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Evolution of residential segregation patterns in the Netherlands between 2015 and 2020

Lucas Spierenburg [a,*], Sander van Cranenburgh [b], Oded Cats [a]

[a] *Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, the Netherlands*
[b] *Transport and Logistics Group, Department of Engineering Systems and Services, Faculty of Technology, Policy, and Management, Delft University of Technology, the Netherlands*

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ABSTRACT

We investigate the evolution of residential segregation patterns in the Netherlands, with a focus on the population with a non-western migration background. Unlike previous research relying on predefined spatial structures, this study employs a regionalization approach to track the evolution of social enclaves in 82 municipalities from 2015 to 2020. Enclaves have become more mixed in municipalities with historically homogeneous social enclaves whereas in the other municipalities, they have become more homogeneous. In addition, we find a positive association between the increase in the share of population with a non-western migration background at the municipality level and the spatial growth of social enclaves. These insights contribute to a deeper understanding of residential segregation in the Netherlands, offering a valuable foundation for informed policymaking.

1. Introduction

Residential segregation, defined here as the spatial clustering of communities in distinct residential areas, reduces opportunities for inter-groups interactions while exacerbating inequality (Dong et al., 2020; Farber et al., 2014; Laurence et al., 2019; Levy & Razin, 2019; Morales et al., 2019; Semyonov & Glikman, 2008; Tóth et al., 2021). It can occur along different social dimensions, such as ethnicity, income, education, or migration background. In the Netherlands, residential segregation is particularly pressing issue for populations with a non-western migration background, as it negatively affects their life outcomes, in particular educational achievements and naturalization (Leclerc et al., 2022; van der Greft & Fortuijn, 2017; van Der Laan Bouma-Doff, 2007). As a frequent subject of public discourse, it garners attention from public authorities who regularly express their commitment to mitigate it (Gemeente Amsterdam, 2017; Gemeente Den Haag, 2021). A thorough examination of the temporal changes in residential segregation patterns is crucial. It deepens our understanding of its dynamics, aids in the formulation of targeted policies for specific areas needing intervention, and enables the evaluation of the effectiveness of past policies.

Residential segregation can be characterized along three dimensions, 1) intensity, the extent to which the population of interest is over-represented in certain regions of city, 2) separation, the share of this group living in these regions, and 3) scale, the size of these regions (Spierenburg et al., 2023). Importantly, segregation is not static but a dynamic phenomenon, evolving over time along these three dimensions as people relocate and new immigrants settle in (Boschman & van Ham, 2015; Kauppinen & van Ham, 2019; Zorlu & Mulder, 2008). For instance, an increase in separation with a stable scale might occur if relocation patterns give rise to new social enclaves without affecting the size of existing one. Alternatively, in cities where a particular group predominantly moves out of neighborhoods where they are a minority, intensity would increase with no change in scale. Conversely, in expanding cities, scale may increase while the intensity remains steady if the segregated regions grow in size as the city expands, without any alteration in the group proportions within each region. Monitoring residential segregation through these three dimensions — intensity, separation, and scale — enables the identification of emerging patterns that might not be evident when only considering uni-dimensional indicator such as the dissimilarity or the entropy index (Reardon & O'Sullivan, 2004). Multidimensional frameworks are therefore increasingly favored for investigating the evolution of residential segregation (Lan et al., 2020; Nielsen & Hennerdal, 2017; Sleutjes et al., 2019).

In the Netherlands, the research by Sleutjes et al. (2019) used such a multidimensional framework to assess segregation intensity across

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various scales in the Amsterdam metropolitan region. Their findings revealed that residential segregation remained stable between 2003 and 2014, both in terms of scale and intensity. While this study offers valuable insights at the regional level, the demographic and housing contexts in the Amsterdam metropolitan region differ significantly from those in other Dutch urban areas. For instance, in 2020, the proportion of the population with a non-western migration background was substantially higher than the country average, standing at 24 % compared to 14 % nationwide (Centraal Bureau voor de Statistiek, 2020).

To date, the understanding of the evolution of residential segregation patterns at the country level remains limited. More specifically, little is known about potential differences between dynamic regions such as Amsterdam and other areas, and on potential associations between demographic shifts in cities and changes in residential segregation. This lack of a solid comparative analysis across Dutch municipalities has several negative implications. First, public debates on residential segregation and immigration in the Netherlands is often devoid of empirical evidence. Second, there is a pressing need for authorities to base their policy decisions and resource allocations on robust quantitative data. Third, a thorough grasp of the factors driving changes in residential segregation hinges on having a substantial amount of observational data. Our study aims to fill this knowledge gap, by addressing the following research questions:

How residential segregation patterns along migration background evolved in the Netherlands from 2015 to 2020?

1. What are the geographical trends in the evolution of residential segregation patterns?
2. How do the changes in residential segregation patterns relate to the increase in the population with a non-western migration background?

To this end, we identify residential segregation patterns in the Netherlands and assess how they have evolved between 2015 and 2020. We focus on the segregation of the population with a non-western migration background. Particular attention is given to this group in the Dutch context, as individuals from this group are subject to income inequality and lower educational achievement; and residential segregation contributes to these issues (Albada et al., 2021; Baldwin Hess et al., 2018; Erisen & Kentmen-Cin, 2017; Gracia et al., 2016; OECD, 2018; Thijssen et al., 2021; van de Werfhorst & Heath, 2019).

The remaining part of this study is organized as follows. We describe the method implemented in Section 3, introduce the case study and the data used in Section 4, present the results in Section 5, and conclude our analysis in Section 6.

2. Literature review and theoretical background

A large body of the literature on residential segregation is dedicated to the assessment of the phenomenon. In this section, we review the most commonly used approaches to ground our work in relation to existing studies.

2.1. Segregation indicators

Past studies propose a large variety of indicators for residential segregation. The two most established indicators are the dissimilarity and the entropy indexes, both quantifying the extent to which different groups live separated from each other (Duncan & Duncan, 1955; Theil & Finizza, 1971). Despite being widely used by practitioners and policy-makers, they are often criticized for failing to capture critical aspects of segregation, such as the spatial scale of segregation (Petrovic et al., 2018; White, 1983; Wong, 2004). The spatial scale of segregation is deemed to have detrimental consequences on the potential for intergroup interactions, as a larger scale implies fewer opportunities for social interactions (Farber et al., 2014). This limitation has led to the

development of more comprehensive frameworks integrating spatial scale among other additional dimensions (Brown & Chung, 2006; Feitosa et al., 2007; Fossett, 2017; Massey & Denton, 1988).

Among the different multi-dimensional frameworks developed, the one proposed by Massey and Denton (1988) has been particularly influential. They assess residential segregation along 5 dimensions: Evenness, exposure, concentration, centralization, and clustering. Most current multi-dimensional frameworks still consider dimensions related to evenness and clustering. Evenness is *"the differential distribution of two social groups among areal units in a city"*, higher values indicating larger separation of groups (Massey & Denton, 1988). Clustering is *"the extent to which areal units inhabited by minority members adjoin one another, or cluster, in space"*, larger values implying larger distance between groups (Massey & Denton, 1988). In many studies, clustering is referred to as spatial scale (Lan et al., 2020; Olteanu et al., 2019; Petrovic et al., 2018).

