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The spatio-temporal evolution of social inequalities in cities: a multidimensional, multiscalar and longitudinal approach for neighbourhood classification

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ABSTRACT

Understanding the spatial patterns of social inequalities has been a longstanding concern in urban studies. Geodemographic classifications, which group neighbourhoods based on multiple social and physical dimensions, offer a useful tool for this purpose. However, most classifications rely on fixed single-scale administrative boundaries, while studies that adopt multiscale approaches often focus on a single dimension and cover only limited time periods. This limits our understanding of how urban social inequalities evolve over time and across spatial scales. In this study, we extend the geodemographic approach to incorporate multiple dimensions, time periods, and geographical scales, enabling a more comprehensive analysis of the spatio-temporal configuration of urban change. We develop multidimensional, multiscale, and longitudinal spatial profiles of residential contexts in the Metropolitan Agglomeration of Amsterdam (MAA) using bespoke neighbourhoods constructed from detailed population register data (1999–2022). Our results show that the interaction of socioeconomic status, migration background, life-course stages, and housing tenure provides a richer understanding of urban stratification than traditional models based solely on income or ethnicity. The longitudinal perspective reveals distinct timing differences in urban reconfigurations, such as gentrification and displacement, which emerge locally and consolidate more broadly over time. The multiscale approach highlights how patterns of urban change are scale-dependent, with large-scale dynamics, such as poverty suburbanisation and inner-city gentrification, coexisting with the formation of smaller enclaves in areas undergoing or at risk of change. These findings highlight the need for integrated multidimensional, temporal, and multiscale frameworks to better capture the evolving nature of sociospatial inequalities in cities.

1. Introduction

Understanding the spatial patterns of social inequalities has been a long-standing concern for urban research. The early efforts of the Chicago School of Sociology, which sought to model social urban space a century ago, laid the foundation for a rich body of literature aiming to disentangle the complex dynamics of sociospatial inequalities within urban structures (for a review, see Knaap et al., 2019). Studies have employed geodemographic classifications to capture this complexity, grouping and distinguishing neighbourhoods based on multiple dimensions, such as socioeconomic status, demographic composition, and housing characteristics (see Singleton & Spielman, 2014). Unlike single-variable approaches, geodemographic classifications treat neighbourhoods as ensembles of mutually reinforcing attributes (Galster, 2001; Spielman & Singleton, 2015). This perspective recognises that the interaction of multiple variables shapes the living conditions individuals experience, which in turn influences their life opportunities, often referred to as neighbourhood effects.

By creating geodemographic classifications using multiple socioeconomic, demographic and housing characteristics, researchers can trace processes driving residential differentiation that lie at the intersection of socioeconomic status, ethnicity, age and housing (Hu et al., 2024). As a result of these processes, neighbourhoods undergo short- and long-term transformations, reconfiguring the urban map of sociospatial inequalities. Increasingly, empirical studies have focused on these reconfigurations, employing geodemographic classifications (e.g.,

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Delmelle, 2016; Nelson et al., 2024; Patias et al., 2020; Vogiazides & Mondani, 2023). These studies examine how the interaction of different dimension change over time to make neighbourhoods transition between "types", relying on fixed administrative boundaries to describe these processes.

However, processes shaping urban environments operate differently across spatial scales - from individual blocks and streets to larger neighbourhoods and districts - and fixed boundaries cannot account for this complexity (Fowler, 2016; Manley et al., 2006; Petrović et al., 2020). Methodologically, the composition of spatial contexts is directly influenced by the geographical extent of the spatial unit at which they are measured, defined as part of the modifiable areal unit problem (MAUP; see Manley, 2021 and Oppenshaw & Taylor, 1979). Rather than merely restating this problem, scholars have increasingly sought to embrace this variability of scale by employing representations of social and physical contextual characteristics measured using geographical contexts of increasing extent (e.g., Olteanu et al., 2019; Petrović et al., 2018). Building on the concept of segregation profiles introduced by Reardon et al. (2008), studies increasingly employ bespoke neighbourhoods, which are egocentric and overlapping areas delineated around detailed residential locations (see Johnston et al., 2001), to create neighbourhood classifications based on multiscale population compositions (Andersson et al., 2022; Clark et al., 2015; Fowler, 2016; Hennerdal & Nielsen, 2017; Spielman & Logan, 2013). Through the creation of multiscale classifications it is therefore possible to represent how the social urban space is produced and reconfigured by the interaction of multiple dimensions that shape the sociospatial context of each location differently across spatial scales and over time.

Despite these advancements, the integration of multiple dimensions, spatial scales and time periods in geodemographic classifications remains an important challenge. Existing studies using multiscale approaches either create classifications based on multiple dimensions separately (Andersson et al., 2022) or focus predominantly on ethnicity and income (Clark et al., 2015; Fowler, 2016; Hennerdal & Nielsen, 2017; Spielman & Logan, 2013). Moreover, these studies rely on cross-sectional data or comparisons between a limited number of time points. Without integrating multiple time periods for both short- and long-term multiscale analyses, it remains difficult to understand the timing and spatial diffusion of processes driving urban change or to identify whether short-term changes signal more enduring structural shifts in the urban fabric. This limits our understanding of how social inequalities unfold and persist across both space and time.

This article addresses this gap by expanding the geodemographic classification approach to include simultaneously a multidimensional, longitudinal and multiscale perspective. By doing so, we provide a way of better understanding the spatial configuration of scale-sensitive and time-dependent processes shaping sociospatial variations in urban areas that cannot be identified with single-variable, single-scale or cross-sectional classifications. Focusing on the Metropolitan Agglomeration of Amsterdam (MAA) as a case study, we address the following objectives: i) to develop a typology of residential contexts using socioeconomic, demographic, and tenure variables measured across multiple geographical scales and time periods, and ii) to analyse changes in the urban structure across both short- and long-term periods at different geographical scales. To achieve these goals, we utilised register data from the Central Bureau of Statistics (CBS) of the Netherlands, covering the entire population of the MAA from 1999 to 2022. This data details individuals' places of residence within 100 × 100 meter grid cells. Our methodological approach builds upon the work of Petrović et al. (2018), by delineating bespoke areas around each grid cell at multiple geographical scales. Expanding on the clustering approach proposed by Masías H. et al. (2023), we then assess the socioeconomic, demographic, and tenure compositions of these areas every four years to create a multidimensional, multiscale and longitudinal typology of residential contexts that we employ to analyse the evolution of the social urban structure of the MAA across spatial scales and time.

2. Theoretical framework

2.1. Sociospatial stratification in a multidimensional urban structure

Residential segregation, defined as the uneven distribution of population groups within the urban landscape, is a central focus of research on sociospatial inequalities (Tammaru et al., 2021). Examining segregation patterns helps us understanding sociospatial stratification in cities (Cassiers & Kesteloot, 2012). Individuals tend to cluster with those sharing similar practices and varying forms of capital - namely economic, cultural, and social (Butler & Robson, 2003; Savage et al., 2005). This is especially true for those who possess the resources to choose their place of residence, distancing themselves from disadvantaged groups by clustering in prestigious, desirable areas (Atkinson, 2006; Butler & Robson, 2003; Watt, 2009). Meanwhile, disadvantaged groups are often relegated to more affordable yet marginalised and stigmatised residential contexts, reinforcing segregation through socioeconomic and symbolic exclusion (Marcuse, 1997; Wacquant, 2008). As a result, distinct sociospatial configurations emerge within the urban structure, wherein specific social groups are associated with particular residential environments.

The composition of these sociospatial configurations is multidimensional, encompassing more than just socioeconomic status. While economic capital allows wealthier households to outbid poorer ones for access to better spatial resources (Marcuse, 1997), other dimensions also significantly influence residential choices. For example, migration background continues to be a central axis of social differentiation and exclusion. Certain migrant groups, often labelled as "ethnic minorities", face systematic discrimination in both housing and labour markets (Aalbers, 2007; Thijssen et al., 2021; Uunk, 2017). Furthermore, preferences for co-ethnic living, driven by shared cultural backgrounds and social networks, further contribute to the spatial separation of migrant groups (Boschman & Van Ham, 2015). Other demographic factors, such as age and family structure, also shape residential choices and housing needs, which are met by specific urban areas and housing sectors (Hochstenbach, 2019; Mulder & Hooimeijer, 1999). In Amsterdam, for example, middle- and upper-class families tend to prefer living in suburbs (Tzaninis & Boterman, 2018), while vulnerable groups, such as working-class older adults or single-parent households, are concentrated in the social-rental housing sector (Musterd, 2014).

