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1 **Measuring environmental inequalities: insights from the residential**
2 **segregation literature ‡**

3

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8

9 **Abstract:**

10 Inequalities in exposure to environmental hazards and access to environmental amenities have
11 been documented in many cities, in relation to residential segregation of low-income or
12 minority groups. The literature on residential segregation measurement, however, has not yet
13 been considered a source of insights for the measurement of environmental inequalities. Here,
14 we propose two segregation-based indices – the Environmental Dissimilarity gap index
15 (ΔED_K) and the Environmental Centralization index (EC_d) – and a randomization method to
16 make robust environmental inequality assessments. In addition, to help policy-makers target
17 local policies better, we developed an original approach to identify and map hotspots that
18 have a large influence on environmental inequalities. These methods are applied in Grenoble,
19 France, to study the distribution of green spaces and industrial risks between poor and non-
20 poor households.

21

22 **Keywords:** Environmental Justice; Environmental Equity; Spatial Segregation; Monte Carlo
23 Simulations, Jackknife Simulations; France

24

25

26 1. Introduction

27 The overarching goal of environmental justice (EJ) studies is to inform EJ policies, whose
28 objective according to Harner et al. (2002, p. 318) is “to create environmental equity: the
29 concept that all people should bear a proportionate share of environmental pollution and
30 health risk and enjoy equal access to environmental amenities”. More precisely, Boyce et al.
31 (2016) underline the policy-relevance of studying both inter-individual (i.e. vertical) and
32 between-group (i.e. horizontal) environmental inequalities. Many national constitutions as
33 well as environmental statutes and regulations endorse the normative principle that every
34 person has the right to clean and safe environment. And – in the United States at least – the
35 requirement of equity across groups defined on the basis of race, ethnicity and economic
36 status is explicitly inscribed in environmental policy.

37 In practice, a large number of EJ studies are conducted at a city or metropolitan area scale.
38 They focus on interactions between population groups unequally distributed in space and
39 spatialized environmental amenities/disamenities. As an example, many studies consider the
40 uneven distribution of urban green spaces (e.g., Apparicio et al., 2016; Frey, 2016; Schwarz et
41 al., 2015; Shanahan et al., 2014; Wen et al., 2013; Zhou and Kim, 2013; Pham et al., 2012;
42 Landry and Chakraborty, 2009) or unequal exposures to urban air pollutants (e.g., Carrier et
43 al., 2014; Zwickl et al. 2014; Harner et al., 2002; Sheppard et al., 1999). They are concerned
44 primarily with between-group inequalities, in accordance with the compelling idea that
45 already disadvantaged groups – such as low-income and racial minorities – should not in
46 addition face environmental disadvantages (Boyce et al., 2016). On a methodological level,
47 these analyses are mainly based on between-group comparisons of means or medians,
48 bivariate correlations and multivariate regressions (Mitchell and Walker, 2005).

49 In an urban context, such environmental inequalities are likely to be linked to residential
50 segregation, i.e. the spatial separation of population groups between urban neighbourhoods.
51 This multidimensional phenomenon has been well conceptualized by Massey and Denton
52 (1988) and its measurement has been abundantly and thoroughly discussed by sociologists,
53 demographers, geographers and economists for the past half-century and more (e.g., Tivadar,
54 *forthcoming*; Reardon and O’Sullivan, 2004; Wong, 1993; Morrill, 1991; White, 1983;
55 Duncan and Duncan, 1955a). Surprisingly enough, however, this rich literature has not yet
56 been considered a source of insights for conceptualizing and measuring environmental
57 inequalities.

58 In this paper, we take advantage of this opportunity and suggest ‘segregation-based’
59 environmental inequality indices, measuring spatial distributions of social groups and
60 environmental phenomena relative to one another. We propose the Environmental
61 Dissimilarity gap index (ΔED_K) to analyse areal-level environmental data (such as vegetation
62 cover or pollution loads in census blocks) and the Environmental Centralization (EC_d) index
63 to analyse multiple-points environmental data (such as geocoded hazardous sites or urban
64 parks). In addition, following a recommendation made by Sheppard et al. (1999), we suggest
65 a randomization strategy based on Monte Carlo experiments to make robust distribution-free
66 environmental inequality assessments at a city-wide scale.

67 The recent residential segregation literature points out that more attention needs to be paid to
68 local areas if the ultimate goal is to contribute to public policies development (Brown and
69 Chung, 2006; Folch and Rey, 2016). Accordingly, we also propose a procedure that allows
70 identifying and mapping hotspots that have a large influence on environmental inequalities.
71 This method uses Jackknife simulations to identify spatial units whose removal would result
72 in significant decreases/increases in the values of ΔED_K or EC_d . This approach may help
73 urban policy-makers target EJ policies better. It could inform public decision about, for
74 instance, where to implement greening policies, or priority actions to protect people from
75 hazards or pollutants, or social housing policies, etc.

76 To illustrate our proposals, we provide a case study with respect to spatial distributions of
77 vegetation (i.e., areal-level data) and dangerous industrial sites (i.e., point data) in Grenoble-
78 Alpes Métropole, France. We examine segregation-based environmental inequalities between
79 low-income households and other households, mobilizing gridded residential data provided at
80 a very fine spatial scale.

81 The next section presents the related literature and our conceptual framework. Section 3
82 introduces methods for global and local environmental inequality analyses. Section 4 presents
83 our case study. Section 5 concludes.

84

85

86 2. Related Literature and Conceptual Framework

87 2.1. Environmental Justice Studies

88 From its beginnings in the late 1970s to the present, Environmental Justice (EJ) has been both
89 an area of academic research and the banner of a civil movement calling for policies to
90 address inequalities in environmental conditions. Originally focused on racial and social
91 inequalities in the distribution of toxics and hazardous waste in the United States, it has since
92 continuously expanded its thematic and geographical scope (Schlosberg, 2013). Inequalities
93 with respect to environmental ‘bads’ (nuisances or risks) have remained a prominent topic
94 (see, for example, Hajat et al., 2015, for a review on air pollutants), but attention has also been
95 paid to environmental ‘goods’ (see, e.g., Jennings et al., 2012, on green spaces). In addition,
96 the field has shifted from documenting inequalities to analysing the underlying reasons for
97 these inequalities (Timmons et al., 2018; Mohai et al., 2009). It has also moved from a
98 conception of distributive equity to a more pluralistic conception of justice, including issues
99 of recognition, participation, capabilities, community justice and justice beyond the humans
100 (Schlosberg, 2013). In parallel, EJ literature and movement have spread out in various
101 countries, with transnational links and consideration of global issues, such as climate justice
102 (Mohai et al., 2009; Schlosberg and Collins, 2014).

103 Today, we can consider that EJ refers to four different types of environmental inequalities
104 (Laurent, 2011): (i) exposure and access inequalities, i.e. unequal distributions of
105 environmental bads and goods between individuals and groups; (ii) policy-effect inequalities,
106 i.e. unequal effects of environmental policies; (iii) policy-making inequalities, i.e. unequal
107 access to environmental policy-making; and (iv) impact inequalities, i.e. unequal
108 environmental impacts of different individuals and social groups. In this respect, our study
109 falls within the first and oldest strand of the EJ literature, about exposure and access
110 inequalities, and is underpinned by a distributive conception of justice such as the above-
111 mentioned one of Harner et al. (2002). More specifically, it focuses on measuring inequalities
112 between social groups in urban contexts. We present here relevant examples of urban EJ
113 studies, which provide an overview of the most standard methods used for this analysis.

114 A first example is Carrier et al. (2014) on air pollutants in Montreal, Canada. They consider
115 three statistical methods widely used in the EJ literature to analyse environmental inequalities
116 with respect to visible minorities, low-income individuals, young and elderly people. First, for
117 each social group, they compute weighted averages of several pollutant indicators at a small

118 dissemination subdivision (i.e. city block level, the weight of a city block being its share of
119 the total group population), and compare them with t-tests to similar averages obtained for the
120 rest of the population. Secondly, they compute Spearman's correlation coefficients to examine
121 statistical dependencies between rankings of proportions of groups and of pollutant indicators
122 across city blocks. Finally, they perform multivariate regressions with each of the pollution
123 indicators as the dependent variable in each case and proportions of groups as independent
124 variables, controlling for spatial dependencies. Their results for low-income population and
125 visible minorities are consistent with the bulk of EJ studies: they tend to reside in more
126 polluted areas.

127 Another example is Schwartz et al. (2015), who examine potential inequities in relationship to
128 race/ethnicity and income associated with distributions of urban tree canopy (UTC) in seven
129 U.S. cities. Data are analysed at the Census Block Group level using Spearman's correlations
130 and multivariate regressions. Schwartz et al. (2015, p. 11) stress that the key question – “is
131 UTC cover distributed equally in the cities examined?” – is answered relying on Spearman's
132 correlations. A significant coefficient implies that: “regardless of what drives the pattern, the
133 pattern exists”. This method provides a baseline picture that is comparable across all cities.
134 Multivariate regressions help to get closer to causation and answer supplementary questions:
135 “what other variables drive the distribution of UTC cover?” and “do the data have significant
136 spatial structure?” With respect to the baseline diagnostic, Schwartz et al. (2015) find a
137 significant positive correlation with income across all cities, but less striking results for races.

138 The two examples presented above analyse areal-level data, but EJ studies also deal with
139 geocoded environmental data. In an older but still relevant study, Sheppard et al. (1999)
140 examine associations between toxic sites and minority/poor populations in Minneapolis, MN,
141 comparing commonly used spatial coincidence and analytical buffering methods. In the first
142 method, proximate populations are defined as those residing in census enumeration units
143 containing toxic sites. In the second, a GIS-based buffer analysis is performed, in which
144 proximate populations are defined as those residing within a predefined distance from a toxic
145 site. These proximity measures being defined, poverty rates of proximate and non-proximate
146 subpopulations – or other socio-demographic or racial characteristics – can be compared.

147 Sheppard and colleagues examine the sensitivity of their results to proximity measures and
148 buffer distances.¹

149 In addition, Sheppard et al. (1999) suggest a methodology for evaluating the statistical
150 significance of their results. The hypothesis investigated is whether the ratios of poverty
151 percentages between proximate and non-proximate subpopulations are large by comparison to
152 what would have been observed if the toxic sites had been placed randomly within the city.
153 They carried out a series of randomization experiments to simulate a hypothetical set of toxic
154 sites distributions. Simulation results indicate that, broadly speaking, observed toxic site
155 locations in Minneapolis were associated with unusually high poverty rates. However, as far
156 we know, Sheppard et al. (1999) have not been followed (except by Chakraborty and
157 Armstrong, 2001) in their recommendation to use randomization strategies for the generation
158 of robust distribution-free environmental inequality assessments.

