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How can we analyze environmental health resilience and vulnerability? A joint analysis with composite indices applied to the north of France

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20 **Abstract**

21 In environmental health, vulnerability reflecting the cumulative harmful constraints and nuisances to
22 which populations are subjected and resilience defined as the capacity of a territory to cope with
23 health inequalities have been little extensively investigated together with the same importance.
24 Besides the diversity of factors involved, there is no consensual framework to develop composite
25 indices, one recognized methodology to deal with a multifaceted issue. Therefore, this research aims
26 to establish a new transferable approach to assess the spatial heterogeneity of territorial
27 inequalities. This new strategy relies on the simultaneous evaluation of resilience and vulnerability
28 and the joint analysis based on the cross-interpretation of the spatialized composite indices of
29 resilience and vulnerability. A case study was conducted to demonstrate the feasibility of this
30 methodology, using the municipality as a spatial unit of analysis within a region in the north of
31 France. To provide the most holistic description possible of the 3,817 studied municipalities, 50
32 variables related to the economic, environment, policy, health, services and social dimensions were
33 used to develop the composite indices. The vulnerability Index has a median value of 0.151 with an
34 IQR of [0.126-0.180] and the Resilience Index has a median value of 0.341 with an IQR of [0.273-
35 0.401]. The joint analysis was conducted to classify each municipality among four defined typologies:
36 1,687 municipalities (44.2%) belong to the “To monitor” category, 1,646 (43.1%) to the “Resilient”
37 category, 329 (8.6%) to the “Have resources” category and 155 (4.1%) to the “Territorial blackspot”
38 category. The methodology herein may be a diagnostic tool to identify and prioritize municipalities
39 that could benefit from the implementation of specifically tailored public health policies.

40 **Highlights**

- 41 • *Transdisciplinary research is mandatory for assessing environmental health issues*
- 42 • *Data reuse overcomes the difficulties of data accessibility*
- 43 • *Proposed use of composite indices to assess the accumulation of health determinants*
- 44 • *Spatial heterogeneity of resilience and vulnerability can be mapped at local scale*
- 45 • *Joint analysis enables stakeholders to prioritize future public health actions*

46 **Keywords**

47 Environmental health determinants, territorial inequalities, multidimensional indices, territorial
48 blackspot, diagnostic tool

49

50 1 Introduction

51 Territorial inequalities in environmental health are regarded as an accumulation of unfavourable
52 health determinants in a given geographical area. The complex interactions between these
53 determinants of health, which are interconnected and evolve over time and space, strongly influence
54 the health of populations (Sarkar and Webster, 2017). The 2012 Lancet Commission report highlights
55 the need for a complex systems approach to characterize the multi-level processes (*e.g.*
56 environmental, social, urban planning) that influence the health of populations (Rydin et al., 2012).

57 The diversity of factors involved in environmental health, the complexity of the interactions to be
58 considered and the spatial and temporal variability of the phenomena observed require the
59 validation and use of multidimensional approaches that are more than a simple aggregation of health
60 determinants (Briggs, 2008). One recognized method used to analyse this type of complex problem is
61 based on the creation of spatialized composite indices combining different indicators that measure
62 and transcribe the multifaceted nature of a phenomenon (Beale et al., 2008; European Commission
63 et al., 2008; Flacke, 2015; Nascimento and Carrage, 2007). We have identified 23 spatialized health-
64 environment indices at the international level (Brousmiche et al., 2020a). The indices published to
65 date are consistent with the consensual definition of territorial inequalities. They focus mainly on the
66 vulnerability of territories, and reflect the cumulative harmful constraints and nuisances to which
67 populations are subjected. This solely permits the measurement of damage (*e.g.* greenhouse gas
68 emissions) and of the elements characterising the societal factors that shape society's vulnerability to
69 these hazards (*e.g.* the share of the population with a higher education qualification). These
70 publications primarily seek to assess the accumulation of health determinants in a territory. A holistic
71 description of a territory therefore requires an approach that is as global as possible and goes
72 beyond the negative aspects to include the positive factors that are still poorly represented in
73 composite indices.

74 Many studies deal with environmental health issues, focusing generally on vulnerability, *i.e.* on
75 determinants that have a negative impact on territorial inequalities (Angeon and Bates, 2015). To a
76 lesser extent due to a recent awareness, the positive impact of health determinants are also taken
77 into account (Fong et al., 2018; Hartig et al., 2014). These studies are generally based on proximity to
78 green spaces in municipalities and have revealed, for example, a consequent decrease in
79 cardiovascular mortality and the occurrence of cardiovascular accidents (Rojas-Rueda et al., 2019;
80 van den Bosch and Ode Sang, 2017; Yeager et al., 2019), or an improvement in mental health
81 (Houlden et al., 2019; Mukherjee et al., 2017). To our knowledge, articles and research works
82 combining these two groups of determinants with the same importance are scarce (Estoque and
83 Murayama, 2014; Miller et al., 2017). These are embedded in their territory and do not propose a
84 conveniently transposable methodology. The concept of resilience, defined as the capacity of a
85 territory to cope with health inequalities (Lanier et al., 2020), is closely intertwined with vulnerability,
86 but resilience is not the antonym of vulnerability (Fekete, 2018). The challenges are therefore to
87 define a set of data to characterize resilience and to submit a methodological approach that would
88 be easily transferable.

89 The information included in existing spatialized indices is disparate: it can describe environmental,
90 health, social, economic, political or territorial management and organization dimensions. Only 9
91 articles present an index that is simultaneously based on these 6 dimensions (Angeon and Bates,
92 2015; Braconnier et al., 2011; Cutter et al., 2010; Estoque and Murayama, 2014; Etsy et al., 2005;
93 Kerényi, 2011; Sadd et al., 2011; Zuindeau and Lipovac, 2009). The need to develop a process of
94 interoperability between data in different formats and the difficulty of accessing data in certain
95 contexts means that it is practically impossible to obtain a holistic description of the territory.

96 Authors often choose to focus their study on a national scale because standardized data are readily
97 available and international comparisons are facilitated (Biggeri and Mauro, 2018; Estoque and
98 Murayama, 2014; García-Sánchez et al., 2015). Overall trends are observable and can be tracked over
99 time. However, this approach does not allow users to take account of territorial specificities or to
100 integrate spatial variations for certain types of information. A finer spatial scale (*i.e.* city,
101 neighbourhood) facilitates a more precise description of phenomena, with the possible use of data
102 that may not exist in other territories (*e.g.* local initiatives). The local dimension of territorial
103 inequalities particularly meets the expectations of political decision-makers within the framework of
104 their concrete urban planning and public health actions (Hat and Stöglehner, 2019).

105 The aim of this research is to optimize the assessment of the spatial heterogeneity of territorial
106 inequalities. We propose a new strategy based on a joint analysis of two optimized composite sub-
107 indices. This balance between resilience and vulnerability allows the simultaneous evaluation of the
108 negative aspects of the territory in the Vulnerability Index (VI) and the positive aspects of the
109 territory in the Resilience Index (RI). On this basis, a cross-classification is validated with the objective
110 to distribute spatial units within territorial typologies. These homogeneous groups can be analyzed in
111 terms of health, environmental, political, services, social and economic dimensions. A case study was
112 conducted to demonstrate the feasibility of the methodology, using the municipality as a spatial unit
113 of analysis within a region in the north of France.

