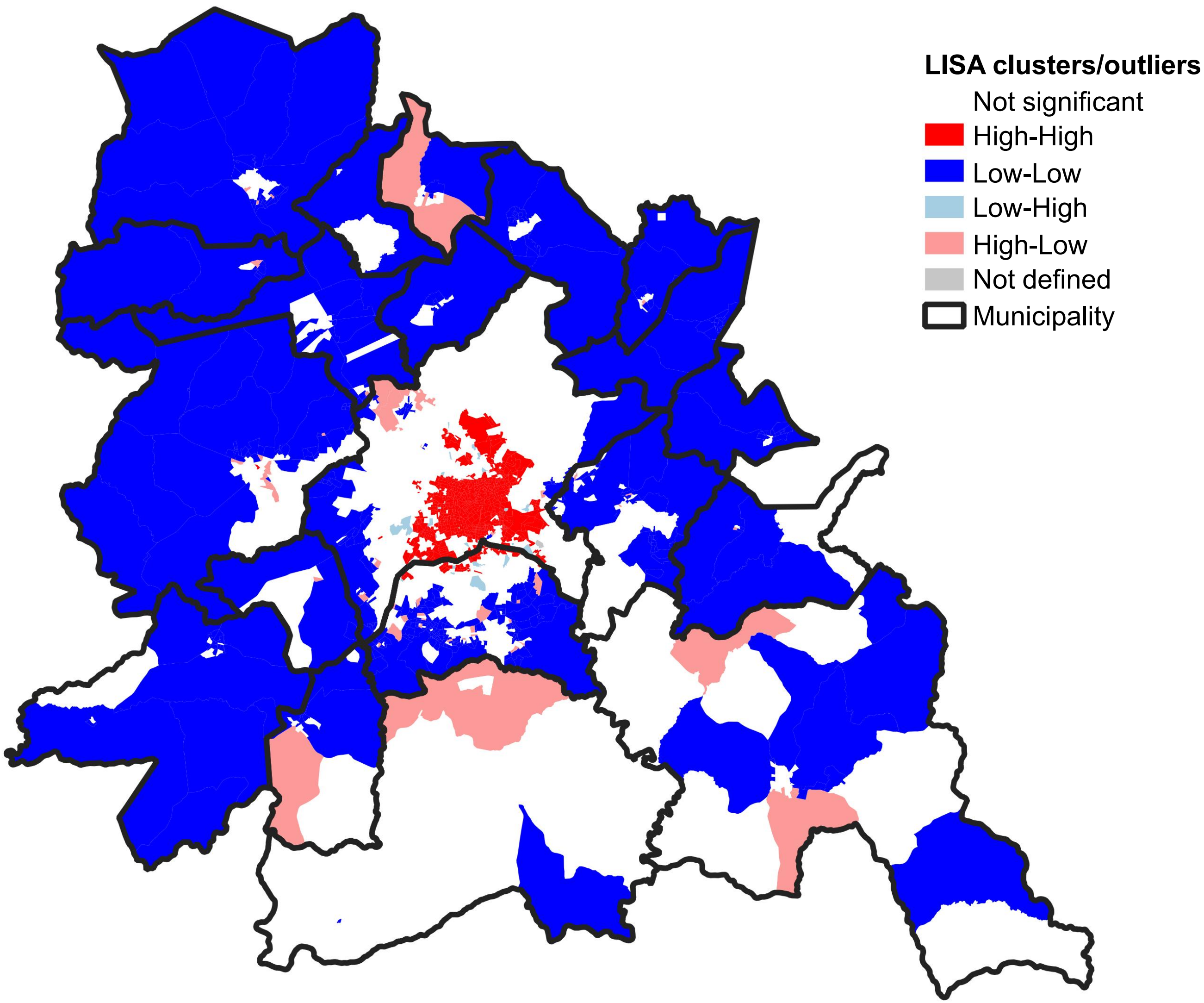
Source: 2010 Brazilian Demographic Census.

Literate population



Source: 2010 Brazilian Demographic Census.

