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Measuring residential segregation using spatial metrics in Berlin

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Abstract

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Although residential segregation is an inherently spatial process of vital concern in modern urban societies, traditional measuring methods have historically deviated the focus from the spatial aspect of the issue. Applied landscape metrics and spatial segregation indices offer a complementary method to examine residential segregation patterns in Berlin, a multi-ethnic capital with a historical political division between East and West Berlin. This research utilises high-resolution demographic data from 2011 to evaluate the potential of landscape metrics in measuring residential segregation from a strictly spatial perspective. Moreover, the local segregation patterns of the city have been assessed for the five most populous minority groups in terms of segregation dimensions. Results found differences between East and West Berlin ethnic compositions as well as focal clusters of segregation by origin group. Furthermore, the study confirmed the value of landscape metrics in segregation studies while offering insights for policymakers in Berlin. The method is provided as an alternative pathway to conventional segregation studies with an interdisciplinary approach.

Keywords: segregation, Berlin, GIS, landscape metrics, ethnic composition, social dynamics, residential patterns, spatial analysis

CERCS Code: S230 - Social geography

Abstrakt

Elukohasegregatsiooni hindamine ruumiliste mõõdikutega Berliini näitel

Kuigi elukohasegregatsioon on oluline ruumiline protsess tänapäeva linnakeskkonnas, on traditsioonilised mõõtmismeetodid osaliselt kõrvale jätnud segregatsiooni ruumilise olemuse. Maastikuindeksid ja ruumilised segregatsiooniindeksid pakuvad täiendavat võimalust segregatsioonimustrite uurimiseks. Käesolev magistritöö keskendub Berliinile, paljurahvuselisele Saksamaa pealinnale, mis Teise maailmasõja järel Ida- ja Lääne-Berliiniks lahutati. Uuring kasutab kõrglahutusega demograafilisi andmeid aastast 2011 ja ruumilisi segregatsiooni- ja maastikumõõdikuid, et paremini tuvastada Berliini elukohasegregatsiooni mustreid. Eesmärgiks on analüüsida viie kõige rahvarohkema vähemusgrupi paiknemismustreid Berliinis ning kinnitada varasemates uuringutes tuvastatud Berliini müüri mõju ja arutleda maastikumõõdikute potentsiaali üle segregatsiooni ruumilise mõõtme kirjeldamisel. Tulemused näitasid erinevusi Ida- ja Lääne-Berliini etnilises koosseisus ning tuvastasid vähemusgruppide paiknemise klastrid. Lisaks kinnitas uuring maastikuindeksite väärtust segregatsiooni-uuringutes, pakkudes olulist teavet poliitikakujundajatele. Magistritöö interdistsiplinaarne metoodika demonstreerib alternatiivset võimalust uurida segregatsiooni arvestades protsessi ruumilist olemust, mis traditsiooniliste metoodikatega on jäänud pigem tagaplaanile.

Märksõnad: Segregatsioon, Berliin, GIS, maastikuindeksid, etniline koosseis, sotsiaalne dünaamika, paiknemismustrid, ruumiline analüüs

CERCS kood: S230 – sotsiaalne geograafia

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Introduction

For the last decades, European countries, including Germany, have been facing major migration fluxes, not only within their borders but also from other parts of the world. The differences in terms of culture, religion, language and socio-economic background have resulted in distinct residential patterns for the minorities and the majority populations (Poulsen et al., 2002; van Kempen & şule Özüekren, 1998). Spatial segregation is a broad term whose definition varies according to the nuances acquired over time and the scope of different researchers. In essence, spatial segregation can be defined as the unequal distribution of different groups in a predefined space. Nevertheless, this basic definition focusing on the over and underrepresentation of the groups (Massey & Denton, 1988), has evolved to stress various aspects, such as stating that the process takes part in the urban space (Feitosa et al., 2007; Yao et al., 2019), pointing out the importance of the residential sphere (van Kempen & şule Özüekren, 1998) or a taking person-based approaches combining the spheres where segregation may be experienced and taking into consideration the activity space (Silm et al., 2018; Wong & Shaw, 2011).

Segregation has been measured in multiple ways over the decades. Traditional measures such as Dissimilarity Index (D) and Gini (G) have been used for many studies that focused on the evenness dimension of residential segregation (Massey & Denton, 1988). However, there is yet to be a consensus on which measurements should be used for each case study. Data availability and technological progress make segregation susceptible to new ways of measuring and analysing residential patterns (Li et al., 2022; van Kempen & Wissink, 2014; Wong & Shaw, 2011). Therefore, introducing and combining different indices and technologies for a global understanding of the segregation phenomena seems to be a fair path for new studies (Cortes et al., 2020; Li et al., 2022). Geographic databases and how local, regional, and national governments manage and share spatial data give the opportunity to address residential segregation issues distinctively (Alessandrini et al., 2017; Crews & Peralvo, 2008). This sets the ideal framework for the inclusion of landscape metrics, also known as landscape indices, as an asset to the qualitative analysis of residential segregation dynamics with a deep spatial-based perspective (Crews & Peralvo, 2008; Uuemaa et al., 2009).

Landscape metrics could potentially be integrated with the social sciences and segregation analysis to give a higher spatial sense to the phenomena, preventing the prebuilt unnatural borders and stereotypes from distorting the analysis, results and following policies (Charles, 2003). The use of landscape metrics for urban or human geography studies has not been spread yet. Still, previous research done from an anthropological perspective has proved the existing relationship between ecology and its impact on the urban environment and people's lives (Stoetzer, 2018). As an exception to the lack of studies that combine demographic data and landscape ecology, Crews & Peralvo (2008) used landscape metrics for spatial demography based on US census data. However, the metrics were not used as a complementary tool for segregation measures. At the same time, their analysis can be described as purely statistical, as it does not bring visual patterns of the variables through the landscape metrics. Newer versions of the traditional aspatial indices have been created by researchers to provide better results and no longer ignore the relationship between neighbouring statistical units (Feitosa et al., 2007; Morrill, 1991; Oka & Wong, 2015; Wong, 1993; Yao et al., 2019).

This research considers non-visual index results not to be able by themselves to fill the gap in terms of spatial analysis. Hence, in order to complement these indices, landscape metrics will be used to address residential segregation of the main minority population groups in Berlin, a city that is known as a multi-ethnic capital and whose contemporary history, being split in half for decades, gives an extra interest in terms of spatial patterns. This work aims to gain a better understanding of the residential segregation patterns in Berlin by using spatial segregation metrics and landscape metrics. More specifically, the aims were to 1) identify segregation patterns in Berlin and whether the historical political division has had an effect on the segregation patterns and 2) discuss whether landscape metrics have added value in measuring spatial aspects of segregation.

Throughout the research, the following research questions will be addressed:

1. How are the five most populous minority groups spatially distributed in Berlin?
2. How do these groups compare in terms of segregation and its dimensions if determined by spatial segregation metrics and landscape metrics?
3. What is the difference between East and West Berlin in terms of residential patterns of ethnic groups?

1. Theoretical overview

1.1. Segregation

No matter what period of history is to be analysed, segregation has been an inherent feature of all societies and all times. The term, broadly defined as the statistical overrepresentation or sub-representation of a group in the space, can be measured for ethnic, gender, age, origin and socioeconomic groups (Haandrikman et al., 2021; Massey & Denton, 1988; Silm et al., 2018). Different studies have shown the deep roots of segregation, including the connection between different spheres of life, such as school, residence or workplace (Elliott-Cooper et al., 2020; Frankenberg, 2013; Marcuse, 2015; Tammaru et al., 2016). The effects include the lack of equal opportunities, struggles to social and economic upgrade, access to good quality education, political activity and general well-being deprivation (Bolt et al., 1998; Marcuse, 2015; van Kempen & şule Özüekren, 1998; Yao et al., 2019).

Even though it is usually understood as a negative phenomenon, segregation is known to have some positive aspects in the short term, especially when it comes to arriving in the hosting country and having to face the same problems that other people have faced before (Bolt et al., 1998; Peach, 1996; van Kempen & Wissink, 2014). Many factors can affect the spatial patterns of populations, from cultural, such as spoken language, religion or country of origin (Massey & Denton, 1988) to socio-economical ones, for example, personal and family income or education level (Haandrikman et al., 2021). Sharing the same space with those who have a similar background makes it easier for minority populations to build social networks and overcome issues with bureaucracy, housing, finding a job, or even economic support for growing a business (Bolt et al., 1998; van Kempen & şule Özüekren, 1998).

The location hosting the deepest ethnic segregation has been shown to be the residential. Whereas workplaces and schools locate a significant interaction between different economic, social, and ethnic groups, the residential space resulted to be the primary location where segregation is depicted (Li et al., 2022; Silm et al., 2018; Wong & Shaw, 2011). Thus, segregation may be overestimated without knowledge about the populations' activity space, as this includes life spheres in which the interaction with other groups is higher. This issue can be particularly relevant in case studies whose analysis and conclusions are merely based on residential segregation, as the situation outside of their residential location might be potentially better or less segregated (Frankenberg, 2013; Li et al., 2022; Silm et al., 2018; Wong & Shaw, 2011). Examples of new datasets used to measure activity space segregation are Global Positioning System (GPS) and Call Detail Records (CDR) (Silm et al., 2018; Wong & Shaw, 2011). Nevertheless, residential segregation plays a significant role in people's lives and, as such, should be studied by scholars either simultaneously or together with other spaces that host segregation.

Segregation can be both the consequence and cause of diverse social processes seen in the urban sphere. These processes in which different population groups gain unique residential patterns are mostly perceived by the authorities as harmful or undesirable, resulting in social housing policies that differ among countries and cities (Haandrikman et al., 2021; Wong & Shaw, 2011). The presence of ethnic residential segregation in cities is caused by both, external forces that deliberately or not divide the population, gentrify and displace through their influence in the liberalised housing market, and the will of the segregated population to keep their own values, language, culture, and general identity traits (Andersson & Turner, 2014; Elliott-Cooper et al., 2020; Peach, 1996). The last explains those cases in which segregation has not been forced by external agents or inequalities in terms of socio-economic status. Instead, they are a consequence of the minority group's life choices and own personal preferences. Nevertheless, segregation has bad outcomes despite being chosen or forced, preventing integration into society and restricting access to socio-economic development, mainly due to added difficulty in learning the local language, as their social interaction with the majority group is limited (Bolt et al., 1998; Peach, 1996). This is also the cause of scarce access to social networks, besides those built around their own group, and an overall lack of opportunities compared to the majority (Peach, 1996; van Kempen & şule Özüekren, 1998).

Residential segregation relates to the uneven distribution of the different groups, mainly in an urban environment but referring to their residential location (Feitosa et al., 2007; Massey & Denton, 1988; Yao et al., 2019). Residential segregation is a complex process that needs to be studied case by case and characterised in terms of the dimensions of segregation. The dimensions include evenness (1), exposure (2), concentration (3), centralisation (4), and clustering (5) (Massey & Denton, 1988). Each of these five aspects needs to be taken into account and analysed carefully, as they all are meaningful and have to be considered for further work and spatial planning.

1. *Evenness* or *unevenness* is the main segregation dimension which refers to the spatial extent of a group (or two) regarding the distribution in the local measurement units normalised with the entire study area distribution. The formulations of the traditional Segregation Index (IS) and Dissimilarity Index (D) were conceptualised as aspatial without any adjacency involved in the measure (Duncan & Duncan, 1955; Feitosa et al., 2007; Massey & Denton, 1988).
2. *Exposure* or *isolation* is the dimension that refers to the probability of both groups interacting with each other and sharing the same space (Bell, 1954; Massey & Denton, 1988). Same as with evenness, the traditional measures of exposure (xPx and xPy (Bell, 1954)) include no neighbourhood statistical units in their formulation, being a *de facto* aspatial dimension as they merely account for the cohabitation of the groups inside of each statistical unit (Feitosa et al., 2007; Morrill, 1991; Reardon & O'Sullivan, 2004).
3. *Concentration* refers to the area that a group occupies in the urban space. A population will be concentrated when they are not sparse in relation to the general relative population or another chosen group (Massey & Denton, 1988). From concept to formulation, this dimension is purely spatial, as it naturally relies on neighbours (Reardon & O'Sullivan, 2004).
4. *Centralisation* measures up to what degree a particular group has the tendency of being in the centre of the urban area (Brown & Chung, 2006; Massey & Denton, 1988), which can be understood as a historical city centre, the centroid of the study area or a location based on the particular case. As a result of taking distance to a given location, this dimension is also spatial (Feitosa et al., 2007; Massey & Denton, 1988; Reardon & O'Sullivan, 2004)
5. *Clustering* takes into account the spatial relation of the members among the same group, giving the level of grouping or clustering so that the continuity and ghettoisation can be recognised, avoided, and fixed with concrete policies (Cortes et al., 2020; Massey & Denton, 1988). It is, as the previous two dimensions, strictly spatial and needs adjacency or neighbouring information (Brown & Chung, 2006; Massey & Denton, 1988).

These five dimensions have been the base for further research on the topic. Since sociologists had a very significant role in the first steps of segregation measures (Oka & Wong, 2015), the evenness and exposure dimensions based on either census tracts or neighbourhoods resulted in studies that failed to account for the local patterns of segregation due to the aspatial formulation of the indices (Reardon & O'Sullivan, 2004; Wong, 1993, 2003). At the same time, scholars have historically given more attention to global segregation indices, overlooking local measures that were conceived for purposes other than segregation, such as Location Quotient (LQ) (Isard, 1966). LQ was created to identify the concentration of an industry at a local scale in comparison to the general importance of it for the whole study area; in this sense, it can be used to map and describe the segregation patterns at a micro-scale that global D index fails to capture (Brown & Chung, 2006; Yao et al., 2019).

The inter-dependence of the segregation dimensions described by Massey & Denton (1988) has been pointed out repeatedly by geographers (Feitosa et al., 2007; Morrill, 1991; Reardon & O'Sullivan, 2004; Wong, 1993; Yao et al., 2019). More specifically, Yao et al. (2019) suggested that, as segregation is intrinsically a spatial phenomenon, dimensions overlap when the geographical relationship between units is considered. Consequently, different authors have developed distinct dimension frameworks merging dimensions attending to their view on the issue. For instance, Reardon & O'Sullivan (2004) described 1) evenness-clustering 2) exposure-isolation dimensions, and Brown & Chung (2006) found that the 1) evenness-concentration 2) clustering-exposure structure was more adequate for their study. In the conceptual framework of Reardon & O'Sullivan (2004) containing two spatial dimensions, both concentration and centralisation are seen as possible sub-dimension of spatial evenness-clustering in cases where those are relevant for the analysis.

In the present matter, Berlin has a well-founded city centre in Mitte, specifically in Alexanderplatz (Arandjelovic, 2014), the location used to address the centralisation sub-dimension due to its high importance for the study case. In addition, concentration has also been measured not to overlook any possible insight (Massey & Denton, 1988; Reardon & O'Sullivan, 2004). The principles behind this two-dimensional spatial perspective visible in *Figure 1* are that exposure and isolation are the opposite patterns, the same as evenness and clustering. Hence, unevenness cannot be distinguished from clustering at a certain scale, and both concentration and centralisation are more specific patterns of a lack of evenness. Therefore, this study will be based on an evenness-clustering spatial dimension referring to the residential space distribution and the isolation-exposure, which addresses the level of interaction between members of a group or two different groups (Feitosa et al., 2007; Reardon & O'Sullivan, 2004).

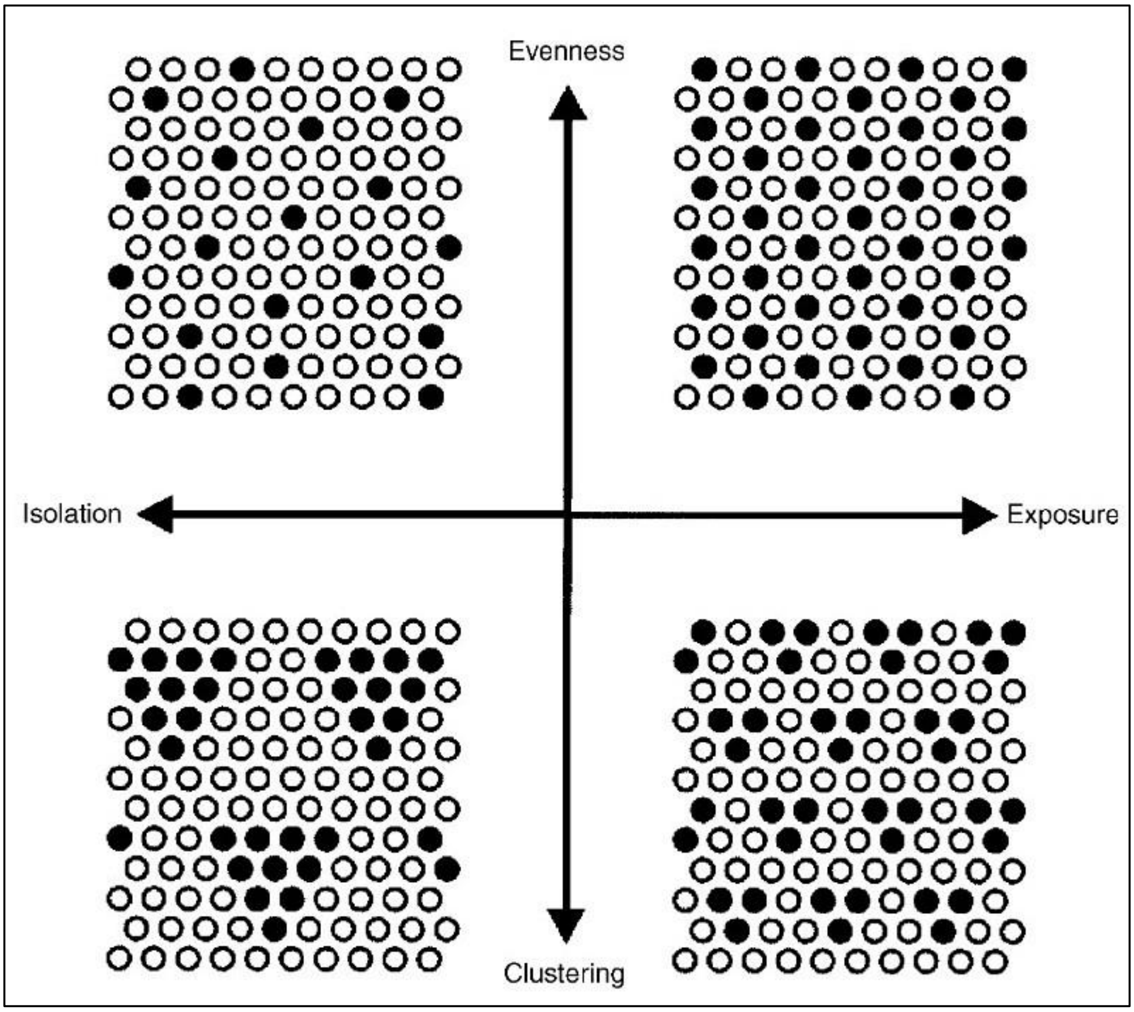

Figure 1. *Spatial dimensions of segregation. Source: Reardon & O'Sullivan, 2004.*

Despite being voluntary segregation for origin, religion, language or any other, it is undoubtable that there is an interest in integrating the distinct groups that conform a society. Moreover, in many cases, the situation is forced by external agents abusing their economic status and with its roots in discrimination and stereotypes (Hamann & Türkmen, 2020; Peach, 1996). Being isolated, clustered, or both have been shown to impact behaviour, life quality, and social exclusion, making it essential to deeply and successfully analyse the dynamics and challenges without excluding local measures and multi-disciplinary approaches that can result in better-adapted policies (Crews & Peralvo, 2008; Peach, 1996).

1.2. Measuring segregation

The beginnings of the conceptualisation of segregation measures, grounded in the sociology field, generated global measures that were in perfect harmony with the technology at the time (Duncan & Duncan, 1955; Massey & Denton, 1988; Wong, 2003). Several scholars have expressed their disapproval over the use of the first and most widespread indexes due to their failure to identify spatial patterns by not taking into account the geographical relation of the different statistical divisions (Feitosa et al., 2007; Reardon & O'Sullivan, 2004; Wong, 2003; Yao et al., 2019). However, the dissimilarity index (D) (Duncan & Duncan, 1955) and entropy index (H) (Shannon, 1948) were crucial for the growth of segregation studies as they were possible to compute without GIS software for the census tracts or neighbourhoods (Reardon & O'Sullivan, 2004).

The aforementioned disapproval of traditional spatial methods is based on two major problems, the "Modifiable Areal Unit Problem" or MAUP (*Figure 2*) and the "Checkerboard Problem" (*Figure 3*) (Li et al., 2022; Reardon & O'Sullivan, 2004; White, 1983). When using aspatial measures, each cell, grid, census tract or neighbourhood contains counts for each group. MAUP refers to the fact that the measured units will be neighbouring each other and, since the statistical boundaries are generally not based on population composition, the edge of one unit can be more similar to the composition of the neighbouring cell than to the distant areas of its own.

