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Using comparative approaches to model deprivation in Antananarivo, Madagascar: a multidimensional analysis using principal components analysis and weighting system across meso and macro scales

Abstract

Rapid population growth and global urbanization pose socio-economic challenges, causing inequalities in Global South (GS) cities, such as the proliferation of deprived areas. This study aims to develop methods for mapping and characterizing urban deprivation in GS cities using the IDEAMAPS framework, focusing on household, area, and area-connect levels. The methodology employs 23 indicators across five domains, with a weighting system applied at macro (agglomeration of Antananarivo) and meso (Urban Commune of Antananarivo - CUA) scales, alongside Principal Component Analysis (PCA) and population-weighted analysis. A variable reduction process assessed the impact of simplifying indicators while retaining explanatory power. Results demonstrated significant spatial contrasts in deprivation between central and peripheral areas and eastern and western neighborhoods. The equal weighting system provided an intuitive overview, showing that 53% of neighborhoods were privileged at the macro scale, while 15% were highly deprived. At the meso scale, 27% of neighborhoods were highly deprived, emphasizing the importance of finer spatial scales to uncover localized disparities. PCA reduced data complexity and identified key deprivation dimensions but remains sensitive to outliers. Population-weighted analysis revealed the misalignment between deprivation level and population density, highlighting the need for targeted interventions in densely populated neighborhoods. Variable reduction confirmed model robustness but underscored the importance of retaining critical variables. This study highlights the need for accurate, multi-scale assessments to inform policies addressing urban inequalities. Future research should integrate advanced spatial techniques, temporal dynamics, and additional indicators, such as governance and environmental hazards, to refine deprivation analyses and guide inclusive urban policies.

Keywords

Multidimensional analysis; Deprived urban areas; Weighting system; Principal Component Analysis; Scale; Global South cities; Antananarivo

1. Introduction

According to the United Nations, more than half of the world's population now resides in urban areas, and this will rise to 68% by 2050, with an even higher percentage in developing regions, notably sub-Saharan Africa and South Asia (UN-Habitat, 2018). This demographic shift and rapid urbanization have generated massive population growth in small spaces (Amponsah et al., 2022; Ritchie & Roser, 2018) and have exacerbated urban poverty and social marginalization (Zahra et al., 2018; Zhang, 2016; UN-Habitat, 2022).

In the Global South (GS), deficient urban governance has resulted in the segmentation of cities, thus straining local authorities' capacities to meet their citizens' needs (Oranje et al., 2020; Watson, 2009; Yunda & Sletto, 2020). This has led to what is commonly called "deprived urban areas," including informal settlements and slums (Thomson et al., 2020; Kuffer et al., 2021; Abascal, Rodríguez-Carreño, et al., 2022; Luo et al., 2022). These areas reflect the persistent inequalities in the urban centers, where inhabitants face precarious living conditions, widespread poverty, limited access to essential services such as drinking water, sanitation and decent housing, and inadequate infrastructure (Campos et al., 2022; Murillo, 2012; Satterthwaite & Mitlin, 2013; Sridhar & Mavrotas, 2021).

The concept of "deprived urban areas" is crucial in understanding contemporary socio-economic dynamics in GS cities (Thomson et al., 2020), particularly concerning Sustainable Development Goal (SDG) 11 aimed at "making cities and human settlements inclusive, safe, resilient and sustainable." More concern for the difficulties residents face in these areas would enable governments, international organizations, and local stakeholders to better target policies and programs to improve their resident's quality of life (Ajami et al., 2019; Kuffer et al., 2021). Furthermore, by recognizing and addressing the specific challenges these areas face, efforts can significantly contribute to reducing social inequalities, promoting social and economic inclusion, and strengthening the resilience of cities to challenges such as climate change and natural disasters (Chamhuri et al., 2012; Thomson et al., 2019; Abascal, Rothwell, et al., 2022).

Various characteristics have been put forward to define deprived urban areas; however, those characteristics are often limited to indicators related to households or specific aspects of the regions (Thomson et al., 2019; Lilford et al., 2019). For example, although widely adopted, the United Nations' definition of slums focuses mainly on household characteristics (UN-Habitat, 2004). Similarly, informal settlements are often defined in terms of their development without state control, irregular development patterns, and morphological structures (Dovey & King, 2011; Kamalipour & Dovey, 2019; Wang et al., 2022), thus neglecting other dimensions of urban deprivation. While helpful, these approaches fail to capture the multidimensional complexity of urban deprivation

(Mahabir et al., 2016; Thomson et al., 2020). It may even bias the identification of deprived areas by failing to account for intra-zonal disparities, where some households may be deprived but located in apparently privileged areas or households classified as privileged but located in deprived areas (Lemma et al., 2006; Engstrom et al., 2013; Thomson et al., 2020), due to several environmental factors such as exposure to risk or lack of green space, services and infrastructure (Graesser et al., 2012; Engstrom et al., 2015; Ezeh et al., 2017; Thomson et al., 2019).

In this perspective, Thomson et al. (2020) have highlighted the need for an analytical framework that captures the complex dynamics of deprived urban areas. The IDEAMAPS framework developed by Abascal, Rothwell, et al. (2022) is a promising response to this need, standing out as an innovative method for assessing urban deprivation at different spatial scales. It proposes a structure combining criteria at three levels of analysis: household, area, and area connectivity levels, enabling a more comprehensive and nuanced assessment of the challenges facing deprived urban areas. By integrating household characteristics, housing conditions, structure, and spatial connectivity of urban neighborhoods, this framework offers a comprehensive and contextualized approach to guide efforts to improve living conditions in these areas.

Several approaches can be used to implement this framework and generate interesting deprivation level mappings, among them the use of advanced technologies such as visual or machine-learning classification of remote sensing data (Duque et al., 2017; Kuffer et al., 2018; Williams et al., 2018; Ibrahim et al., 2019; Dufitimana & Niyonzima, 2023). While these methods identify signs of urban precariousness, they are usually limited to specific criteria and do not always encompass essential variables concerning housing or social factors (Owusu et al., 2021). In addition, they often require high-resolution data, which is costly and computationally demanding, and they may not sufficiently consider the needs of poor people living in sustainable housing and facing multiple deprivations (Mahabir et al., 2018; Thomson et al., 2020).

Although integrating various indicators of urban deprivation is complex (McLennan et al., 2019), two methods can represent and analyze the multifaceted nature of deprivation. Firstly, the weighted summative approach, widely used to represent deprived urban areas, allows a customized weighting of each variable according to its influence on the urban areas studied (Baud et al., 2009; Cabrera-Barona & Ghorbanzadeh, 2018; McLennan et al., 2019; Kitsuki & Managi, 2022; Kuffer, Ali, et al., 2023). This method enables a rapid assessment of deprivation across the three levels of analysis (McLennan et al., 2019; Allik et al., 2020). Secondly, Principal Component Analysis (PCA), a proven approach for detecting deprived urban areas, elucidates the integration of variables and their impact within the IDEAMAPS framework (Krishnan, 2015; Aungkulanon et al., 2017; Basu & Das, 2021; Luo et al., 2022). PCA is a robust bottom-up approach capable of rapidly unraveling this framework, highlighting the observed discrepancies and the various sub-dimensions of urban deprivation that influence living conditions in deprived areas (Luo et al., 2022).

The geographical aspects of urban deprivation, the specific challenges urban communities face at more local levels, and intra- and inter-urban disparities in deprivation are often insufficiently examined (Lemma et al., 2006; Thomson et al., 2020; Luo et al., 2022). Furthermore, the representation of these areas often neglects population size, which can lead to a distorted representation of urban deprivation due to the impact of sparsely populated areas on the analysis, hindering the prioritization of interventions (Engstrom et al., 2015; Patel et al., 2020). As we scrutinize the deficiencies of customary delineations of deprived urban regions and assess the constraints of standard mapping techniques, a pivotal inquiry arises: How can we develop more comprehensive and nuanced methods for identifying and mapping deprived urban areas in GS cities, considering the multiple dimensions of urban deprivation, intra- and inter-urban disparities, and specific geographical and demographic aspects?

The area studied is the agglomeration of Antananarivo, which has a population with diverse socio-economic characteristics showing significant differences in housing, neighborhoods, availability of infrastructure, and services. Disparities between communes are apparent, but even within communes, essential distinctions exist. Post-colonial fragmentation of neighborhoods and marked differences in urban planning create highly fragmented areas (Ranaivoarimanana, 2017; MAHTP & JICA, 2019). Some neighborhoods enjoy privileges while others are neglected, suffering from a lack of investment and a lax approach to risks, exposing them to multiple deprivation and classifying them among the most deprived areas. Although some studies of deprivation in Antananarivo exist (Wachsberger, 2009; Rabemalanto, 2018), their ability to capture multidimensionality at the agglomeration scale remains limited.

2. Study area

Antananarivo's agglomeration (Greater Antananarivo - GT) extends over the central highlands of the Malagasy capital, with a total surface area of 76,800 hectares. It includes the urban commune (CUA) and thirty-seven peripheral communes. The agglomeration is subdivided into a dense mesh of 571 neighborhoods called "Fokontany", representing the smallest recognized administrative unit (Figure *1*). According to projections from the INSTAT (Institut National de la Statistique) for 2022, the agglomeration had a population of around 3.3 million, with 48.5% residing in the CUA. At the Fokontany level, population densities vary widely, ranging from 2 to 2,405 inhab/ha, with an average of 174 inhab/ha. These neighborhoods cover 2 to 1,245 hectares, with an average area of 130 hectares, equivalent to a radius of approximately 643 meters.

The distribution of population and buildings in the agglomeration follows a historical trajectory. The first buildings sprang up mainly on the hills of the CUA (

a. Population density (inhab/ha) b. Elevation of built-up areas at ground level

Figure 1.b). Population density is lower in the central neighborhoods where service activities are concentrated (

a. Population density (inhab/ha) b. Elevation of built-up areas at ground level

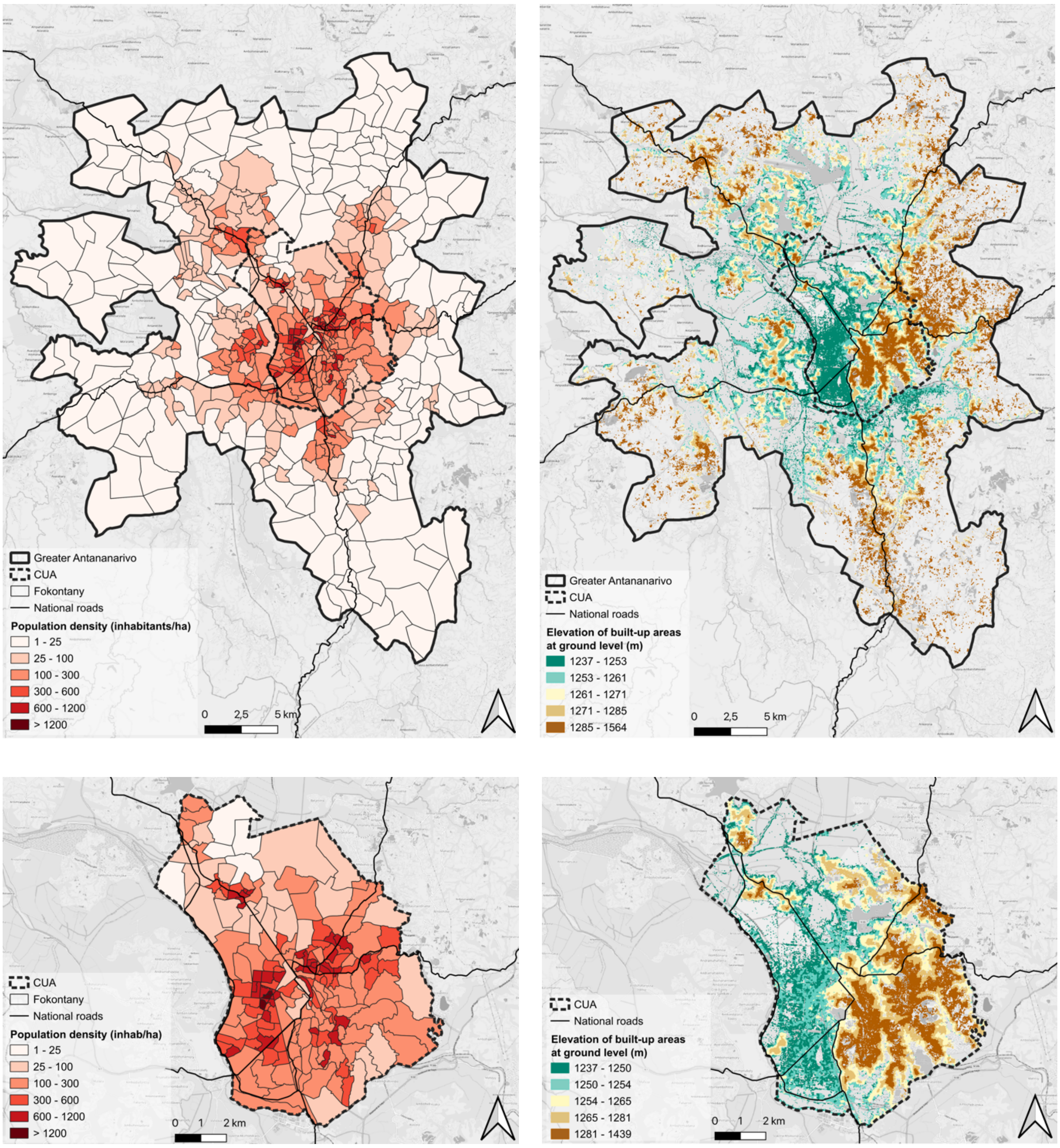
Figure 1.a) (Rabemalanto, 2018).