2.2. Comparative analysis

Comparative analyses examine several case studies to unravel general trends in a phenomenon (Robinson, 2011; Ward, 2010). They are extensively used in urban science studies as they allow to build theory from the overarching pattern observed (Nijman, 2007; Storper & Scott, 2016). Several studies have conducted comparative analyses to assess the evolution of residential segregation by systematically measuring segregation indicators in a set of cities for several time periods (Bellman et al., 2018; Chodrow, 2017; Delmelle, 2017; Farrell & Lee, 2011; Lan et al., 2020; Zwiers et al., 2018). For instance, in their comparative studies of neighborhood change across the largest U.S. metropolitan areas, Farrell and Lee (2011) and Delmelle (2017) identified a sharp decline in the white population in the presence of a large increase in the population from minority groups between 1980 and 2010, a phenomenon coined as tipping point by Schelling (1969). In the Netherlands, Zwiers et al. (2018) observed a consistent stability of residential segregation along migration background in the four largest municipalities between 1999 and 2013.

2.3. Data-driven approaches

A recurring limitation in the literature is the reliance on predetermined spatial structures, due to the use of administrative boundaries or distance-based grouping of spatial units (Clark et al., 2015; Ellis et al., 2018; Lan et al., 2020; Nielsen & Hennerdal, 2017; Wright et al., 2014). Such approaches may not fully capture the evolution of segregation patterns, which often transcend these predefined spatial structures (Chodrow, 2017). To address this limitation, a body of literature proposes approaches to identify the spatial structure of residential segregation from the data, moving away from fixed layout (Chodrow, 2017; Cottrell et al., 2017; Kirkley, 2022; Olteanu et al., 2020; Sousa & Nicosia, 2022; Spierenburg et al., 2023). These approaches typically involve constructing demographically homogeneous regions, a process called regionalization, before quantifying residential segregation along one or several dimensions. This first step aims to maximize within-region homogeneity and between-regions differences, given certain exogenous parameters (e.g. the number of regions). Such parameters are usually tuned by the analyst based on prior knowledge (Chodrow, 2017; Cottrell et al., 2017; Olteanu et al., 2020). Yet, this process is tedious and arbitrary, especially when the parameters are tuned for each city and each time period in the dataset. Therefore, state-of-the-art approaches strive to simplify the parameter tuning stage (Kirkley, 2022; Spierenburg et al., 2023). For instance, in the approach of Spierenburg et al. (2023), a single exogenous parameter needs to be tuned once, and the method can be applied to any other city from the same dataset.

2.4. Theoretical framework

This study aims to assess the evolution of residential segregation

patterns in the Netherlands using a comparative analysis. In addition to the 4 largest cities considered by Zwiers et al. (2018), we include sub-urban and secondary towns, as these municipalities are deemed to exhibit radically different patterns than urban cores (Hochstenbach & Musterd, 2018). We consider 82 municipalities in the analysis. This requires the quantification of residential segregation along several dimensions for a large number of cities and several time periods. Therefore, we adopt the theoretical framework presented by Spierenburg et al. (2023), for its agnosticism towards predetermined spatial structure and minimal parameter tuning requirements.

Spierenburg et al. (2023)'s approach involves identifying demographically homogenous regions within cities, focusing on a specific group of interest. These regions are categorized as under-representing, over-representing, or mixed in relation to the group of interest. Segregation is then analyzed along three dimensions: intensity, separation, and scale. **Intensity** is the extent to which the group of interest is over-represented in regions labeled as such. **Separation** measures the share of the group of interest living in regions in which they are over-represented. **Scale** is the spatial extent of segregated regions.

These indicators can be mapped against the framework proposed by Massey and Denton (1988). Evenness in Massey and Denton (1988) is disaggregated into two dimensions: intensity and separation. This allows us to differentiate a situation where a small part of the population of interest is strongly over-represented in certain regions (low separation, high intensity), from a situation where a large part of the population of interest is slightly over-represented in certain regions (high separation, low intensity) (Spierenburg et al., 2023). Clustering in Massey and Denton (1988) is equivalent to scale in Spierenburg et al. (2023).

3. Method

We adopt the approach of Spierenburg et al. (2023), and adapt it so as to obtain consistent regions over several periods of time. The method of Spierenburg et al. (2023) consists of three steps. First, they filter out noise in the demographic data using a spatial moving average (see middle maps in Fig. 1 and Section 3.1). Second, they delineate regions that are homogeneous in terms of demographics. This step is called regionalization (Sections 3.4 and 3.5). Third, they summarize the observed segregation patterns along three dimensions: intensity, separation, and scale (Section 3.6). In this work, we perform two additional steps before performing the regionalization, to ensure that the variable of interest is comparable across time periods. We normalize the variable of interest across cities and time periods (Section 3.2), then we apply a statistical transformation to limit the influence of extreme values in the regionalization process (Section 3.3). The normalization, handling of extreme values, and regionalization are illustrated in the right maps of Fig. 1.

3.1. Spatial moving average

There are small-scale local discrepancies in the data (see left maps in Fig. 1). We use a spatial moving average to filter local discrepancies (see Eq. 1), while preserving larger-scale patterns in the data (see middle maps in Fig. 1). In eq. 1, variable x in unit j is weighted by the coefficient c_{ij} in the spatial average y_i. The weight c_{ij} depends on the total population n_j living in j, and the walking time t_{ij} between i and j, in seconds. The weight c_{ij} increases with the population of unit j and the spatial proximity of j and i. In this case study, x_j is the proportion of individuals with a non-western migration background living in unit j. This spatial moving average can also been seen as the potential to encounter an individual with a non-western migration background in the spatial unit, relative to the potential to encounter anyone, regardless of its group (Spierenburg et al., 2023). In the following, we also name it **potential exposure**, as do Spierenburg et al. (2023).
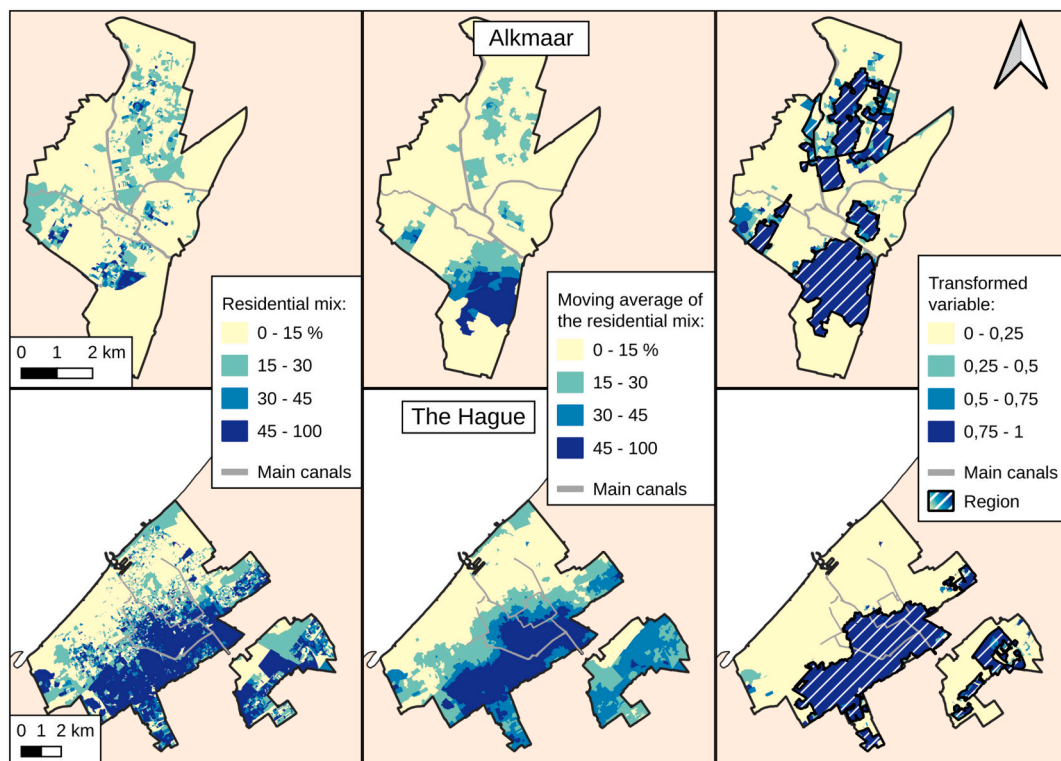