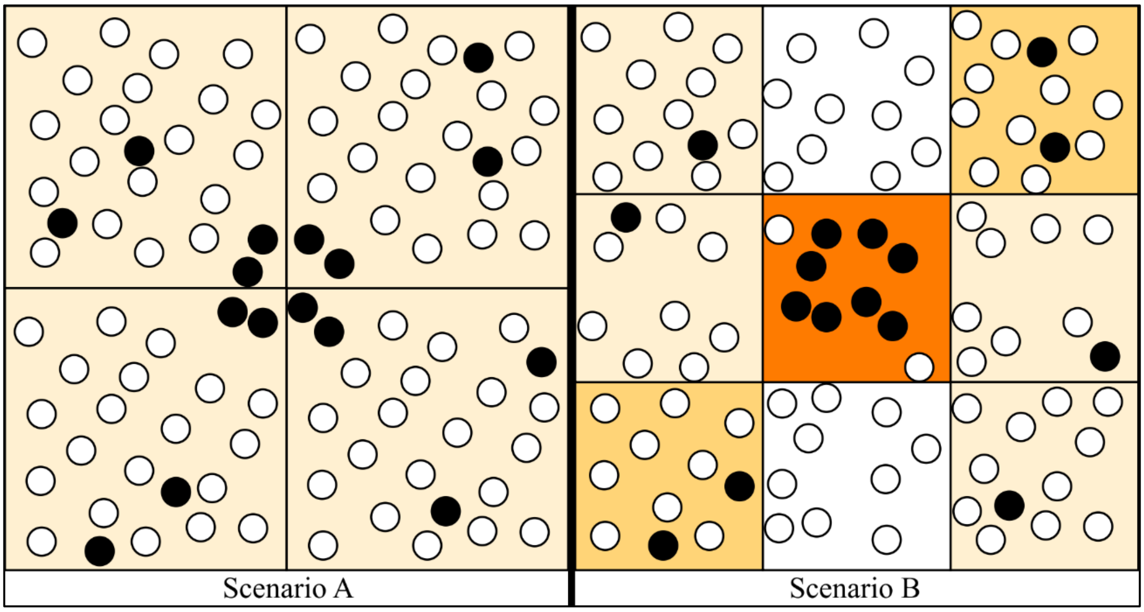

Figure 2. *Visual example of Modifiable Areal Unit Problem (MAUP).*

Translated to residential segregation, a significant cluster of migrant population (black dots) representing 80% in the statistical unit of *Scenario B* can be ignored entirely or correctly identified based on data aggregation and resolution. *Scenario A* shows the case where a segregated population remains unnoticed despite being spatially close due to poorer data quality and aspatial measures. As a consequence, it is imperative to take into account the accuracy of the data and use spatial measures so that MAUP does not represent a menace to the quality of the results and possible policies (Buyantuyev & Wu, 2007; Li et al., 2022; Reardon & O'Sullivan, 2004).

The Checkerboard Problem, on the other hand, refers to a problem where the result will not vary if the composition of the statistical units remains the same, regardless of whether it is surrounded by similar composition units or opposite ones. In *Figure 3*, the problem is represented in a simple case where each cell consists entirely of either majority or minority populations, represented by each colour. The homogeneity in terms of population origin on each of the cells would result in the same value for aspatial measures like D, as the neighbouring cells are not taken into account. As a consequence of ignoring the geographical aspect, the index fails to identify the higher segregation of *Scenario B*, where the interaction between the two groups is much lower (Massey & Denton, 1988; Reardon & O'Sullivan, 2004; White, 1983).

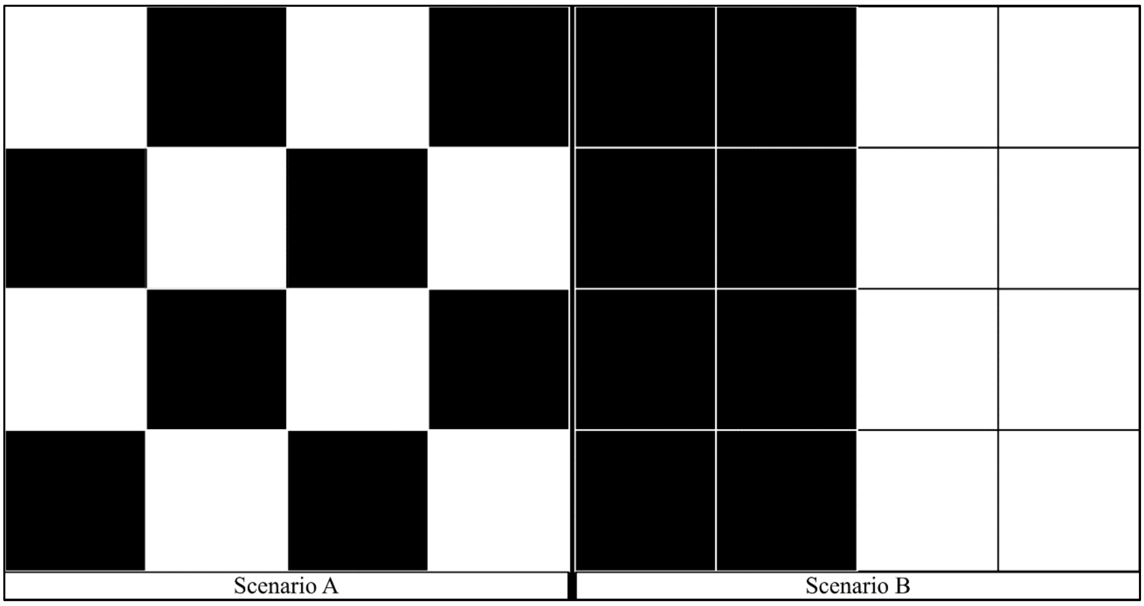

Figure 3. *Representation of the Checkerboard Problem.*

Other relevant problems have appeared with several studies based on neighbourhoods and aspatial methods (Brown & Chung, 2006; Kemper, 1998), as they provide incomplete analyses misunderstanding the spatial processes and patterns of segregation. The use of these boundaries can be explained by the fact that the authorities might be interested in getting results based on limits which they are familiar with, missing important conclusions for proper intervention in the segregated areas. However, the increasing amount of accessible data and GIS software development provides a favourable context for more detailed spatial analyses using aggregated estimations on equal-area units or grids (Alessandrini et al., 2017; Reardon & O'Sullivan, 2004). Using these alternative statistical units is a positive change, as it avoids inadequate policies resulting from policymakers' stereotypes concerning specific neighbourhoods or areas that are immediately associated with ethnic minorities (Charles, 2003; Marcuse, 2015). Stereotypes are great predictors of segregation; therefore, aggregation can force those with the capacity to resolve the problems to overlook subjective conclusions and hold the results open for scrutiny (Charles, 2003).

All these identified problems have been mitigated by technological developments, and the adoption of new variants of the traditional indices allowed new studies to include the geographical aspect to their measures at the expense of the aspatial ones, with spatial versions of D and entropy (H) in their methods (Oka & Wong, 2015; Reardon & O'Sullivan, 2004; Theil & Finizza, 1971; Yao et al., 2019). Other studies were focused on local indices such as the Location Quotient (LQ) and Poulsen's ruled-based typology instead of traditional global indexes (Poulsen et al., 2002; Yao et al., 2019). Another alternative perspective taken involves the creation of local indices based on the original D and H (Oka & Wong, 2015). However, these will not be used throughout this study as their implementation is more challenging. It is argued that other existing measures, specifically the Location Quotient, is underutilised, has a high explanatory potential, and its formulation aligns particularly well with the data and tools employed for this research (Brown & Chung, 2006).

The global spatial dissimilarity measures developed include D_{adj} (Morrill, 1991), D_w and D_s (Wong, 1993). D_{adj} is the spatial version of D that accounts for adjacent cell values when measuring evenness. D_w was adjusted adding the boundary length to the calculation of dissimilarity, and lastly, D_s includes not only the boundary length but also the perimeter/area ratio (Apparicio et al., 2014; Morrill, 1991; Wong, 1993). Since this study seeks to take the most spatial-based approach, D_s will be used as a spatial measure of evenness for being the most complete version. Considering the neighbouring statistical units in the measure of evenness is a good starting point. Nonetheless, other indices that measure segregation from a broader scope have been implemented. The Deviational ellipse index (S) uses the dispersion, orientation and location of each group in the space to calculate the level of segregation attending to the overlap between the ellipses for different groups (Wong, 1999). In cases where the statistical units are small, or, in other words, the data quality is high, S can potentially be a great indicator of segregation as the ellipses cover smaller scales and may capture clustering patterns better than adjusted dissimilarity indices.

Beyond the aspatial-spatial and global-local dichotomies, three types of segregation measures can be discerned; one-group, two-group and multigroup indices (Apparicio et al., 2014; Cortes et al., 2020; Wong, 2003). One-group indices take into account only the selected group and the total population for the statistical units, resulting in an intra-group analysis of the different dimensions without comparison (Apparicio et al., 2014; Wong, 2003). Even though it is important to know the internal distribution and situation of the groups, the characteristics of the city can vary the results depending on the population density of each area and the physical geography of the site. Thus, two-group indices, such as the well-discussed D, put a specific group against another, giving as a result a better understanding of their circumstances as the value will not reflect the "segregation" of a group in the global of the study area but in comparison to a second. Most studies have used this type of indices to compare the local or majority population to the minority or migrant populations (Charles, 2003; Wong & Shaw, 2011), although it is presumed in this study that comparing minority groups containing similar population counts can deliver meaningful insights regarding residential segregation patterns. Lastly, multi-group indices can be seen as the measure of segregation level across the whole study area being useful to compare cities (global multi-group indices) or the local diversity for each track (local multi-group indices) (Apparicio et al., 2014; Reardon & Firebaugh, 2002).

Despite evenness being the most important and studied dimension (Feitosa et al., 2007; Massey & Denton, 1988), collecting information on other spheres is critical for understanding the processes going on. As three dimensions were formulated as spatial, the indices of absolute concentration, centralisation and clustering (ACO, ACE and ACL, respectively) for intra-group measures, and the relative ones for two groups (RCO, RCE and RCL, respectively) are great to characterise the residential segregation (Duncan & Duncan, 1955; Massey & Denton, 1988; White, 1983). In terms of exposure and isolation, the aspatial measures of Isolation index (xPx) and Exposure index (xPy) used to be the traditional indices for intra-group interaction between two different groups (Bell, 1954; Massey & Denton, 1988). The aspatial characteristics of their formulations have led to new distance-based calculations to measure inter-group or intra-group exposure or interaction, Distance-decay isolation (DPxx) and Distance-decay exposure (DPxy) (Morgan, 1983).

Given the positive evolution in geographical terms of how segregation is assessed, the real question lies in actually using these spatial measures and being able to map and visualise the phenomena beyond merely obtaining and analysing segregation values. Although local indices can be visualised and have not been used widely, the interdisciplinary focus of this research will likely help fill the visual aspect gap and support the statistical results from the spatial measurements.

1.3. Landscape metrics

Landscape metrics are a methodology that originated in the ecology field, more concisely, landscape ecology. Although human geography and demography scholars and studies have not typically been related to landscape ecology, the multidisciplinary essence of these domains and, more specifically, the versatility of the methods provide an incentive to benefit from the exchange of knowledge between fields (Paudel & Yuan, 2012). In Berlin, a ruderal ecology human-plant analysis proved the relationship between ecologic changes and their impact on the urban landscape, involving social exclusion and displacements (Stoetzer, 2018). Landscape ecology analyses living species in the form of patches; this means using aggregations of landscapes instead of species, which is what ecology usually does (Crews & Peralvo, 2008). All this leaves a unit with a concrete distribution and specific balance, or homogeneity based on those species' pattern, distribution and density, providing an open concept where the patches can be of different shapes and sizes (Crews & Peralvo, 2008). The perspective of interdisciplinary exchange and suggested connections and flexibility of the patch analysis to accommodate demographic variables is one of the initial premises of this study.

Patches consist of two parts, the core, referring to the central area that is protected from the interaction with neighbouring patches and the edges, which are the ones surrounding the core and have a higher interaction with the contiguous patches (Crews & Peralvo, 2008). This context brings back the MAUP (*Figure 2*), as the adjacent edges can be significantly more similar to each other than the cores of those same patches. As stated with the aspatial methods of segregation, despite being susceptible to this problem, a neighbourhood analysis or the moving window analysis method (*Figure 4*) can help to diminish its effect on the results (Buyantuyev & Wu, 2007; Uuemaa et al., 2009; Wu et al., 2006; Zawadzka et al., 2021). Moving window consists of a neighbourhood analysis performed on each cell considering the neighbours at a selected distance. In *Figure 4* the window moves to the right and collects the information for A and B, respectively, through the chosen distance, allowing to understand how the method moves on covering the study area.

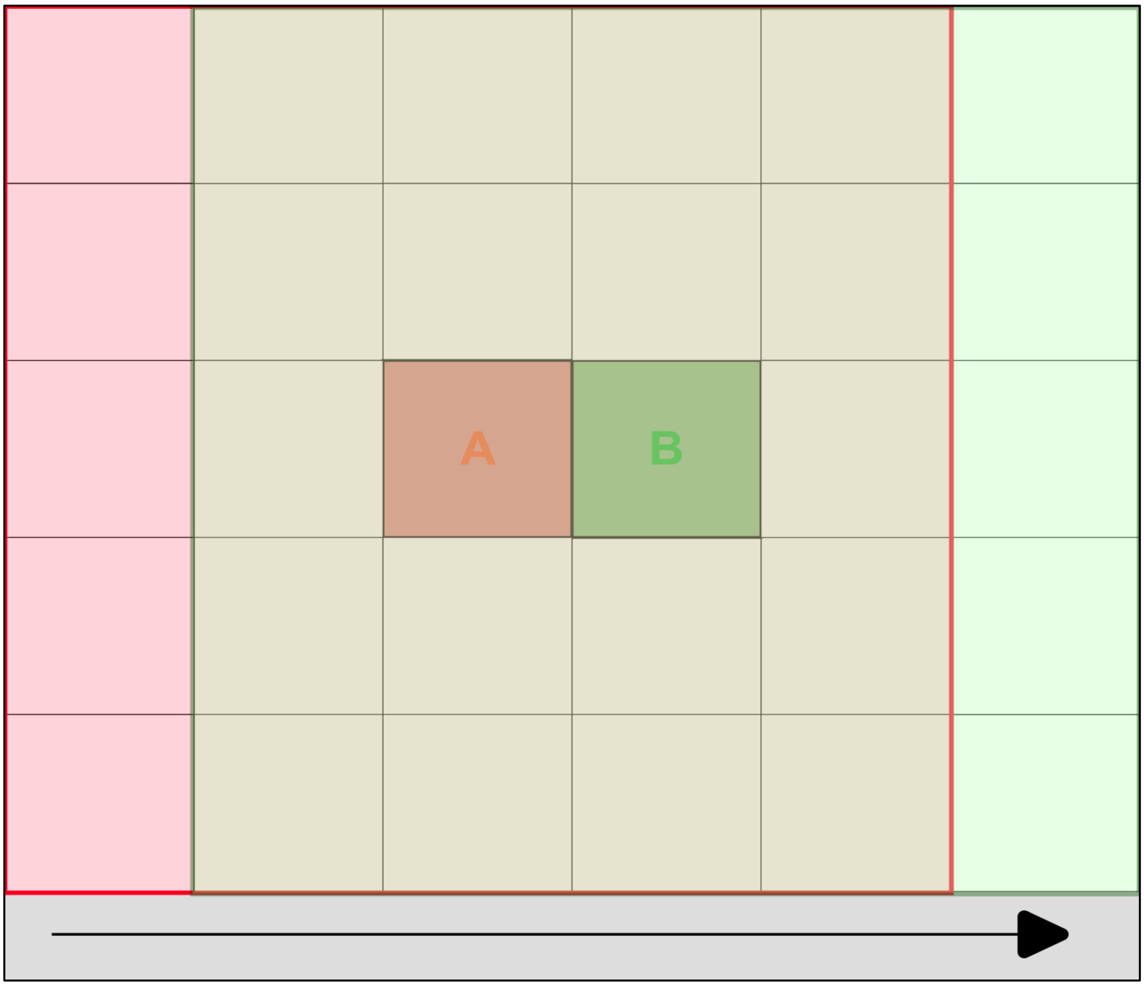

Figure 4. *Moving window method example with 5x5 cell analysis.*

At the same time, the spatial analysis comes together with the dilemma of what should be considered adjacent. In *Figure 5*, the two neighbourhood models in which landscape metrics can be measured are described. Moreover, the landscape metrics are particularly sensitive to the method adopted to classify the data, as the results will vary significantly depending on the number of classes and the underlying statistical criteria for the categorisation. This has to be done prior to the patch analysis, as it requires categorical or qualitative data (Buyantuyev & Wu, 2007; McGarigal & Marks, 1995). All this means that the classes must be chosen appropriately, as the conclusions may depend on it just as much as on the quality of the aggregated data. As the spatial distribution of a segregated ethnic group might differ along the geographical extent of the segregated statistical unit, all these geographical measures are necessary to shift the research focus to the spatial aspect of the segregation relying more on the interaction of units than on the mere location where each value was assigned by default during the data aggregation process or survey (Cortes et al., 2020). Using the spatial distribution of the origin country groups and landscape metrics based on their normalised populations will help characterise the segregation issues in Berlin.

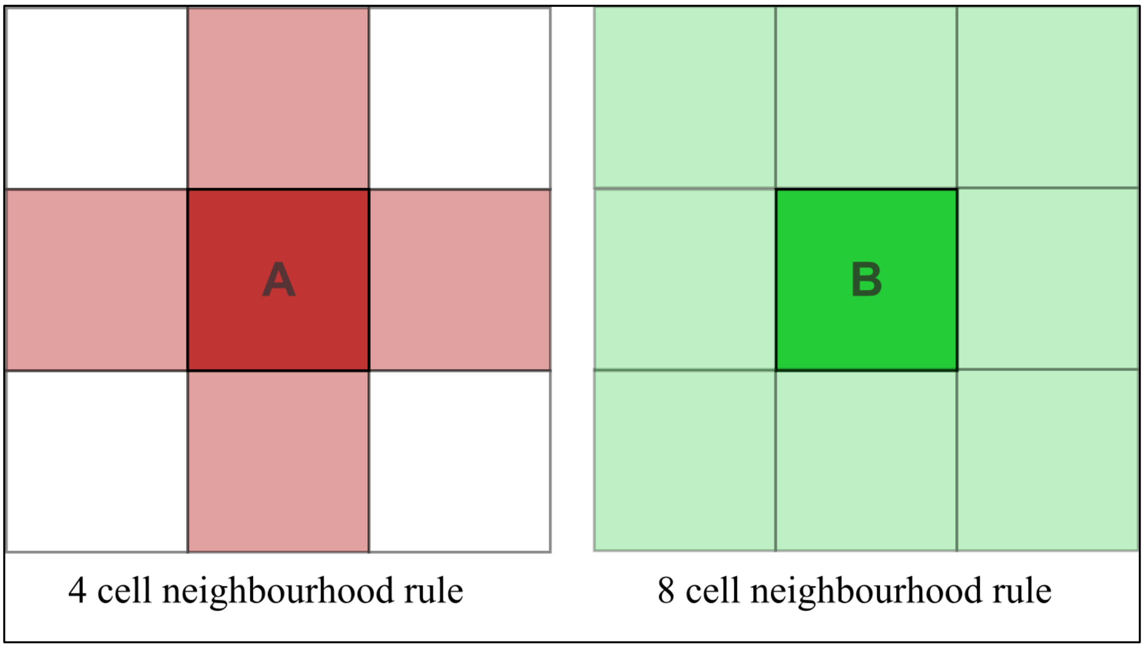

Figure 5. *Adjacency or neighbourhood analysis methods.*

In the same way as segregation dimensions are grouped in different ways by researchers, landscape metrics are also susceptible to being grouped in several forms. For example, based on the software used, these can be divided into: area-edge (1), shape (2), core-area (3), contrast (4), aggregation (5) and diversity (6) (McGarigal, 2015; McGarigal & Marks, 1995), or area (1), patch density and size (2), edge (3), shape (4), diversity and interspersion (5) and core area (6) (Paudel & Yuan, 2012). Still, these can also be grouped based on what they measure as; area size/density (1), edge length/density (2), shape complexity (3), connectivity (4) and diversity (5) (Crews & Peralvo, 2008). Aware of this research's scope and the data's characteristics, connectivity and diversity will be the most relevant spheres to analyse residential segregation.

1.4. Demographic & urban foundations of contemporary Berlin

Berlin, the capital city of Germany, has been one of the leading destination points for migrants coming from a wide range of countries and social environments (Kemper, 1998). The turbulent contemporary historical context of the city, separated into two areas by a physical and ideological wall for decades, shaped the actual openness of Berlin and the multicultural atmosphere that has risen inside of it (Stoetzer, 2018).

However, the newly built open society after the fall of the Soviet Union has also had its ups and downs in terms of accepting the migrant population. As a consequence of the policies that followed the migration crisis in the Middle East, and new conflicts and problems with the rising housing and rent prices, migration remains a current topic of public debate with a shift towards a more apprehensive view for minorities (Hamann & Türkmen, 2020; Stoetzer, 2018).

Berlin is intriguing for measuring residential segregation due to its historical variations and particularities. As introduced in the previous part, the city being divided for decades after World War II largely impacted the shape and urban dynamics. West Berlin, controlled by the capitalist block, was physically separated from the rest of the country, which meant being dependent on aid from the government of the Federal Republic of Germany (FDR). In contrast, East Berlin was connected to the rest of the communist block and the German Democratic Republic (GDR), being one of the main destinations for migrants from the rest of the country (Kemper, 1998; Urban, 2018).