114 2 Material and Methods

115 2.1 Study setting

116 This study was carried out in the Hauts-de-France region, located in the north of France. This densely
117 populated area of 31,813 km² with 6,009,976 inhabitants, *i.e.* an average of 189 inhabitants/km², is
118 located at the crossroads of Europe and includes 3,817 municipalities that contrast in terms of their
119 respective sizes, population diversity, socioeconomic backgrounds and levels of environmental
120 pollution (Cuchère and Terra, 2017). These municipalities have a median [interquartile range (IQR)]
121 population of 423 [211 – 1,014] inhabitants and a median surface area of 6.91 [4.73 - 10.30] km². The
122 multiple sources of environmental pollution, including road traffic, residential heating, industries,
123 contaminated lands and conventional agriculture, are heterogeneously distributed across the
124 territory.

125 2.2 Methodology

126 The proposed methodological framework is as follows (Fig. 1):

- 127 (i) Data collection and analysis for each of the six dimensions (health, environment, social,
128 economics, services, policy) that characterize the multifaceted phenomena involved in
129 environmental health, all of which are recognized as playing a role in health inequalities,
- 130 (ii) the calculation of the resilience and vulnerability indices,
- 131 (iii) the evaluation of the spatial distribution of resilience and vulnerability indices,
- 132 (iv) the discretization of the resilience and vulnerability indices,
- 133 (v) the joint analysis of these two indices and the categorization of municipalities ($n = 3,817$)
134 into different typologies.

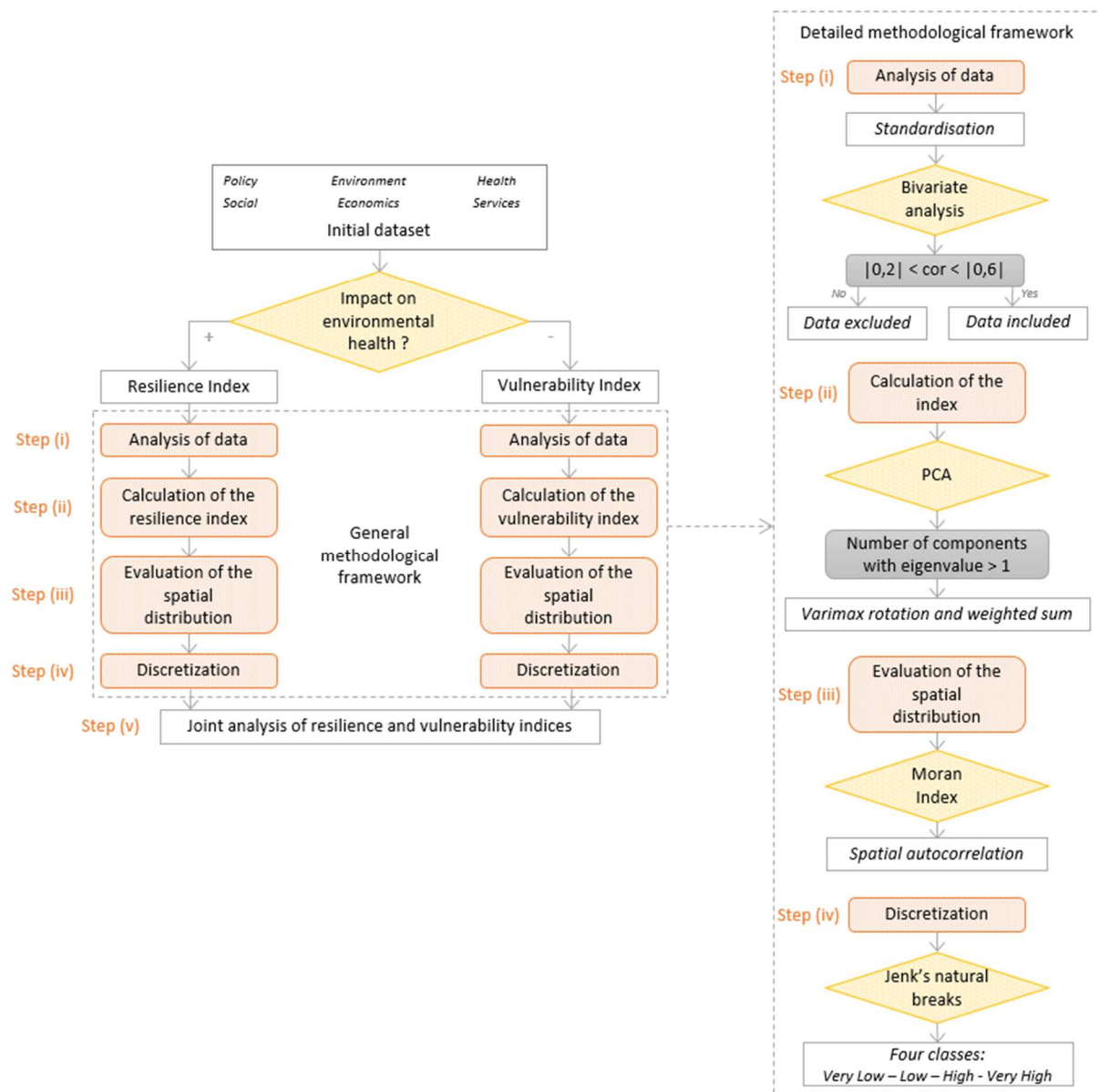


Figure 1. A comprehensive methodology for the development of composite indices to assess environmental health inequalities.

The general methodological framework presents the main steps to be followed for the development of composite indices, while the detailed methodological framework explains the different methods proposed for each step (step (i): analysis of data, step (ii): calculation of the index, step (iii): evaluation of the spatial distribution, step (iv): discretization and step (v): joint analysis of resilience and vulnerability indices)

2.2.1 Database development – inclusion/exclusion criteria

Data to be included were selected on the basis of three inclusion criteria:

- (i) the data was plausibly associated with environmental health in the literature and led to a characterization of a descriptor within a dimension,
- (ii) comprehensive, spatially contiguous and contemporary data were available for the entire study area,
- (iii) data monitoring was reliable and temporal monitoring was performed, thereby ensuring acceptable data quality.

The following exclusion criterion was applied: the data had been associated with individual behavior (*i.e.* smoking, food habits or physical activities).