The recognition of sociospatial stratification as a multidimensional phenomenon dates back to the early works of the Chicago School, with Burgess (1925) positing that urban form is shaped by "natural economic and cultural grouping" processes (p.56). Although the "natural" character of these processes can be refuted by the role that institutions and welfare structures have in shaping segregation (e.g., Tammaru et al., 2015), the idea that urban areas develop through multiple processes is still valid (Sampson, 2012). This multidimensional approach was further developed through the fields of factorial ecology and social area analysis, which utilised latent factors - underlying variables inferred from data - to describe the complex spatial patterns that emerge in cities (for a review, see Singleton & Spielman, 2014). Building on these foundations, geodemographics emerged as a field dedicated to classifying neighbourhoods into discrete typologies based on their sociospatial characteristics. Recent studies within geodemographics have increasingly employed dimensionality reduction techniques to distil the key latent factors and to cluster residential areas based on these shared factors (e.g., Masías H. et al., 2023; Shi & Yeh, 2023; Singleton et al., 2022). This contextual approach operationalises neighbourhoods as "bundles of spatially based attributes" (Galster, 2001, p. 2111), reflecting the complex and multidimensional nature of residential contexts and sociospatial stratification in cities (Spielman & Singleton, 2015).

Understanding the nature of these differentiated spatial contexts is essential for investigating sociospatial inequalities and subsequent consequences for life-opportunities. The exposure to unequal residential configurations leads to disparate individual and group outcomes which can reinforce sociospatial inequalities (van Ham et al., 2018). The mechanisms through which residential attributes affect individual outcomes are complex, with effects that are often interdependent and multiplicative rather than merely additive (Galster, 2012). A conceptualisation of residential contexts as ensembles of reinforcing attributes, aligns with this idea of compounding effects developed in the neighbourhood effects literature (Galster, 2012).

2.2. *The role of scale: spatial profiles*

Spatial scale is critical for understanding sociospatial configurations, as the processes shaping the distribution of residential attributes operate across multiple geographical scales (Manley et al., 2006). For instance, the processes behind residential (im)mobility vary depending on the scale considered (Owen et al., 2021). In that sense, some households may identify with a large city area but select a smaller, more localised zone for their place of residence (Manley et al., 2015). The scale at which tenure types, such as social or owner-occupied housing, are concentrated is also vital for understanding residential choices and the sociospatial dynamics of urban areas, as these tenure forms often overlap with sociodemographic composition (Andersson et al., 2022). In the Netherlands the social rental housing sector has historically dominated large-scale housing estates (Bolt et al., 2010). However, recent reforms have sought to replace these estates with smaller-scale, mixed-income developments (Savini et al., 2016). As such, understanding how socioeconomic, demographic, and tenure attributes vary across multiple scales provides insights into the processes that underpin sociospatial inequality in urban environments.

Segregation manifests differently depending on the spatial scale considered. Thus, individuals' experiences within segregated urban structures are not confined to a single geographic scale (Petrović et al., 2022). Galster and Sharkey's (2017) concept of "spatial opportunity structure" emphasises that various geographical contexts, from the immediate surroundings to the metropolitan scale, affect individual outcomes in distinct ways. The underlying idea is that the mechanisms by which spatial contexts influence individuals vary across scales (Petrović et al., 2020).

A major methodological challenge in segregation and neighbourhood effects research lies in capturing this scalar variability when measuring sociospatial contexts. The aggregation of residential attributes and the definition of the appropriate geographical context that affects individuals is sensitive to the boundaries employed to delimit the spatial units. To harness these issues of aggregation (MAUP; see Oppenshaw & Taylor, 1979; Manley, 2021) and definition of the relevant geographical context (UGCoP; Kwan, 2012), scholars have increasingly moved beyond fixed administrative boundaries to multiscale definitions of neighbourhoods (see Petrović et al., 2018). Bespoke neighbourhoods, defined as areas centred around an individual's residential location, have been increasingly adopted for this purpose since its introduction in the early 2000s (Johnston et al., 2001). By delineating bespoke neighbourhoods at multiple scales, researchers can generate a more precise depiction of the sociospatial complexity of urban landscapes (Hipp & Boessen, 2013).

Reardon et al. (2008) concept of "segregation profiles", employed to measure multiscale segregation based on bespoke neighbourhoods, inspired the development of "spatial profiles" that characterise residential contexts based on residential attributes measured across multiple scales. These multiscale profiles reveal the underlying spatial structure of cities, as seen in the work by Spielman and Logan (2013) who calculated the concentration of different socioeconomic and ethnic groups across multiple scales, clustering these "egocentric signatures" using microdata from the 1880 decennial US census. Similarly, Clark et al. (2015) used multiscale profiles to cluster locations within the Los Angeles metropolitan area based on their ethnic composition in 2000 and 2010. Fowler (2016) expanded this approach, clustering multiscale profiles to describe their functional form and map exposure patterns among different ethnic groups in Seattle in 1990, 2000 and 2010. Despite these advancements, integrating multiple dimensions -such as demographic, socioeconomic, and tenure compositions- into multiscale profiles over time remains a significant challenge.

2.3. *Temporal dynamics: urban structure reconfigurations and neighbourhood change*

The sociospatial conditions of urban environments evolve not only across scales but also over time. Classic models, such as Burgess' (1925) concentric zone theory, Hoyt's (1939) filtering model, or Hoover and Vernon's (1959) life-cycle model sought to explain the decline of inner-cities and suburbanisation of wealthier groups observed in many US cities through shifts in the built environment and social composition of these urban areas. More recent research in Western Europe and the U.S. has focused on gentrification and suburbanisation of poverty, examining how the inflow of wealthier residents into inner-city neighbourhoods displaces lower-income groups, pushing them to the urban periphery (Hochstenbach & Musterd, 2018; Marcuse, 1985).

Several demographic, economic, cultural, and social processes have driven these shifting sociospatial inequalities in recent decades. Demographic transitions such as population ageing, changes in family arrangements, and reduced household size have been linked to gentrification (Hochstenbach & Musterd, 2018; Hochstenbach & van Gent, 2015). Younger age groups are increasingly opting for smaller dwellings in gentrified neighbourhoods due to lifestyle changes (Moos, 2016). Rising income inequalities, wage polarisation, and the liberalisation of the housing sector have also contributed to the gentrification of inner-city areas and the displacement of lower-income populations to suburbs (Bailey et al., 2023). However, it is important to note that suburbanisation is not limited to poverty. In the Netherlands, for instance, high-income families, especially natives, continue to prioritise suburban living (Booi et al., 2021).

In the case of Amsterdam, the sociospatial reconfiguration reflects a combination of class and age segregation that is fuelled by the liberalisation and segmentation of the housing market. Younger, single-person households increasingly prefer living in gentrifying neighbourhoods in the urban core. However, due to the liberalisation of both private and social rental sectors, only more affluent young households can access these upgrading areas, resulting in the displacement and exclusion of lower-income groups to peripheral locations (Howard et al., 2024). Older residents, by contrast, follow divergent patterns: high-income households secured homes in elite urban areas during earlier waves of gentrification and have since accumulated wealth through rising property values, while older lower-income households have remained in upgrading neighbourhoods thanks to longstanding social housing and protected tenancy agreements (Hochstenbach, 2019). In the Netherlands, with a historically large social housing stock and a strong regulated rental sectors, the push for homeownership and housing market liberalisation has significantly restructured the urban social fabric (Boterman & van Gent, 2014; Howard et al., 2024). This process has intensified asset-based stratification along both class and age lines (Wigger, 2021), highlighting the need to incorporate socioeconomic, demographic, and housing dimensions into analyses of evolving sociospatial inequalities, beyond traditional frameworks focused solely on race or income.

To fully understand these urban transformations, a multiscale and longitudinal approach is also required. Processes of neighbourhood change can differ significantly depending on the scale and time frame of analysis. At a finer scale, such as city blocks or streets, change may be driven by highly localised factors like small property developments or the in-situ change of residents. In contrast, at a coarser geographical scale, larger sociospatial trends become more visible, including housing market shifts or large-scale urban developments. We could expect that small scale changes could be visible in the short term (Bilal et al., 2020), while long run changes might be linked to broader processes related to large scale demographic, socioeconomic and housing transformations (Champion, 2001; Meen et al., 2013; Zwiers et al., 2016).

Additionally, the broader context of a residential location can significantly influence its trajectory of change (Delmelle et al., 2016). Multiscale operationalisations of residential contexts serve to depict this contiguous space of influence. Nevertheless, empirical studies that have begun to map trajectories of change using multidimensional classifications often overlook the scalar complexity that underpins urban transformations (e.g., Delmelle, 2016; Nelson et al., 2024; Patias et al., 2020). By using multiple scales rather than fixed administrative units, we capture processes that emerge at specific scales during particular time periods, revealing short-term, small-scale transformations that may be obscured at coarser resolutions, while also accounting for the broader contextual influences shaping local change over time.