Fig. 1. Map representation of the regionalization method in the cities of Alkmaar and the Hague in 2015. The left maps represent the raw data, being the share of individuals with a non-western migration background —called residential mix— per spatial unit. The maps in the middle show the spatial moving average of that residential mix. The maps on the right represent the transformed variable (normalization and handling of extreme values) and regions obtained after the regionalization process (for clarity, this map displays only regions over-representing the population with a non-western migration background).

$$y_i = \frac{\sum_j c_{ij} \cdot x_j}{\sum_j c_{ij}} \quad \text{where} \quad c_{ij} = \begin{cases} n_j & \text{if } 0 \le t[s] < 60 \\ 3600 \cdot n_j \big/ t_{ij}^2 & \text{if } 60 \le t < 1200 \\ 0 & \text{if } t \ge 1200 \end{cases} \quad (1)$$

3.2. Normalization

The share of the population with a non-western migration background varies significantly from a time period to another and from a municipality to another. For instance, in 2015, it was 12 % in Alkmaar and 35 % in the Hague. The value for the spatial moving average per spatial unit in these two cities are not directly comparable. A value of 15 % in a spatial unit would imply an over-representation of the population with a non-western migration background in Alkmaar, whereas, in the Hague, it would imply an under-representation of that group (see middle maps in Fig. 1). We normalize the variable of interest to enable the comparison of values across cities and different time periods. To this end, for each spatial unit, we measure the deviation of the moving average y_i to its theoretical value μ, considering a case in which groups are randomly allocated in space (see Eq. 2). In Eq. 2, μ is the proportion of individuals with a non-western migration background in the city for the time period considered. It is also the expected value of y_i. the value σ_{y_i} is the standard deviation of y_i if groups were to be randomly distributed in space. The normalization z_i can be seen as the scaled difference of the moving average y_i in i to its theoretical value in a random allocation of groups. z_i is positive if unit i over-represents the group of interest and negative if it under-represents the group of interest. The derivation of σ_{y_i} is provided in Appendix A.

$$z_i = \frac{y_i - \mu}{\sigma_{y_i}} \quad (2)$$

3.3. Statistical transformation

The normalization process described above introduces extreme values and regionalization processes tend to overfit extreme values. Numerous spatial units show a potential exposure deviating significantly from the value yielded by the random allocation of social groups. We compress the extreme values resulting from the normalization process using a sigmoid function bounded between 0 and 1. We use the cumulative distribution function of the standard normal Gaussian (see Eq. 3). Therefore, the transformed value can be seen as the probability that a random allocation would result in a lower potential exposure than the one observed in the spatial unit considered. If the potential exposure to individuals with a non-western migration background is significantly larger — respectively smaller — than the city average, the probability will be close to 1 — respectively 0 —. The right maps in Fig. 1 illustrate this transformation.

$$p_i = P(z_i \le Z_i) = \int_{-\infty}^{Z_i} \frac{1}{\sqrt{2\pi}} e^{-z_i^2/2} dz_i \quad (3)$$

3.4. Regionalization

A regionalization task consists in delineating regions that are homogeneous according to either a variable or a set of variables from spatial units. In this work, we use spatially-constrained agglomerative clustering. We apply it to the statistical transformation described in Section 3.3. In the initialization phase of this algorithm, all units are considered as individual regions. Then, regions are iteratively merged together, minimizing the within-regions variance (Ward Jr., 1963). The agglomerative process is spatially constrained, meaning that only adjacent regions can be merged. We stop aggregating regions when the within-cluster sum-of-squares exceeds a certain threshold, tuned empirically (see Appendix B for more details).

3.5. Labeling regions

After delineating regions that are homogeneous in terms of demographics, we classify them into three categories: 1) regions over-representing individuals with a non-western migration background ($s = 1$), 2) regions under-representing individuals with a non-western migration background ($s = -1$), 3) mixed regions ($s = 0$). We use the same criterion as in Spierenburg et al. (2023). For each region, we compute the average potential exposure to individuals with a non-western migration background $\overline{y_R}$ of all spatial units pertaining to that region R, weighted by the units' population (see Eq. 4). We also compute the theoretical standard deviation $\sigma_{\overline{y_R}}$ of the average potential exposure in the scenario where groups are randomly allocated in space (see Appendix C for the derivation of $\sigma_{\overline{y_R}}$). Then, if the observed average potential exposure is more than two standard deviations away from its theoretical average μ, we label the region as either over- or under-representing individuals with a non-western migration background (depending on the sign), otherwise, the region is labeled as mixed (see eq. 5). The regions highlighted in the right maps of Fig. 1 are the ones that over-represent the population with a non-western migration background.

$$\overline{y_R} = \frac{\sum_{i \in R} n_i y_i}{\sum_{i \in R} n_i} \quad (4)$$

$$s = \begin{cases} -1 & \text{if} \quad \frac{\overline{y_R} - \mu}{\sigma_{\overline{y_R}}} \le -2 \\ 0 & \text{if} \quad -2 < \frac{\overline{y_R} - \mu}{\sigma_{\overline{y_R}}} < 2 \\ 1 & \text{if} \quad \frac{\overline{y_R} - \mu}{\sigma_{\overline{y_R}}} \ge 2 \end{cases} \quad (5)$$

3.6. Residential segregation indicators

To characterize residential segregation patterns, we adopt the indicators of Spierenburg et al. (2023), which characterize the observed pattern along the dimensions of intensity, separation, and scale. **Intensity** is the extent to which individuals with a non-western migration background are over-represented in the regions labeled as over-representing them ($s = 1$ in Eq. 5). It is the difference between the potential exposure to individuals with a non-western migration background in these regions and the city average. **Separation** corresponds to the proportion of individuals with a non-western migration background experiencing segregation. We measure it as the proportion of individuals with a non-western migration background living in regions in which they are over-represented. **Scale** is the spatial extent of regions in which individuals with a non-western migration background are over-represented. We measure it using the median size of regions over-representing individuals with a non-western migration background, in population terms. We express it in percentage terms, relatively to the total city population.

