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Exploring street visual audits to make sense of unequal urban landscapes

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Abstract

With the growing availability of panoramic street-level imagery, on platforms such as Google Street View, researchers can investigate urban landscapes in innovative ways. Virtual neighbourhood audits enable the use of this information to describe urban landscapes and their implications for people. However, most publications exploring these possibilities rely on highly specialized programming skills not yet generalized among social researchers. In this study, we make use of panoramic street-level imagery to assess five municipalities and the territorial and spatial inequalities that shape them. It adds to the literature by proposing a mixed method approach that accounts for urban landscape multi-thematic dimensionality, combining a non-computational data extraction procedure with a multivariate analysis that researchers with low programming expertise can replicate. Observational data not only captured the differences between territories as previously known but also provided new insights into territorial inequalities, offering considerations for potential urban management priorities. Illustrating alternative ways to use open visual data enhances the possibility of insight and understanding of urban landscapes, identifying promising areas for multidisciplinary partnerships.

Keywords Street-level imagery · Visual audit · Spatial inequality · Urban landscapes

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1 Introduction

There is a substantial level of interest in how the built environment impacts health and well-being (e.g. Fleckney and Bentley 2021; Gianfredi et al. 2021) as our surroundings have a profound influence on our lives, increasing or reducing exposure to environmental hazards and stressful situations (lower levels of security), restricting or promoting health-enhancing behaviour, and facilitating or challenging social connections and civic participation (e.g. Diez Roux and Mair 2010). These are often referred to as "neighbourhood effects" and are studied by urban, health, and social researchers from diverse backgrounds and methodologies to account for the effects of place, area, or neighbour on fellow residents, on health, and other outcomes. These studies typically focus either on underline the connection between specific physical features and health and behaviour (the contextual effects: the territory as a social space of opportunities and constraints) or to analyse how area-population composition relates to population health, providing clues on how the living conditions of the population relates to their health and well-being (compositional effects) (Pliakas et al. 2017).

Multiple terms and concepts have been put forward to better understand neighbourhood effects (Galter 2012 cited in Visser et al. 2021). When focusing on the environmental (physical) implications, neighbourhood effects can be framed in the scope of the "environmental justice" topic. Environmental justice refers to the unequal distribution of threats and benefits between individuals and groups where positive and negative features of the environment are unevenly spread across areas, cities, regions, or countries (Schaeffer and Tivadar 2019).

Neighbourhood effects can also be understood in within the framework "health inequality". Neighbourhood effects can generate relative advantages/disadvantages in health and wellbeing related to differential exposure to beneficial and negative factors, understood as systematic, socially generated, and unjust (Whitehead and Dahlgren 2007).

As a result of spatial segregation, those with more favourable social positions tend to live in healthier environments, whereas those from lower social classes are confined to more affordable areas that are less conducive to healthy living (Antunes 2011; Davino et al. 2021; Krieger 2014; OECD 2019). Neighbourhood effects are one of the multiple pathways by which social advantages result in health advantages in the extent that social inequalities, capital accumulation and class struggle determine where people live in cities (Slater 2013).

There is a multitude of studies reporting the connection between health and the built environment, including access to green or open spaces, walkability, access to amenities and public transport, and overall quality of the neighbourhood (e.g., Goldfeld et al. 2015; Ige-Elegbede et al. 2020; Jokela 2020; Kepper et al. 2019; McCartney et al. 2013; Pliakas et al. 2017; Visser et al. 2021). However, it is still difficult to draw robust conclusions on causality and the mechanisms involved in these connections. Assessment and methodological issues have been identified as key fragilities in the field (e.g., Fleckney and Bentley 2021; Gianfredi et al. 2021).

There is, therefore, a need to improve our understanding of urban environments and innovate in methods in use.

1.1 Neighbourhood virtual audits

Neighbourhood virtual audits allow the use of powerful new approaches in exploring urban landscapes and their implications for daily life (e.g., Bader et al. 2017; Biljecki and Ito 2021; Cinnamon and Jahiu 2021; Kang et al. 2020; Rzotkiewicz et al. 2018; Mooney et al. 2016). By "virtual audits", we mean the use of images rather than in-person and on-site observations. Before the wide availability of panoramic street-level imagery in platforms such as Google Street View (GSV), researchers could only collect information on specific physical features of neighbourhoods through observation grids and systematic social observation protocols in prescribed locations. Not only are such methods costly and time consuming, but they also limit the geographic scope under study (Bader et al. 2017; Biljecki and Ito 2021; Cinnamon and Jahiu 2021; Kang et al. 2020; Odgers et al. 2012; Rzotkiewicz et al. 2018). Virtual audits greatly reduce costs, and there is some evidence that they can provide data that is just as viable as that from on-site audits (Badland et al. 2010; Fox et al. 2021; Mooney et al. 2020; Pliakas et al. 2017; Pocock et al. 2020).

Cinnamon and Jahiu (2021), as well as Biljecki and Ito (2021) have published updated literature reviews presenting the use of street-level imagery for urban analysis, reporting increasingly greater usage of these data in research. Street-level imagery facilitates the systematic assessment of the pedestrian perspective on-site, while saving time and funds and reducing personal risk, building our understanding of the urban environment as it is experienced by the people who live there (e.g., Bader et al. 2017; Biljecki and Ito 2021; Cinnamon and Jahiu 2021; Kang et al. 2020; Rzotkiewicz et al. 2018).

Recent uses of these data in urban modelling and demographic surveillance illustrates the growing possibilities offered by virtual audits. Street-level images are used to build (or feed) models to that infer socioeconomic and demographic trends in large-scale computational models of urban settings and populations (Cinnamon and Jahiu 2021).

A well-established application in research concerns the use of such imagery to further our understanding of the connections between place and well-being, by identifying correlations between urban features and physical activity, obesity, mental health, walking behaviours, pedestrian and cycling safety, and even COVID-19 risk (Biljecki and Ito 2021; Cinnamon and Jahiu 2021).