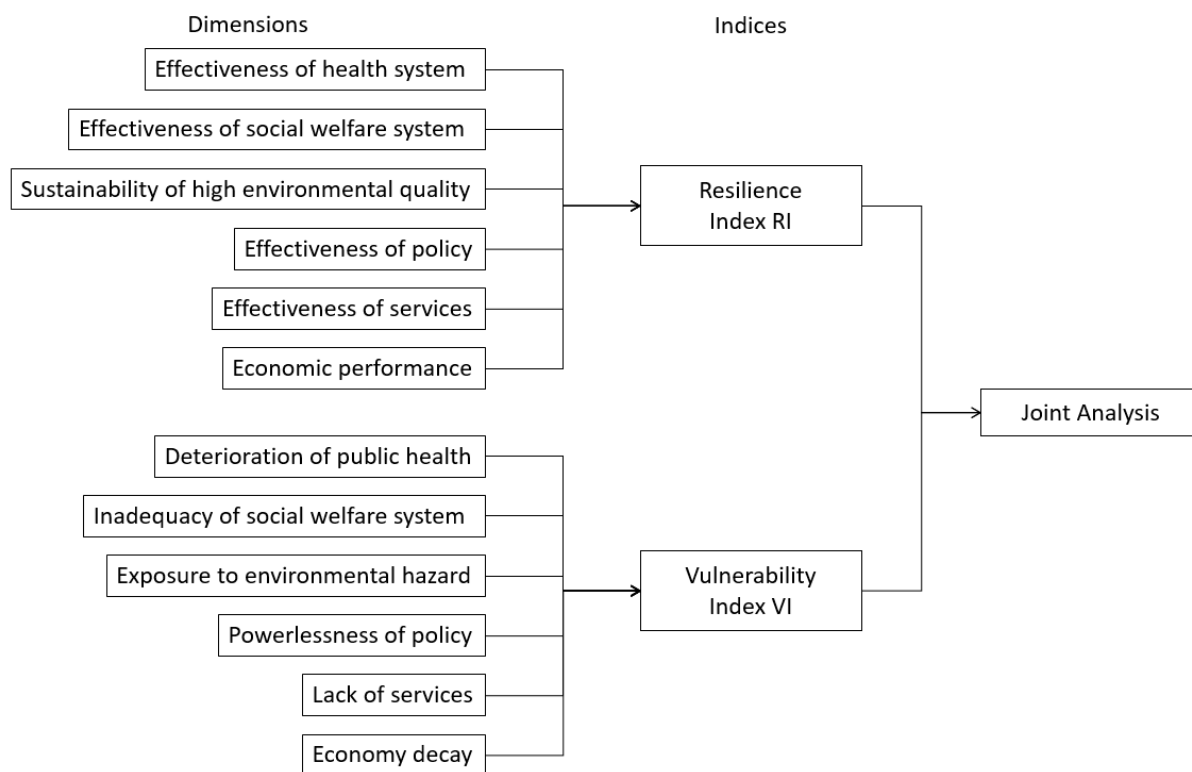
152 As part of our study on the Hauts-de-France region, 50 variables were collected from public national
 153 databases (accessible in *Open data*) in order to describe multiple facets of each dimension (Table I).
 154 Of these 50 variables, 36 % (18 variables) were obtained directly from official and national databases
 155 and were integrated into the dataset for use with no modification. The remaining 64 % (32 variables)
 156 were (i) derived from a straightforward calculation (*e.g.* a proportion calculated in relation to the
 157 number of inhabitants), or (ii) derived from more complex calculations inspired by previous works
 158 such as the valuation of ecosystem services or the Shannon-Weaver index (Estoque and Murayama,
 159 2014; Salvati and Carlucci, 2014). Further details concerning the dataset can be found in Brousmiche
 160 et al. (2020b) and in Brousmiche et al. (2020c).

161 **Table I. Presentation of sub-dimensions that aim to describe multiple facets for each of the six dimensions**

Dimension	Sub-dimension
Health	General population health
	Health care facilities
Environment	Anthropogenic pressures
	Natural resources
	Biodiversity
	Environmental risks
Social	Integration and anomy
	Population sensitivity
	Level of education
	Social resources
	Urbanization
Economics	Employability
	Diversity and economic drive
	Incomes
Services	Access to the homeownership market
	Access to basic needs
	Access to information and communication
	Mobility
Policy	Environmental governance
	Budget
	Anticipation

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163 The selected variables will be assigned to the resilience or vulnerability index according to the impact
 164 of an increase in each variable on environmental health. If an increase in the variable can be related
 165 to a broadly beneficial effect on environmental health, then the variable is considered to belong to
 166 the resilience index, while an increase that corresponds to a deleterious or negative effect of the
 167 variable leads to its classification in the vulnerability index (Fig. 2).



168

169 **Figure 2. Diagram illustrating the orientation of variables towards resilience or vulnerability index, according to the effect**
 170 **of an increase in the variable, for use in joint analysis**

171 **2.2.2 Construction of the resilience and vulnerability composite indices**

172 **2.2.2.1 Data pre-processing**

173 **Management of missing data.** This step is necessary to provide a complete data set and avoid bias
 174 due to missing information (European Commission et al., 2008). Missing data management was
 175 carried out using two imputation methods for two cases of missing data:

- 176 • Case 1: If (i) there was a history of a merger/creation of a new municipality and (ii) there was
 177 a value for the newly created municipality, this value was attributed to the those
 178 municipalities in the group for which data was lacking;
- 179 • Case 2: If there was no previous history of a merger / creation of municipality, the values of
 180 the neighboring municipalities (i.e. those sharing a border) were identified and the median of
 181 these values was attributed to the municipality for which the data was missing.

182 **Standardization.** Since data can be expressed in very different units and/or generated by different
 183 producers for different purposes and according to different reference systems, standardization is
 184 necessary to ensure that the indicators are comparable (Böhringer and Jochem, 2007; Saib et al.,
 185 2015). Each of the variables was therefore standardized according to the z-score methodology, which
 186 is recommended before using Principal Component Analysis (PCA) (Marzi et al., 2018). For a spatial
 187 unit i , the z-score z_i is defined by $z_i = (x_i - \bar{x})/sd$, where x_i corresponds to the raw value of the
 188 variable for spatial unit i , \bar{x} is the mean of the variable in all spatial units and sd corresponds to
 189 standard deviation. Thus, all variables are converted into a common scale with a mean equal to zero
 190 and a standard deviation equal to 1. This method is (i) less sensitive to extreme values than other
 191 methodologies and (ii) maintains correlation structures between variables (European Commission et
 192 al., 2008; Kolenikov and Angeles, 2004).

193 2.2.2.2 Bivariate correlation analysis

194 A selection of variables is necessary to obtain the most concise description possible of the initial
195 dataset (European Commission et al., 2008). This selection is based on a bivariate correlation analysis
196 which identifies redundant variables and thus summarizes the major information contained in the
197 initial dataset (King and Jackson, 1999). As mentioned by European Commission et al. (2008), the
198 choice of variables is first guided by a theoretical criterion: at least one correlation coefficient in the
199 range $[|0.2|; |0.6|]$. This made it possible to introduce into the PCA only variables having a minimum
200 correlation structure with the other variables, thus avoiding that certain principal components are
201 carried by a single variable (noise) or are strongly influenced by a few redundant variables. The
202 balance and consistency in the diversity of dimensions and sub-dimensions considered in the dataset
203 is then validated by experts representing a wide spectrum of knowledge and experience to ensure
204 the implementation of an adequate characterization system. Particular care should be taken in
205 selecting the variables that will minimize the mirror effect between resilience and vulnerability.

206 2.2.2.3 Weighting and aggregation

207 Resilience and vulnerability indices are constructed through a PCA-based weighting and aggregation
208 process. Only the *p*-first principal components (PCs) with an eigenvalue above 1 were retained for
209 the index construction. A rotation of the factorial axes is applied to components by means of a
210 VARIMAX rotation to increase the readability and facilitate the interpretation of the outcomes
211 (Kaiser, 1958). The index (either resilience index or vulnerability index) is thus expressed as follows:

$$212 \quad Index = \sum_{j=1}^p w_j PC_j,$$

213 where *p* corresponds to the number of retained principal components, and w_j indicates the
214 proportion of variance explained by the principal component PC_j .

215 Finally, to simplify the interpretation, the final index is standardized by the min-max method to
216 obtain values in a common value range that is easily comprehensible (*i.e.* [0;1]). The min-max
217 standardization is carried out as follows:

$$218 \quad z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)},$$

219 where z_i is the standardized value of the resilience or vulnerability index, x_i is the initial value of the
220 resilience or vulnerability index, and $\min(x)$ and $\max(x)$ correspond respectively to the minimal and
221 maximal values of the resilience or vulnerability indices.

222 2.2.3 Spatial assessment of the resilience and vulnerability indices

223 2.2.3.1 Mapping of the spatial distribution

224 To observe the spatial distribution of the composite indices within the study area, the indices are
225 discretized using Jenks natural breaks classification method (Jenks, 1967). This method allows the
226 creation of homogeneous classes with minimized intra-class variance and maximized inter-class
227 variance. Three thresholds were calculated for each index, yielding four classes (Very Low, Low, High,
228 Very High), making it possible to obtain a cartographic representation that can be rapidly interpreted
229 without over-simplifying the information provided by the composite index. The maps were made
230 using ArcGIS software (Environmental Systems Research Institute, 2011).