4. Data and case study

4.1. Dataset

We use open data from the Netherlands National Bureau of Statistics to measure the demographic composition of neighborhoods (van Leeuwen, 2020). The spatial units employed in this study are the 6-digits postcodes, with each unit covering a surface smaller than 100×100 square meters in urbanized areas (see Fig. 2), enabling a fine-resolution examination of demographic trends. We consider two demographic groups: 1) individuals with a non-western migration background, and 2) the rest of the population which includes individuals with a western migration background and individuals without a migration background.

Fig. 2. Spatial units (6-digits postcodes) in the demographic data used.

The non-western migration background is defined based on the criteria provided by the National Bureau of Statistics, encompassing individuals born abroad or having at least one parent born abroad in countries excluding European and North American countries, along with Japan, Indonesia, Australia, New Zealand (Centraal Bureau voor de Statistiek, 2016). The dataset does not disaggregate further the migration background which prevents from studying the segregation by country of origin. Moreover, the data values are rounded to the closest 5 for absolute values and to the closest 10 % for percentage values in the raw dataset, and they are not disclosed if less than 10 people live in the spatial unit. Data are available and consistent across all years between 2015 and 2020. We therefore investigate the evolution of residential segregation patterns between 2015 and 2020.

4.2. Situation in 2015

The composition of the population with a non-western migration background and the patterns of segregation vary significantly from a city to another, influenced by differences in economy, demography, and urban planning. In the Netherlands as of 2015, 12 % of the population had a non-western migration background. However, this figure showed considerable variation across municipalities, ranging from as low as 1 % to as high as 37 %. Our analysis focuses on municipalities with larger populations, specifically those exceeding 50,000 inhabitants, which includes 82 municipalities in total. Less populated municipalities typically have a smaller share of population with a migration background and are less dense. The census data are less reliable in these situations, as they are not disclosed in sparsely populated spatial units (see 4.1). We therefore choose to filter out less populated municipalities from our analysis. We consider the municipality boundaries of 2020 (van Leeuwen, 2020). There are some clear geographic trends related to the share of the population with a non-western migration background across Dutch municipalities. In the densely populated and urbanized Randstad[1], individuals with a non-western migration background represented 26 % of the population, compared to 7 % in the rural provinces in the North of the Netherlands (Groningen, Friesland, and Drenthe)[2], see top maps in Fig. 3. Moreover, within the Randstad itself, there is a notable gap between the four largest urban cores (Amsterdam,

Rotterdam, the Hague, and Utrecht) and the neighboring suburban towns regarding the share of population with a non-western migration background (see top right map in Fig. 3).

Residential segregation patterns exhibited clear geographic trends in 2015. Urban cores in the Randstad showed much higher intensity than towns in the province of Noord-Nederland (bottom-left map in Fig. 3). Intensity in 2015 was actually strongly correlated with the share of the population with a non-western migration background (Pearson correlation of 0.76). Meanwhile, the degree of separation was lower in the Randstad compared to the other municipalities, as illustrated in the middle map at the bottom of Fig. 3). Scale did not exhibit any particular spatial trend.

5. Results

After presenting the overall evolution of residential segregation patterns between 2015 and 2020 in Subsection 5.1, we organize our analysis in three parts. First, in Subsection 5.2, we uncover trends across municipalities based on their location (cities from the Randstad compared to other municipalities) and city type (urban cores compared to suburban towns). Second, in Subsection 5.3, we observe a convergence in segregation patterns across Dutch municipalities. Third, in Subsection 5.4, we investigate the relation between the rise in the proportion of individuals with a migration background and changes in segregation patterns.

5.1. Descriptive statistics

We first investigate the distribution of the change in the residential segregation patterns between 2015 and 2020 (see Fig. 4). There is no clear uniform trend in the evolution of segregation intensity, separation, and scale across Dutch municipalities between 2015 and 2020. On average, intensity decreased by 0.5 percentage point (pp), with a standard deviation of 0.6 pp. across municipalities. The change in intensity is centered around 0, and is positive for 52 % of the 82 municipalities considered in our analysis. Separation increased for most municipalities (73 %, with an average increase of 2 pp), but exhibits considerable heterogeneity. Few municipalities show a substantial increase in separation (exceeding 10 pp), while the others show a limited increase or even a decrease in separation. This distribution is skewed to the right, with a standard deviation exceeding the mean. The evolution of the relative scale follows a similar trend to that of separation. It increases for 67 % of the municipalities, the average evolution is 0.9 pp. while the standard deviation is 1.2 pp. These results underscore the heterogeneity in the evolution of residential segregation patterns across municipalities. In the subsequent sections, we examine the trends across different municipality characteristics, e.g. geographic location and demographic shift.

5.2. Geographical trends

While we do not observe overarching trends in the evolution of segregation across Dutch municipalities, we do identify specific trends associated with geographic characteristics between 2015 and 2020. Regarding intensity, we find a notable decrease in cities in the Randstad region, particularly in larger municipalities, reflecting a potential trend towards a more balanced distribution of individuals with a non-western migration background (map A and chart D in Fig. 5). Interestingly, municipalities outside of the Randstad exhibit an opposite trend, marked by an upswing in segregation intensity. As for separation, we observe a contrasting evolution between core and suburban municipalities within the Randstad. Separation decreased in the urban cores of the Randstad (i.e. Amsterdam, Rotterdam, the Hague, Utrecht) while it increased in suburban town surrounding these cores (map B in Fig. 5). We do not observe any geographic trend regarding the evolution in the relative scale of residential segregation (map C in Fig. 5).
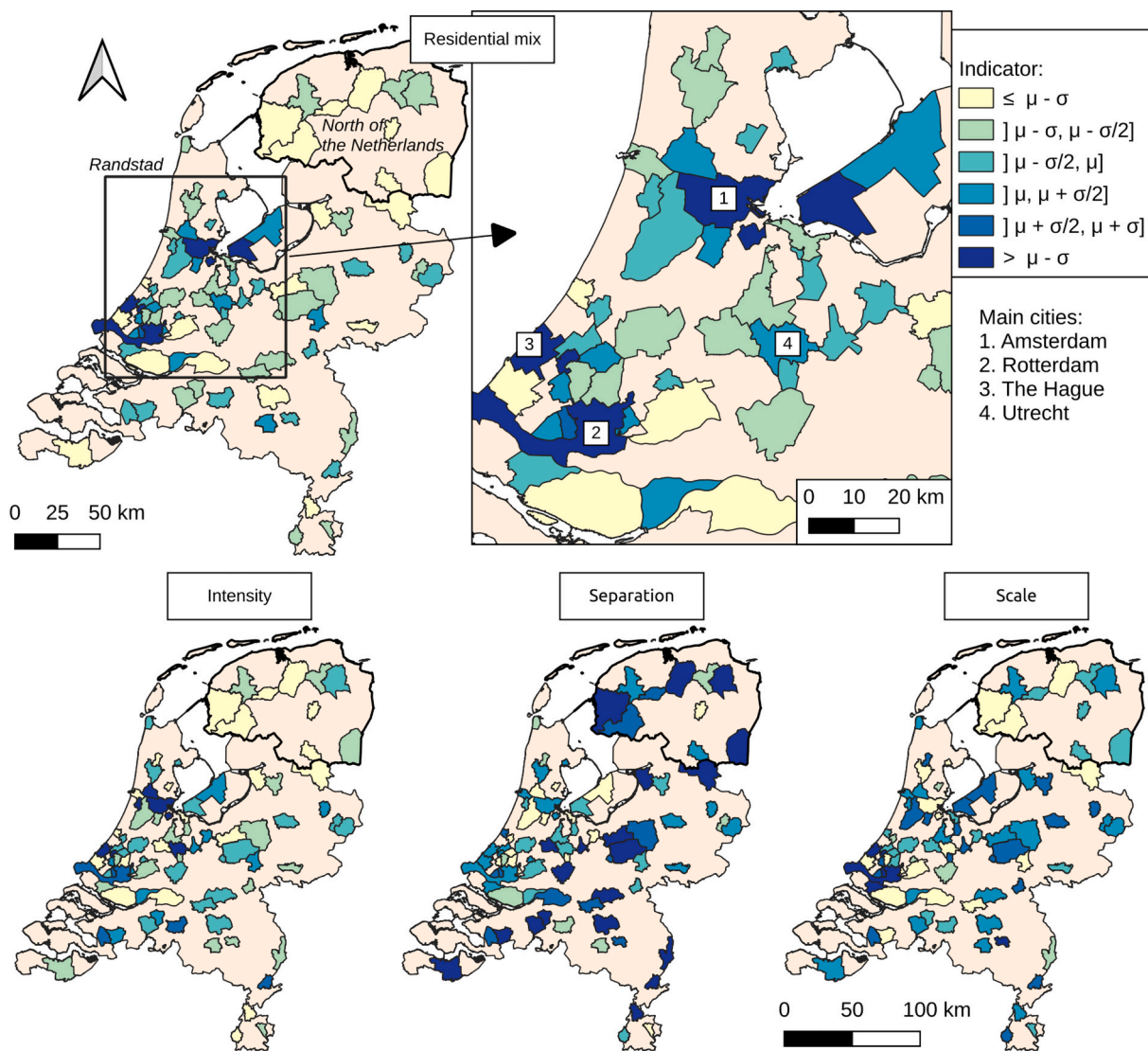
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[1] The Randstad does not have a formal definition, in this work, we include the following municipalities: Alphen aan den Rijn, Amstelveen, Amsterdam, Capelle aan den IJssel, Delft, Gouda, Haarlem, Haarlemmermeer, Katwijk, Krimpenerwaard, Lansingerland, Leiden, Leidschendam-Voorburg, Nieuwegein, Pijnacker-Nootdorp, Rotterdam, Schiedam, Stichtse Vecht, the Hague, Utrecht, Velsen, Vijfheerenlanden, Vlaardingen, Westland, Woerden, Zaanstad, Zoetermeer.