Urban expansion then spread westwards, where buildings are at lower altitudes (

a. Population density (inhab/ha) b. Elevation of built-up areas at ground level

Figure 1.b) (Esoavelomandroso-Rajaonah, 1989). These wetland areas are characterized by high population density and relatively inexpensive land (Godinot et al., 2010).

In the 1990s and 2000s, peri-urbanization led to strong population growth in the CUA's peripheral neighborhoods, with the emergence of specific development hubs (Olisoa, 2012). Figure 1.a shows the high population density of these neighborhoods, particularly those to the north with the national airport, to the west near industrial zones and significant university centers, and along national highways. The neighborhoods furthest from the center are the least densely populated.



a. Population density (inhab/ha) b. Elevation of built-up areas at ground level

Figure 1. Agglomeration of Antananarivo and CUA

Data sources: INSTAT; United States Geological Survey (USGS); Open Buildings

3. Data and methodology

3.1. Data used

Our methodology is based on the IDEAMAPS "Domain Deprivation Framework" developed by Abascal, Rothwell, et al., (2022). This framework conceptualizes urban deprivation as a multidimensional phenomenon across nine domains analyzed at three levels: Household Level (HL), Area Level (AL), and Area-Connect Level (ACL), to capture the complex interactions that shape urban deprivation.

With 70 proposed indicators, the framework requires adaptation to local contexts while maintaining a consistent and robust analysis (Figure 2).

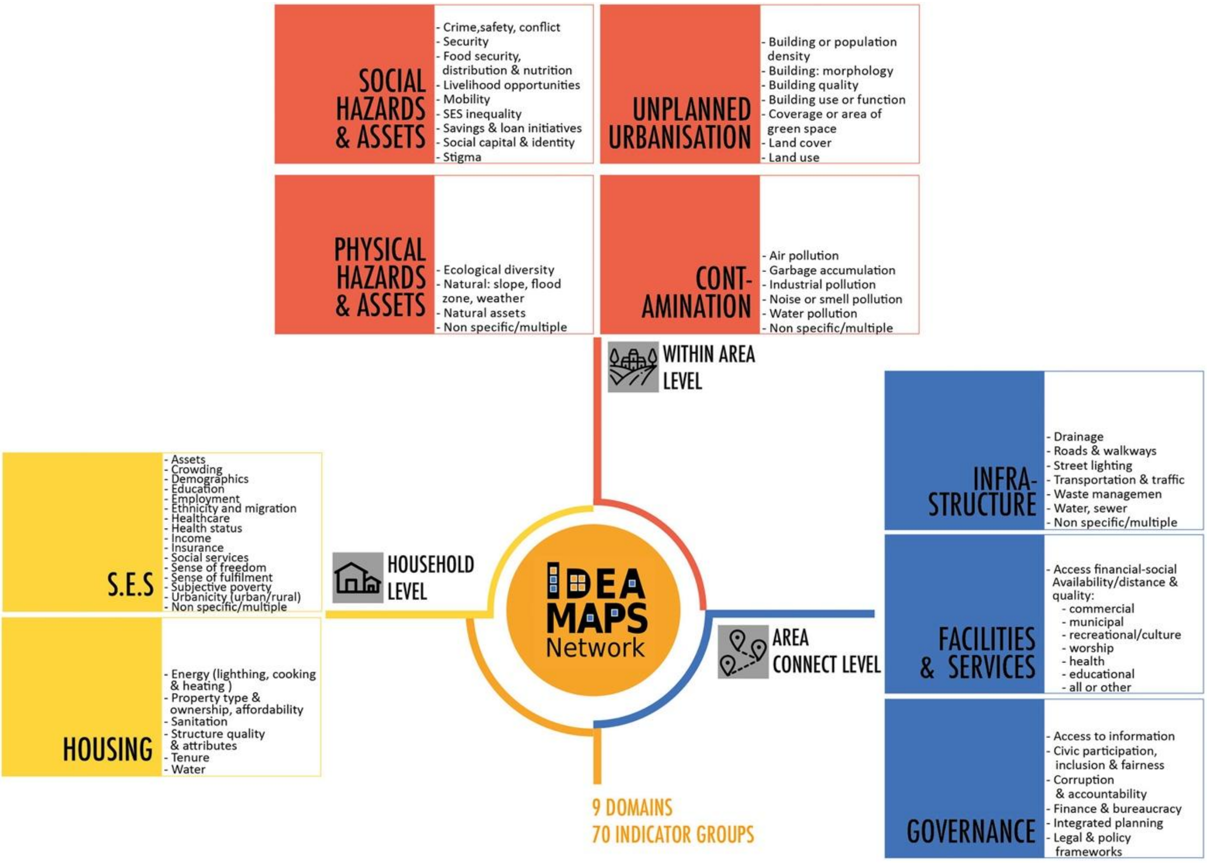


Figure 2. Diagram of IDEAMAPS (Abascal, Rothwell, et al., 2022)

Twenty-three indicators across five domains were selected based on data availability and their relevance to urban deprivation (Figure 3). The primary data source was the INSTAT census, supplemented by satellite observations and public geographic databases. Areas like governance, contamination, and natural hazards were excluded due to a lack of reliable data or the need for specific analyses, particularly for natural hazards.

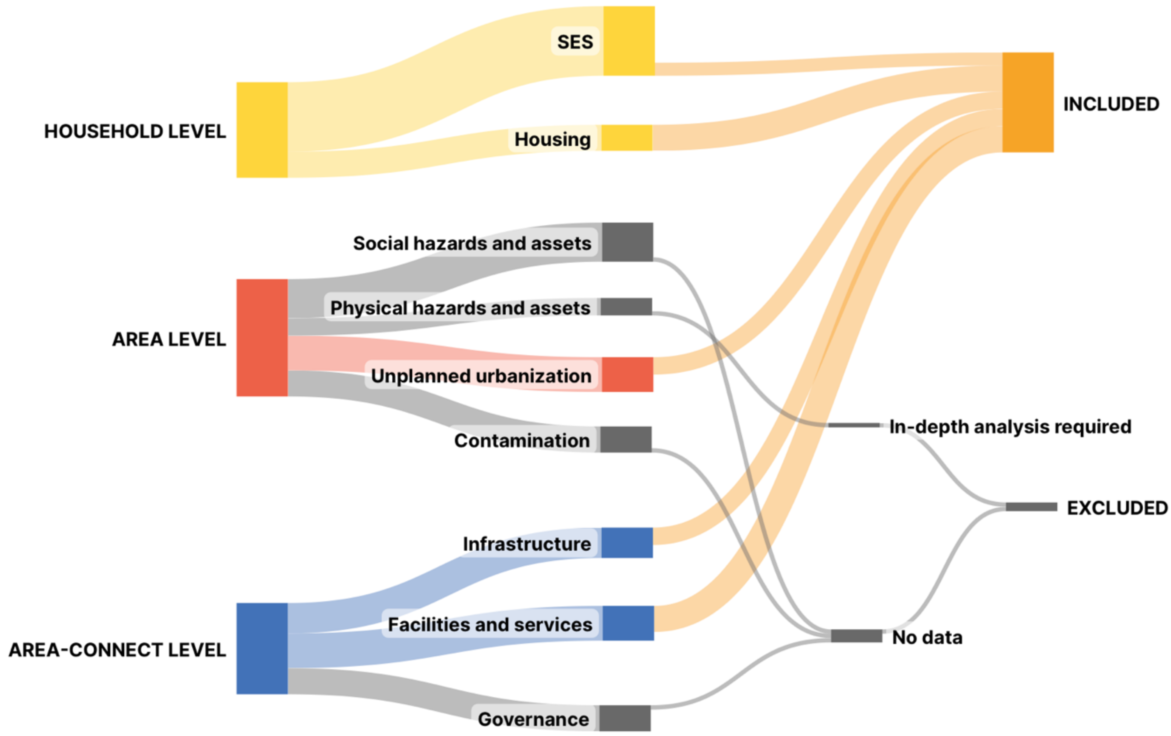


Figure 3. Overview of included and excluded domains in the analysis

The selected indicators reflect key relationships between the dimensions of urban deprivation. For example, socio-economic status (SES), as measured by asset ownership, education, and employment, can influence access to quality housing and essential infrastructure, such as electricity and drinking water. At a broader level, factors like building density can exacerbate overcrowding, limit access to green spaces, and increase heat stress. These interactions show that deprivations in one area often affect others.

While limiting the analysis to five domains may overlook certain aspects of urban deprivation, it aligns with Antananarivo's local priorities and challenges. Rapid urbanization, socio-economic inequalities, and limited infrastructure access are significant issues (Droy & Andrianjaka, 2003; Eudora & Fernandez, 2018; Rabemalanto, 2018). The selected indicators address these challenges while considering data availability constraints.

The following table lists the indicators selected for analysis, with their sources, dates, and brief descriptions.

Table 1. Selected indicators

		Acr.	Indicator	Description (Source & Date)
			HOUSEHOLD LEVEL	
SES	1	Ass	Assets	Assets classified into two categories: personal and household equipment, as well as cars (INSTAT, 2018)
	2	Edu	Education	School attendance and level of education (INSTAT, 2018)
	3	Emp	Employment	Employment and professional status (INSTAT, 2018)
Housing	4	Ten	Tenure	Housing and land tenure status (INSTAT, 2018)
	5	Mat	Material quality	Sustainability of building walls, roofs, and floors (INSTAT, 2018)
	6	Eng	Energy	Lighting and cooking mode (INSTAT, 2018)
	7	Wat	Water sources	Water supply (INSTAT, 2018)
	8	San	Sanitation	Toilet facilities and sharing (INSTAT, 2018)
	9	Was	Waste disposal	Garbage disposal (INSTAT, 2018)
			AREA LEVEL	
Unplanned urbanization	10	Ls	Living space	Floor space per person (INSTAT, 2018 – Open Buildings - OpB, 2022)
	11	Bda	Building area	Housing insecurity: surface area under 30m² (OpB, 2022)
	12	Bds	Building density	Spatial occupation by residential areas (OpB, 2022)
	13	Gsp	Green space area	Green space coverage: m2 per inhabitant (Centre de Coopération Internationale en Recherche Agronomique pour le Développement - CIRAD, 2022)
Infrastructure			AREA-CONNECT LEVEL	
	14	Dra	Drainage	Available network length by neighborhood (OpenStreetMap - OSM, 2022)
	15	Rd	Road	
	16	Wati	Water	
	17	Stl	Street lighting	Accessibility to street lighting in the neighborhood - VIIRS night light (National Aeronautics and Space Administration - NASA, 2021)
Facilities and servicies	18	Com	Commercial	Accessibility to services and facilities Nearest average distance to residential buildings (OSM, 2022)
	19	Cult	Cultural and recreational	
	20	Adm	Administrative	
	21	Wor	Worship	
	22	Hth	Health care	
	23	Edf	Educational	

For confidentiality reasons, HL data were received in aggregate form at the neighborhood level (Table 1).