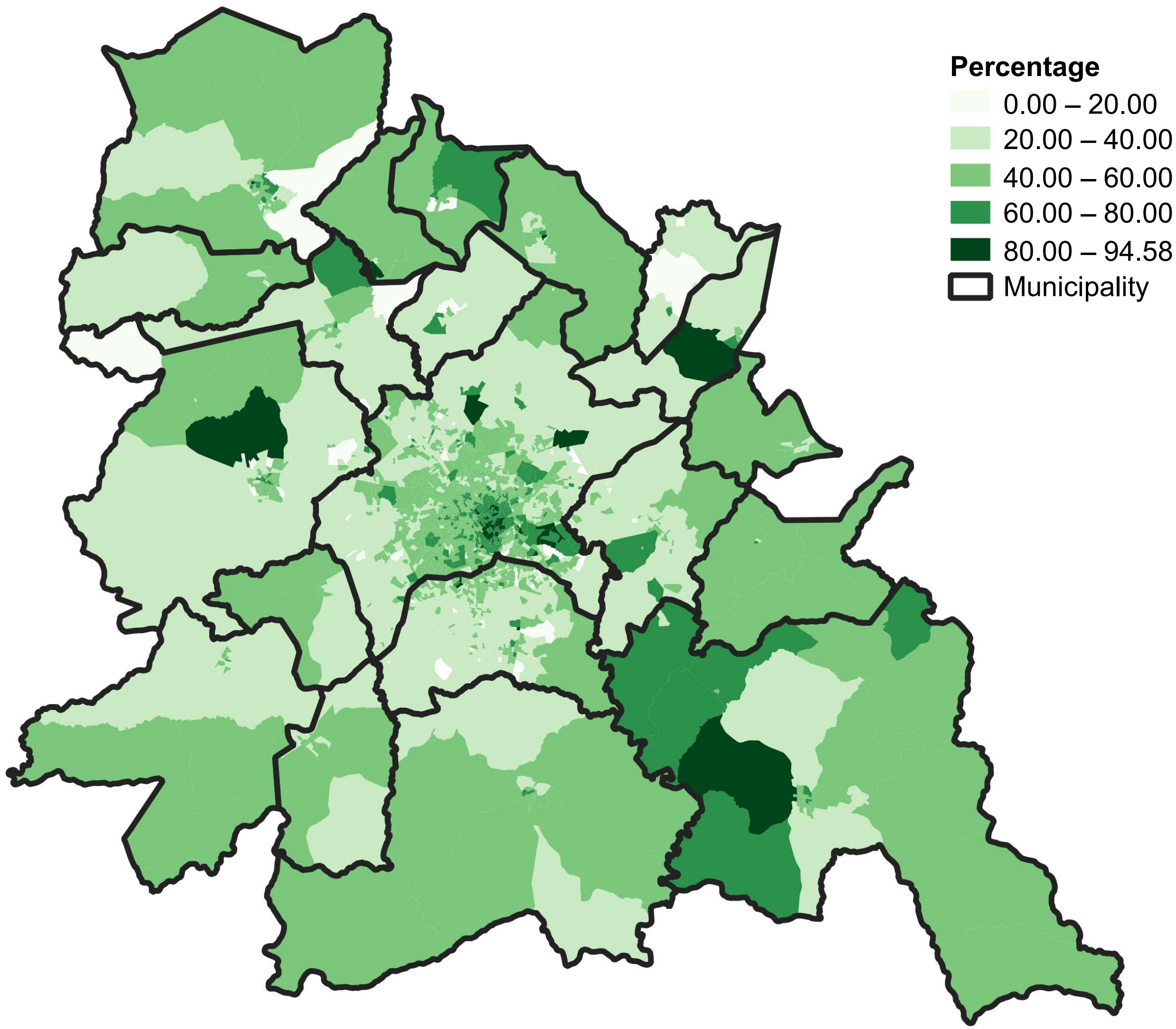
Literate population



Moran's I: 0.4833 (pseudo p-value: 0.001)

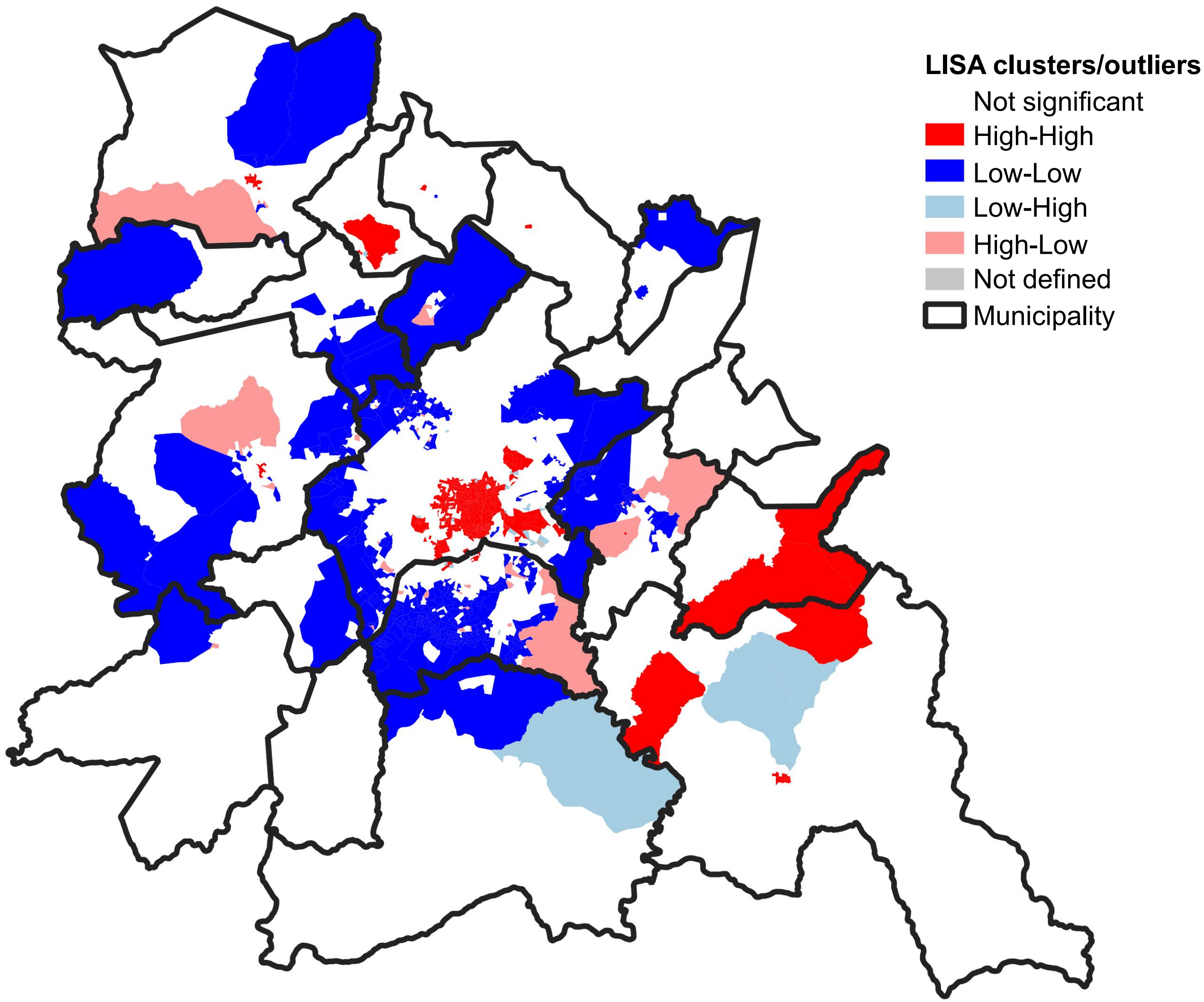
Source: 2010 Brazilian Demographic Census.

White population



Source: 2010 Brazilian Demographic Census.

