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Spatial Segregation, Socioeconomic Disparities and Spatial (in)Justice in a Region of the Mediterranean

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ABSTRACT

In recent decades, interest in residential segregation has increased in Southern Europe and the Mediterranean region, primarily due to immigration. This study explores segregation and its potential links to socioeconomic disparities and social (in)justice. The analysis uses standard segregation indicators, along with their spatial counterparts, and employs permutation tests for inference. These methods are applied to the province of Pescara, a Mediterranean city in Southern Italy, to also explore segregation differences between urban and rural areas. Finally, we discuss how this approach can assist policymakers in identifying segregation pockets in rural outskirts and prevent potential spatial (in)justices and socioeconomic disparities affecting ethnic minorities.

1 | Introduction

Spatial injustice refers to the uneven distribution of opportunities among individuals based on their place of residence (Soja 2013). The literature discusses two key aspects of spatial justice: the "distributive" and the "procedural" (or "process") dimensions (Shucksmith et al. 2021, p. 323). While distributive justice focuses on the redistribution of opportunities, procedural justice aims to modify conditions of the processes that lead to significantly unfair outcomes. Hence, considering procedural aspects can be valuable in addressing unjust outcomes of socioeconomic processes at the local level, particularly those affecting ethnic minorities.

Residential segregation is defined as the process leading to a severely imbalanced distribution of minority groups across space, which might result in exclusion or disadvantage for ethnic groups (Bailey et al. 2017). A highly unequal distribution of minorities can restrict certain groups to areas with limited resources or services (Smets and Salman 2016). In the United States, for example, segregation has limited access to essential services such as healthcare for some communities (Kramer and Hogue 2009).

In the European Union (EU), the Cohesion Policy is the primary initiative for reducing socioeconomic disparities and promoting spatial justice. Using these resources, European institutions have aimed to tackle potential disparities, particularly in Southern Europe, and including those related to segregation of minorities (Ulceluse et al. 2022). Policies have been implemented to effectively reach minorities and ensure their access to services. Hence, keeping low residential segregation in Southern Europe remains a priority on the EU agenda to ensure fair opportunities and reduce socioeconomic disparities.

The relationship between residential segregation, socioeconomic conditions, and spatial injustice has been analysed from multiple perspectives. Lehman-Frisch (2011) examines cases where racial or residential segregation leads to injustice, as when it restricts access to employment, education, and other opportunities or contributes to racial stigmatisation. The author also advises that segregation should not automatically be considered a form of injustice. Marcuse (2009) emphasises that the relationship between residential segregation and spatial justice is constantly evolving and should be interpreted within specific socioeconomic contexts.

Some authors have highlighted the significance of these connections in Southern Europe. Arbaci (2008) stresses how housing and residential marginalisation in Mediterranean cities represent a critical issue for immigrants.[1] Tintori et al. (2018) emphasise the relationship between socioeconomic and demographic factors at the local level in Italy, calling for residential segregation to be analysed in both urban and rural areas. Trends such as gentrification in areas previously devoted to industrial production (Smith and Butler 2007) and growth of city boundaries and urban sprawl (Salvati 2022) call for segregation to be examined beyond city boundaries. Other scholars suggest that more evidence is required to understand the link between segregation and socioeconomic disparities in Southern Europe, taking particular account of the Great Recession of 2008 (Arapoglou 2012; Panori et al. 2019; Benassi et al. 2020a). Studying segregation in Southern Europe requires investigating carefully its socioeconomic effects across different levels of the rural-urban hierarchy (Smith 2019). The study of rural segregation has gained attention in other contexts, such as the United States (Lichter et al. 2021), but it remains underexplored in Southern Europe (Zambon et al. 2017; Pratschke and Benassi 2024).

The analyses of segregation at a granular level require careful consideration of the spatial distribution. Many segregation indices neglect this critical aspect and do not capture interactions between spatial units (Bailey et al. 2017). This issue, known as the "checkerboard problem", is well documented in the case of Duncan's *D* (White 1983). Despite the availability of spatial alternatives that address the "checkerboard problem" in studying segregation at a granular level, standard nonspatial methods continue to be widely used. As a consequence, spatial analysis has received limited attention in segregation studies, particularly those focusing on the Mediterranean area (Benassi et al. 2020a).

In light of the above, this study aims to an in-depth assessment of residential segregation, socioeconomic disparities, and spatial justice in a Mediterranean region. We employ a set of statistical indices to analyse segregation in a densely populated province in Southern Italy. We consider spatial indicators (Reardon and O'Sullivan 2004; Feitosa et al. 2007) to assess the role of spatial interactions. Our approach discriminates between urban and rural areas to better investigate geographical variability in segregation statistics. Finally, we discuss how urban–rural differences in segregation figures relate to imbalances in key socioeconomic indicators and potential injustice, emphasising how this relationship varies across spatial contexts.

The paper focuses on the procedural aspects of injustice, exploring the socioeconomic conditions that disproportionately affect ethnic minorities in rural areas. Many of these areas remain underdeveloped and - given the existing evidence - migrants who settle there could lack effective integration and experience disparities in education, housing, and employment. Our investigation adds on the socioeconomic and spatial implications of residential segregation in urban and rural localities within a Mediterranean region of Southern Italy.

The province of Pescara has been selected as a case study for three main reasons. First, it is situated in Southern Italy, a region that has experienced significant changes in urban settlement patterns over the past few decades (Romano and Zullo 2014). Second, Pescara represents an example of an urban agglomeration in the Mediterranean shaped by rural-to-coastal migration (OECD 2012). Finally, the city has experienced recent growth motivated by a dynamic housing market compared to the rest of a mainly rural region of Abruzzo (Montanari and Staniscia 2013; Compagnucci and Morettini 2024).[2] Data on residents from three ethnic groups are drawn from the 2011 Italian Statistical Institute (ISTAT) census for localities, which provides a more granular geographical level compared to municipalities. Spatial units are classified as urban or inner areas according to the OECD (2012) definition of Functional Urban Area (FUA).

We recognise that segregation is characterised by multiple dimensions (Massey and Denton 1988) and focus on evenness and exposure as these are the most examined dimensions in applied studies (Kramer and Hogue 2009). For statistical inference of all indices we use random permutation approaches, following approaches in previous successful applications (Feitosa et al. 2007; Tivadar 2019). Finally, we address spatial level-related issues associated with the Modifiable Areal Unit Problem (MAUP) by calculating indices for municipalities.

Our findings emphasise the relevance of including spatial indicators into segregation studies in the Mediterranean and Southern Europe. An approach that considers spatial patterns and urban/rural differences could offer policymakers more accurate insights. This is especially relevant for the Mediterranean areas in Italy, where growth of the urban population and migration waves highlight the need for effective integration policies (Ciommi et al. 2022).

The remainder of this paper is structured as follows. Section 2 presents an overview of migration, segregation, and spatial effects in the Mediterranean region. Section 3 describes the methodologies and data used. Section 4 presents the empirical application. Section 5 discusses policy implications regarding the relationship between segregation and spatial justice. Section 6 concludes the paper.

2 | Migration, Segregation, and Spatial Effects in the Mediterranean

Immigration has emerged as a recent trend in many regions of Southern Europe, especially along the Mediterranean coast, because of the economic growth experienced in the late twentieth century and the early 2000s. Migration to Italy, Spain, and Greece was paired with a phase of economic transition, during which foreign workers became an essential part of the labour market. In this context, migration appears as a distinct phenomenon compared to the patterns observed in the United States. Factors such as intraregional mobility, rapid changes in the labour market, and the cyclical shifts of employment and unemployment make migration to Southern Europe challenging to predict (King 2000).

Migration into Mediterranean regions has been closely related to the growth of their urban centres. Panori et al. (2019) highlight that incoming migrants face an unstable environment, where several developmental and transition processes are under way. The authors observe that it is difficult applying Western urban models to explain the segregation processes in Mediterranean regions. Viñuela et al. (2019) note that migrants choose to live in densely inhabited regions in Spain's coastal areas. However, they usually tend to settle in areas on the outskirts of main cities. This evidence is linked to the growth of the service sector and the progressive expansion of areas devoted to tourism in the Mediterranean (see for Sardinia, Costantino et al. 2021). Hence, migrants select regions where agglomerations are strong, and the number of businesses is high. In Italy, these regions are typically located along the coasts. Salvati (2022) stresses how the growth of urban areas in Southern Europe is a 'mosaic' of different economic impulses. During periods of economic expansion, urban agglomeration in cities was particularly strong, combining lack of urban planning and progressive gentrification. In this scenario, rural outskirts has started to represent a viable solution for many migrants.