159 On exposure to hazards in New York City, Jacobson et al. (2005) review advanced
160 geostatistical techniques and discuss several inequity measures. As an alternative to analytical
161 buffering, they adopt a distance-decay modelling approach (or gravity model) to measure
162 exposure gradients to highways within ethnic groups at the block group level. They then
163 define and advocate a class of inequity measures that equates statistical (or conditional)
164 independence between exposure and demographics as 'perfect equity', with degree of
165 inequity computed as degree of departure from independence. They underline that standard
166 regression approaches (either bivariate or multivariate) look only at departures from zero
167 correlations, which is different from independence. On the other hand, the *Theil* index,
168 commonly used to study income inequality, is shown to be relevant to comparing exposure
169 inequality under different grouping frameworks (e.g. race vs class). But again, this index is
170 not grounded on the independence assumption. Jacobson et al. (2005) thus propose a
171 graphical approach allowing a direct comparison of the empirical joint distribution of
172 exposure and ethnic group and the one implied by the conditional independence model
173 (conditioned on block groups' median income). These plots show that Hispanics and Asians
174 are more exposed than average to highways, whatever the income level.

¹ On GIS-based analysis, see also, e.g., Harner et al. (2002), who test several methods for comparing subpopulations in at-risks and not-at-risks zones, or conversely the concentration of risks in disadvantaged areas and elsewhere; or Maantay (2002) and Maantay (2007), who consider issues of optimal study area, spatial resolution, data aggregation, data deficiencies, areal extent of exposure and areal interpolation; or Chakraborty et al. (2011), on similar topics and on emerging geostatistical techniques.

175 The above-mentioned studies provide an overview of methods used to analyse between-group
 176 environmental inequalities. In their review of statistical techniques used in EJ studies,
 177 Mitchell and Walker (2007) note that linear regression is by far the most popular method.²
 178 Although there is a long tradition of using inequality indices to study income and wealth
 179 distributions, few EJ studies have explored their relevance for analysing horizontal
 180 environmental inequalities, Jacobson et al. (2005) and Lopez (2002) being rare exceptions in
 181 this line.³ On the opposite, inequality indices have been widely mobilized and adapted for
 182 studying residential segregation, another kind of between-group (spatial) inequality.

183 **2.2. From Residential Segregation to Segregation-based Environmental Inequalities**

184 Residential segregation refers to the geographic separation of social groups, usually in an
 185 urban context. According to Park and Kwan (2017), it was only in the early 21st century that
 186 some scholars have sought to understand the association between segregation and
 187 environmental inequalities. This association has been investigated primarily with respect to
 188 air pollution in U.S. metropolitan areas. Several studies have confirmed that increased
 189 segregation tends to be associated with increased racial inequality in exposure to health risks
 190 (e.g., Morello-Frosch and Lopez, 2006; Lopez, 2002), but more ambiguous results have
 191 sometimes been obtained (Downey al., 2008). More recently, Saporito and Casey (2015) have
 192 investigated residential segregation and differences in exposure to green space in U.S.
 193 metropolitan areas. Findings show that lower-income people and members of minority groups
 194 live in neighbourhoods with much less vegetation than their wealthier, white counterparts, and
 195 these differences are exacerbated in racially and economically segregated cities.

196 These studies have examined statistical links between residential segregation and
 197 environmental inequalities. Yet they have not reconsidered how horizontal environmental
 198 inequalities are defined and measured and the conceptual and methodological perspectives
 199 that the segregation literature could bring to this issue.

200 The conceptual framework of our methodological proposals is as follows:

- 201 ▪ Environmental (dis-)amenities are defined as place-based environmental attributes that
 202 provide *local* (dis-)services to people, where geographical proximity between

² But referring to Bowen (2002), they underline that few studies adequately report on diagnostic tests (non-linearity, multi-collinearity, heteroscedasticity, etc.) so that the adequacy of this approach is questionable.

³ Lopez (2002) adapts the net difference score, based upon cumulative frequency distributions, to measure Black/White inequality in exposure to air toxics. Inequality indices have also been suggested to measure vertical (i.e., inter-individual) environmental inequalities (Boyce et al., 2016).

203 attributes and people enhances the amounts of (dis-)services delivered (Schaeffer and
204 Dissart, 2018).

- 205 ▪ We name ‘Environmental Segregation’ the geographic separation between a social
206 group and an environmental (dis-)amenity. The more this group is segregated from an
207 amenity, the less likely it is to benefit from it. The more it is segregated from a
208 disamenity, the less likely it is to be harmed by it.
- 209 ▪ A ‘Segregation-based Environmental Inequality’ is then a difference between two
210 social groups as for their respective degrees of environmental segregation. A social
211 group is disadvantaged, relative to another group, when it is more segregated from an
212 environmental amenity or less segregated from an environmental disamenity.

213 Residential segregation is classically conceptualized and measured along five dimensions
214 identified by Massey and Denton (1988): evenness, exposure, concentration, centralization,
215 and clustering. Evenness refers to inequalities in the distribution of population groups
216 between neighbourhoods. Exposure (or isolation) captures opportunities for contacts between
217 members of different (or similar) groups within neighbourhoods. Concentration refers to
218 inequalities in regard to the physical space occupied by groups. Centralization describes the
219 distribution of groups around a city centre. Finally, clustering consider the proximity of
220 groups within and across neighbourhoods.

221 Some of these dimensions are interrelated and several simplifications of this typology have
222 been suggested (Reardon and O’Sullivan, 2004; Brown and Chung, 2006; Wong, 2008). To
223 study segregation-based environmental inequalities, we believe two dimensions are
224 particularly relevant: evenness (incorporating clustering and concentration notions) and
225 centralization.

226 Evenness is the long-standing dominant dimension in segregation analysis. To date, the most
227 standard measures of segregation still are Duncan and Duncan’s (1955a, 1955b) Dissimilarity
228 (*D*) and Segregation (*IS*) indices. Yet, in the early 80s, these indices have been criticized for
229 not taking account of local spatial interactions between social groups (White, 1983, Morrill,
230 1991, Wong, 1993). In an urban residential context, it is indeed obvious that people interact
231 with one another across neighbourhoods’ boundaries, so that the geographical configuration
232 of the neighbourhoods matters. Morrill (1991), Wong (1993) and other scholars have thus
233 proposed ‘spatial evenness’ indices (i.e., adjusted *D* indices) that incorporate the clustering
234 dimension in an evenness framework. Concentration is also strongly connected to evenness.

235 Duncan and Duncan (1961) have proposed the *Delta* index, which is mathematically
236 equivalent to the *D* index: the latter measures the extent to which two population groups'
237 distributions among spatial units differ, while the former measures the extent to which the
238 distribution of a population group differs from the one of land.

239 Centralization has been especially studied in relation to the 'white flight' hypothesis
240 (Crowder, 2000): the idea that large and growing populations of Blacks spurred Whites to
241 leave urban neighbourhoods in which they would have otherwise remained. But this
242 dimension has been deemed less and less important due to the emergence of sprawled and
243 polycentric cities (Brown and Chung, 2006, Wong, 2008), and the gentrification of many
244 central districts (Hwang and Lin, 2016). Centralization measures have also been considered
245 weaker as they require defining a city 'centre', which is not a straightforward geographical
246 feature (Folch and Rey, 2016). Recently, however, scholars have shown that the standard
247 Relative Centralization index (*RCE*) – originally proposed by Duncan and Duncan (1955b) to
248 study centralization at a city-wide scale – could easily be generalized to a polycentric context
249 (Tivadar, *forthcoming*), or recast into a local centralization index useful for exploring local
250 segregation around any relevant reference location (Folch and Rey, 2016).

251 Hence, we propose: (i) to adapt *D* and its spatialized versions to the measurement of
252 inequalities related to areal-level environmental data (such as vegetation cover or pollution
253 loads), and (ii) to adapt *RCE* and its local version to the measurement of inequalities related to
254 multiple points environmental data (such as urban parks or hazardous sites). The following
255 section presents these proposals. It also suggests a method based on randomization
256 experiments to perform global (i.e. city-wide) environmental inequality assessments, and a
257 procedure that allows identifying and mapping hotspots that have a large influence on
258 segregation-based environmental inequalities.

259

260

261 3. Measuring Environmental Inequalities

262 3.1. Segregation-based Environmental Inequality Indices

263 3.1.1. Environmental Dissimilarity

264 Duncan and Duncan's (1955a) Dissimilarity index D is one of the most widely used measures
 265 of segregation. It measures – for two social groups – departure from the perfectly
 266 unsegregated situation, where relative distributions of minority and majority groups across
 267 spatial units are similar. It ranges theoretically between 0 and 1 and corresponds to the share
 268 of the minority group that would have to change its place of residence – moving from one
 269 spatial unit to another – to make the unsegregated situation occur.

$$270 \quad D^{x,y} = \frac{1}{2} \sum_{i=1}^n \left| \frac{x_i}{X} - \frac{y_i}{Y} \right|$$

271 (1)

272 where n is the number of spatial units, x_i and y_i the population of each group in unit i ,
 273 and $X = \sum_{i=1}^n x_i$ and $Y = \sum_{i=1}^n y_i$ are each group total population.

274 As mentioned above, this framework has already been adapted by Duncan and Duncan (1961)
 275 to analyse the relation between the people and an environmental data (the amount of land).
 276 The *Delta* index measures the concentration of a given social group, that is, the dissimilarity
 277 between its distribution and the one of the land among spatial units.

278 Following them, we propose that the Environmental Dissimilarity index ED measures the
 279 dissimilarity between the distribution of a population group and the one of an environmental
 280 (dis-)amenity among spatial units. The *Delta* index then corresponds to a particular ED index,
 281 where land area is supposed to be an environmental amenity.