Visual data are also used to measure green, blue and open spaces, optimized by computation modelling technology that allow for more robust studies on the association between these features and health and social outcomes (e.g., Biljecki and Ito 2021; Cinnamon and Jahiu 2021; Gianfredi et al. 2021; Ige-Elegbede et al. 2020).

The visual data on urban landscapes are improving our ability to assess the built environment and land uses on a scale never before possible (e.g., Biljecki and Ito 2021; Cinnamon and Jahiu 2021). Data are extracted from images of urban landscapes using both computational (automatic audits run by programs) and non-computational methods (visual audits made by raters) (Cinnamon and Jahiu 2021). Neighbourhood virtual audits have been used for assessing the quality of urban areas with measures that account for correlations between physical features and levels of crime and inequality or socially disruptive behaviours (e.g., Biljecki and Ito 2021; Cinnamon and Jahiu 2021).

It is also used to better assess specific attributes of the urban landscape including, but not limited to accessibility (e.g., Steinmetz-Wood et al. 2019), walkability (e.g., Koo et al. 2022), physical disorder (e.g., Bader et al. 2015), and traffic signs (e.g., Jiang et al. 2020 cited in Cinnamon and Jahiu 2021).

Multi-theme and multidimensional assessments are less frequent in the literature and mostly rely on computerized categorization processes that combine street-level imagery and scenes to generate alternative classification processes of land uses (Cinnamon and Jahiu 2021). Most of these approaches reported in the literature rely on highly specialised programming skills not yet generalized among social researchers.

The low-level data literacy in social sciences appears to constrain the action and delegitimization of these disciplines in an era where, paradoxically, some of the crucial skills of these disciplines are needed to navigate and make sense of the increasing volume of data available (Capogna 2022). Illustrating ways to combine traditional approaches to data analysis with the new possibilities offered by open data platforms is therefore needed and may foster new insights for while mapping new venues for interdisciplinary communication.

2 Research aims and context

In this paper we address the results of a study that makes use of panoramic street-level imagery to assess five municipalities in Portugal. This study contributes tothe literature by proposing an approach that captures the multidimensionality of urban landscapes. It combines a non-computational data extraction procedure with multivariate analysis that can be replicated by researchers with low programming expertise. Additionally, the study uses street-This analysis is incorporated into a wider mixed-method study on place-based inequalities in Portugal. The research aimed to understand the opportunities and constraints that shape everyday experiences and interactions, going beyond mere administrative territorial segmentation, which often lacks real meaning for the relationships in local contexts. The research focused on the socioeconomic inequalities that characterise different configurations of territories and on how they shape the well-being of populations in those territories (Mauritti et al. 2022).

In the first stage of the research, an extensive analysis was supported by the construction of a database with statistical information on the different variables addressed, comprising 29 indicators of social inequality for the 278 municipalities of mainland Portugal.[1] We started by carrying out an analysis of the correlations (both bivariate and multivariate) between the variables of the model, and specifically, through a characterization of the complex and multidimensional intersections between distributional inequalities (of income and education) and categorical inequalities (economic activity status, social class, gender, and age) (Costa et al. 2018). Cluster analysis was performed using both hierarchical and non-hierarchical methods. Based on the results of the cluster analysis, we proposed a typology of five municipally-based territorial configurations: "Low-Density Territories"; "Industrial Territories in Transition"; "Intermediate Territories"; "Networked Urban Territories"; and "Innovative Territories". In each territorial configuration, the municipalities within it have relatively homogeneous characteristics among themselves in relation to urban density, the

[1] The selected indicators included information on: 1) territory (typology of urban areas: % of predominantly urban areas, median urban areas, predominantly rural areas); 2) population (% of resident population by main age groups; rate of change of population aged 0–14 and 65+; population density and rate of change of population density); 3) income and consumption (average gross declared income; Gini coefficient of gross declared income); 4) social classes (5 categories: Entrepreneurs and Executives; Professionals and Managers; Self-Employed; Routine Employees; Industrial Workers); 5) schooling (% of active population with no schooling, basic, secondary, tertiary; rate of change of working population with secondary and with tertiary education); 6) mobility (work or study in another municipality).

age distribution of their population, their socio-occupational profile and qualifications, and income patterns. Also, these same characteristics of social inequality tend to differentiate them from municipalities located in the other groupings.

The full characterization of these territorial profiles is beyond the aims of this publication and can be consulted elsewhere (Mauritti et al. 2022). For the purposes of this publication, a brief illustration of these territorial configurations is provided:

- "Low-Density Territories" (involves 8% of the national population and a vast spatial extension that covers the entire interior of Portugal, corresponding to 35% of the mainland's municipalities)–in this cluster we find small towns and villages with impoverishment trends, intensified by depopulation and ageing, with negative impacts on economic activities and social experiences; the vast majority of the population is over 65 years old and is economically inactive, with basic education or even no education at all; regarding the active population, itis primarily engaged in in low-skilled work (self-employed, routine employees, and industrial workers); the average monthly income levels of the populations are around 750 euros per month.
- "Industrial Territories in Transition" (concerns 13% of mainland municipalities and 17% of the national population)–this cluster is characterized by a significant presence of people up to 25 years old, and by a notable increase in the numbers of young people at secondary and higher education, while most adults have basic education profiles; in terms of socio-occupational structure, this configuration is distinguished by the presence of industrial workers, reflecting a socio-economic context heavily influenced by a diffuse industrial activity, still reliant on the use of low-skilled labour, with average monthly incomes of around €780.
- "Intermediate Territories" (concerns 35% of Portugal's municipalities and just over 20% of the national population)–are characterized by a prevalence of low-density urban areas, intensive ageing trends, and demographic loss. Despite this, these territories are also marked by a potential for renewed dynamics, driven by their cross-border location and by the presence of innovation and higher education units; in terms of the socio-professional structure, there is a prevalence of routine employees, with low qualification profiles, as well as agricultural and industrial workers, with average monthly incomes of €900.
- "Networked Urban Territories" (the most populous group, concentrating 40% of the national population and having the greatest potential for demographic growth)–consist primarily of large and medium-sized cities, organized in densely populated areas, and are characterized by intense mobility related to study and work; service activities dominate in socio-professional terms. One segment involves low and intermediate qualification jobs in office, commerce and social and security services (routine employees), and another segment includes professionals with higher qualification profiles who perform technical and management functions in the public sector (professionals and managers). The average monthly incomes in these territories are around €1050.
- "Innovative Territories" (concern 13% of the national population, and only 2% of the municipalities, including the main municipalities in the two metropolitan regions of Lisbon and Porto)–this cluster is consists of densely populated cities with a strong capacity to attract business organizations based on scientific and technological innovation, generating conditions for the development of differentiated urban services, and attracting a highly qualified population. The territories have a higher prevalence of top managers in public and private entities (entrepreneurs and executive social class), as well as workers with high scientific and technical expertise (such as professionals