231 2.2.3.2 Evaluation of spatial auto-correlation

232 The presence or absence of spatial autocorrelations among the municipalities is quantified using
233 Moran's index (Moran, 1948), in which a value greater than 0 indicates the presence of
234 autocorrelation, and probed using Moran's test (Cliff and Ord, 1981). The statistical analyses are
235 carried out using R software (version 3.4.3; package: DCluster). The threshold for statistical
236 significance is set to $p < 0.05$.

237 2.2.3.3 Result appraisal of resilience and vulnerability indices

238 A comparison with other indicators is carried out to appraise the contribution of our approach to the
239 strategies that are commonly used to assess the spatial heterogeneity of inequalities. According to
240 their distribution, the composite indices will be compared through the calculation of the Spearman
241 correlation coefficient. We appraise our results using the Human Development Index (HDI4)
242 composite indices described by Marlier (2009), French Ecological Deprivation Index (EDI) as described
243 by Pernet et al. (2012) and French social Deprivation index (FDep) as described by Rey et al. (2009).
244 HDI4 reflects a concentration of populations with a certain degree of monetary, educational and
245 health resources (Marlier et al., 2015). French EDI aims to provide a methodology to develop an
246 "intercultural" ecological indicator of socio-economic level, while FDep was created to provide a
247 geographic index of social disadvantage specifically adapted to health studies on the French
248 population (Ghosn, 2018).

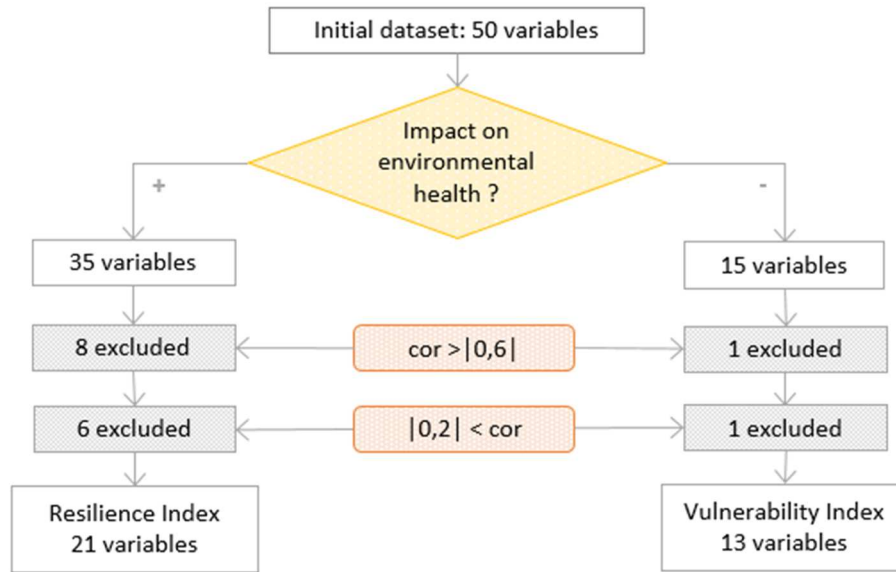
249 2.2.4 Joint analysis of resilience and vulnerability indices

250 The joint analysis aims to classify each municipality of the studied region among the four defined
251 typologies. It is based on the cross-interpretation of resilience and vulnerability indices. The four
252 classes of resilience and vulnerability are therefore grouped into two categories (Very High-High and
253 Very Low-Low), leading to the four territorial profiles. Further details concerning the cross-
254 interpretation of resilience and vulnerability indices can be found in supplementary material and
255 results.

256 As regards vulnerable territories, two profiles can be distinguished according to their level of
257 resilience: territorial blackspots, which do not have sufficient environmental, socio-economic or
258 health resources, and territories that have resources they can implement to counteract sources of
259 vulnerability (Maclachlan et al., 2007). Given their lower levels of resources, territories with a lower
260 RI should be nevertheless be monitored.

261 3 Results

262 Fig. 3 presents the results of the variable selection stages, from the initial dataset to the number of
263 variables included in the resilience and vulnerability indices. Nine variables were excluded due to
264 correlation values above $|0.6|$, seven others were discarded due to correlation values below $|0.2|$.
265 VI was calculated from 13 variables, while 21 variables were included in RI. Supplementary material
266 and results present the results of the correlation matrix, the correlogram of the 50 variables which
267 illustrates the general structure of the correlations between each variable and PCAs prior to the
268 Varimax rotation.



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Figure 3. Flowchart summarizing the variable selection steps, from the initial dataset (50 variables) to the Resilience Index (21 variables) and the Vulnerability Index (13 variables)

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3.1 Vulnerability Indice (VI)

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The VI values vary from 0 to 1, with 1 representing the highest possible vulnerability value in the area studied. The VI has a median value of 0.151 with an IQR of [0.126-0.180]. Fig. 4 (a) presents the spatial distribution of the VI calculated for the Hauts-de-France region and the threshold values used to create the vulnerability classes. A total of 1,623 (42.5%) municipalities belong to the Very Low vulnerability category, 1,710 (44.8%) to the Low vulnerability category, 479 (12.6%) to the High vulnerability category and 5 (0.1%) to the Very High vulnerability category. Moran Index results show a weak but significant spatial autocorrelation ($I = 0.063$, $p < 0.001$). A particular group of municipalities with a high level of vulnerability is located between Bethune, Lens, Douai and Valenciennes: this spatial trend is located on the former coal-mining basin, area for which multiple vulnerabilities have already been identified. Municipalities with higher vulnerability index values tend to gather around large urban areas (Dunkerque, Lille, Arras, Compiègne, Amiens), but to a small extent. Municipalities with lower vulnerability index values are more randomly located within the Hauts-de-France region.

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3.2 Resilience Index (RI)

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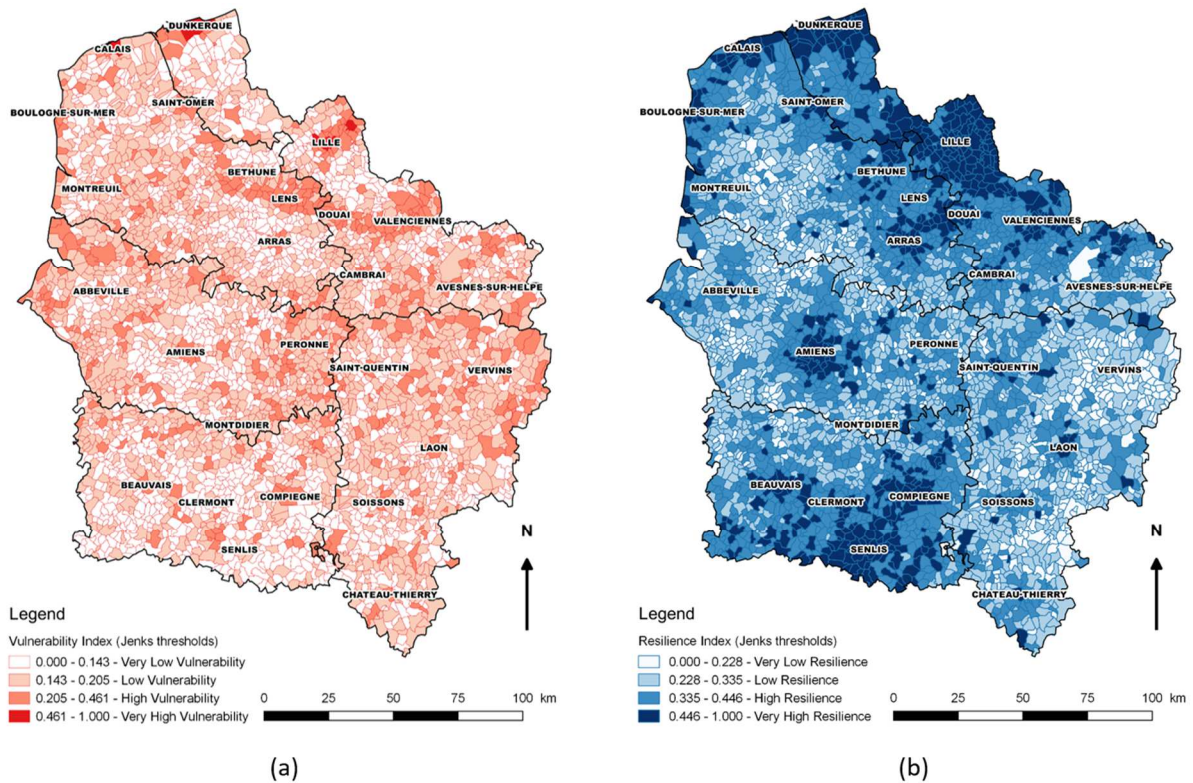
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The RI values vary from 0 to 1, with 1 the highest possible resilience value in the area studied. The RI has a median value of 0.341 with an interquartile range of [0.273;0.401]. Fig. 4 (b) presents the spatial distribution of the RI calculated for the Hauts-de-France region and the threshold values used to create the resilience classes. A total of 519 municipalities (13.6%) belong to the Very Low resilience category, 1,323 (34.7%) to the Low resilience category, 1,401 (36.7%) to the High resilience category and 574 (15.0%) to the Very High resilience category. Moran index results show a significant spatial autocorrelation ($I = 0.597$, $p < 0.001$), indicating that similar resilience values tend to aggregate spatially. A geographical variation can be observed in the distribution of the municipalities within these four categories, with a specific group of municipalities belonging to the Very High resilience category around large urban areas. The large urban areas that include a number of municipalities with higher resilience index values are mainly located around Amiens, Arras, Compiègne, Douai, Dunkerque, Lille and Senlis. Municipalities with lower resilience index values tend