These factors contribute to segregation in Southern Italy, which can be seen as the result of various interconnected forces. The expansion of the service sector attracts incoming populations by offering job opportunities, yet it also creates pockets of inequality within urban enclaves. At the same time, some foreign-born individuals choose to settle outside cities, due to factors such as lower housing costs and reduced congestion. Additionally, some migrants move directly to rural areas to meet labour demands in seasonal agriculture (King et al. 2021). These processes suggest the need to examine spatial patterns in both urban centres and rural outskirts, which remain relatively understudied (Tintori et al. 2018). A deeper understanding of these patterns could lead to more accurate segregation analyses in the Mediterranean region and assist policymakers in preventing unintentional segregation in specific neighbourhoods or areas.

The analysis of segregation has traditionally focused on measuring the distribution of foreign residents within a given area. One of the most common methods is Duncan's dissimilarity index, which captures the extent to which two groups are evenly distributed across different neighbourhoods (Duncan and Duncan 1955). However, as Massey and Denton (1988) point out, segregation is a multidimensional phenomenon that goes beyond the concept of evenness. It also involves exposure, which reflects the chances of possible contacts between majority and minority groups. Another dimension is concentration, which refers to the amount of physical space occupied by a minority group. Centralisation measures how close minority groups are to the city centre, while clustering indicates how likely minority-inhabited areas tend to be located next to one another.

White (1983) emphasises that standard indices of dissimilarity suffer from the checkerboard problem. Wong (1993) observes that a large part of the literature relies on standard segregation measures that do not adequately consider territorial patterns. More recently, Brown and Chung (2006) have pointed out that the analysis of spatial dynamics and the socioeconomic aspects of urban settlements are crucial for assessing segregation.

In response to these challenges, spatial alternatives have been introduced to measure segregation (Reardon and O'Sullivan 2004; Feitosa et al. 2007). Reardon and Firebaugh (2002) propose new criteria to better account for the spatial distribution of minority populations in segregation indices, based on the framework established by James and Taeuber (1985). To this aim, spatial indicators that respect the conditions of scale interpretability and arbitrary boundary independence are defined for evenness and exposure concepts.

Another issue in the spatial analysis of segregation is the differences between urban and rural areas, particularly the urban-rural divide. Most studies on segregation focus on cities, often neglecting the dynamics occurring beyond metropolitan boundaries. As Lichter et al. (2021) argue, extending the analysis to rural and peri-urban areas can offer a more comprehensive understanding of local segregation patterns. Factors such as the job market and housing prices, for instance, drive migration to the outskirts, especially in Southern Italy. Although the spatial dimension is acknowledged as crucial for understanding segregation in the Mediterranean context, few studies explicitly address spatial effects (Benassi et al. 2020b). In this sense, adopting a spatial perspective, both conceptually and methodologically, could improve policy decisions on key social issues.

In this paper, we refer to spatial effects as typical features of geographically observed data. Two spatial effects are recognised in the analysis of spatial data (Anselin 1995). Spatial dependence (in its weakest form, spatial autocorrelation) refers to the propensity of nearby locations to exhibit similar attributes. Spatial heterogeneity, on the other hand, describes the lack of stability in the statistical parameters over different geographic areas.

Accounting for spatial dependence in the distribution of minorities allows us to discuss the role of spatial patterns in segregation (Reardon and O'Sullivan 2004). This capability is not provided by using standard indices. In addition, it is crucial to consider spatial variation in the segregation figures (Barros and Feitosa 2018). In the presence of an urban/rural divide, spatial heterogeneity offers a valid conceptual framework to account for the variations between urban and rural areas in empirical analyses.

In this paper, we apply spatial measures proposed by Feitosa et al. (2007), testing the statistical significance of both the spatial evenness and spatial exposure indices. We consider the heterogeneity between urban and rural groups of localities to identify underlying patterns of segregation. Finally, we perform an exploratory spatial data analysis to investigate the potential relationships between specific socioeconomic variables and segregation.

3 | Data and Methods

3.1 | Standard Indicators of Segregation

The D index of dissimilarity is widely used to analyse residential segregation (Fossett 2017). In region R, for $j, k = 1, \ldots, M$ population groups, the dissimilarity index D can be expressed as (Duncan and Duncan 1955):

$$D = \frac{1}{2}\sum_{i=1}^{N}\left|\frac{t_{ij}}{T_j} - \frac{t_{ik}}{T_k}\right|, \quad (1)$$

where t_{ij} and t_{ik} are the population of the two groups j and k in each spatial unit $i = 1, \ldots, N,\ i \in R$, with $k \neq j$, T_j and T_k are the total population of two different groups. Here, j indicates the majority group, while the other index refers to any ethnic minority of interest.

Theoretically, Duncan's D ranges from zero to one, where $D = 0$ indicates complete integration, meaning both groups are distributed in the same proportion across all spatial units considered (i.e., evenness). Conversely, $D = 1$ indicates total segregation, where each area i is populated by members of only one group. Duncan's D is typically interpreted as the percentage of minorities that would need to be relocated to achieve a perfectly balanced distribution.

However, as noted by Cortese et al. (1976) and Fossett (2017), evenness (i.e., $D = 0$) may be difficult to achieve in real scenarios. This issue often occurs when the share of the minority is significantly unbalanced (i.e., the number of minority members T_k is quite low) and the number of spatial units under study (i.e., N) is large. Consequently, the concept of evenness, in contrast to full segregation, may not be appropriate and should be replaced with the more appropriate concept of randomness.

Based on this rationale and following Boisso et al. (1994), we use an approximate randomisation test to make inferences on index D, under the null hypothesis of the random allocation of minorities. The underlying idea is that random allocation leads to substantial unevenness when units or minority shares are small (Carrington and Troske 1997).

In this case, due to more recent waves of migration, the overall number of minority members could be low throughout the localities. This is not only evident when all residents from the minorities are considered together, but especially when those are considered separately.

To build the test, individuals in the original data (both majority and minorities) are randomly reallocated among the spatial units without replacement, and the population size of the localities is maintained constant (Tivadar 2019). The procedure is iteratively performed 9999 times to obtain multiple combinations. Duncan's D is calculated at each iteration, obtaining an empirical distribution under the null hypothesis of randomness. The rank of the original value of D is, then, observed in the empirical distribution and a pseudo p-value is computed as one minus its relative rank in the reference distribution. This p-value can be interpreted as the statistical significance of the segregation index under the randomness hypothesis (Rey 2004).

Furthermore, as Lieberson (1981) and Massey and Denton (1988) point out, dissimilarity indices focus only on the evenness dimension. It is also useful to consider the exposure dimension to estimate the probability of possible interactions between groups to promote broader social integration. To this purpose, indicators have been defined to measure exposure/isolation (Bell 1954; Lieberson and Carter 1982).

The exposure index measures the chance that a member of one group is exposed to any member of other groups, and is calculated as:

$$_{j}P_k = \sum_{i=1}^{N}\frac{t_{ij}}{T_j}\cdot\frac{t_{ik}}{T_i}\ . \quad (2)$$

The index in (2) is interpreted as the probability that a random person from group j may have a potential contact with a member of group $k \neq j$ in area i, and its value is bounded between zero and one. This index is based on two assumptions: contacts occur only between people of the same area, and every person has an equal chance of meeting any other person in the spatial unit i. Deviations from these assumptions would generally favour higher within-group contacts rather than between-groups, as connections are more likely to occur between people of the same ethnicity. Therefore, the index in (2) does not measure the “actual” interactions but rather produces a measure of the potential contacts between different ethnic groups (Bell 1954).

Conversely, the isolation index indicates the probability that a person from a group will be in contact with others from the same group, as:

$$_{j}P_j = \sum_{i=1}^{N}\frac{t_{ij}}{T_j}\cdot\frac{t_{ij}}{T_i}\ . \quad (3)$$

Inference for both the exposure and isolation indices is carried out using the randomisation method outlined for Duncan's D in this paper (Tivadar 2019).

Traditional segregation indices have major limitations in the analysis of geographically distributed data. As noted by Wong (1993), different population permutations between spatial units can provide the same figures as standard indices of segregation. In other words, these measures fail to capture any geographical information, making the results insensitive to the distribution of ethnicities. Wong (2016) suggests that new approaches should be adopted to incorporate spatial information into segregation measures when the distribution of ethnicities is influenced by spatial autocorrelation. In addition, average segregation measures can hide significant heterogeneity (Lichter et al. 2021) and instabilities between urban and rural areas.

In essence, traditional measures of segregation have left many problems related to the presence of spatial effects, spatial dependence and spatial heterogeneity, unresolved. For these reasons, in the next section we reconsider spatial indicators of segregation to complement standard indicators in the presence of spatially dependent data and introduce an exogenous partition to address spatial heterogeneity.