Although both parts were split in 1949, the period of most significant contrast between them began in 1961, with the creation of the Berlin Wall and the physical partition of the city (Kemper, 1998). Even though large housing estates are usually characteristic in socialist countries, both West and East Berlin constructed this type of residential building. However, the critical voices that emerged around those urban developments were not equally treated on both sides of the city. In the western part, the construction of large housing estates stopped with the critics, whereas the East continued its policies (Urban, 2018). All this has caused people in West Berlin to have a neutral opinion about the housing estates, whereas the inhabitants of East Berlin automatically think about the socialist times and all that it entails, from negative ideas such as forced collectivism to some positive aspects like lower rent prices and little inequality. Some other main differences can be found in tenure, with East Berlin having a more considerable percentage of ownership than West Berlin, controlled by the market economy and processes and not by the state (Kemper, 1998; Urban, 2018).

This historical separation of Berlin and the differences in terms of residential location and ideologies caused a clear distinction regarding the minorities living on both sides of the wall. In general, the West received more immigrants than the East, where the immigrants were primarily people married to Germans or workers from other socialist countries such as Vietnam or Cuba (Kemper, 1998). Those countries being far from Berlin might have been one of the key issues explaining the difference with the West, which had a relevant flux of immigrants from Mediterranean countries, especially Turkey. Still, segregation had some similarities, most notably during the first years until the housing offer and demand stabilised in the West. In this sense, both immigrants coming from Turkey to the Federal Republic of Germany or FRG (West Berlin) and those coming from socialist countries to the German Democratic Republic or GDR (East Berlin) were hosted in similar housing options near their workplaces, with high levels of concentration (Kemper, 1998). Segregation keeps existing in the city, up to the point that the far-right discourses, racism and xenophobia are currently a major challenge for society as the stereotypes over segregated neighbourhoods spread based on the untrue (Hamann & Türkmen, 2020).

2. Data & Methods

2.1. Study area

Berlin is the capital city of Germany, located in the northeastern part of the country. With over 3 million inhabitants, this large city hosts a great diversity of population origins and is divided into twelve boroughs or districts. These can be observed in the location map of Berlin (*Figure 6*), where these are displayed together with the layout of the Berlin Wall in 1989 and the location of Alexanderplatz, which has been considered the centre of the city (Arandjelovic, 2014).

The wall is still nowadays a relevant landmark that, despite no longer representing a physical obstacle, has influenced the geography of the city in terms of district borders, as illustrated by the map. Since the reunification and the end of the USSR brought the disappearance of the so-called Iron Curtain and Berlin Wall, the interest in analysing how other socio-demographic variables, such as ethnic minority presence on each side, have been affected is of special interest.

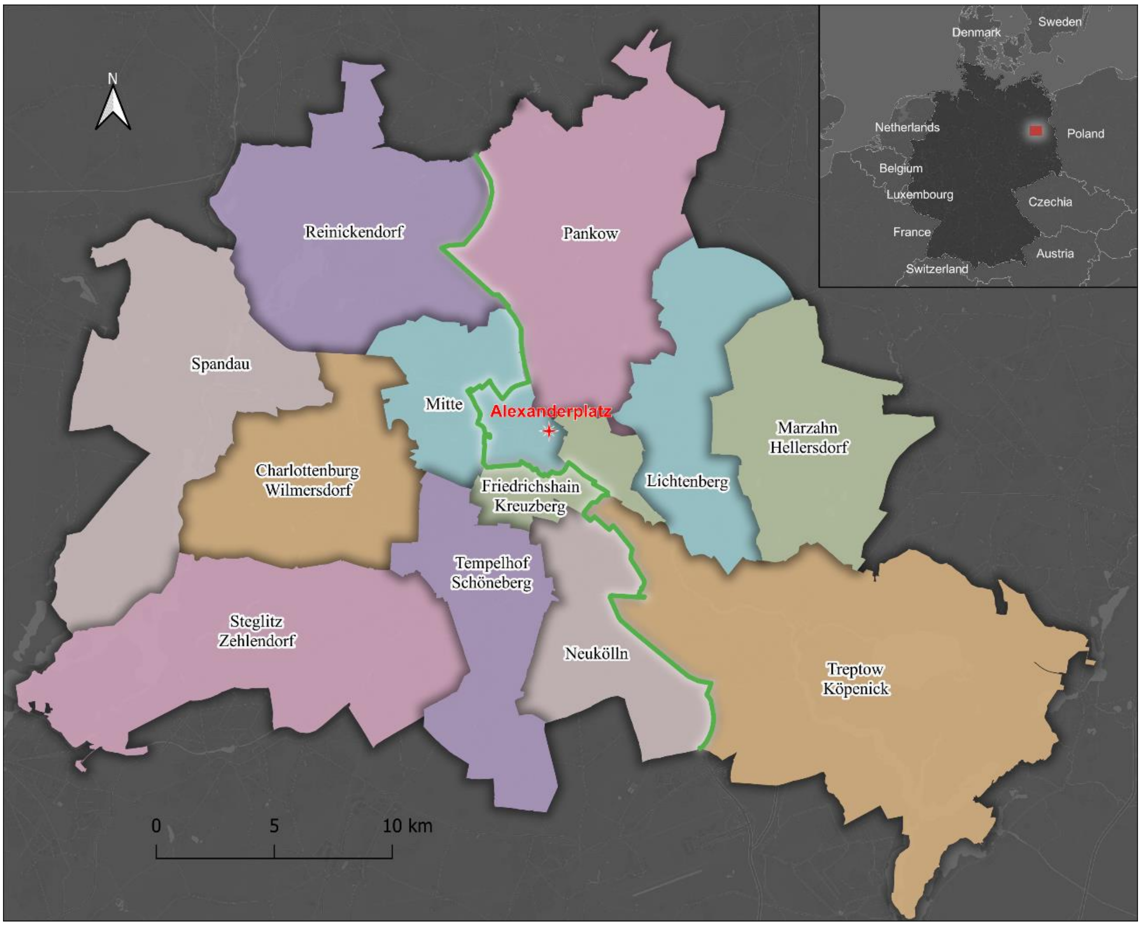

Figure 6. *Location map of the study area and factors of analysis.*

2.2. Data

The results of this study have been obtained using a main dataset 1) *high-resolution map of migrants in the EU* (Alessandrini et al., 2017). This core layer consists of a vector dataset with disaggregated population counts by country of birth and/or citizenship built based on census data 2011. The population counts were obtained from the national statistical institutes of the EU country members to be later harmonised and disaggregated by the JRC science hub of the European Commission. For the latest, land cover from Corine and the European Settlement Map were used due to the different geometry types and resolutions of each country. The meaning of population counts differs across countries; for instance, in France, it is based on citizenship; in the UK, it is based on birth; in Germany, it is based on citizenship and country of birth. The chosen terms for this study are “origin group” and “minority/majority group”. The disaggregation process was done via dasymetric mapping, which aims a redistribution of the population counts from census tracts to equal area grids of high resolution (100m) using the building and land cover data to relocate the values where a higher density is expected. In countries where the data quality is higher than the harmonised final dataset, the population data was up-scaled, whereas low-quality ones were down-scaled to the 100m grids. As the German census data contained the exact resolution in origin, it was not up or down-scaled (Alessandrini et al., 2017).

Additional datasets were used as an analysis and visualisation factor: 2) *Berlin Wall* and 3) *Districts of Berlin city* (ESRI Deutschland, 2022; Geoportal.de, 2007). In addition, 4) the *World Countries* layer has been used for the labels and borders of the location map (*Figure 6*) (Natural Earth, 2022). Besides the downloaded data, 5) East and West sides of the *Berlin Wall* polygon vector layer has been manually digitised for the analysis, and all the maps in the study include *Dark Matter (no labels) retina* base map with adapted brightness levels (Carto, n.d.).

2.3. Methods

2.3.1. Pre-processing

In order to calculate the segregation measures and landscape metrics, some cleaning and processing of the data was done prior to the analysis. First, the total population and total minority population were calculated as new fields, and then the origins not covered by this study were removed from the dataset. At the same time, the centre was added as a field containing binary values, 1 for the cell in Alexanderplatz and 0 for the rest. Therefore, the columns for the following groups were kept Germans (DEU), Polish (POL), Turkish (TUR), Russian (RUS), Lebanese (LBN) and Kazakh (KAZ), presented in sample-size descending order.

After the data cleaning, the population percentages for each group and cell were calculated, and the average percentage was found. A total of six classes have been defined for each origin group; based on the average percentage, the dataset was separated into two: upper and lower classes. Equal count or quantiles method has been used for the classification of both layers using three classes on each, ending up with the three under-represented (Q_1, Q_2 and Q_3) and three over-represented categories (Q_4, Q_5 and Q_6) that as described in *Table 1* where the ranges of these classes can be found.

Table 1. *Classification breaks of the origin groups***.**

Classes	Poland	Turkey	Russia	Lebanon	Kazakhstan
No Data	0	0	0	0	0
Q1	≤3.11 %	≤1.64 %	≤0.87 %	≤0.57 %	≤0.56 %
Q2	≤4.10 %	≤2.96 %	≤1.25 %	≤1.01 %	≤1.07 %
Q3	≤5.07 %	≤5.03 %	≤1.92 %	≤1.76 %	≤1.72 %
Q4	≤6.02 %	≤6.76 %	≤2.53 %	≤2.43 %	≤2.27 %
Q5	≤7.45 %	≤10.49 %	≤3.41 %	≤3.32 %	≤3.17 %
Q6	≤100 %	≤100 %	≤100 %	≤16 %	≤17 %

At the same time, these classes shown in the table refer to those used for calculating landscape metrics, as the data had to be categorised prior to the analysis. Thus, the pre-processing consisted of rasterising each group field and reclassifying the defined classes.

In general, the adequacy of the data to the methods and tools used has been satisfactory; however, throughout the data analysis process, issues with spatial segregation measures such as $ID_{(S)}$, RCL and DP_{xy} were encountered due to the low population numbers of some groups and their absence in large areas of the city. As the formulation of the indexes consider the area and boundary length of the patches, the *K-means clustering* tool was used to cluster the 39.531 cells into 10.000, collecting the population sums using the cluster ID's. To confirm that there would not be any potential miscalculations due to resolution differences between the datasets, results were compared over the indices that could be calculated with both datasets, finding no significant change and consequently enabling its usage.

2.3.2. Residential segregation pattern analysis

The analysis using segregation measures has been done in two steps, 1) characterisation of the residential patterns and 2) global measures of segregation. Firstly, the population percentage of each group and the local measures described in *Table 2* have been used for the maps. The table includes global measures as well, presented with the dimension they belong to, range and brief description. These are included in the second part of the results containing all groups in matrix form that compares their values.

On the one hand, Location Quotient (LQ) and multi-group Entropy (H) have been used with two different normalisations, the total population (German origin included) and total minority population giving them the same manual class breaks and being mapped together in order to visualise the differences. H accounts for the general heterogeneity or homogeneity of each patch, as the mean percentage of Germans at the patch level is close to 90; four classes in diverging colours are shown, representing the origin diversity at the local level. Classes under 0.1 show a high homogeneity of Germans, and areas with higher entropy represent a mixed environment with at least another group in the area. However, this index can be more significant if the Germans are excluded, as some areas shown as diverse might host only one specific origin and be susceptible of being segregated. In the same way as LQ, it was considered necessary to observe the diversity among minority groups and the dominance in each location, excluding the noise coming from the majority group.

On the other hand, global measures use the total population as the normaliser for most of the calculations. However, this is not the case for distance-decay exposure (DP_{xy}), as the sample size gaps between groups, especially between Germans and the rest, made the results hard to read. To overcome this issue, results between minority groups have been calculated excluding the German origin, using the minority population as the total so that the values between these are more significant and of more straightforward interpretation.

The pre-processed datasets were used to compute the residential segregation measures, whereas Location Quotient and multigroup Entropy Index were directly saved to shapefile and mapped.

Table 2. *Spatial measures of segregation.*

	Index name	Code	Range	Normaliser	Dimension	Author	Description
One-group	**Spatial Segregation**	IS(s)	[0.1]	Total	Evenness Clustering	(Wong, 1993)	Intra-group measure using local proportion compared to the general proportion. 0 = Perfectly even / 1 = Perfectly uneven
	Absolute concentration	ACO	[0.1]	Total	Concentration	(Massey & Denton, 1988)	Intra-group measure using the inhabited area compared to smallest and largest areal units. 0 = Deconcentrated / 1 = Concentrated
	Absolute clustering	ACL	[0.1]	Total	Evenness Clustering	(Massey & Denton, 1988)	Intra-group measure using a contiguity matrix. 0 = Not clustered / 1 = Clustered
	Absolute centralisation	ACE	[0.1]	Total	Centralisation	(Massey & Denton, 1988)	Intra-group measure using distance to the defined centre. 0 = Decentralised / 1 = Centralised
	Distance-decay isolation	DPxx	[0.1]	Total	Isolation Exposure	(Morgan, 1983)	Intra-group measure for the probability of interaction using distance. 0 = Isolated / 1 = Not isolated
Two-group	**Spatial Dissimilarity**	ID(s)	[0.1]	Total	Evenness Clustering	(Wong, 1993)	The inter-group version of IS(s). 0 = Perfectly even / 1 = Perfectly uneven
	Deviational ellipse	S	[0.1]	Total	Evenness Clustering	(Wong, 1999)	Inter-group measure using the proportion of overlap between the groups' standard deviation ellipses. 0 = No segregation / 1 = Perfect segregation
	Relative concentration	RCO	[-1.1]	Total	Concentration	(Massey & Denton, 1988)	The inter-group version of ACO. -1 = B concentrated / 0 = Equally concentrated / 1 = A concentrated
	Relative clustering	RCL	[-∞.∞]	Total	Evenness Clustering	(White, 1983)	The inter-group version of ACL. (-) = B clustered / 0 = Equally clustered / (+) = A clustered
	Relative centralisation	RCE	[-1.1]	Total	Centralisation	(Massey & Denton, 1988)	The inter-group version of ACE. -1 = Decentralised / 0 = Even distribution / 1 = Centralised
	Distance-decay exposure	DPxy	[0.1]	Minority	Isolation Exposure	(Morgan, 1983)	Inter-group measure for exposure using the distance between group members. 0 = Isolated / 1 = Exposed
Local	**Location quotient**	LQ	[0.∞]	Total & Minority		(Isard, 1966)	Inter-group local measure using the local proportion compared to the global one. < 1 = Underrepresented / 1 = Equally represented / > 1 = Overrepresented
	Entropy (diversity)	H	[0.1]	Total & Minority		(Theil & Finizza, 1971)	A multigroup measure of diversity at the local level. 0 = No diversity / 1 = Maximum diversity

2.3.3. East-West analysis

For the analysis on the wall sides, the Berlin Wall dataset was used as a snapping layer to digitise a new shapefile with two polygon objects for East and West Berlin. The pre-processed dataset with population counts was cut by the new layer using *intersection* tool, splitting the patches that were on both sides of the wall. The population counts have been estimated for the divided patches using the area on each of the new polygons (*Figure 7*).

In order to get the data for each side, *statistics by category* has been used for each of the groups, using the wall-side field of the digitised dataset as the category. The process was done in *QGIS*, and the sum values were eventually gathered in *MS Excel* and presented on the results.

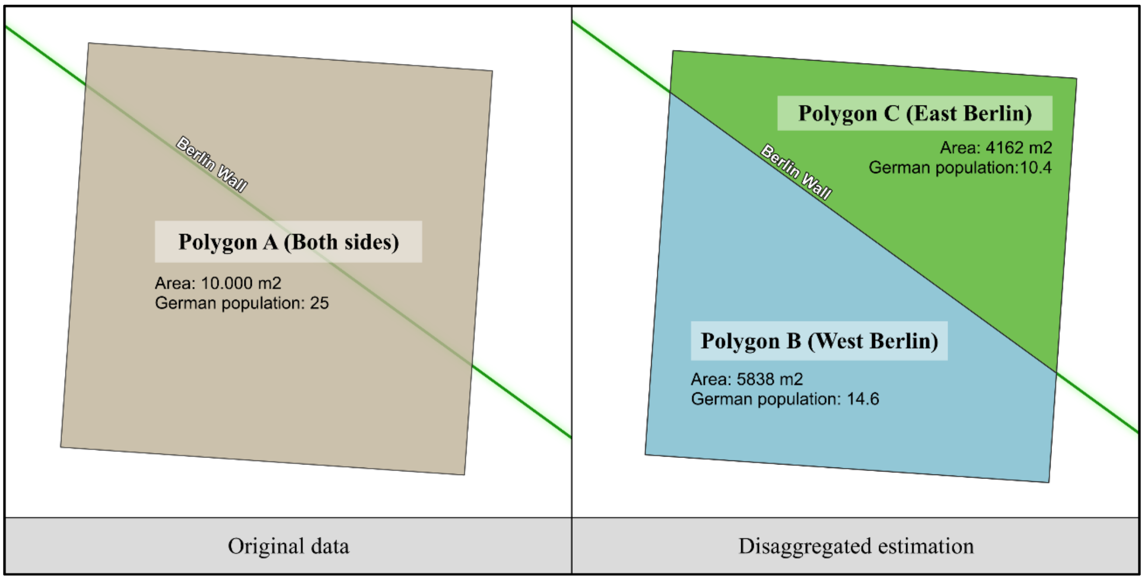

Figure 7. *Example of spatial disaggregation for East-West Berlin analysis.*

2.3.4. Landscape metrics

To characterise residential segregation using landscape metrics, the 100m resolution grid cells were taken as patches, and the percentage ranges functioned as classes for the metrics. Besides the calculation of class and landscape metrics for each population group, this research aimed to visualise the patterns, in contrast with the previous research that combined landscape ecology and demography (Crews & Peralvo, 2008). For this aim, a moving window analysis has been performed over the different rasters using the 8-cell neighbourhood rule and a round radius of 500m.

Filling the gap in terms of visualisation of the demographic situation of migrants in cities is one of the objectives of this study. Thus, the raster results of landscape metrics were vectorised and used to map the origin groups, putting these against the population proportion classes and generating bivariate maps to show the spatial patterns of segregation. These bivariate maps have been done using the PLADJ metric in a 3x3 bivariate legend, classifying the values into “low” (0 to 33.3), “moderate” (0.34 to 0.66) and “high” (0.67 to 1). For percentages of the population, the classification from *Table 1* is used, grouping the values as follows; “low” (Q1 to Q2),” moderate” (Q3 to Q4) and “high” (Q5 to Q6).

The landscape metrics used for this research are described and listed in *Table 3*. Due to the data characteristics and uncertainty about the significance of some available metrics for segregation analysis, these have been excluded. Instead, the ones with a clear interpretation and added value for the aim have been examined.

Table 3. *Computed class and landscape metrics. Source: McGarigal, 2015.*

Metric name	Code	Range	Unit	Description
Mean area	AREA_MN	[0.∞]	Hectares (ha)	The sum of the area of each patch type divided by the total number of patches of the same class
Mean proximity	PROX_MN	[0.∞]	None	The sum of the patch area divided by the edge-to-edge distance between the focal patch and same-class patches within the selected radius.
Mean Euclidean nearest neighbour distance	ENN_MN	[0.∞]	Meters (m)	Mean nearest distance between same class patches measured in meters.
Percentage of like-adjacencies	PLADJ	[0.100]	Percentage (%)	Number of adjacent patches of each class divided by the total number of patches multiplied by 100.
Connectance index	CONNECT	[0.100]	Percentage (%)	The number of connected patches of each class divided by the total number of possible connections and multiplied by 100

Landscape metrics have been designed for their application in ecology; hence their intended meaning in this work will be completely new. In this sense, the interpretation is described broadly as follows:

1. *Mean area* shows the spatial extent of a class, meaning that a higher area value in an overrepresented class, for instance, Q5-Q6, would potentially suggest segregation for the group, and a lower value that the group is more evenly distributed or less clustered. Nevertheless, the mean area metric should be considered only together with other landscape metrics.

2. *Mean proximity* can be understood as a measure of the general homogeneity or heterogeneity of the group. A lower proximity value will mean that the landscape is more fragmented, and thus, different classes will be exposed to each other. A lower value in highly populated classes will be a good sign, and the high proximity of higher classes will represent a segregation case.
3. *Mean Euclidean nearest neighbour distance* measures how close the same-class patches are from each other. Lower distance values would refer to a possible clustering of the group, and high distances can represent the isolation of the specific class or group in certain patches.
4. *Percentage of like-adjacencies* accounts for the similarity of the focal patches in terms of their neighbouring cells. A 0 value represents complete isolation of the patch; lower percentages show the diversity of classes, and values closer to 100 suggest homogeneous landscapes. In the over-represented areas for a group, a high adjacency level may be used to identify residential segregation.
5. *Connectance index* is an excellent metric to depict the group's spatial extent and classes. Lower values represent more isolated patches or unconnected from peers of the same class. In contrast, higher values reflect a bigger number of same-class patches being clustered or within the chosen radius.

In terms of software, landscape and class metrics have been calculated in *FRAGSTATS* (McGarigal et al., 2012) and segregation measures in *Geo-Segregation Analyzer* (Apparicio et al., 2013). The statistical analysis between East and West Berlin and table design has been done in *Excel* (Microsoft, n.d.). For the pre-processing, *R and R Studio* (R Core Team, 2022; RStudio Team, 2022), together with *ArcMap* (ESRI, 2017), have been used. Finally, the cartographic work and explanatory figures have been done in *QGIS* (QGIS Development Team, 2021).

3. Results

The city of Berlin is well-known for its diversity; however, if the country of birth or citizenship are the variables counted, the foreign population is not as large as one could initially think, as many members of each minority will potentially have German citizenship or be born in the country as second or third generation immigrants. Altogether, the total population estimated by the JRC Science Hub of the European Commission for the city of Berlin in 2011 was 3.184.442 inhabitants. From this, 2.673.062 form the German majority and the rest, 511.380, are minorities. Among these, the largest five minorities sum 274.233 people altogether (53.63% of all minority population), whereas other population groups not addressed by this study represent the missing 237.147 inhabitants. In *Figure 8*, these statistics are synthesised.