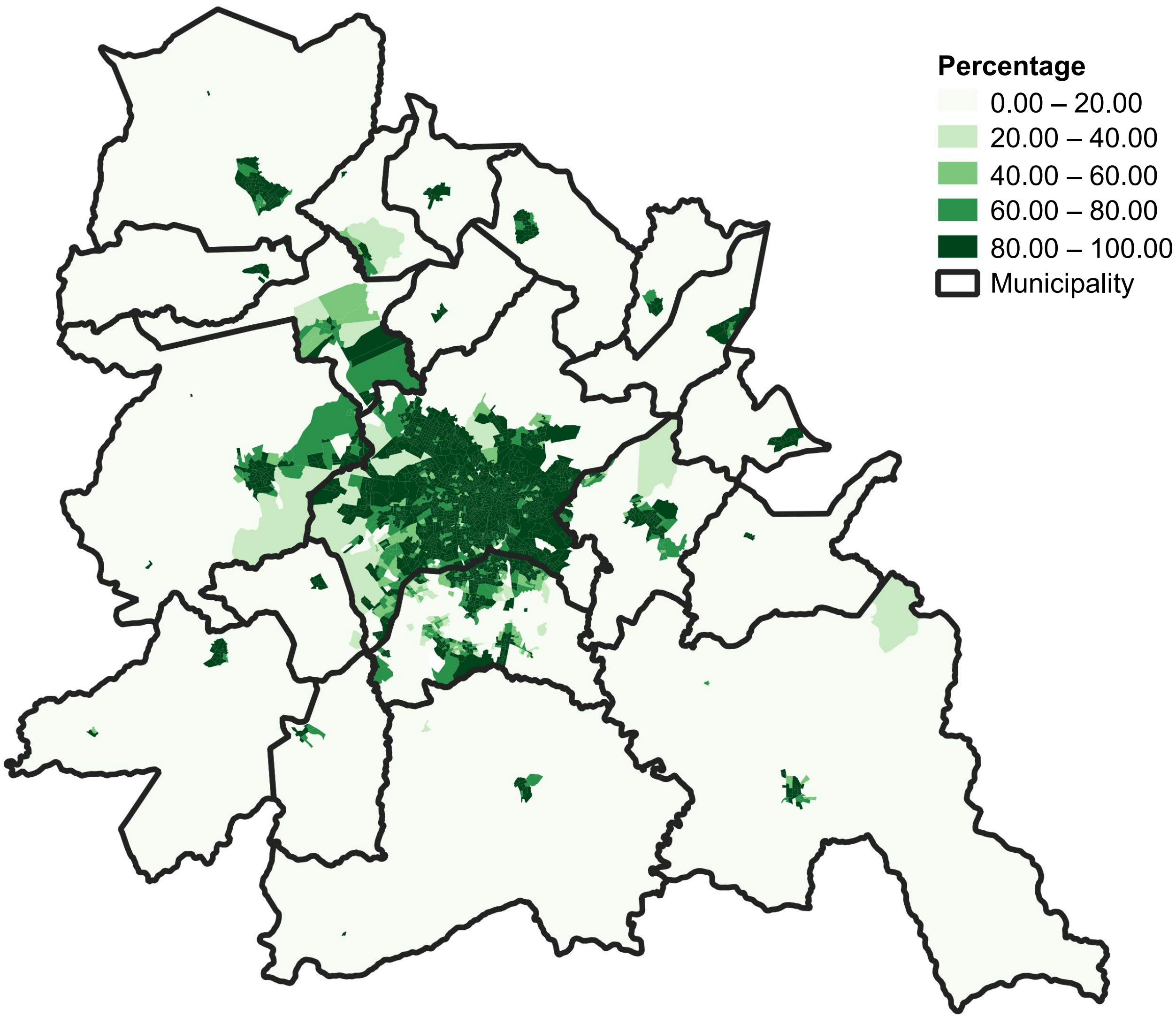
White population



Moran's I: 0.6155 (pseudo p-value: 0.001)

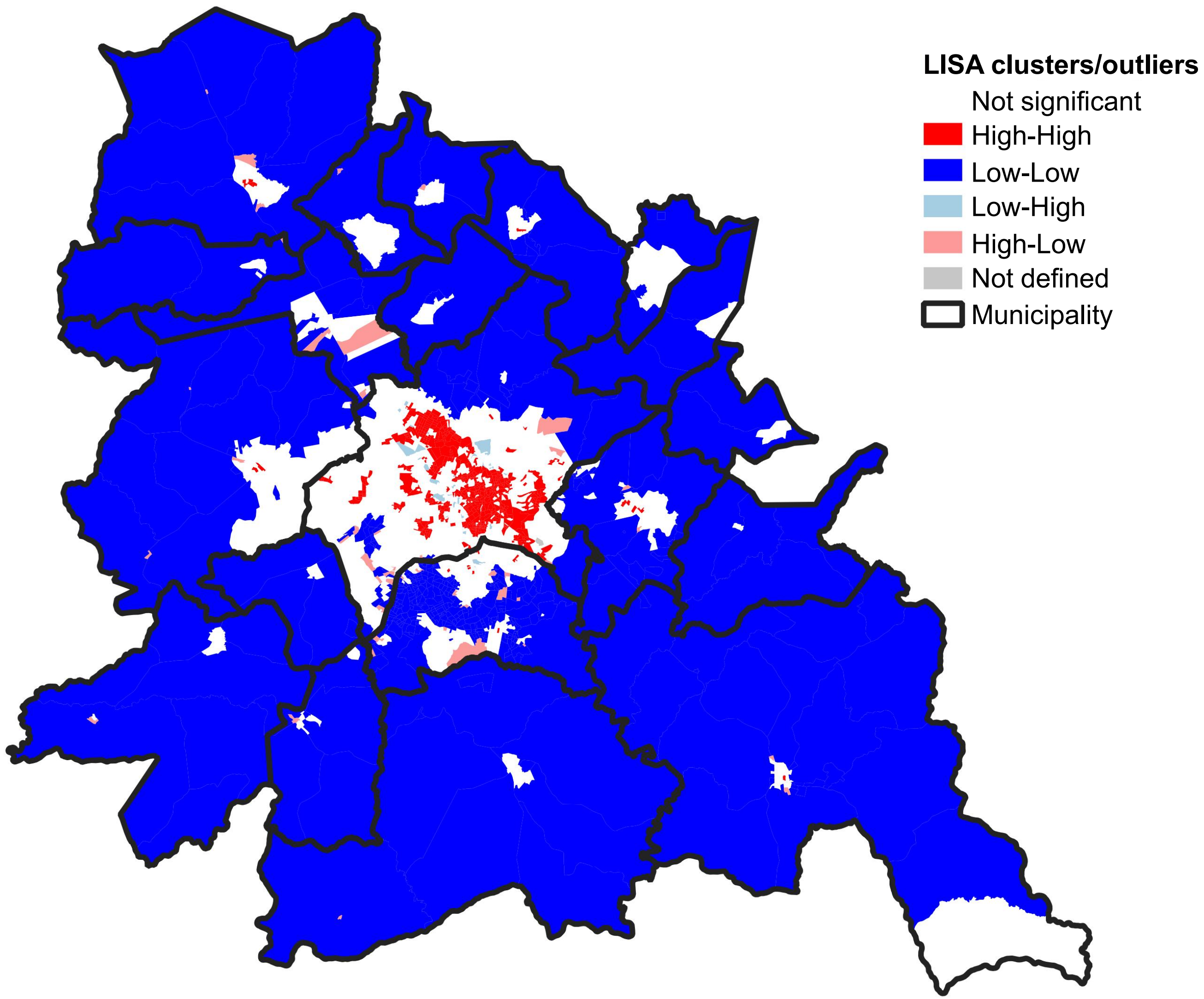
Source: 2010 Brazilian Demographic Census.

Households with regular water supply



Source: 2010 Brazilian Demographic Census.