3.2 | Spatial Indicators of Segregation

We now move a step ahead in the analysis by considering spatially augmented measures of residential segregation. Morrill (1991) summarises several strategies for incorporating spatial interactions into Duncan's D and addressing the checkerboard problem. He builds on White (1983) idea of accounting for the disproportions of minorities in neighbouring cells, in which adjacency is based on a geographical proximity matrix. These versions of the D index aim to capture spatial autocorrelation based on the definition of an exogenous proximity matrix (Getis 1991; Rey and Folch 2011). Wong (1993, 1998) proposes improvements to this strategy accounting for polygon characteristics and multi-ethnic populations.

Reardon and O'Sullivan (2004) build on the idea of incorporating spatial interactions into indicators of dissimilarity and exposure. Their method produces segregation metrics based on the "population density of the local environment", which is calculated as the weighted average of the population densities in the study area (Reardon and O'Sullivan 2004, p. 129). The approach aims to measure segregation within a continuous geographical space by using weights obtained from a distance-decay kernel functions and therefore accounting for potential connections of ethnic groups in the local environment of i.

Feitosa et al. (2007) argue that the use of the local population intensity may be more appropriate for building spatial indicators in urban areas than using the population density in the local environment. They introduce spatial segregation measures conceptually similar to those introduced by Reardon and O'Sullivan but based on local population intensity - a subset of the concept of population count introduced by Wong (1998, 2005). The local population count is calculated as the weighted average of population counts at each location, with weights determined by a distance decay kernel function that accounts for the geographical distance between the centroids of spatial units. These centroids serve as reference points for each spatial unit within the analysed region. Furthermore, as noted by Wong (2005), segregation measures based on population count are always bounded between zero and one, ensuring a clear and interpretable range, similar to their corresponding aspatial versions.

According to this narrative, we decide to use the indicators proposed by Feitosa et al. (2007). The local population intensity is defined as the population of group j in the local environment of unit i as:

$$\tilde{t}_{ij} = \sum_{l=1}^{N} k_{il} t_{lj}, \tag{4}$$

where t_{lj} is the population of group j in area l, k_{il} are the weights generated by a Gaussian kernel function defined as:

$$k_{il} = \exp\left(-\frac{1}{2}\left(\frac{d_{li}}{\gamma}\right)^2\right). \tag{5}$$

The weights k_{il} are based on the geographical distance d_{li} between two units l and i, and γ is the bandwidth. The kernel function is defined in such a way that as the geographical distance d_{li} increases, k_{li} decreases. Conversely, when d_{li} is small, k_{li} increases. In the special case where $d_{ii} = 0$ (i.e., the point of interest coincides with the data point) $k_{ii} = 1$. This class of measures is robust to the choice of kernel, which can take forms other than Gaussian. However, careful attention should be given to the selection of bandwidth (O'Sullivan and Wong 2007).

Now, we define the local proportion of group j in locality i as:

$$\tilde{\tau}_{ij} = \frac{\tilde{t}_{ij}}{\tilde{t}_i}, \tag{6}$$

where $\tilde{t}_i$ is the all-groups population for the local environment of i according to the same kernel as in (5). Finally, we define the spatial version of the dissimilarity index according to Feitosa et al. (2007) as:

$$\tilde{D} = \sum_{i=1}^{N} \sum_{j=1}^{M} \frac{T_i}{2TI} |\tilde{\tau}_{ij} - \tau_j|, \tag{7}$$

where $\tilde{\tau}_{ij}$ is the ratio calculated as in (6), T_i is the total population in unit i, τ_j is the proportion of population for each group $j = 1 \dots M$, T is the total population and $I = \sum_{j=1}^{M} (\tau_j)(1 - \tau_j)$.

This indicator differs from the aspatial case in two features. First, the proportion of minorities is not merely computed for a single area but also considers the effects in the local environment. Second, the $\tilde{D}$ should be interpreted as the extent to which the intensity of the groups in local environments differs from the intensity in the overall area.

The spatial version of the exposure and isolation indices is also based on the concept of local environment. The spatial exposure index can be defined as:

$${}_j\tilde{P}_k = \sum_{i=1}^{N} \frac{t_{ij}}{T_j} \tilde{\tau}_{ik}, \tag{8}$$

where $\tilde{\tau}_{ik}$ is the local population intensity of other groups $k \neq j$ calculated on the local environment of i, t_{ij} is the population of group j in location i, and T_j is the total population of group j in the whole area R. Similarly, spatial isolation can be written as:

$${}_j\tilde{P}_j = \sum_{i=1}^{N} \frac{t_{ij}}{T_j} \tilde{\tau}_{ij}, \tag{9}$$

where $\tilde{\tau}_{ij}$ is local population intensity of group j calculated in the local environment of i.

For spatial indices of segregation, it is extremely important to test the statistical significance of the results against randomness. This helps to verify whether the obtained results are simply a consequence of an equally probable allocation of individuals or if they are linked to the actual presence of spatial patterns of segregation in the data (Rey and Folch 2011; Yao et al. 2019).

To test the statistical significance of spatial indicators for evenness and exposure dimensions, we propose implementing statistical inference following the same rationale as Feitosa et al. (2007) and Panzera et al. (2022). The proposed methodology can be summarised in four steps:

1. Individuals for the majority and each of the minority groups are randomly reassigned to different units $i = 1, \ldots, N$, while keeping the population size of each spatial unit T_i fixed to that observed in the real data.
2. We consider a large number of such permutations (ideally 9,999) and, for each of these configurations, we calculate the segregation indices (7, 8), and (9).
3. The 9,999 values of the segregation indices obtained in Step 2 are used to obtain a computationally based distribution.
4. Given the null hypothesis that each pattern is equally likely, the true value of the index is added to the computationally based distribution, and a pseudo p-value level is calculated using the position of the actual value in the obtained ranked distribution.

We apply the proposed statistical methodology to the entire region and test the spatial indicators of segregation both when all the minorities are considered as one group and when they are considered in different subgroups. Finally, spatial measures are tested for urban and rural partitions.

3.3 | Data and Region Under Study

The empirical evidence is based on official data from the ISTAT population Census of 2011.[3] The analysis focuses on 434 localities in the province of Pescara (Italy). According to ISTAT, localities are an intermediate geographic level between municipalities and census tracts. They are defined as '*more or less extended areas where inhabited houses are situated*'. In the case of Italy, the concept of locality can be used for capturing within-municipality differences, distinguishing between densely inhabited areas and less urbanised locations.

To consider urban-rural differences, we adopt the OECD definition of FUAs. In this context, the localities in the municipalities of Francavilla al Mare and San Giovanni Teatino municipalities (which belong to another contiguous province), are included alongside the other municipalities in the province of Pescara. The OECD classification is used as a reliable source to classify the region under investigation into urban and rural localities of the inner area (Benassi et al. 2020a). The localities outside the FUA consist primarily of former rural towns, partly inhabited by foreign people seeking affordable housing at commutable distances from the main city. Among the 434 localities in the region, 70 belong to the urban category, while 364 are in the rural group.

Finally, we analyse data of municipalities for the 2011 population census to verify whether the MAUP affects the analysis of segregation at different levels of the administrative hierarchy.

4 | Results

As of 2011, there are 15,055 foreigners in the study area, representing 4.29% of the total population of 351,210 residents. The geographical distribution of foreign resident shares at the locality level over the study area is depicted in Figure 1, along with a map of the province.

For all maps, we use the 'natural breaks' algorithm suggested by Anselin et al. (2022). This algorithm classifies the target variable in a given number of intervals such that the within-group variance is minimised. In our case, we obtain four intervals for the distribution of each minority group's share, and the intervals are reported in the maps' legends. This choice is made because the natural breaks criterion is more effective in grouping extreme observations.