3. Data and methods

To consider all these multidimensional, temporal and scalar variabilities, we used register data provided by the Central Bureau of Statistics (CBS) of the Netherlands, covering the full population of individuals, households and residential units in the country, geocoded on 100 m × 100 m grid cells from 1999 to 2022. Our case study focuses on the Metropolitan Agglomeration of Amsterdam (MAA), the most populated city of the Netherlands, which has experienced a significant demographic and urban growth in the recent decades.

We developed spatial profiles of residential contexts considering their socioeconomic, demographic, and tenure compositions. The selection of these dimensions is informed theoretically and responds to relevant domains we identified in the social sciences literature regarding social differentiation in (Dutch) cities. For the socioeconomic dimension, we assessed the percentage of social benefit recipients and the proportion of households within each quintile of the national distribution of standardised household income from work, social benefits and pensions. The demographic composition was characterised by the percentage of individuals grouped by migration background,[1] age, and student status, as well as the distribution of households by family composition. For the tenure dimension, we calculated the proportion of residential units occupied by owners, in opposition to those that are rented. Among relevant variables measuring each dimension, we selected only the ones which were available and consistent across all years within the study's time window (1999–2022). For example, educational level of individuals was omitted due to the large number of missing records, particularly at the start of the time window. All variables were computed for the years 1999, 2003, 2007, 2011, 2015, 2019 and 2022, with household income adjusted for inflation. For a more detailed description of each variable and how they are calculated, refer to Table A.1 of Appendix A.

We propose a two-step methodological approach (Fig. 1) to examine multidimensional and multiscale changes over time in urban structure.

Step 1: Multiscale Composition of Residential Contexts

We calculated the composition of residential contexts following the multiscale approach proposed by Petrović et al. (2018). The base unit of analysis is the 100 m × 100 m grid cell. Six bespoke areas spread around each grid cell as concentric circles with radii doubling from 100 m to 3200 m. We measured the composition of these bespoke areas for each time period and all variables, considering all individuals, households, and residential units within the specific radius. We then pooled the data from all cells and bespoke areas across all time periods, treating each cell and bespoke area at each time period as an individual observation. Only grid cells in the MAA with complete data across all years were included (exactly 10,000 cells and their 6 bespoke areas: 70,000 yearly observations). Bespoke areas could include cells outside city boundaries. The exponential increase in bespoke area size provided a detailed picture of the closest residential environment while covering a large area at the largest scale. This approach balances the need for detailed local information and extensive coverage, adhering to the principle of declining exposure with distance (Petrović et al., 2022; Tobler, 1970).

Step 2: Multiscale and Longitudinal Cluster Classification

To identify the relevant sociospatial configurations, we applied a clustering strategy based on the pooled data set consisting of all grid cells and bespoke areas across all years (70,000 yearly observations over 7 years: 490,000 total observations). Working with a pooled data set allows us to obtain a consistent classification comparable across time periods and spatial scales. To produce the cluster classification, we employed a Nonnegative Matrix Factorization (NMF) technique using the NMF package for R (Gaujoux & Seoighe, 2010). NMF is an unsupervised machine learning algorithm for dimensionality reduction of multivariate data through the decomposition of its nonnegative[2] parts (see Lee & Seung, 2000). NMF decomposes a given high-dimensional matrix V into two lower-rank nonnegative matrices W and H, such that:

$$V \approx WH$$

Each column of the original matrix V is approximated by a linear combination of the columns of W weighted by the components of the corresponding column of H. As the objective is to reduce the dimensionality of the data, relatively few columns are used in W to approximate V. As such, to obtain a good approximation, the columns of W (i.e. basis components) should retrieve the latent factors explaining the original data. In other words, the rows of W indicate the importance of each latent factor for a given observation while the columns of H indicate the importance of a given variable to each latent factor.

All observations within the original dataset are organised into clusters based on their predominant latent factor, as indicated by the W matrix. The latent factor exhibiting the highest value for a given observation is considered the most relevant to describe the composition of that particular observation. To interpret the characteristics of each latent factor, we refer to the matrix H, which shows the significance of each original variable across all latent factors.

Masías H. et al. (2023) recently introduced this clustering technique to the literature on neighbourhood classification and residential segregation, applying it to study the multifaceted patterns of residential segregation in Berlin. In this paper, we expand their approach to a multiscale and longitudinal framework. When identifying and interpreting latent patterns existing across scales and time using exclusively nonnegative variables, NMF offers several advantages compared to other dimensionality reduction methods such as Principal Component Analysis (PCA) or Independent Component Analysis (ICA). Contrarily to PCA and ICA, NMF does not produce negative factors or coefficients. The nonnegative nature of the results facilitates a more intuitive interpretation of the data which, in this case, cannot be negative. This nonnegativity constraint ensures that the factors are additive rather than subtractive, which enables the construction of patterns in the data from separate parts (Lee & Seung, 1999). From methodological and conceptual perspectives, the additivity property is crucial to extract the sociospatial configurations within the urban structure as residential contexts are not exclusively composed by one specific factor and their composition also changes over time and with scale. Finally, NMF does not restrict

[1] We employ a classification of migration background provided by CBS which identifies countries of origin with historically strong migration ties with the Netherlands and a significant presence in the country.

[2] This method considers only the parts of the data that are either positive or zero, making it particularly suitable for our analysis because all the variables used are percentages, which are inherently nonnegative and range between 0 and 1.

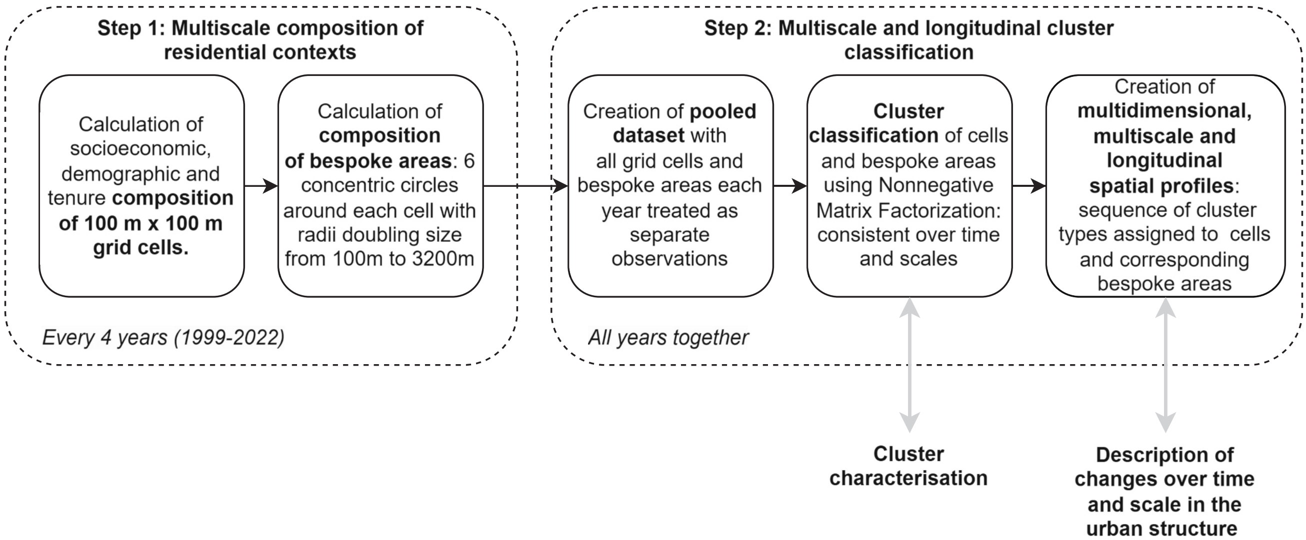

Fig. 1. Methodological framework.

the factors to be linearly uncorrelated or statistically independent (Gaujoux & Seoighe, 2010), allowing for the capture of interrelated patterns.

To ensure we are capturing the latent structure of the data, we need to estimate the W and V matrices by minimizing the discrepancy between the original data and the approximation. This optimization problem can be solved using several iterative algorithms and loss functions (Berry et al., 2007). In this study, we employed the approximation algorithm proposed by Lee and Seung (1999), which relies on multiplicative updates and a Euclidean distance loss function. Furthermore, we executed the algorithm 100 times with different random initial values for W and H, drawn from a uniform distribution bounded to the values of the original data, to minimise the likelihood that the solution corresponds to a local optimum.