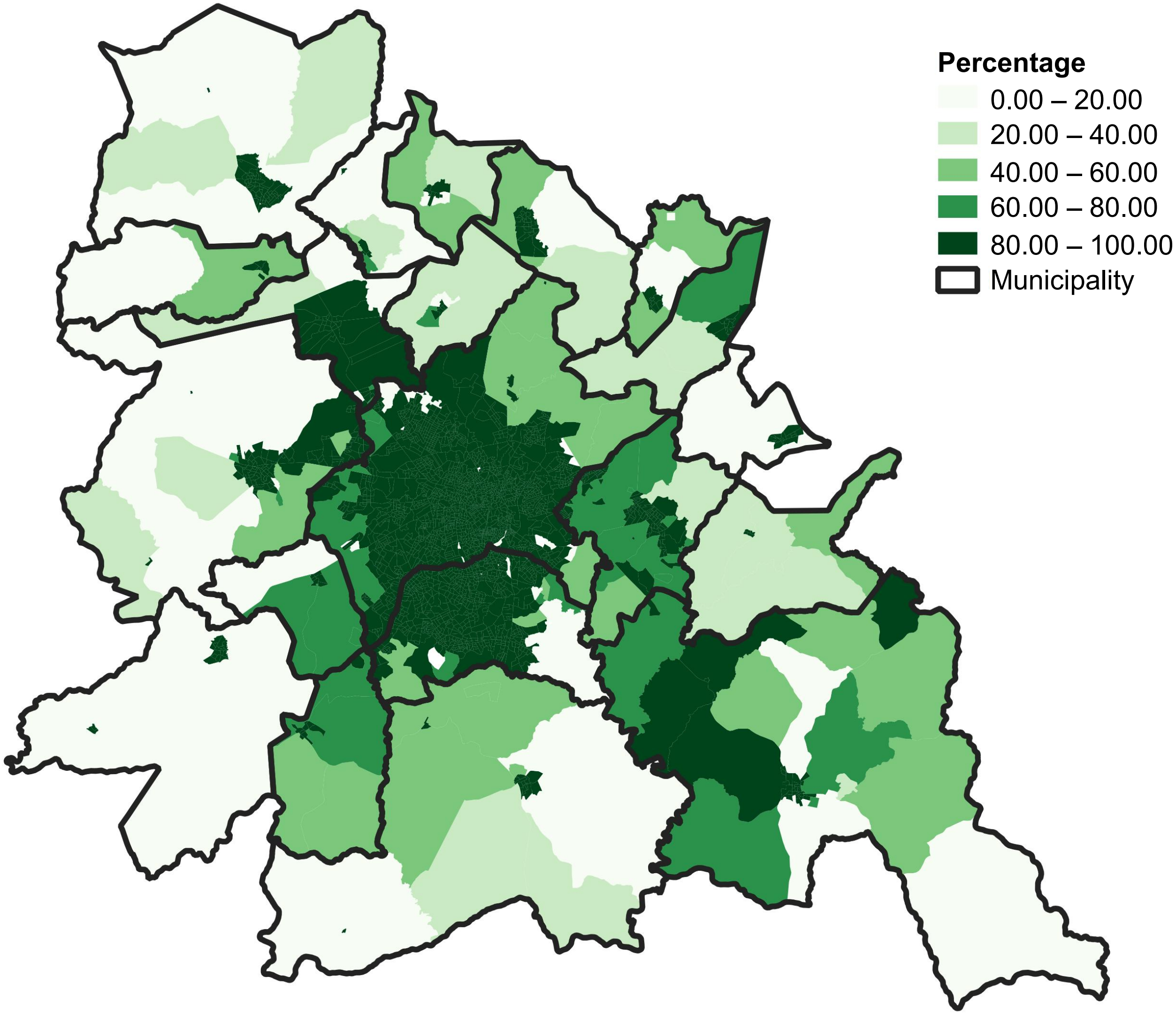
Households with regular water supply



Moran's I: 0.6611 (pseudo p-value: 0.001)

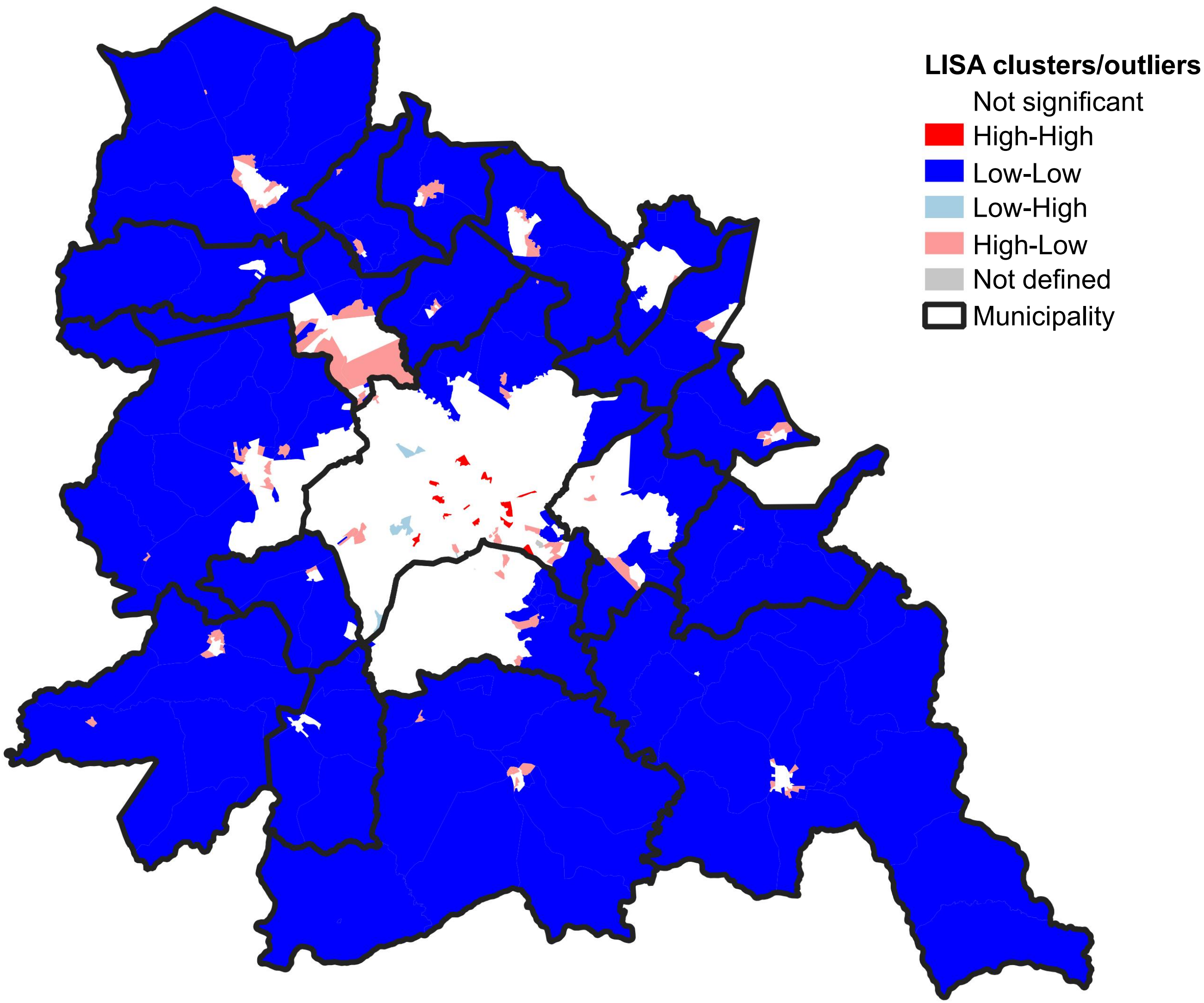
Source: 2010 Brazilian Demographic Census.