3.2. Methodology

We compared two approaches to assess multidimensional deprivation: a multi-level classification using an equitable weighting system at the meso and macro scales and a PCA. We also included an assessment based on the share of the population residing in each neighborhood relative to the total number of inhabitants at the agglomeration level. Additionally, a variable reduction process was applied to assess the impact of reducing the number of indicators (Figure 4).

- **Equal weighting system**

The weighting method adopts a top-down approach, following the three-dimensional structure provided by the IDEAMAPS framework. This approach is part of a Spatial Multi-Criteria Evaluation (SMCE), which aims to evaluate and guide decisions by incorporating various spatial criteria (Van Herwijnen, 1999; Zucca et al., 2008). SMCE considers that different criteria can influence a decision in different magnitudes.

The indicators were firstly pre-processed to generate deprivation scores for each neighborhood, rated from 1 (most privileged) to 5 (most deprived), based on quintiles balanced according to the number of neighborhoods. The appendix provides detailed information on this pre-treatment process.

We considered each dimension to be equally important, with the same weight (1/3) assigned to each level: household, area, and area-connect levels. This decision stems from a lack of specific local knowledge that would allow for significant differentiation among indicators (Decancq & Lugo, 2013). The results of the deprivation analysis were obtained by weighting the values of each indicator at each scale. These results were then classified into five levels of deprivation (from 1 for the most privileged to 5 for the most deprived), ensuring that a fair number of neighborhoods were included in each category. This methodological approach was designed to ensure that each spatial scale makes a uniform contribution to the assessment of deprivation.

This method was applied at two scales, covering the entire agglomeration and the CUA. This staggered approach provided an in-depth understanding of deprivation at the agglomeration level, enabling analysis of disparities between urban and rural areas and between urban areas. This dual perspective reinforces our findings' relevance for various applications, from local policies to a more global vision (Thomson et al., 2020).

- **Principal Component Analysis (PCA)**

PCA is an exploratory approach that focuses on the most influential factors, analyzes the relationships between variables, and seeks to identify hidden patterns and intrinsic structures in the data (Jackson, 2005). PCA groups variables into new, independent dimensions through an orthogonal transformation of the original data, improving variable interpretability while limiting the loss of information (Jolliffe & Cadima, 2016). It relies on data adequacy using the Pearson correlation matrix, the Kaiser-Mayer-Olkin (KMO) test, and Bartlett's sphericity test (Cerny & Kaiser, 1977; Dziuban & Shirkey, 1974; Kaiser, 1970; Tabachnick et al., 2013).

Data were standardized beforehand to eliminate bias resulting from the diversity of measurement units. To quantify deprivation levels, we adopted the "SoVi" method, initially designed for vulnerability analysis (Ajtai et al., 2023) but adaptable to multidimensional deprivation analysis (Luo et al., 2022). The extracted components were then subjected to varimax rotation to identify significant variables with high factor loadings and eigenvalues greater than 1 (Cerny & Kaiser, 1977). The resulting scree plot illustrates the relevance of the selected components, defining multiple deprivation sub-domains based on specific indicators.

The normalized scores for each principal component reveal various aspects of deprivation and were combined to calculate the global index of multiple deprivation.

Variable reduction

A systematic approach to variable reduction was implemented to assess whether a reduced set of indicators could produce results comparable to those obtained with the complete set of variables.

The process began with the complete set of variables. At each step, one variable was removed based on its contribution to the first two principal components and its correlation with other variables. Variables with low contributions to the principal components and high correlations with others were prioritized for exclusion. After each reduction, the PCA was recalculated to ensure the retention of key data patterns.

Variables were excluded in the following order:

- Low contribution and low correlation variables.
- Low contribution and high correlation variables.
- Medium contribution and low correlation.
- Redundant medium or high contribution variables.

High contribution variables with little or no correlation were retained.

The impact of variable reduction was assessed through two analyses, using the set of 23 variables as a reference:

- Global classification: Percentage of correctly classified neighborhoods, calculated as:

$$\mathrm{I_g} = \frac{\text{Number of neighborhoods correctly classified}}{\text{Total number of neighborhoods}} \text{ x 100}$$

- Deprivation classification: Percentage of neighborhoods correctly classified within each deprivation class, calculated as:

$$\mathrm{I_c} = \frac{\text{Number of neighborhoods correctly classified per class}}{\text{Total number of neighborhoods per class}} \text{ x 100}$$

- **Population weight**

This method is based primarily on the results of the deprivation score derived from the PCA with the complete set of variables. It goes beyond simple indicator-based deprivation mapping by considering each neighborhood's demographic importance. It aims to mitigate the impact of sparsely populated areas and guide intervention policies more precisely (Engstrom et al., 2015; Durán & Condorí, 2019). Thus, areas combining a high deprivation and a significant number of residents were given greater weight in the analysis.

The deprivation level was adjusted according to the percentage of the population of each neighborhood to the total population of the agglomeration using the following equation:

$$S_i = P_i \times \frac{Pop_i}{\sum_{j=1}^{n} Pop_j}$$

S_i is the weighted score for neighborhood i
P_i is the deprivation level of neighborhood i
Pop_i is the number of inhabitants of the neighborhood i
$\sum_{j=1}^{n} Pop_j$ represents the total number of inhabitants of all neighborhoods in the agglomeration.

After obtaining the weighted scores, the neighborhoods were ranked according to their degree of deprivation, from lowest to highest (from 1 to 5). This classification aims to target interventions in the most disadvantaged neighborhoods, where needs are most pressing, thus concentrating resources where they are most needed.

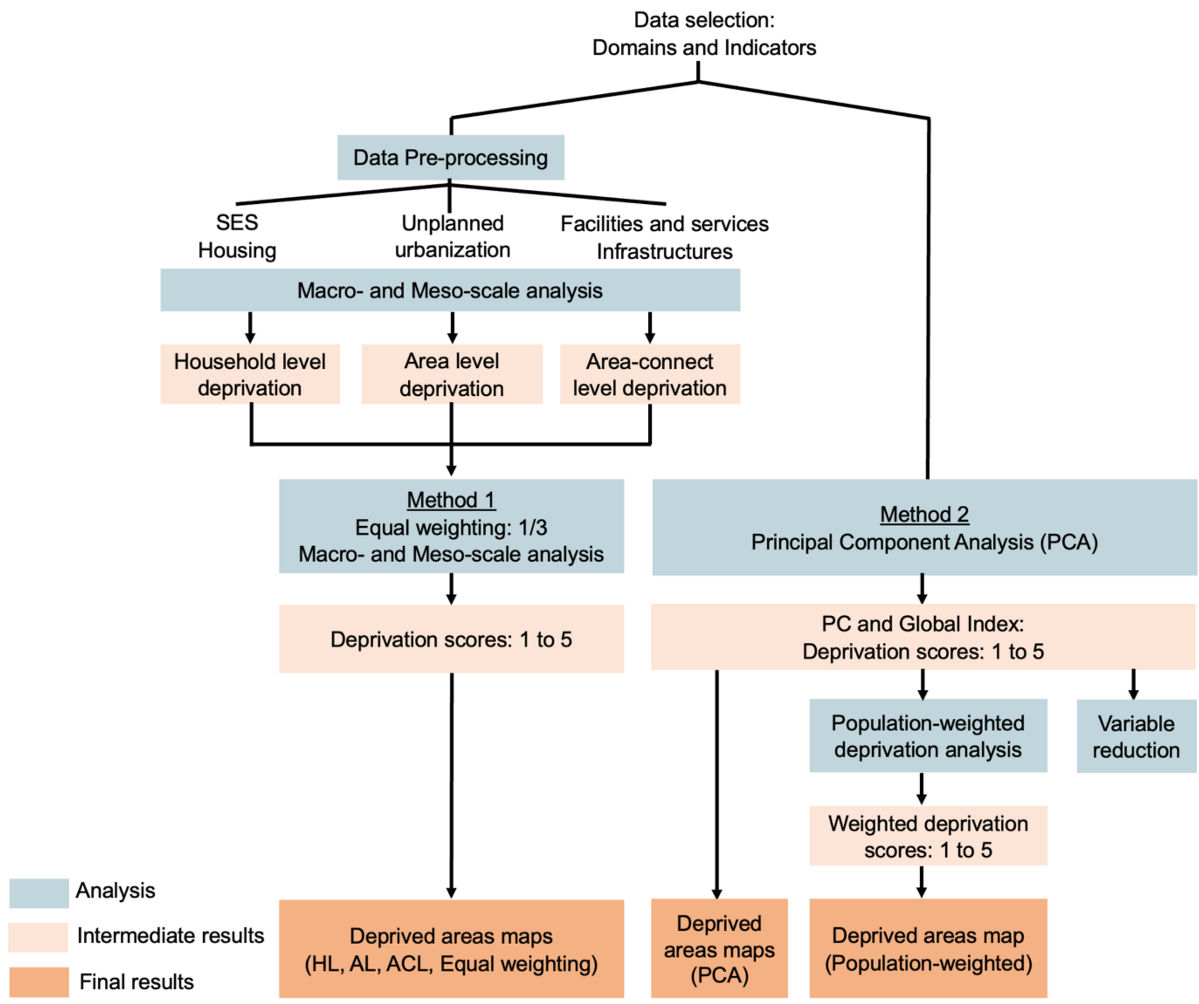


Figure 4. Methodology

Analyses were conducted using SPSS and R Studio for statistical analysis and QGIS for mapping.

4. Results

4.1. Correlation and analysis of variables

An examination of the variables revealed significant disparities at HL. According to Table 2, nearly half the population (49%) live in privileged areas (levels 1 and 2) in terms of asset ownership (Ass), while 14% reside in more deprived areas (level 5). Similar trends are observed in housing materials (Mat, 5% - level 5), education access (Edu, 9% - level 5), energy (Eng, 4% - level 5), and water sources (Wat, 6% - level 5). However, sanitation (San) and waste management (Was) are more evenly distributed. Regarding land tenure (Ten), 47% of the population is deprived (levels 4 and 5), indicating that better living conditions do not always mean land ownership, indicating that people with better living conditions do not necessarily own land and housing.

At AL, a significant proportion of the population resides in areas with high residential density (Bds) (61% - levels 4 and 5), limited green space (Gsp: 64% - levels 4 and 5), and restricted living space (Ls: 59% - levels 4 and 5) (Table 2). Concentrating on dense urban environments highlights the quality of life and challenges of green space access.

At ACL, a large share of the population benefits from high accessibility to infrastructure and services (Dra, Rd, Wati, Stl, Com, Cult, Adm, Wor, Hth, Edf), with over 50% of the population classified as privileged (levels 1 and 2).

Table 2. Descriptive analysis and population distribution in GT: Darker orange indicates higher shares, while blue represents lower shares.

Level	Indicators	Value		Share of population (%)				
				Most Privileged				Most Deprived
		Mean	Std. Deviation	1	2	3	4	5
HL	Ass (%)	48,10	5,81	24	25	22	15	14
	Edu (%)	77,81	3,56	26	28	21	16	9
	Emp (%)	91,02	3,58	9	24	22	25	20
	Ten (%)	70,18	10,18	8	18	27	24	23
	Mat (%)	80,91	16,83	29	32	21	13	5
	Eng (%)	78,73	23,45	25	33	27	11	4
	Wat (%)	57,26	39,62	23	31	26	14	6
	San (%)	41,59	17,96	15	25	26	22	12
	Was (%)	96,14	8,17	21	24	21	16	18
AL	Ls (m2/pers)	15,07	11,70	6	13	22	27	32
	Bda (%)	47,66	8,36	28	24	17	18	13
	Bds	0,12	0,11	5	10	24	33	28
	Gsp (m2/inhab)	595,03	1234,58	4	10	22	37	27
ACL	Dra (km/km2)	4,13	6,99	24	30	21	15	10
	Rd (km/km2)	1,63	2,34	26	29	20	10	15
	Wati (km/km2)	2,15	2,77	28	32	25	3	12
	Stl	3,84	3,70	23	40	22	10	5
	Com (km)	0,78	0,94	24	32	27	11	6
	Cult (km)	1,03	0,87	21	25	23	22	9
	Adm (km)	0,70	0,81	23	33	28	11	5
	Wor (km)	0,44	0,38	22	28	28	15	7
	Hth (km)	2,24	1,67	24	35	24	12	5
	Edf (km)	2,65	2,17	27	35	16	15	7

Table 3 shows that in areas where households own more goods (Ass), housing is typically made with high-quality materials (Mat), improving living conditions. These areas also benefit from better access to drinking water (Wat), modern sanitation (San), health services (Hth), public infrastructure (Rd), and education (Edf). With more significant financial resources, these households can invest more in education (Edu), leading to better access to quality education.