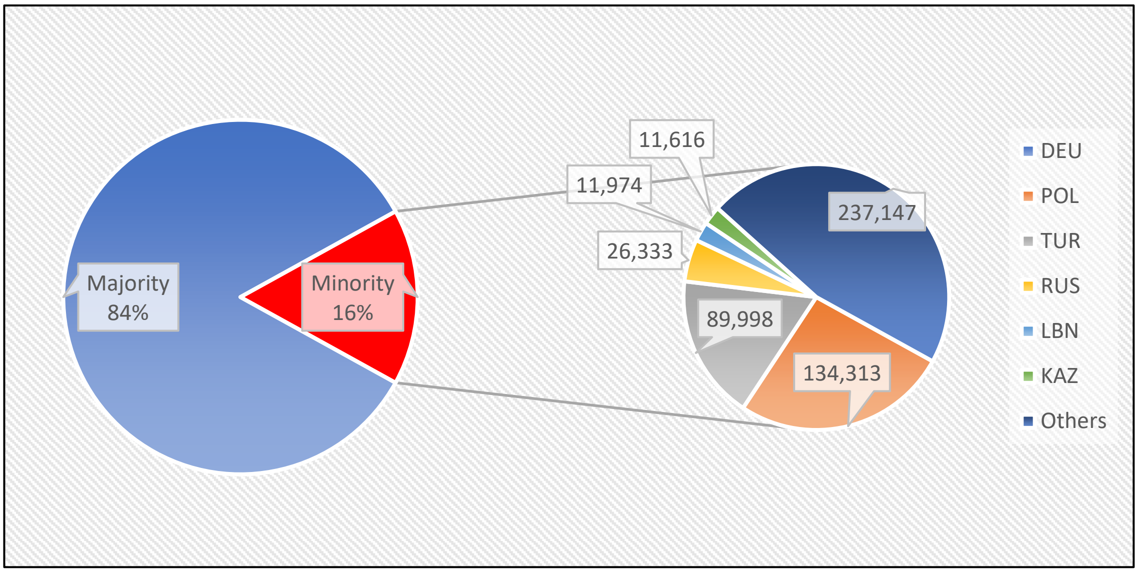

Figure 8. *Demographic landscape of Berlin.*

In terms of the East-West Berlin dynamics, 59.8% of the population lives in the West, while the other 40.2% resides in East Berlin. Based on this fact, several groups (Polish, Turkish, Lebanese and Kazakh) showed unbalanced patterns between East and West Berlin. Only Russians and Germans were relatively balanced.

Figure 9 compares the percentages of the population in East and West Berlin for the different groups. At first glance, it might give the impression of a higher representation of Germans in the West; however, the global numbers suggest that Germans are still slightly more represented in the East, as their proportion in West Berlin is lower than the total percentage of the population living in this area (58 and 59.8%, respectively).

Regarding the minority groups, we can differentiate four patterns. Russians have more population located in the west, yet under the threshold of 59.8%, meaning that they are relatively more represented in East Berlin. In contrast, the Polish minority has a higher presence in West Berlin but still hosts a significant population in the other half of the city. Conversely, Kazakh hosts a relevant percentage in West Berlin; however, the East is generally less populated (40.2%), and thus, the Kazakh minority is rather one-sided to East Berlin. Lastly, the two most one-sided patterns can be observed for Turkish and Lebanese minorities, which contain almost their entire population in West Berlin.

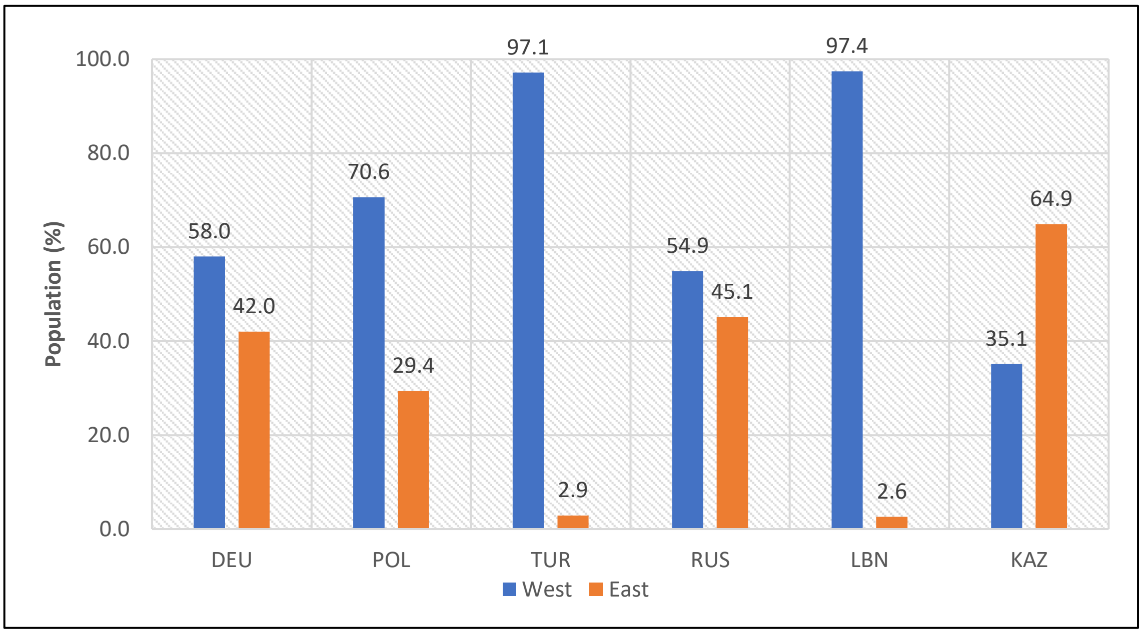

Figure 9. *Comparative population distribution between West and East Berlin.*

3.1. Residential pattern analysis

3.1.1. Spatial characterisation of the ethnic groups

To provide an introduction and spatial contextualisation of all groups, their distribution in Berlin by the percentage of the population in 2011 has been mapped. The German majority is hegemonic in most of the grid cells of Berlin, having an average percentage of 88.26% (*Figure 10*). However, this majority becomes particularly dominant in the outskirts of the city, most notably in East Berlin but also in Reinickendorf borough. Yet, the spatial distribution of the German majority population is somewhat mixed between both sides of the city, as mentioned earlier.

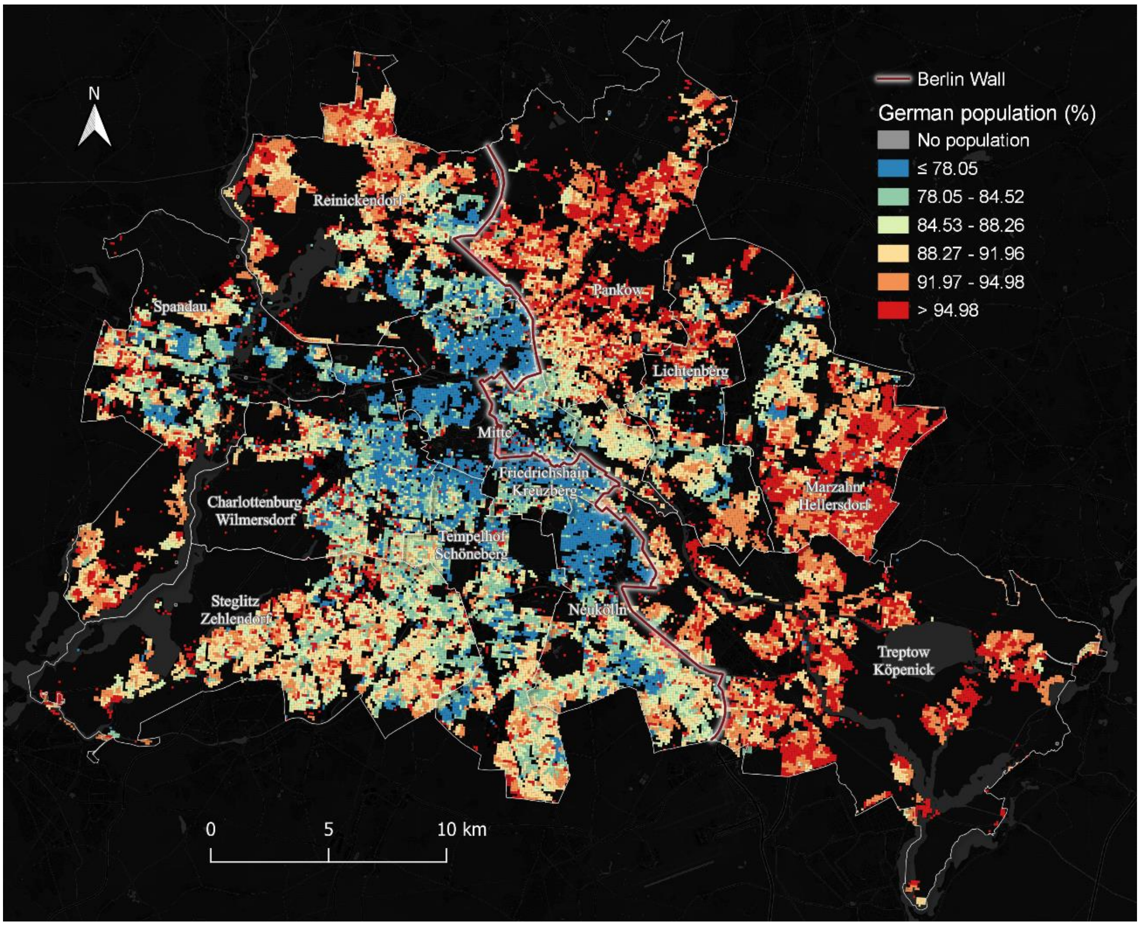

Figure 10. *Spatial distribution of German origin population in Berlin.*

The largest minority for the study period is Poland (*Figure 11*), with an average population of 5.07% and a relatively widespread population. As for their spatial distribution, the Polish population are more represented in West Berlin but with relatively low percentages in Kreuzberg (mostly <3.11%), where other minorities, predominantly the Turkish, have more presence. Despite having a less significant presence in East Berlin, some smaller clusters of high percentage (>7.45) can be observed, sign of a spatial mix with the Germans that are overrepresented in those areas as well.

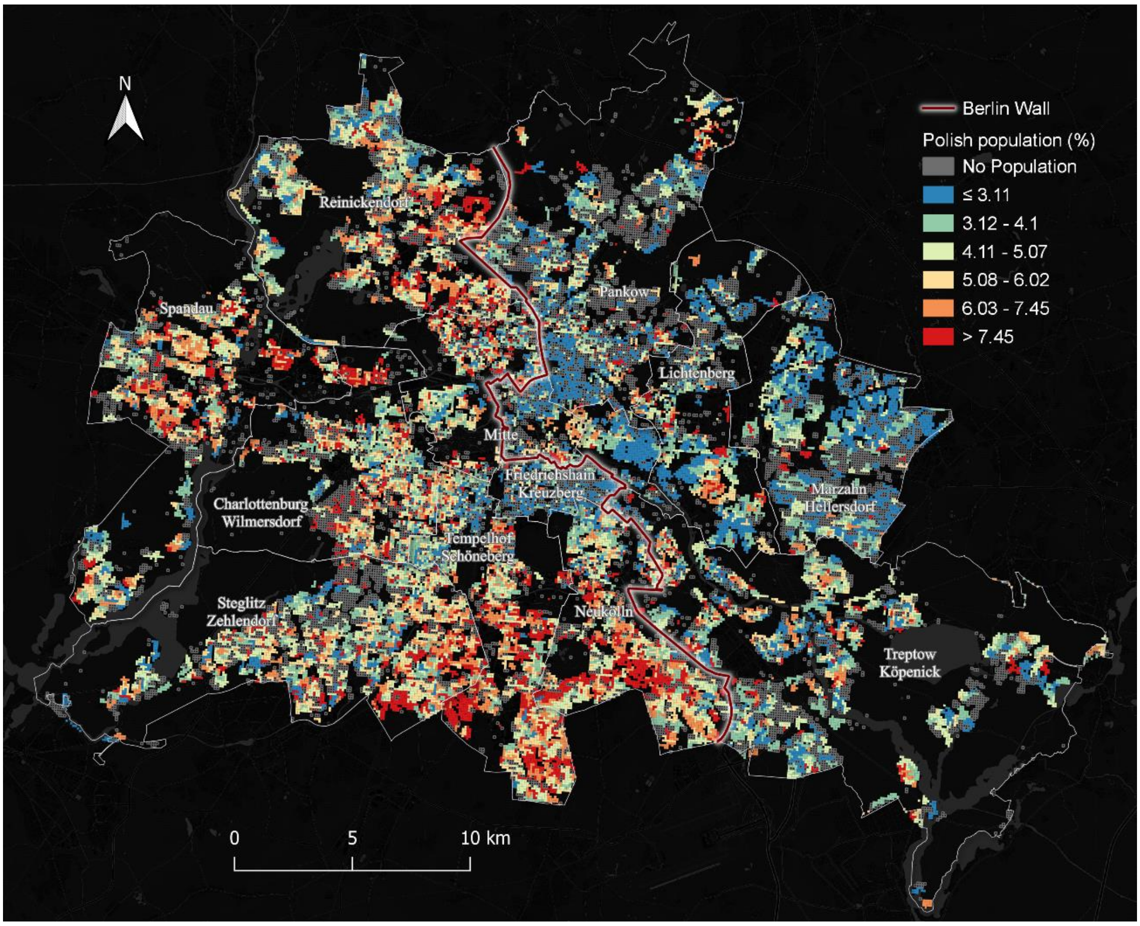

Figure 11. *Spatial distribution of Polish origin population in Berlin.*

Whilst the Polish settlements lie in the north of Pankow and most of Treptow-Köpenick, the third largest demographic group, the Turkish minority, has no representation in those areas (*Figure 12*). With a very similar population average per cell to the Polish minority (5.03%), the Turkish group has the most prominent contrast regarding the Berlin Wall. However, another pattern of great interest is its location, clearly centred in contrast to the German majority and the Polish minority, which had their higher values (>94.98 and >7.45%, respectively) in the outskirts of West Berlin.

In *Figure 12*, the contrast between the eastern and western parts of the Friedrichshain-Kreuzberg district is particularly remarkable about the role that the wall played in the recent history of the city and the people who inhabit it, but it is not the only case; also, Mitte shows similar values and patterns with areas over 10.5% in West Berlin and primarily up to 2.96% in East Berlin.

Even though the Turkish population is noticeable in the outer suburbs of Neukölln, Reinickendorf and Tempelhof-Schöneberg, the central areas hoard the highest percentages for the group (>6.77%). As secondary patterns, it can be observed that the grids with some representation located in East Berlin are rather contiguous, and almost all correspond to the lowest class under 1.64%.

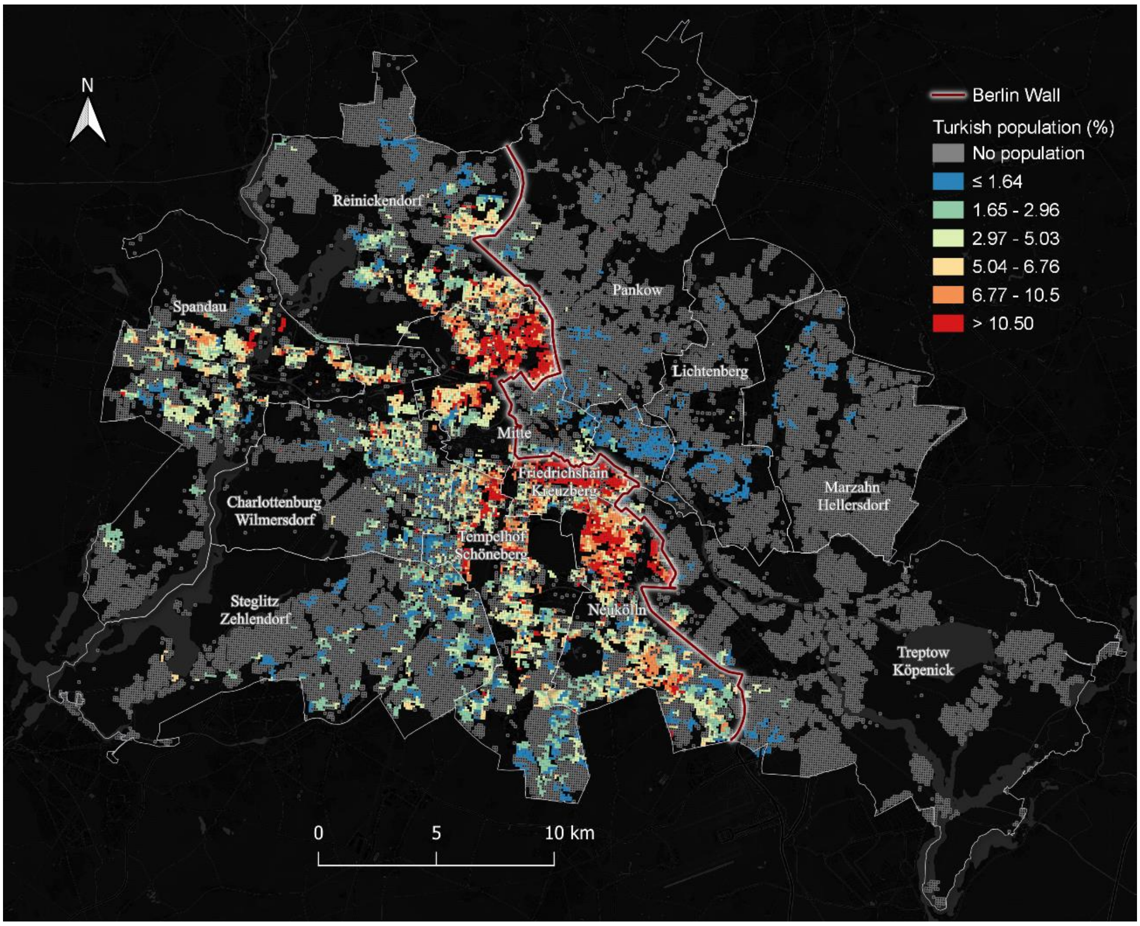

Figure 12. *Spatial distribution of Turkish origin population in Berlin.*

The third largest minority group is Russians, but the total and percentual population gap with Polish and Turkish is quite big, with an average of 1.92% (*Figure 13*). In addition to being a relatively smaller group in population size than the previous two, it also stands out for having a diffuse pattern in terms of the East-West Berlin separation without being entirely unbalanced for either of the sides.

Although outer suburbs contain more prominent clusters of high values (>3.42%), some central areas in Mitte stand out for the same reason and, opposite to Turkish, see no changes on both flanks of the wall. At a glance, less spatial continuity may be seen, with small clusters of similar percentages that are interrupted by cells of lower values, Lichtenberg being the perfect example of this dynamic. In short, the north of Marzahn-Hellersdorf, Spandau and the southern edge of Tempelhof-Schöneberg and finally, the aforementioned case of the central borough of Mitte are the main areas where the Russian minority is located.

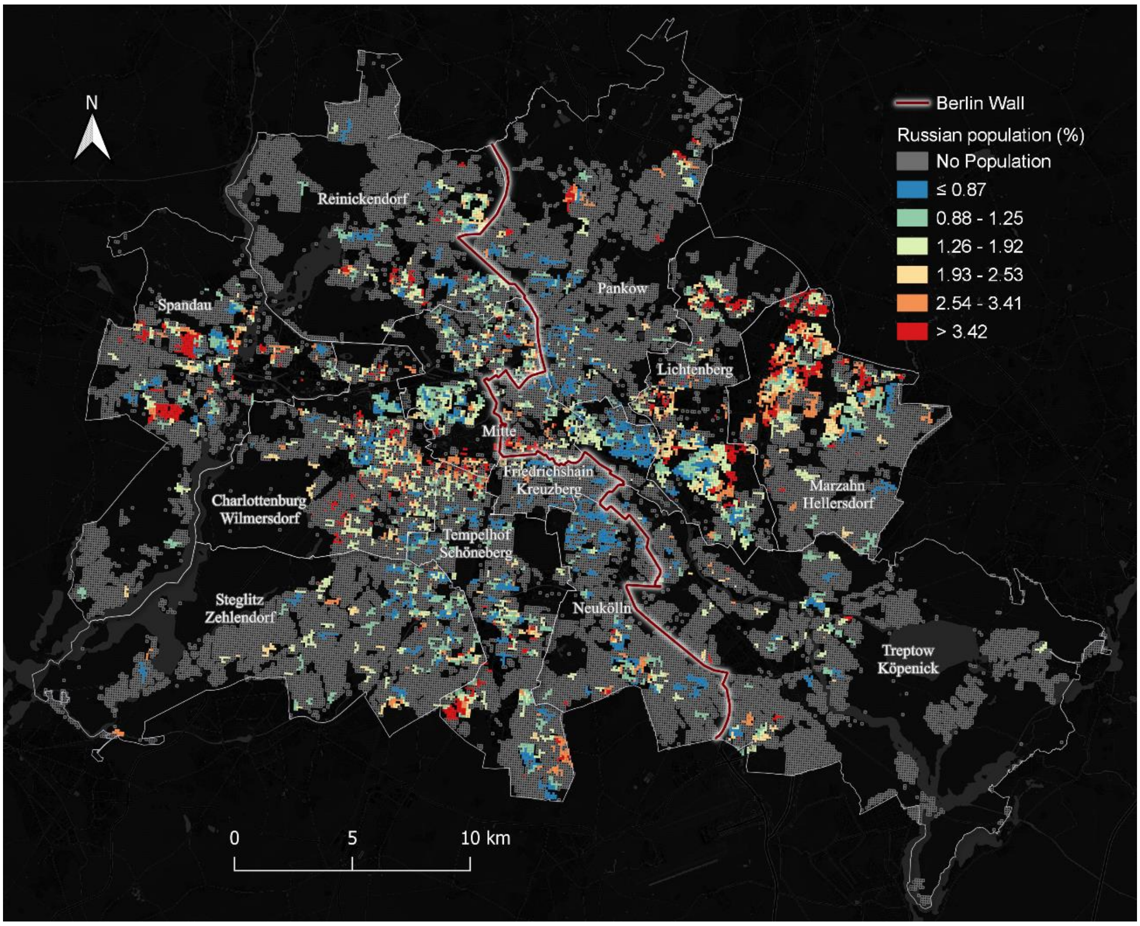

Figure 13. *Spatial distribution of Russian origin population in Berlin.*

The fourth minority group by size is Lebanese (*Figure 14*), with an average of 1.76% per cell. Although the population difference between Russian and Lebanese minorities is significant, the higher clustering that the Lebanese minority shares with the Turkish group makes their occupied space much narrower. Continuing with the similarities between Turkish and Lebanese, they both occupy mainly West Berlin areas, such as north Neukölln, Mitte and Kreuzberg. However, the situation for Lebanese in Kreuzberg is less clear, with a mix of low and high values, whereas in Mitte and Neukölln, these are mostly high (>1.77%).

