



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

Delphine Brousmitche, Michaël Genin, Florent Occelli, Lukas Frank, Annabelle Deram, Damien Cuny, Caroline Lanier

► To cite this version:

Delphine Brousmitche, Michaël Genin, Florent Occelli, Lukas Frank, Annabelle Deram, et al.. How can we analyze environmental health resilience and vulnerability? A joint analysis with composite indices applied to the north of France. *Science of the Total Environment*, 2021, 763, pp.142983. 10.1016/j.scitotenv.2020.142983 . hal-03216540

HAL Id: hal-03216540

<https://hal.science/hal-03216540>

Submitted on 3 Feb 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

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

Delphine Brousmiche¹, Michaël Genin², Florent Occelli^{1,3}, Lukas Frank¹, Annabelle Deram^{1,3}, Damien
Cuny^{1,4}, Caroline Lanier^{*1,3}

¹ Univ. Lille, IMT Lille Douai, Univ. Artois, Yncrea Hauts-de-France, ULR 4515 - LGCgE, Laboratoire de
Génie Civil et géo-Environnement, F-59000 Lille, France

² Univ. Lille, CHU Lille, ULR 2694 – METRICS, F-59000 Lille, France

³ Faculté d'Ingénierie et Management de la santé (ILIS)/Faculté de pharmacie de Lille – LSVF

⁴ Faculté de Pharmacie de Lille – LSVF

*Corresponding author

Dr Caroline Lanier

University of Lille, ULR 4515

3, Rue du Professeur Laguesse, B.P. 83, 59006 Lille Cedex, France

E-mail address: caroline.lanier@univ-lille.fr

Abstract

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

1 Introduction

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

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

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

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

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

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

2 Material and Methods

2.1 Study setting

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

2.2 Methodology

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

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

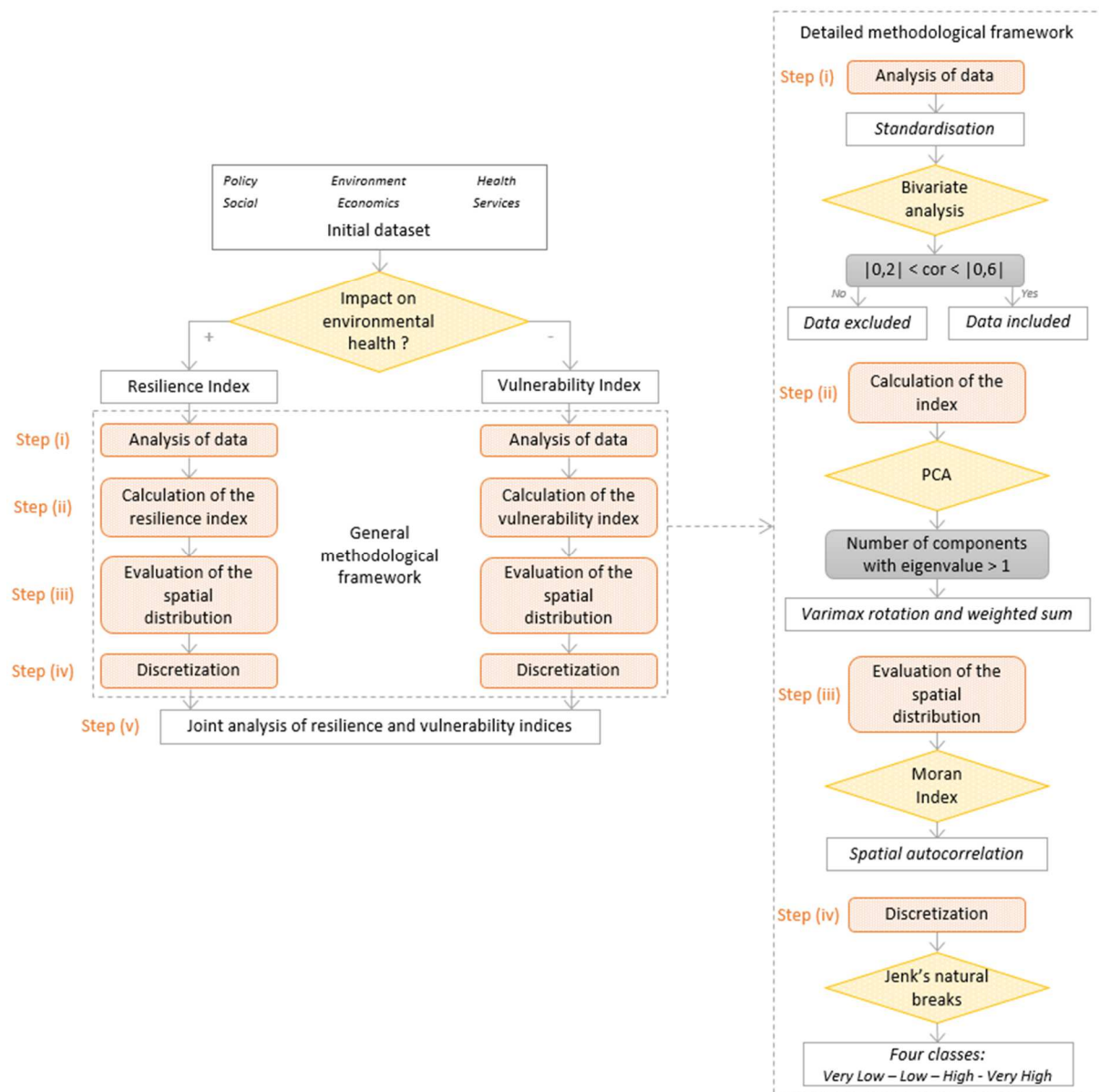


Figure 1. A comprehensive methodology for the development of composite indices to assess environmental health inequalities.