Another important parameter is the number of columns of W – the factorization rank – which determines the number of clusters. Following Masías H. et al. (2023), we combine multiple quality measures to determine a factorization rank that provides a parsimonious solution in terms of reducing the estimation error while maintaining the simplicity of the results. These measures include the cophenetic coefficient, which assesses the stability of the cluster solutions across all 100 executions with different random initial values for W and H; the silhouette coefficient, which evaluates how well observations within the same cluster are grouped based on their similarity and how distinct they are from observations in other clusters; and the level of sparseness, which reflects the variance explained by the model (for further details, see Masías H. et al., 2023). The preferred solution is the one that provides relatively high values of all quality measures, preferably closer to 1, while maintaining the parsimony and interpretability of the model.

Fig. 2 shows the cophenetic coefficient, silhouette coefficient, and sparseness for a series of factorization ranks. The cophenetic coefficient remains close to 1, indicating stable cluster solutions across multiple iterations. However, a trade-off emerges between increased model variance explained (sparseness) and decreased factorization consistency (silhouette coefficient) as the number of ranks increases. We selected a factorization rank of 4 as it offers an acceptable balance of consistency (silhouette coefficient: 0.56), explanatory power (sparseness: 0.51), stability (cophenetic coefficient: 0.97), and parsimony. In the following section, we provide a detailed characterisation of these four clusters depicting the sociospatial structure of the MAA.

As a result of this multiscale and longitudinal classification of bespoke areas, we obtain a multidimensional, multiscale and longitudinal spatial profile for each 100 × 100 m grid cell. This spatial profile corresponds to the cluster type assigned to the cell and each respective bespoke area every year. Fig. 3 visually represents a hypothetical spatial profile for a given 100 × 100 m cell illustrating how a residential location changes with scale and over time. In this hypothetical case, in 1999, the grid cell is assigned to cluster 1 at the grid cell level and when using bespoke areas up to 1600 m radius, while it is assigned to cluster 4 when using a 3200 m bespoke area. In 2022, the same grid cell remains in cluster 1 at the grid cell level but is assigned to cluster 2 when using bespoke areas between 100 m and 400 m and to cluster 4 when using larger bespoke areas.

By constructing these spatial profiles, it is possible to study how residential locations change between scales for a given year (within a row) and compare how these changes across scales evolve over time (between rows). Similarly, it enables us to examine how a residential location changes over time at a given scale (within a column) and how the trajectories of change over time differ between scales (between columns). The consistency of the cluster typology across years and bespoke areas ensures the comparability over time and spatial scales, and provides a flexible framework for different types of analyses. This flexibility represents a key advantage over spatial profiles that assign residential locations to a unique cluster category using information from all scales simultaneously, as those do not permit this type of longitudinal and multiscale decomposition for comparative analyses. In this study, we analyse these spatial profiles by mapping and comparing the spatial distribution of clusters in the urban space of the MAA across scales and time.

4. Results

4.1. The residential configurations in the sociospatial structure of the metropolitan agglomeration of Amsterdam

The cluster analysis returns a typology of distinct residential configurations that structure the urban landscape of the MAA. We describe the clusters using the scaled H matrix coefficients (Fig. 4), normalised so the sum of the coefficients for each variable equals one, highlighting each variable's relative contribution across clusters:

- **Cluster 1:** Dominated by an older, Dutch population, with significant concentrations of middle- and low-income households, and couples without children. It also includes a considerable proportion of social benefit recipients, individuals with an Indonesian background, and single-person households.

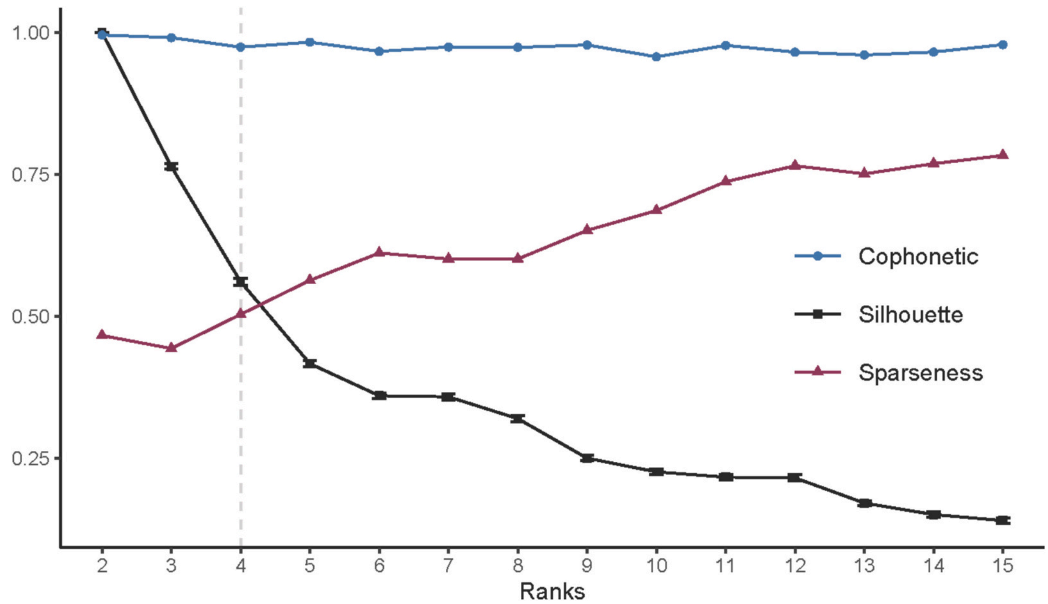

Fig. 2. Statistics for optimal NMF rank selection: cophonetic coefficient, sparseness and silhouette coefficient for multiple ranks.
Source: Authors' calculations using non-public microdata from Statistics Netherlands (CBS).
Note: We present the 95 % confidence intervals of the silhouette coefficient obtained from a bootstrap estimation based on 1000 random resampling instances with replacement using each time the 2.5 % of the whole sample.

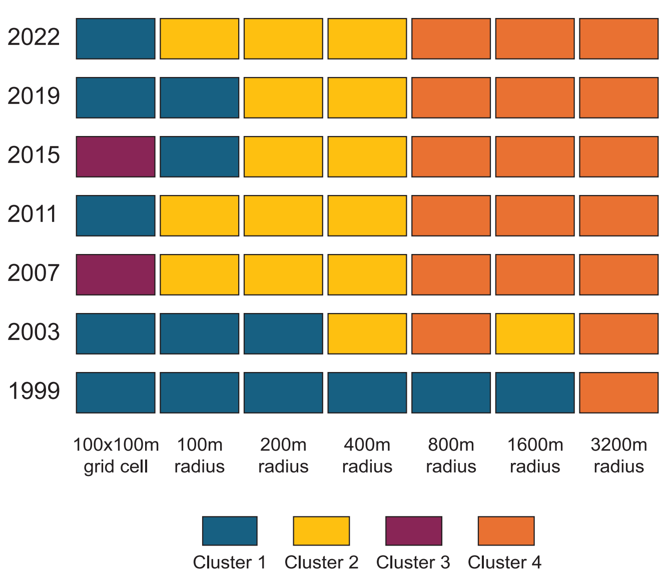

Fig. 3. Multidimensional and longitudinal spatial profile: visual representation for a single 100×100 m grid cell.

- **Cluster 2:** Characterised by high home-ownership rates, affluent households (especially in the top 20 % of the national income distribution), couples with children, and a significant presence of Dutch individuals. Europeans, Indonesians, and other Asians are also relevant. This cluster features a notable share of children under 18 and adults aged 36–65.
- **Cluster 3:** Composed mainly of individuals with migration backgrounds from Turkey, Morocco, Suriname, Dutch Caribbean, other African countries, and to a lesser extent, other countries from Asia, America and Oceania. This cluster exhibits low socioeconomic status, with a high share of low-income households (particularly in the lower 20 % of the national distribution) and social benefit recipients. In terms of household composition, single-parent households is an important variable for this cluster. We also observe a prevalence of couples with children, single-person households, and students. It has fewer individuals over 65 compared to Clusters 1 and 2.
- **Cluster 4:** Defined by high-income households (especially in the top 20 %), single-person households, students, and young adults aged 18–35. It includes significant proportions of individuals from Europe, other American and Oceanian countries, Indonesia,[3] and other Asian countries. Home-ownership rates are higher than in Clusters 1 and 3, and the presence of older adults and children is minimal. It is important to note that this cluster exhibits a relatively higher share of low-income households (poorest 20 %) compared to the other affluent cluster (Cluster 2). The socioeconomic and demographic composition suggests that this cluster relates to areas experiencing processes of gentrification.