282 Formally, ED is given by:

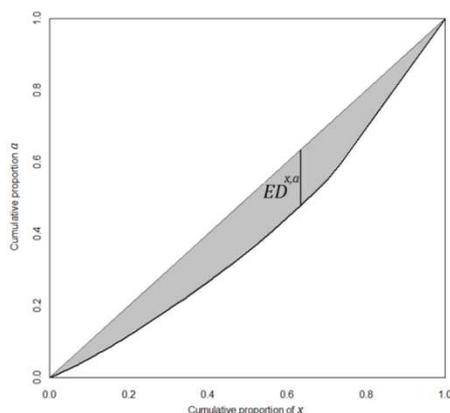
$$283 \quad ED^{x,a} = \frac{1}{2} \sum_{i=1}^n \left| \frac{x_i}{X} - \frac{a_i}{A} \right|$$

284 (2)

285 where a_i is the environmental value in spatial unit i and $A = \sum_{i=1}^n a_i$ the total value of the
 286 environmental variable.

287 *ED* measures – for a social group – the departure from the ‘environmentally unsegregated’
 288 situation, where the distribution of this group among spatial units is similar to the one of the
 289 environmental (dis-)amenity. It ranges between 0 and 1 and can be interpreted as the share of
 290 the population group that would have to move to reach the ‘environmentally unsegregated’
 291 state.

292 *ED* has a geometrical interpretation based on an adaptation of the Lorenz curve, standard in
 293 economic inequality analysis. Figure 1 presents a Lorenz-like curve, where the horizontal axis
 294 shows the cumulative proportion of population x in spatial units ordered by the density of the
 295 environmental variable per inhabitant, and the vertical axis shows the cumulative proportion
 296 of a . *ED* is the maximum distance between this ‘environmental segregation curve’ and the
 297 diagonal corresponding to the environmentally unsegregated situation. A spatialized *Gini*
 298 index applied to environmental segregation could also be defined based on this curve: it
 299 would correspond to the grey surface between the curve and the diagonal.



300

301 **Fig. 1.:** Environmental Segregation curve

302 *Notes:* The curve indicates, e.g., that 50% of the population X located in the spatial units where the density
 303 of the amenity A is the lowest benefits from less than 40% of the total amount of amenity; The
 304 *Environmental Dissimilarity* index corresponds to the maximal distance between the diagonal (i.e. the
 305 perfectly unsegregated state) and the environmental segregation curve; An environmental *Gini* index
 306 would correspond to the grey area between the diagonal and the curve.

307

308 The first strength of *ED* is its ease of interpretation. It has a more intuitive meaning than the
 309 corresponding *Gini* index, or than the *Theil* index used by Jacobson et al. (2005). The second
 310 strength of the *ED* index is that it can be adjusted to account for local spatial interactions.

311 Morrill (1991) has first developed an adjusted *D* index, where *D* is scaled down when
 312 opportunities to interact across adjacent spatial units are present. As it is possible that relevant
 313 local interactions go beyond the first order contiguity, the Morrill’s adjusted *D* index has been

314 generalized to the k -th order contiguity (Tivadar, *forthcoming*). We can adapt this approach to
 315 define an adjusted ED index, given by:

$$316 \quad ED_K^{x,a} = ED_0^{x,a} - \sum_{k=1}^K f(k) \frac{\sum_{i=1}^n \sum_{j=1}^n c_{ij}^k ED_{ij}^{x,a}}{\sum_{i=1}^n \sum_{j=1}^n c_{ij}^k} \quad (3)$$

317 where $ED_0^{x,a} = ED^{x,a}$, $f(k)$ is a distance-decay function defined by contiguity order k , with
 318 $f'(k) < 0$, $f(1) = 1$ and $f(k)_{k \rightarrow \infty} = 0$. In the empirical case below, we use the usual negative
 319 exponential function: $f(k) = \exp(1-k)$. c_{ij}^k are the elements of the spatial weights matrix
 320 defined as the k order contiguity matrix. For each level of contiguity, these elements equal 1
 321 when spatial units i and j are contiguous of order k , 0 otherwise. $ED_{ij}^{x,a}$ captures the potential
 322 of interactions across borders between the population and the (dis-)amenity located in two
 323 contiguous (of order k) spatial units i and j : the more dissimilar their spatial distributions are,
 324 the more local interactions across borders are likely to occur, in the spirit of Morrill's original
 325 expression of local interactions between two population groups.⁴

326 After Morrill, Wong (1993) has developed more refined spatial weights matrices: one where
 327 interactions between two contiguous spatial units are proportional to the length of their shared
 328 boundary, and another that takes account of spatial units' shapes (i.e., their perimeter/area
 329 ratios). These methods can also be transposed to environmental dissimilarity measurement
 330 and would be particularly relevant when spatial units have irregular forms (e.g., Census Block
 331 Groups), which is not the case in our empirical case.

332 So far we have presented environmental segregation measures, but we are more specifically
 333 interested in between-group environmental inequalities. Thus we define the Environmental
 334 Dissimilarity Gap (ΔED) to measure – for two social groups – the difference in their degrees
 335 of environmental segregation. ΔED ranges between -1 and 1 and is given by:

$$336 \quad \Delta ED^{x,y} = ED^{x,a} - ED^{y,a} = \frac{1}{2} \sum_{i=1}^n \left(\left| \frac{x_i}{X} - \frac{a_i}{A} \right| - \left| \frac{y_i}{Y} - \frac{a_i}{A} \right| \right) \quad (4)$$

337 We also define an adjusted version of the Environmental Dissimilarity gap:

⁴ Morrill's original interaction term for adjusting the D index is based on group proportions in contiguous spatial units: between-group interactions across borders are more likely to occur when spatial units have very distinct shares for the two groups (e.g. one is dominated by black people and the other by white people).

$$338 \quad \Delta ED_K^{x,y} = ED_K^{x,a} - ED_K^{y,a} \quad (5)$$

339 which can be rewritten as:

$$340 \quad \Delta ED_K^{x,y} = \Delta ED_0^{x,y} - \sum_{k=1}^K f(k) \frac{\sum_{i=1}^n \sum_{j=1}^n C_{ij}^k \Delta ED_{ij}^{x,y}}{\sum_{i=1}^n \sum_{j=1}^n C_{ij}^k} \quad (6)$$

341 where $\Delta ED_0^{x,y} = \Delta ED^{x,y}$.

342 **3.1.2. Environmental Centralization**

343 The Relative Centralization (*RCE*) index has been proposed by Duncan and Duncan (1955b).
 344 It allows comparing the locations of two social groups around a point, typically the Central
 345 District of a city. It equals 0 when the two groups have similar locations relative to the centre
 346 and ranges between -1 and +1 otherwise, the sign indicating which group is closer to this
 347 centre. It is given by:

$$348 \quad RCE^{x,y} = \left(\sum_{i=2}^n x_{i-1} y_i \right) - \left(\sum_{i=2}^n x_i y_{i-1} \right) \quad (7)$$

349 where x_i and y_i are ordered by the distance to the city centre. If $RCE^{x,y} > 0$, population x is
 350 located closer to the centre than population y , and conversely if $RCE^{x,y} < 0$.

351 This index is a particular form of the spatialized Gini index, based on a Lorenz-like curve
 352 similar to the one presented on Fig. 1, but where the vertical axis is the cumulative proportion
 353 of y and the spatial units are ordered according to their distance to the centre: *RCE* is the
 354 surface between the curve and the diagonal.

355 *RCE* can be used to compare locations around a specific environmental (dis-)amenity (Folch
 356 and Rey, 2016). But EJ studies are generally interested in (dis-)amenities present in multiple
 357 locations (e.g., U.S. toxic release inventory sites, as in Harner et al., 2002 or Sheppard et al.,
 358 1999). The easiest way of generalizing the *RCE* index to multiple locations is to consider, for
 359 each spatial unit, its distance to the closest (dis-)amenity (Tivadar, *forthcoming*). Another

option – advantageous when all (dis-)amenities do not have the same importance and/or their impacts are cumulative – could be to consider weighted distances to multiple (dis-)amenities.⁵

Folch and Rey (2016) have defined a local version of *RCE*, by selecting either the k nearest neighbours to the reference centre, or the spatial units that fall within a set distance band around this centre. We propose to recast this method in a polycentric context to obtain a spatially constrained global index. This Environmental Centralization (EC_d) index is thus formally equivalent to *RCE*, but generalized to polycentrism and applied to spatial units located at a distance less than d from their closest environmental (dis-)amenity:

$$EC_d^{x,y} = \left(\sum_{i=2}^k x_{i-1} y_i \right) - \left(\sum_{i=2}^k x_i y_{i-1} \right) \quad (8)$$

where x_i and y_i are ordered by the distance to the closest environmental (dis-)amenity, and k is the rank of the last spatial unit who respect the spatial constraint: $d_i = \min_a \{d_i^a\} \leq d$. If $EC_d^{x,y} > 0$ population x is located closer to environmental (dis-)amenities than population y , and conversely if $EC_d^{x,y} < 0$.

If we take into account all spatial units, $k = n$, we obtain the unconstrained form of the index

$$EC_{d_{\max}}^{x,y} = \left(\sum_{i=2}^n x_{i-1} y_i \right) - \left(\sum_{i=2}^n x_i y_{i-1} \right), \text{ where } d_{\max} = \max_i \{d_i\} \text{ is the maximal distance to the}$$

closest (dis-)amenity in the study zone.

3.2. Statistical Approaches

3.2.1. Method for Global Analysis

To make a robust global (i.e., city-wide) environmental inequality analysis, one also needs a statistical approach appropriate to spatial data. Following Sheppard et al. (1999), we propose a randomization strategy. The general idea is to test whether the *empirical value* of an environmental inequality index (which measures differences in locations between groups in relation to spatialized environmental attributes) is statistically different from its *expected*

⁵ The population-weighted distance approach (Zhang et al., 2015) would be particularly relevant for implementing this option since it uses a measure of spatial interaction (a gravity model incorporating a distance decay function and a factor of importance for amenities) as weights to calculate a weighted distance measure.

383 *value* under the null hypothesis that all groups come from the same population (i.e. are
384 distributed in space in a similar way).⁶

385 In practice, we developed a Monte Carlo permutation test. In a simulation, all households in
386 both groups (poor and non-poor) are randomly assigned to residential locations, and their
387 probability of being assigned to a given location is proportional to the residential capacity of
388 that location (i.e. the actual number of households observed in it).⁷ Thus a simulation
389 generates a counterfactual spatial distribution of the population on which an inequality index
390 (ΔED_K or EC_d) can be calculated. We make 499 simulations to obtain a distribution of
391 *simulated values* for this index. Adding the empirical value in this distribution and looking at
392 its position allows computing a (pseudo) p-value and test the null hypothesis.