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).

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

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

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

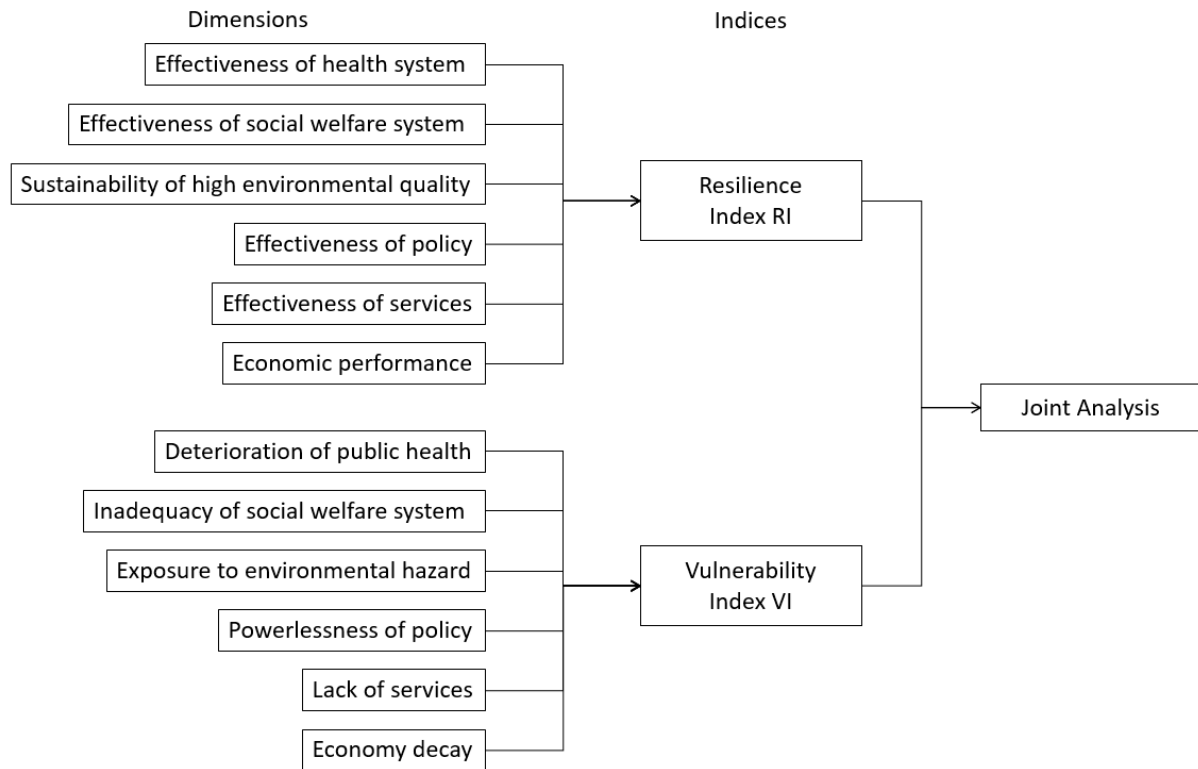


Figure 2. Diagram illustrating the orientation of variables towards resilience or vulnerability index, according to the effect of an increase in the variable, for use in joint analysis

2.2.2 Construction of the resilience and vulnerability composite indices

2.2.2.1 Data pre-processing

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

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

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

2.2.2.2 Bivariate correlation analysis

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

2.2.2.3 Weighting and aggregation

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

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

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

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

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

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

2.2.3 Spatial assessment of the resilience and vulnerability indices

2.2.3.1 Mapping of the spatial distribution

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

2.2.3.2 Evaluation of spatial auto-correlation

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

2.2.3.3 Result appraisal of resilience and vulnerability indices

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

2.2.4 Joint analysis of resilience and vulnerability indices

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

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

3 Results

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

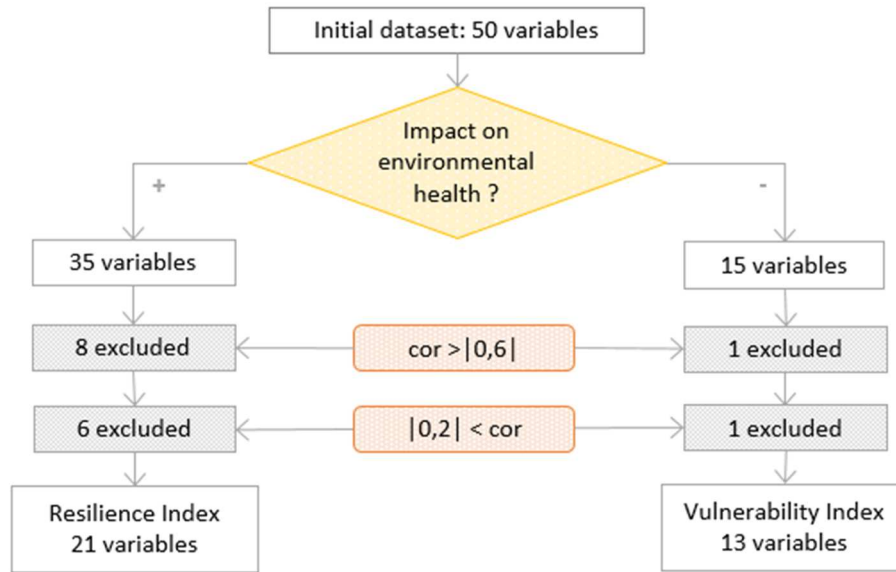


Figure 3. Flowchart summarizing the variable selection steps, from the initial dataset (50 variables) to the Resilience Index (21 variables) and the Vulnerability Index (13 variables)

3.1 Vulnerability Indice (VI)

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.