The size of each cluster for selected years (1999, 2011 and 2022) and scales (100 × 100 m grid cell, 800 m radius and 3200 radius) is presented in Table 1 (for a full overview of the distribution of the clusters across all years and scales, see Fig. B.1 in Appendix B).

The composition of clusters confirms that sociospatial stratification is influenced by socioeconomic status, migration background, life-course stages and home ownership. However, these results also highlight that these dimensions intersect in various ways within the different clusters. For instance, while Clusters 2 and 4 share a similar socioeconomic status, they differ significantly in terms of home ownership rates, migration background and other demographic characteristics, such as household composition and age distribution. Similarly, Clusters 1 and 3, despite having comparable socioeconomic status, show distinct

[3] Indonesian migrants differ from other major groups in the Netherlands due to their colonial ties, earlier arrival (1950s), and smoother integration process. In contrast, Turkish and Moroccan migrants arrived later as guest workers (1960s), often employed in low-skilled labour sectors. Language barriers, lower educational attainment, and limited integration programs contributed to greater socioeconomic disadvantage over time. Surinamese and Dutch Caribbean migrants (1970s), while more diverse, generally benefitted from their knowledge of the Dutch language and cultural familiarity linked to their historical and ongoing colonial ties, especially compared to other migrant groups from the Global South.

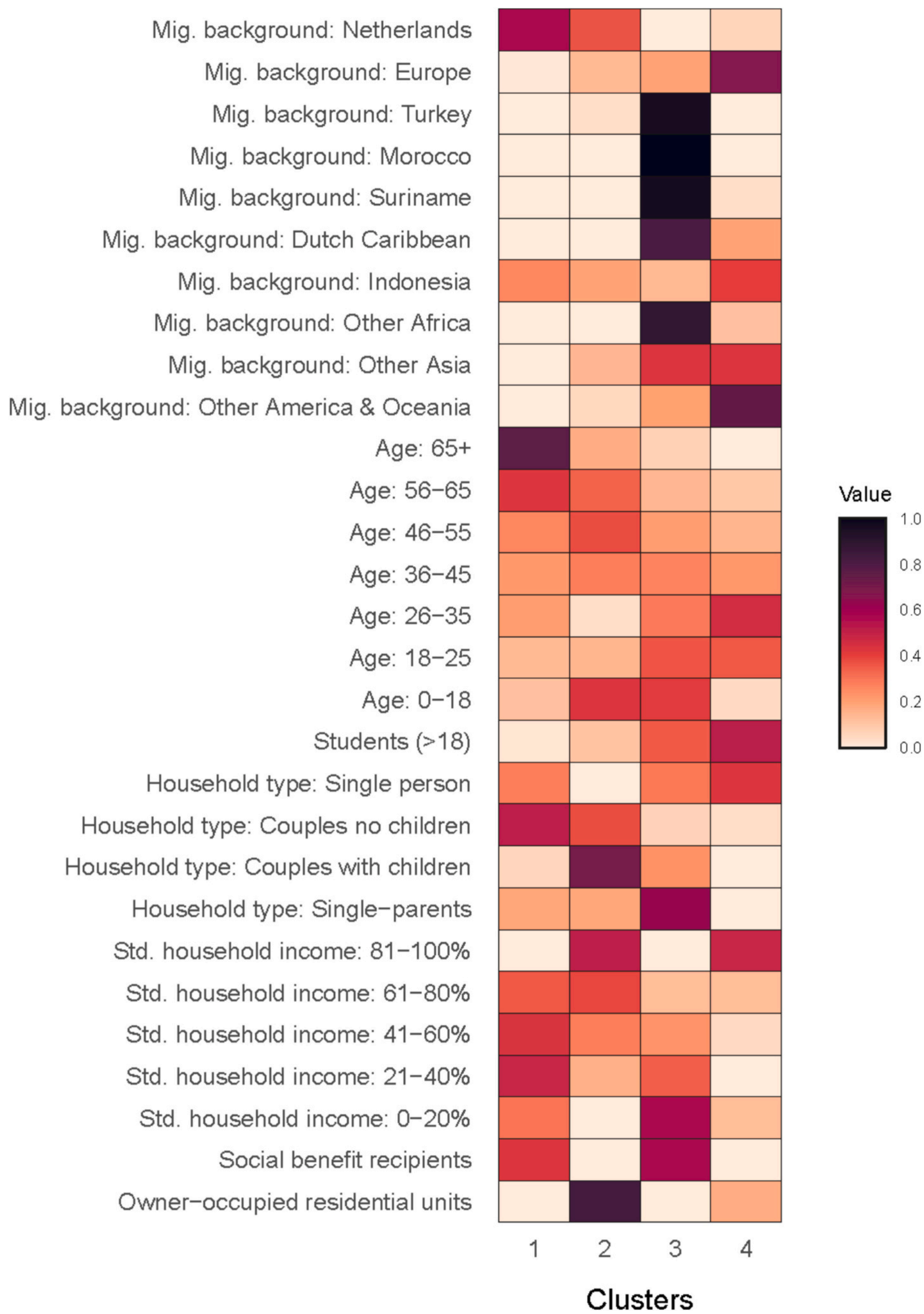

Fig. 4. Cluster description based on the H matrix coefficients: normalised coefficients depicting each variable's relative contribution across clusters.
Source: Authors' calculations using non-public microdata from Statistics Netherlands (CBS).

differences in demographic traits. Thus, there is a variation in the way that, for instance, homeownership plays out in the MAA for different sub sections of society showing the complexity of sociospatial stratification.

The analysis provided here offer a general overview of the clusters. For a more detailed composition of these clusters, we encourage readers to study closely Fig. 4. We have refrained from labelling the clusters due to their complexity, which extends beyond a single-line descriptor. This approach helps to avoid generalisations that could lead to the stigmatisation of particular social groups or places. Our descriptions focus on dominant characteristics to facilitate the analysis, but we acknowledge that there is greater complexity of experiences beyond these dominant traits.

4.2. Changes in the sociospatial structure of the metropolitan agglomeration of Amsterdam over time and scale

Besides being multidimensional, the cluster classification is longitudinal and multiscale, allowing analysis over time and across spatial scales. Fig. 5 maps the cluster distribution in the urban space of the MAA across three scales (100 × 100m grid cells, 800 m radius, 3200 m radius) at three time points (1999, 2011, 2022). The MAA's sociospatial structure generally follows a concentric pattern: Cluster 4 dominates the city centre of Amsterdam municipality, Cluster 3 is prevalent in the west and southeast of the same municipality, and clusters with higher shares of Dutch populations (Clusters 1 and 2) are predominant in the suburbs of the south (Amstelveen municipality) and northwest (Zaanstad, Oostzaan, Landsmeer and Wormerland municipalities).

When comparing urban changes across scales, we observe that this

Table 1
Number of 100 × 100 m grid cells assigned to each cluster in 1999, 2011 and 2022 for selected scales.

Scale	Cluster 1	Cluster 2	Cluster 3	Cluster 4
1999				
100 × 100 m grid cell	2590	3416	1889	2105
800 m radius	2555	2707	2634	2104
3200 m radius	2514	1797	2373	3316
2011				
100 × 100 m grid cell	1696	3620	2220	2464
800 m radius	1222	3017	2890	2871
3200 m radius	198	2844	3324	3634
2022				
100 × 100 m grid cell	997	3699	2577	2727
800 m radius	496	3055	3067	3382
3200 m radius	26	2647	3126	4201

Source: Authors' calculations using non-public microdata from Statistics Netherlands (CBS).
Note: For every scale and year, the total number of 100 × 100 m grid cells is exactly 10,000. For a complete overview of the cluster size for all scales and years, see Fig. B.1 in Appendix B.

concentric pattern becomes clearer as the scale increases. This consolidation of large city areas with the same cluster type is expected, as larger scales mean a greater overlap between bespoke areas. Although, even at the smallest scale (100 × 100 m grid cells) - where there is no overlap - the concentric arrangement is still visible. The consistency across scales suggests that many grid cells maintain their cluster categorisation at multiple scales, indicating a degree of stability in the sociospatial configuration of residential contexts in particular locations. Nevertheless, this pattern is punctuated by locations where the classification shifts, reflecting changes in sociospatial compositions and the emergence of social frontiers within the urban structure.