Households with daily garbage collection service



Source: 2010 Brazilian Demographic Census.

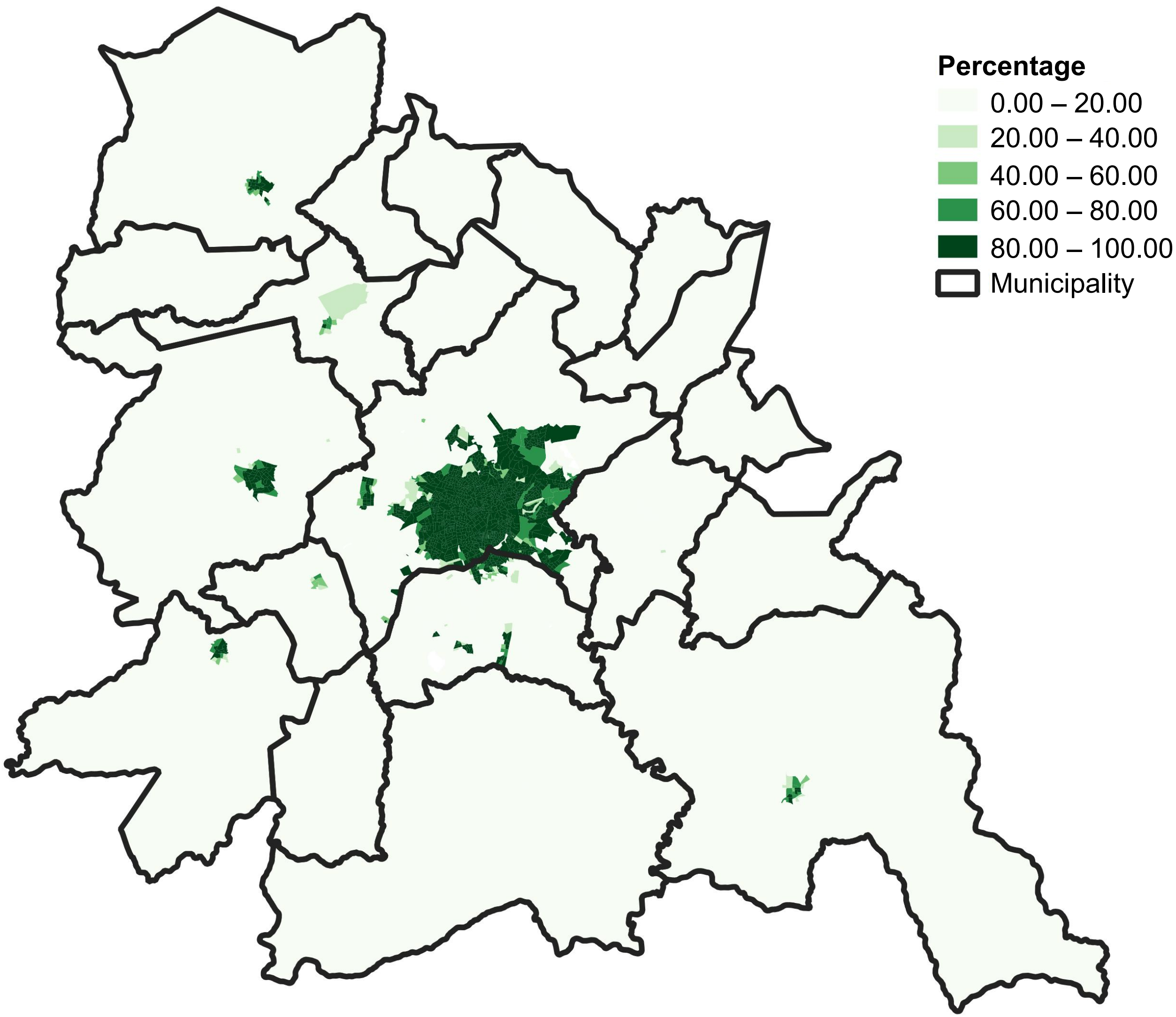
Households with daily garbage collection service



Moran's I: 0.4751 (pseudo p-value: 0.001)