3.2 Resilience Index (RI)

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

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

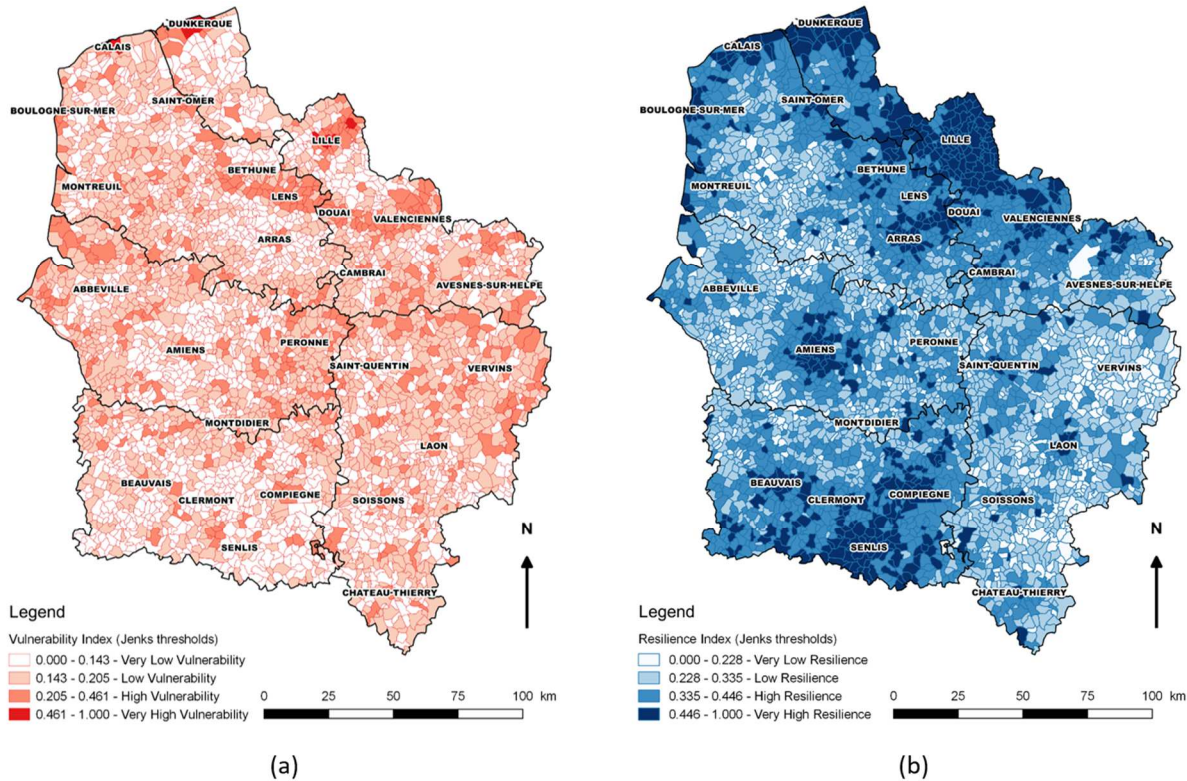


Figure 4. (a) The Vulnerability Index for the municipalities in the Hauts-de-France region. Three Jenks's natural breaks were calculated (0.143, 0.205, 0.461) to obtain four classes of vulnerability (very low, low, high, very high). (b) The Resilience Index for the municipalities in the Hauts-de-France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

3.3 Comparison with others indicators

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

Table II. Correlation matrix between the Vulnerability Index, the Resilience Index and other indicators (HDI4, French EDI, 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

3.4 Joint analysis and interpretation

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

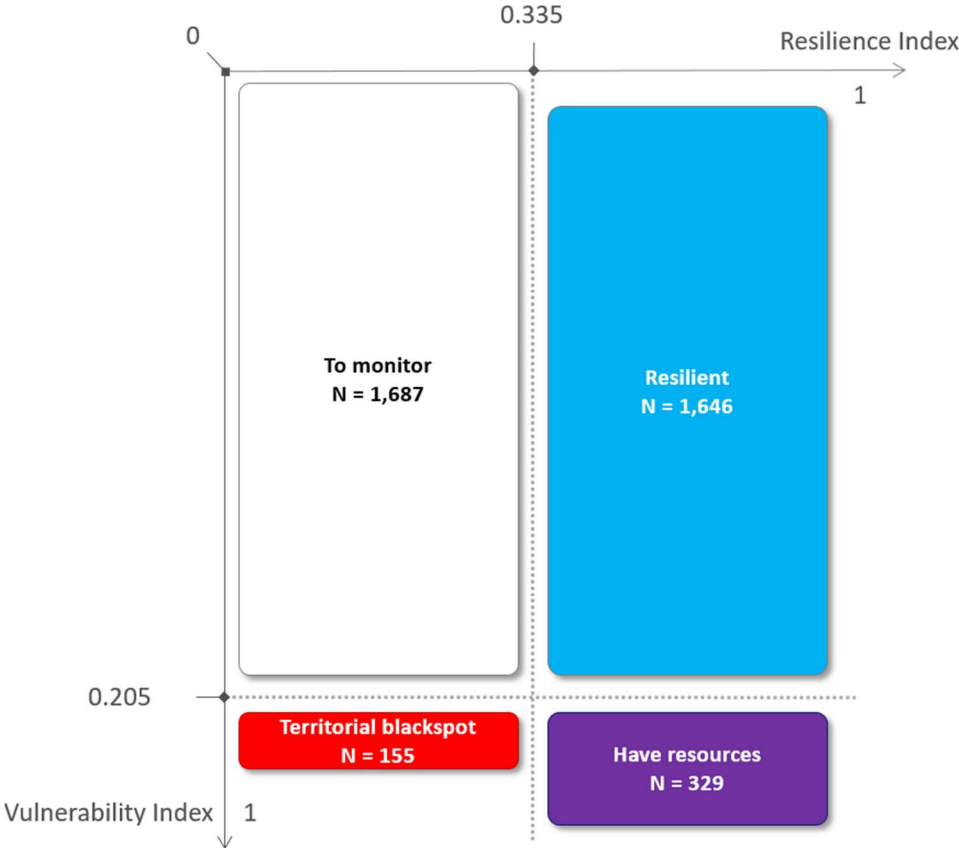


Figure 5. Diagram showing the distribution of the number of municipalities among each typology (To monitor, Resilient, Have Resources, Territorial blackspot) after the cross-classification of resilience (RI) and vulnerability indices (VI) in the Hauts-de-France region