and managers), and a relevant segment of direct execution workers, involved in service, commerce, administrative, and security activities (routine employees). Average monthly gross incomesis around €1500 euros, well above the national average, and linked to the highest Gini coefficient of the country.

Having identified these territorial profiles, a series of case studies were conducted to understand the interconnections between inequality and well-being at the municipal level with data taken from multiple sources, including secondary data, interviews, focus groups, and observational data. This article focuses only on observational data from GSV platform collected through visual audits. To achieve this, we adapted a systematic observation protocol and applied it to a random sample of streets in the selected municipalities. We then conducted multivariate analyses on this data to select the key features that distinguish one place from another, highlighting trends in these urban landscapes across different geographic scales. We detail the methodological and analytical procedures to illustrate the potential uses of street-level visual data in analysing urban landscape diversity and describing unequal territories across and within municipalities.

The article is structured as follows: the methods expand on our scope of study, procedures, instruments, measures, and our rationale concerning statistical analysis. Results summarize the quantitative insights from this analysis. We conclude the article with the Discussion and Conclusion sections, that includes a summary of the advantages and limitations of our approach, proposing potential improvements for future research.

3 Methods

3.1 Study sample

A set of quantitative and qualitative criteria was devised to define the units of observation under analysis at the municipal, parish, and neighbourhood levels. We chose to combine these criteria to ensure that the analysis captures a wider axis of territorial differentiation.

3.1.1 Municipal level criteria.

Firstly, we selected locations for virtual audits within the five municipalities chosen to represent the identified territorial profiles– “Low-Density Territories”, “Intermediate Territories”, “Industrial Territories in Transition”, “Networked Urban Territories”, and “Innovative Territories”. For each profile, the municipal case study selection was informed by two criteria: (i) proximity (Euclidean distance) to the cluster centre and (ii) NUTSII region. Selected case studies exhibit the highest (or among the highest) proximity to the cluter centre and are from the most prevalent region of the profile.

3.1.2 Parish level criteria.

In Portugal, each municipality is organized by different boroughs or parishes that may manage different local resources. To capture disparities within the territories under analysis, we targeted two parishes for observation in each municipality: the municipality headquarters (referred to as central parish) and the parish with fewer inhabitants in the municipality (referred to peripheral parish), available for viewing in the GSV tool.

3.1.3 Neighbourhood level criteria.

Finally, a criterion was defined to select areas for visual audits at the neighbourhood level. Since there are no administrative bodies at the neighbourhood level or clear spatial limits, we opted to consider streets as observation units (rather than of neighbourhoods). A simple random procedure was set for street selection, based on an open-source street directory, organized by boroughs (www.codigo-postal.pt). For each parish considered, street names were listed and numbered, and a random number generator was used to select 20 numbers to determine the streets to be observed. In cases where a street name in the directory did not match the GSV description, the next numbered street was selected. In total, 100 streets were observed (20 per municipality), with 3 streets excluded from the analysis after the audit due to a lack of information.

3.2 Instrument and measures

3.2.1 Instrument

The neighbourhood digital visual audits were conducted based on a systematic social observation protocol, resorting to GSV street-level imagery. The instrument was adapted from the "SSO i-Tour" protocol proposed by Odgers and collaborators (2012), that records the characteristics and maintenance of urban equipment and structures, the functionality of spaces and buildings, and the intensity of human occupation (Odgers et al. 2009; Odgers et al. 2012). Following the initial translation of the materials, a pre-test was conducted. The protocol was applied to eight streets to train the visual audit procedure and refine the observation grid. Adaptations of the original grid included changing items dedicated to the characterization of the local bar (which we adapted to define the street *café* instead) and complementary items, namely the presence of food gardens, schools for higher education, and non-fast-food restaurants. Given the difficulty of applying subjective criteria, the pre-test advised against the inclusion of more subjective items such as "If you could, would you live on a street like this?", "People living on this street seem to belong to what social group?" and "What percentage of cars on this street seem to be luxury or high-end?". Thus, the final grid includes 113 observation items organized into three thematic sections (infrastructure and equipment, uses and functionalities, and human occupation), and is composed of mostly dichotomous items (presence/absence), some ordinal items (such as good conditions, reasonable conditions, and poor conditions). Also, the instrument includes an initial section, dedicated to identifying the street and the observer, and a final section, dedicated to the registration of attributes of the observed images and comments on the application.

3.2.2 Measures

Each observation item was itself considered an individual measure. Following the authors' indications, we generated a set of ordinal scales (Odgers et al. 2009). These include a physical disorder scale derived from counting the signs of physical disorder: garbage or litter on the street, graffiti (including painted over graffiti), abandoned or burned-out cars and vandalized/faded signs. Likewise, we also created a physical decay scale which measures the number of signs of physical decay of sidewalks, streets, residential units and/or residential gardens in 'poor' or' badly deteriorated' conditions and a street safety scale which shows the number of signs of street safety measures, namely traffic control signs for speed or vehicle access, speed humps, crosswalks, and bike lanes. The authors also proposed a dangerousness scale based on subjective ratings, omitted from our version of the observation grid. Instead, we use a territoriality scale (a set of observation units to assess the level of territorial defence and security concerns) counting the signs of security defence measures, such as barbed wire, broken glass inserted into walls, and shutters or iron gates, inspired by Caughy and collaborators' (2001) territoriality observation measure.