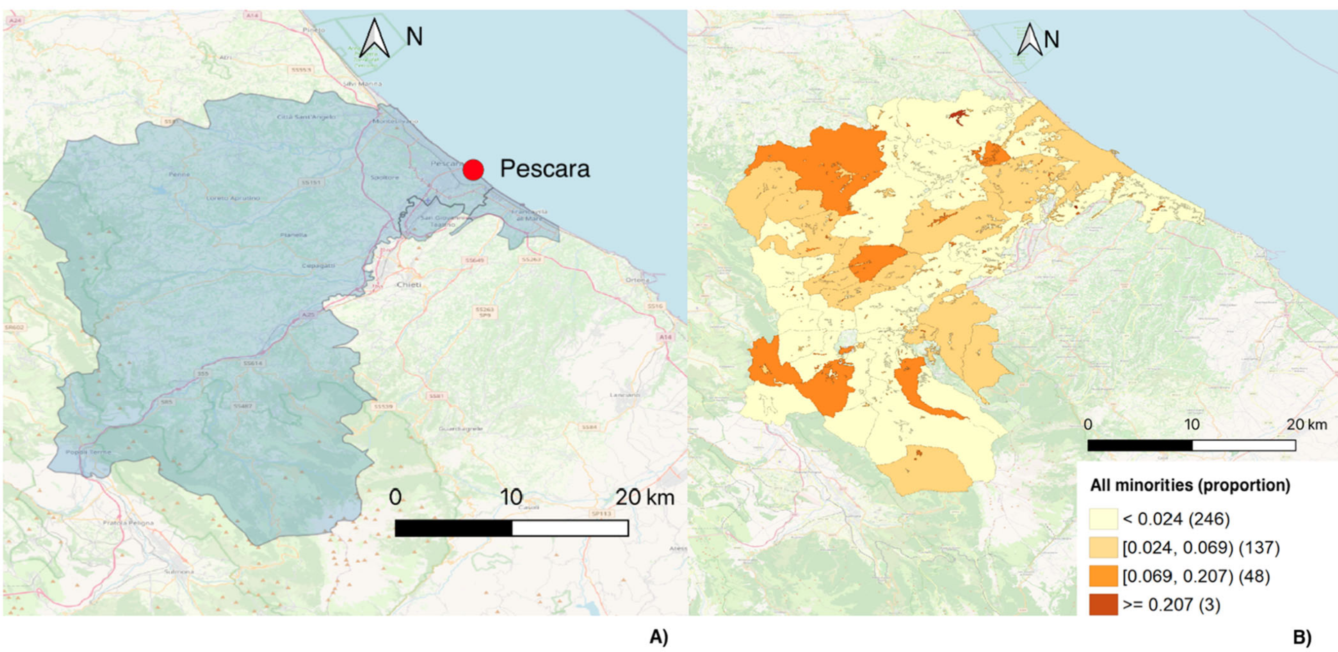

FIGURE 1 | Map of the province of Pescara as of 2011 (A) and geographical distribution of the proportions of resident population from all minorities (B).

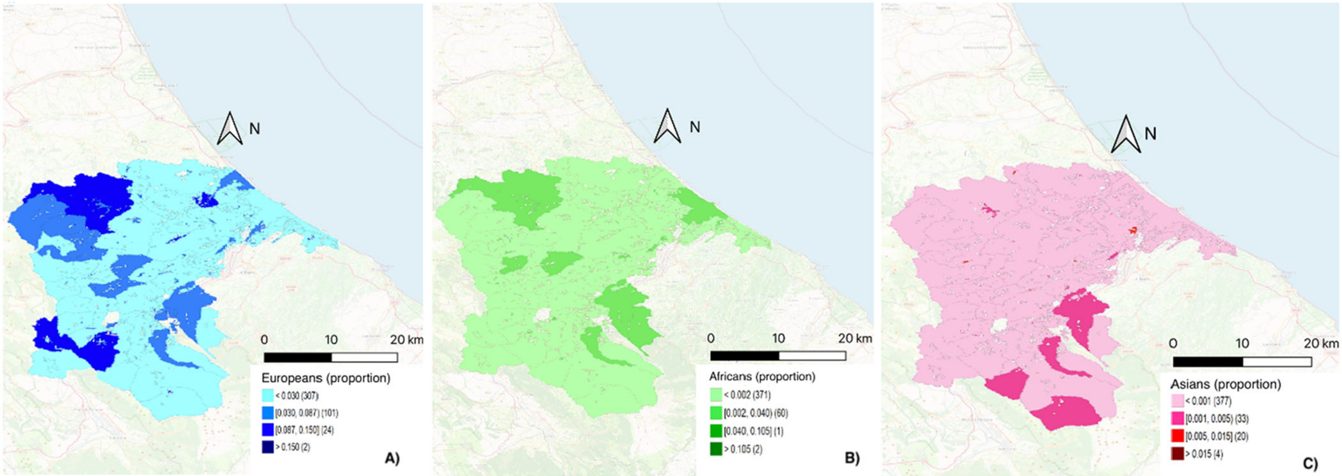

FIGURE 2 | Geographical distribution of the proportions of resident population from Europe (A), Africa (B), and Asia (C) in Pescara province.

TABLE 1 | Duncan's D dissimilarity indices and spatial $\tilde{D}$ for all minorities and different groups by origin across 434 localities in Pescara province.

	All minorities	Europeans	Africans	Asians
D	0.1966 (0.000)	0.2144 (0.000)	0.3387 (0.000)	0.3337 (0.000)
$\tilde{D}$	0.1406 (0.000)	0.1289 (0.000)	0.2104 (0.000)	0.3209 (0.000)

Note: p values in brackets.

With regard to specific origin, 3.11% of residents come from other European countries (10,922 residents), while 0.50% (1756 residents) and 0.40% (1405 residents) come from African and Asian countries. The areas with the greatest presence of foreign residents are along the Pescara River and the *Vestina* area (North). The spatial distributions of these different origins are presented in Figure 2.

A comparison of the maps in Figure 2 indicates that certain groups tend to form local pockets of higher density. For instance, the areas with the highest concentration of migrants from African countries are *Vestina* and the surrounding areas of Pescara, while Asian migrants are in a larger proportion in the southwest.

The level of residential segregation for the whole foreign population (i.e., all minorities considered as one group) and for different origins is measured by Duncan's D (see equation (1)) and reported in Table 1. The D value for the entire foreign population is 0.1966, indicating a low level of segregation. Migrants from Europe exhibit lower levels of segregation ($D = 0.2144$), while the D values increase for Africans ($D = 0.3387$) and Asians ($D = 0.3337$). These values are statistically significant against the null hypothesis of randomness, evidencing the presence of systemic segregation in the area under investigation.

Table 1 also reports the spatial dissimilarity index $\tilde{D}$. The optimal bandwidth for the kernel function is obtained following O'Sullivan and Wong (2007) and using the average nearest neighbour as a rule to determine the bandwidth. Moreover, as O'Sullivan and Wong (2007) and Östh et al. (2015) suggested, the number of nearest neighbours can be established considering the population size. In this analysis, we set the number of nearest neighbours to 12, which allows us to consider a sufficient population threshold of 10,000 people. This choice corresponds to a bandwidth of 2000 m, which is used in the kernel function. All spatial dissimilarity indices are statistically significant, highlighting that spatial interactions must be considered when analysing segregation in the area.

Results for the $\tilde{D}$ index are lower when compared to their standard (aspatial) alternatives. This result is in line with previous applications. The $\tilde{D}$ is a measure of dissimilarity that incorporates interactions between closer localities and its value depend on the potential interactions through boundaries. Therefore, the $\tilde{D}$ index produces lower values compared to the standard D index, proportionally to the greater concentration of the majority group in localities adjacent to those inhabited by ethnic minorities.

Another useful interpretation can be offered from the simulation study by Feitosa et al. (2007). They find that the spatial dissimilarity index reaches 86% of Duncan's D in the case of strong spatial patterns, while it reaches around 5% when spatial dependence is not significant. This measure helps in distinguishing cases with strong spatial autocorrelation from others in which this issue is absent or not as important. In our study, the value of spatial dissimilarity index for all minorities is 0.1240. When compared with the a-spatial values, the spatial dissimilarity reaches approximately 63% of the aspatial Duncan's D value. In the analysis of single ethnicities, it is relevant to note how spatial measures $\tilde{D}$ represent a higher percentage of the D, especially for Asian migrants.

TABLE 2 | Exposure (off-diagonals) and isolation (main diagonal) indices for 434 localities in Pescara province using aspatial and spatial indices.

		Italians	Europeans	Africans	Asians
Exposure	Italians	0.9602 (0.452)	0.0308 (0.000)	0.0050 (0.500)	0.0040 (0.500)
	Europeans	0.9494 (0.000)	0.0402 (0.000)	0.0061 (0.000)	0.0043 (0.000)
	Africa	0.9466 (0.000)	0.0377 (0.000)	0.0102 (0.000)	0.0056 (0.000)
	Asia	0.9535 (0.000)	0.0331 (0.000)	0.0069 (0.000)	0.0064 (0.000)
Spatial Exposure	Italians	0.9650 (0.047)	0.0295 (0.183)	0.0038 (0.023)	0.0018 (0.000)
	Europeans	0.9661 (0.002)	0.0288 (0.305)	0.0034 (0.002)	0.0016 (0.000)
	Africa	0.9692 (0.000)	0.0260 (0.047)	0.0033 (0.000)	0.0015 (0.000)
	Asia	0.9688 (0.000)	0.0264 (0.136)	0.0036 (0.000)	0.0012 (0.000)

Note: p values in brackets.