299 to be located in less densely populated areas, more particularly (i) along a north-west/south-east axis
 300 from Montreuil to Vervins and (ii) in the south-east of the region.



301 (a) (b)
 302 **Figure 4. (a) The Vulnerability Index for the municipalities in the Hauts-de-France region. Three Jenks’s natural breaks**
 303 **were calculated (0.143, 0.205, 0.461) to obtain four classes of vulnerability (very low, low, high, very high).**
 304 **(b) The Resilience Index for the municipalities in the Hauts-de-France region. Three Jenks’s natural breaks**
 305 **were calculated (0.228, 0.335, 0.446) to obtain four classes of resilience (very low, low, high, very high).**

306 3.3 Comparison with others indicators

307 Table II presents the Spearman correlation coefficients which were calculated in light of the indices
 308 distributions. VI shows a relatively strong correlation with EDI and FDep (coefficient value of 0.70 and
 309 0.65, respectively; for both, $p < 0.001$). These three indices roughly outline the same negative
 310 aspects, including unemployment rate, house tenancy rate, low level of education. However, the
 311 correlation is higher between VI and EDI than between VI and FDep, because a greater dichotomy
 312 occurs between urban and rural contexts in EDI than in FDep. RI has a moderate correlation with the
 313 other indices, suggesting that RI integrates distinct aspects. The architectural composition of RI
 314 actually seeks to be more holistic to take into consideration the multiple facets of phenomena
 315 involved in environmental health. The RI successfully integrates positive aspects, notably in the
 316 environmental and policy dimensions, which are not covered in the deprivation indices (FDep, EDI)
 317 and in the HDI4. Moreover, RI provides different information to that provided by VI (coefficient value
 318 of -0.01; $p = 0.57$), highlighting the weak mirror effect between resilience and vulnerability.

319 **Table II. Correlation matrix between the Vulnerability Index, the Resilience Index and other indicators (HDI4, French EDI,**
 320 **FDep). Results of the significant Spearman’s correlation tests (i.e. $p < 0.001$) are marked with an asterisk “*”**

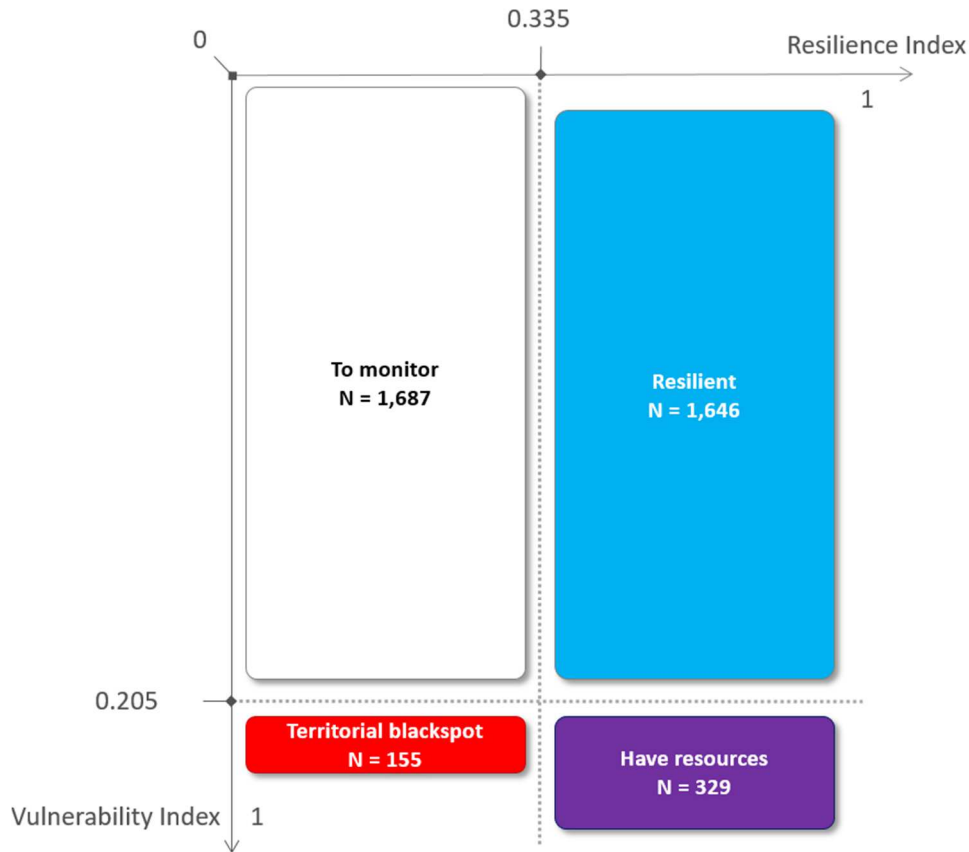
	VI	EDI	FDep	RI	HDI4
VI	1	0.70*	0.65*	-0.01	-0.58*
EDI		1	0.74*	-0.10*	-0.69*
FDep			1	-0.28*	-0.76*

RI				1	0.28*
HDI4					1

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322 3.4 Joint analysis and interpretation