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

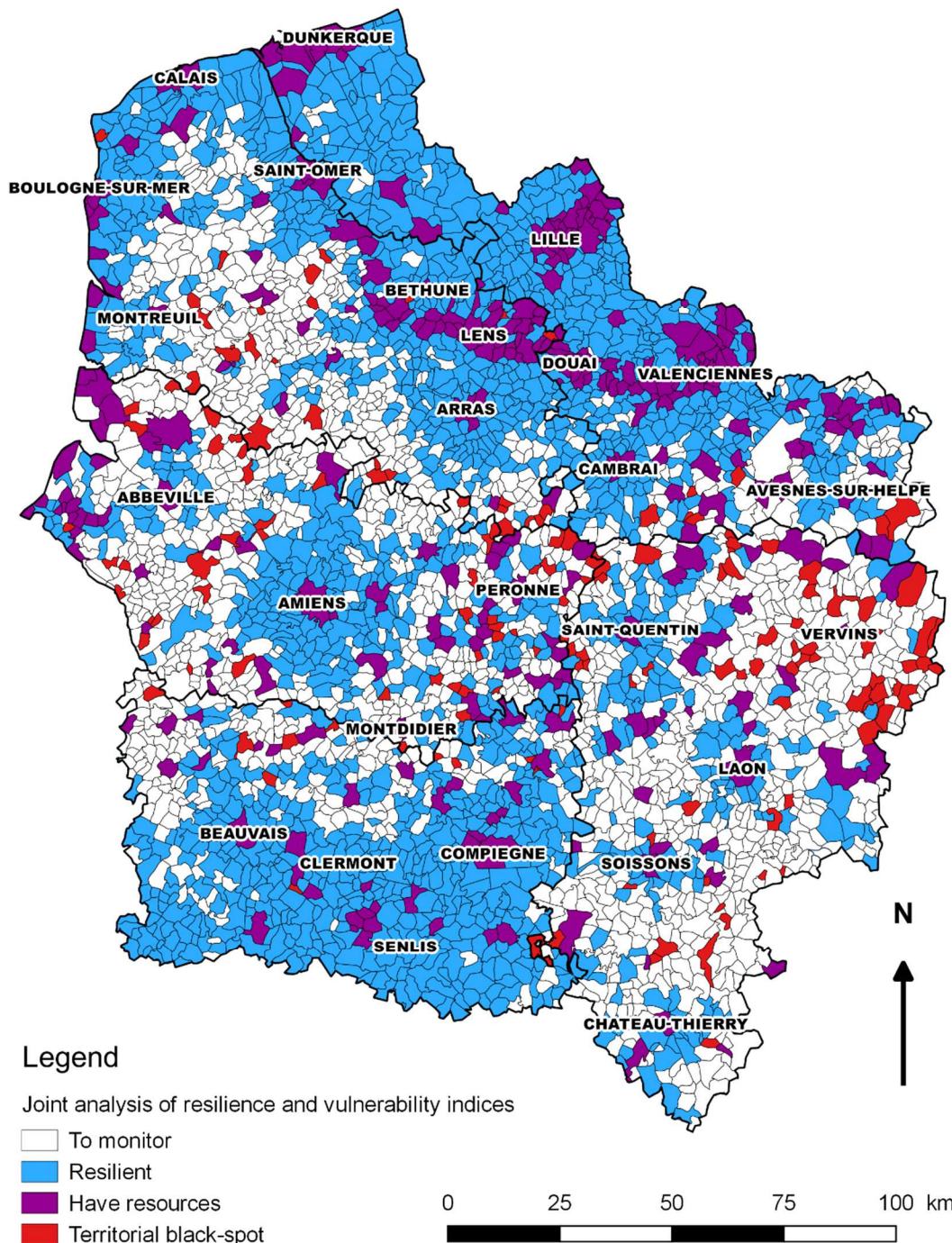


Figure 6. Spatial distribution of the joint analysis of resilience and vulnerability indices for the 3,817 municipalities of the Hauts-de-France region. The “Territorial blackspots” are characterized by a high (or very high) vulnerability, paired with a low (or very low) resilience. The municipalities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

4 Discussion

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

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

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

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

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

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

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

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

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

5 Conclusion

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

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

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

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

Declarations of interest

None

Acknowledgments

This work was supported by the Conseil Régional Hauts-de-France, the Agence Régionale de Santé Hauts-de-France and the Ministère de l’Enseignement Supérieur et de la Recherche (CPER Climibio).