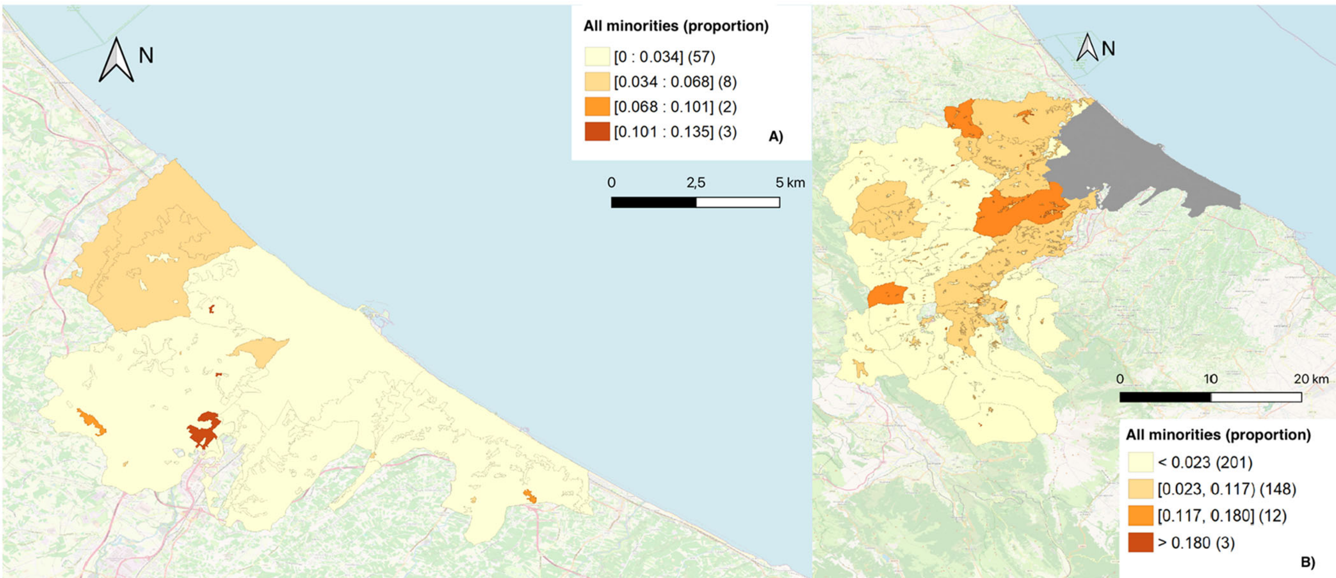

FIGURE 3 | Geographical distribution of the proportions of resident population from all minorities in the urban area (A) and rural area (B) of Pescara province.

We now examine exposure in both the aspatial and spatial versions presented in Table 2 for the entire region. Notably, the spatial isolation indices for minorities, as well as the spatial exposure to minority groups, tend to be lower. In contrast, the spatial exposure of minorities to Italians is higher, reflecting the status of Italians as the majority group. This pattern aligns with Feitosa et al. (2007), who show that spatial isolation indices tend to decrease when minority areas are surrounded by neighbourhoods predominantly inhabited by the majority group. Therefore, adopting spatial measures that account for interactions between adjacent units usually increases the chance for minorities with the ethnic majority.

To investigate how residential segregation varies, we now classify localities into rural and urban groups according to the FUA definition. The urban area comprises 70 localities (about 63% of the overall population), while rural areas include 364 localities (37% of the overall population). Figure 3a presents the distribution of urban areas based on the share of foreign residents. Figure 3b shows the same data for the rural group. All maps are constructed using the natural breaks criterion.

Foreign residents account for 4.35% of the total population in urban areas and 4.18% in inner areas. Figure 4 shows the geographical distribution of various ethnic groups in urban and rural areas.

The incidence of Europeans is higher along the coast, while individuals of African or Asian origin are more concentrated in the northeast. In the rural areas, the presence of residents from other European countries is more visible near the border with the urban area of Pescara, while African and Asian communities are more notable in Alanno (centre), Moscufo, and Picciano (north).

Duncan's D and spatial $\tilde{D}$ indices for both zones, as well as for all ethnic groups, are shown in Table 3. There are some differences in the values of the indices for the two groups. In the urban area of Pescara, residential segregation is relatively low, whereas the African group exhibits higher values. Conversely, segregation increases in rural areas, where the values of the aspatial indices for African and Asiatic groups are higher.

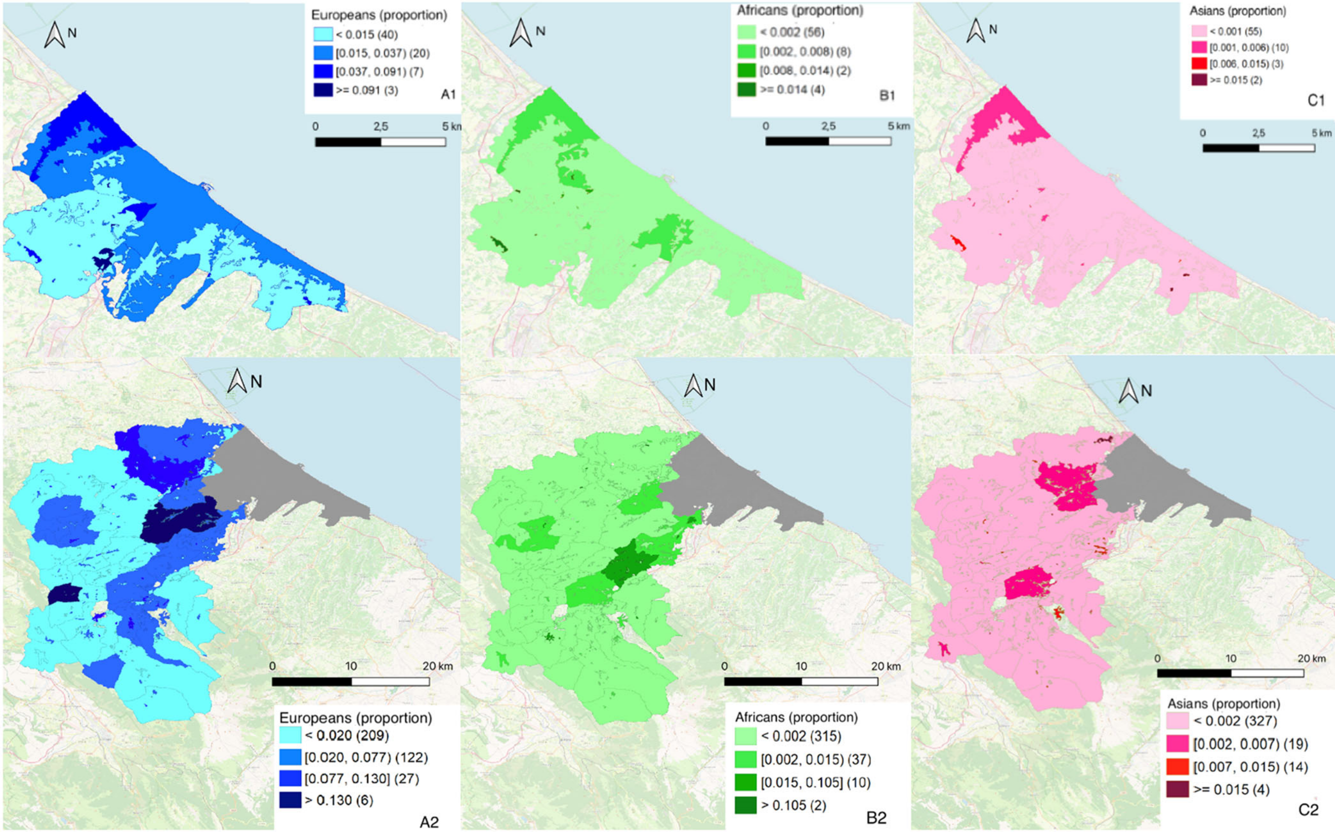

FIGURE 4 | Geographical distribution of the proportions of resident population from Europe (A), Africa (B), and Asia (C) in the urban (top) and rural (bottom) areas of Pescara province.

TABLE 3 | Duncan's D dissimilarity and spatial $\tilde{D}$ calculated for urban (70 localities) and rural (364 localities) groups in Pescara province for all minorities and different groups by origin.

		All minorities	Europeans	Africans	Asians
Urban area	D	0.1722 (0.000)	0.1853 (0.000)	0.2947 (0.000)	0.1706 (0.000)
	$\tilde{D}$	0.1194 (0.000)	0.1124 (0.000)	0.1538 (0.000)	0.1798 (0.000)
Rural area	D	0.2431 (0.000)	0.2489 (0.000)	0.5036 (0.000)	0.5620 (0.000)
	$\tilde{D}$	0.1026 (0.000)	0.1024 (0.000)	0.3290 (0.000)	0.3138 (0.000)

Note: p values in brackets.