Additionally, diversity scores were created for urban equipment, commercial uses, institutional uses, and land uses by counting the number of items observed in the street of each of these topics (urban equipment, commercial uses, institutional uses, and land uses, respectively).

3.2.3 Procedure

The observation protocol was devised as an online survey (Qualtrics). Raters make several digital walks through streets while recording specific features on each walk. They start by identifying the street on their list within the application. They then take a virtual walk along its entire length, taking care to fill in the street identification details. Next, they cover the street again from both directions before rating each survey section, starting first with items pertaining to roads, sidewalks, and urban equipment, then moving on to the lots and building conditions and uses. Finally, raters record the presence of people, cars, and publicity posters. The very last stage was a final revision with a section dedicated to the registration of attributes of the observed images and comments on the application. The observation team was composed of three raters who were trained on how to use the instrument and who participated in the pre-test. Estimated by pairs of observers and by item, the level of inter-rater (pair) agreement was calculated in the final stage of the pre-test with Cohen's Kappa coefficient (e.g., McHugh 2012). Full correspondence was observed in more than 80% of the items (83–91%, kappa = 1). All inconsistencies were reviewed and discussed in detail before the implementation of the systematic observation protocol on the selected streets. After implementation, control observations were conducted that recorded complete inter-rater congruence on over 85% of the items (87–88%, kappa = 1).

3.2.4 Analysis

Data from 97 streets were considered. Data preparation included the creation of ordinal scales (disorder scale, physical decay scale, road security, and territoriality) and diversity scores (urban equipment, commercial uses, institutional uses, and land use). Preliminary analyses informed a set of data cleaning procedures needed for data summary and accuracy: constant observational items were eliminated (e.g., all selected streets were residential streets), other thematically congruent observation items were aggregated (e.g., presence of schools of different levels and restaurants of different types), and adjacent ordinal categories were also aggregated to avoid residual categories (those with lower than 5% of responses). After these operations, 60 variables were included in the analysis, comprising observational items, aggregated items, and ordinal scales.

The analysis assumed as its main aim the identification of key distinctive features in the built environment in the Portuguese landscape to describe unequal territories across and within municipalities. A Multiple Correspondence Analysis (MCA) was performed on the observational data to address these objectives.

MCA is a factorial method designed for nominal data, suitable to identify underlying structures in a data set with minimal loss of information. Generally, it is used as a dimensionality reduction technique to identify case profiles or associations between categories. The MCA is also used to perform perceptual mapping, that is, to transform numerical information into a graphical display in which the relationships among multiple variables are represented on a two-dimensional plot to characterize specific observations or groups (Hair et al. 2014).

The procedure was run in IBM SPSS Statistics. R software was used to optimize the graphical representations. Following the approach proposed by Carvalho (2008), the MCA analysis proceeded by (1) deciding the number of dimensions to be retained, (2) assessing the meaning of each dimension, and (3) assessing the meaning of categories' configurations in the quadrants of the plot.

To decide on the number of dimensions to be retained in the analysis, a preliminary MCA was performed requesting the maximum number of dimensions (Table S1. supplementary materials). The study of this solution suggested that a two-dimensional solution would capture the greatest data variability, seeing as the inertia value drops steadily after retaining two dimensions (**0.24, 0.18**, 0.13, 0.11, 0.11, …). The procedure also allowed identifying variables with a low contribution in differing the observational units that are omitted in the final solution. The final MCA considers 23 variables (with a total of 64 categories) in a two-dimension solution (Table S2, supplementary materials).

4 Results

The MCA was interpreted using statistical and graphical representations. Discriminant measures quantify how well a variable's categories are separated along particular dimensions and quantify how strongly each variable contributes to the formation of the factorial axes (dimensions). They are computed as the squared correlations between the coordinates of objects and the optimally transformed variables (dimensions). We started to make sense of the urban landscape by interpreting each multivariate dimension, considering in each those street attributes (variables) with the highest discriminant measures and the categories opposed across that axis (categories with negative coordinates versus categories with positive coordinates). Overall, Dimension 1 on the table is closely linked to urban equipment, services, and human presence opposing streets with a higher and lower supply of facilities and services and human presence, while Dimension 2 relates to the urban occupation intensity, differentiating places with higher and lower urban density. Both dimensions present high internal consistency (alpha > 0.80) and a clear set of variables with high discriminant measures. The first dimension is named "*Supply of infrastructures and services*", and the second, "*Urban density and maintenance of public space*". In total, the two dimensions account for 41.9% of the variance of the data (Table 1).

The graphical representation of the MCA provides additional insights into the structure of observational data (Fig. 1). Although there is some dispersion in the categories in each quadrant and no clear clusters are observed, each quadrant is associated with some sort of configuration of street attributes that inform the observed built environments. The level of association between categories (street attributes) is expressed by distance, meaning that categories ensembles close to each other can be interpreted as profiles of urban landscapes (features that are related to each other).