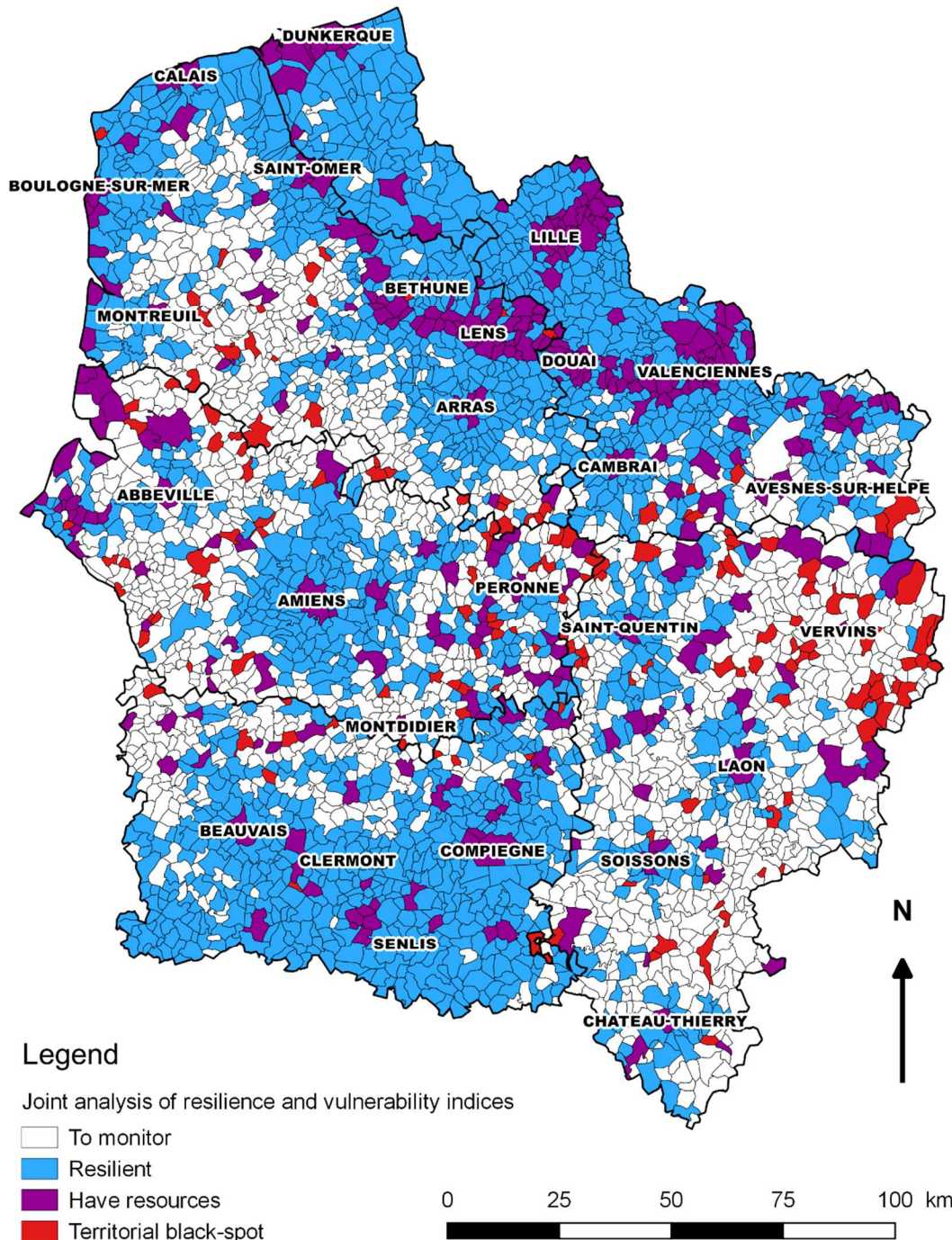
323 Each municipality of the studied region had been classified among the four defined typologies
 324 through the joint analysis of resilience and vulnerability. Thus, 1,687 (44.2%) municipalities belong to
 325 the “To monitor” category, 1,646 (43.1%) to the “Resilient” category, 329 (8.6%) to the “Have
 326 resources” category and 155 (4.1%) to the “Territorial hotspot” category (Fig. 5).



327

328 **Figure 5. Diagram showing the distribution of the number of municipalities among each typology (To monitor, Resilient,**
 329 **Have Resources, Territorial hotspot) after the cross-classification of resilience (RI) and vulnerability indices (VI) in the**
 330 **Hauts-de-France region**

331 Fig. 6 presents the spatial distribution of the joint analysis of resilience and vulnerability indices in
 332 the Hauts-de-France region. Most of municipalities belonging to the “To monitor” category are
 333 located along a north-west/south-east axis, reflecting the results observed for resilience and
 334 vulnerability where lower values for both indices had been highlighted. Although other municipalities
 335 also had high vulnerability values, the integration of resilience revealed that they have resources.
 336 Municipalities belonging to this “Have resources” category are mainly located in the north or south
 337 of the region, particularly in and around large urban areas (Compiègne, Douai, Dunkerque, Lens, Lille,
 338 Valenciennes) where resilience values were higher. Municipalities that belong to the “Resilient”
 339 category are also primarily located in the north and south of the region. The municipalities classified
 340 in the “Territorial hotspot” category tend to be more randomly distributed, confirming that
 341 management decisions must be taken at the municipality level.



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343 **Figure 6. Spatial distribution of the joint analysis of resilience and vulnerability indices for the 3,817 municipalities of the**
 344 **Hauts-de-France region. The “Territorial blackspots” are characterized by a high (or very high) vulnerability, paired with a**
 345 **low (or very low) resilience. The municipalities classified in the “Resilient” category are characterized by a low (or very**
 346 **low) vulnerability and a high (or very high) resilience. The municipalities classified in the “Have resources” category are**
 347 **characterized by a high (or very high) vulnerability and a high (or very high) resilience. The municipalities classified in “To**
 348 **monitor” are characterized by a low (or very low) vulnerability and a low (or very low) resilience.**

349 4 Discussion

350 This study establishes a new approach to assess the spatial heterogeneity of territorial inequalities
 351 among municipalities by integrating multiple health determinants. This novel approach based on an
 352 inventory of local data removes the difficulties of characterizing the accumulation of health

353 determinants and provides an opportunity to build a diagnostic tool for stakeholders. To our
354 knowledge, this is the first study to base the assessment the resilience / vulnerability balance on two
355 spatialized sub-indices, combining the same dimensions for each sub-index. The transposability of
356 the proposed framework is above all conceptual and methodological because the availability and / or
357 accessibility of data may differ from one territory to another (Brousmiche et al., 2020a). In a strategy
358 of transposability, the points of attention relate in particular to the selection of specific data by
359 including the data the most adapted to the spatial scale of study, demonstrating the strongest
360 discriminating capacity between the spatial units, and the most in adequacy with territorial
361 particularities (e.g. technological and / or economic development) in order to collect the greatest
362 diversity and richness of information.

363 Although the level of vulnerability can be described at the local level, current methodology generally
364 focuses on a small number of descriptors. Thus, previous French studies concerning our study area
365 have already identified the former coal-mining basin, the Urban Community of Dunkerque and the
366 Urban Community of Lille as areas of high and multiple vulnerability (Becuwe and Lecomte, 2015;
367 Belhakem and Lerméchin, 2018; Fleury et al., 2010; Salem, 1995). These studies were based on the
368 poverty rate, on the unemployment rate or on life expectancy. The different vulnerability assessment
369 strategies used in these studies limit the comparison of the latter and hinder the ranking of
370 municipalities. The present study has developed a multidimensional vulnerability index that
371 successfully highlights these vulnerable territories. It allows comparison between municipalities and
372 the monitoring of numerous parameters of interest through a construction from the same dataset,
373 whatever the municipality.