The spatial indices are statistically significant over the two different areas. A Gaussian kernel is used and ad hoc optimal bandwidths for both the urban (1800 m) and rural (2100 m) groups are calculated following the suggestions of O'Sullivan and Wong (2007). Interestingly, when comparing the spatial indices with their corresponding aspatial versions, it is clear that the ratio between $\tilde{D}$ and D in the urban area is noticeably higher than in the rural area.

Exposure indices for the two zones are reported in Tables 4 and 5. Statistical significance is verified for almost all value, especially in urban areas. In rural areas, however, the spatial exposure of minorities to Italians is not significant. This is again consistent with the interpretation that when the probability of a minority member meeting Italians increases, the spatial indices tend to be lower compared to the aspatial counterparts.

We also check for the impacts of changes at the geographical level by analysing the municipalities. Table 6 shows the results for the D and $\tilde{D}$ indices at the municipal level. When considering the 46 municipalities instead of localities, we obtain lower D values. The shift is more evident for the spatial dissimilarity indices, indicating a loss of information that could potentially lead to misleading policy decisions.

Many studies indicate that segregation is better identified at a finer geographical level (Jones et al. 2018). This is particularly true in the Mediterranean context, where urban areas coexist with surrounding, more rural towns (Benassi et al. 2020a). In this situation, considering a finer spatial level of analysis allows to uncover local patterns and small minority pockets that might be ignored with a higher definition of analysis (Saabneh 2022).

TABLE 4 | Exposure (off-diagonals) and isolation (main diagonal) indices for the urban group (70 localities) in Pescara province using aspatial and spatial indices.

		Italians	Europeans	Africans	Asians
Exposure	Italians	0.9597 (0.211)	0.0294 (0.000)	0.0058 (0.000)	0.0051 (0.000)
	Europeans	0.9525 (0.000)	0.0348 (0.000)	0.0073 (0.000)	0.0055 (0.000)
	Africa	0.9479 (0.000)	0.0368 (0.000)	0.0091 (0.000)	0.0062 (0.000)
	Asia	0.9552 (0.000)	0.0317 (0.005)	0.0071 (0.000)	0.0060 (0.000)
Spatial Exposure	Italians	0.9698 (0.000)	0.0229 (0.000)	0.0040 (0.000)	0.0033 (0.000)
	Europeans	0.9702 (0.000)	0.0226 (0.000)	0.0038 (0.000)	0.0034 (0.001)
	Africa	0.9705 (0.000)	0.0224 (0.000)	0.0037 (0.000)	0.0034 (0.001)
	Asia	0.9703 (0.000)	0.0227 (0.000)	0.0039 (0.000)	0.0031 (0.000)

Note: p values in brackets.

TABLE 5 | Exposure (off-diagonals) and isolation (main diagonal) indices for rural group (364 localities) in Pescara province using both aspatial and spatial indices.

		Italians	Europeans	Africans	Asians
Exposure	Italians	0.9610 (0.004)	0.0333 (0.000)	0.0035 (0.000)	0.0022 (0.000)
	Europeans	0.9446 (0.000)	0.0486 (0.000)	0.0042 (0.000)	0.0026 (0.000)
	Africa	0.9427 (0.000)	0.0403 (0.000)	0.0132 (0.000)	0.0038 (0.123)
	Asia	0.9467 (0.000)	0.0391 (0.000)	0.0061 (0.000)	0.0081 (0.002)
Spatial exposure	Italians	0.9597 (0.396)	0.0345 (0.000)	0.0035 (0.000)	0.0023 (0.000)
	Europeans	0.9602 (0.165)	0.0341 (0.000)	0.0034 (0.000)	0.0023 (0.000)
	Africa	0.9597 (0.377)	0.0338 (0.000)	0.0040 (0.000)	0.0025 (0.000)
	Asia	0.9575 (0.000)	0.0363 (0.000)	0.0038 (0.000)	0.0024 (0.000)

Note: p values in brackets.

TABLE 6 | Duncan's D and spatial dissimilarity indices for the 46 municipalities in Pescara province, calculated for all minorities and different groups by origin.

	All minorities	Europeans	Africans	Asians
D	0.1538 (0.000)	0.1589 (0.000)	0.2931 (0.000)	0.2933 (0.000)
$\tilde{D}$	0.0511 (0.000)	0.0521 (0.000)	0.0923 (0.000)	0.1025 (0.000)

Note: p values in brackets.

The segregation figures observed in Pescara are relatively low when compared to larger Mediterranean cities, like Athens or Palermo (Busetta et al. 2015). For the exposure dimension, our results are in line with those of other Italian cities, such as Milan (Rimoldi and Terzera 2017).

5 | Discussion

The results obtained for the province of Pescara suggest that the geographical distribution of the data is relevant for a deeper analysis of segregation in Southern Italy. Based on these results, we identify three key issues for policymakers to address.

First, our evidence is consistent with the findings of Benassi et al. (2020a) for Italy, suggesting that segregation figures can be lower in FUAs, likely because of the well-functioning job market. However, the spatial patterns in urban areas should also be considered, due to the fact that the concentration of migrants in one locality can influence the composition of neighbourhoods within a densely inhabited FUA. This is consistent with the findings by Salvati (2022) for Athens, where a lack of planning policies contributes to the presence of spontaneous urban patterns. Patterns of segregation should be interpreted using spatial indicators to inform local planners and improve ethnic integration.

The second aspect pertains to the rural outskirts surrounding urban areas. In this paper, we show that segregation in rural outskirts is higher than in urban localities. This is the result of increasing trends in tourism activities in coastal municipalities and rising living costs in urbanised areas (Montanari and Staniscia 2013; Costantino et al. 2021). Rural localities offer a valid option for incoming households to avoid these problems.

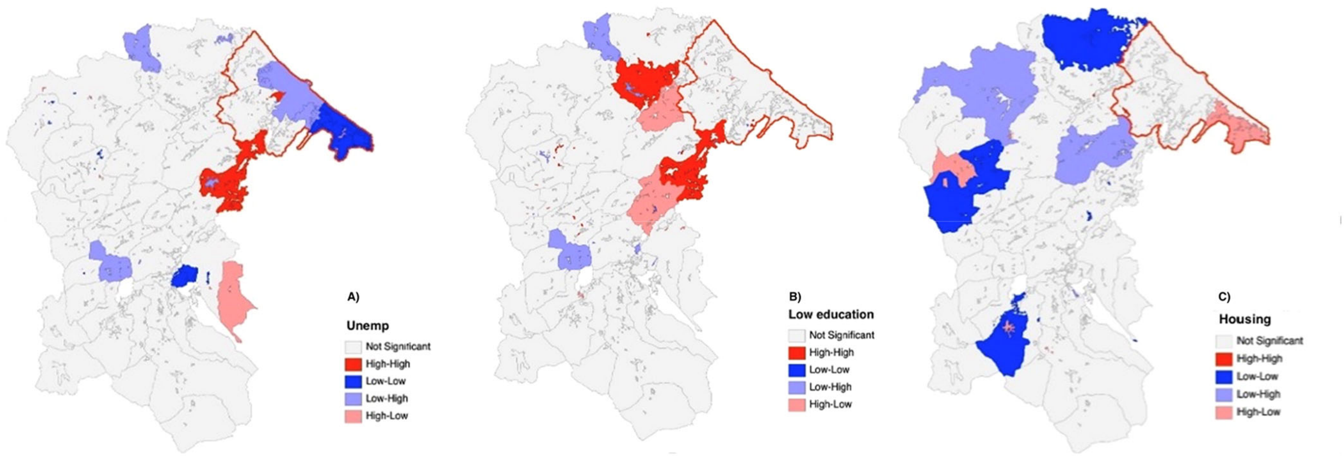

FIGURE 5 | LISA cluster maps for three variables in the Pescara province: unemployment rate (unemp; A), illiteracy rate (low education; B), and the share of recently built houses (housing; C) on the right. The urban cluster perimeter (70 localities) is highlighted in red.

In addition, unemployed migrants can fill seasonal job demands in rural locations, which have been abandoned by the majority of the residents born in Italy. This justifies the need to study rural outskirts in Southern Italy, as in the United States (Lichter et al. 2021), albeit for different reasons.

Finally, the results for rural localities provide insights on the critical isolation of foreign communities, which may be considered as a sign of persistent spatial injustice. Rural outskirts in Southern Italy tend to be heavily underdeveloped compared to urban areas and are experiencing rapid depopulation. This abandonment phenomenon may create space for migrants to live in marginal peripheral areas (Vendemmia et al. 2021; and for Pescara, Compagnucci and Morettini 2024). Investigating and testing the 'rural' segregation of ethnic minorities could help policymakers to prevent weaker groups from being confined to areas of lacking access to opportunities.