With better access to modern energy sources (Eng), these areas also benefit from a more reliable water supply and better street lighting (Wati, Stl), contributing to perceptions of safety. This link extends to other services and infrastructures: Com, Cult, Wor, Adm, Dra (Table 3).

These characteristics, indicating higher living standards and better access to amenities, are generally observed in densely populated areas (Bds), often linked to reduced green space (Gsp). This highlights the distinct nature of urban centers, especially in the GS (Bille et al., 2023; Verma & Das, 2024). In contrast, rural areas are less likely to exhibit these features.

Table 3. Pairwise correlations between all variables; p-values (NS: p-value > 0,05)
The dark orange color indicates very high correlations (-1 to -0.75 and 0.75 to 1), the light orange color indicates high correlations (-0.75 to -0.5 and 0.5 to 0.75), and the light blue color represents low correlations (-0.5 to 0.5).

		HL									AL				ACL									
		Ass	Edu	Emp	Ten	Mat	Eng	Wat	San	Was	Ls	Bda	Bds	Gsp	Dra	Rd	Wati	Stl	Com	Cult	Hth	Wor	Adm	Edf
HL	Ass	1,00																						
	Edu	0,86	1,00																					
	Emp	0,04 NS	-0,01 NS	1,00																				
	Ten	0,13	0,03 NS	0,03 NS	1,00																			
	Mat	0,50	0,63	-0,16	-0,19	1,00																		
	Eng	0,55	0,72	-0,21	-0,20	0,90	1,00																	
	Wat	0,36	0,52	-0,14	-0,25	0,50	0,60	1,00																
	San	0,54	0,51	0,13	0,17	0,13	0,16	0,28	1,00															
	Was	0,33	0,40	0,06 NS	0,07 NS	0,15	0,24	0,10	0,19	1,00														
AL	Ls	-0,12	-0,29	0,01 NS	0,05 NS	-0,34	-0,43	-0,50	-0,05 NS	0,00 NS	1,00													
	Bda	0,70	0,72	0,05 NS	0,03 NS	0,34	0,43	0,24	0,39	0,45	0,01 NS	1,00												
	Bds	-0,43	-0,59	0,10	0,14	-0,48	-0,63	-0,64	-0,25	-0,25	0,49	-0,38	1,00											
	Gsp	-0,37	-0,50	0,18	0,12	-0,74	-0,77	-0,39	-0,04 NS	-0,11	0,45	-0,25	0,45	1,00										
ACL	Dra	0,50	0,56	-0,03 NS	-0,02 NS	0,25	0,40	0,49	0,40	0,18	-0,37	0,31	-0,67	-0,26	1,00									
	Rd	0,50	0,54	0,03 NS	-0,02 NS	0,27	0,39	0,45	0,36	0,16	-0,29	0,37	-0,43	-0,25	0,62	1,00								
	Wati	0,60	0,71	0,00 NS	0,00 NS	0,45	0,54	0,60	0,43	0,23	-0,40	0,50	-0,66	-0,35	0,58	0,58	1,00							
	Stl	0,59	0,69	-0,02 NS	-0,13	0,46	0,61	0,70	0,42	0,20	-0,46	0,45	-0,66	-0,40	0,70	0,65	0,68	1,00						
	Com	0,46	0,59	-0,20	-0,21	0,70	0,76	0,62	0,21	0,16	-0,31	0,40	-0,55	-0,60	0,36	0,35	0,48	0,55	1,00					
	Cult	0,43	0,52	-0,09	-0,11	0,52	0,57	0,46	0,28	0,17	-0,18	0,42	-0,43	-0,44	0,32	0,27	0,42	0,45	0,73	1,00				
	Hth	0,48	0,66	-0,17	-0,17	0,76	0,83	0,61	0,16	0,13	-0,48	0,38	-0,64	-0,68	0,47	0,42	0,58	0,67	0,73	0,59	1,00			
	Wor	0,43	0,57	-0,19	-0,07 NS	0,62	0,69	0,45	0,06 NS	0,17	-0,36	0,39	-0,53	-0,57	0,35	0,31	0,44	0,46	0,57	0,41	0,65	1,00		
	Adm	0,46	0,59	-0,15	-0,24	0,75	0,78	0,55	0,12	0,16	-0,34	0,37	-0,55	-0,61	0,36	0,34	0,47	0,55	0,72	0,66	0,77	0,54	1,00	
	Edf	0,41	0,55	-0,12	-0,16	0,65	0,72	0,67	0,22	0,07 NS	-0,48	0,20	-0,60	-0,57	0,47	0,41	0,54	0,63	0,60	0,43	0,67	0,54	0,56	1,00

When statistical significance is assessed by calculating p-values, these correlations take on their whole meaning. A p-value < 0.05 indicates a statistically significant correlation (Andrade, 2019).

Table *3* shows non-significant (NS) p-values associated with weak correlations, which means the result of chance or other unconsidered variables. For example, correlations between employment and professional status (Emp) and other variables, as well as between housing and land tenure status (Ten) and other variables, have high p-values (> 0.05), suggesting no significant relationship. Conversely, strong correlations are linked to very low p-values (< 0.001), reinforcing the validity of these relationships.

4.2. Level of deprivation in each dimension

Household level

Table 4 highlights disparities in deprivation at the HL. In the CUA, 45% of residents live in highly deprived neighborhoods (levels 4 and 5), compared to 22% in GT. In contrast, affluent neighborhoods (level 1) represent only 12% of households in the CUA but 26%

in GT, mainly located in the central core of the agglomeration (Table 4; Figure 5.a; Figure 6.a).

A notable concentration of deprivation is observed in the western neighborhoods of the CUA, where the level of deprivation is significantly higher in the overall CUA analysis (Figure 6.a).

Area level

At the AL, 32% of GT's population lives in highly deprived areas (level 5), while only 6% reside in well-planned areas (level 1), primarily located in rural zones (Table 4 ; Figure 5.b).

At the CUA level, intra-urban differences are more pronounced, with central and eastern neighborhoods, which account for around 42% of the population (level 1 and level 2 - Table 4, Figure 6.b), less impacted by uncontrolled urbanization.

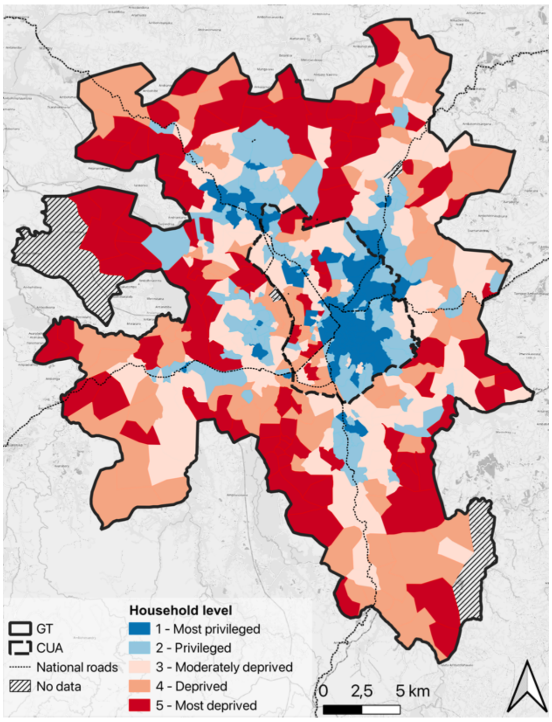
Area-connect level

At the ACL, a monocentric spatial structure emerges. In GT, the most deprived neighborhoods (levels 4 and 5), representing 14% of the population, are predominantly on the outskirts. In contrast, well-serviced neighborhoods (levels 1 and 2), comprising 60% of the population, are centrally located within the CUA Table 4 ; Figure 5.c). Within the CUA, western and northern neighborhoods (Figure 6.c), where 24% of the population resides (level 5), experience significant deprivation in terms of connectivity (Table 4).

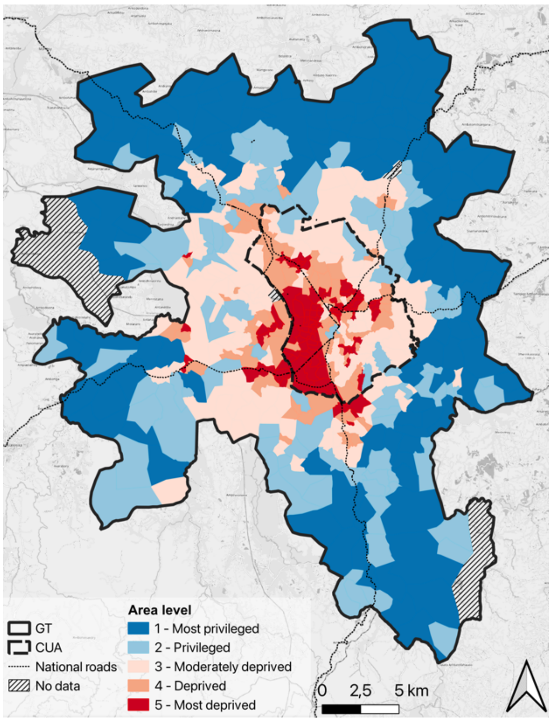
Peripheral neighborhoods generally lack adequate infrastructure and services, reflecting stark disparities compared to central neighborhoods regarding socio-economic status, housing conditions, and infrastructure (Figure 5.a,b). This highlights the numerical weight of peripheral neighborhoods with high deprivation despite their low population density.

Table 4. Level of deprivation in each dimension (% of the population)

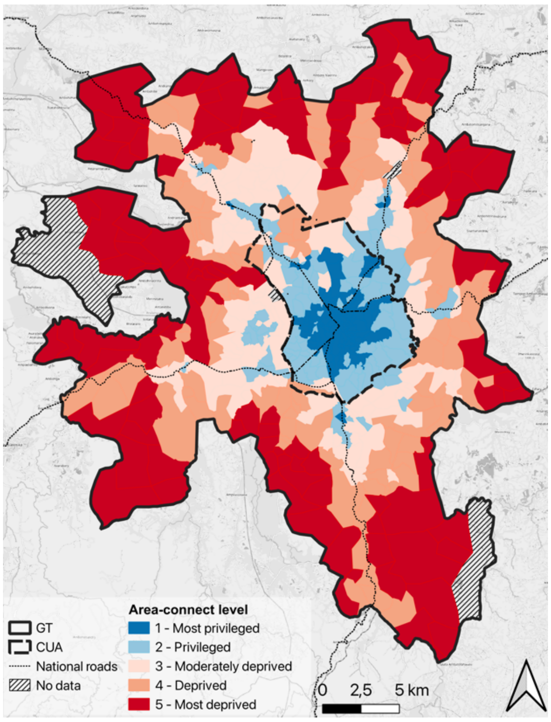
	GT					CUA				
Deprivation level	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Household level	26	28	24	14	8	12	19	24	21	24
Area level	6	12	27	23	32	24	18	21	13	24
Area-connect level	24	36	26	9	5	12	17	24	23	24