374 Little attention has been paid to the impact of positive aspects of a territory on human health. Few
375 studies have simultaneously considered resilience and vulnerability (Kumar et al., 2019), and
376 resilience has rarely been calculated in as much detail as vulnerability (Estoque and Murayama, 2014;
377 Miller et al., 2017). In the proposed framework, this issue is addressed by deriving and considering RI
378 and VI in the same way. Initial attempts are being made to interpret the spatial distribution of the
379 level of resilience, particularly by focusing on the link between resilience and demographics. For
380 example, although the links between resilience and population density are equivocal in the literature,
381 some authors confirm this relationship through different approaches of this demographics variable,
382 *i.e.* either as a factor to be included in the study or as an explanatory factor for the level of resilience.
383 Rural/urban status, population density and urbanisation ratio have been mentioned by Estoque and
384 Murayama (2017), García-Sánchez et al. (2015), Monteiro et al. (2012), Pearson et al. (2013) and
385 Zhang et al. (2015). In this study, we used a population density as a direct indicator, as described in
386 Estoque and Murayama (2017) and Monteiro et al. (2012), and other indirect indicators related to
387 the population of municipalities, such as the area of natural space per capita. When possible,
388 considering data per inhabitant highlights the efforts made by a municipality for each of its
389 inhabitants: although raw data for densely populated municipalities could have higher values than
390 those of sparsely populated municipalities, data per inhabitant could actually be greater for
391 municipalities with smaller populations (*e.g.* total expenditures for municipal equipment vs total
392 expenditures for municipal equipment per inhabitant). However, our results reinforce all the
393 evidence suggesting that resilience is higher in urban areas than in rural areas. The approach
394 developed in this study meets the need for analytical tools by developing a composite resilience
395 index that is adapted to European data and easy to appropriate.

396 To offset the classic approach based on the weaknesses of municipalities, our strategy of joint
397 analysis aims to include the efforts that a municipality has made to improve the living environment
398 of its inhabitants. The joint analysis provides an original and powerful approach that EDI, FDep and

399 HDI4 failed to achieve, *i.e.* one that permits the assessment of the spatial heterogeneity of territorial
400 inequalities. To a certain extent, VI identifies the same territories as indices based only on
401 deprivation. VI thus highlights the accumulation of socio-economic, environmental and health
402 determinants and the addition of RI sharpens the description of the territory in terms of resources;
403 together, these indices summarize a wide range of data. The development of spatialized composite
404 indices is also complicated by a lack of consensus on a methodology (Brousmiche et al., 2020a).
405 Certain weighting and aggregation methods that are commonly used to develop composite indices
406 (arithmetic or geometric mean, weighted or not) do not successfully resolve (i) the issue of
407 compensability between variables (*i.e.* is a given variable more influential than others?) and (ii) the
408 objectification of a ranking which may be affected by the aggregation method. RI and VI obtained by
409 PCA are based on the statistical structure of the data and are not automatically affected by the
410 influence of individual data on the measured phenomenon. This methodology is notably suitable to
411 develop composite indices insofar that it provides the best contrasts between spatial units, an
412 advisable property for inter-territorial comparisons (European Commission et al., 2008; Lalloué et al.,
413 2013). A flexible and adaptable framework that allows the integration of new or different data is
414 required to take into account the specificities of the study area, namely (i) the contextualization of
415 data related to technological development (*e.g.* number of landlines per 1,000 inhabitants vs internet
416 access), (ii) the availability of representative data, which may be ample for some countries but less so
417 or even non-existent for others (*e.g.* percentage of specific places of worship) and (iii) the absence of
418 data for the geographical study area (*e.g.* data related to ethnicity in France) (Brousmiche et al.,
419 2020a). The power of the proposed framework is based on the respect of the dimensions to be
420 explored, and allows users to freely integrate relevant and available data for the study area. The
421 resulting composite indices demonstrate good discriminating power, making it possible to highlight
422 disparities and to prioritize spatial units according to the vulnerability/resilience balance.

423 However, this approach does have some limitations that may actually be opportunities for future
424 research work on composite indices. Some health determinants are only characterized at a global
425 (*i.e.* national) scale and are not defined on a local scale, thus resulting in a lack of accessible variables
426 at the appropriate scale. This lack of accessibility of fine-scale data meant that we did not include
427 data that might have been relevant in RI or VI, such as the poverty rate, which measures the living
428 standards in relation to the living standard of the population as a whole (relative approach) (Miller et
429 al., 2017; Stewart et al., 2014). There is a particular need to include more data to characterize
430 environmental quality. This issue has received less attention (Flacke, 2015; Nieuwenhuijsen, 2016;
431 Sharifi, 2016) despite the fact that 22.7 % of the global disease burden was attributed to
432 environmental factors in 2012 (Prüss-Üstün et al., 2016). Despite the unavailability of this kind of
433 data at a small scale for the region as a whole or the difficulty to obtain them reported by numerous
434 authors (Huang and London, 2012; Sadd et al., 2011; Zhang et al., 2015), future composite indices
435 should include more environmental data, primarily concerning air quality (indoor and outdoor),
436 drinking water quality, pesticide measures or heavy metal contents in soil. Finally, an essential aspect
437 of the evaluation of territorial inequalities is that the method implemented should take into account
438 the relationships between health determinants to avoid over- or underestimating their respective
439 importance. This requires the use of reliable statistical methods such as PCA, which take into account
440 (i) the subjectivity in the classification of a given variable within a dimension and (ii) the interrelations
441 of health determinants over time and space (Sarkar and Webster, 2017), and above all developing
442 the knowledge of the entire territorialized exposome. The concern for completeness supported by
443 this notion of territorialized exposome is essential in all studies evaluating territorial inequalities.

444 Researchers and stakeholders lack screening methods, and the need for characterization tools is
445 mentioned regularly (Cutter et al., 2010; Rothenberg et al., 2015; Saib et al., 2015). The provision of a

446 suitable process would facilitate the identification and prioritizing of locations, for example focusing
447 on those with both higher vulnerability and lower resilience values compared to the region as a
448 whole. The proposed cross-classification of RI and VI meets this challenge. In total, we collected a set
449 of 50 robust (*i.e.* consistent, non-redundant, exhaustive) variables that are relevant to environmental
450 health issues in the region and outline the environmental, health, social, economic, policy or service
451 dimensions (Brousmiche et al., 2020c). We thus linked 3,817 municipalities to one of 4 typologies,
452 taking into account the weight of the negative aspects of the environment (VI) and the weight of the
453 positive aspects of the environment (RI) related to environmental health issues. This approach offers
454 a more comprehensive view of how stakeholders are addressing social, health and environmental
455 issues and could help the former to improve their public health policy. The interpretation of the
456 results leads to different action according to the typology. The “Territorial blackspots” must benefit
457 from a rapidly implemented action plan. The territories belonging to the categories “To monitor” and
458 “Have resources” should be monitored to prevent their degradation into “Territorial blackspots”.
459 Health policies should be encouraged in these territories so that they evolve towards the “Resilient”
460 category. The territories belonging to the “Resilient” category could be considered as demonstrators
461 of good practices that could be replicated. A further challenge of this approach is to encourage the
462 exchange of good environmental health practices between territories (Nieuwenhuijsen et al., 2017).
463 This diagnostic tool can also become a prospective tool for the optimization of future preventive
464 health policies or urban policies (Ramirez-Rubio et al., 2019; Saib et al., 2015) and a tool for
465 monitoring the impact of the implemented actions.

466 5 Conclusion

467 This study aimed to establish a new transferable approach to assess the spatial heterogeneity of
468 territorial inequalities and to provide a diagnostic tool for stakeholders. In the field of environmental
469 health, no consensus has been made to date concerning the best methodology for developing
470 composite indices, resulting in a subjectivity between the frameworks and limiting comparisons
471 between different composite indices and thus between territories. To the best of our knowledge, this
472 article presents the first joint analysis, at fine scale for a large study perimeter, of positive and
473 negative impacts leading to four territorial profiles. The flexible and adaptable framework proposed
474 for database development has overcome a main issue in developing composite indices, *i.e.* data
475 availability. This development principle also offers the opportunity to improve the characterization of
476 territories by integrating the most suitable information for the context of the geographical
477 perimeter. To provide the broadest possible depiction of the territory, both resilience (the capacity of
478 a territory to cope with health inequalities) and vulnerability (negative constraints and nuisances to
479 which a population is subjected) were considered to be equally essential and important factors in the
480 assessment of the resilience/vulnerability balance. Further studies should be conducted to confirm
481 the benefit to draw on a joint analysis to assess the environmental and social inequalities of health.

