

FROM SPATIAL SEGREGATION TO ENVIRONMENTAL INEQUALITIES

The between-group spatial environmental inequalities arise from the fact that social groups are spatially distributed differently relative to an environmental variable (such as natural amenities or environmental hazards). Intuitively, when members of two groups have similar spatial distributions, environmental inequalities should be nonexistent. Thus, segregation and environmental inequalities are phenomena linked by a key variable: space. Despite this strong connection, the number of studies interested in the association between spatial segregation and spatial environmental inequality is small, and a formal demonstration of the links between these phenomena is missing.

Environmental inequalities may occur between individuals (also called vertical inequalities) and between social groups (horizontal or between-group inequalities) (Boyce et al., 2016). In the case of horizontal spatial environmental inequalities, they arise from the fact that social groups are distributed differently in space relative to an environmental variable. There are several studies concerned with horizontal inequalities, considering the uneven distribution of the city's greenery (e.g., Apparicio et al., 2016; Landry and Chakraborty, 2009) or the unequal exposure to urban air pollutants (e.g., Carrier et al., 2014; Sheppard et al., 1999). On a methodological level, analyses are mainly based on between-group comparisons of means or medians, bivariate correlations, and multivariate regressions (Mitchell and Walker, 2005), and no conceptual and mathematical connection is made between spatial segregation and environmental inequalities.

According to Park and Kwan (2017), it was only in the early 21st century that some works tried to understand the association between residential segregation and environmental inequalities, mainly concerning air pollution. Several studies have empirically confirmed that increased segregation tends to be associated with increased racial inequality in exposure to health risks (e.g., Morello-Frosch and Lopez, 2006), but more ambiguous or contradictory results have sometimes been obtained (Downey et al., 2008). More recently, Saporito and Casey (2015) investigated residential segregation and differences in exposure to green space in US metropolitan areas. Findings show that lower-income people and members of minority groups live in neighborhoods with much less vegetation than their wealthier, white counterparts, and these differences are exacerbated in racially and economically segregated cities. Despite their interest, these papers remain empirical, and no formal description of the links between segregation and environmental inequalities has been provided.

In a recent work, Schaeffer and Tivadar (2019) proposed a structured methodology to measure environmental inequalities using indices from residential segregation literature. The authors adapted two types of segregation indices for environmental inequalities measurement. First, they based their analysis on spatial dissimilarity for the examination of areal-level environmental data, such as vegetation cover or pollution loads in census blocks. Second, they employed relative centralization for the analysis of multiple points environmental data, such as geocoded hazardous sites or urban parks. Additionally, the authors developed adjusted indices that consider the impacts of local interactions across spatial units' boundaries and the distance to amenities/disamenities selected for analysis. They employed randomization methods developed in the segregation literature (Tivadar, 2019) for statistical inference to test the robustness of the indices. Moreover, they developed an original statistical approach based on jackknife methods for identifying and mapping the spatial units with the largest influences on environmental inequalities.

The article represents an important step in the process of interconnection between the two fields, as it utilizes segregation methodology to define environmental inequalities while explicitly considering spatial aspects. However, a formal description of the connections between segregation and environmental inequalities is still missing. Furthermore, an in-depth analysis of the spatial aspects and properties of indices appears necessary to deepen our understanding of these interrelated phenomena.

In this article, we demonstrate mathematically that environmental inequalities and spatial segregations are linked: the level of environmental inequalities is bounded by the level of spatial segregation. Put differently, social segregation is a necessary but insufficient condition for environmental inequalities: if the segregation level is low, inequalities will also be low, and with high levels of segregation, the inequalities can be high as well (but not necessarily).

The first type of analysis is adapted to areal-level data, which includes variables that are or can be aggregated at a spatial unit level. Among the numerous indices proposed in the segregation literature, the choice of dissimilarity-based indices is justified by several reasons. First, the dissimilarity index (Duncan and Duncan, 1955a) is the most widely used measure of residential segregation due to its simplicity and intuitive interpretation. The dissimilarity index measures the departure from an even relative population distribution across spatial units and ranges between 0 (indicating an even relative distribution of two social groups) and 1 (representing perfect dissimilarity). It can be interpreted as the share of a social group that would need to change its location to achieve an even relative spatial distribution compared to another group.