Yet, there is a more pronounced difference between them, as the Lebanese minority has more empty cells and less representation both in the outskirts of the city and in East Berlin, where the Turkish population gets shallow values (<1.64% in *Figure 12*) but in a contiguous layout form, while the Lebanese population is almost non-existent.

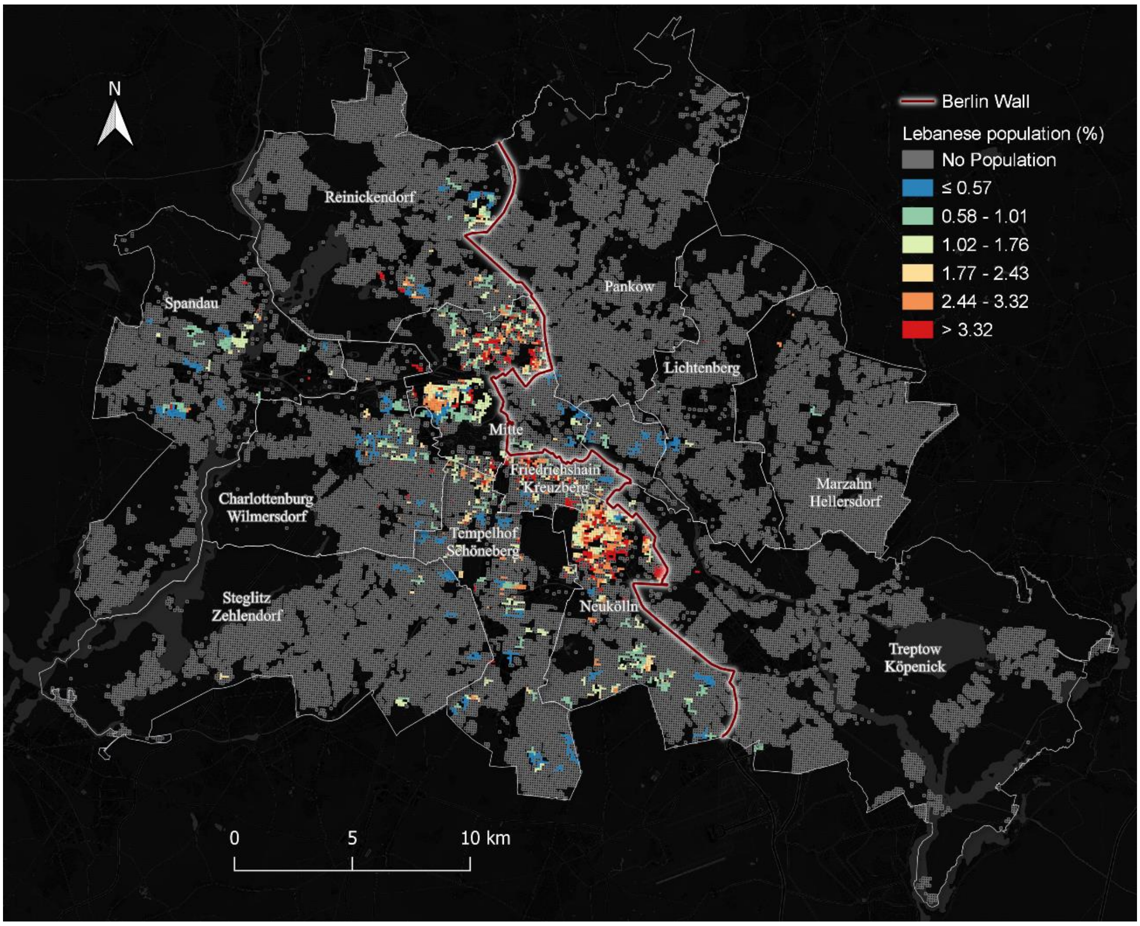

Figure 14. *Spatial distribution of Lebanese origin population in Berlin.*

Kazakh minority is the last and smallest group reviewed throughout this research, with 1.72% as their cell average. With a very similar population to the Lebanese minority, the Kazakh spatial distribution is the complete opposite, having negligible representation (<0.56%) in most areas of Mitte and Kreuzberg while getting their higher values (>3.17%) in the outskirts of the city, forming similar residential patterns to the Russian minority in the area. This is evident in the north of Marzahn-Hellersdorf, Lichtenberg and Spandau if we compare *Figure 13* with *Figure 15*. Their main clusters locate in Marzahn-Hellersdorf and Spandau for East and West Berlin, respectively, and they show some smaller representations between 0.57 and 2.27% in other outer areas on both sides of the wall. Still, the map in *Figure 15* suggests an East Berlin-leaning pattern.

In spite of the shared locations among both Russian-speaking countries, there are some differences. Besides the central district of Mitte, the main difference for the Kazakh population is their absence in Charlottenburg-Wilmersdorf, where Russians have a significant presence.

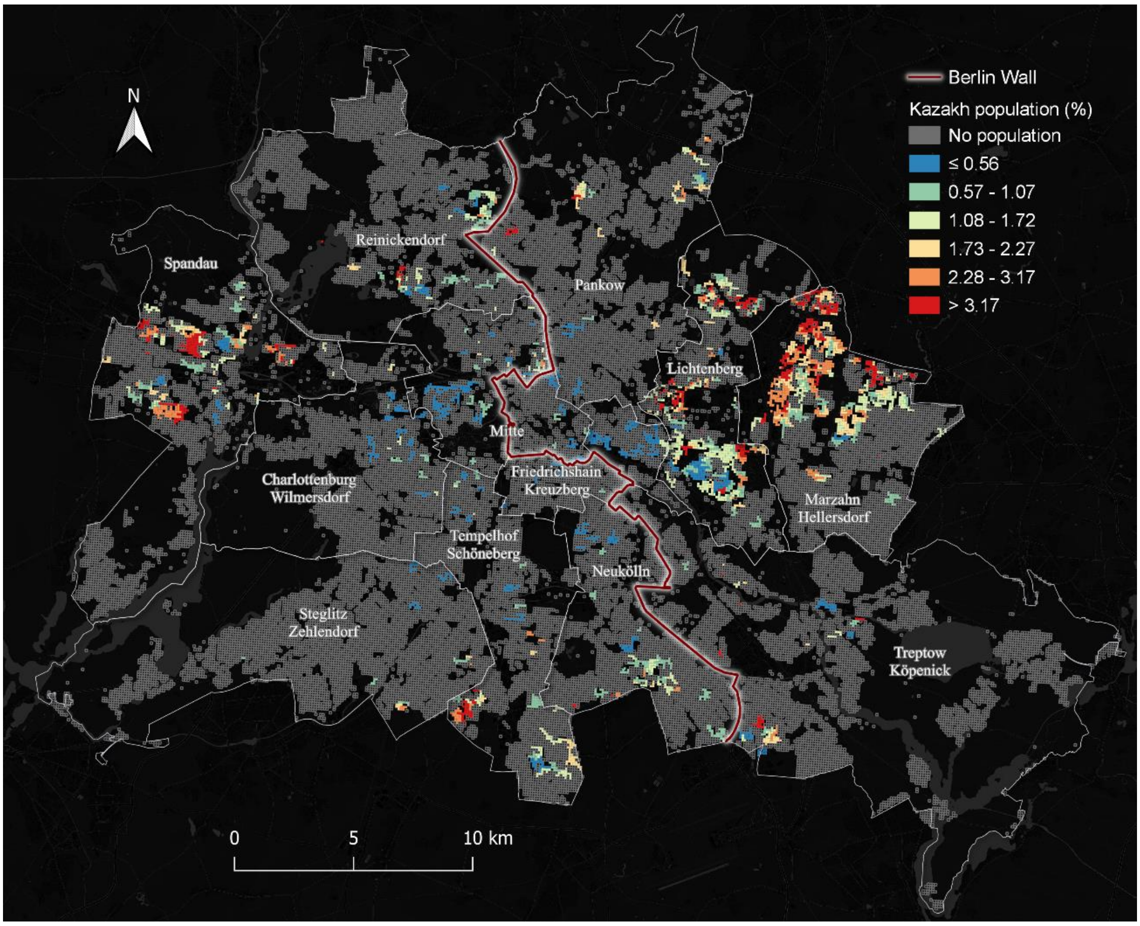

Figure 15. *Spatial distribution of Kazakh origin population in Berlin.*

3.1.2. Local measures

The local measures are an excellent tool for understanding the spatial patterns of the data. *Figure 16* reflects the general multigroup Entropy Index (H); due to the high representation of the German group in the whole study area (around 90%), this index does not necessarily imply higher or lower diversity or segregation in the higher value areas, but simply that other groups besides Germans can be found in that patch. On the other hand, low H values show homogeneous locations where Germans constitute roughly the entire population. The general portrait that can be obtained from this index is in line with the previous section, having a clear division west-east in the vicinity of the Berlin Wall and with those central areas on the western side as the highest entropy ones.

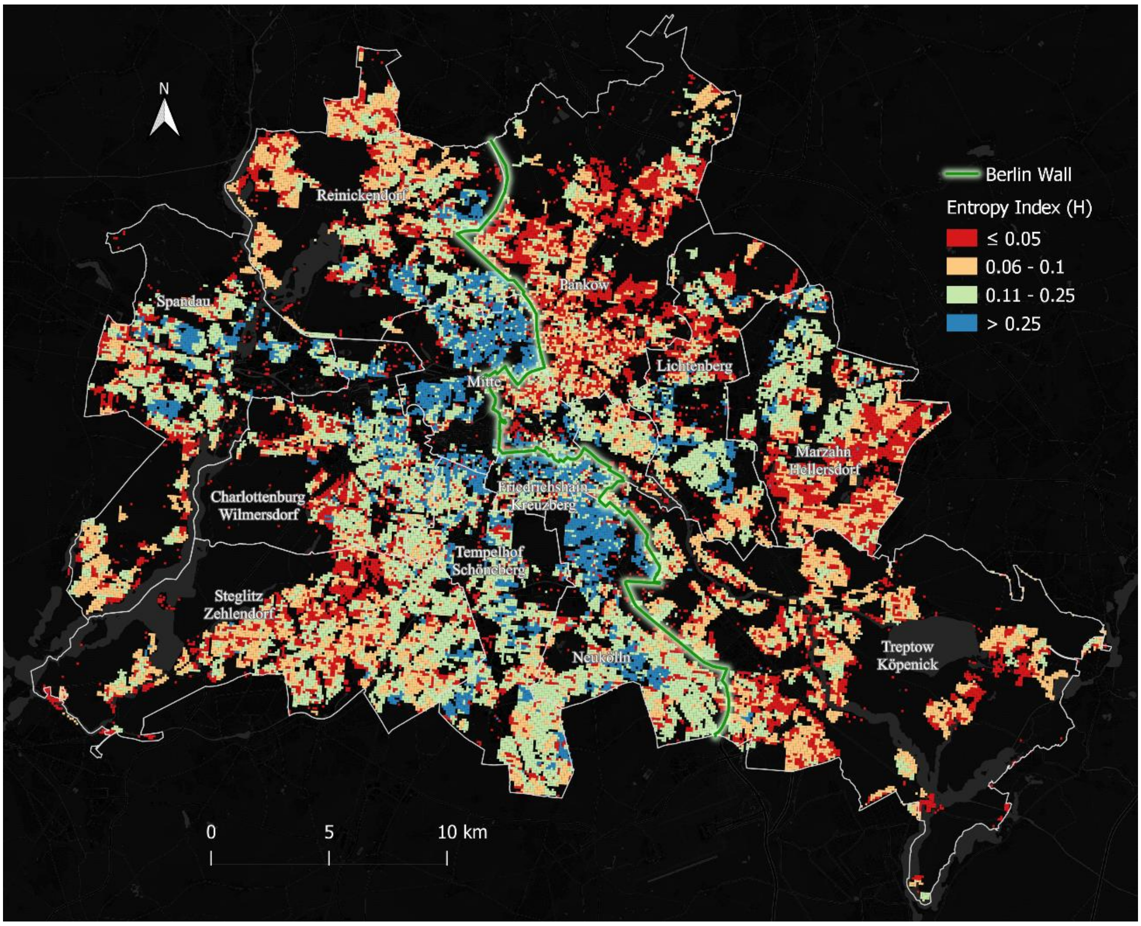

Figure 16. *Local multigroup Entropy Index (H) map including German origin.*

Besides Mitte, Friedrichshain-Kreuzberg and north Neukölln, some suburbs host significant minority populations, for example, Spandau. Still, the small values of minority origin population in most areas of Berlin require another approach excluding the majority population to explore the local heterogeneity in terms of minorities.

To better depict the group diversity in Berlin, German origin needs to be excluded. In *Figure 17*, Spandau, Mitte, Neukölln and north Marzahn-Hellersdorf show up as diversity clusters in a similar pattern to the general entropy map (*Figure 16*). However, the key insight is different, as the low entropy outskirts of the city are due to the Polish population being dominant and, thus, not as different from Germans as the rest. For instance, Steglitz-Zehlendorf, south of Spandau or the northwest limits of Reinickendorf, appear to be reserved or exclusive for Polish and Germans.

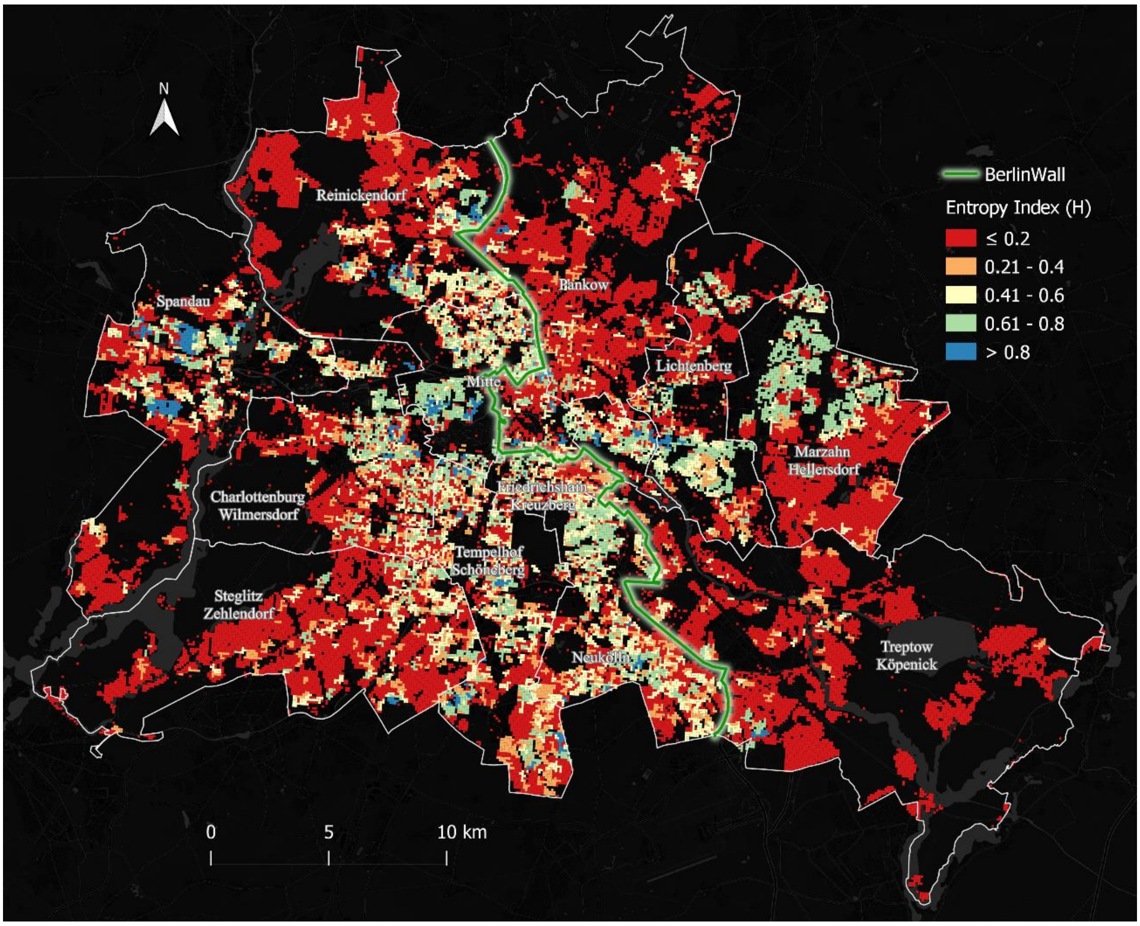

Figure 17. *Local multigroup Entropy Index (H) map on minority groups.*

Russians are commonly located in north Marzahn-Hellersdorf, where diversity varies from 0.4 to 0.8, and Turkish live primarily in central areas on the western side of the wall, north to south from Mitte to the north of Neukölln, with similar H values. Nevertheless, an exception to this pattern is located in Kreuzberg, where the Turkish majority seems to be highly segregated and hosts almost no other migrant origin despite being mixed in many other parts of Berlin, especially with the Lebanese minority population.

Figure 18 shows the Location Quotient for the Polish population. Same as with H, these maps are an excellent example of how the perspective of the spatial distribution can be vastly different in relation to what is being compared with. In terms of the total population, the Polish group appears under-represented in many areas located on the outskirts of the city; however, the same areas are where Polish are predominant compared to the rest of the minority groups. Good examples of this pattern are Treptow-Köpenick, Pankow and the north of Reinickendorf, where LQ gets values under 1 against the total population and over 3 when compared only to minority origins.

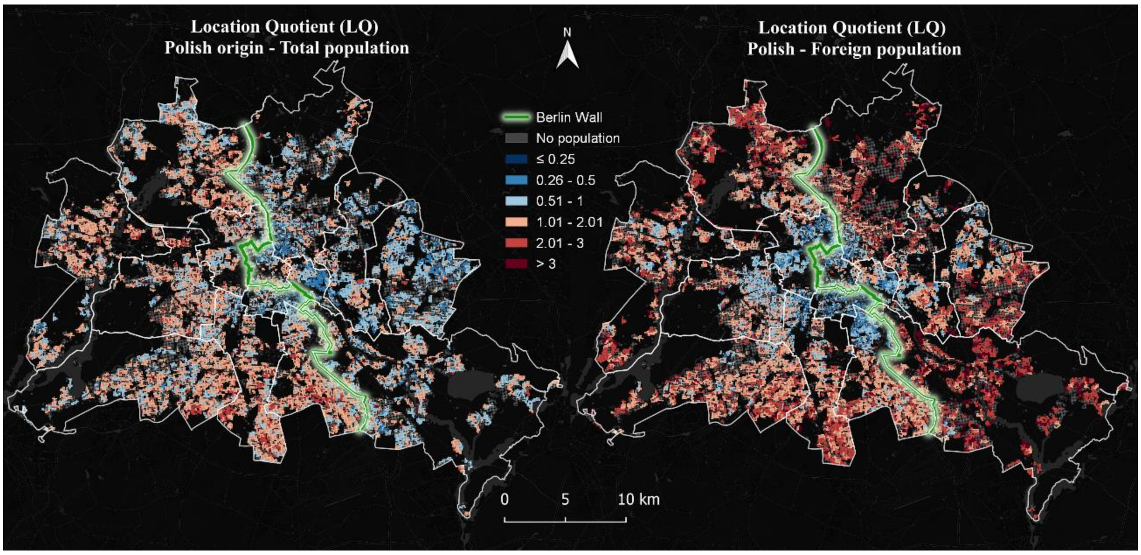

Figure 18. *Maps of Location Quotient (LQ) for Polish origin population.*

This can be explained by the fact that other groups, such as Turkish, are mainly located in the city centre of Berlin. *Figure 19* shows the same local measure for the Turkish population, observing much more minor changes due to the lower spread of the group over the study area. However, some extreme values emerge, which can be a symptom of residential segregation, especially in Kreuzberg. Nevertheless, while the Polish population gets values closer to 1 with the Germans included in the analysis, the Turkish group gets milder values in comparison to the minority population, suggesting a closer spatial distribution between Polish and Germans and between Turkish and migrant groups, respectively.