[2] Considering only the municipalities with more than 50,000 inhabitants in the Randstad and in Noord-Nederland.

Fig. 3. Spatial distribution of the proportion of the population with a non-western migration background (called residential mix), segregation intensity, separation, and scale in 2015.
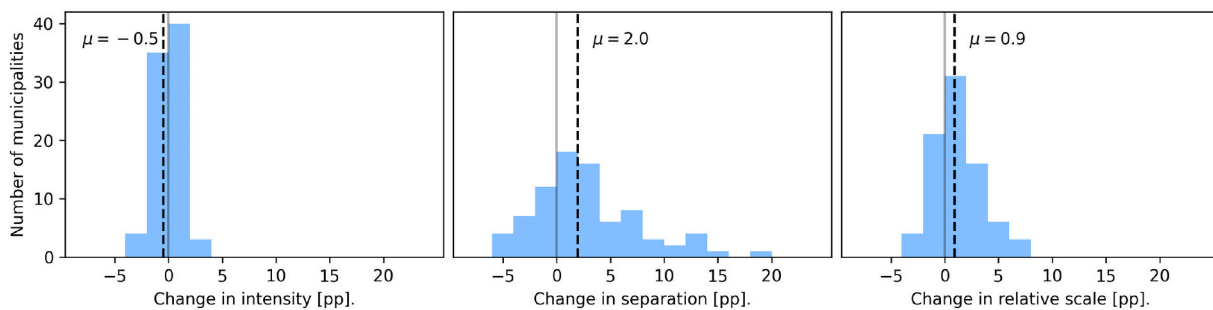

Fig. 4. Statistical distribution of the change in intensity, separation, and relative scale in percentage points (pp).

5.3. Convergence of segregation patterns

Our analysis reveals a noteworthy convergence of residential segregation patterns along intensity and separation among Dutch municipalities between 2015 and 2020. Regarding intensity, we observe a reduction in the dispersion of the distribution in 2020 compared to 2015 (top left histogram in Fig. 6). The standard deviation of intensity across