Secondly, this index can be employed for a combination of population and areal-level data (Duncan and Duncan, 1961): the Delta index is an adaptation of the dissimilarity index that incorporates both population and areal data. Regarded as a spatial concentration index (Massey and Denton, 1988), it quantifies the dissimilarity between the distribution of a group and the distribution of available space. In a similar way, we can define the environmental dissimilarity index as the dissimilarity between the distribution of a population group and the distribution of an environmental variable among spatial units.

$$ED^{x,a} = \frac{1}{2} \sum_{i=1}^n \left| \frac{x_i}{X} - \frac{a_i}{A} \right| \quad (1)$$

where n is the number of spatial units, x_i the population of group in spatial unit i , $X = \sum_{i=1}^n x_i$ is the group total population, a_i is the environmental value in spatial unit i and $A = \sum_{i=1}^n a_i$ the total value of the environmental variable.

As our interest lies in measuring horizontal environmental inequalities between social groups, we define the differential of environmental dissimilarity as the difference between environmental dissimilarity levels:

$$\Delta ED^{x,y} = ED^{x,a} - ED^{y,a} = \frac{1}{2} \sum_{i=1}^n \left(\left| \frac{x_i}{X} - \frac{a_i}{A} \right| - \left| \frac{y_i}{Y} - \frac{a_i}{A} \right| \right) \quad (2)$$

We demonstrate that the maximum environmental inequality is limited by the level of social segregation. In other words, social segregation is a necessary but insufficient condition for environmental inequality:

$$|\Delta ED^{x,y}| \leq D^{x,y} \quad (3)$$

Another significant advantage of dissimilarity-based indices is the ability to incorporate spatial interactions. We adapt the generalized version of the Morrill index (Morrill, 1991), developed by Tivadar (2019), where spatial interactions are modeled via k-th order contiguity matrices. We construct a new spatial interaction term that allows the combination of two different types of data.

In the case of data represented as points (such as geocoded hazardous sites, urban parks, etc.), we consider relative centralization-based indices because they can directly compute environmental inequality between two social groups by simultaneously considering the spatial distribution of social groups and the environmental variable. The relative centralization index (Duncan and Duncan, 1955b) is a particular form of the Gini index that measures the uneven localization of two groups around a specific point (the center) by ordering spatial units according to their distance to the center. One reason centralization was somewhat abandoned in the literature is because it has little meaning in increasingly polycentric and sprawled modern cities. To address this problem, Tivadar (2019) adapted centralization indices to polycentric spatial configurations by computing the distance between spatial units and each center, and then considering only the distance to the closest point. With this approach, the index can be straightforwardly used to compare the location of two groups around a punctual environmental variable.

An alternative to the distance to the closest point is to consider weighted distances to multiple locations of an environmental variable. This option is advantageous when the variables in different locations do not have the same importance and/or their impacts are cumulative. According to Folch and Rey (2016), we can spatially limit the effect of centrality, an interesting feature, especially when considering only people located at certain proximity to the points. Similar to Tivadar (2019), we can consider two options: to limit the space around each point to the number of k nearest neighbors or to choose a certain distance of influence (considering only spatial units located within this distance to each point).

The index equals 0 when the two groups have similar locations around the punctual data and ranges theoretically between -1 and +1, with the sign indicating which group is located closer to the environmental variable:

$$RCE_a^{x,y} = \left(\sum_{i=2}^n x_{i-1} y_i \right) - \left(\sum_{i=2}^n x_i y_{i-1} \right) \quad (4)$$

where x_i and y_i are ordered by the distance to closest environmental variable (or alternatively a weighted measure of distance to multiple locations of the variable). If $RCE_a^{x,y} > 0$, the x population is located closer to the environmental variable than y, and contrary if $RCE_a^{x,y} < 0$.

As for dissimilarity-based indices, social segregation is a necessary (but insufficient) condition for environmental inequality: the absolute value of the centralization index is bounded by the Gini index,

as its maximum and minimum are obtained when the ordering of the spatial units by distance to the points is identical to the ordering based on population shares (Foch and Rey, 2016).

$$\left| RCE_a^{x,y} \right| \leq G^{x,y} \quad (5)$$

To verify these results, we conduct an empirical analysis of the relationship between the two phenomena in French urban areas. First, we analyse the pattern of environmental inequalities for poor households in French urban areas and test whether there is a strong relationship between segregation and environmental inequalities, and whether there are any significant differences between types of urban areas.

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