393 This statistical approach is consistent with our overall conceptual framework, inspired by the
394 residential segregation literature. Randomizing the spatial distribution of households
395 eliminates every kind of between-group inequalities related to places of residence. It thus
396 provides counterfactual simulations for testing the significance of both residential segregation
397 measures and segregation-based environmental inequalities indices.

398 **3.2.2. Method for Local Analysis**

399 The global environmental inequality analysis provides answers to environmental inequality
400 questions at the study zone level. But policy-makers, to implement EJ policies, must target
401 their interventions on the ground. They have to decide for instance where to implement
402 greening policies, or priority actions to protect people from hazards or pollutants, or social

⁶ That is, we randomize the spatial distribution of households rather than the one of amenities or dis-amenities. Sheppard and colleagues test whether their empirical measures of unequal exposition to industrial toxics are statistically different from those obtained when randomizing the locations of toxic installations (i.e. selecting Cartesian coordinates within municipal boundaries). In other words, they test whether the observed spatial distribution of toxic sites is more socially unequal than a random one. One obvious advantage of this strategy is computational since toxic sites are much less numerous than households. However, it is far from realistic to consider that every point in space could have been a possible candidate for a facility (e.g. topographical reasons make some points unsuitable). Instead, toxic facilities could be randomly assigned only to sites that could have been elected (but these latter are generally unknown to the researcher). Randomizing households is an alternative which we believe is much more compelling.

⁷ We test whether population groups are distributed unequally *in the existing housing stock* in relation to environmental (dis-)amenities. So the spatial distributions of dwellings and residential areas are considered exogenous. Alternatively, we could have considered counterfactual spatial distributions of dwellings and/or non-developed areas. But we don't know the constraints on the spatial distribution of dwellings and whether non-developed areas are so for choice or because they are improper to be developed. Physical geography, density regulations and growth control policies would have to be taken into account. In that respect, an analysis making endogenous all the space would be much more difficult to justify and implement. We thank an anonymous reviewer for raising this issue.

403 housing policies, etc. Thus we also provide a statistical approach that allows identifying – and
404 mapping – the local hotspots that have the largest influences on environmental inequalities.
405 This method is based on Jackknife simulations, where the spatial units of the study zone are
406 successively withdrawn.⁸ For each simulation, the inequality index (ΔED_K or EC_d) is
407 computed, and we obtain at the end of the process a distribution of simulated index values.
408 Then we look at outliers in the tails of this distribution.⁹ Each of these outlier values is
409 attached to a particular simulation, where one spatial unit has been removed from the whole
410 set of spatial units. So we can identify the ‘outlier’ spatial units whose removal has the
411 greatest impacts on the inequality index. We can map them and thus visualize hotspots for
412 potential policy interventions.

413

414 **4. Empirical example**

415 This section is not intended to be a comprehensive analysis of environmental inequalities in
416 Grenoble-Alpes Métropole, but aims to illustrate our methodological proposals.

417 **4.1. Background and Data**

418 In France, a Métropole is an administrative entity organized around a large city, in which
419 several municipalities co-operate to plan their development. Grenoble-Alpes Métropole is
420 located at the foot of the French Alps in the South-East of France. It comprises the city of
421 Grenoble and 48 neighbouring municipalities, hosting altogether a population of about
422 450,000 inhabitants on an area of about 550 km². **It is an attractive place for students and
423 highly-skilled workers, thanks to its renowned university and advantageous labor market. The
424 unemployment rate is low and job opportunities are numerous in international high-tech
425 companies and more generally in a very dynamic industrial sector. Households are thus on
426 average wealthier and more educated than in most French urban areas of comparable size.
427 However, this generally favourable situation does not come without strong income
428 inequalities and residential segregation dynamics. Indeed, Grenoble-Alpes Métropole is also
429 known for its deprived urban districts, with a high concentration of poor, unemployed, low-
430 skilled and immigrant people, and its hilly suburbs, where affluent households flock.**

⁸ The number of simulations is thus equal to the number of spatial units.

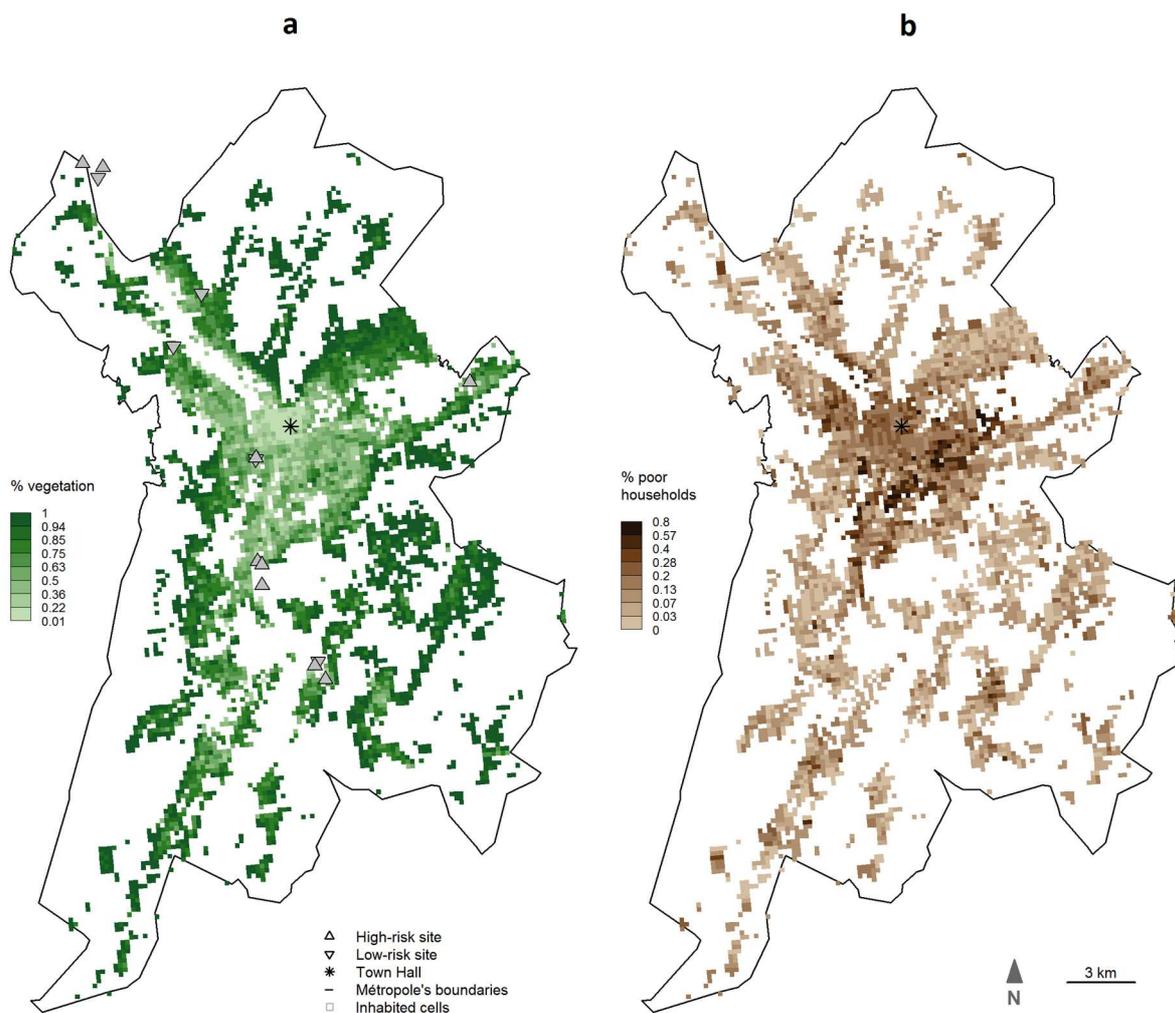
⁹ Several approaches can be used to define outlier values. In the example presented below, outliers are obtained using the boxplot method: they are values that deviate from the mean of the simulated distribution by two standard deviations or more. Other standard techniques that could be employed are the different scores methods (normal, t Student and chi-squared scores) and the median absolute deviation method.

431 In this respect, it is a place where issues of environmental equity could be quite acute.
432 Specifically, some industrial sites pose risks to the people living in their vicinity, and the
433 exposition to these risks might be socially unequal due to residential segregation. Another
434 potential problem concerns access to vegetation and the resulting health benefits. Although
435 there are underprivileged neighborhoods with large urban parks, disadvantaged populations
436 tend to live in the central part of the Métropole, which has little vegetation in general, while
437 richer populations tend to live in the green urban periphery.

438 The study uses gridded socio-economic data provided by the National Institute of Statistics
439 and Economic Studies (Insee), based on administrative fiscal data for 2010. For each
440 inhabited cell of a rectangular 200x200m grid, we have estimations of both the total number
441 of households and the number of low-income households. Low-income households are those
442 whose income per consumption unit (before taxes and benefits) is less than 60% of the
443 median of Metropolitan France distribution (i.e. 11,249.40 euros). In what follows, for the
444 sake of simplicity, low-income households will often be referred to as ‘poor’ and the other
445 households as ‘non-poor’. The right panel of Figure 2 presents the share of low-income
446 households in the 4,342 inhabited cells of the study area. The ‘holes’ in the map, covering
447 about two thirds of the total area of the Métropole, correspond to uninhabited areas occupied
448 either by infrastructures, industrial and commercial zones, water bodies and agricultural
449 fields, or – mainly – by forests and natural areas located on mountains.

450 As an example of areal environmental data, we consider vegetation cover. Each pixel of 5x5m
451 located in the study zone is classified as vegetated or not, depending on the value of a
452 Normalized Difference Vegetation Index (NDVI) obtained by remote sensing (RapidEye
453 images, 2010). A pixel is considered vegetated for NDVI values greater than 0.35. Then we
454 count the number of vegetated pixels in each inhabited cell and thus obtain a proxy for the
455 vegetation cover. In this example, we focus on the distribution of vegetation across inhabited
456 cells. The vegetation of the uninhabited part of the study zone also provides services to the
457 population and would be important to consider in further research.