municipalities decreased from 5.7 pp. in 2015 to 4.8 pp. in 2020. Notably, the municipalities where intensity was previously the highest experienced a decrease. Conversely, we observe an increase in intensity in municipalities where intensity was initially the lowest (bottom left plot in Fig. 6). For separation, we also observe a decrease in the distribution's dispersion in 2020 compared to 2015 (top center plot in Fig. 6). The standard deviation of separation across municipalities reduced from
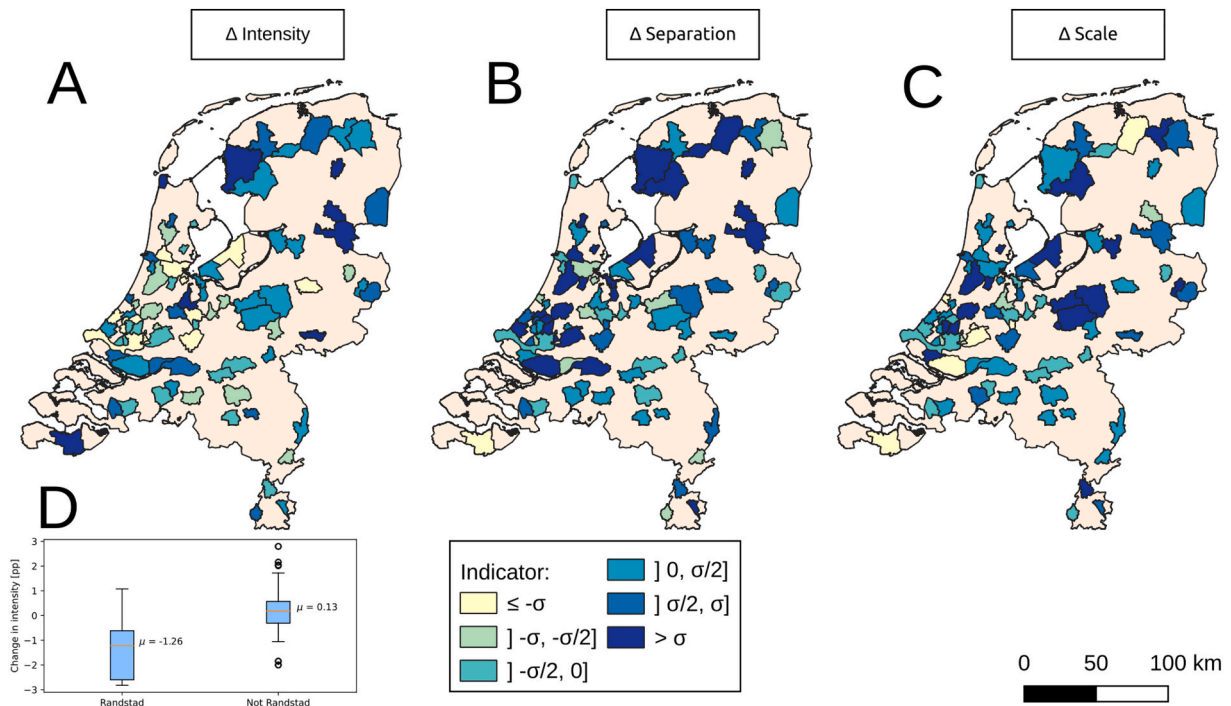
Fig. 5. Evolution of segregation patterns along intensity, separation, and scale between 2015 and 2020 in Dutch municipalities.
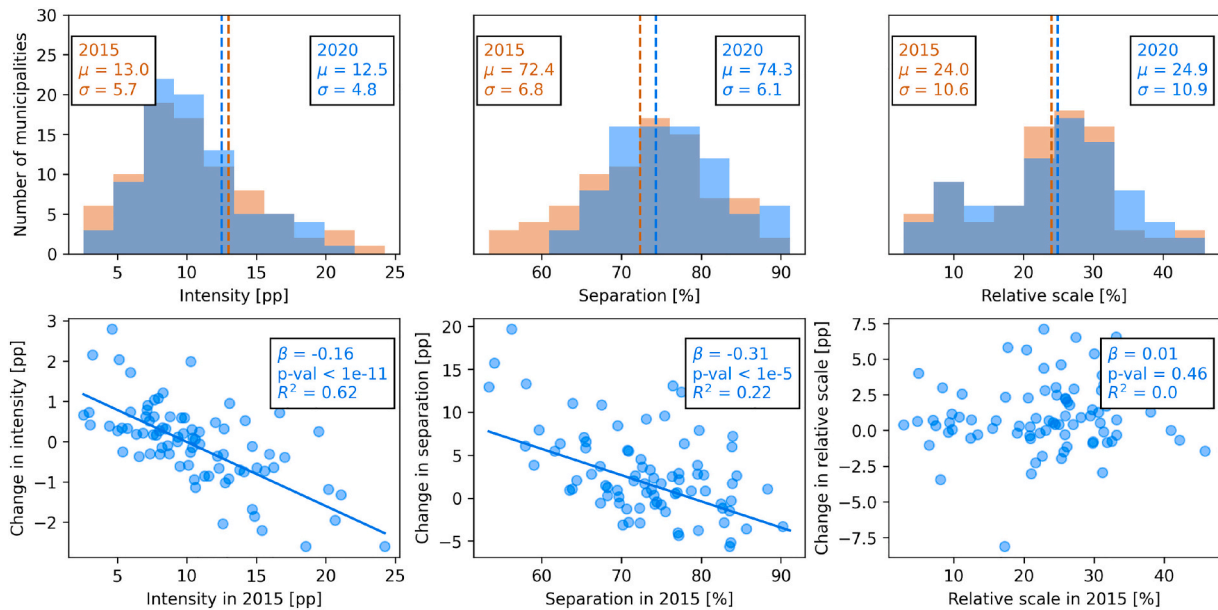

Fig. 6. Evolution in the distribution of intensity, separation, and relative scale indicators between 2015 and 2020 (top), and relation of the change in the indicators to their levels in 2015 (bottom). pp. stands for percentage points.

6.8 pp. in 2015 to 6.1 pp. in 2020. As for intensity, the largest increases in separation occurred in municipalities where separation was initially the lowest (bottom center plot in Fig. 6). In contrast, the indicator of relative scale does not demonstrate any specific trend, indicating that the spatial distribution of segregated regions remained relatively stable over the five-year period (top and bottom right plots in Fig. 6).

Regression to the mean could exacerbate the convergence observed. Regression to the mean occurs when extremely high or low measurements, influenced by random variation, tend to move closer to the average in later assessments. For instance, if high or low levels of intensity and separation in 2015 were a product of random variation, we could expect to see these values return closer to the mean by 2020. In practice, randomness in the measurement is weak. The correlation between intensity in 2015 and intensity in 2020 is 0.98 (0.79 in the case of separation), higher correlations suggesting weaker random variations. Moreover, regression to the mean falls short of explaining the reduced variance in intensity and separation over these periods, as illustrated in Fig. 6.

5.4. Relation between share of population with a non-western migration background and change in segregation patterns

Between 2015 and 2020, the share of the population having a non-western migration background increased in all municipalities considered by 1.9 percentage points (pp) on average. This upward trend varied, with increases ranging from a modest 0.7 to a significant 6.7 percentage points. This increase is notably higher in suburban towns surrounding urban cores in the Randstad region (see left map in Fig. 7).

Surprisingly, we observe a negative correlation between the change in intensity and the share of the population with a non-western migration background — also called residential mix in this section — in 2015 (top left plot in Fig. 8). Municipalities with lower residential mix in 2015 experienced an increase in intensity, while those with higher residential mix saw a decrease in intensity and the relationship appears to be proportional. This nuanced finding reveals that the strong correlation between intensity and residential mix in 2015 (Subsection 4.2) is weakening between 2015 and 2020. Additionally, there is no significant correlation between the increase in residential mix and the change in intensity, indicating that municipalities with higher increases in the share of the population with a non-western migration background did not necessarily experience larger changes in intensity.

The change in separation and scale is positively associated with the increase in the share of population with a non-western migration background (bottom middle and right plots in Fig. 8). For instance, in the Randstad region, urban cores experienced a low increase in residential mix and a decrease in separation and scale, meanwhile the high increase in residential mix in the suburbs came with an increase in separation and scale (Fig. 7).

Hence, the high increase in the population with a non-western migration in suburban towns in the Randstad did not come with an increase in intensity — social enclaves have not become more homogeneous —. Instead, either the scale of segregation increased (such as in Harlemmermeer), or new segregated regions emerged (such as in Zaanstad).

6. Discussion and conclusion

This study focuses on the 82 largest municipalities in the Netherlands, covering 60 % of the Dutch population. We choose to exclude rural municipalities due to a limitation associated with the census data used. The dataset provides open data at a highly granular resolution, yet variables on the migration background are (1) not disclosed when less than 5 people live in a spatial unit, (2) rounded to the

closest 10 % otherwise (van Leeuwen, 2020). In cities with lower density or with lower populations with a non-western migration background, that population may be under-reported. We have filtered out these cities by focusing only on the largest municipalities. This limitation could be addressed by using the microdata from the National Bureau of Statistics Centraal Bureau voor de Statistiek (2023).

Our investigation yielded several key findings. First, we do not observe any overarching trend in the Netherlands, as residential segregation neither uniformly improved nor worsened across municipalities. Second, we observe a convergence in residential segregation patterns along segregation intensity and separation between 2015 and 2020. Third, the evolution of segregation patterns associates with the change in the population with a non-western migration background relative to the city population. The higher the increase in the share of population with a non-western migration background, the higher the increase in separation and scale, while intensity does not correlate with the change in city demographics.

In the following subsections, we hypothesize on potential causes for our findings, identify limitations in our approach, and suggest directions for further research.