a. Household level

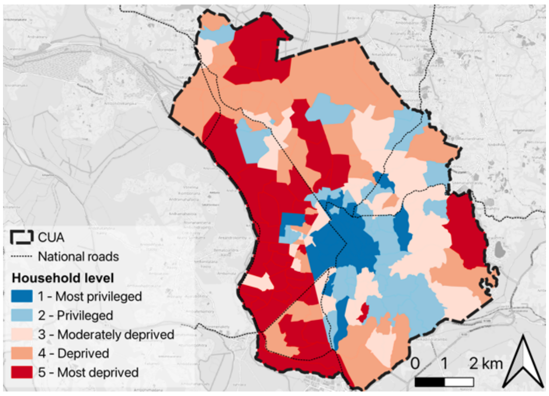


b. Area level

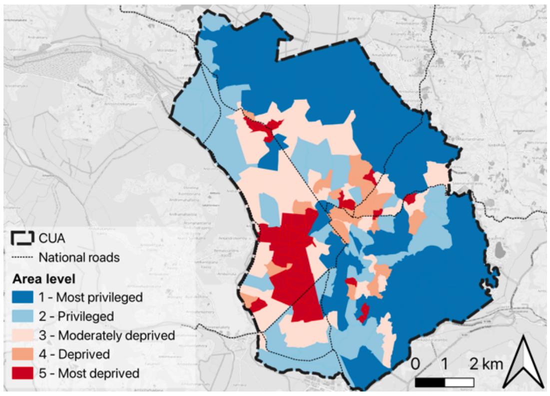


c. Area-connect level

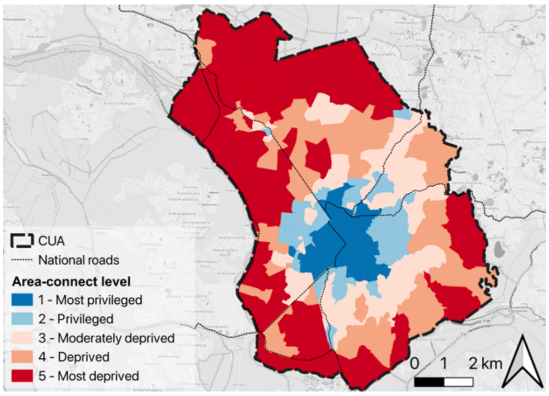
Figure 5. Level of deprivation – GT



a. Household level



b. Area level



c. Area-connect level

Figure 6. Level of deprivation – CUA

These results highlight a complex duality between dimensions while revealing significant differences between the GT and CUA scales of analysis. The high correlation between HL and ACL (0.724) on the GT scale indicates that affluent neighborhoods benefit from better infrastructure accessibility (Table 5). On the other hand, the negative correlation between HL and AL (-0.453) shows that these often very dense neighborhoods have limited living space and access to green spaces. The strong opposition between AL and ACL (-0.722) underscores the contrast between densely populated neighborhoods with limited access to green spaces and neighborhoods well served by infrastructure (Table 5).

In the CUA, these relationships are attenuated. The correlation between HL and ACL remains strong (0.702), confirming that affluent neighborhoods continue to benefit from better access to infrastructure. The correlations between AL and ACL (-0.182) and AL and HL (0.138) indicate that these neighborhoods are less exposed to the constraints of density, limited space, and reduced access to green spaces. They also show that access to infrastructure is reduced, reflecting a more balanced distribution of services (Table 5).

Table 5. Correlations between HL, AL, and ACL in the CUA and GT

	GT	CUA	Observation
HL-AL	-0,453	0,138	Negative in the GT and weakly positive in the CUA
HL-ACL	0,724	0,702	Strongly positive in both cases
AL-ACL	-0,722	-0,182	Strongly negative in GT, weaker in the CUA

These correlations are reflected in the distribution of CUA neighborhoods according to deprivation levels for HL, AL, and ACL, as illustrated in Table 6.

Table 6. Distribution of CUA neighborhoods according to deprivation levels for each pair of dimensions (HL-AL, HL-ACL, AL-ACL). Darker orange indicates higher proportions of neighborhoods in each deprivation level, while blue represents lower proportions.

	Proportion of neighborhoods (%)					
	1	**2**	**3**	**4**	**5**	**Total**
HL-AL	5	3	4	1	7	19
HL-ACL	14	9	7	6	10	45
AL-ACL	4	3	3	1	4	14

4.3. Equal weighting system

The equal weighting system results at the GT level (Figure 8. Level of deprivation – Weighted values – GT
) highlight three key elements. First, the eastern part of the agglomeration is less deprived than the western part. Second, neighborhoods near significant infrastructures, such as national roads and the airport, tend to be more advantaged, likely due to household and area-connectivity factors (

). Third, urban neighborhoods are more privileged than outlying areas, with 53% of the population in favored neighborhoods (levels 1 and 2), compared to 15% in the most deprived areas (level 5) (Figure 7). Some neighborhoods are reclassified at a medium level, notably those with different levels of deprivation in all three dimensions.

At the CUA level (Figure *9*), deprivation is more nuanced. Although some neighborhoods appear privileged compared to GT, this perception decreases internally compared to more deprived areas (27% at level 5). A consistent trend shows that neighborhoods in the west of the CUA face more deprivation (Figure 8. Level of deprivation – Weighted values – GT
, Figure 9. Level of deprivation – Weighted values – CUA
).

Population density is key in shaping perceptions of deprivation across different scales. The higher concentration of people in the CUA intensifies the deprivation-related challenges.

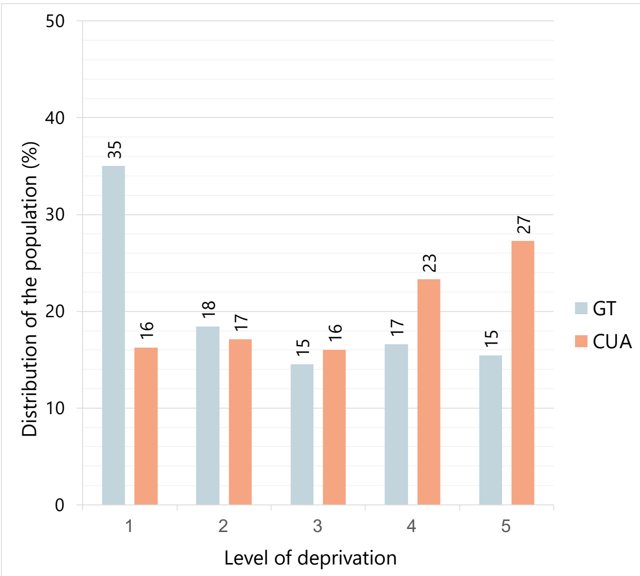


Figure 7. Distribution of the population according to deprivation levels at GT and CUA scales - Weighted values

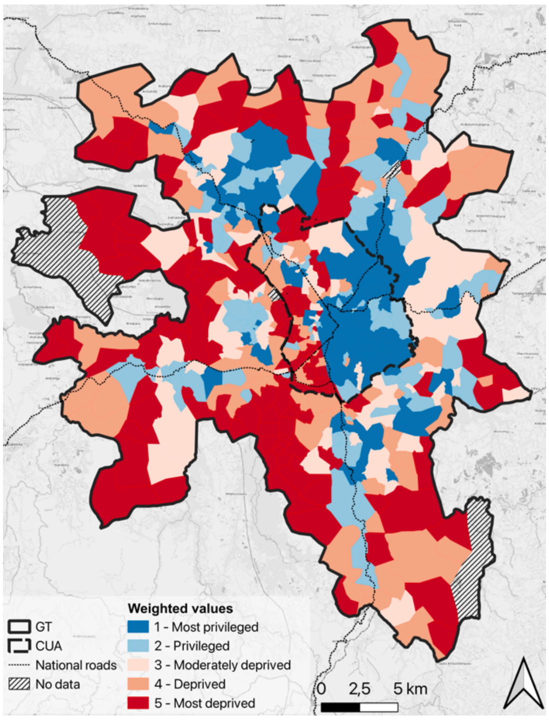


Figure 8. Level of deprivation – Weighted values – GT

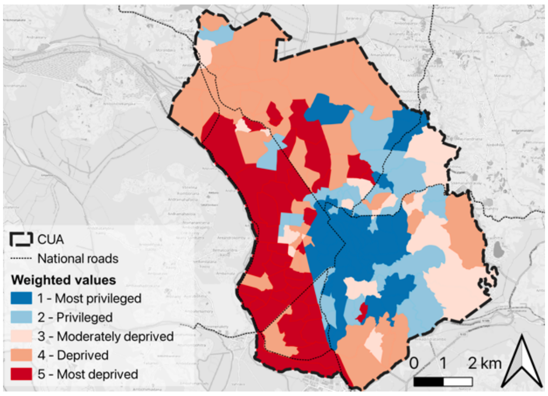


Figure 9. Level of deprivation – Weighted values – CUA

4.4. PCA

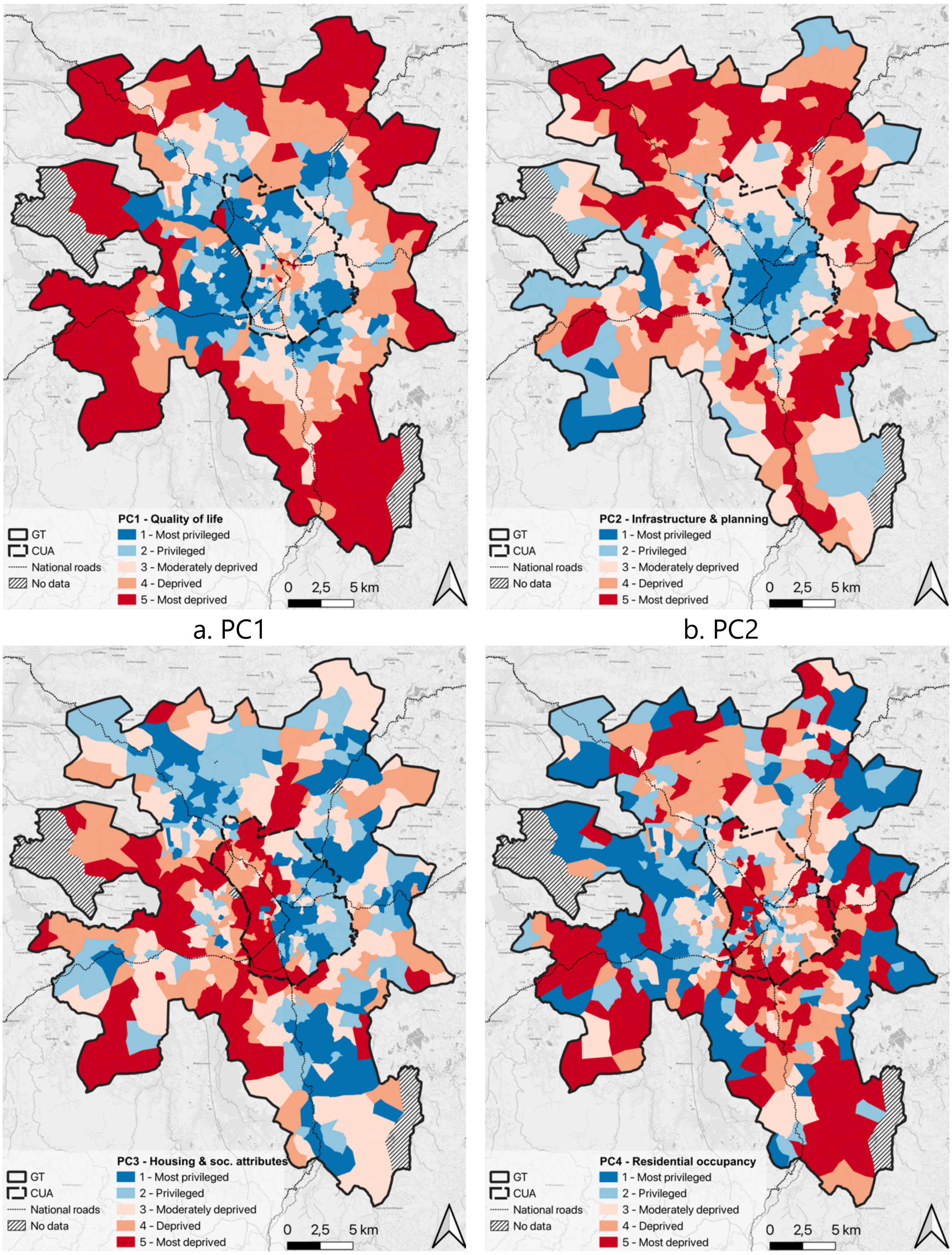
Multidimensional deprivation assessed through PCA scores

The statistical tests in SPSS revealed a KMO index of 0.93 and a high significance of Bartlett's sphericity test (p < 5%), confirming that the data is suitable for PCA (Kaiser, 1970; Dziuban & Shirkey, 1974; Cerny & Kaiser, 1977; Hair, 2009). We identified four principal components, considering only those with an eigenvalue greater than 1 (Table 7, Figure 11). These components explain 68.84% of the variation in the data.