458 As for point data, we consider hazardous industrial sites located in the metropolitan area. This
459 geocoded data is provided by the French Ministry of Ecology 2016, as an application of the
460 European Seveso-III Directive (Directive 2012/18/EU) on Technological Disaster Risk
461 Reduction. It provides the location of industrial establishments where dangerous substances
462 are used or stored in large quantities, with either a low or a high threshold of risk.



463

464 **Fig. 2.** Vegetation cover, industrial hazards and low-income households465 *Sources:* Own treatments based on French tax database Insee RFL, 2010, RapidEye, 2010, French Ministry
466 of Ecology Seveso database 2016.467 *Notes:* Variables are classified based on Jenks natural breaks.

468

469

470 Table 1 presents basic descriptive statistics for socio-economic and environmental data.

471 Overall, there are 184,485 households and 18% of low-income households in our study zone,

472 which comprises 4,342 inhabited cells. The mean value of the number of households is quite

473 low (42.5) and the one of the vegetation cover is quite high (3.1 ha) due to the high number of

474 cells located in outer suburbs or peri-urban areas. The standard deviation of the number of

475 poor households is very high (21.9) relative to the mean (7.7), as a result of their strong

476 concentration in cells of the urban core and the inner suburbs (see Figure 2).

477

478 **Table 1**
479 Basic statistics for environmental and socio-economic data

	Grid cell level				Study zone level
	Mean	SD	Min	Max	
Households ^{a,d}	42.5	10.9	0.3	684	184,485
Low-income households ^{a,d}	7.7	21.9	0	385	33,537
Low-income households (%) ^{a,d}	10.5	10.9	0	0.8	18.2
Vegetation (ha) ^{b,e}	3.1	0.9	0.03	4	13,271
Vegetation (%) ^{b,e}	76.5	23.4	0.01	100	76.5
Number of dangerous industrial sites ^c					14
Number of high-risk industrial sites ^c					9
Distance to the closest industrial site (km) ^c	4	2.6	0	17.8	
Distance to the closest high-risk site (km) ^c	4.5	2.6	0	17.8	

480 *Sources:* Own calculations based on: ^a French tax database Insee RFL, 2010; ^b RapidEye, 2010 (treatments
481 L. Martinez); ^c French Ministry of Ecology Seveso database 2016.

482 *Notes:* ^d These proxies provided by Insee accept values below 1; shares of low-income households are
483 bounded to 0.8 for confidentiality reason (see insee.fr/fr/statistiques/2520034#documentation); ^e A pixel
484 is considered vegetated for NDVI values greater than 0.35.

485

486

487 4.2. Results

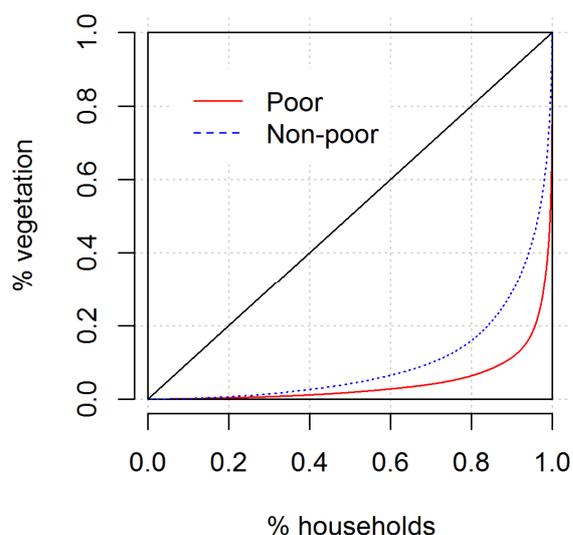
488 4.2.1. Global Dissimilarity Analysis for the Vegetation Cover

489 The first empirical case considers the environmental segregation of poor and non-poor
490 households with respect to vegetation. Figure 3 shows the environmental segregation curves
491 corresponding to ED_0 indices for poor and non-poor households, and Table 2 (and Figure 4)
492 displays values of ED_K and ΔED_K for distinct K . Obviously, as they are always many more
493 people and much less vegetation in the centre of an urban region than in its fringe, obtaining
494 low values for ED_K indices would be rather odd. Indeed, both poor and non-poor households
495 appear to be highly segregated from green spaces: ED_0 values (respectively 0.79 and 0.64)
496 indicate that more than a half of them would have to be displaced to reach the unsegregated
497 state (the diagonal line on Fig. 3). Regarding inequalities, **and as might be expected given the**
498 **local context (see 4.1)**, these values show that the poor are more segregated from green spaces
499 than the non-poor, with a difference of 15 points in the shares of households to be displaced.

500 Incorporating local interactions, the environmental segregation of poor and non-poor
501 households decrease strongly (from $K=0$ to 4) and then stabilize as the spatial scale of the

502 adjustment widens (for $K \geq 5$).^{10,11} Since poor people are more segregated from green spaces
 503 than non-poor people at the residence cell scale (without spatial adjustment), we expect that
 504 the former benefit more than the latter from local interactions with neighbouring cells. Indeed,
 505 the absolute decrease of ED_K with K is larger for poor than for non-poor households: ΔED_K
 506 decreases strongly and then stabilize around 0.05. In sum, there are opportunities of local
 507 interactions with green spaces in our study zone, which contribute to reducing the
 508 environmental inequality, but that do not make it disappear.

509



510

511 **Fig. 3.** Environmental Segregation curve for vegetation cover

512 *Notes:* e.g., the 80% of the poor households living in the less vegetated grid cells benefits from less than
 513 10% of the total amount of vegetation (as indicated by the red curve), whereas the same proportion of
 514 non-poor households benefits from nearly 20% (as indicated by the blue curve).

515

516

¹⁰ Adjusted- ED indices equal the ED index less the mean value of the local spatial interactions. The fact that ED_7 is much lower than ED_0 means there are strong local interactions: indeed, many densely inhabited cells with low greenery are neighbouring low density cells with high greenery, especially along the urban fringe.

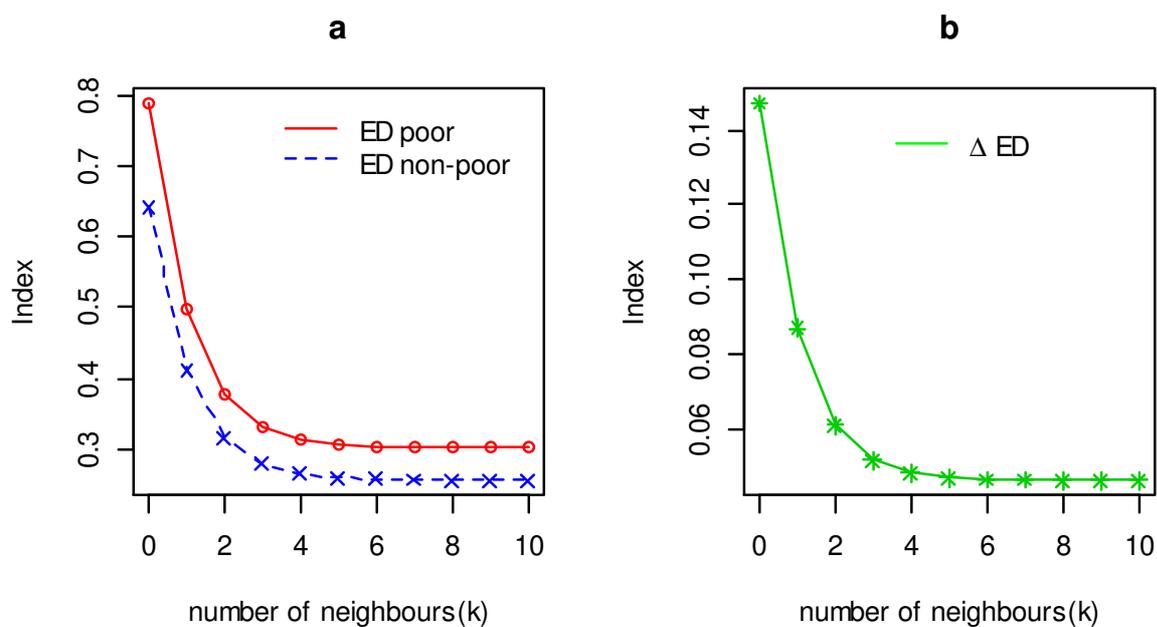
¹¹ Interactions are weighted by a distance decay function, which explains the stabilization of ED_K values when K is increased from 5 to 10. Interactions at the first, second, third, fourth and fifth order contiguity are weighted respectively by a factor of 1, 0.37, 0.14, 0.05, 0.02 and 0.01, and weights beyond the fifth contiguity are very close to zero. The choice of a negative exponential in this empirical example reflects the assumption that proximity is of great importance for people's interactions with the greenery. In a comprehensive analysis, the choice of the distance decay function and its implications should be considered more in depth.

517 **Table 2**
 518 Global dissimilarity analysis for vegetation cover: observed and simulated indices

		Empirical ED_K	Simulated ED_K (mean)	Rank ^a	Pseudo P-value
K=0	Poor	0.789	0.67	500	0.002
	Non-poor	0.642	0.664	1	0.002
	Difference	0.147	0.006	499	0.004
K=1	Poor	0.498	0.401	500	0.002
	Non-poor	0.411	0.411	340	0.322
	Difference	0.087	-0.01	500	0.002
K=2	Poor	0.377	0.292	500	0.002
	Non-poor	0.316	0.308	500	0.002
	Difference	0.061	-0.016	500	0.002
K=3	Poor	0.330	0.251	500	0.002
	Non-poor	0.278	0.269	500	0.002
	Difference	0.052	-0.017	500	0.002
K=4	Poor	0.313	0.236	500	0.002
	Non-poor	0.265	0.254	500	0.002
	Difference	0.048	-0.018	500	0.002
K=5	Poor	0.306	0.23	500	0.002
	Non-poor	0.259	0.248	500	0.002
	Difference	0.047	-0.018	500	0.002

519 Notes: ^a The rank is the position of the observed index value in the distribution of simulated values.

520



521 **Fig. 4.** Environmental Dissimilarity indices for vegetation cover
 522

523

524 To reach robust conclusions, we must check that the observed differences between the ED_K
 525 values of the poor and the non-poor do not reflect random differences in the spatial
 526 distributions of the two groups. Table 2 provides pseudo p-values for ED_K and ΔED_K indices,
 527 computed based on 499 Monte Carlo spatially constrained random draws (see section 3.2.1
 528 for details). It shows that all but one value is highly statistically significant. Most importantly,
 529 the environmental segregation of poor households is always significantly higher in the
 530 empirical case than in the random scenario, as well as the degree of environmental inequality
 531 between poor and non-poor households. The only non-significant value is the ED_I index
 532 computed for the non-poor (see below for more explanations).