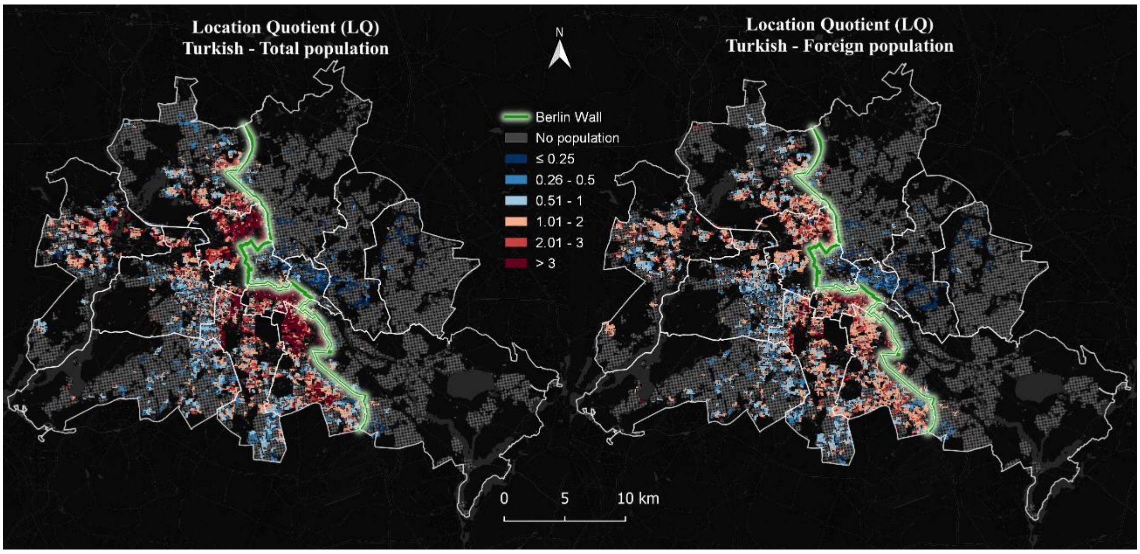

Figure 19. *Maps of Location Quotient (LQ) for Turkish origin population.*

In contrast to the LQ analysis for both Polish and Turkish groups, Russians show slight differences between both maps, having minor changes in values when compared with minority origins (*Figure 20*). This can be a sign of lower segregation as the Russians seem to coexist with both Germans and minorities in distant parts of the city. The most significant changes can be observed in the western part of Mitte, where Germans are not that hegemonic, and the heterogeneity is high, but also in Marzahn-Hellersdorf, where Germans host mid-high values while Turkish and Polish are almost non-existent.

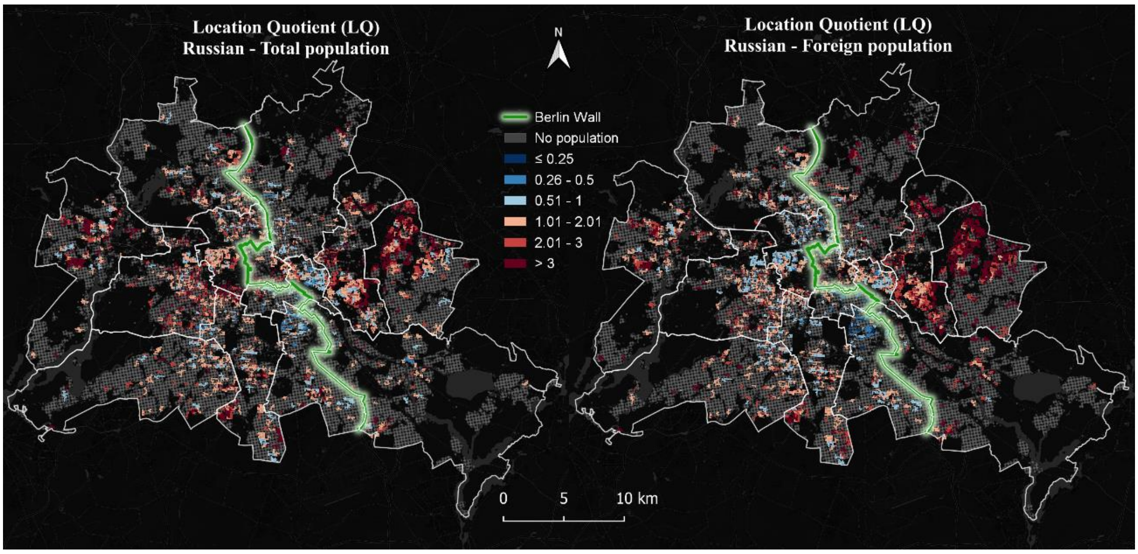

Figure 20. *Maps of Location Quotient (LQ) for Russian origin population.*

This perfectly matches the first impressions on the spatial distribution of Russians, with unclear patterns in terms of city division by the Berlin Wall, spread populations both in central and outer areas, and the additional insight of interacting with Germans to a certain extent in East Berlin.

Regarding the Lebanese group (*Figure 21*), the changes are very similar to Turkish, as their population is located in central areas; the contrast considering Germans is higher, and LQ decreases compared to minority groups.

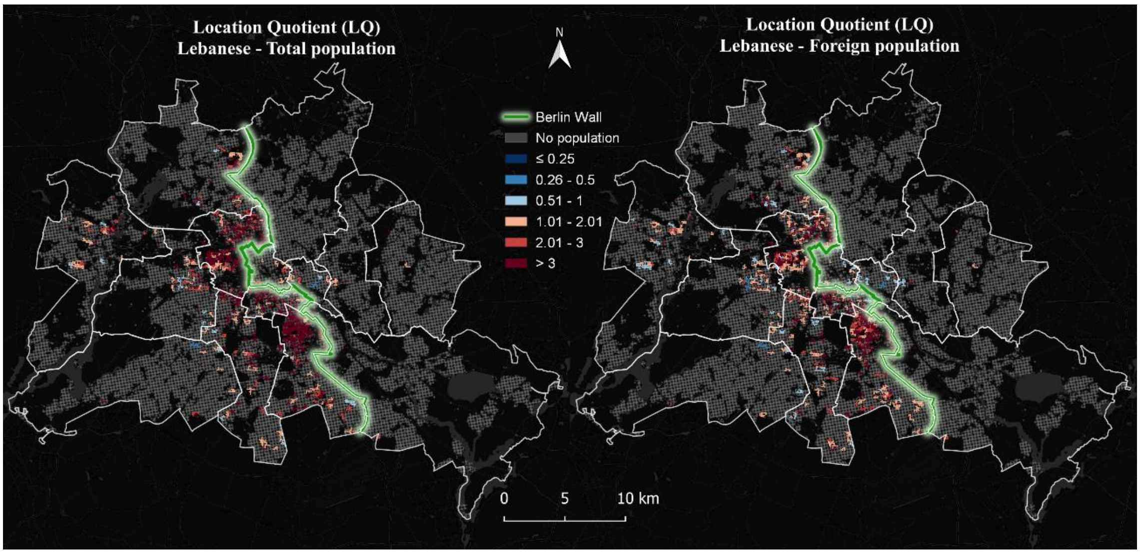

Figure 21. *Maps of Location Quotient (LQ) for Lebanese origin population.*

The Kazakh population is comparable to the Lebanese population in their subordinate status to the dominant Russian and Turkish populations, respectively. Both Kazakh and Russians share an overrepresentation in Lichtenberg, Marzahn-Hellersdorf and south Tempelhof-Schöneberg.

In *Figure 22*, the LQ can be observed for Kazakhs; despite minor changes, the perceived connection between Kazakhs and Russians is undoubtedly the most relevant pattern for the group. Both minorities are present in the western district of Spandau, characterised by having very different housing types. The central areas are where Russian and Kazakh minorities locate, and these show high-rise urban landscapes mixed with industrial hubs. In contrast, detached housing areas in the western limits are occupied mainly by Germans and Polish. However, proximity and cases of socio-economic growth can strengthen intergroup interaction lowering the negative aspects of segregation, such as social network issues and disadvantages to ascend economically.

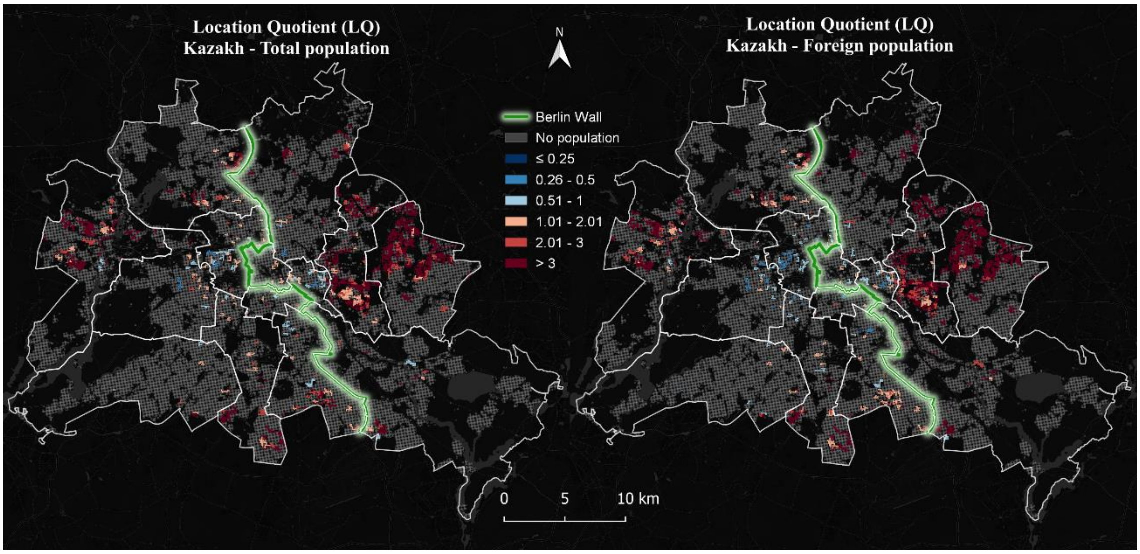

Figure 22. *Maps of Location Quotient (LQ) for Kazakh origin population.*

3.2. Global segregation measures

3.2.1. Intra-group measures

One-group measures are a good starting point for analysing the segregation patterns of the selected populations in an overall term. In this case, due to the disproportionate contribution of Germans to the total population in Berlin, the internal measures are a reasonably realistic reflection of their differences with German origin.

In *Table 4*, the results of segregation measures are displayed. The intra-group analysis suggests a lower evenness in the cases of Lebanese and Kazakh populations with an IS(s) over 0.74, although Turkish appears as the most clustered with an ACL of almost 0.1. On the other hand, Polish is the most evenly distributed group by far. Regarding centralisation, Lebanese and Turkish are ahead with ACE values over 0.5, whereas Polish, Russian and Kazakh populations are mainly in the outer areas. In terms of concentration, both Russians and Kazakh obtain the highest values, but the differences are rather slight. In terms of isolation-exposure, both Polish and Turkish appear to be less isolated; however, isolation measures are sensitive to the sample size, which explains the significant differences between these two groups and the rest. It is significant, though, that the probability of each Turkish-origin person finding their peers is higher than for Polish, despite having a lower total population in the city.

Table 4. *One-group residential segregation results.*

Name	IS(s)	ACO	ACL	ACE	DPxx
POL	0.22	0.51	0.03	0.21	0.04
TUR	0.57	0.50	0.10	0.54	0.05
RUS	0.50	0.56	0.02	0.24	0.01
LBN	0.74	0.51	0.02	0.62	0.01
KAZ	0.74	0.54	0.02	0.05	0.01

3.2.2. Inter-group measures

Two-group measures are a great option to compare the groups against each other and observe how they relate and oppose. On the basis of the notion that both evenness and clustering dimensions are connected and form an only spatial dimension, the measures for this are shown in *Table 5*. Going into detail, the spatial version of D seems to overestimate the unevenness of both Kazakh and Russians in their comparison to Germans. This can be interpreted by looking at the values of the deviational ellipse index that contemplates the interaction beyond adjacency, providing the halfway point between clustering and evenness.

Table 5. *Results of two-group spatial evenness-clustering dimension indicators.*

	Origin group	DEU	KAZ	LBN	POL	RUS	TUR
Spatial Dissimilarity Index D(s)	DEU		0.74	0.76	0.22	0.51	0.58
	KAZ	**0.74**		0.87	0.73	0.44	0.84
	LBN	**0.76**	0.87		0.72	0.74	0.43
	POL	**0.22**	0.73	0.72		0.48	0.53
	RUS	**0.51**	0.44	0.74	0.48		0.65
	TUR	**0.58**	0.84	0.43	0.53	0.65	
Deviational ellipse index (S)	DEU		0.41	0.68	0.17	0.20	0.58
	KAZ	**0.41**		0.74	0.51	0.31	0.67
	LBN	**0.68**	0.74		0.68	0.67	0.27
	POL	**0.17**	0.51	0.68		0.31	0.57
	RUS	**0.20**	0.31	0.67	0.31		0.56
	TUR	**0.58**	0.67	0.27	0.57	0.56	
Relative clustering index (RCL)	DEU		-0.64	-0.79	-0.03	-0.32	-0.70
	KAZ	**1.80**		-0.40	1.73	0.92	-0.15
	LBN	**3.70**	0.68		3.58	2.21	0.43
	POL	**0.03**	-0.63	-0.78		-0.30	-0.69
	RUS	**0.46**	-0.48	-0.69	0.43		-0.56
	TUR	**2.29**	0.18	-0.30	2.21	1.25	

The lower RCL of Russians and Kazakh, if put against Germans (0.46 and 1.80, respectively) compared with Turkish and Lebanese (2.29 and 3.70, respectively), implies a higher spatial evenness and lower clustering of the first two groups, even though the Kazakh D(s) value is exceptionally high. Thus, S serves as the perfect example of how evenness and clustering should be considered as the same dimension whose insights will depend on the scale. Therefore, outcomes suggest that the Lebanese are the most uneven-clustered group, followed by Turkish and Kazakh, whereas Polish remains the most evenly distributed and less segregated group.

Following the chosen framework, both centralisation and concentration can be considered subsidiary dimensions of evenness-clustering if their patterns are significant. In this case, all possible measures have been taken into consideration; thus, *Table 6* presents the results of two-group secondary patterns. However, in a similar way as with the ACO, the relative concentration did not bring any relevant outcome, in contrast to the centralisation, where the higher presence of Turkish and Lebanese in the central areas and the characteristic of Kazakhs being solely in outer areas stands out once more. An interesting added pattern can also be obtained from this measure, the Germans are more centralised than Polish and Russians, even though they are all relatively more represented in the suburbs.

Table 6. *Results of two-group centralisation and concentration indicators.*

	Name	**DEU**	**KAZ**	**LBN**	**POL**	**RUS**	**TUR**
Relative centralisation index (RCE)	**DEU**		0.23	-0.39	0.05	0.02	-0.32
	KAZ	-0.23		-0.66	-0.19	-0.22	-0.56
	LBN	0.39	0.66		0.48	0.45	0.05
	POL	-0.05	0.19	-0.48		-0.03	-0.39
	RUS	-0.02	0.22	-0.45	0.03		-0.36
	TUR	0.32	0.56	-0.05	0.39	0.36	
Relative concentration index (RCO)	**DEU**		0.06	0.00	0.01	0.06	-0.02
	KAZ	0.06		0.05	0.05	0.01	0.07
	LBN	0.00	0.05		0.00	-0.04	0.02
	POL	0.01	0.05	0.00		0.04	-0.02
	RUS	0.06	0.01	-0.04	0.04		0.06
	TUR	-0.02	0.07	0.01	-0.02	0.06	

With several hypotheses about the possible high interactions between groups, such as Turkish-Lebanese, Russian-Kazakh and Polish-Germans, as well as isolation between groups in outskirts and centralised groups, for instance, Kazakh-Lebanese, *Table 7* presents the outcomes of spatial isolation-exposure dimension. The distance-decay exposure (DP_{xy}) refers to the probability of interacting with the opposite group in space. In terms of German origin, the interaction is high due to their hegemony and presence in almost every cell of the study area. Still, two distinct patterns can be observed from the results of this index; firstly, Kazakh, Polish and Russians have a relatively high probability of interaction, whereas Turkish and Lebanese have a notably lower chance of being exposed to the German majority population.

Table 7. *Results of two-group exposure-isolation dimension indicators.*

The distance-decay isolation index (DPxy)	Name	DEU	KAZ	LBN	POL	RUS	TUR
	KAZ	**0.88**		0.00	0.32	0.09	0.05
	LBN	**0.80**	0.01		0.23	0.03	0.21
	POL	**0.87**	0.02	0.01		0.04	0.11
	RUS	**0.86**	0.04	0.01	0.30		0.09
	TUR	**0.82**	0.01	0.02	0.25	0.03	

With the Germans filtered out, the DP_{xy} is calculated for minority groups based on the fact that the smaller scale of Lebanese and Kazakh groups brings their values down, and their spatial distribution is opposed; their possibility of interaction between them is close to 0 in a residential sphere. The similarity between Lebanese and Turkish raises these values up to 21%, while Kazakhs have a 9% of exposure probability to Russians and 32% to Polish, driven by the larger census of Polish origin.

Due to the Russian sample size being between two extremes, the relatively highly populated groups, Polish and Turkish, and the low-populated ones, Lebanese and Kazakh. Therefore, the results analysed from this perspective give the best insights in terms of what origins are exposed to which. For instance, the outcomes show a higher similarity of Russians to Kazakh than to Lebanese (0.04 and 0.01, respectively) and higher exposure to Polish than to Turkish (0.30 and 0.09, respectively).

3.3. Landscape Metrics

3.3.1. Metric results

The landscape metric results (*Table 8*) show a relationship between the Euclidean distance between patches of the same class (ENN_MN) and the sample size; at the same time, the proximity (PROX_MN) between similar size groups suggests a higher proximity of similar percentages of population for Turkish than for Polish and Kazakh than for Lebanese, despite their higher clustering, as seen in the RCL measure (*Table 5*). The latest may suggest a more homogeneity of the Kazakh population in space and a more heterogeneous landscape for Lebanese, with mixed classes neighbouring each other. Nevertheless, the segregation will highly depend on the class that hosts the high proximity or adjacency. The PLADJ at the landscape level has the same trend, as Kazakh are the ones with a higher value, and Lebanese get the lowest, while the rest obtain similar results.

The most exciting metric at the landscape level is the connectance index (CONNECT) which reflects the clustering or dispersion of a group. Firstly, Turkish shows more than double the Polish value and, despite the difference in terms of sample size, has a higher connectance than Russian. On the other hand, Lebanese result stands out compared to Kazakh as a consequence of how dispersed the Kazakhs are from each other and driven by the centralisation of Lebanese.

Table 8. *Landscape metric results by origin group.*

ORIGIN	AREA_MN	PROX_MN	ENN_MN	PLADJ	CONNECT
POL	7.02	2.61	360.32	49.77	0.31
TUR	6.97	2.71	412.93	49.89	0.68
RUS	7.12	1.26	563.92	49.02	0.52
LBN	6.08	1.07	638.41	47.13	1.45
KAZ	8.80	1.15	798.89	52.03	1.08

Going through the class metric results for the origin groups in *Table 9*, a general pattern to highlight is the higher PLADJ of the Q1 for most groups, which may respond to the relationship between unevenness and clustering, as the areas with scarce representation results in certain closeness but not enough to be counted in the same patches. Clustering and residential segregation can also be depicted by looking at metrics in the highest population classes. Turkish shows a very high percentage of like-adjacencies for the Q6, and both proximity and connectance suggest that their most populated areas could be susceptible of hosting the highest levels of residential segregation in Berlin. Lebanese being the most clustered and segregated origin is not shocking after the segregation measure results, yet, class metrics support this idea, with high levels of connectance in Q5 and Q6, although their PLADJ is the lowest due to their common spatial distribution with Turkish. As for Kazakh, their situation is concerning as their most populated class is the most connected and, although not as high as Turkish, the adjacency is also relatively high, with over 52%.

Table 9. *Class metric results by origin groups.*

ORIGIN	CLASS	AREA_MN	PROX_MN	ENN_MN	PLADJ	CONNECT
POL	Q1	11.23	6.83	374.51	55.57	0.42
	Q2	7.73	2.34	339.57	50.65	0.29
	Q3	7.37	2.15	344.28	49.92	0.28
	Q4	5.91	1.55	374.58	46.12	0.28
	Q5	5.88	1.77	373.76	47.24	0.31
	Q6	5.11	2.14	362.80	45.91	0.31
TUR	Q1	12.58	3.09	503.72	55.29	0.56
	Q2	7.25	2.00	422.88	49.45	0.58
	Q3	6.70	2.54	367.67	48.71	0.64
	Q4	4.69	1.23	395.05	42.87	0.65
	Q5	4.58	2.18	372.26	42.73	0.78
	Q6	8.06	7.43	482.21	56.42	1.26
RUS	Q1	12.84	2.31	647.53	54.43	0.67
	Q2	9.12	1.43	535.93	50.41	0.48
	Q3	7.04	1.43	493.54	48.23	0.43
	Q4	5.02	0.56	615.61	44.23	0.48
	Q5	4.73	0.95	569.13	43.58	0.56
	Q6	4.95	0.98	575.94	46.75	0.63
LBN	Q1	13.44	1.14	774.55	54.48	1.23
	Q2	8.76	0.73	813.45	49.65	0.93
	Q3	6.03	1.25	526.45	46.64	1.16
	Q4	4.29	0.99	638.16	42.62	1.51
	Q5	4.09	1.02	564.94	42.35	1.66
	Q6	3.72	1.19	628.04	39.17	1.88
KAZ	Q1	14.87	1.43	1012.60	56.56	1.08
	Q2	9.13	0.95	850.48	51.00	0.82
	Q3	8.77	1.36	621.65	51.28	0.90
	Q4	6.74	0.91	930.91	49.74	1.01
	Q5	6.41	0.83	691.73	49.43	1.23
	Q6	8.16	1.58	765.56	52.22	1.96

In contrast with the highly segregated groups, Polish and Russian show values according to their extent and sample sizes and no alarming patterns. Nevertheless, a visual approach is necessary to identify at a local scale the spaces where residential segregation occurs.