Table 7 and Figure 10 detail the extracted PCs and their effects on deprivation, eigenvalue, and percentage of variance explained, with dominant loadings.

Table 7. Rotated components matrix

Component name	Effect	Eigen value	% variance explained	Rotated Component Matrix					
						Component loadings			
				Variables	Level	PC1	PC2	PC3	PC4
Quality of life	-	10,63	46,23	Mat	HL	**0,845**	0,174	0,23	0,146
				Eng	HL	**0,841**	0,328	0,263	0,142
				Gsp	AL	**-0,818**	-0,191	-0,07	0,025
				Hth	ACL	**0,743**	0,444	0,18	0,166
				Adm	ACL	**0,714**	0,266	0,244	0,338
				Wor	ACL	**0,707**	0,273	0,19	-0,066
				Com	ACL	**0,693**	0,284	0,282	0,344
				Edf	ACL	**0,586**	0,57	0,027	0,121
				Cult	ACL	**0,504**	0,182	0,399	0,383
				Emp	HL	**-0,416**	0,083	0,189	0,148
Infrastructure and planning	-	2,48	10,79	Dra	ACL	0,093	**0,801**	0,232	-0,002
				Stl	ACL	0,292	**0,78**	0,299	0,168
				Rd	ACL	0,068	**0,695**	0,305	0,025
				Wati	ACL	0,264	**0,694**	0,387	0,016
				Wat	HL	0,4	**0,68**	0,041	0,301
				Bds	AL	-0,423	**-0,675**	-0,165	-0,096
				Ls	AL	-0,393	**-0,623**	0,294	0,15
Housing and social attributes	-	1,66	7,25	Bda	AL	0,205	0,15	**0,823**	0,055
				Ass	HL	0,283	0,37	**0,759**	-0,08
				Edu	HL	0,447	0,466	**0,687**	-0,014
				Was	HL	0,089	0,005	**0,589**	-0,074
				San	HL	-0,163	0,433	**0,58**	-0,025
Residential occupancy	+	1,05	4,56	Ten	HL	-0,108	-0,017	0,261	**-0,846**
Total Variance explained			68,84						



a. PC1 b. PC2

c. PC3 d. PC4

Figure 10. Principal components

PC1 (46.23%) represents quality of life (Table 7). It indicates that better housing and access to services enhance quality of life, but these benefits can be offset by reduced green spaces and employment challenges. The most privileged neighborhoods are in the city center, while the most deprived are on the periphery (Figure 10.a).

PC2 (10.79%) reflects infrastructure and urban planning (Table 7). It shows that well-developed infrastructure attracts denser populations, reducing living space. CUA neighborhoods and low-density areas are more privileged regarding infrastructure accessibility (Figure 10.b).

Infrastructure and service accessibility, typically grouped under the ACL (Table 1), are classified into two distinct components in this analysis. Basic infrastructure and services have different impacts and are not always correlated.

PC3 (7.25%) relates to housing and social attributes (Table 7). It suggests that well-equipped homes are linked to higher education levels, effective waste management, and improved living conditions. Western neighborhoods within the CUA and agglomeration are the most disadvantaged and often have precarious housing (Figure 10.c).

PC4 (4.56%) relates to residential occupation (Table 7). It emphasizes that unstable land and housing tenure contribute to less favorable residential conditions, highlighting its role as a key independent factor (Figure 10.d).

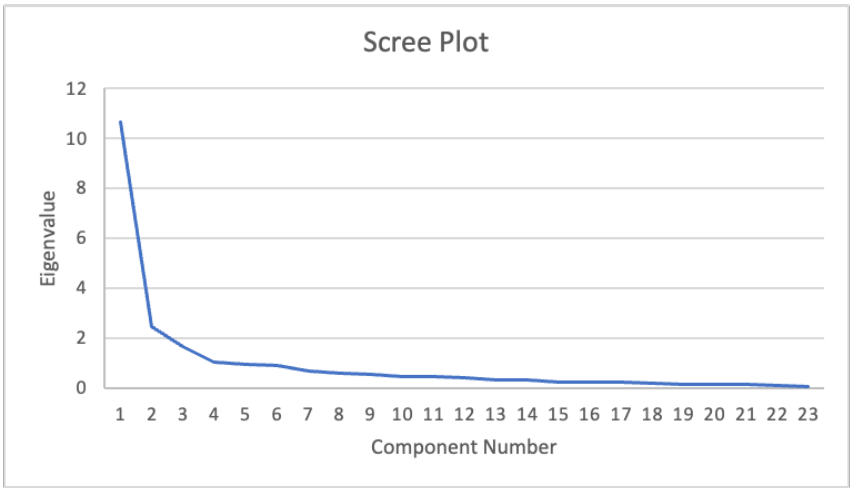
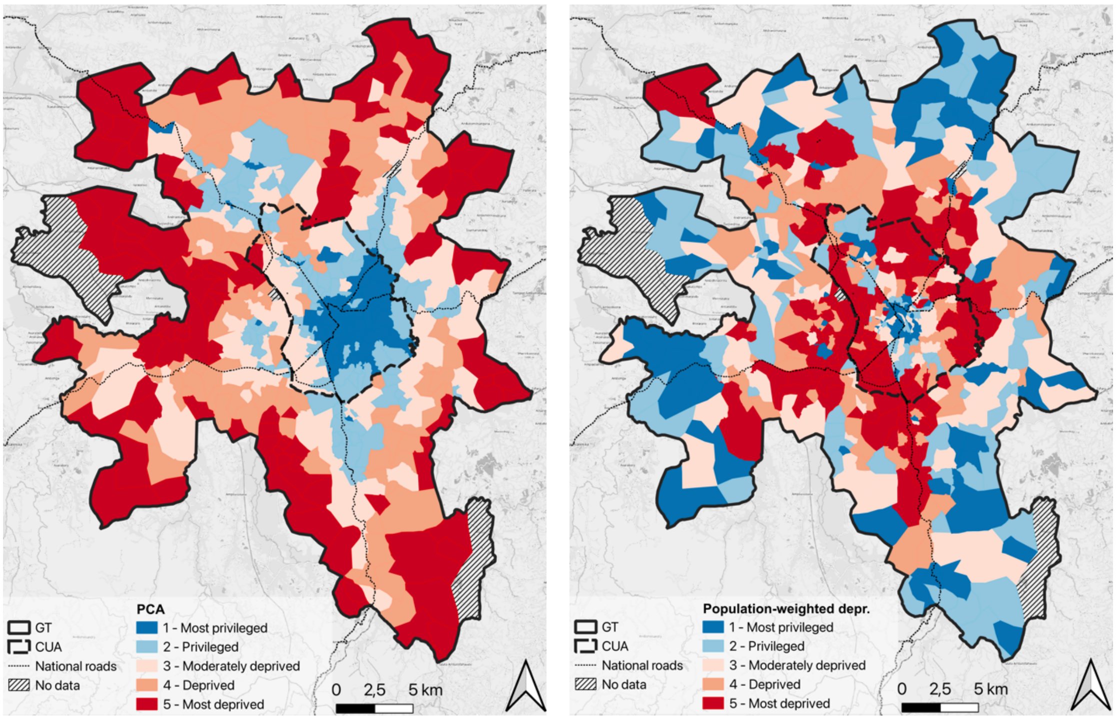


Figure 11. Scree plot of eigenvalues explained by the resulting components

The PCA analysis reveals two distinct patterns: a monocentric structure and an east-west structure as in the previous approach (Figure 8. Level of deprivation – Weighted values – GT

). The monocentric pattern is evident in the CUA neighborhoods and those along national highways, which are more privileged (Figure 12.a). These areas have good quality of life, well-developed infrastructure, efficient urban planning, favorable housing conditions, positive social attributes, and varied residential occupancy. The eastern part of the agglomeration shares similar characteristics. In contrast, peripheral neighborhoods, which account for 6% of the population (level 5 - Table 8), are farther from the center and face less favorable living conditions (Figure 12.a).

Prosperity within the CUA is unevenly distributed. While many neighborhoods, especially in the west, experience less favorable living conditions, the eastern neighborhoods, representing more than half of GT's population (levels 1 and 2 - Table 8), enjoy many advantages (Figure 12.a).



a. PCA b. Population-weighted deprivation PCA

Figure 12. Level of deprivation - PCA

When considering the population size of each neighborhood relative to the total agglomeration, the analysis identifies path areas within the CUA or its immediate periphery (Figure 12.b). Despite being highly deprived, rural areas on the agglomeration's outskirts concentrate a much smaller number of inhabitants (15% - levels 1 and 2 - Table 8, Figure 12.b). Some eastern neighborhoods, previously considered favored, are among the most deprived.

The following table compares the percentage of the neighborhood population according to the level of deprivation based on the PCA and Population-weighted deprivation results.

Table 8. Level of deprivation – PCA and population-weighted deprivation results at GT level

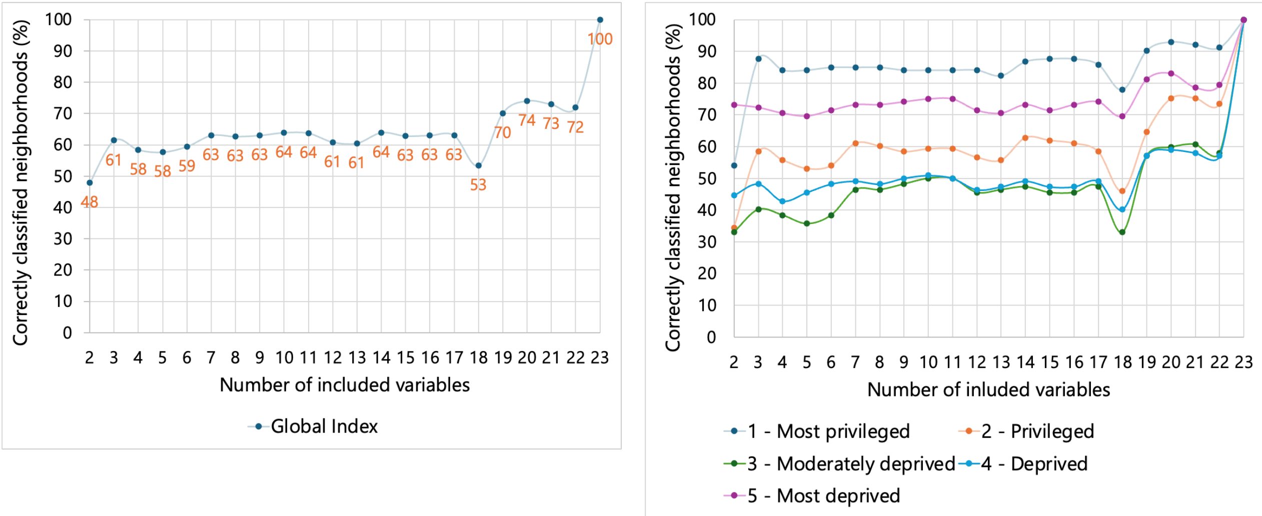
	1	2	3	4	5
PCA	25	34	25	10	6
Population-weighted deprivation	6	9	14	22	49

Variable reduction

The variables were excluded based on their contribution to PC1 and PC2 and their correlation with other variables. The excluded variables are listed in the Appendix. The initial model with 23 variables identified an independent component (PC4) for Ten. After excluding this variable, the PCA identified three main components, which captured most of the variance, remaining stable even with 19 variables, confirming the model's robustness.

The model's performance remained stable between 70% and 72% during early variable reduction (Figure 13.a). Excluding variables like Ten, Was, Ass, and Bda, which had low contributions or high redundancy, did not significantly affect performance. However, excluding San caused a sharp drop to 53%, highlighting its importance in explaining specific deprivation dimensions, especially in PC3. While performance recovered to 63% with 17 variables, a noticeable loss of explanatory power occurred (Figure 13.a).