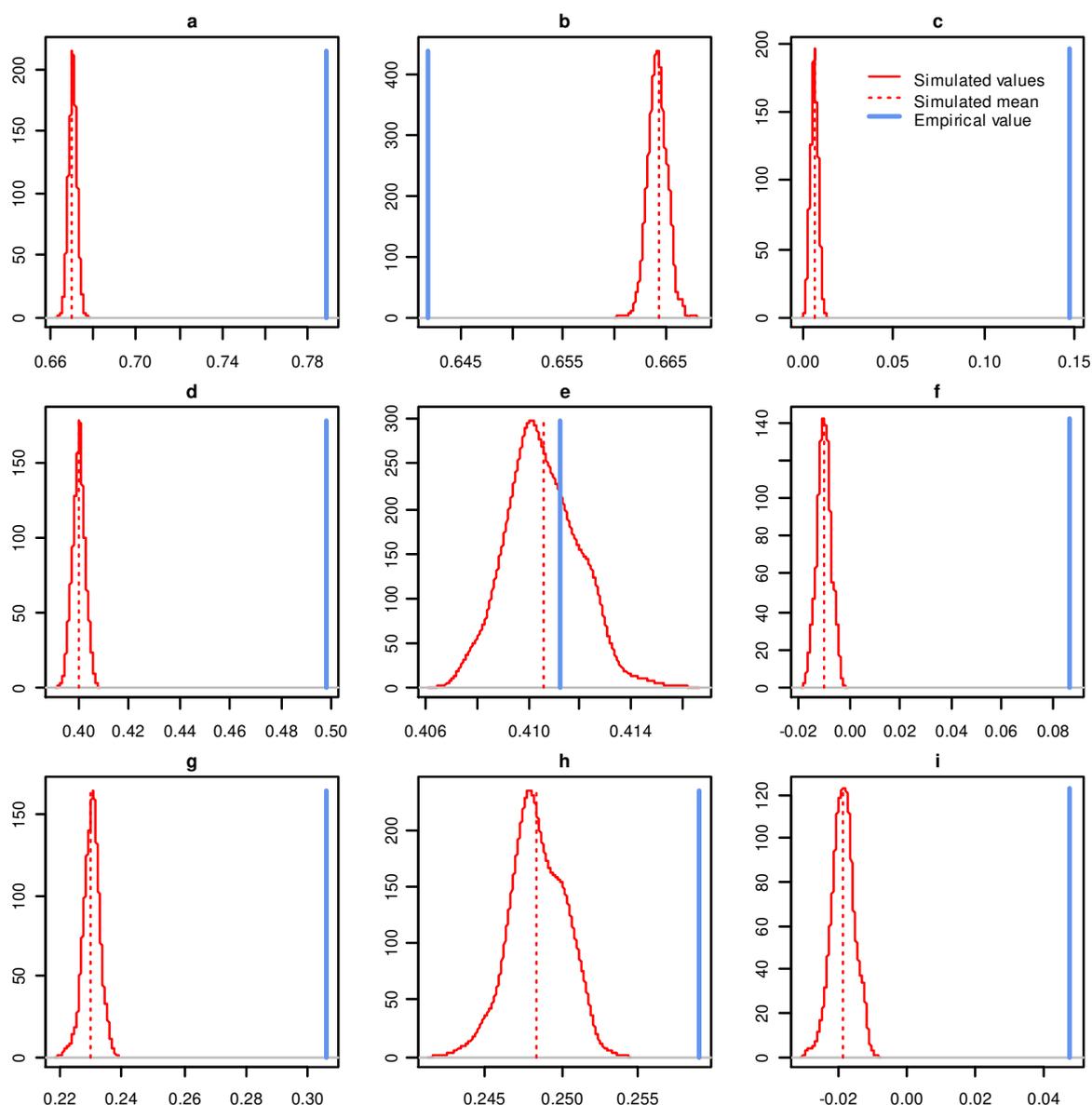
533 Since the results presented in Table 2 are qualitatively equivalent for $K=2$ to 5, we comment
 534 more on $K=0$, $K=1$ and $K=5$. Figure 5 presents the position of the empirical value in the
 535 distribution of simulated values for the ED_K indices of the poor (first column) and the non-
 536 poor (second column), and for ΔED_K (third column), either without adjustments for local
 537 spatial interactions (first row) or with adjustments at the 2nd (second row) or 5th contiguity
 538 order (third row).

539 As expected, on subfigures *a*, *d*, *g*, empirical ED_K values are much larger than simulated
 540 values: poor households always have a highly significant degree of environment segregation:
 541 non-random factors push them away from green spaces. Similarly, on subfigures *c*, *f*, *i*,
 542 environmental inequality, as measured by ΔED_K , is always positive and statistically
 543 significant. The poor are always more environmentally segregated than the non-poor.

544 Results concerning non-poor households require further reflection. The subfigure *b* reveals
 545 that non-poor households are significantly *less* environmentally segregated than when
 546 allocated randomly: there are non-random factors that make the non-poor choose greener
 547 locations. But at the 1st order contiguity (subfigure *e*), the empirical ED_I index of non-poor is
 548 in the middle of the simulated distribution: they are segregated ‘just as expected’ in the
 549 random case. Lastly, at the 5th order (subfigure *h*), non-poor households are significantly *more*
 550 environmentally segregated than expected (and the graphic would be equivalent for all $K \geq 2$).

551 Here we should recall that the adjusted index equals the unadjusted index less the mean value
 552 of the local interactions. This implies that simulated local interactions for non-poor
 553 households are larger than observed local interactions for $K=1$, and even more for $K=5$: there
 554 are *fewer local interactions* than would be in a random scenario. Our interpretation is as
 555 follows: non-poor households have fewer local interactions with the vegetation than when

556 allocated randomly – with probabilities based on housing stocks – because they are more
 557 dispersed than the dwellings: they are disproportionately more represented in low-density
 558 areas and less in dense urban neighbourhoods. Since local interactions are maximal between
 559 high-density highly artificialized neighbourhoods and low-density heavily vegetated ones and
 560 minimal between neighbourhoods of similar population density and vegetation cover, a
 561 greater dispersion of non-poor households is associated with fewer local interactions.



562

563 **Fig. 5.** Global dissimilarity analysis for the vegetation cover: empirical and simulated indices

564 *Notes:* Each subfigure provides the probability density function for simulated values, the mean of the
 565 simulated values and the empirical value of the index, for *ED* indices computed for the poor (1st column),
 566 the non-poor (2nd column), and for ΔED (3rd column), either without adjustments for local spatial
 567 interactions (1st row) or with adjustments at the 2nd (2nd row) or 5th contiguity order (3rd row).

568

569 Non-poor households are thus segregated ‘just as expected’ for $K=1$ and more segregated than
 570 in a random scenario for $K \geq 2$, but in any case they remain less environmentally segregated
 571 than the poor: the significant (non-random) environmental segregation of the poor always
 572 generates a significant (non-random) environmental inequality with the non-poor.

573 **4.2.2. Local Dissimilarity Analysis for the Vegetation Cover**

574 The global analysis has confirmed that the poor are more segregated from green spaces than
 575 the non-poor. Against this background, we may consider alternatively two political goals: (i)
 576 the first focuses on the poor and aims to bring closer together the poor and the vegetation
 577 cover; (ii) the second focuses on reducing the environmental inequality between the poor and
 578 the non-poor. The former is focused on the absolute situation of the poor, and the second on
 579 their relative situation compared to the non-poor. In accordance with these goals, the local
 580 analysis may focus on identifying: (i) the hotspots having the largest influences on the ED_0 of
 581 the poor; or (ii) the ones that have the largest influences on ΔED_0 .¹²

582 In line with the first goal, the left panel of Figure 6 shows the box plot of the Jackknife
 583 simulations of ED_0 for poor households, and maps the cells whose removal is associated with
 584 an important decreasing ED_0 (i.e., corresponding to low outliers on the box plot, see 3.2.2).
 585 We will call them ‘A’ cells. Compared to others, they are much less vegetated and much more
 586 populated, with higher shares of low-income households (Table 3). On the map (subfigure a),
 587 we can distinguish a group of cells (say ‘A1’ cells, coloured in blue) located in the centre of
 588 the city, where vegetation is scarce (see Fig. 2a), and a second group of cells (say ‘A2’ cells,
 589 coloured in red) located mainly in the South-East suburb of the city, where shares of poor are
 590 very high (see Fig. 2b).¹³

591 In line with the second goal, the right panel of Figure 6 shows the box plot corresponding to
 592 Jackknife simulations of ΔED_0 , and maps the hotspots having the largest positive impacts on
 593 the environmental inequality between the poor and the non-poor (i.e., corresponding to low
 594 outliers on the box plot). Clearly, this second set of cells – say ‘B’ cells – is quite different
 595 from the former. Overall, B cells appear much more vegetated and less inhabited than A cells
 596 (see Table 3). The B set comprises cells (say ‘B1’ cells, coloured in blue on Fig. 6) with very
 597 low shares of poor, mainly located in the peri-urban part of the study zone. They also contain

¹² For space reasons, we perform the local analysis only on non-adjusted ED values.

¹³ The value of 0.3 retained to highlight red cells with high shares of poor households (vs blue cells with low shares) corresponds to the threshold of high outliers in the distribution of this variable (see Table 1).

598 cells (say ‘B2’ cells, coloured in red, cf. footnote 14) that were also part of the A2 group, with
 599 high shares of poor and located in the suburbs of Grenoble. But the cells of the A1 group –
 600 precisely the less vegetated and the most populated – do not pertain to this new set.

601 These results are interesting as they show that the two political goals stated above should not
 602 be confused and may require different spatial targets. If the political goal is focused on the
 603 absolute situation of the poor, it may be worth targeting the urban heart of the city (A1 cells),
 604 where the poor are numerous, to introduce more vegetation where possible. But the centre of
 605 the city is populated by poor as well as non-poor households, so that this targeting may not be
 606 the most relevant to reduce the environmental inequality. If the political goal is primarily to
 607 reduce this inequality, then targeting more specifically the places where the shares of low-
 608 income households are the highest (A2 and B2 cells) may be more effective. Also, the
 609 environmental inequality stems from the quasi-absence of poor households in peri-urban
 610 communities. Thus, helping more low-income households to settle in these areas (B1 cells),
 611 for instance through social housing programmes, may be another relevant political option.