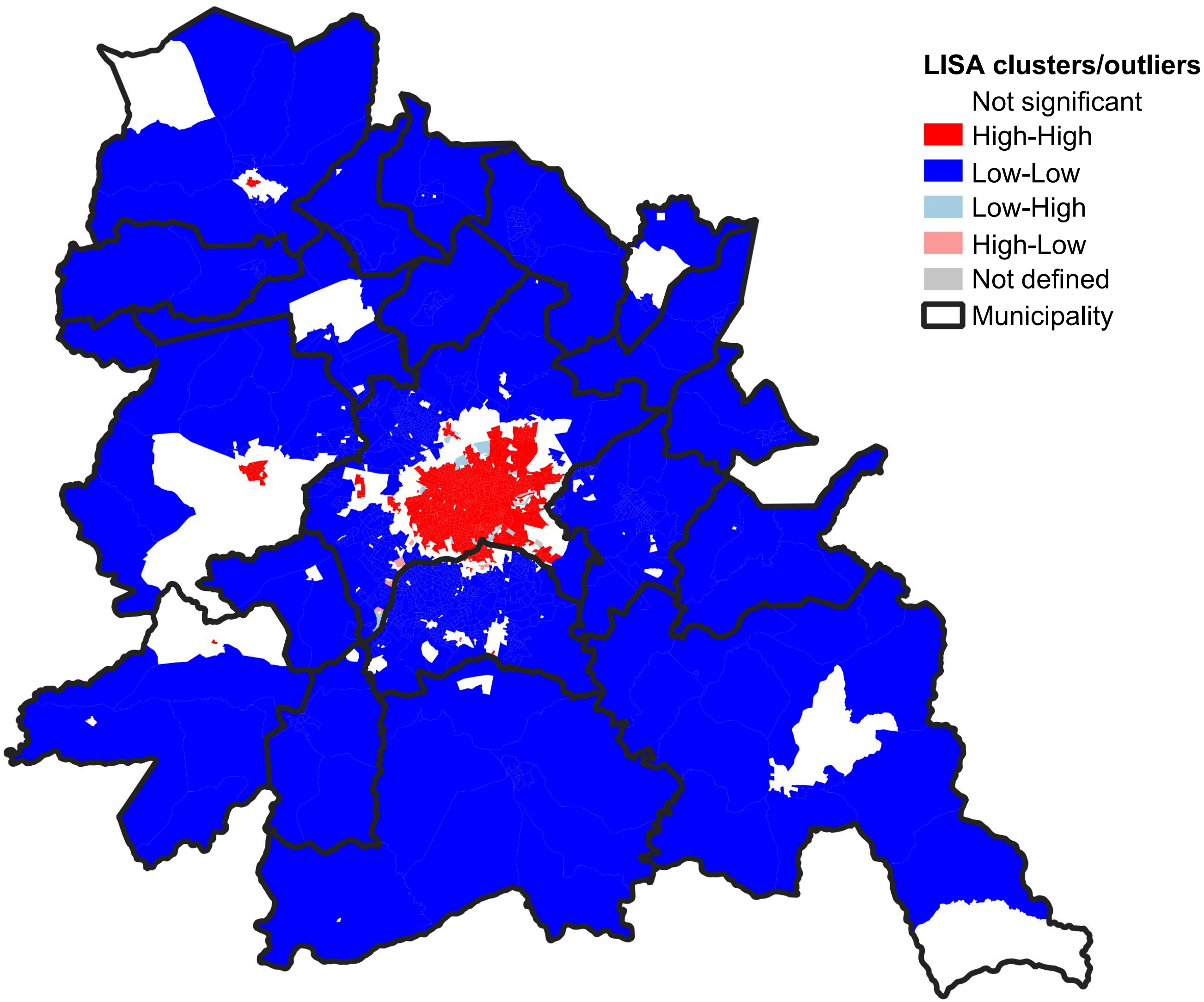
Source: 2010 Brazilian Demographic Census.

Households with regular sewer system



Source: 2010 Brazilian Demographic Census.

Households with regular sewer system



Moran's I: 0.8726 (pseudo p-value: 0.001)

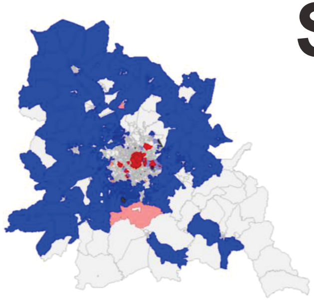
Source: 2010 Brazilian Demographic Census.

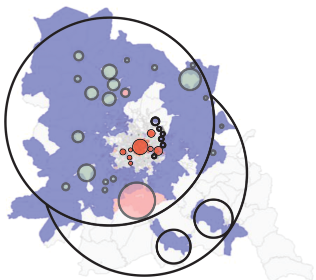
Summary diagram

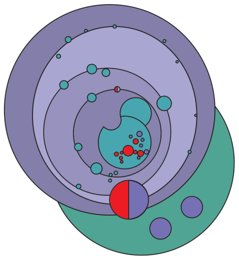
- We developed a critical approach to illustrate the spatial structure of segregation in the metropolitan region

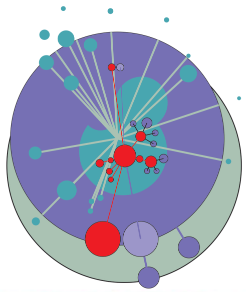
- The intention was to take advantage of the quantitative analysis and provide a deeper interpretative summary about the region