Furthermore, we also note that some clusters are only visible in certain places at particular scales, shedding light onto the scale at which certain population groups cluster in space. Across all time periods, the cluster related to affluent family households (Cluster 2) is more concentrated at smaller scales (3416 and 3699 cells at the 100 × 100 m grid cell scale in 1999 and 2022, respectively, compared to 1797 and 2647 cells at the 3200 m radius scale). By contrast, Clusters 3 and 4, which are associated with non-native individuals, predominate at larger scales, especially Cluster 4 with a high share of young individuals, affluent households and single-person household composition. More specifically, Cluster 4 has 2105 and 2727 cells at the 100 × 100 m grid cell scale in 1999 and 2022, respectively, compared to the 3316 and 4201 cells at the 3200 m radius scale (for more details on cluster size see Table 1, and Fig. B.1 in Appendix B). In 1999, Cluster 1 is visible across all scales because it covers large areas throughout the city (2590, 2555 and 2514 cells at the 100 × 100 grid cell, 800 m radius and 3200 m radius scales, respectively). However, by 2022, Cluster 1 is only visible in small enclaves at the smallest scale (997 cells at the 100 × 100 m grid cell scale). At larger scales (496 cells at the 800 m radius and only 26 cells at the 3200 m radius), it is confined to a specific part of the northwest suburb (north of Zaanstad and west of Wormerland). This pattern reveals the suburbanisation of this cluster and its fragmentation through the dilution of the spatial concentration of its dominant social groups. Spatial scale, therefore, reveals specific parts of the city that consolidate with particular sociospatial conditions across large areas and others that work as smaller enclaves for certain social groups. Moreover, the persistence or change in residential characteristics across bespoke areas highlights the complexity of exposure to different sociospatial conditions that individuals experience in their residential environment (Petrović et al., 2018).

By comparing the maps over time within each row, we note that temporal changes of the urban structure in the long run consolidate this concentric pattern across scales. Cluster 4 expands in the city centre of Amsterdam, replacing Cluster 1 in the south and Cluster 3 in the east and west, indicating a gentrification process. This growth of Cluster 4, while involving the replacement of lower-income households in both cases, reflects distinct demographic shifts. The replacement of Cluster 1 in the south primarily affects older adults and Dutch individuals, whereas the replacement of Cluster 3 in the east and west impacts non-native groups, suggesting that the underlying causes and consequences of these changes differ significantly. The expansion of Cluster 3 in the west, north, and southeast of Amsterdam municipality, along the disappearance of Cluster 1 areas, suggests that gentrification is displacing Cluster 3 groups which are replacing older adults and Dutch populations. In contrast, Cluster 2 remains relatively stable within each row, reflecting the consistent residential preferences of affluent families and homeowners for specific suburban zones. These findings highlight a dual process of suburban consolidation of affluent and native families, and gentrification and youthification of the city centre, involving the replacement of older native groups and the suburbanisation of non-native low-income households.

However, how the distribution of clusters changes over time (i.e. across columns of Fig. 4) differs between spatial scales (i.e. between rows of Fig. 4), revealing additional layers of complexity in the socio-spatial evolution of the MAA. Cluster 1's rapid decrease at the 3200 m radius scale suggests spatial fragmentation of its social groups (from 2514 cells in 1999 to 198 in 2011 and 26 in 2022), while Cluster 4's consistent growth across all scales indicates a large scale expansion (for a detailed description of the evolution of cluster size by scales, see Fig. B.1 in Appendix B). When we focus on particular residential locations, such as the one located in the south part of the MAA (Groenelaan in Amstelveen), we observe that they experience changes at one scale while persisting or changing differently at another. In particular, certain grid cells classified as Cluster 1 in 1999 at the 100 × 100 m grid cell level remain unchanged throughout the study period, whereas at the 800 m radius scale, they change to clusters 4, 3, and 2 by 2022. At the 3200 m scale, they change to Cluster 2 by 2022. This highlights the importance of considering multiple scales in studying neighbourhood change as the underlying mechanisms might vary with scale.

One key advantage of our approach is the ability to examine neighbourhood change within short-term windows, rather than being limited to decennial transitions. This enables a more nuanced analysis of the trajectories and timing of temporal reconfigurations in the urban structure at varying geographical scales. In Fig. 6, we present the flow of 100 × 100 m grid cells between clusters across all time periods at the 100 × 100 m grid cell level (Fig. 6a), the 800 m radius (Fig. 6b), and 3200 m radius (Fig. 6c) (for the remaining scales, see Fig. B.2 in Appendix B). In these plots, the thickness of the connecting lines represents the volume of grid cells transitioning between clusters. While most of neighbourhoods tend to remain in the same cluster type over time at both small and large scales, especially in the short term, transitions still occur over time and over scales, highlighting the dynamism of certain residential locations.

Crucially, we identify scale-specific differences in certain processes of change: for instance, transitions are more frequent at a larger scale in the replacement of Cluster 1 by Cluster 3. Conversely, the scale difference is less pronounced in the replacement of Clusters 1 and 3 by Cluster 4. Additionally, we observe temporal variations in these transitions between scales: at the 3200 m radius, the replacement of Cluster 1 by Cluster 3 is concentrated at the beginning of the time window, whereas both at the 100 × 100 m grid cell level and 800 m radius, this type of transition is more evenly distributed across the period. This disparity is linked to the rapid fragmentation of Cluster 1 and could also be tied to the distinct spatial diffusion patterns of Cluster 3 and 4. Cluster 4 expands outward from the city centre, with its growth spreading out the borders with the other clusters, leading to marginal, but steady increases. This diffusion process reflects an outward expansion of affluent

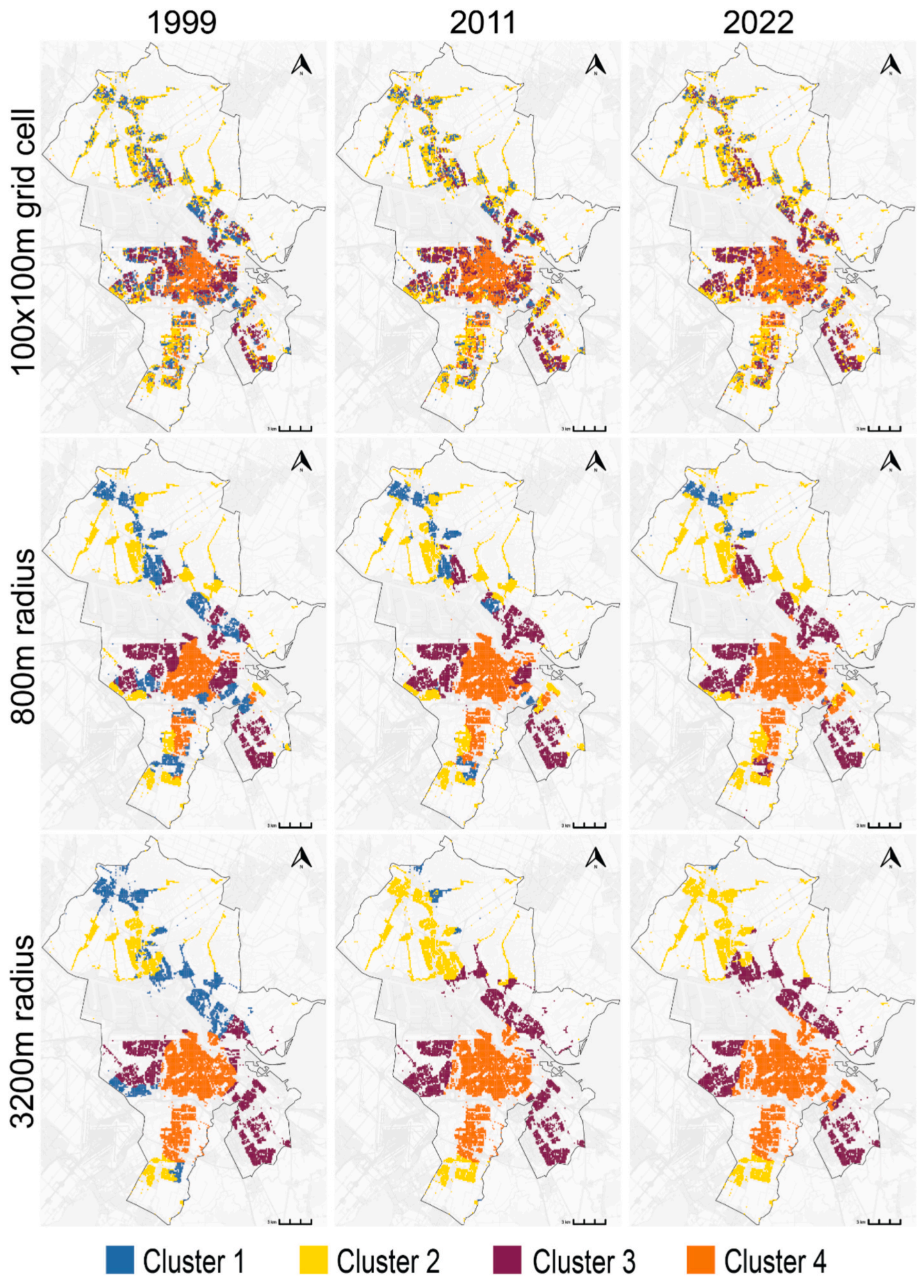

Fig. 5. Maps of Amsterdam in 1999, 2011 and 2022 for three selected scales: cluster to which the 100 × 100m grid cells is assigned based on the composition of bespoke areas with different radii.
Source: Authors' calculations using non-public microdata from Statistics Netherlands (CBS).
Note: To ensure the confidentiality of household and individual information, 100 × 100m grid cells with less than 5 individuals and 3 households are not shown in the maps. Nevertheless, they are considered in all calculations. The maps have 9400 grid cells in 1999, 9463 in 2011 and 9519 in 2022. See Table A.2 in Appendix A for the whole distribution of 100 × 100m grid cells by year.