In this paper, we also aim to investigate the potential links between the drivers of potential socioeconomic disparities and segregation figures. Several studies (Cousin 2017; Uwayezu & de Vries 2018) underlined the importance of the housing market and housing renewal, education, and the labour market as fundamental elements driving people's development. These factors are considered central in our analysis. We perform an explorative spatial data analysis (Anselin 1995) on variables such as the unemployment rate (unemp), the proportion of individuals without a high school diploma (low education), and the percentage of newly built houses (houses built after 2000, housing). This analysis allows us to individuate clusters of the drivers of spatial justice. We then compare these Local Indicators of Spatial Association (LISA)[4] clusters with segregation indices to observe if they coincide with higher segregation levels in rural localities. Figure 5 displays the LISA cluster maps, with the red line dividing the rural and urban areas. Figure 5a shows the clusters of low values (blue) of the unemployment rate in urban areas, while rural areas exhibit higher levels (red) of unemployment. Figure 5b confirms the potential disadvantages regarding the education dimension in rural areas, where the illiteracy rate is notably high. Regarding the housing variable, Figure 5c shows that rural areas present lower levels of this indicator.

Comparing these patterns with the segregation values provided in Table 3, we observe how segregation in rural areas is closely linked to lower performance of these socioeconomic variables. This situation highlights the need for a proper evaluation of rural segregation in the Mediterranean regions. The specific characteristics of migrant groups in Southern Italy might lead them to settle in disadvantaged rural locations, where chances for improving their socioeconomic conditions are limited.

Policymakers should account for the peculiarities of both urban and rural localities in the Mediterranean to improve a more inclusive mix and prevent minorities to settle in areas of potential disadvantage. As Panori et al. (2019) stressed, cohesive urban development should avoid differentials in opportunities. In this context, consideration of spatial effects can be successful in the analysis of segregation and this study highlights how this is crucial for gaining deeper insights in the Mediterranean.

6 | Conclusions

Residential segregation has been increasingly investigated in the Mediterranean region. In this study, we propose a spatial approach for analysing segregation in the Mediterranean context. To this aim, spatial indices are calculated and tested for evenness and exposure dimensions using a spatial permutation approach. This approach also extends the analysis of spatial heterogeneity in segregation figures, considering rural areas and emptied towns.

Our focus is on Pescara, a province in the Abruzzo region along the Adriatic coast, which has faced significant demographic and urban changes in recent decades.

The results evidence the need for considering spatial effects in the analysis of segregation. In particular, deeper attention to rural areas surrounding the FUA could help policymakers avoid the concentration of minorities into underdeveloped areas where opportunities and services are limited.

Nevertheless, the spatial analysis of segregation in Southern Europe represents an interesting area for further study both from an applied and methodological perspective. Our approach can be adapted to other Mediterranean regions, particularly when considering the peculiarities of the socioeconomic challenges posed by different Italian regions and their peri-urban areas. In addition, future research could improve the methodological framework in segregation by considering spatial dimensions of other evenness measures (Panzera et al. 2022).

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available in ISTAT at https://www4.istat.it/en/population-and-housing-census/population-and-housing-2011.

Endnotes

[1] https://www.eesc.europa.eu/en/news-media/news/eu-needs-pan-european-policy-response-its-housing-crisis

[2] https://www.eib.org/attachments/documents/jessica_abruzzo_en.pdf

[3] https://www4.istat.it/en/population-and-housing-census/population-and-housing-2011.

[4] Local Moran Index is calculated as $I_i = \frac{x_i - \bar{x}}{S_i^2} \sum_{j=1, j \neq i}^{N} w_{ij}(x_j - \bar{x})$, where $\mathbf{W}$ matrix is defined as a k-nearest neighbours with k=12 (Anselin 1995).

References

Anselin, L. 1995. "Local Indicators of Spatial Association—LISA." *Geographical Analysis* 27: 93–115.

Anselin, L., X. Li, and J. Koschinsky. 2022. "GeoDa, From the Desktop to an Ecosystem for Exploring Spatial Data." *Geographical Analysis* 54, no. 3: 439–466.

Arapoglou, V. P. 2012. "Diversity, Inequality and Urban Change." *European Urban and Regional Studies* 19, no. 3: 223–237.

Arbaci, S. 2008. "(Re) Viewing Ethnic Residential Segregation in Southern European Cities: Housing and Urban Regimes as Mechanisms of Marginalisation." *Housing Studies* 23, no. 4: 589–613.

Bailey, N., W. P. C. Van Gent, and S. Musterd. 2017. "Remaking Urban Segregation: Processes of Income Sorting and Neighbourhood Change." *Population, Space and Place* 23, no. 3: e2013.

Barros, J., and F. F. Feitosa. 2018. "Uneven Geographies: Exploring the Sensitivity of Spatial Indices of Residential Segregation." *Environment and Planning B: Urban Analytics and City Science* 45, no. 6: 1073–1089.

Bell, W. 1954. "A Probability Model for the Measurement of Ecological Segregation." *Social Forces* 32: 357–364.

Benassi, F., C. Bonifazi, F. Heins, F. Lipizzi, and S. Strozza. 2020a. "Comparing Residential Segregation of Migrant Populations in Selected European Urban and Metropolitan Areas." *Spatial Demography* 8: 269–290.

Benassi, F., R. Iglesias-Pascual, and L. Salvati. 2020b. "Residential Segregation and Social Diversification: Exploring Spatial Settlement Patterns of Foreign Population In Southern European Cities." *Habitat International* 101: 102200.

Boisso, D., K. Hayes, J. Hirschberg, and J. Silber. 1994. "Occupational Segregation in the Multidimensional Case." *Journal of Econometrics* 61, no. 1: 161–171.

Brown, L. A., and S. Y. Chung. 2006. "Spatial Segregation, Segregation Indices and the Geographical Perspective." *Population, Space and Place* 12, no. 2: 125–143.

Busetta, A., A. Mazza, and M. Stranges. 2015. "Spatial Segregation, Segregation Indices and the Geographical Perspective." *Genus* 71, no. 2-3. https://www.jstor.org/stable/pdf/genus.71.2-3.177.pdf?casa_token=1z2EEwl0daMAAAAA:Eqd_YFt8h04bdNVKnmvUDSigW5pxdeqWu0xMCliRHaDP2iFZMG3_ljKwkh5PQlA1llh7pB7Z9iP7y2MTIbETYBhw0eAHx-UOEGQlw1aqKgItXuSzppU.

Carrington, W. J., and K. R. Troske. 1997. "on Measuring Segregation in Samples With Small Units." *Journal of Business & Economic Statistics* 15, no. 4: 402–409.

Ciommi, M., G. Egidi, I. Vardopoulos, F. M. Chelli, and L. Salvati. 2022. "Toward a 'Migrant Trap'? Local Development, Urban Sustainability, Sociodemographic Inequalities, and the Economic Decline in a Mediterranean Metropolis." *Social Sciences* 12, no. 1: 26.

Compagnucci, F., and G. Morettini. 2024. "Inner Areas Matter: A Place-Sensitive Approach for the Identification of the Daily Life Spaces in the Italian Abruzzo Region." *Socio-Economic Planning Sciences* 93: 101859. https://doi.org/10.1016/j.seps.2024.101859.

Cortese, C. F., R. F. Falk, and J. K. Cohen. 1976. "Further Considerations on the Methodological Analysis of Segregation Indices." *American Sociological Review* 41: 630–637.

Costantino, S., M. F. Cracolici, and D. Piacentino. 2021. "A New Spatial Shift-Share Decomposition: An Application to Tourism Competitiveness in Italian Regions." *Geographical Analysis* 53, no. 4: 708–735.

Cousin, B. 2017. "Refounded Neighbourhoods and Spatial Justice: The Inhabitants' Attitudes Towards Urban Segregation." In *Identity, Justice and Resistance in the Neoliberal City*, edited by G. Erdi and Y. Şentürk, 63–83. Palgrave Macmillan.

Duncan, O. D., and B. Duncan. 1955. "A Methodological Analysis of Segregation Indexes." *American Sociological Review* 20: 210–217.

Feitosa, F. F., G. Câmara, A. M. V. Monteiro, T. Koschitzki, and M. P. S. Silva. 2007. "Global and Local Spatial Indices of Urban Segregation." *International Journal of Geographical Information Science* 21, no. 3: 299–323.

Fossett, M. 2017. *New Methods for Measuring and Analyzing Segregation*. Springer Nature.

Getis, A. 1991. "Spatial Interaction and Spatial Autocorrelation: A Cross Product Approach." *Environment and Planning A: Economy and Space* 23: 1269–1277.

James, D. R., and K. E. Taeuber. 1985. "Measures of Segregation." *Sociological Methodology* 15: 1–32.