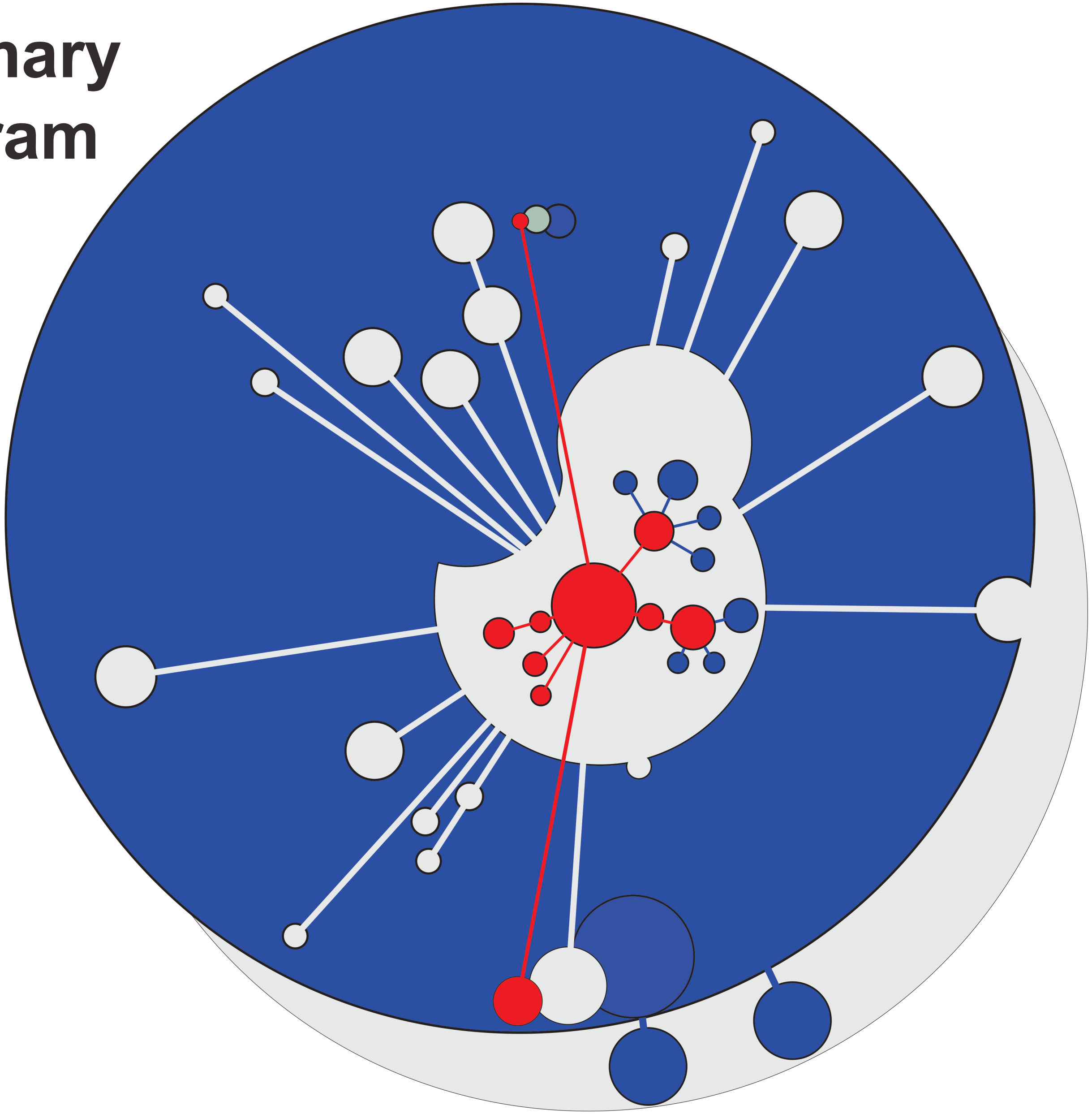
Summary diagram





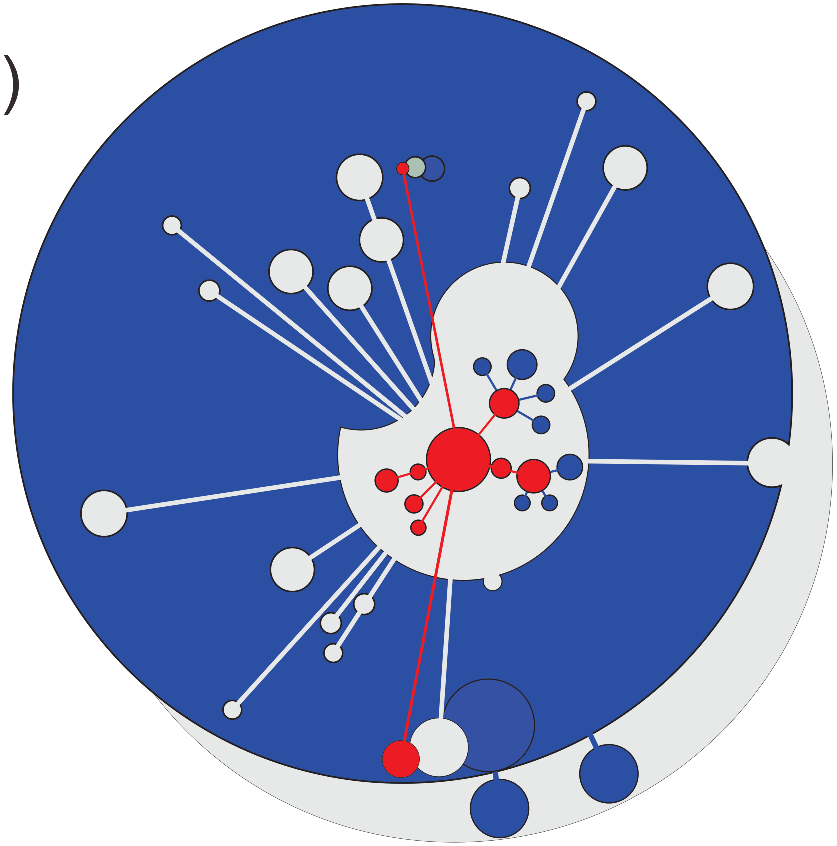






First ring

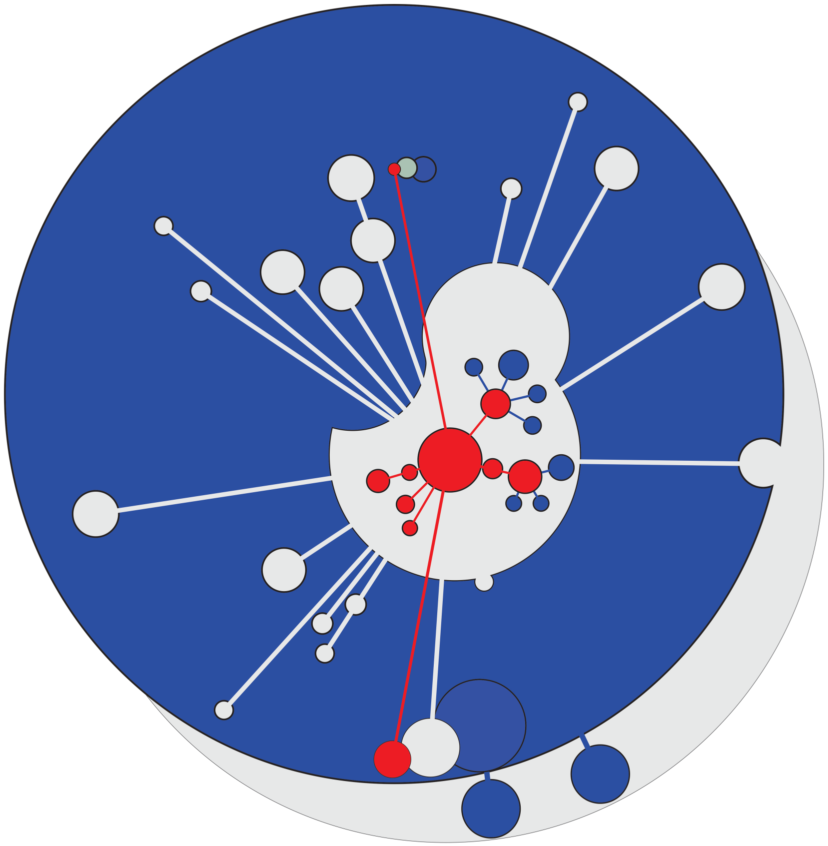
- Stable area with various income levels and lower levels of segregation (first grey ring)
  - Rich areas in the center (red)
  - Other rich areas
    - Santo Antônio de Goiás (North)
    - Hidrolândia (South)
  - Blue circles within first ring (Northeast and East)
    - Poor satellites surrounding rich areas