young populations into surrounding areas, contributing to a gradual transformation of adjacent neighbourhoods over time (Vogiazides & Mondani, 2023). In contrast, the replacement of Cluster 1 by Cluster 3 is a faster, more decentralised process, occurring primarily at the beginning of the study period across diverse city areas. This shift is particularly marked at larger scales, where the fragmentation of Cluster 1 accelerates and Cluster 3 consolidates in previously scattered enclaves. By analysing different scales and multiple time intervals, we capture distinct trajectories and timing in the broader patterns of change that have unfolded over two decades in Amsterdam.

5. Discussion

This study expanded the neighbourhood classification approach to include longitudinal and multiscale perspectives, enabling the analysis of changes in the urban structure across both the short- and long -term and multiple geographical scales. We created multidimensional, multiscale and longitudinal spatial profiles of residential locations to examine the evolution of urban social structures. Empirically, these spatial profiles consist of scalable bespoke areas that are classified based on their socioeconomic, demographic and tenure characteristics, measured every four years over a 23-year period. This paper demonstrated the utility of spatial profiles for analysing the dynamics of sociospatial

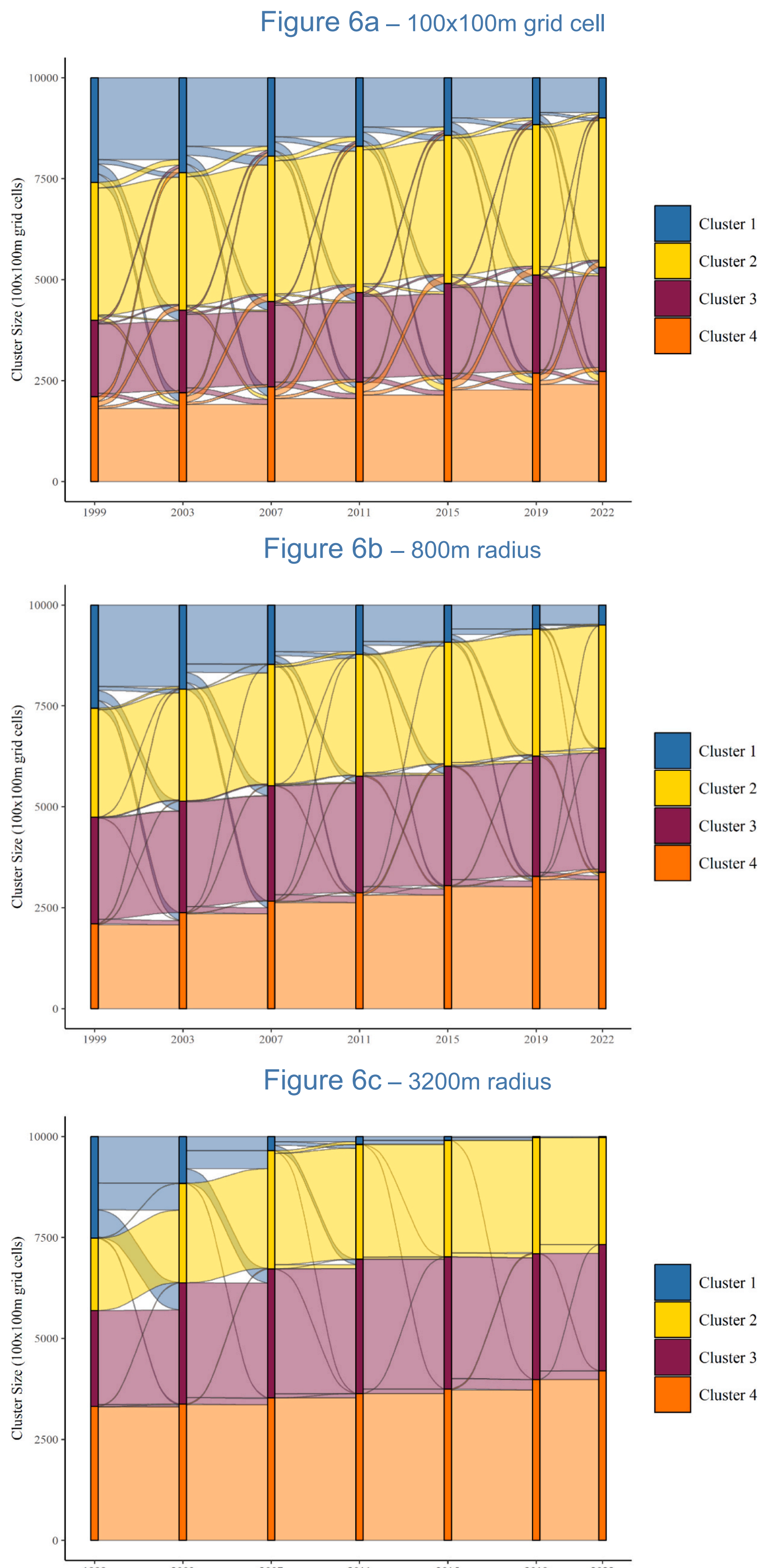

Fig. 6. Short term transitions between cluster types at small and large scales: alluvial plots of cluster transitions between 1999 and 2022 using bespoke areas with 200 m and 1600 m radii.
Source: Authors' calculations using non-public microdata from Statistics Netherlands (CBS).

stratification using the Metropolitan Agglomeration of Amsterdam as a case study. We visually presented how multiple socioeconomic, demographic and tenure attributes interact to produce a hierarchical typology of places and mapped the spatio-temporal evolution of this typology in the urban landscape.

Our approach identified assemblages of residential attributes that characterise the residential configurations composing the latent structure of the urban social landscape using simultaneously multiple dimensions traditionally studied separately. We identified four types of sociospatial configurations differentiated by the interplay of socioeconomic status, migration background, life-course stages, and homeownership patterns. By applying a clustering technique that quantifies the relative importance of these attributes, we highlighted several dominant features driving sociospatial variation in the urban landscape.

First, the intersection of socioeconomic status and migration background emerged as a significant axis of sociospatial differentiation, with distinct high- and low-income clusters within both native and non-native population groups. Second, life-course stages further shape the sociospatial structure of Amsterdam on the basis of the socioeconomic status and ethnicity. Our results show that age and household type composition differ within areas with a high concentration of natives and non-natives, respectively. This indicates that sociospatial differentiation is structured not only by migration background and socioeconomic status, but also by distinct life-course stages for natives and non-natives areas separately. Moreover, the prominence of students and individuals with a migration backgrounds from Europe, America and Oceania in areas with characteristics linked to gentrification hints to the particular nature of this process in a globalised city such as Amsterdam. Besides its international character (Aalbers, 2019; Hayes & Zaban, 2020; López-Gay et al., 2021), gentrification in the city centre of Amsterdam also responds to a process of studentification, where the concentration of students creates a pool of future gentrifiers that adopt certain lifestyles and residential consumption preferences, further reinforcing gentrification over time (Smith & Holt, 2007). Finally, the higher prevalence of homeownership in affluent clusters, but in particular in areas with higher concentration of older adults, reflects broader patterns of wealth and asset inequality along the life-course. In sum, the multidimensional characterisation of the latent features of the sociospatial structure of the city reveals a new pattern of complexity shaped by class, age, and tenure-based segregation rather than purely ethnic or socioeconomic stratification.