3.3.2. Residential segregation analysis using landscape metrics

Given the aim and opportunities that landscape metrics provide in visual terms for segregation analysis, these have been used to find not only which group is segregated but where the segregation takes place for the people behind the data. Going from the largest group to the smallest, Polish origin presented in *Figure 23*, considered as the least segregated minority population of this analysis, shows an overall equally distributed and not concerning distribution pattern. Nevertheless, a large cluster can be found in Marienfelde (southwest of Tempelhof-Schöneberg), specifically in the high-density building areas that occupy the north of this locality. Still, the main concerning residential segregation case is located on the eastern border of Reinickendorf, in the locality of Märkisches Viertel.

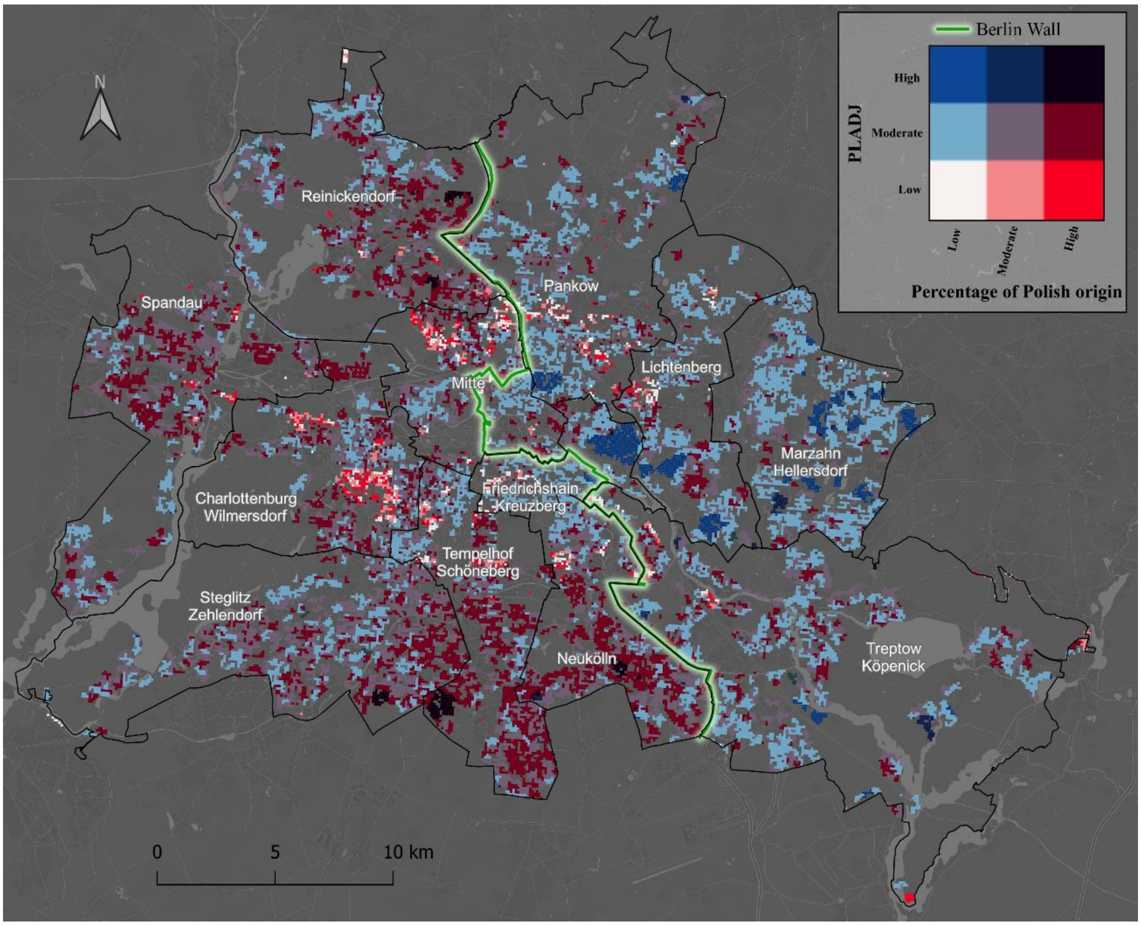

Figure 23. *PLADJ and relative population bivariate map of Polish origin group.*

However, the overall situation for the group is good, and despite their apparent majority in West Berlin, their presence reaches most of the city, resulting in minimal isolation.

In *Figure 24*, the landscape metric approach identifies the most significant case of segregation found in the city, the cluster of Turkish population on the western side of Friedrichshain-Kreuzberg, and smaller ones in Mitte and Neukölln. However, it also enables the visualisation of zones where a bigger diversity takes place, for instance, Spandau or Charlottenburg-Wilmersdorf, places that also see no extreme patterns for the Polish group.

At the same time, a similar process can be observed for both Turkish and Polish regarding populations that are isolated in terms of their peers, in other words, areas where the group population is low and the adjacency is high. These areas have to be looked after as the population often might experience difficulties due to the lack of social networks and the inexistence of similar culture, language or background populations in the area, but, at the same time, it may be just a high diversity zone where many ethnicities converge in small amounts without major issues.

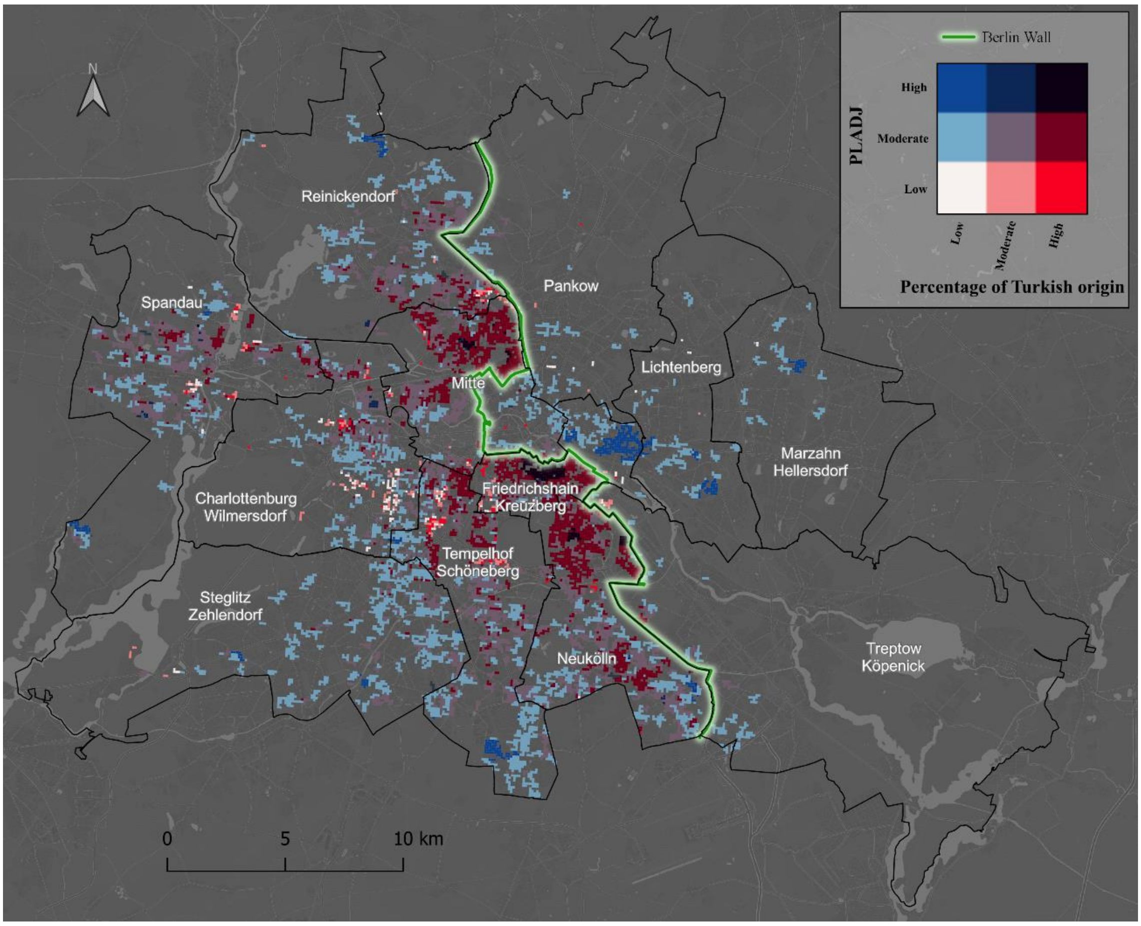

Figure 24. *PLADJ and relative population bivariate map of Turkish origin group.*

The main example of this is Friedrichshain in the eastern wall side of Friedrichshain-Kreuzberg, but the Turkish group has smaller clusters of such in south Lichtenberg, north Marzahn-Hellersdorf and limits of the city, such as the aforementioned locality of Marienfelde where Polish are mainly in high-rise buildings, and Germans locate in the lower density housing areas nearby.

Looking at the Russian group in *Figure 25*, the high diversity of Mitte, Charlottenburg-Wilmersdorf and the low-per cent mix in Friedrichshain get confirmed. However, other patterns of possible segregation are also discernible in the suburbs that have so far not been spotted through other measures and visualisations. These can be split into two types, the high PLADJ and population clusters on Spandau and Marienfelde (both located in West Berlin) and the clusters in Friedrichsfelde (Lichtenberg) and central Marzahn-Hellersdorf, where some Housing Estates are located. West Berlin clusters host a significant interaction with other groups, such as Polish and Kazakh, and have German populations in the vicinity, whereas those in East Berlin host mostly Russians and Kazakh, and the proximity of German-dominated areas is lower than in previous cases.

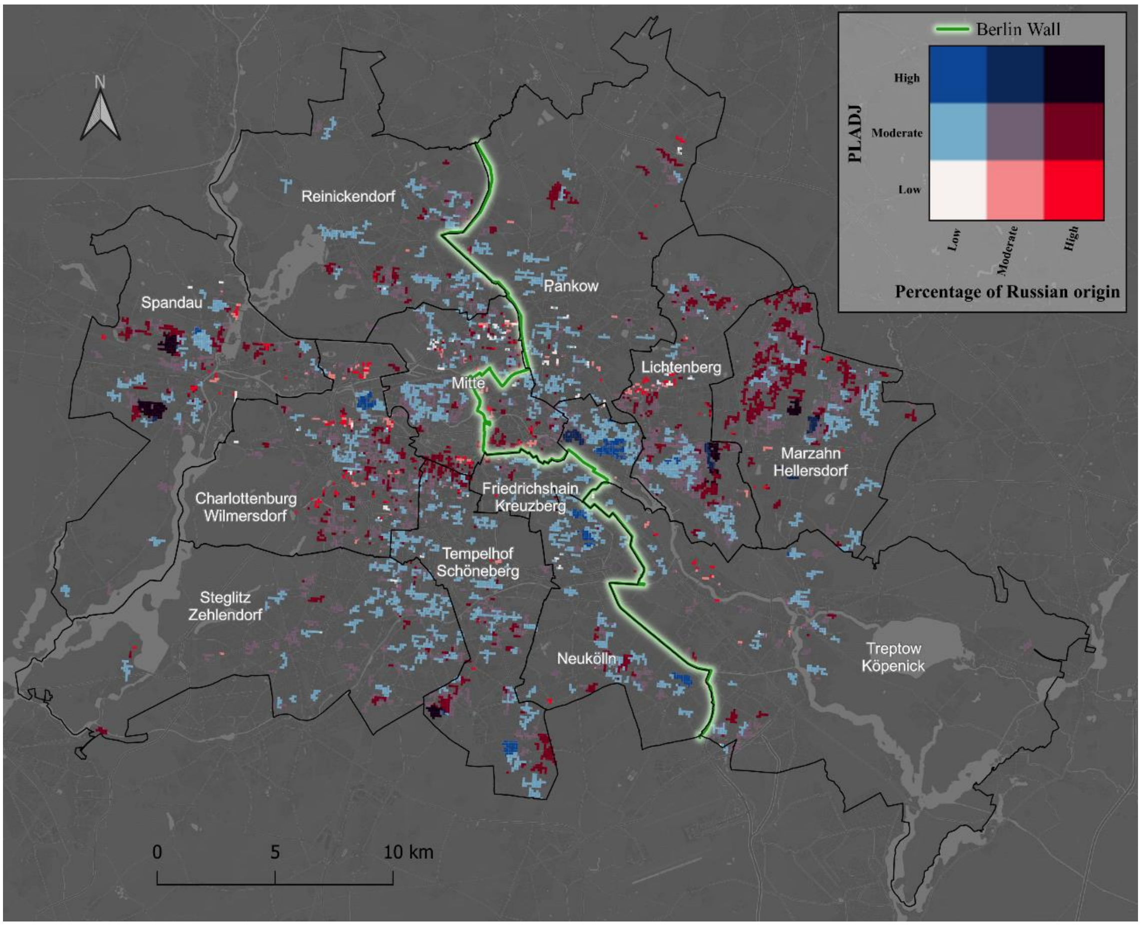

Figure 25. *PLADJ and relative population bivariate map of Russian origin group.*

In general terms, Russians are more segregated than Polish driven by their situation in East Berlin; however, exclusion from Germans is lower than for the Turkish minority, considering their residential segregation as moderate or not as concerning as the patterns seen in Kreuzberg.

Following with the Lebanese (*Figure 26*), despite having similar spatial distribution to Turkish, they also share a high clustering and, as a result, two main areas of high residential segregation can be observed. The main area is located on the western side in the vicinity of the wall, where Neukölln borders Treptow-Köpenick. The secondary cluster locates in the western part of Mitte. However, unlike the Turkish, the genuine concern for the Lebanese minority is the isolation of their smaller groups located in outer areas such as Spandau, south Tempelhof-Schöneberg or north Reinickendorf. The importance of moderate adjacency but high population areas should also be noted, mainly when two groups show this same pattern in a specific location.

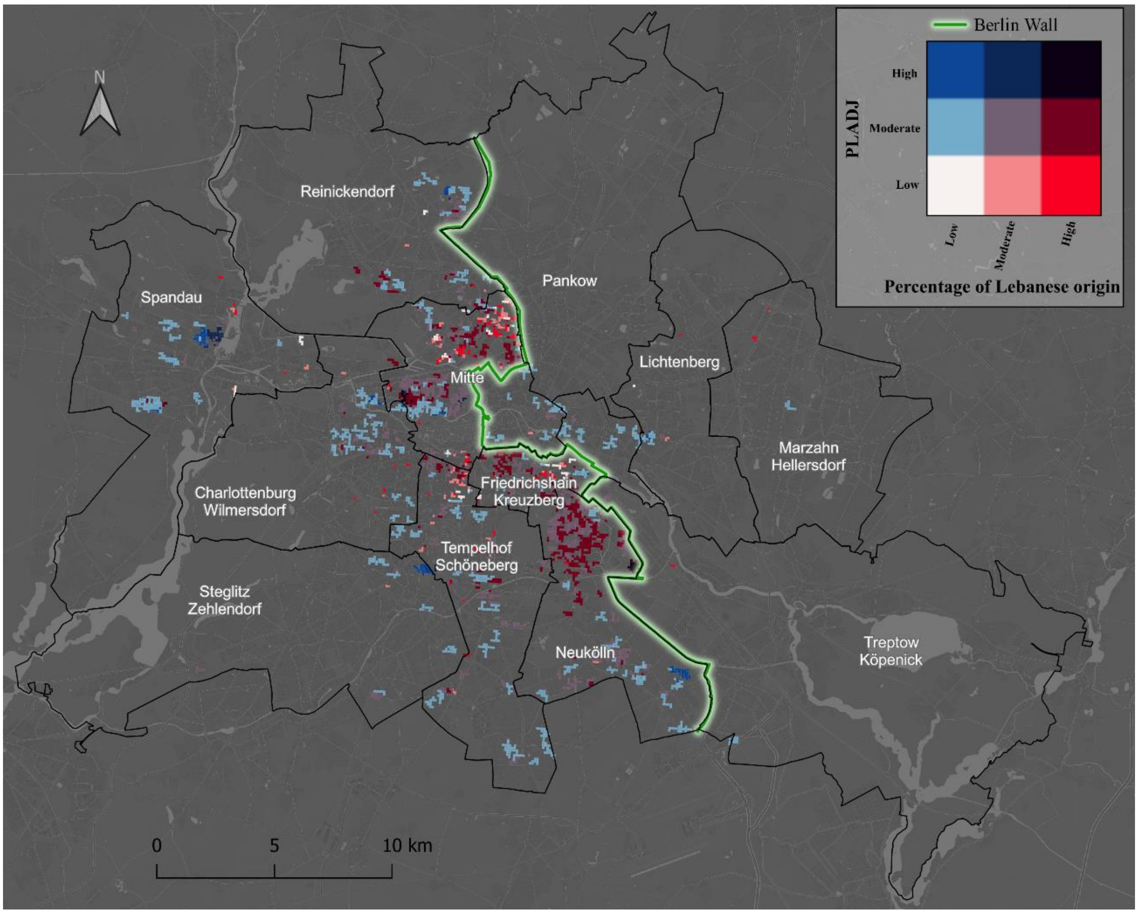

Figure 26. *PLADJ and relative population bivariate map of Lebanese origin group.*

Thus, the areas where both Lebanese and Turkish maintain a high presence and moderate adjacency can be related to a high segregation of these two as a whole. This way, exclusive Turkish, Lebanese and joint segregation zones can be distinguished.

Lastly, the Kazakh (*Figure 27*) show the absolute opposite to the Lebanese, with isolated lows in the central areas and significant clusters in the outskirts, with the most extensive high-high zone in the Falkenhagener Feld Housing Estate, in Spandau. However, the most interesting pattern again is the lack of Polish, Turkish and Lebanese in the north of Marzahn-Hellersdorf, a space of joint segregation shared by Kazakh and Russians that shows a high population for both and, primarily, moderate adjacency.

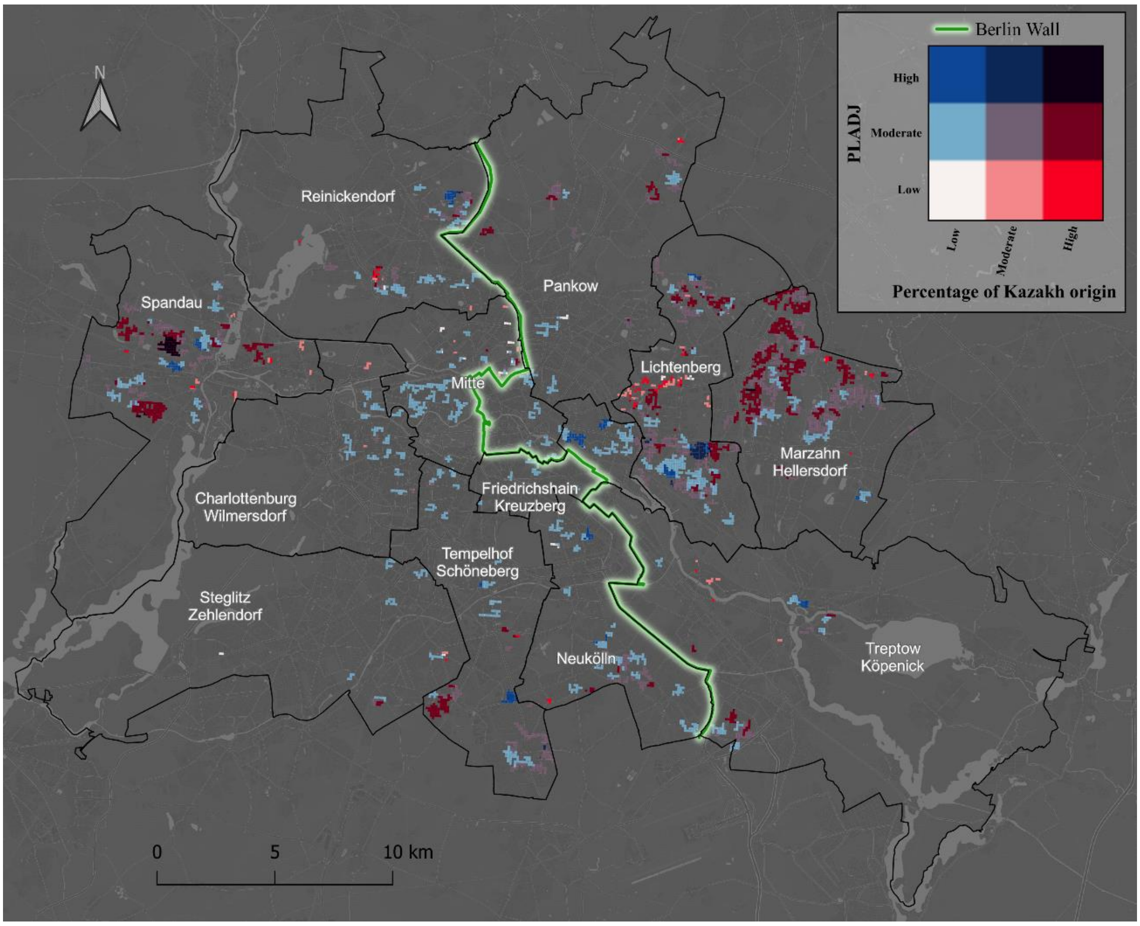

Figure 27. *PLADJ and relative population bivariate map of Kazakh origin group.*

4. Discussion

Residential segregation is a relevant feature present in modern cities that threatens the socioeconomic ascent, political participation and the general well-being of citizens. Despite the development of transport systems and the multiple life spheres where populations can interact, the location of the residence remains a driving factor of inequalities and social exclusion. Thus, providing new methods for the assessment of residential segregation has up-to-date significance. Due to the study period (2011), the limitation of the observed patterns is considerable, as the housing market changes are fast in big cities like Berlin (Holm, 2021). Still, proving the value of the methods for the characterisation of the groups in the urban space makes it worth using outdated information and allows to check the quality of the results by cross-checking with the current information.