The class-specific performance showed that extreme classes (1 and 5) maintained high and stable performance with fewer variables (Figure 13.b), reflecting their distinct characteristics captured by PC1 and PC2. In contrast, intermediate classes (2, 3, and 4) were more sensitive to variable reduction. Class 3 experienced a significant drop in performance, indicating that more variables are needed to distinguish these classes accurately (Figure 13.b).



a. Percentage of neighborhoods correctly classified according to the number of variables included

b. Percentage of neighborhoods correctly classified by deprivation class according to the number of variables included

Figure 13. Level of deprivation - PCA

5. Discussion

Developing a robust method for identifying deprived neighborhoods is essential, particularly in complex urban environments like the GS, where urban fragmentation is common and the state's capacity to manage the city and distribute resources equitably is limited (Smit, 2021; Chakraborty et al., 2024; Aguilar & Hernandez-Lozano, 2024). The analysis emphasizes the need to address all three levels of deprivation, as most frameworks, such as UN-Habitat's Slum Indicator, focus primarily on the household level (UN-Habitat, 2018), neglecting deprivation at the area and connection levels.

Central vs. Peripheral Areas

The complexity of urban deprivation is clearly illustrated in the agglomeration of Antananarivo, where certain central areas, as the city's economic hubs, stand out for their relative prosperity, having always been more active (Fournet-Guérin, 2006). These areas attract residents due to abundant employment opportunities, with numerous companies and financial institutions (Esoavelomandroso-Rajaonah, 1989; Eudora & Fernandez, 2018). This economic focus leads to higher living standards and more excellent homeownership rates (Wachsberger, 2009). Educational opportunities are more accessible in these neighborhoods than in disadvantaged areas, where financial constraints and limited access to learning centers reduce the likelihood of residents pursuing higher education (Droy & Andrianjaka, 2003; Rabemalanto, 2018).

This privileged situation is partly due to urban planning during colonial times, prioritizing the needs of colonial neighborhoods while mainly neglecting the local population (King, 2015; Ranaivoarimanana, 2017). These colonial planning decisions created lasting disparities, mirroring the ongoing effects of historical policies on urban deprivation dynamics in cities like Accra (Ghana), Johannesburg (South Africa), and Dar es Salaam (Tanzania), where modern infrastructure, quality amenities, and economic opportunities characterize privileged neighborhoods (Goerg, 2006; Coquéry-Vidrovitch, 2012; Andersson, 2017).

Conversely, despite the low population density of peripheral neighborhoods—reducing land pressure and, with minimal geographical constraints, making them ideal for spacious housing (MAEP, 2003) — and their rural character offering vast green spaces (Defrise et al., 2017; Dupuy et al., 2018), these areas still face significant challenges. Urban financial policies and community preferences have often failed to address their specific needs and characteristics (Andriamanga et al., 2024). This neglect hampers access to services and infrastructure, contributing to higher levels of deprivation (ARTELIA, 2014). Additionally, as these areas will likely experience population growth, substantial public investment in infrastructure and services will be necessary to reduce deprivation levels.

East vs. West disparities

Disparities between the east and west of Antananarivo are notable. Eastern neighborhoods, linked to the strategic axis connecting the capital to Madagascar's port, benefit from economic and logistical centrality, fostering growth poles and urban development projects (Olisoa, 2012; MAHTP & JICA, 2019). Despite relatively high population density, this centrality promotes economic growth.

In contrast, most western neighborhoods are underprivileged except for a few rare 1970s public housing developments renowned for their high construction standards (Ranaivoarimanana, 2017). These areas suffer from unplanned urbanization, driven by rapid population growth, high migration (Rakotonarivo, 2011; Rakotonirina & Cheng, 2015), and ineffective housing policies, leading to an imbalance between demand and limited supply (MAHTP & JICA, 2019; Rabemalanto, 2018). Consequently, these neighborhoods experience high residential density, limited green spaces, and restricted living space (Bds, Gsp, Ls) (Godinot et al., 2010; Razafindrakoto, 2014; MAHTP & JICA, 2019). These patterns are consistent with conditions seen in cities like Dhaka (Bangladesh), Nairobi (Kenya), and various Indian metropolises, where high density and limited green spaces reflect similar urban deprivation in rapidly growing cities with poor urban planning (Ramaiah & Avtar, 2019; Kuffer, Abascal, et al., 2023; Misty et al., 2024). In the western neighborhoods of Antananarivo, this issue is further compounded by geographical constraints, such as floodplains, which highlight land management and production (Razafindrakoto, 2014; Rabemalanto, 2018; Ramiaramanana & Teller, 2021) challenges.

Impact of infrastructure

Infrastructure plays a key role in the distribution of economic and social benefits. Areas near the national airport and industrial zones, particularly in the north of Antananarivo, enjoy conditions conducive to economic development (Eudora & Fernandez, 2018; MAHTP & JICA, 2019). Similarly, neighborhoods located along road infrastructures often benefit from a significant increase in the value of adjacent land, attracting private and public investment (Ranaivoarimanana, 2017). This dynamic improves access to essential services and enhances residents' quality of life. However, less connected areas remain marginalized.

Comparison of methods

Table 9 presents the advantages, disadvantages, and suitability of the different methods.

Table 9. Comparison of Weighting system and PCA

Method	Weighting system	PCA
Advantages	• Allows direct use of IDEAMAPS variable structure • Simplifies overview • Facilitates understanding, communication, and decision-making • Weights can be adapted to context (Dibben et al., 2007; Cabrera-Barona & Ghorbanzadeh, 2018; Kuffer, Ali, et al., 2023)	• Reduces data complexity while preserving variability • Identifies trends and correlations between the variables (S. P. Mishra et al., 2017; S. V. Mishra, 2018; Basu & Das, 2021) • Provides robust data exploration (Abdi & Williams, 2010)
Disadvantages	• Can mask nuances of deprivation when grouping variables • Can lead to bias due to subjective weight assignment (Decancq & Lugo, 2013; Allik et al., 2020) and requires frequent adjustments • Risk of oversimplification, data quality issues, and double counting (Deas et al., 2003; Thomson et al., 2020)	• Requires data normalization, sensitive to outliers (Vyas & Kumaranayake, 2006; Jolliffe & Cadima, 2016) • Can make interpretation of correlation between variables difficult

	• Common issues with data quality and availability, including population data	
Suitability	• For global assessment within a pre-established framework • When specific dimensions of deprivation are deemed more important than others	• For unstructured data, exploratory approach • For identifying underlying structures and correlation

Meso analysis and relative disparity corrected by population weight

Deprivation is less noticeable on a macro-local scale, such as the agglomeration, whereas it becomes more pronounced at the meso scale, such as the CUA. This highlights how the observation scale accentuates or attenuates inequalities and underscores the importance of a finer perspective to understand urban complexity (Luo et al., 2022).

Analyzing deprivation by neighborhood reveals that the most deprived areas do not always correspond to densely populated communities. High population density can worsen deprivation by placing additional strain on urban infrastructure and services, necessitating a strategic response to address these specific needs (Grant, 2010; Li et al., 2023). Densely populated areas may require additional social and economic infrastructure investment to promote employment and local growth (Bolay, 2020). This requires a proactive strategy, including innovative zoning policies and public-private partnerships to finance infrastructure projects (Willoughby, 2013; Monkkonen, 2018).

Variable reduction

The results show that the model is somewhat robust with variable reduction, confirming that simplification can effectively reduce complexity, particularly in data-limited contexts. However, this robustness depends on retaining key variables that capture specific dimensions of deprivation. The exclusion of San illustrates a critical point where further simplification undermines the model's ability to explain social dimensions of deprivation. This emphasizes the need to evaluate variables based on their statistical contribution and relevance to the model's objectives.

Intermediate classes were more sensitive to the reduction, highlighting the challenge of distinguishing these groups with fewer variables. Oversimplifying the model could distort results, posing challenges for policy targeting.

The findings highlight the importance of balancing simplification with retaining explanatory power to capture the full complexity of deprivation. While this method applies to other urban contexts, further validation is needed to ensure its broader applicability, as each city presents unique data priorities and constraints.

Research limitations

This research initially assesses urban deprivation in Antananarivo but does not capture neighborhood evolution over time. Future studies could address this gap using approaches like the English Deprivation Index, which tracks changes over time (McLennan et al., 2019). Additionally, while geographically focused, the analysis lacks advanced spatial methods like clustering or geostatistical techniques, which could improve the identification of complex deprivation patterns.

Indicators were selected based on local data availability and the IDEAMAPS framework. Excluding dimensions like social hazards, contamination, and governance due to data constraints limits the comprehensiveness of the analysis and may omit key contributors to urban deprivation. This reliance on available data shapes the indicators used and may hinder comparability with other studies.

The "local indicators" concept introduces complexities, as priorities vary across neighborhoods. For instance, access to green spaces may be more or less important depending on a neighborhood's socio-economic context, emphasizing the need for participatory approaches to ensure indicators reflect local realities.

Finally, HL data aggregation, necessary for confidentiality, loses granularity, potentially masking intra-neighborhood disparities critical for targeted interventions in heterogeneous urban areas (Patel et al., 2014).

Conclusion

Increasing urbanization, combined with the adverse effects of past and present urban governance, has led to high levels of inequality and fragmentation in the GS cities, giving rise to areas of concern known as deprived areas. Although these areas have been extensively studied, urban poverty remains complex and is often analyzed one-dimensionally, limited to households or surrounding areas.

This study uses the IDEAMAPS conceptual framework to understand the multidimensional complexity of deprivation in the agglomeration of Antananarivo. It highlights pronounced disparities between favored eastern neighborhoods and deprived western ones and between central and peripheral neighborhoods, albeit with some distinct subtleties.

The weighting system effectively represents the data of the IDEAMAPS framework, highlighting the three aspects of urban deprivation. However, the levels of deprivation in each dimension may vary, leading to a significant loss of information when aggregated. Although adjustment of the weights is possible, it must be carried out with care. Furthermore, the substantial variability in the data increases the likelihood of multicollinearity, necessitating careful consideration.

A PCA confirms the structure predefined by the IDEAMAPS framework and highlights the influence of each variable and the need to address certain variables separately to better understand urban inequalities. Despite its simplicity, adequate standardization of variables is necessary to avoid errors, as PCA remains sensitive to outliers.

This study highlights the importance of considering different scales of observation for a thorough understanding of the dynamics of urban deprivation. It highlights the need to integrate population size into the analysis to avoid less populated neighborhoods being unfairly affected by deprivation measures and to improve the prioritization of interventions. Using fewer deprivation indicators may benefit contexts with limited data; however, this reduction must be done carefully to ensure that critical variables are retained, preserving the model's explanatory power. Analyzing these results' political and social implications to inform public policy would be essential. The perspectives of residents in the neighborhoods studied could also enrich our understanding. Finally, this research raises questions for future research, notably on the mechanisms underlying the formation of urban inequalities and the effectiveness of policy interventions.

Appendix

1. Data pre-processing

1.1. Household level

The data come from the 2018 national census conducted by INSTAT and were already aggregated at the neighborhood level. Classifications are based on INSTAT standards, except for asset ownership, which follows the poverty assessment framework for deprived neighborhoods in Antananarivo (Rabemalanto, 2018).

i. Socio-Economic Status

- **Assets (Ass - %)**

The asset ownership data reflects the proportion of households owning specific assets at the neighborhood level. Since the data is aggregated, it does not provide details on the exact number of assets owned per household. Two categories of assets were analyzed:

- Asset 1 (%): Percentage of households owning at least one of the following: radio, TV, video, stove, refrigerator, washing machine, sewing machine, computer, internet equipment, air conditioner, motorcycle/scooter, landline phone, cell phone, or bicycle.

Asset 1 (%) = max (Percentage of households owning each good in Asset 1 category)

- Asset 2 (%): Percentage of households in each neighborhood that own at least one car.

The final asset percentage (Ass) for each neighborhood is calculated as:

$$\text{Ass (\%)} = \frac{\text{Asset 1 (\%)} + \text{Asset 2 (\%)}}{2}$$

- **Education (Edu - %)**

The education data represents the population proportion by school attendance and educational attainment levels at the neighborhood level. The data were categorized as follows:

Variable	Categories	Variable characteristics
School attendance (%)	Having attended	Attended Currently attending
	Did not attend	Did not attend
Achieved educational level (%)		Elementary (A), Primary (B), Secondary (C), Technical secondary (D), Higher education (E)

- Having attended (%): Percentage of the population in the neighborhood who have attended school (either in the past or currently).