6.1. Interpretation of the patterns observed

The observed decrease in intensity in the Randstad may be partly attributed to the phenomenon of gentrification (Janssen et al., 2023). Affordable neighborhoods, where households with a non-western migration background are often over-represented, become increasingly attractive to young professionals seeking affordable housing in the large urban cores. Consequently, this influx of new residents from diverse backgrounds contributes to a decrease in segregation intensity. However, it is important to recognize that this trend might be temporary. Gentrification tends to drive up property prices and rents, exerting pressure on lower-income households — including those with a non-western migration background — to move out to other affordable neighborhoods (Hochstenbach & Musterd, 2018). As a result, this transitional process is viewed as a shift between two distinct segregation patterns by many researchers (Atkinson et al., 2011; Zuk et al., 2018).

Another plausible explanation for this could be the influence of public actions and urban planning priorities. Municipalities with higher intensity and separation levels might have segregation issues at the forefront of their agendas (Gemeente Amsterdam, 2017; Gemeente Den Haag, 2021). Consequently, they may implement targeted urban planning measures to address residential segregation, which could, if successful, lead to a reduction in these indicators over time. Conversely,
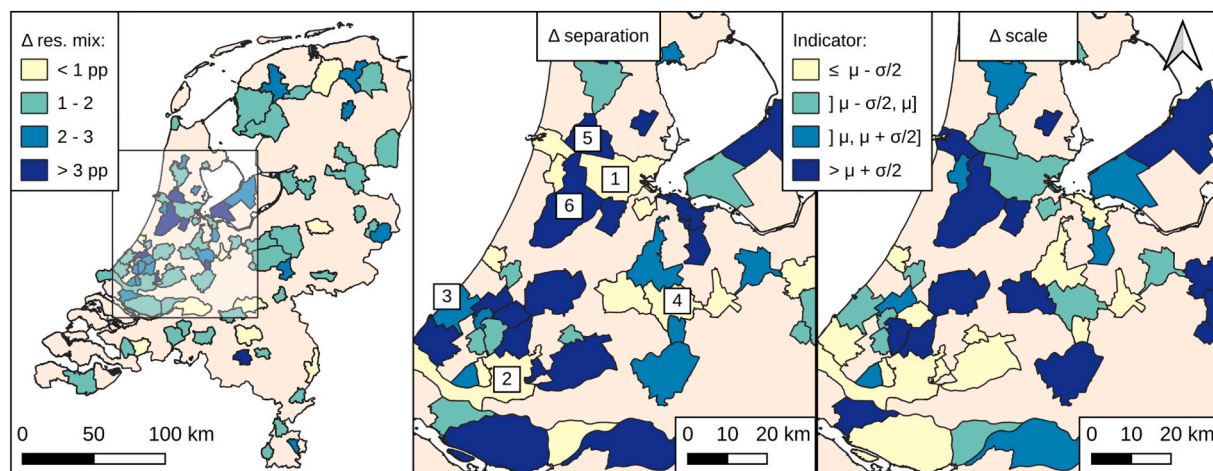

Fig. 7. Left: Geographic distribution in the evolution of the proportion of population with a non-western migration background (called residential mix), in percentage point (pp). Middle and right: evolution of separation and scale, focusing on the Randstad area. Largest municipalities 1: Amsterdam, 2: Rotterdam, 3: the Hague, 4: Utrecht. Other municipalities mentioned: 5: Zaanstad, 6: Harlemmermeer.
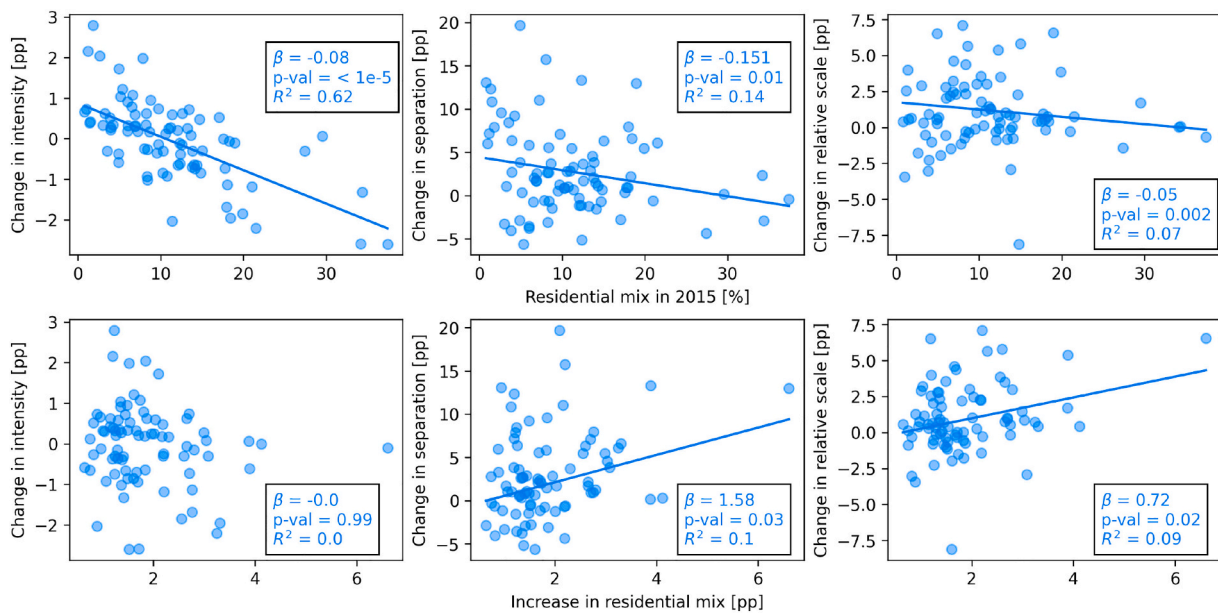
Fig. 8. Change in the intensity, separation, and scale indicators between 2015 and 2020 related to the proportion of the population with a non-western migration background in 2015 (top) and to the increase in this proportion between 2015 and 2020 (bottom). Percentage points are noted pp. in this figure.

municipalities with lower intensity and separation levels might have different priorities, resulting in fewer explicit measures to combat segregation.

6.2. Limitation and further research

One limitation of this study is the relatively short time span considered for assessing the evolution of residential segregation patterns. The analysis is conducted over a five-year period, spanning from 2015 to 2020, during which the Netherlands has seen a sharp increase in non-western migration. While this timeframe allows us to capture notable changes in segregation trends, it may not fully account for longer-term dynamics, especially given that urban development can span over a more extended period. While open data on demographics exist from 2010, the variables are consistent only from 2015. Access to data from earlier years, which could be obtainable through the National Bureau of Statistics, would enable the construction of a more extensive temporal dataset (Centraal Bureau voor de Statistiek, 2023). Investigating trends over a more extended period could reveal historical patterns and help in understanding the long-term effects of policies and socio-economic changes on residential segregation in the Netherlands.

This study focuses on the 82 largest municipalities in the Netherlands, covering 60 % of the Dutch population. We do not investigate rural municipalities. This limitation is due to the census data used. The dataset provides open data at a highly granular resolution, yet variables on the migration background are (1) not disclosed when less than 5 people live in a spatial unit, (2) rounded to the closest 10 % otherwise (van Leeuwen, 2020). In cities with lower density or with lower population with a non-western migration background, that population may be undersampled. We have filtered out these cites by focusing only on the largest municipalities. Using the microdata from the National Bureau of Statistics would allow to address that limitation Centraal Bureau voor de Statistiek (2023).