Table 1 Discriminant measures

Variable	Dimension 1	Dimension 2
Sidewalk	**0.270**	0.060
Benches	**0.224**	0.003
ONGs_facilities	**0.303**	0.080
Public_gardens	**0.393**	0.000
Sport_facilities	**0.254**	0.012
Recreative_facilities	**0.493**	0.036
Deacay_scale(a)	0.086	0.003
Security_scale(a)	**0.419**	0.012
Equipments_index(b)	**0.532**	0.087
Institutions_index(b)	**0.283**	0.154
Commercial_index(b)	**0.462**	0.081
People	**0.409**	0.013
Cars	**0.313**	0.039
Buildings	**0.359**	0.047
Housing	0.115	**0.498**
Food_gardens	0.026	**0.416**
Empty_lots	0.002	**0.269**
Private_garden	0.070	**0.625**
Lots	0.070	**0.625**
Garbage	0.011	**0.245**
Desorder_scale(a)	0.105	0.095
Uses_index(b)	0.394	**0.410**
Territoriality_scale(a)	0.028	**0.204**
Total	5.620	4.014
Inertia	0.244	0.175

[(a)]Ordinal scales as proposed by Odgers et al. 2009 and Caughy et al. 2001; [(b)]Diversity scores indexes created by summing the items (own authors)

Values in bold represent the dimensions with the highest levels of discrimination for the variable

In Quadrant 1(upper, right), street attributes related to the absence of urban equipment (no urban equipment and lower level of road security [signs] scale), facilities (recreative or sport facilities), services (null diversity scores of commercial offers, institutional offer, and multifunctionality), cars or empty lots, and signs of good maintenance (no garbage, low levels of disorder). This quadrant describes *kept vacant urban landscapes*.

Quadrant 2 (upper, left) joins street attributes related to the presence of people, expensive cars, apartments, urban facilities (benches, good sidewalks, medium road security scale, and medium urban equipment diversity score), commercial and institutional services provision (medium commercial diversity score and high institutional diversity score), and the absence of houses, houses with gardens, empty lots, or food gardens. Categories related to territoriality (null and medium levels) and decay (high decay) are also placed in the same quadrant. This quadrant describes *multifunctional dense urban landscapes.*

Quadrant 3 (bottom, left) collects street attributes that signal the presence of recreative urban equipment (sport and recreative facilities, medium equipment diversity score,

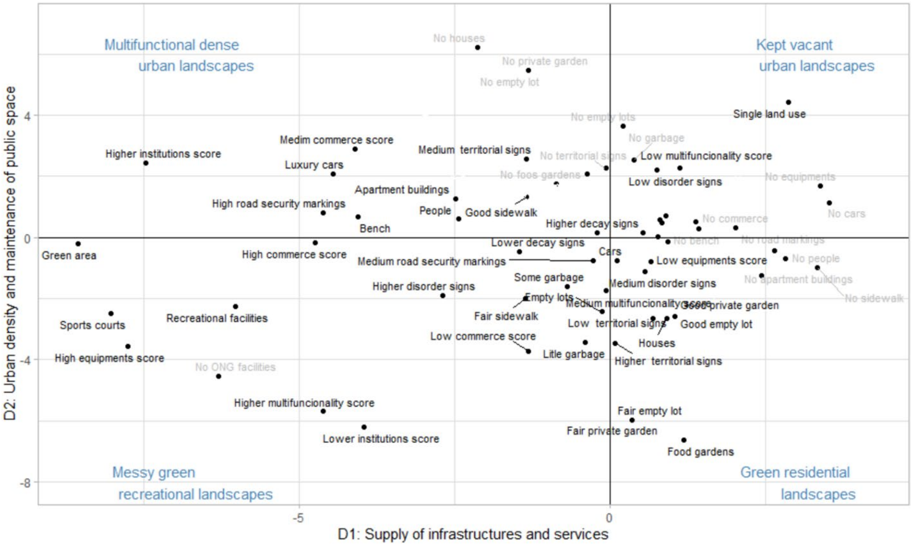

Fig. 1 Multiple Correspondence Analysis *perceptual map*. Notes. Points represent the quantifications of the categories in dimensions 1 and 2. Categories' texts referring to the absence of street features are colored in gray. MCA. Object principal method on 23 active variables

and medium road security scale), multifunctionality of land uses, green areas, some provision of commercial and institutional offer (low and medium levels), and empty lots, signs of decay (garbage) and (high) physical disorder. This quadrant describes *messy green recreational landscapes*.

Quadrant 4 (bottom, right) joins attributes that report the presence of houses, houses with gardens, food gardens, empty lots, low on the road security scale, low provision of equipment diversity scores alongside signs of disorder (medium level) and territoriality. This quadrant describes *green residential landscapes.*

The MCA quantification process is generated for each variable (dimensions), category (street attributes) and object (observation units: streets). The process can be extended for additional variables (passive variables), meaning that we can plot additional information about the observation units on the same graph. This feature can be used to explore differences between territories of different scales. Because we are interested in comparing different municipalities, we have plotted municipality and parish variables. The coordinates (or quantifications) for each category are calculated as the average of the object scores (streets) in each dimension. In this way, the position of the categories in the graph illustrates the associations between each setting (municipality and parish) and specific urban landscapes (Fig. 2).

Municipality B ("Intermediate Territories") is placed in the quadrant *kept vacant urban landscapes quadrant*. The municipalities representing "Innovative Territories" (A) and "Networked Urban Territories" (C) are located in the quadrant associated with *multifunctional dense urban landscapes*. The municipality representing "Low-Density Territories" (D) is positioned in the quadrant of *messy green recreational landscapes*. Finally, Municipality E ("Industrial Territories in Transition") is placed in the quadrant of *green residential landscapes*.