612 **4.2.3. Global Centralization Analysis for Industrial Hazards**

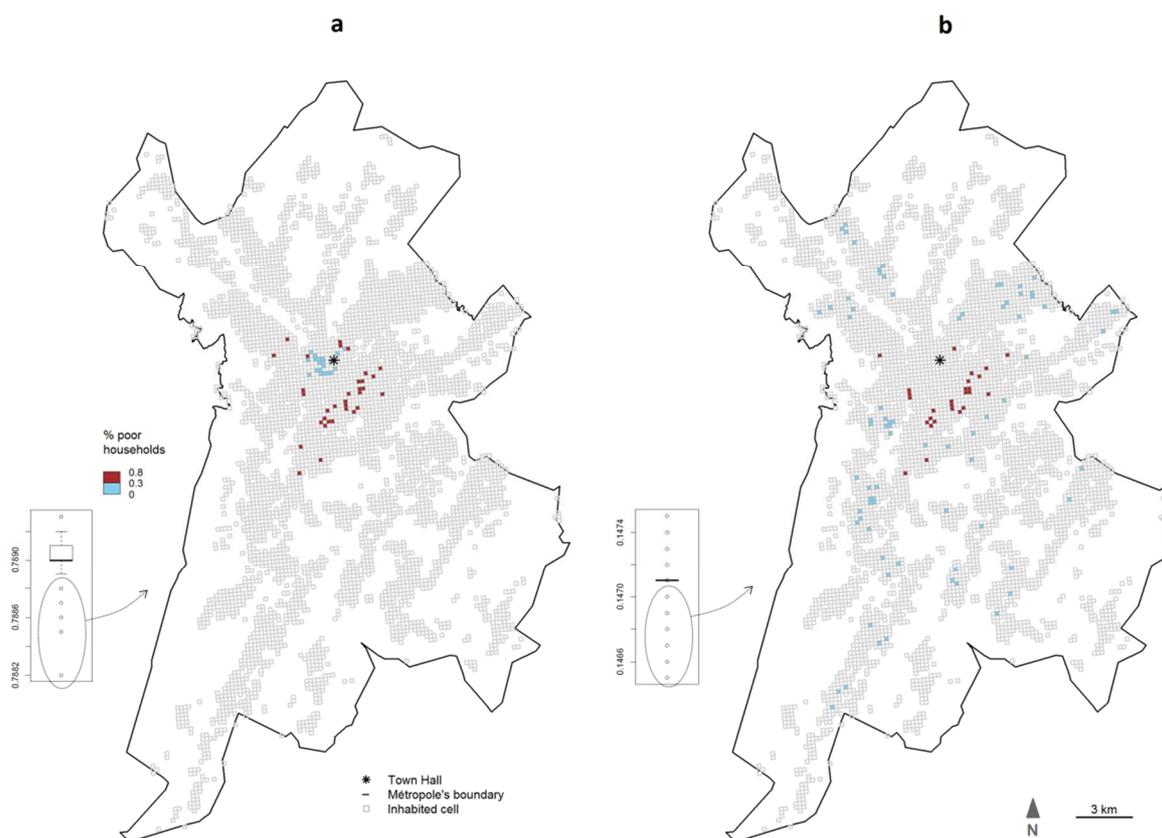
613 The second empirical example concerns disamenities, namely hazardous industrial sites. The
 614 values of the unconstrained EC index ($EC_{d=dmax}$) are positive (0.036 and 0.99 respectively for
 615 all and high risks), showing that the poor are globally more centralized than the non-poor with
 616 respect to dangerous sites (Table 4). The Monte Carlo significance tests confirm this
 617 environmental inequality: observed values do not reflect random differences in the spatial
 618 distributions of the two groups. **These results aren’t surprising given the local context (see**
 619 **again 4.1): the segregation dynamics that separates poor and non-poor people is likely to be**
 620 **linked to both amenities (e.g., vegetation) and disamenities (e.g. industrial risks) and the**
 621 **presence of environmental inequalities was the expected outcome.**

622 These inequalities can be visualized on Figure 7, which shows the segregation curves for all
 623 risks or high risks, where the EC index is the area between the curve and the diagonal (see
 624 section 3.1.2). For all risks (subfigure *a*), considering spatial units at short distances from
 625 dangerous sites (the left side of the graph), either poor or non-poor households can be
 626 overrepresented (the curve is successively under or above the diagonal), but considering the
 627 whole area, poor households are clearly closer to dangerous sites. For high risks, poor
 628 households are unambiguously closer to dangerous sites (the curve is always under the
 629 diagonal); the curve deviates more from the diagonal when more distant spatial units are taken

630 into account. We can conclude that the inequality is mainly driven by a strong over-
 631 representation of non-poor households in residential locations that are the farthest from
 632 industrial hazards.

633 **Table 3**
 634 Local dissimilarity analysis for the vegetation cover: descriptive statistics of hotspots

	A cells				B cells			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Households	397.4	135.1	158	684	106.5	126.2	29.7	684
Low-income households	145.7	51	90	385	44.4	79.4	0	385
Low-income households (%)	40.7	17	17	74.2	16.4	25.5	0	79.5
Vegetation (ha)	1.3	0.7	0.1	2.7	3.1	0.7	0.6	3.9
Vegetation (%)	32	17.4	2.5	68.6	71.7	17.7	13.8	98.7



635 **Fig. 6.** Local dissimilarity analysis for the vegetation cover: box plots and hotspots
 636

637 *Notes:* Subfigure a shows the box plot of Jackknife simulations of ED_0 for the poor, and the map of those
 638 hotspots whose removal is associated with a lower environmental segregation (i.e., low outliers);
 639 subfigure b shows the same box plot for ΔED_0 and the map of those hotspots whose removal is associated
 640 with a lower environmental inequality (i.e., low outliers). The value of 0.3 retained to highlight cells with
 641 high shares of poor households corresponds to the threshold of high outliers (mean+2*SD) in the
 642 distribution of this variable in the study zone (see Table 1).
 643

644 **Table 4**
645 Global centralization analysis for industrial hazards: observed and simulated indices

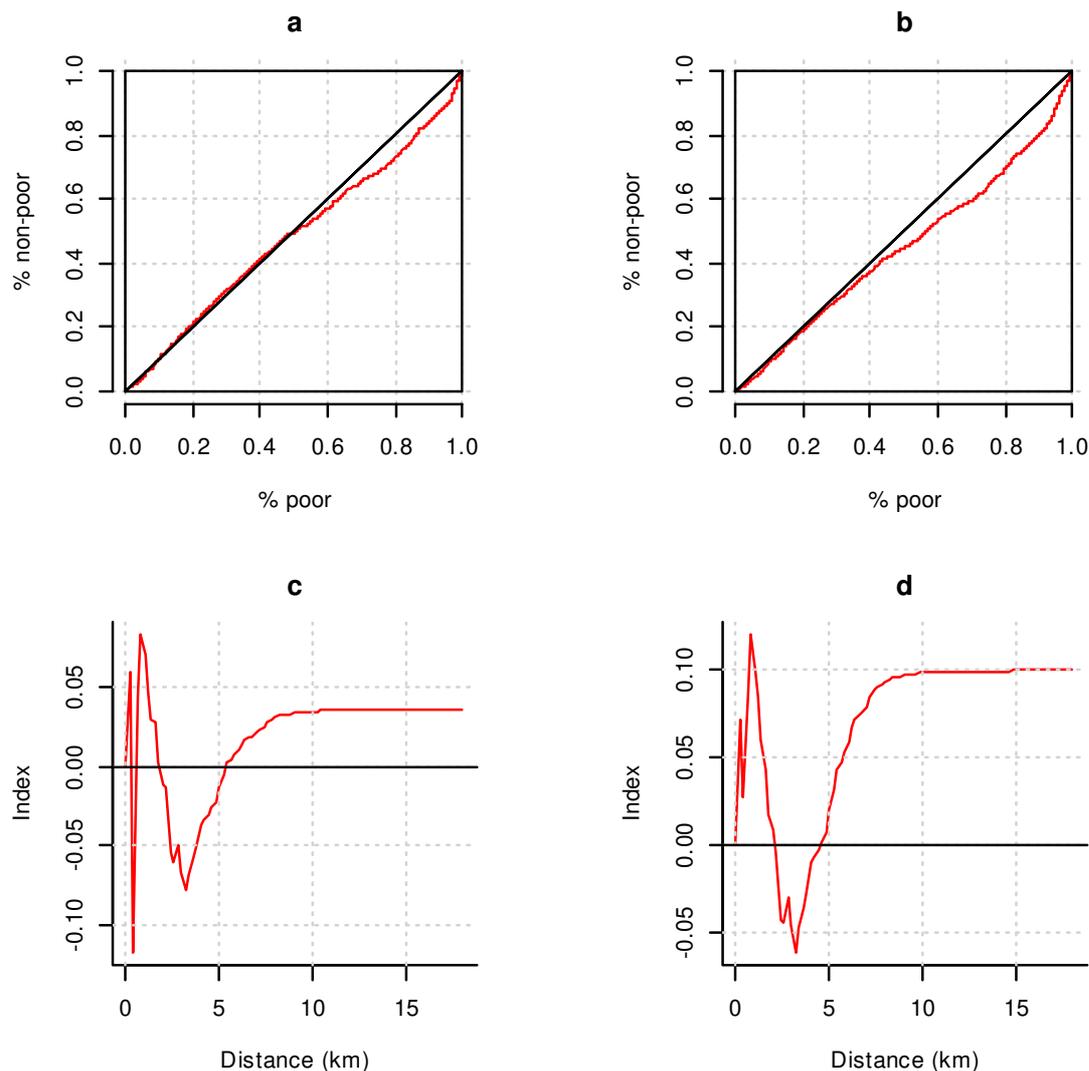
	Distance bound (d)	Empirical EC_d	Simulated EC_d (mean)	Rank ^a	Pseudo P-value
All dangerous industrial sites	Maximum distance ^b	0.036	0	500	0.002
	15 km	0.036	0	500	0.002
	12 km	0.035	0	500	0.002
	9 km	0.033	0	500	0.002
	6 km	0.01	0	497	0.008
	3 km	-0.066	0	1	0.002
	1 km	0.07	0	500	0.002
High-risk industrial sites only	Maximum distance ^b	0.099	0	500	0.002
	15 km	0.099	0	500	0.002
	12 km	0.098	0	500	0.002
	9 km	0.096	0	500	0.002
	6 km	0.059	0	500	0.002
	3 km	-0.046	0	1	0.002
	1 km	0.097	-0.001	500	0.002

646 *Notes:* ^a The rank corresponds to the position of the observed index value in the distribution of simulated
647 values; ^b The maximum distance between a grid cell and a dangerous site in the study zone equals 17.9 km;
648 the corresponding EC_d index covers all spatial units and population comprised within the study zone.