References

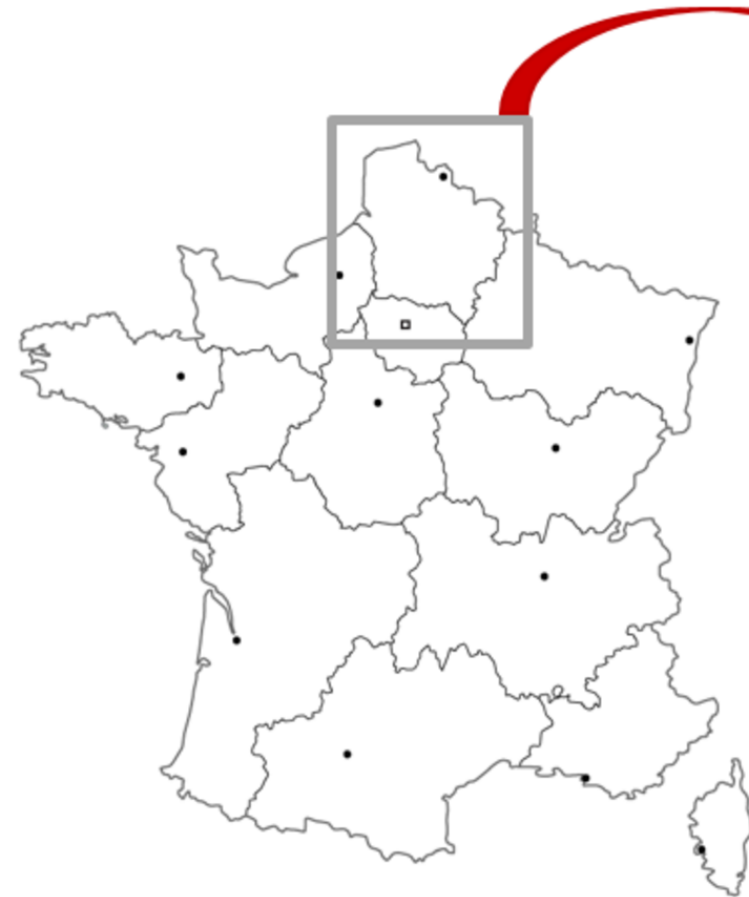
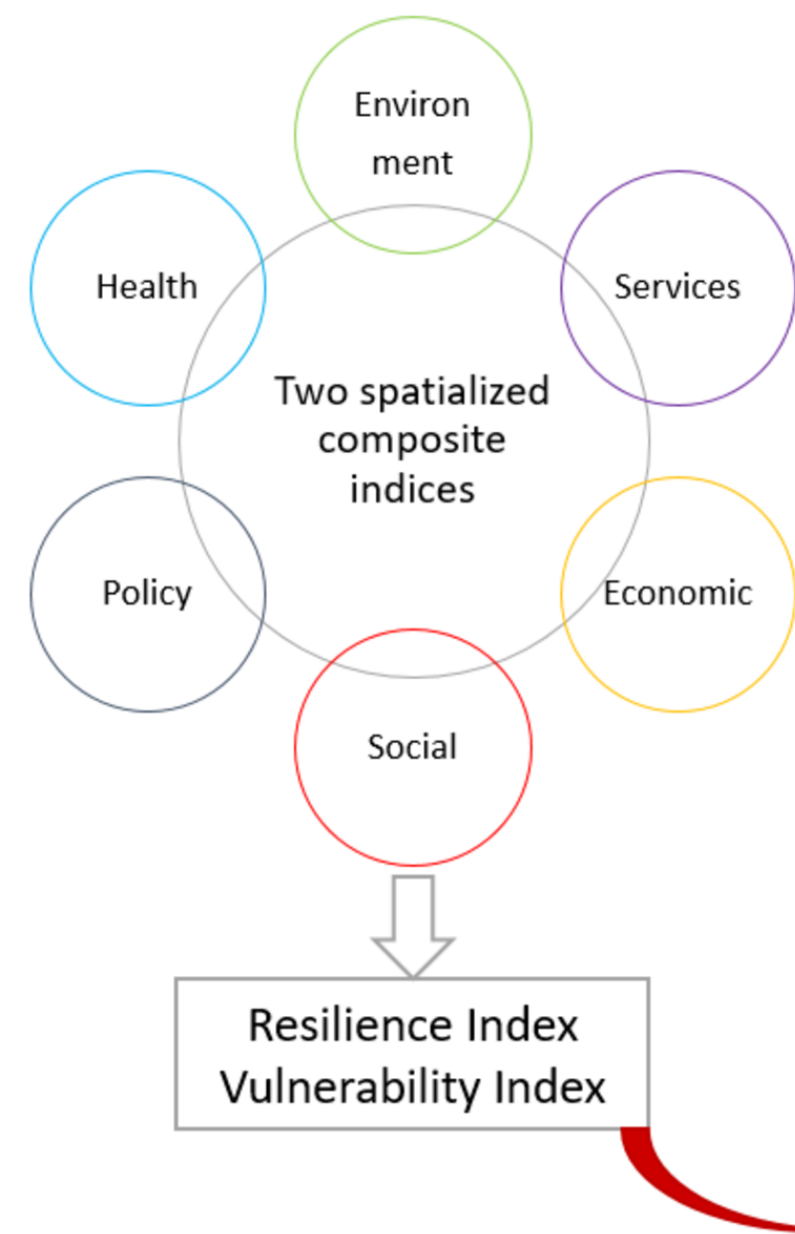
- Angeon, V., Bates, S., 2015. Reviewing Composite Vulnerability and Resilience Indexes: A Sustainable Approach and Application. *World Dev.* 72, 140–162. <https://doi.org/10.1016/j.worlddev.2015.02.011>
- Beale, L., Abellan, J.J., Hodgson, S., Jarup, L., 2008. Methodologic Issues and Approaches to Spatial Epidemiology. *Environ. Health Perspect.* 116, 1105–1110. <https://doi.org/10.1289/ehp.10816>
- Becuwe, B., Lecomte, M., 2015. Des trajectoires sociales différenciées entre les territoires du Nord-Pas de Calais. *INSEE Anal. Nord-Pas--Calais* 4.
- Belhakem, N., Lerméchin, H., 2018. Une pauvreté très élevée, mais moins intense. *INSEE Anal. Hauts Fr.* 4.
- Biggeri, M., Mauro, V., 2018. Towards a more ‘Sustainable’ Human Development Index: Integrating the environment and freedom. *Ecol. Indic.* 91, 220–231. <https://doi.org/10.1016/j.ecolind.2018.03.045>
- Böhringer, C., Jochem, P.E.P., 2007. Measuring the immeasurable — A survey of sustainability indices. *Ecol. Econ.* 63, 1–8. <https://doi.org/10.1016/j.ecolecon.2007.03.008>
- Braconnier, P., Caire, G., Dupuy, R., Jahan, E., Le Masne, P., Nivoix, S., 2011. Une évaluation du bien-être au sein des régions françaises dans une approche de développement durable. *Innovations* 34, 93. <https://doi.org/10.3917/inno.034.0093>