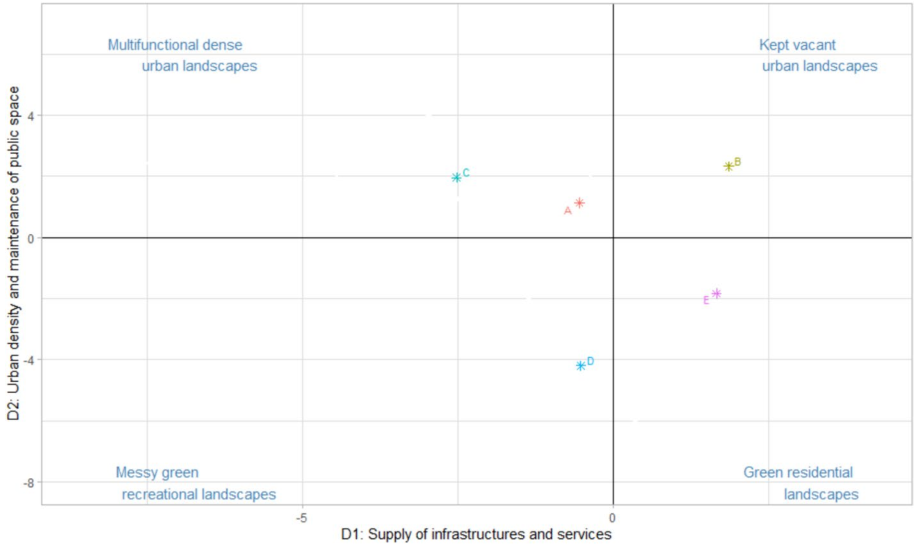

Fig. 2 Projection of the municipalities' quantifications in the Multiple Correspondence Analysis *perceptual map*. Notes. The letters represent the quantifications of the municipalities in dimensions 1 and 2 (**A**–Innovative territories. **B**–Intermediate Territories. **C**–Networked Urban Territories. **D**–Low-Density Territories. **E**–Industrial Territories in Transition). MCA. Object principal method on 23 active variables

Replicating the exercise with the parish categories allows us to reveal, to some extent, the degree of municipality disparities in the built environment by assessing the relative position between central and peripherical parishes–identified next to the municipality letter code in the graph by "c" for central and "p" for peripheral (Fig. 3).

Overall, it is interesting to note that the central parishes are positioned more to the left (across the first-dimension axis (horizontal) than the peripheral parishes, signalling a greater association with the provision of urban equipment, services provision, and human occupation.

Additionally, it is possible to indicate the municipalities with more unequal landscapes. Municipality E (Industrial Territories in Transition) stands out insofar as the streets observed in the central parish are close to *multifunctional dense urban landscapes*, along with the observations of "Networked Urban Territories" (C) and "Innovative Territories" (A), while the streets observed in the peripheral parish are associated with the opposite quadrant, characterized by *green residential landscapes*. The central and peripheral parish of Municipality B ("Intermediate Territories") also diverge greatly with the first placed in the quadrant *kept vacant urban landscapes* and the second in the quadrant *messy green recreational landscapes.*

5 Discussion

In this paper, we present an approach to make sense of multivariate data from street visual audits and unequal urban landscapes. By exploring MCA features, it was possible to identify key differential features among observed street attributes, synthesize the

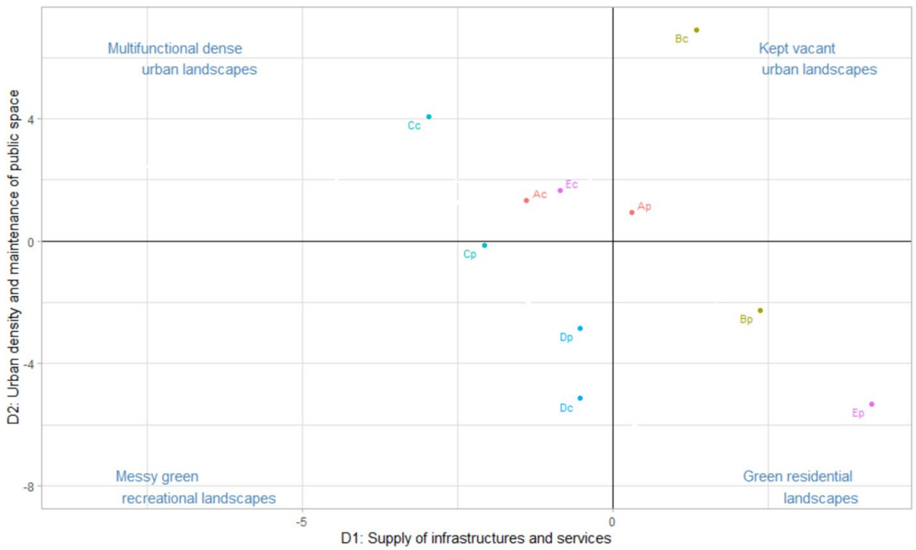

Fig. 3 Projection of the parishes' quantifications in the Multiple Correspondence Analysis *perceptual map*. The letters represent the quantifications of the central (c) and peripherical (p) parishes of each municipality (**A**–Innovative territories. **B**–Intermediate Territories. **C**–Networked Urban Territories. **D**–Low-Density Territories. **E**–Industrial Territories in Transition). MCA. Object principal method on 23 active variables

multidimensionality of data, identify different urban landscapes, and compare the settings in different scales (parishes, municipalities) in meaningful graphical presentation.

Our study was focused on describing and comparing different territories. To achieve this, we opted to use composite indices generated by a multivariate analysis, identifying emerging dimensions from the data. Previous studies have reported the superiority of this approach over aggregating information based on themes or subscales defined a priori (Evenson et al. 2009; Marco et al. 2017), that often lack strong psychometric qualities (Marco et al. 2017; Evenson et al. 2009; Comstock et al. 2010). Acknowledging this, we adopted a prudent approach, treating the predefined scales (physical disorder, physical decay, territoriality) as multinomial rather than ordinal and use the MCA scores to compare settings.