Jones, K., D. Manley, R. Johnston, and D. Owen. 2018. "Modelling Residential Segregation as Unevenness and Clustering: A Multilevel Modelling Approach Incorporating Spatial Dependence and Tackling the MAUP." *Environment and Planning B: Urban Analytics and City Science* 45, no. 6: 1122–1141.

King, R. 2000. "Southern Europe in the Changing Global Map of migration." In *Eldorado or Fortress? Migration in Southern Europe*, edited by R. King, G. Lazaridis, and G. Tsardanidis. Palgrave Macmillan UK.

King, R., A. Lulle, and E. Melossi. 2021. "New Perspectives on the Agriculture–Migration Nexus." *Journal of Rural Studies* 85: 52–58.

Kramer, M. R., and C. R. Hogue. 2009. "Is Segregation Bad for Your Health?" *Epidemiologic Reviews* 31, no. 1: 178–194.

Lehman-Frisch, S. 2011. "Segregation, Spatial (in) Justice, and the City." *Berkeley Planning Journal* 24, no. 1: 70–90.

Lichter, D. T., D. L. Brown, and D. Parisi. 2021. "The Rural–Urban Interface: Rural and Small-Town Growth at the Metropolitan Fringe." *Population, Space and Place* 27, no. 3: e2415.

Lieberson, S., and D. K. Carter. 1982. "Temporal Changes and Urban Differences in Residential Segregation: A Reconsideration." *American Journal of Sociology* 88, no. 2: 296–310.

Lieberson, S. 1981. "An Asymmetrical Approach to Segregation." In *Ethnic Segregation in Cities*, edited by C. Peach, V. Robinson, and S. Smith. Croom Helm.

Marcuse, P. (2009). Spatial Justice: Derivative but Causal of Spatial Injustice. *Justice Spatiale/Spatial Justice*, 1.

Massey, D. S., and N. A. Denton. 1988. "The Dimensions of Residential Segregation." *Social Forces* 67, no. 2: 281–315.

Montanari, A., and B. Staniscia. 2013. "An Overview of Territorial Resources and Their Users in the Rome and Chieti-Pescara Areas." In *Sustainability in the Coastal Urban Environment: Thematic Profiles of Resources and their Users*, edited by A. Z. Khan, L. X. Quynh, E. Corijn, and F. Canters, 61–108. Sapienza Università Editrice. https://doi.org/10.7357/DigiLab-l0168.

Morrill, R. L. 1991. "On the Measure of Geographic Segregation." *Geography Research Forum* 11, no. 1: 25–36.

O'Sullivan, D., and D. W. S. Wong. 2007. "A Surface-Based Approach to Measuring Spatial Segregation." *Geographical Analysis* 39, no. 2: 147–168.

OECD. 2012. Redefining "Urban": A New Way to Measure Metropolitan Areas. OECD Publishing. https://doi.org/10.1787/9789264174108-en.

Östh, J., W. A. V. Clark, and B. Malmberg. 2015. "Measuring the Scale of Segregation Using K-Nearest Neighbor Aggregates." *Geographical Analysis* 47, no. 1: 34–49.

Panori, A., Y. Psycharis, and D. Ballas. 2019. "Spatial Segregation and Migration in the City of Athens: Investigating the Evolution of Urban Socio-Spatial Immigrant Structures." *Population, Space and Place* 25, no. 5: e2209.

Panzera, D., A. Cartone, and P. Postiglione. 2022. "New Evidence on Measuring the Geographical Concentration of Economic Activities." *Papers in Regional Science* 101, no. 1: 59–79.

Pratschke, J., and F. Benassi. 2024. "Population Change and Residential Segregation in Italian Small Areas, 2011–2021: An Analysis With New Spatial Units." *Spatial Demography* 12, no. 2: 3.

Reardon, S. F., and G. Firebaugh. 2002. "2. Measures of Multigroup Segregation." *Sociological Methodology* 32, no. 1: 33–67.

Reardon, S. F., and D. O'Sullivan. 2004. "3. Measures of Spatial Segregation." *Sociological Methodology* 34, no. 1: 121–162.

Rey, S. J. (2004). Spatial Analysis of Regional Income Inequality. In *Spatially Integrated Social Science*, edited by M. F. Goodchild, and D. G. Janelle, 280–299.

Rey, S. J., and D. C. Folch. 2011. "Impact of Spatial Effects on Income Segregation Indices." *Computers, Environment and Urban Systems* 35, no. 6: 431–441.

Rimoldi, S. M. L., and L. Terzera. 2017. "Neighbours and Friends? Can Residential Segregation Explain Ethnic Separation? The Case of Milan (Italy)." *Spatial Demography* 5: 193–214.

Romano, B., and F. Zullo. 2014. "The Urban Transformation of Italy's Adriatic Coastal Strip: Fifty Years of Unsustainability." *Land Use Policy* 38: 26–36.

Saabneh, A. 2022. "Health Inequalities Between Palestinians and Jews in Israel: The Role of Extreme Spatial Segregation." *Population, Space and Place* 28, no. 5: e2539.

Salvati, L. 2022. "Seeking (Desperately) for Gentrification? Population Change, Immigration and Economic Recovery in a Mediterranean City." *Population, Space and Place* 28, no. 1: e2502.

Shucksmith, M., E. Brooks, and A. Madanipour. 2021. "LEADER and Spatial Justice." *Sociologia Ruralis* 61, no. 2: 322–343.

Smets, P., and T. Salman. 2016. "The Multi-Layered-Ness of Urban Segregation." *Habitat International* 54: 80–87.

Smith, D. P. 2019. "Population Geography II: The R/Age of Migration." *Progress in Human Geography* 43, no. 4: 729–738.

Smith, D. P., and T. Butler. 2007. "Conceptualising the Sociospatial Diversity of Gentrification: 'To Boldly Go' Into Contemporary Gentrified Spaces, the 'Final Frontier'?" *Environment and Planning A: Economy and Space* 39, no. 1: 2–9.

Soja, E. W. 2013. *Seeking Spatial Justice*. University of Minnesota Press.

Tintori, G., A. Alessandrini, and F. Natale. 2018. *Diversity, Residential Segregation, Concentration of Migrants: A Comparison Across EU Cities*. Publications Office of the European Europe.

Tivadar, M. 2019. "OasisR: An R Package to Bring Some Order to the World of Segregation Measurement." *Journal of Statistical Software* 89: 1–39.

Ulceluse, M., B. Bock, and T. Haartsen. 2022. "A Tale of Three Villages: Local Housing Policies, Well-Being and Encounters Between Residents and Immigrants." *Population, Space and Place* 28, no. 8: e2467.

Uwayezu, E., and W. T. De Vries. 2018. "Indicators for Measuring Spatial Justice and Land Tenure Security for Poor and Low-Income Urban Dwellers." *Land* 7, no. 3: 84.

Vendemmia, B., P. Pucci, and P. Beria. 2021. "An Institutional Periphery in Discussion. Rethinking the Inner Areas in Italy." *Applied Geography* 135: 102537. https://doi.org/10.1016/j.apgeog.2021.102537.

Viñuela, A., D. Gutiérrez Posada, and F. Rubiera Morollón. 2019. "Determinants of Immigrants' Concentration At Local Level in Spain: Why Size and Position Still Matter." *Population, Space and Place* 25, no. 7: e2247.

White, M. J. 1983. "The Measurement of Spatial Segregation." *American Journal of Sociology* 88, no. 5: 1008–1018.

Wong, D. W. 2005. "Formulating a General Spatial Segregation Measure." *Professional Geographer* 57, no. 2: 285–294.

Wong, D. W. 2016. "From Aspatial to Spatial, From Global to Local and Individual: Are we on the Right Track to Spatialize Segregation Measures?" In *Recapturing Space: New Middle-Range Theory in Spatial Demography*, edited by M. Howell, R. J. Porter, and S. A. Matthews, 77–98. Springer International Publishing.

Wong, D. W. S. 1993. "Spatial Indices of Segregation." *Urban Studies* 30, no. 3: 559–572.

Wong, D. W. S. 1998. "Measuring Multiethnic Spatial Segregation." *Urban Geography* 19, no. 1: 77–87.

Yao, J., D. W. S. Wong, N. Bailey, and J. Minton. 2019. "Spatial Segregation Measures: A Methodological Review." *Tijdschrift voor economische en sociale geografie* 110, no. 3: 235–250.

Zambon, I., P. Serra, D. Sauri, M. Carlucci, and L. Salvati. 2017. "Beyond the 'Mediterranean City': Socioeconomic Disparities and Urban Sprawl in Three Southern European Cities." *Geografiska Annaler: Series B, Human Geography* 99, no. 3: 319–337.