- Achieved educational level is calculated by weighting the percentage of the population in each educational category, with weights ranging from 1 (elementary) to 5 (higher education):

Educational attainment (%) = (A x 1/5) + (B x 2/5) + (C x 3/5) + (D x 4/5) + (E x 5/5)

The final education percentage (Edu) for each neighborhood is calculated as:

$$\text{Edu (\%)} = \frac{\text{Having attended (\%)} + \text{Educational attainment (\%)}}{2}$$

- **Employment (Emp - %)**

The employment data represents the percentage of the population in each neighborhood categorized by activity status. The data were structured as follows:

Variable	Categories	Variable characteristics
Activity (%)	Active	Employed
	Not active	Housewife, retired, unable to work, unemployed, looking for a first job, other

Emp (%) = Percentage of people who are actively employed.

ii. Housing

- **Tenure (Ten - %)**

The tenure data represents the proportion of households in each neighborhood categorized by housing and land tenure status. The data were structured as follows:

Variable	Categories	Variable characteristics
Housing tenure status (%)	Owner	Owner
	Non-owner	Free, corporate housing, tenant
Land tenure status (%)	Secured occupancy	Land title, cadastre, carnet, certificate of regulation
	Unsecured occupancy	Untitled ancestral land, anarchic occupation

- Owners (%): Percentage of households owning their homes.
- Secured occupancy land (%): Percentage of households with secured land occupancy.

The final tenure percentage (Ten) for each neighborhood is calculated as:

$$\text{Ten (\%)} = \frac{\text{Owners (\%) +Secured occupancy land (\%)}}{2}$$

- **Material quality (Mat - %)**

The material quality data represents the proportion of households in each neighborhood based on the sustainability of materials used for walls, roofs, and floors. The materials were categorized as follows:

Variable	Categories	Variable characteristics
Wall (%)	Sustainable materials	Concrete block, stone, clay brick
	Precarious materials	Earth/Uncooked brick, Thatch/palm/leaves, sheet metal, cardboard, straw, recycled materials
Roof (%)	Sustainable materials	Tile, sheet metal, cement/fibrocement
	Precarious materials	Straw, thatch/palm/leaves, recycled materials
Floor (%)	Sustainable materials	Waxed wood, cement, vinyl, tile, carpet
	Precarious materials	Bare ground, Thatch/palm/leaves/bamboo, mat, rudimentary board

The percentage of households using sustainable materials for walls, roofs, and floors was averaged to calculate the final material quality percentage (Mat):

$$\text{Mat (\%)} = \frac{\text{Sustainable walls (\%) + Sustainable roofs (\%) + Sustainable floors (\%)}}{3}$$

- **Energy (Eng - %)**

The energy data represents the proportion of households in each neighborhood by the energy sources used for lighting and cooking. The data were categorized as follows:

Variable	Categories	Variable characteristics
Lighting (%)	Modern light sources	Electricity
	Non-modern light sources	Oil lamp, candle, other
Cooking (%)	Improved cooking mode	Charcoal, oil, gas, electricity
	Unimproved cooking mode	Dung, wood/branches

- Modern lighting sources (%): Percentage of households in the neighborhood using modern lighting sources.
- Improved cooking mode (%): Percentage of households in the neighborhood using improved cooking modes.

The final energy percentage (Eng) for each neighborhood is calculated as:

$$\text{Eng (\%)} = \frac{\text{Modern lighting sources (\%)} + \text{Improved cooking mode (\%)}}{2}$$

- **Water (Wat - %)**

The water supply data represents the proportion of households in each neighborhood categorized by their access to water sources. The data were structured as follows:

Variable	Categories	Variable characteristics
Water supply (%)	Improved water sources	Faucet at home, outdoor individual faucet, outdoor communal tap, public fountain, borehole, human-powered well
	Unimproved water sources	Protected well, unprotected well, protected spring water, unprotected spring water, surface water (river, lake...), rainwater, water seller

Wat (%) = Percentage of households using improved water sources.

- **Sanitation (San - %)**

The sanitation data represents the proportion of households in each neighborhood distributed across two variables: type of toilet and whether toilets are shared with others. The data were structured as follows:

Variable	Categories	Variable characteristics
Type of toilet (%)	Improved	Toilet with a seat, toilet without seat, toilet slab in concrete (cement), or porcelaine, or glassfiber
	Non-improved	Latrine slab in wood, or mud, simple hole, none
Toilet shared with others (%)	Yes	
	No	

- Improved toilets (%): Percentage of households in the neighborhood using improved toilets.
- Not shared (%): Percentage of households in the neighborhood that do not share their toilet with others.

The sanitation percentage (San) for each neighborhood is calculated as:

$$\text{San (\%)} = \frac{\text{Improved toilets (\%)} + \text{Not shared (\%)}}{2}$$

- **Waste (Was - %)**

The waste data represents the proportion of households in each neighborhood based on their waste disposal methods. The data are categorized as follows:

Variable	Categories	Variable characteristics
Household waste disposal (%)	Improved	Throw it into public waste bin, into a hole or burried
	Unimproved	Throw into the public wastewater channel, throw it into the river, throw it anywhere

Was (%) = Percentage of households using improved disposal methods.

1.2. Area level

Unplanned urbanization

- **Living space (Ls - m2/pers)**

Population density is the proposed indicator for IDEAMAPS. However, as the available data is limited to building footprints, calculating the average floor space per person is a more accurate measure to avoid overestimating population density.

The floor space per person for each neighborhood is calculated as follows:

$$\text{Ls (m2/person)} = \frac{\text{Total floor space (m2)}}{\text{Number of population}}$$

- **Building area (Bda - %)**

This analysis aims to determine the level of housing-related precariousness in each neighborhood of the agglomeration. The Antananarivo Integrated Sanitation Program (PIAA) assumed dwellings of less than 30 m2 are considered precarious (Eudora & Fernandez, 2018). We have, therefore, adopted this threshold. The percentage of residential buildings under 30 m2 in each neighborhood is calculated as:

$$\text{Bda (\%)} = \frac{\text{Number of residential buildings} < 30\text{ m2}}{\text{Number of residential buildings}} \times 100$$

- **Building density (Bds)**

The building density indicator measures the extent of construction in each neighborhood by calculating the proportion of residential areas relative to the total neighborhood area. It is calculated as:

$$\text{Bds} = \frac{\text{Residential area (m2)}}{\text{Neighborhood area (m2)}}$$

- **Green space coverage (Gsp - m2/inhab)**

The green space coverage indicator evaluates the availability of green spaces for residents in each neighborhood. The analysis uses the land use classification published by CIRAD in 2022 (Dupuy et al., 2018). Elements considered green spaces include watercress beds, fruit and vegetable crops, agricultural plots, forest plantations, rice fields, and savannahs (tree, shrub, and herbaceous). The green spaces coverage is calculated as:

$$\text{Gsp (m2/inhab)} = \frac{\text{Green space area (m2)}}{\text{Number of population}}$$

1.3. Area-connect level

i. Infrastructures

- **Drainage, roads, water (Dra, Rd, Wati – km/km2)**

This indicator evaluates the availability of drainage, road, and drinking water infrastructure in neighborhoods by calculating the network length per square kilometer.

- Drainage: Main drainage channels.
- Roads: Primary trunk roads, secondary and tertiary roads linking zones to primary highways and interconnecting zones.
- Drinking Water: Based on JIRAMA (Jiro sy Rano Malagasy) water supply connections, as provided by the TaToM project (JICA, 2019).

The availability of each infrastructure type is calculated as:

$$\text{Indicator (km/km2)} = \frac{\text{Total network lenght (km)}}{\text{Neighborhood area (km2)}}$$

- **Street lighting (Stl)**

The street lighting indicator measures the accessibility and operation of street lighting in neighborhoods using data from the day-night band of the VIIRS system (Visible Infrared Imaging Radiometer Suite). Data for 2021 were used, as more recent data were unavailable. Monthly raster data from Google Earth Engine were averaged to obtain annual values for each neighborhood.

ii. Facilities and services

- **Commercial, administrative, educational, health care, cultural and recreational, worship (Com, Adm, Edf, Hth, Cult, Wor – km)**

These indicators measure accessibility to key urban amenities by calculating the average nearest distance from residential buildings to facilities in each neighborhood. Distances were computed using the Distance Matrix tool in QGIS, which calculates the shortest distance between residential buildings and the nearest facility or service. The neighborhood average was then determined by aggregating these distances.

The analysis covers the following facility categories:

- Commercial (Com): Shops, markets, and retail services.
- Administrative (Adm): Government offices and administrative buildings.
- Educational (Edf): Schools, colleges, and universities.
- Health care (Hth): Hospitals, clinics, and health centers.
- Cultural and recreational (Cult): Museums, parks, and recreational facilities.
- Worship (Wor): Churches, mosques, temples, and other religious institutions.

1.4. Calculation of quintiles

A quintile classification was applied to classify neighborhoods based on their indicator values. This process ensures a consistent division of neighborhoods into five groups of equal size (20% each), ranked from the most privileged (1) to the most deprived (5). The steps are as follows:

- Neighborhoods were ranked from highest to lowest for each indicator based on their calculated values.

- Quintiles were defined such that each group contained 20% of the neighborhoods, ensuring an equitable distribution of neighborhoods across the five groups.

- Each quintile was associated with a deprivation class to represent relative levels of advantage or disadvantage:

  Class 1: Neighborhoods in the top 20% (1st quintile) (most privileged).
  Class 2, 3, and 4: Neighborhoods with intermediate indicator values, representing the 2nd, 3rd, and 4th quintiles.
  Class 5: Neighborhoods in the bottom 20% (5th quintile) (most deprived).

The table below illustrates the process of classifying neighborhoods into quintiles and deprivation classes using an indicator (Ind) as an example:

Neighborhood	Ind (%)	Quintile	Deprivation Class
Q1	95	Top 20%: 1st quintile	1
Q2	90	Top 20%: 1st quintile	1
Q3	85	2nd quintile	2
Q4	80	2nd quintile	2
Q5	75	3rd quintile	3
Q6	70	3rd quintile	3
Q7	65	4th quintile	4
Q8	60	4th quintile	4
Q9	55	Bottom 20%: 5th quintile	5
Q10	50	Bottom 20%: 5th quintile)	5

2. **Descriptive analysis and population distribution in GT** (cf. Table *2*)

- **Mean and Standard Deviation**

The mean and standard deviation of each indicator were calculated as follows:

$$M = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\text{Std. D} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - M)^2}$$

M is the mean value of the indicator
Std. D is the standard deviation of the indicator
n is the total number of neighborhoods
x_i is the value of the indicator for neighborhood i

- **Calculation of population percentages**

Neighborhoods were classified into quintiles for each indicator described in the quintile classification section (**Erreur ! Source du renvoi introuvable.**). The total population percentage for each deprivation class was calculated by summing the population percentages of neighborhoods in that class. The calculation follows the equation:

Population percentage for class k = $\sum_{q \epsilon k} P_q$

k is the deprivation class (1, 2, 3, 4, or 5)
q represents neighborhoods in class k
P_q is the percentage of the population in neighborhood q

This process was repeated independently for each indicator to produce Table *2*, which summarizes population distributions across deprivation classes.

3. Variable reduction

A systematic variable reduction was applied based on each variable's contribution to PC1 and PC2 and its correlation with other variables. The table below lists the excluded variables, their contributions, and their exclusion order.

Variable	**Contribution to PC1 and PC2 and correlation with other variables**	**Exclusion order**
Ten	Very low contribution, weakly correlated	1
Was	Very low contribution, weakly correlated	2
Ass	Low contribution, very high correlation	3
Bda	Low contribution, high correlation	4
San	Low contribution, high correlation	5
Emp	Medium contribution, very weak correlation	6
Rd	Medium contribution, high correlation	7
Cult	Medium contribution, high correlation	8
Edf	Medium contribution, high correlation	9
Edu	Medium contribution, very high correlation	10
Bds	Medium to high contribution, high correlation	11
Ls	Medium to high contribution, high correlation	12
Hth	High contribution, very high correlation	13
Adm	High contribution, very high correlation	14
Com	High contribution, very high correlation	15
Gsp	High contribution, very high correlation	16
Stl	High contribution, high correlation	17
Wati	High contribution, high correlation	18
Wat	High contribution, high correlation	19
Wor	High contribution, high correlation	20
Dra	High contribution, high correlation	21
Eng	Very high contribution, very high correlation	22

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