While we do not claim that our findings represent a definitive sociospatial structure of Amsterdam, our selection of dimensions is based on a sound theoretical rationale that produces an empirically meaningful classification that aligns with recent research on sociospatial inequalities in the Netherlands, particularly in Amsterdam and Rotterdam (e.g., Boterman, 2020; Hochstenbach, 2019; Nelson et al., 2024; van Gent & Musterd, 2016), offering a more nuanced understanding of residential contexts. We achieved this by constructing a cluster typology which serves as a tool for visualising and understanding how multiple social and spatial dimensions interact to shape urban differentiation over time, rather than using characterisations with a single variable, a single spatial scale and a single point in time.

Our findings reveal a concentric pattern in the sociospatial structure of the Metropolitan Agglomeration of Amsterdam and a growing centre-periphery polarisation that emerged through several dynamics of change at the metropolitan level. First, our findings suggest direct and exclusionary displacement in the city centre, where gentrification has led to the replacement of lower-income households with younger, mobile, and affluent international populations, leading to the increasing suburbanisation of non-native low-income households. This process of gentrification in upgrading areas near the urban core is fuelled by the gradual replacement of ageing low- and middle-income residents by wealthier households. Dutch working-class households were able to stay in these upgrading areas thanks to timing differences in when they could secure social housing or protected tenant agreements (Hochstenbach, 2019). Previous research on Amsterdam has documented ageing and tenure transformations involved in the privatisation of social housing and the rental market liberalisation as drivers of the gentrification process experienced in these areas (Boterman & van Gent, 2014; Hochstenbach & van Gent, 2015). In contrast, in peripheral post-war housing estates areas with historically high shares of low income migrants such as Nieuw-West and Amsterdam-Noord, older working class natives are being replaced by low-income and migrant households. This shift aligns with research on ethnic residential preferences and financial constraints among (older) migrants (Greft et al., 2016). Unlike gentrified areas, tenure conversions upon the passing of older adults in these peripheral zones do not lead to socioeconomic upgrading but rather to an increasing ethnic divide between the inner city and post-war suburbs (Boterman & van Gent, 2014).

Second, upper classes have consolidated in elite suburban areas, where homeowners have benefited from real estate value appreciation, reinforcing residential privilege (Hochstenbach & van Gent, 2015). Our results confirm that access to homeownership is highest among middle-age and older, high-income residents in established elite areas, suggesting that tenure status protects certain groups from displacement and strengthens residential privilege over time. In contrast, within the affluent, younger, and more international population of the urban core, homeownership plays a less dominant role, indicating further tenure-based distinctions within upper-class groups. This aligns with research showing that Amsterdam's growing liberalised rental sector has primarily absorbed young, high-income households, excluding young lower and middle classes from the city's most desirable areas where only working class native older adults could secure affordable housing and controlled tenant agreements in the past (Howard et al., 2024). These findings highlight the critical role of tenure in shaping new patterns of class and age segregation in contemporary Amsterdam.

These trends suggest an intensification of inequalities within the sociospatial structure of Amsterdam within a national context of increasingly liberalised housing and economic policies. More specifically, our findings support previous research that has shown that the Dutch policy shifts in the past decades regarding the deregulation of the rental sector, the increasing privatisation of social housing, and incentives for homeownership have consolidated a more polarised social structure of the city of Amsterdam (Savini et al., 2016). Our findings also align with broader international trends such as the gentrification, studentification and youthification of city centres, the suburbanisation of both poverty and affluence, and the unequal spatial distribution of ageing populations, particularly among low-income groups (Bailey et al., 2017; Hochstenbach, 2019; Hochstenbach & Musterd, 2018, 2021; Hochstenbach & van Gent, 2015; Moos, 2016; Musterd, 2014).

The approach presented in this article goes beyond the identification of spatial patterns and dynamics of change of social inequalities at the metropolitan level. A key contribution of this study is the integration of multidimensional, multiscale and longitudinal approaches that provides a more nuanced picture of how the sociospatial structure evolves differently across scales and at different locations within the urban space. Although it is possible to determine a general pattern in the dynamics of social inequalities in cities, with this approach we uncover the multiscale and temporal complexity of sociospatial stratification observed in different locations of the urban space.

Importantly, neighbourhood changes over time are not consistent across all spatial scales and locations. While a neighbourhood's characteristics may appear stable at one geographical level, significant transformations may occur at another. Space plays a critical role in this variability, as the broader environment of a residential location can influence changes within that location while being simultaneously shaped by transformations in surrounding areas (Delmelle et al., 2016). Comparing changes at different scales allows us to identify the areas that might be vulnerable (or alternatively resilient) to transformation (Fowler, 2016). The ability of our approach to decompose neighbourhood classification across multiple geographical scales provides a robust framework for identifying such spatial dynamics.

Our analysis underscores that broader urban transformation trajectories vary across scales and timeframes. A key finding is that some processes of change are more scale-sensitive than others, emphasising the relevance of using multiple scales to identify differing mechanisms driving urban transformations at distinct geographical scales. This disparity is tied to the way certain neighbourhood types expand or shrink and, ultimately, how the spatial distribution of social groups evolves differently across spatial scales. Gentrified areas tend to show an outward expansion from the city centre into surrounding areas, whereas the cluster with older adults and natives that is scattered outside the city centre exhibits a rapid fragmentation as it is being replaced by non-natives and low-income groups predominantly at larger scales. This replacement is a short-term and decentralised process occurring mainly at the beginning of the study period, highlighting the importance of timing and of analysing short-term transitions when capturing urban change dynamics.

Despite some areas experiencing change, others exhibit a stable sociospatial configuration across both scale and time. The persistent dominance of each cluster in different city areas reinforces their distinct sociospatial characteristics. Our multidimensional, multiscale and longitudinal approach serves to assess the geographical extent and temporal persistency of these areas, having significant implications for sociospatial stratification in cities. The spatial extent of these areas that consolidated over time can impact the social meanings and perceptions residents attach to the urban space and its structure (Lynch, 1960), shaping their residential prestige and further contributing to the socio-spatial separation of population groups (Permentier et al., 2008; Wacquant, 2007).

6. Conclusion

In sum, different areas of the city evolve differently over time and scale, illustrating the importance of location within the urban space. Residential contexts are shaped not only by their immediate surroundings but also by the characteristics of adjacent areas (Petrović et al., 2018). Thus, the dynamics of neighbourhoods depend on their relative position within the urban structure. By integrating space and time into our analysis, we reveal the critical role they play in shaping the social stratification of urban areas. This integration allows us to identify the specific scales at which social groups cluster and the ways in which these clusters evolve according to their location within the urban landscape.

By creating spatial profiles as multiscale sequences of neighbourhood typologies across several short term intervals, this study presents a flexible framework for conducting contextual analyses on the spatio-temporal evolution of urban structures. This framework can be applied to other cities or at a national level to compare different urban forms. Even though this study relies on administrative microdata, this approach can be used in any country or city with census data linked to any type of (administrative) spatial unit. It can be adapted to include additional variables, such as cultural and social capital, enhancing our understanding of urban sociospatial stratification. Furthermore, in future research, our methodology can be incorporated with more systematic tools of analysis, facilitating the identification of specific patterns of exposure to different sociospatial configurations and trajectories of change over time. This would allow analytical comparisons across scales, years and urban spaces.

In conclusion, the integration of multiple dimensions, spatial scales, and time periods enriches our understanding of sociospatial inequalities by uncovering multidimensional, multiscale and longitudinal processes shaping social urban structures. The identification of these processes raises the need of further investigating the impact of sociospatial stratification in cities on social mobility and individual outcomes through the creation of unequal living environments. A multidimensional, multiscale and longitudinal classification provides researchers with the tools needed to better understand how the variety of sociospatial configurations to which individuals are exposed to within their residential context at different moments of their life affects their life opportunities. Furthermore, this approach can summarise and visually present in an apprehensible manner the highly complex nature of sociospatial inequalities, representing a valuable resources for urban planners and policymakers to visualise the composition of urban areas beyond static neighbourhood definitions. Leveraging time and spatial scales within a multidimensional approach has thus the potential to equip researchers and policymakers with the necessary tools to better understand and, therefore, better address the causes and consequences of sociospatial inequalities in cities around the globe.

CRediT authorship contribution statement

Ignacio Urria: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Ana Petrović:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Maarten van Ham:** Writing – review & editing, Supervision, Conceptualization. **David Manley:** Writing – review & editing, Supervision, Conceptualization.

Disclosure statement

During the preparation of this work the authors used ChatGPT/chat.openai.com to get assistance with certain formulations in the English language in some parts of the text. After using this tool, the authors reviewed and edited the content as needed and they therefore take full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2025.106089.

Data availability

The authors do not have permission to share data. However, under certain conditions, these data are accessible for statistical and scientific research. For further information: microdata@cbs.nl.

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