482 To characterize health, environmental, social, service, policy and economic dimensions for the
483 development of the two composite indices, a total of 50 variables were collected from public
484 national databases. A methodology based on PCA was designed to develop the resilience and the
485 vulnerability indices. PCA makes it possible to summarize a large amount of information while
486 maximizing the proportion of total variance of the initial dataset and avoiding redundant
487 information. The composite indices were discretized using the Jenks natural breaks classification
488 method in order to observe their spatial distribution. Thereafter, a cross-classification of the different
489 groups of resilience and vulnerability made it possible to distribute each municipality among the four

490 territory typologies: 1,687 municipalities belong to the “To monitor” category, 1,646 to the
491 “Resilient” category, 329 to the “Have resources” category and 155 to the “Territorial blackspot”.

492 The joint analysis of resilience and vulnerability indices provides a powerful methodology to assess
493 the spatial heterogeneity of territorial inequalities. It also facilitates the identification and the
494 prioritization of municipalities that could benefit from the implementation of specifically tailored
495 public health policies, *i.e.* an action plan for the territorial blackspots. This diagnostic tool contributes
496 to the establishment of monitoring for the municipalities with lower levels of resilience. The
497 comparison of our results with other major indicators shows a relatively strong correlation between
498 vulnerability indices (FDep, VI, French EDI), reflecting the results of previous studies describing
499 aspects such as unemployment rate or low educational levels. The results also showed a moderate
500 correlation between HDI4 and RI and highlighted a weak correlation between RI and VI, confirming
501 that (i) RI provides a more holistic characterization of the territory and (ii) RI and VI measure different
502 phenomenon. Although the availability of spatialized information is increasing, certain data for
503 health determinants (*e.g.* environmental data concerning factors such as drinking water quality,
504 pesticide measures or the presence of heavy metals in soil) are still lacking or only accessible at a
505 mid- or large-scale despite their recognized impact on health. The availability of this type of fine-
506 scale indicator would substantially enrich current indices of resilience and vulnerability and meet the
507 needs of decision-makers seeking to improve the contextualisation of local policies in all health-
508 related domains.

509 **Declarations of interest**

510 None

511

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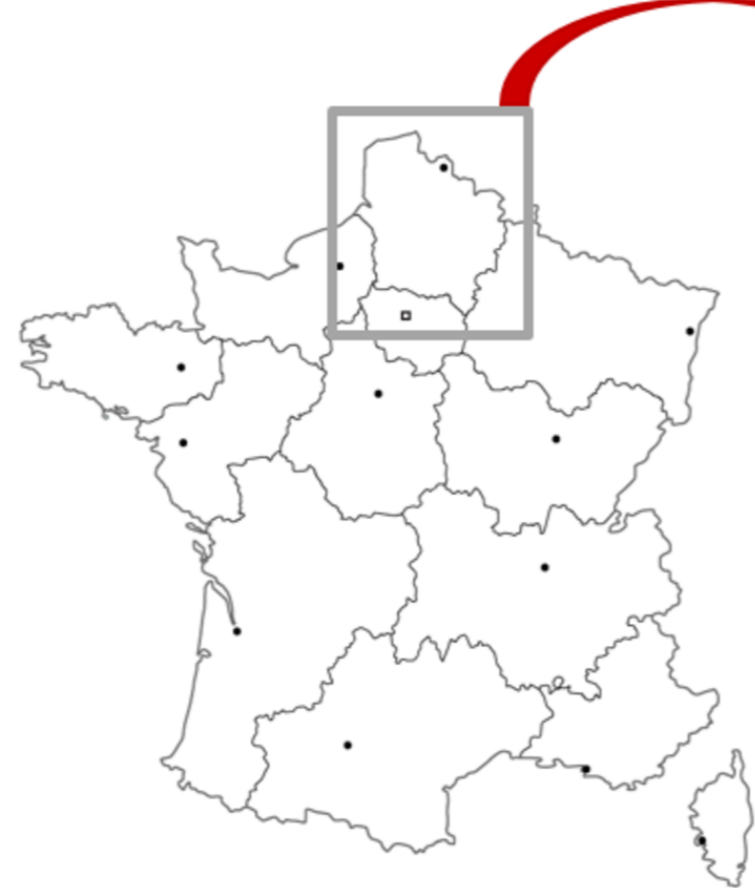
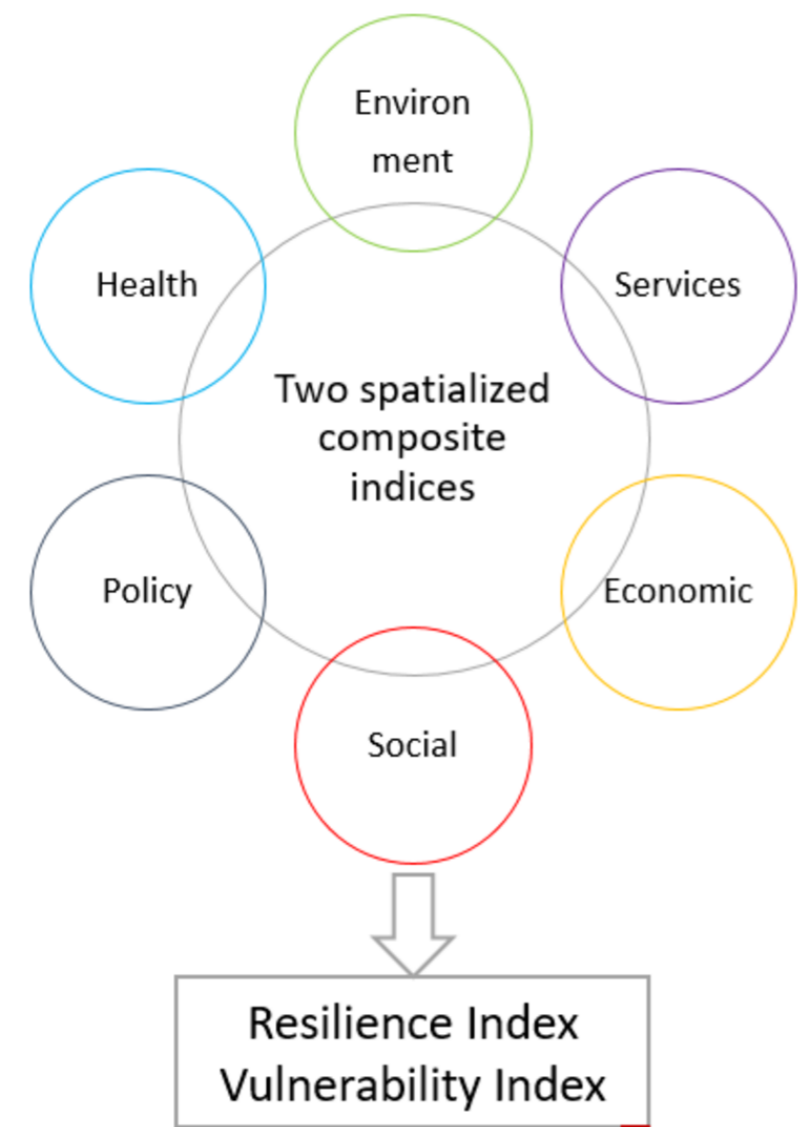
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Case study: a region in the north of France with 3,817 municipalities (6,009,976 inhabitants). Data reuse: 50 variables