The MCA analysis allowed us to reduce the captured information into two dimensions. These two dimensions were: (1) supply of infrastructures and services; (2) urban density and maintenance of public space. These factors resonate with theoretical distinctions identified in a recent literature review on measures of urban disorder, presented by Ndjila et al. (2019), which distinguishes between stable elements (predominant in dimension 1) and temporary elements (predominant in dimension 2), as well as social elements (more frequent in dimension 1) and physical elements (such as Buildings, almost exclusive in dimension 2). We can also find congruence with other studies using multivariate approaches to identify internal structural of neighbourhood observational data, specially concerning our second dimension, which aggregates elements of physical disorder and physical decay. Marco et al. (2017) assessed physical disorder in Valencia, Spain, through virtual and in-person audits, identifying a bifactor model where physical decay and disorder formed a second-order factor. Similarly, Evenson et al. (2009) developed a neighborhood audit tool incorporating elements from our protocol, grouping physical disorder and decay under "physical incivilities". "..Although these results are consistent with ours, direct comparisons are limited. Despite similarities in the overarching observation approach, the specific observation grids used differ. Implementing a systematic observation protocol in a context different from its original design involves several modifications, such as eliminating, reconfiguring, or adding items, as well as defining composite measures—as described here and by others (e.g., Evenson et al. 2009). While these adaptations may hinder direct comparisons with other studies, they facilitate the customization of observational measures to specific research contexts and objectives, thereby enhancing the protocol's reliability across various settings. Evenson et al. (2009) demonstrated that emergent factors from the data tend to be more stable across rural and urban landscapes compared to pre-defined factors. Given the objective of this study to compare urban and rural landscapes with distinct characteristics, customizing the protocol and utilizing data-driven emergent indicators is proven to be more suitable compared to standardized measures, which may not capture the contextual nuances as effectively.

The topological space defined by the graphical representation of street attributes across the two dimensions allowed us to differentiate between multifunctional dense urban landscapes, kept vacant urban landscapes, messy green recreational landscapes, and green residential landscapes.

The MCA perceptual map provided a relevant framework to assess urban landscape diversity between and within municipalities. This analysis complemented case study reports, linking quantitative indicators-based research (cluster analysis based on municipality secondary data) and qualitative data approaches (observational data).

It facilitated an effective summary and comparison of different areas within a unified framework, aiding local stakeholders in discussions about territorial inequalities, explored in a separate publication (Mauritti et al. 2022).

The generalizability of these results cannot be assessed within the scope of this study. Still, they appear to be somewhat consolidated as they express theoretical and empirical distinctions presented in other studies and align with the secondary data collection description, separating the areas accordingly. For example, the most urbanized municipalities are associated with scores indicating relatively high urban density and the availability of urban infrastructure (A and C), especially the municipality C, which makes sense considering the specific features of these territories (such as intense commutes). In contrast, less urban territories are correlated with low urban density landscapes (B and D). The positioning of Municipality E was more unexpected considering its relatively high population density, this appears to reflect significant territorial fragmentation: the municipality shows significant differences between central and peripheral parishes—green residential landscapes are related to the peripheral parish areas, while observations from the urban parish present the multifunctional dense landscapes expected in more urbanized settings. Interesting, observational data allowed to capture the differential aspects between the territories in comparison previously know (degree of urbanization, for example), but also brought new insights into territory inequalities.

This approach is not without its strengths and limitations. We address them by first looking at advantages and disadvantages of the use of GSV data.

We cannot be certain that the observational data collected through virtual audits would exactly mirror those collected through physical audits. However, previous studies have reported consistently high coherence between observations gathered through both methods across various settings, including urban and rural landscapes (Badland et al. 2010; Fox et al. 2021; Gull et al. 2023; Marco et al. 2017; Mooney et al. 2020; Pliakas et al. 2017; Pocock et al. 2020). No such studies were found in the consulted literature for Portuguese landscapes, where only a few publications report observational neighbourhood audits results (e.g. Hoffimann et al. 2017, direct observation; Santos et al. 2022, secondary data and digital observation).

Savings in time, costs, or personal risks in collecting data are often cited in the literature as key advantages of resorting to virtual instead of on-site observations (e.g., Biljecki and Ito 2021; Cinnamon and Jahiu 2021). Given that the period of data collection was just after the first detected infections of the COVID-19 pandemic in Portugal, it was of paramount importance to access the field without the need for displacing research teams. GSV allowed researchers to observe places from a pedestrian's viewpoint. It also permitted us to make a complementary assessment of the locations needed for our case studies, by including observation from peripheral parishes, which would not be possible if using in person street audits, due to logistic and budget constraints.

In opposition, the available geographic coverage, image detail, and update rate constrain the scope of the studies using this kind of data and exclude some contexts from the analysis (e.g., Biljecki and Ito 2021; Cinnamon and Jahiu 2021). Most street level image databases are stored on private digital platforms owned by corporations, such as Google, Microsoft or Apple that control this information, advancing data sharing and data modelling technologies not for research applications but for their own interests (e.g., Biljecki and Ito 2021; Cinnamon and Jahiu 2021). The risks include no consistent land coverage, which implications were illustrated in our research as it is our aim to observe urban, suburban, and rural settings. The randomization process for the selections of streets in each parish was hindered by the total GSV coverage in more peripheral areas, potentially harming our estimate of landscape diversity within municipalities. In addition, images from more densely populated municipalities (such as C or D municipalities) were more recent than those from lesspopulated municipalities (E).

Even in the urban setting the accessibility of some streets or no disclosed interest (as commercial interests) may result on underrepresentation of some urban features such informal settlements. The decision regarding which areas are represented appears to depend more on these companies' revenue strategies than on systematic coverage. Conversely, large-scale classification of urban and rural landscapes may reinforce image capturing without consent or awareness. Overreliance on these types of indicators may contribute to discourses that reduce the complexity of lived spaces to dataficable indicators (in this case, visually identifiable ones). This, in turn, may reinforce place differentiation, which can also be biased to reflect concealed interests, driven by corporate gatekeepers (e.g., Biljecki and Ito 2021; Cinnamon and Jahiu 2021). More discussions are needed to address the benefits and security risks posed by detailed urban imagery, as well as the ethical use of these platforms. This should include fostering community oversight and advocacy for regulatory measures that ensure transparency and protect user privacy.