- Briggs, D.J., 2008. A framework for integrated environmental health impact assessment of systemic risks. *Environ. Health* 7, 61. <https://doi.org/10.1186/1476-069X-7-61>
- Brousmiche, D., Occelli, F., Genin, M., Cuny, D., Deram, A., Lanier, C., 2020a. Spatialized composite indices to evaluate environmental health inequalities: Meeting the challenge of selecting relevant variables. *Ecol. Indic.* 111, 106023. <https://doi.org/10.1016/j.ecolind.2019.106023>
- Brousmiche, D., Genin, M., Occelli, F., Frank, L., Deram, A., Cuny, D., Lanier, C., 2020b. Data for the assessment of vulnerability and resilience in the field of environmental health in the north of France. *Data In Brief*. (submit)
- Brousmiche, D., Genin, M., Occelli, F., Frank, L., Deram, A., Cuny, D., Lanier, C., 2020c. Research data supporting for “Data for the assessment of vulnerability and resilience in the field of environmental health in the north of France”. *Data repository: Zenodo*. Doi: 10.5281/zenodo.3701558.
- Cliff, A.D., Ord, J.K., 1981. *Spatial processes: models & applications*. Pion, London.
- Cuchère, E., Terra, S., 2017. Atouts et défis de la région Hauts-de-France. *INSEE Anal. Hauts Fr.* 4.
- Cutter, S.L., Burton, C.G., Emrich, C.T., 2010. Disaster Resilience Indicators for Benchmarking Baseline Conditions. *J. Homel. Secur. Emerg. Manag.* 7. <https://doi.org/10.2202/1547-7355.1732>
- Estoque, R.C., Murayama, Y., 2017. A worldwide country-based assessment of social-ecological status (c. 2010) using the social-ecological status index. *Ecol. Indic.* 72, 605–614. <https://doi.org/10.1016/j.ecolind.2016.08.047>
- Estoque, R.C., Murayama, Y., 2014. Social–ecological status index: A preliminary study of its structural composition and application. *Ecol. Indic.* 43, 183–194. <https://doi.org/10.1016/j.ecolind.2014.02.031>
- Etsy, D.C., Levy, M., Srebotnjak, T., de Sherbinin, A., 2005. *Environmental Sustainability Index: Benchmarking Nationale Environmental Stewardship*. Yale Center for Environmental Law and Policy, New Haven.
- European Commission, Organisation for Economic Co-operation and Development, SourceOECD (Online service) (Eds.), 2008. *Handbook on constructing composite indicators: methodology and user guide*. OECD, Paris.
- Fekete, A., 2018. Societal resilience indicator assessment using demographic and infrastructure data at the case of Germany in context to multiple disaster risks. *Int. J. Disaster Risk Reduct.* 31, 203–211. <https://doi.org/10.1016/j.ijdr.2018.05.004>
- Flacke, J., 2015. Spatial urban health equity indicators – a framework-based approach supporting spatial decision making, in: Köckler, H. (Ed.), . Presented at the SUSTAINABLE DEVELOPMENT AND PLANNING 2015, Istanbul, Turkey, pp. 365–376. <https://doi.org/10.2495/SDP150311>
- Fleury, D., Peytavin, J.F., Alam, T., Godillon, S., Saint-Gérard, T., Medjkane, M., Millot, M., 2010. Inégalité sociale et risque routier. L’apport d’une approche territorialisée. (No. hal-00850864). *Les cahiers scientifiques du transport*.
- Fong, K.C., Hart, J.E., James, P., 2018. A Review of Epidemiologic Studies on Greenness and Health: Updated Literature Through 2017. *Curr. Environ. Health Rep.* 5, 77–87. <https://doi.org/10.1007/s40572-018-0179-y>
- García-Sánchez, I.-M., Almeida, T.A. das N., Camara, R.P. de B., 2015. A proposal for a Composite Index of Environmental Performance (CIEP) for countries. *Ecol. Indic.* 48, 171–188. <https://doi.org/10.1016/j.ecolind.2014.08.004>
- Ghosn, W., 2018. Indicateurs écologiques synthétiques du niveau socio-économique pour la recherche en Santé (Note méthodologique). Institut national de la santé et de la recherche médicale (INSERM), Centre d’épidémiologie sur les causes médicales de décès CépiDc.
- Hartig, T., Mitchell, R., de Vries, S., Frumkin, H., 2014. Nature and Health. *Annu. Rev. Public Health* 35, 207–228. <https://doi.org/10.1146/annurev-publhealth-032013-182443>
- Hat, K., Stöglehner, G., 2019. How Resilient is Growth? Resilience Assessment of Austrian Municipalities on the Basis of Census Data from 1971 to 2011. *Sustainability* 11, 1818. <https://doi.org/10.3390/su11061818>