649

650 To confirm this conclusion, we now consider spatially constrained EC_d indices, with the
651 spatial scope of the analysis – d – varying from 1 to 15 km by steps of 200m. For each d , the
652 analysis is restricted to spatial units located at a distance less than d from the closest
653 hazardous site. In other words, we make a focus on ‘intra-buffers’ environmental inequalities.
654 The results obtained (subfigures *c* and *d* on Figure 7 and Table 4, which offers significance
655 tests) show as expected that either one group or the other can be significantly more centralized
656 for small value of d . But as d becomes sufficiently large ($d \geq 9$ km), the constrained indices
657 converge toward the unconstrained ones, and the poor appear significantly more centralized.

658 The sensitivity for small values of d reflects complex social segregation patterns around and
659 moving away from dangerous sites: spatial units where poor people are overrepresented are
660 followed by spatial units where they are underrepresented and so on; as the spatial scope of
661 the analysis is extended, new rings of cells are included gradually in the calculation of the
662 index, and the relative centralization of poor households decreases (resp. increases) when
663 these new and most distant rings have high (resp. low) shares of poor households. However,
664 non-poor households are unambiguously overrepresented in the spatial units that are the
665 farthest from the dangerous sites, what explains the convergence toward unrestricted values.



666

667 **Fig. 7.** Global centralization analysis for industrial hazards: graphical approaches

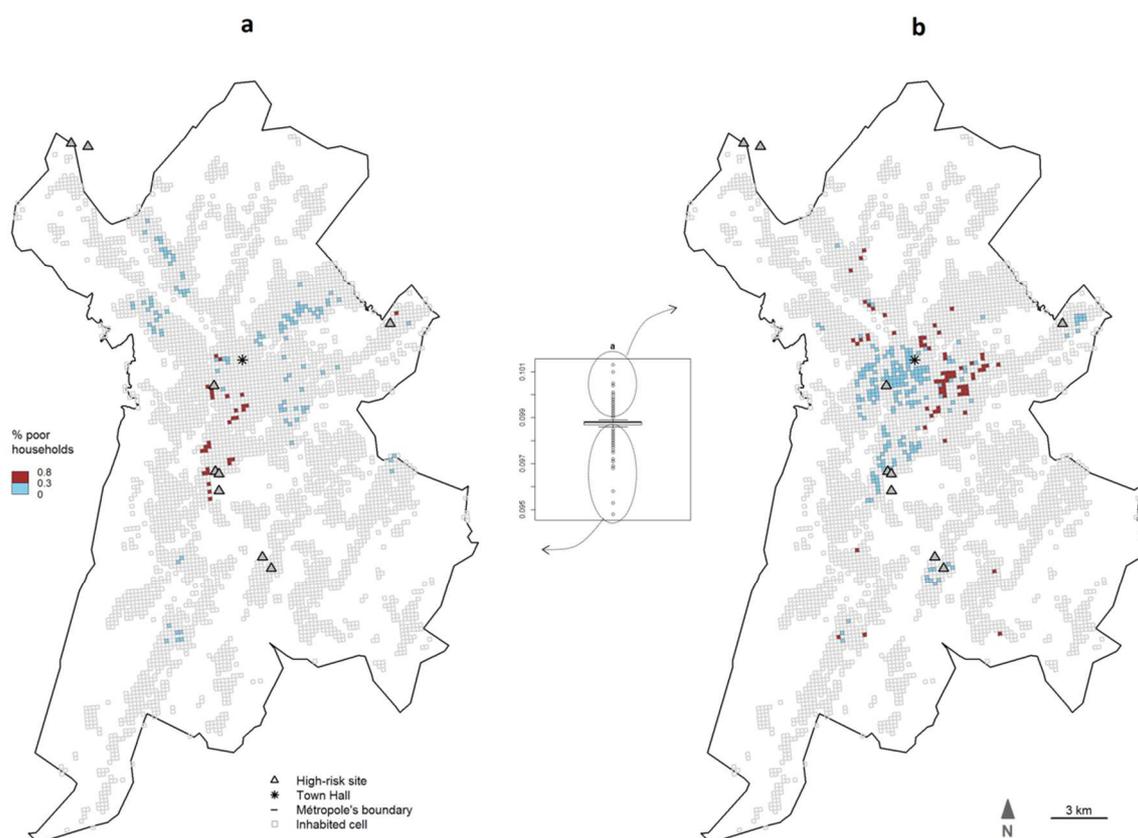
668 *Notes:* The left panel refers to all hazardous sites and the right one to very dangerous sites; Subfigure *a*
 669 and *b* are Lorenz-like curve: the curve on *b* shows that the spatial units which are the closest from hazards
 670 and that house, e.g., 80% of the poor, only house 70% of the non-poor (subfigure *a* reads in the same way);
 671 $EC_{d=dmax}$ is the area between the curve and the diagonal; Subfigures *c* and *d* provide the values of EC_d
 672 indices calculated by varying d in steps of 200m.

673

674 4.2.4. Local Centralization Analysis for Industrial Hazards

675 Since the EC index measures a *relative* centralization, it is tailored to inform a policy aiming
 676 at reducing the inequality between the poor and the non-poor. The local analysis allows
 677 identifying the hotspots that have the largest influences on this inequality. In this example, we
 678 focus specifically on the uneven exposure to *very* dangerous industrial sites, without assuming
 679 any spatial constraint for the analysis.

680 Figure 8 shows the box plot of the distribution of simulated *EC* values, and maps the spatial
 681 units associated with *low* (map a) and *high* (map b) outlier values of this distribution (see
 682 section 3.2.2). The former spatial units have the largest *positive* impacts on the environmental
 683 centralization of the poor (i.e., their removal makes *EC* increase), whereas the latter have the
 684 largest *negative* impacts (i.e., it makes *EC* decrease).



685

686 **Fig. 8.** Local centralization analysis for industrial hazards: box plot and hotspots

687 *Notes:* Subfigure *a* shows the map of hotspots whose removal is associated with a lower environmental
 688 inequality (i.e. low outliers on the box plot of the Jackknife simulations of *EC* values); subfigure *b* presents
 689 the hotspots associated with a higher environmental inequality (i.e. high outliers). The value of 0.3
 690 retained to highlight cells with high shares of poor households corresponds to the threshold of high
 691 outliers (mean+2*SD) in the distribution of this variable in the study zone (see Table 1).
 692

693 On the map *a*, we can distinguish spatial units with higher shares of low-income households
 694 (say 'C' cells, coloured in red), and others with lower shares (say 'D' cells, coloured in blue).
 695 As expected, C cells are close to dangerous sites, whereas D cells are quite distant from all
 696 sites. This map highlights well the hotspots which make the poor more centralized than the
 697 non-poor. It may help policy-makers target their policies: for instance, if a new social housing
 698 programme were to be implemented, or if new hazardous facilities were to be installed, then

699 the political goal of reducing environmental inequality with respect to hazards would
700 recommend avoiding C cells and wherever possible choosing locations in D cells.

701 Conversely, the map *b* shows cells that ‘play against’ the environmental inequality. Although
702 the poor are globally more centralized than the non-poor with respect to dangerous sites, there
703 are cells nearby high-risk sites where non-poor households are numerous and more distant
704 cells with high shares of poor households. This map illustrates the complexity of the
705 environmental segregation patterns already emphasized in the previous section. It also shows
706 the ‘egalitarian’ hotspots in the current spatial distribution of households that should not be
707 compromised by inappropriate actions.

708

709 5. Conclusion

710 Robust methods for assessing environmental inequalities are needed to help define and
711 evaluate environment justice policies. We have developed such methods to measure between-
712 group environmental inequalities related to residential segregation patterns. **All will soon be**
713 **available in a dedicated R package called *SegEnvIneq*.** This approach is particularly suited to
714 environmental inequality assessments in urban context.

715 Inspired by the residential segregation literature, we propose the Environmental Dissimilarity
716 index (ΔED_K) and the Environmental Centralization index (EC_d) to analyse ‘segregation-
717 based’ environmental inequalities. These indices allow working with, respectively, areal-level
718 (e.g., vegetation cover) or multiple-points (e.g., dangerous sites) environmental data. Both
719 indices are genuinely spatial: ΔED_K can incorporate local interactions between people and
720 environment across spatial units’ borders, and EC_d can be spatially constrained to better
721 understand segregation patterns around and moving away from environmental centralities. To
722 ensure the robustness of this analysis, we also suggest a distribution-free significance test
723 based on Monte Carlo experiments, relevant for ΔED_K and EC_d indices.

724 Beyond these useful tools for carrying global (city-wide) analyses, we propose a consistent
725 method to identify local (neighbourhood scale) hotspots. The procedure based on Jackknife
726 simulations highlights the spatial units most responsible for environmental inequalities, as
727 measured by ΔED_K or EC_d .

728 These methods are applied in Grenoble-Alpes Métropole, France, and reveal inequalities
729 between poor and non-poor households in terms of access to green spaces and exposure to
730 industrial risks. This illustration uses data available at very fine spatial scales (i.e. a 200 m x
731 200 m grid for population data, and even finer scales for environmental data). To explore the
732 sensitivity of our methods, an extension left for future research would be to compare these
733 results with additional results obtained at coarser and less regular spatial scales (e.g. using
734 population data from French census tracks).

735 We believe that designing global and local segregation-based approaches to measuring
736 environmental inequalities is a useful step forward in the environmental justice literature. Past
737 research has shown that taking the environment into account help understanding residential
738 segregation dynamics (Wu, 2006; Schaeffer *et al.*, 2016). Further researches are still required
739 to deepen our comprehension of theoretical and empirical relationships between residential
740 segregation and segregation-based environmental inequalities.

741

742

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749

750

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752

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