The randomization of street selection was also challenged by difficulties in identifying a street in GSV, due to the differences in street names between GSV and the address repositories. Other procedures of location selection may provide the answer to these problems, such as the drop and spin method (e.g., Plascak et al. 2020) or aerial view maps to pre-identify observation targets (e.g., Less et al. 2015).

Researchers are also concerned about the highly intrusive nature of accessing visual information of people and populations, generating a "hyper visibility" phenomenon, and contributing to stereotyping places and groups (e.g., Shapiro 2018; Cinnamon 2019). Our approach evaded this pitfall by adhering to strict empirical criteria in selecting the distinguishing features, avoiding specific markers of social distress, high or low socioeconomic markers, or by not targeting areas or populations considered as problematic. It may also be beneficial to mitigate the biases generated by corporate gatekeepers by utilizing alternative platforms that promote community participation and offer greater transparency in data use and privacy. Services like OpenStreetMap and Mapillary can provide such alternatives.

Our approach illustrates how to extract and analyse street visual data to interpret key distinguishing features in each setting. The selection of the observation units was informed by theoretically relevant empirical criteria for researching place-based inequalities in Portugal. Supported by previous analysis, the observation data was collected from five municipalities that represent different territorial inequality profiles. Within the same municipality, population size (and GSV coverage) determined the selection of two parishes and a sample of streets from both. The mix of criteria used in the selection of observation units ensures a thorough analysis, combining the strengths of the broad secondary analysis (territorial profiles are included) and the depth of the observational data in each setting (e.g., Johnson et al. 2007). The sample of residential streets selected for each set however cannot be considered a representative sample of the residential streets of the parishes or municipalities. Instead, the sample is a theoretical one, designed to include diversity in the observational data with no thought of providing statistical representation for the total of streets in the parishes of municipalities–our case studies are qualitative. More robust conclusions about urban landscapes in Portugal could be made by including more observation units to show statistical representations in each setting. Still, the qualitative approach employed at this stage allowed for the identification key of vectors of territory inequality, offering insights into context-specific issues that might be overlooked in purely quantitative analyse.

The data extraction protocol was developed based on the adaptation of previously validated instruments and procedures (Odgers et al. 2012). Given that data extraction is made by raters and not by computers ("manual" versus "computational" approach; Cinnamon and Jahiu 2021), the approach can be easily adapted for future social research without the need for specialised programming skills. The instrument was selected for its breadth of data collection and exhaustive support materials. Many other options are available, and the selection of the tool ought to serve the aims of the study.

Generally, manual approaches described in the literature tend to support narrower urban assessments and typically propose the summarization of data into specific scores to describe the setting or correlate with other data such as accessibility features, walkability, physical disorder, coffee shop layouts, and seismic risk (Cinnamon and Jahiu 2021). Our proposal illustrates a technique of analysing and interpreting multi-thematic and multidimensional data through a process of data reduction with a strong analytical and interpretative value. The approach exemplifies the value of moving beyond the traditional quantitative and qualitative divide, and traditional and innovative data approaches.

The graphical representation of the results shows an intuitive way of comparing different territorial observation scales. The procedure can also be employed to create quantitative indexes (e.g., Reed 2002). At this point, it is important to mention that the MCA is used to focus on key distinguishing features and a significant amount of information is excluded from the analysis due to their low discrimination power. Basing a comparative assessment between settings of only high discrimination features can provide biased territorial portraits and place-based inequalities.

The data quality control procedures are another significant aspect to discuss. Considering the relatively small geographic scope under analysis and because the same team of trained raters were used in the protocol pre-test, the monitoring procedures applied were not very robust at first (inter-rating assessment of a total of eight streets). Crowdsourcing neighbour assessments could be a good strategy to get more observational units from highly motivated voluntary raters (e.g., Hanibuchi et al. 2019). Challenges related to rater fatigue, street boundary identification and observation rating settings (remote work) should be better assessed in future designs. Automatization procedures should also be considered for the future, including multidisciplinary partnerships with complementary skills in urban research.

6 Conclusion

We have described in this paper an approach for the extraction and analysis of street-level imagery. As part of a wider research programme, data from five municipalities were extracted and analysed to identify key distinguishing features of Portugal's landscapes and compare territories of different scales under a context-specific empirical framework. By focusing on analysing the most differentiating street attributes, we were able to identify two particularly relevant dimensions which were both empirically and thematically consistent: (1) supply of infrastructures and services; (2) urban density and maintenance of public space.

With this approach, an indicators-based study was linked to non-administrative data for an in-depth exploration of spatial inequality features, focusing on specific case studies. Observational data not only captured the differences between territories as previously known but also provided new insights into territorial inequalities.

Assessing the positioning of municipalities and their central and peripheral parishes across the two dimensions allows for consideration of potential urban management priorities. According to the data, Municipality A ("Innovative Territories") should ensure that the relatively higher concentration of infrastructure and services in the central parish is not hindering equitable access for all populations; Municipality B ("Intermediate Territories") should strengthen the provision of infrastructure and services to stimulate new economic dynamics, particularly in peripheral areas; Municipality C ("Networked Urban Territories") should prioritize urban maintenance in peripheral parishes to minimize signs of physical disorder; Municipality D ("Low-Density Territories") should enhance the maintenance of recreational areas and public equipment and assess their alignment with population needs; and Municipality E should mitigate urban space discontinuity by strengthening the offer of urban equipment and services and improving connectivity between areas.

In this paper, we link empirical portraits drawn from official statistics with observational data from panoramic street-level imagery to describe five municipalities in Portugal. The approach captured expected similarities and distinctions between the territories as well as exposed new layers of territorial inequalities not captured in the official statistics. This study contributes to the literature by emphasizing the multidimensionality of urban landscapes, using a non-computational data extraction method combined with multivariate analysis, which can be replicated by researchers with limited programming expertise. It is our hope that by exposing its potential and its limitations, street-level imagery may be better applied in urban research across social disciplines, even where specialized programming skills are uncommon and encourage multidisciplinary partnerships.

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Declarations

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