- Houlden, V., Porto de Albuquerque, J., Weich, S., Jarvis, S., 2019. A spatial analysis of proximate greenspace and mental wellbeing in London. *Appl. Geogr.* 109, 102036. <https://doi.org/10.1016/j.apgeog.2019.102036>
- Huang, G., London, J.K., 2012. Cumulative Environmental Vulnerability and Environmental Justice in California's San Joaquin Valley. *Int. J. Environ. Res. Public Health* 9, 1593–1608. <https://doi.org/10.3390/ijerph9051593>
- Jenks, G.F., 1967. The Data Model Concept in Statistical Mapping, Frenzel K. Rand McNally&Co. ed, International Yearbook of Cartography. Kirschbaum Verlag, Bonn, Germany.
- Kaiser, H.F., 1958. The varimax criterion for analytic rotation in factor analysis. *Psychometrika* 23, 187–200. <https://doi.org/10.1007/BF02289233>
- Kerényi, Á., 2011. The Better Life Index of the Organisation for Economic Co-operation and Development. *Public Finance Q., Journal of economic literature* LVI, 518–538.
- King, J.R., Jackson, D.A., 1999. Variable selection in large environmental data sets using Principal Components Analysis. *Environmetrics* 10, 67–77.
- Kolenikov, S., Angeles, G., 2004. The Use of Discrete Data in PCA: Theory, Simulations, and Applications to Socioeconomic Indices (Working paper No. WP-04-85). University of North Carolina.
- Kumar, P., Druckman, A., Gallagher, J., Gatersleben, B., Allison, S., Eisenman, T.S., Hoang, U., Hama, S., Tiwari, A., Sharma, A., Abhijith, K.V., Adlakha, D., McNabola, A., Astell-Burt, T., Feng, X., Skeldon, A.C., de Lusignan, S., Morawska, L., 2019. The nexus between air pollution, green infrastructure and human health. *Environ. Int.* 133, 105181. <https://doi.org/10.1016/j.envint.2019.105181>
- Lalloué, B., Monnez, J.-M., Padilla, C., Kihal, W., Le Meur, N., Zmirou-Navier, D., Deguen, S., 2013. A statistical procedure to create a neighborhood socioeconomic index for health inequalities analysis. *Int. J. Equity Health* 12, 21. <https://doi.org/10.1186/1475-9276-12-21>
- Lanier, C., Brousmiche, D., Deram, A., Frank, L., Genin, M., Occelli, F., Cuny, D., 2020. Characterization of the spatial heterogeneity of environmental and social inequalities in health: a spatialized approach to the resilience-vulnerability balance. *Environ. Risques Santé* 19, 250–256. <https://doi.org/10.1684/ers.2020.1451>
- Maclachlan, J.C., Jerrett, M., Abernathy, T., Sears, M., Bunch, M.J., 2007. Mapping health on the Internet: A new tool for environmental justice and public health research. *Health Place* 13, 72–86. <https://doi.org/10.1016/j.healthplace.2005.09.012>
- Marlier, G., 2009. Note D2DPE n°24 - Un indicateur de développement humain à l'échelle des territoires du Nord-Pas de Calais. Observation Régionale et Analyse Spatiale, Direction du Développement Durable, de la Prospective et de l'Évaluation, Région Nord Pas de Calais.
- Marlier, G., Dallery, T., Chusseau, N., 2015. Le Nord-Pas-de-Calais, entre mutations économiques et développement humain. *Rev. OFCE* 143, 225. <https://doi.org/10.3917/reof.143.0225>
- Marzi, S., Mysiak, J., Santato, S., 2018. Comparing adaptive capacity index across scales: The case of Italy. *J. Environ. Manage.* 223, 1023–1036. <https://doi.org/10.1016/j.jenvman.2018.06.060>
- Miller, K.K., Johnson, A., Dabson, B., 2017. Research Methodology of Resilience and Vulnerability Indexes. Institute of Public Policy Harry S Truman School of Public Affairs, University of Missouri.
- Monteiro, A., Carvalho, V., Velho, S., Sousa, C., 2012. Assessing and monitoring urban resilience using COPD in Porto. *Sci. Total Environ.* 414, 113–119. <https://doi.org/10.1016/j.scitotenv.2011.11.009>
- Moran, P.A.P., 1948. The Interpretation of Statistical Maps. *J. R. Stat. Soc. Ser. B Methodol.* 10, 243–251.
- Mukherjee, D., Safraj, S., Tayyab, M., Shivashankar, R., Patel, S.A., Narayanan, G., Ajay, V.S., Ali, M.K., Narayan, K.V., Tandon, N., Prabhakaran, D., 2017. Park availability and major depression in individuals with chronic conditions: Is there an association in urban India? *Health Place* 47, 54–62. <https://doi.org/10.1016/j.healthplace.2017.07.004>