The population with a non-western migration background is in itself inherently diverse, encompassing variations in education levels, income, country of origin, and migrant generation (Boterman et al., 2021; Custers & Engbersen, 2022). Subgroups defined along these dimensions within the broader category may experience residential segregation differently, both in terms of the level of segregation they encounter and the impact it has on their life outcomes. It is important to exercise

caution against committing the fallacy of division, wherein observations made on the group as a whole may not necessarily apply uniformly to its subgroups. For instance, a recent immigration of highly-skilled migrants moving in neighborhoods where Dutch natives are over-represented would decrease residential segregation of migrants as a whole, while the situation would remain unchanged for low-skilled migrants. The data used in this work do not allow to disaggregate the population with a non-western migration background into smaller subgroups. Further research could segment the analysis using subcategories such as income and education levels, using the microdata provided by the National Bureau of Statistics (Centraal Bureau voor de Statistiek, 2023).

Finally, while we could identify trends in the evolution of residential segregation across cities, we have left aside trends within cities. In practice, residential segregation patterns may vary within municipalities. For instance, intensity could increase in certain regions while simultaneously decreasing in others within the same urban area. Exploring such regional variations within municipalities could offer a more comprehensive understanding of the underlying dynamics driving residential segregation. The regionalization method used in this work enables the investigation of trends within cities. However, we believe that a meaningful analysis of within-city trends necessitates context-specific information, such as related to the local housing stock, historical urban development, and existing policies. Therefore, we recommend research investigating within-city trends to focus on selected case studies and incorporate contextual information.

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CRediT authorship contribution statement

Lucas Spierenburg: Supervision, Software, Resources, Project administration, Methodology, Investigation, Validation, Visualization, Writing – original draft, Writing – review & editing, Conceptualization, Data curation, Formal analysis. **Sander van Cranenburgh:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization, Formal analysis, Funding acquisition, Investigation. **Oded Cats:** Writing – review & editing,

Appendix A. Standard deviation of the spatial moving average in a random allocation of groups

This section derives the variance of the spatial moving average of the share of population from a group in spatial units — called residential mix —, when the group is randomly distributed across space.

A.1. Variance of the residential mix in a spatial unit

We model the residential mix in a spatial unit as a random process (Bernoulli process) in equation A.1. Each household h belongs to the group of interest with probability μ, being the share of that group in the city, under the following assumptions: (1) each household is composed exclusively by one group, (2) the distribution of household size is the same across groups. The random variable G_h indicates whether household h belongs to the group of interest or not.

$$X_j = \frac{1}{n_j}\sum_h n_h \cdot G_h \quad \text{where } G_h = \begin{cases} 1 & \text{if } h \text{ belongs to the group of interest} \\ 0 & \text{Otherwise} \end{cases} \tag{A.1}$$

$$Var[X_j] = \frac{1}{n_j^2}\sum_h n_h^2 \cdot Var[G_h] \tag{A.2}$$

$$= \frac{\sum_h n_h^2}{\left(\sum_h n_h\right)^2}\cdot Var[G_h], \quad \text{where } Var[G_h] = Var[G] = \mu\cdot(1-\mu) \tag{A.3}$$

A.2. Variance of the spatial moving average of the residential mix

The residential mix is spatially averaged, using a weighted mean, we represent this weighted average in unit i using the random variable Y_i (see equation A.4). In a random allocation of groups in space, the residential mix X_j is not spatially autocorrelated, and the variance of Y_i can be expressed as a weighted sum of the variances $Var[X_j]$ of all random variables X_j, without any covariance term (see equation A.5).

There is spatial autocorrelation for variable Y. The covariance matrix Σ_Y can be derived from the weights c_{ij} and the variances $Var[X_j]$, see equations A.6 and A.7. The coefficient c_{ij} are computed using eq. 1.

$$Y_i = \sum_j c_{ij}X_j \tag{A.4}$$

$$Var[Y_i] = \sum_j c_{ij}^2 Var[X_j] \tag{A.5}$$

$$\Sigma_Y = C^T \times \left(C\cdot\sigma_X^2\right) \tag{A.6}$$

$$C = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1N} \\ c_{21} & & & \\ \vdots & & & \\ c_{N1} & & & c_{NN} \end{bmatrix} \tag{A.7}$$

Appendix B. Threshold for the maximum within-cluster sum-of-squares

B.1. Computing the theoretical total sum-of-squares

We stop the aggregation process in the clustering method when the within-cluster sum-of-squares exceeds a certain threshold. This threshold is based on the expected total sum-of-squares (TSS) in the city if groups would be randomly allocated across space, see equations B.1 to B.5. This enables to have a standard threshold for all cities. In equation B.5 α is tuned empirically. $Var[P_i]$ is 1/12 (see Subsection B.2 below).

$$TSS = \sum_i \left(p_i - \mu_p\right)^2 \tag{B.1}$$

$$E[TSS] = E\left[\sum_i \left(P_i - \mu_p\right)^2\right] \tag{B.2}$$

$$= \sum_i E\left[\left(P_i - \mu_p\right)^2\right] \tag{B.3}$$

$$= \sum_i Var[P_i] \tag{B.4}$$

$$= \alpha \cdot N_{units} \cdot Var[P_i] \tag{B.5}$$

B.2. Computing the theoretical variance of the p-value

The derivations below allow to compute $Var[P_i]$.

$$Var[P_i] = \int_{-\infty}^{\infty} \left(\frac{1}{2}\left[1 + erf\left(\frac{z}{\sqrt{2}}\right)\right] - \frac{1}{2}\right)^2 \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2} dz \tag{B.6}$$

$$= \int_{-\infty}^{\infty} \frac{1}{4} erf\left(\frac{z}{\sqrt{2}}\right)^2 \cdot \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2} dz \tag{B.7}$$

$$= \int_{-\infty}^{\infty} \frac{1}{4} erf(\zeta)^2 \cdot \frac{1}{\sqrt{2\pi}} e^{-\zeta^2} \sqrt{2} d\zeta \quad \text{with } d\zeta = \sqrt{2} dz \tag{B.8}$$

$$= \frac{1}{8} \int_{-\infty}^{\infty} erf(\zeta)^2 \cdot \frac{2}{\sqrt{\pi}} e^{-\zeta^2} \sqrt{2} d\zeta \tag{B.9}$$

$$= \frac{1}{8} \left[\frac{1}{3} erf(\zeta)^3\right]_{-\infty}^{+\infty} \tag{B.10}$$

$$= \frac{1}{12} \tag{B.11}$$

Appendix C. Theoretical variance of the average exposure in a region

The variance of the average exposure in a region $\overline{y_R}$ can be computed analytically from the equations below.

$$\overline{y_R} = \sum_{i \in R} \theta_i y_i \tag{C.1}$$

$$Var(\overline{y_R}) = \sum_{i \in R} \sum_{j \in R} Cov\left(\theta_i y_i, \theta_j y_j\right) \tag{C.2}$$

$$= \sum_{i \in R} \sum_{j \in R} \theta_i \theta_j Cov\left(y_i, y_j\right) \tag{C.3}$$

The coefficients θ_i are computed from equation C.4.

$$\theta_i = \frac{n_i}{\sum_{i \in R} n_i} \tag{C.4}$$

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