4.1. Residential patterns and local measures

The spatial distribution of the origin groups has been mapped and analysed, providing a clear impression of their extent, residential location and possible signs of segregation. At the same time, these have been compared with each other, discerning the parallel and opposite situations between them. To sum up, two main patterns have been discovered from the analysis; 1) centralisation: Turkish and Lebanese minorities and, 2) decentralisation: Polish, Russian and Kazakh minorities and German majority.

On the other hand, local measures have helped to find locations of higher and lower diversity areas. Areas with low diversity represent two different patterns: 1) the isolation in low-density housing areas in the outskirts by the German majority and Polish minority and 2) the potential "ghettoisation" of the Turkish minority in Kreuzberg. Either of these are clear examples of phenomena to be monitored, both concerning the possible growth of anti-minority discourses in areas where the majority is isolated from other groups and the lack of equal opportunities for the highly segregated minority, respectively (Stehle, 2006). In contrast, areas with high entropy or diversity represent the consequences of the urban sprawl and better integration of minorities in the city. For instance, Spandau hosts a significant ethnic diversity, and the potential interaction between the German majority and the minority groups is higher, as the distance between the respective low and high-density housing areas where majority and minority groups locate is relatively low. Nevertheless, as stated by Bartzokas-Tsiompras & Photis (2020), the built environments in the city of Berlin do not enhance efficient social diversity, with minorities living in less walkable areas.

As for Location Quotient, results show that the spatial distribution of Polish and Russian is closer to the German majority, whereas Turkish, Lebanese and Kazakh show more contrast with the majority being more similarly distributed to the minority populations. In addition, LQ has shown to be valuable for identifying the main focal residential areas of each group, hence, needing consideration in further segregation analyses (Brown & Chung, 2006). Digging into the reasons for the similarities between Lebanese and Turkish groups, the socio-economic status might be the main driving force together with possible religious-cultural elements in the case of the Muslim population, although Lebanon is known for its religiously plural heritage and the cause of the pattern would need additional research (Polat, 2020). These populations are susceptible to new gentrification waves taking place in Neukölln, which could potentially displace poor groups towards other areas in the city where housing options are cheaper (Polat, 2020). Thus, breaking the supportive networks built within their peers, consequently increasing their vulnerability.

4.2. Spatial segregation metrics and landscape metrics

The residential segregation analysis has compared the minority groups determining their situation. In ascending order, the lowest unevenness and clustering was found for Polish and Russians, followed by Kazakh, Turkish and Lebanese minorities that were found to be significantly more segregated. The sub-dimension of centralisation has shown to be of great interest in the study case as both extremes of this measure were linked to the highly segregated origin, with Lebanese and Turkish as the most centralised and Kazakh as the least, whereas concentration brought no relevant insight. In terms of exposure-isolation, patterns of interaction between Middle Eastern countries (Turkey-Lebanon) and between Russian-speaking countries (Russia and Kazakhstan) were found. This could potentially respond to the common culture between minorities in both cases (Blokland & Vief, 2021; Polat, 2020).

In line with the results obtained throughout this study, Kil & Silver (2006) and Stehle (2006) suggested a more remarkable reticence or hostility towards Muslim migrants, which would hypothetically cause higher segregation levels within the Turkish, Lebanese and Kazakh minorities than within Russian and Polish. Despite Lebanon being known for its religiously plural heritage, a significant part of their group is likely to be Muslim; in addition, the vulnerable situation on arrival as refugees might have had an effect on their levels of segregation and conflicts with the German majority (Kemper, 1998; Polat, 2020). At the same time, the lowest segregation corresponds to the Polish minority, which has been mostly successfully embraced by the majority population (Szczepaniak-Kroll & Szymoszyn, 2023). The global segregation measures helped to characterise the overall situation of the minorities in Berlin.

Landscape and class metric results offered a general idea of how each minority was displayed and built hypotheses on how big the segregated areas of each group could be. The main obstacle for the metric analysis was the sample differences between groups, which is determinant for the values. At the landscape level, the results showed a higher connectance (CONNECT) for Turkish than Polish and Russians, and for Lebanese than for Kazakh. These results relate to the patch-level homogeneity; thus, more homogeneous focal landscapes have been found for Turkish and Lebanese. At the class level, the most remarkable finding is the potentially sharp segregation of Turkish origin within their highest percentage population class, looking at the percentage of like-adjacencies (PLADJ) and mean area (AREA_MN) metrics. At the same time, Lebanese and Kazakh also showed concerning connectance in the larger classes but lower adjacency than the Turkish minority. Through the moving window analysis and bivariate mapping, it has been possible to identify the spots where the maximum segregation occurs and speculate about other possible negative processes. These would include gentrification, unwanted dispersion and isolation from the members of the same origins, which, as described by Crews & Peralvo (2008), can generate a lack of social network and support from people with a shared background.

In broad terms and despite some groups being more segregated and hosting less interaction with the German population, specific residential segregation cases have been found for all the groups. Polish minority, the least segregated, is clustered in Märkisches Viertel Housing Estate, known for being the largest in West Berlin and a marginalisation hotspot in the 1960s (Vasudevan, 2022), and in Marienfelde, where Russians are also located. The results for the Russian group suggest a higher segregation than for Polish, as they share segregated areas in both West and East Berlin. On the western side, the Falkenhagener Feld Housing Estate has been identified as a focal point of residential segregation for Russians and Kazakh (Urban, 2018). The same happens with the high-rise areas in Marzahn where, according to Kil & Silver (2006), the loss of population after the fall of the Berlin Wall and high building vacancies made it a perfect spot for the newest waves of immigrants. However, another critical point is the migration waves from East Berlin to West Berlin after the fall of the iron curtain and the reunification, which brought fast urban changes, gentrification and displacement with the changes in the housing market (Bernt, 2016). Meanwhile, the presence of both Russian and Kazakh minorities in Spandau may be linked to the low cost of housing, as the district is seen as working-class and not attractive (Blokland & Vief, 2021). Nevertheless, the situation for the Russian minority is not as bad as for Turkish, Lebanese or Kazakh, as their extent and interaction with Polish and Germans is higher. Despite being clustered alongside Russians, Kazakh's absence in highly diverse areas such as Mitte supports the idea of them being in a more isolated and, thus, vulnerable situation (Tleugazina et al., 2022).

However, the most segregated groups and those more likely to suffer from gentrification in the districts in which they were segregated in the year of this study were Turkish and Lebanese. Both Kreuzberg and Neukölln areas host significant segregation, yet the Turkish case in Kreuzberg has shown to be the most vivid case of residential segregation in Berlin as a whole. More recent studies demonstrate the outstanding performance of the methods used to find the patterns accurately, as the gentrification and displacement in the specific areas occupied by these groups have been documented (Döring & Ulbricht, 2018). Exclusively Turkish, Lebanese and joint segregation zones can be distinguished in the results, with the Turkish minority in Kreuzberg as the most concerning case. Yet above all, the narrative of Kreuzberg becoming a "ghetto" alongside the racism coming from the majority population and the resistance towards a successful integration has also been well documented (Stehle, 2006).

Despite the effectiveness in locating evidence of residential segregation, some limitations and obstacles must be noted. On the one hand, local spatial segregation measures proposed by Feitosa et al. (2007) have a complex computation, whereas landscape metrics are challenging to interpret, and the underlying data classification may result in inaccuracies if mishandled. On the other hand, a temporal comparison could be a great pathway to detect the segregation dynamics in cities; however, data availability might be a constraint for this matter. In terms of applicability, this research can give context and help to balance the adverse outcomes of processes such as the gentrification described by (Döring & Ulbricht, 2018), allowing the policymakers to address internal phenomena in the specific districts and the groups that have been found vulnerable.

4.3. East-West Berlin distribution

Addressing the question of differences between East and West Berlin, this study has identified three distinct patterns: 1) One-sided in the East: Kazakh origin, 2) One-sided in the West: Turkish, Lebanese, and Polish origins, and 3) East-leaning: German and Russian origins. These patterns provided further evidence of the historical impact of the Berlin Wall on the configuration of ethnic residential distribution in the city. Thus, confirming the potential benefit of considering it for analyses conducted in Berlin.

The origins of these patterns refer to the major migrations that took place during the Cold War, for example, Turkish migrants to West Berlin and former USSR countries to East Berlin (Urban, 2018); however, there are some nuances. The links with the 20th century have to be taken with caution, as the data on which the current study is based refers to place of birth or citizenship status in 2011. Thus, root or social network-based movements by the minority groups are relevant, but also modern migrations that may differ spatially from the historical reasons and locations associated with those minorities.

For instance, Russian and Kazakh populations share much of their spatial distribution, but Russians are more spread out and balanced between the two parts of the city. Besides the difference in the amount of population, the higher importance given by Kazakh to ethnicity, self-identity and will to preserve their language, customs, and traditions are possible causes of the differences between both groups, as well as the religious differences (Tleugazina et al., 2022). The presence of Russians in West Berlin may be due to the fall of the Berlin Wall since, as Kil & Silver (2006) described, many had to find work in order not to be repatriated.

The higher presence of the Polish minority in the West is related to the immigrant wave in the ’80s that made it through the iron curtain, although their excellent integration with the German majority and high acceptance compared to other minority groups slightly balanced their current situation on both sides (Szczepaniak-Kroll & Szymoszyn, 2023). Last but not least, Turkish and Lebanese minorities are almost exclusively located in West Berlin. As described by Kemper (1998), Turkish migrants arrived in West Berlin as guestworkers, whereas Lebanese stayed in the country as refugees due to the Lebanese Civil War. Briefly, the roots developed through decades in West Berlin appear to have anchored both minorities on that side, which significantly increases their residential segregation and vulnerability.

5. Conclusion

Nowadays, ethnic segregation is widely discussed by urban planners due to its adverse social and economic implications in cities and the increasing spatial mobility and diversity. Modern cities are characterised by their dynamism, mobility and mass transport, bringing in concepts such as activity space to the segregation studies at the expense of those that used to focus on residential segregation (Silm et al., 2018; Wong & Shaw, 2011). However, residential location can determine social-mobility prospects and well-being and cause disadvantages that are perpetuated for generations (Li et al., 2022). Thus, further research on the topic can be helpful for more liveable cities and better integration of minorities.

Through this study, it was aimed to gain a better understanding of the residential segregation patterns in Berlin using spatial segregation metrics and landscape metrics, with an emphasis on understanding the effect of the historical political division and discussing whether landscape metrics provide an additional value to the spatial characterisation and measure of segregation. For this matter, the spatial distribution of the five largest minorities has been mapped, and spatial metrics were calculated. The results identified higher segregation, clustering and isolation from the majority group for Turkish, Lebanese and Kazakh minorities, whereas the lowest values were found for Russian and, above all, Polish minorities. Nevertheless, landscape metrics found segregated zones for all minority groups. Regarding the city's historical division, Turkish, Lebanese and, to a lesser extent, Polish were found overrepresented in West Berlin. In contrast, Russian, and particularly Kazakh, had a more extensive representation in East Berlin.

When carrying out work that mixes diverse domains, such as demography and landscape ecology, the application of the methods from one to another can be challenging as the logic that applies to the subject of study will differ. Yet, this case is an excellent example of a successful interdisciplinary approach, in which the challenges, such as converting the quantitative data (population percentages) to qualitative (classes) in order to calculate metrics, have been resolved. Different approaches can be taken in the pre-processing depending on the specific aim of the research, always considering the crucial role of the class definition in the results. It is important to mention that the methods have to be always linked to the data characteristics.

Although landscape metrics have worked to complement both analytically and visually the residential segregation patterns, it is considered that an easier computation of local spatial measures of segregation as the ones provided by Feitosa et al., (2007) should hypothetically provide excellent results and have more straightforward interpretation than landscape metrics. Nevertheless, the method showed an example of the correct use of some metrics, especially the bivariate mapping approach using the Percentage of Like Adjacencies (PLADJ). Yet, other landscape metrics could also be used similarly in order to find hidden or overlooked patterns.

Moreover, the mixed analysis and opportunities that GIS environments provide can be the ideal breeding ground for targeted studies using multi-criteria analysis from multi-disciplinary perspectives, as the raster resulting layers from the moving window analysis can be combined in diverse forms, for instance, with a raster overlay that seeks to find a specific urban process that the authorities are aware of. Despite this, it is important to note that up-to-date data would be necessary for some analyses that aim to be used in urban planning, as urban processes are very rapid and will depend to a large extent on policies, thus, being susceptible to political changes (Holm, 2021). With regard to this research, it can help policymakers understand the vulnerability of different minority groups in specific hotspots of residential segregation and recap how such issues have been dealt with or left aside since 2011, but it does not enable them to base their current policies on the results, as the context is too distant in time. However, the use of these methods to carry out further research with data that is closer in time would indeed represent a great opportunity to deal with minority integration and the harmful outcomes of residential segregation in cities.

To conclude, the adoption of new approaches, such as the one presented in the current study, may be prioritised over obsolete analyses that use aspatial indices by scholars. Segregation in general, and residential segregation in particular, shall not be measured without taking space into account, as the essence of the term is purely geographical; instead, priority needs to be given to existent spatial indices, new methodological approaches and innovative index developments that can help track the segregation dynamics more accurately.

6. Summary

This thesis focuses on residential segregation patterns and employs spatial segregation metrics and landscape metrics, intending to gain a deeper understanding of the phenomena in Berlin. The research addresses the spatial distribution of the five largest minority groups, compares them through existing spatial segregation indices and landscape metrics, and examines the differences between East and West Berlin in terms of residential patterns using high-resolution demographic data together with FRAGSTATS and Geo-Segregation Analyzer software and GIS.

The results reveal distinct residential patterns for all the studied minority groups, with specific areas identified as hotspots of residential segregation. Turkish and Lebanese groups exhibit high levels of segregation in focal areas such as Kreuzberg and Neukölln. Although less segregated, Kazakh and Russian minorities were found having similar hotspots in Housing Estates located in Spandau and Marzahn, while the Polish minority showed the lowest segregation in Berlin, sharing the space with minorities, such as Kazakh and Russians, but also with the German majority. The study also explored the impact of the Berlin Wall, identifying that Turkish and Lebanese were highly concentrated in West Berlin and Kazakh extremely concentrated in the East. Weaker patterns were found for Polish and Russians being slightly overrepresented in West and East Berlin, respectively.

By visualising and locating high segregation areas, the study demonstrates the value of landscape metrics in enhancing residential segregation studies. To sum up, this study offers an alternative pathway for further research to address a complex subject, residential segregation, integrating methods from different disciplines and tailoring the approach to the existing challenges.

Elukohasegregatsiooni mõõtmine ruumiliste mõõdikutega Berliini näitel

Raúl García Estévez

Kokkuvõte

Elukoht mängib inimeste jaoks olulist rolli sotsiaalses ja majanduslikus mobiilsuses. See tähendab, et elukohasegregatsioon on kriitilise tähtsusega uurimisvaldkond, kui vastavad asutused soovivad inimeste jaoks sotsiaalset võrdsust ja võrdset juurdepääsu võimalustele. Traditsiooniliste segregatsiooni mõõtmise viisidel on konkreetsete statistiliste üksuste ruumiliste piiride mõju uurimistulemustele tähelepanuta jäänud. Lähtudes mitmete teadlaste kriitikast traditsiooniliste meetodite suhtes ja uute tehnoloogiate potentsiaalist, on viimased uuringud püüdnud indeksitesse lisada ruumilist komponenti. Siiski pakub ka praegu geograafiat teadvustavate alternatiivide otsimine lisateavet elukohasegregatsiooni käsitlemisel, mistõttu kasutatakse käesolevas uurimistöös maastikuökoloogia meetodeid, et täiendada olemasolevaid ruumilisi segregatsiooniindekseid. Töö rõhutab interdistsiplinaarse lähenemisviisi abil mustrite visuaalset aspekti.

Käesoleva töö eesmärk on paremini mõista Berliini elukohasegregatsiooni mustreid, kasutades ruumilise segregatsiooni ja maastikuindekseid. Täpsemalt oli eesmärkideks 1) tuvastada segregatsioonimustrid Berliinis ja ajaloolise poliitiline lõhe mõju segregatsioonimustritele ning 2) arutleda, kas maastikuindeksitel on segregatsiooni ruumiliste aspektide mõõtmisel lisaväärtust. Eesmärkide täitmiseks käsitleti järgmisi küsimusi:

1. Milline on Berliini viie kõige arvukama vähemusrahvuse ruumiline jaotus?
2. Kuidas kõrvutuvad need rühmad segregatsiooni ja selle dimensioonide poolest, kui need on määratletud ruumilise segregatsiooni mõõdikute ja maastikuindeksitega?
3. Mis vahe on Ida- ja Lääne-Berliinil etniliste rühmade paiknemismustrite osas?

Traditsioonilised ühtluse ja kokkupuute mõõtmete meetodid, nagu Duncani segregatsiooniindeks (D) (Duncan & Duncan, 1955) ja kokkupuute indeks (xPy) (Bell, 1954) võivad põhjustada vigaseid või ebatäpseid analüüse, milles segregatsiooni võidakse naaberühikute arvestamata jätmise tõttu üle hinnata ja seega ignoreerida võimalikke kokkupuuteid rühmade vahel (Li et al., 2022; Massey & Danton, 1988; Reardon & O'Sullivan, 2004; White, 1983). Käesolev uurimus tugineb erinevate autorite ruumilistele

indeksitele, sealhulgas Wongi (1993, 1999) välja töötatud tasasus-klastrite dimensioonile ja Morgani (1983) välja pakutud kaugusindeksitele kokkupuute-isolatsiooni käsitlemiseks. Lisaks on Stoetzeri (2018) väitnud, et ökoloogia ja sotsiaalse ebavõrdusse vahel on seosed ja Crews & Peralvo (2008) on näidanud potentsiaalset võimalust kasutada maastikuindekseid segregatsiooni uurimisel.

Käesolevas uurimistöös kasutatakse 100 m lahutusvõimega vektorvõrgu andmestikku, mille on koostanud 2011. aasta rahvaloenduse andmete põhjal Euroopa Komisjoni Teadusuuringute Ühiskeskus (Alessandrini et al., 2017) ja Berliini müüri vektorandmestiku (Geoportal.de, 2007). Lisaks on uuringus Ida- ja Lääne-Berliini jaoks käsitsi digiteeritud lisakiht. Uurimistöö eesmärkide saavutamiseks on Geo-Segregation Analyzer (Apparicio et al., 2014) abil arvutatud 13 ruumilise segregatsiooni indeksit, võttes arvesse nii globaalseid indekseid, nagu ruumiline erinevus (ID) ja distantsipõhine ekspositsioon (DPxy) kui ka kohalikke indekseid nagu asukoha koefitsient (LQ) ja entroopia (H). FRAGSTATSi abil arvutati 5 maastikuindeksit, sealhulgas sama tüüpi alade (ruutude) külgnevuste protsent (PLADJ) ja sidusus (CONNECT). Lisaks on GIS-i abil kaardistatud kohalikud mõõdikud (LQ ja H). Berliini müüri mõjude käsitlemiseks on vähemusrühmade paiknemise põhjal arvutatud mõõdikuid kirjeldatud eraldi nii Ida- kui Lääne-Berliinis.

Tulemused näitasid, et türklaste ja liibanonlaste kõrgem kontsentreeritus on linna keskel ning teised vähemusrühmad olid suurema esindatusega linna välialadel. Segregatsiooni osas leiti, et türklased ja liibanonlased on kõige kõrgema segregatsioonimääraga vähemusrahvused, sealjuures moodustas Kreuzbergi ja Neuköllni piirkond kõige markantsemad enklaavid. Sarnastest piirkondadest lähtus ka venelaste ja kasahhide segregatsioon, samas kui poola vähemus ei ole paiknemiselt hoolimata üksikute klastrite olemusest kuigi kõrge segregatsiooni määraga. Berliini müüri kaudse mõjuna võib välja tuua, et türklased ja liibanonlased on äärmiselt kontsentreerunud Lääne-Berliini ja kasahhid selgelt kontsentreerunud itta. Poolakate ja venelaste jaoks polnud segregatsioonimustrid sedavõrd selged, olles üle-esindatud vastavat Lääne- ja Ida-Berliinis.

Magistritöö demonstreerib maastikuindeksite võimalikku rakendatavust elukohasegregatsiooni uurimisel, leides ja visualiseerides Berliini viie peamise vähemusrühma jaoks kõrgema segregatsiooniga huvipiirkonnad. Kokkuvõttes, see uuring pakub alternatiivset rada edasiseks uurimistöödeks, et tegeleda keerulise teemaga, elukohasegregatsiooniga, integreerides erinevatelt distsipliinidelt pärit meetodeid, et kohandada praeguseid lähenemisviise olemasolevatele väljakutsetele.

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