- Nascimento, I., Carrage, S., 2007. Indicateurs Stratégiques de Développement Durable - Un Indice de Qualité de Vie et Bien-Être pour le Région Île de France.
- Nieuwenhuijsen, M.J., 2016. Urban and transport planning, environmental exposures and health-new concepts, methods and tools to improve health in cities. *Environ. Health* 15, S38. <https://doi.org/10.1186/s12940-016-0108-1>
- Nieuwenhuijsen, M.J., Khreis, H., Verlinghieri, E., Mueller, N., Rojas-Rueda, D., 2017. Participatory quantitative health impact assessment of urban and transport planning in cities: A review and research needs. *Environ. Int.* 103, 61–72. <https://doi.org/10.1016/j.envint.2017.03.022>
- Pearson, A.L., Pearce, J., Kingham, S., 2013. Deprived yet healthy: Neighbourhood-level resilience in New Zealand. *Soc. Sci. Med.* 91, 238–245. <https://doi.org/10.1016/j.socscimed.2012.09.046>
- Porner, C., Delpierre, C., Dejardin, O., Grosclaude, P., Launay, L., Guittet, L., Lang, T., Launoy, G., 2012. Construction of an adaptable European transnational ecological deprivation index: the French version. *J. Epidemiol. Community Health* 66, 982–989. <https://doi.org/10.1136/jech-2011-200311>
- Prüss-Üstün, A., Wolf, J., Corvalán, C., Bos, R., Neira, M., 2016. Preventing disease through healthy environments: a global assessment of the burden of disease from environmental risks, Second edition. ed. World Health Organization, Geneva, Switzerland.
- Ramirez-Rubio, O., Daher, C., Fanjul, G., Gascon, M., Mueller, N., Pajín, L., Plasencia, A., Rojas-Rueda, D., Thondoo, M., Nieuwenhuijsen, M.J., 2019. Urban health: an example of a “health in all policies” approach in the context of SDGs implementation. *Glob. Health* 15, 87. <https://doi.org/10.1186/s12992-019-0529-z>
- Rey, G., Jougl, E., Fouillet, A., Hémon, D., 2009. Ecological association between a deprivation index and mortality in France over the period 1997 – 2001: variations with spatial scale, degree of urbanicity, age, gender and cause of death. *BMC Public Health* 9. <https://doi.org/10.1186/1471-2458-9-33>
- Rojas-Rueda, D., Nieuwenhuijsen, M.J., Gascon, M., Perez-Leon, D., Mudu, P., 2019. Green spaces and mortality: a systematic review and meta-analysis of cohort studies. *Lancet Planet. Health* 3, e469–e477. [https://doi.org/10.1016/S2542-5196\(19\)30215-3](https://doi.org/10.1016/S2542-5196(19)30215-3)
- Rothenberg, R., Stauber, C., Weaver, S., Dai, D., Prasad, A., Kano, M., 2015. Urban health indicators and indices—current status. *BMC Public Health* 15, 494. <https://doi.org/10.1186/s12889-015-1827-x>
- Rydin, Y., Bleahu, A., Davies, M., Dávila, J.D., Friel, S., De Grandis, G., Groce, N., Hallal, P.C., Hamilton, I., Howden-Chapman, P., Lai, K.-M., Lim, C., Martins, J., Osrin, D., Ridley, I., Scott, I., Taylor, M., Wilkinson, P., Wilson, J., 2012. Shaping cities for health: complexity and the planning of urban environments in the 21st century. *The Lancet* 379, 2079–2108. [https://doi.org/10.1016/S0140-6736\(12\)60435-8](https://doi.org/10.1016/S0140-6736(12)60435-8)
- Sadd, J.L., Pastor, M., Morello-Frosch, R., Scoggins, J., Jesdale, B., 2011. Playing It Safe: Assessing Cumulative Impact and Social Vulnerability through an Environmental Justice Screening Method in the South Coast Air Basin, California. *Int. J. Environ. Res. Public Health* 8, 1441–1459. <https://doi.org/10.3390/ijerph8051441>
- Saib, M.-S., Caudeville, J., Beauchamp, M., Carré, F., Ganry, O., Trugeon, A., Cicoletta, A., 2015. Building spatial composite indicators to analyze environmental health inequalities on a regional scale. *Environ. Health* 14. <https://doi.org/10.1186/s12940-015-0054-3>
- Salem, G., 1995. Géographie de la santé, santé de la géographie. *Espace Popul. Sociétés* 13, 25–30. <https://doi.org/10.3406/espos.1995.1667>
- Salvati, L., Carlucci, M., 2014. A composite index of sustainable development at the local scale: Italy as a case study. *Ecol. Indic.* 43, 162–171. <https://doi.org/10.1016/j.ecolind.2014.02.021>
- Sarkar, C., Webster, C., 2017. Urban environments and human health: current trends and future directions. *Curr. Opin. Environ. Sustain.* 25, 33–44. <https://doi.org/10.1016/j.cosust.2017.06.001>
- Sharifi, A., 2016. A critical review of selected tools for assessing community resilience. *Ecol. Indic.* 69, 629–647. <https://doi.org/10.1016/j.ecolind.2016.05.023>

- 688 Stewart, I.T., Bacon, C.M., Burke, W.D., 2014. The uneven distribution of environmental burdens and
689 benefits in Silicon Valley's backyard. *Appl. Geogr.* 55, 266–277.
690 <https://doi.org/10.1016/j.apgeog.2014.09.016>
- 691 van den Bosch, M., Ode Sang, Å., 2017. Urban natural environments as nature-based solutions for
692 improved public health – A systematic review of reviews. *Environ. Res.* 158, 373–384.
693 <https://doi.org/10.1016/j.envres.2017.05.040>
- 694 Yeager, R.A., Smith, T.R., Bhatnagar, A., 2019. Green environments and cardiovascular health. *Trends*
695 *Cardiovasc. Med.* <https://doi.org/10.1016/j.tcm.2019.06.005>
- 696 Zhang, S., Wei, Z., Liu, W., Yao, L., Suo, W., Xing, J., Huang, B., Jin, D., Wang, J., 2015. Indicators for
697 Environment Health Risk Assessment in the Jiangsu Province of China. *Int. J. Environ. Res.*
698 *Public. Health* 12, 11012–11024. <https://doi.org/10.3390/ijerph120911012>
- 699 Zuindeau, B., Lipovac, J.-C., 2009. Elaboration d'un indicateur participatif de bien-être (IPBE) :
700 l'exemple du territoire d'Hénin-Carvin (Nord Pas de Calais). *Rev. Crit. Ecol. Polit.*
701
702



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