Second ring

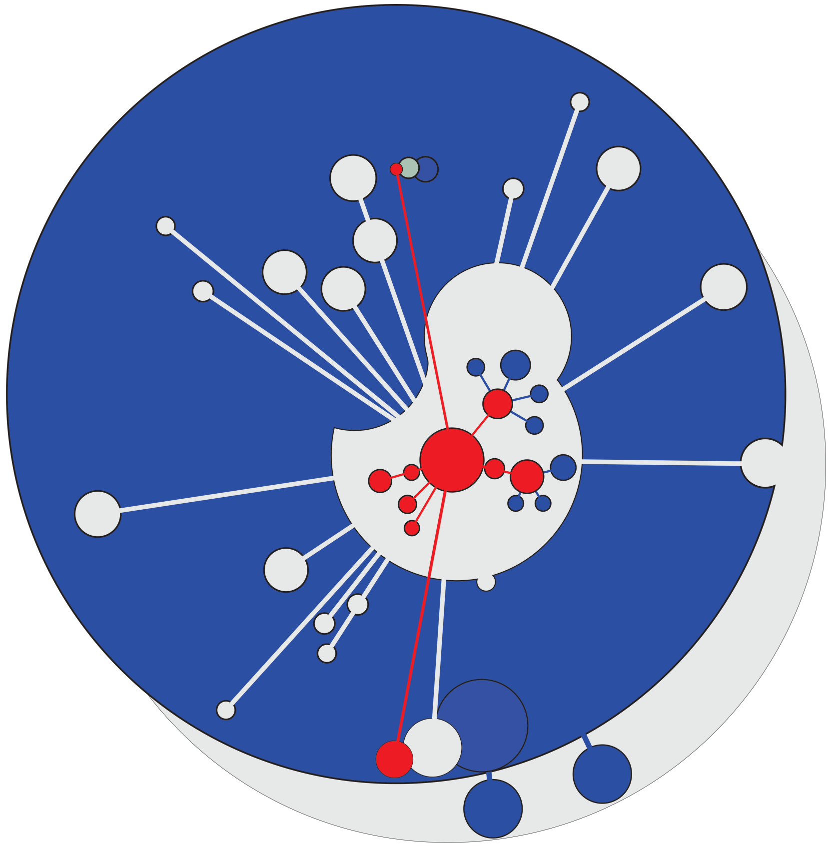
- Large poor area farther away from central areas (second blue ring)

- "Peripheric centers" (grey circles) within large poor area
  - Various income levels
  - Lower levels of segregation



Third ring

- Another stable area with various income levels and lower levels of segregation (third grey ring)
  - South and Southeast
- Poor areas in the Southeast (blue circles)
  - Hidrolândia
  - Bela Vista de Goiás



Final considerations

- Main results indicate that RMG does not have a simple centrality or a multi-centrality
  - There are a series of concentric rings with different types of centralities

- These areas function in an integrated and segregated system (not inclusive)
  - It cannot be summarized by global measures of inequality (Gini) or spatial distribution (Moran's I)
  - It cannot be understood by only analyzing the municipality of Goiânia

Future research

- Provide an analysis of spatial segregation patterns over time to better understand changes in the urban space
- Investigate relationship between migration flows and public policies
- Continue with an interdisciplinary approach
  - These studies are essential to develop well-informed urban planning policies to deal with issues of spatial segregation

Spatial models

- Spatial models can estimate multivariate models to verify the association
  - Of several independent variables (e.g., age, education, color/race, occupation, migration, fertility)
  - With a specific dependent variable (e.g., income)

- These models deal with spatial dependence by measuring the influence of neighboring areas for several variables at the same time (Anselin, Rey 2014; LeSage, Pace 2009)
  - Spatial autoregressive models

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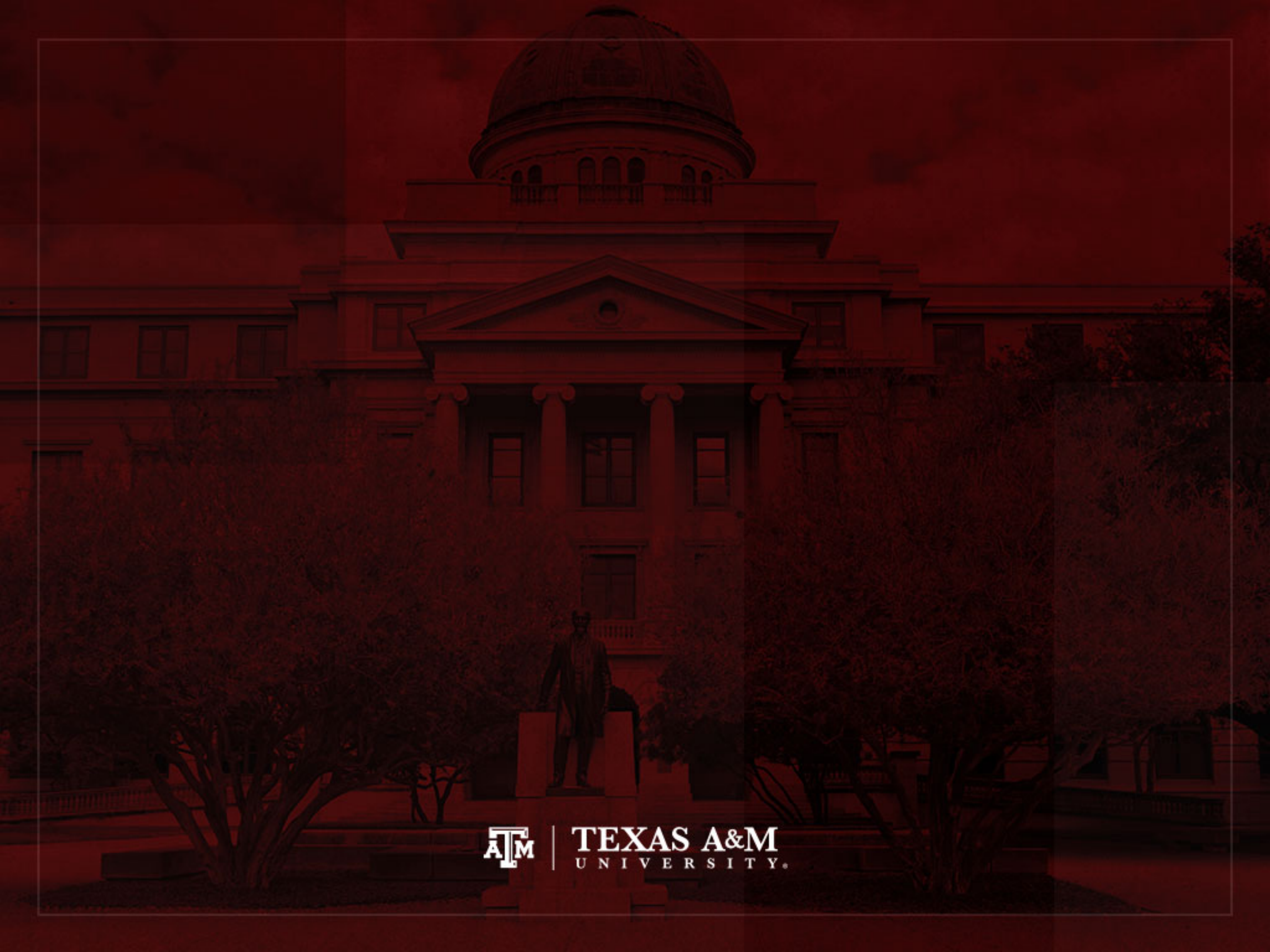
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