Methodological protocol for integrating social inequalities in environmental impact assessments

Protocol | Task 3.4 | Deliverable 3.3

Funded by the European Union BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408.

Deliverable Information	
Deliverable No. & Title	D3.3 Methodological protocol for integrating social inequalities in environmental impact assessments
Work Package No.	3
Work Package Title	Social inequalities methodology
Lead Organisations	LMU, Sciensano
Main authors	Susanne Breitner-Busch (LMU), Vanessa Gorasso (SCI), Carl Baravelli (NIPH), Frederik Priem (VITO), Gaëlle Mogin (SCI)
Contributors	All WP3 members (SCI, NIPH, TAI, STPH, LMU, SpFrance, VITO)
External reviewer	Juanita Haagsma (EMC)
Nature	Protocol
Dissemination Level	*PU*
Deliverable Date	26/02/2025
Version Number	1

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

Contents

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

1 Disclaimer

The opinions in this report reflect the opinion of the authors and not the opinions of the European Commission. The European Union is not liable for any use that may be made of the information contained in this document.

The commercial use of any information contained in this document may require a license from the owner of that information.

All BEST-COST consortium members are also committed to publish accurate and up to date information and take the greatest care to do so. However, the BEST-COST consortium members cannot accept liability for any inaccuracies or omissions, nor do they accept liability for any direct, indirect, special, consequential or other losses or damages of any kind arising out of the use of this information.

Funded by the European Union

BEST-COST is funded by the European Union’s Horizon Europe programme under Grant Agreement No.101095408

2 Introduction

2.1 Background

Environmental quality in Europe has steadily improved in recent decades (1). Nevertheless, environmental factors such as air pollution or noise continuously contribute to the development or exacerbation of many diseases and deaths, especially in urban areas (2-4). Exposure to air pollution and noise can affect individuals differently (5). Individual characteristics such as age or pre-existing health conditions determine how susceptible people are to these environmental risk factors, i.e., how much their health might be affected if they are exposed. Furthermore, people's socioeconomic status (assessed using factors such as income, employment status, or level of education) often shapes both the extent of people's pollutant exposure and their ability to avoid or cope with these environmental health hazards (6). Previous studies have shown that people with lower socioeconomic status tend to be more vulnerable to air pollution and noise than the general population (5). Moreover, these population subgroups also have the least choice on where they live, work, or go to school, which in turn might affect their exposure to these environmental risk factors. As a result, their health suffers the most from exposure to air pollution and noise.

There has been increased attention to environmental inequalities, i.e., differences in the levels of environmental exposures between groups of people according to their socioeconomic position (quite often, this is also referred to as environmental justice). Research also suggests that these differing levels of exposure among different socioeconomic groups contribute to health inequalities, which are defined as "the unfair and avoidable differences in health status seen within and between countries. In countries at all levels of income, health and illness follow a social gradient: the lower the socioeconomic position, the worse the health"[1]. It is, therefore, important to quantify social determinants of health inequalities to identify population groups that health policies should specifically target.

Despite the increased attention to social inequalities in health and the environment, there is no systematic monitoring of environmental health inequalities, i.e., the contribution of social inequalities to the health impact of environmental stressors. Likewise, environmental health inequalities are typically not integrated into health impact assessments. Thus, policymakers cannot assess whether policies would increase or decrease inequalities.

The overall objective of the project BEST-COST is to improve the methodology for the assessment of the socioeconomic cost of environmental stressors to i) enhance regular usage of economic and health modelling in policy impact assessments and policy evaluation by the European Union (EU) and national public authorities, and ii) promote harmonised and consensual population health, quality of life and economic metrics for integrative socioeconomic assessments of impacts of environmental pollution on health in Europe and health impact and cost-benefit assessments of related policies.

BEST-COST comprises a total of nine work packages involving 19 organisations from 10 European countries (Belgium, Switzerland, Germany, Denmark, Estonia, Finland, France, The Netherlands, Norway, and Portugal) and the USA.

[1] https://www.who.int/health-topics/social-determinants-of-health

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

2.2 Overview of BEST-COST Work Package 3

Within the project BEST-COST, work package 3 (WP3) aims to 1) develop a coherent methodological framework for assessing the extent of social inequalities in different EU countries, and 2) develop and implement an innovative and coherent methodological framework for assessing socio-economic inequalities in the health impact of environmental stressors with a focus on air pollution and traffic-related noise. Figure 2.1 visually depicts the three cornerstones of WP3 (Deprivation, Environmental, and Health outcomes) and which tasks are related to one or more of these cornerstones.

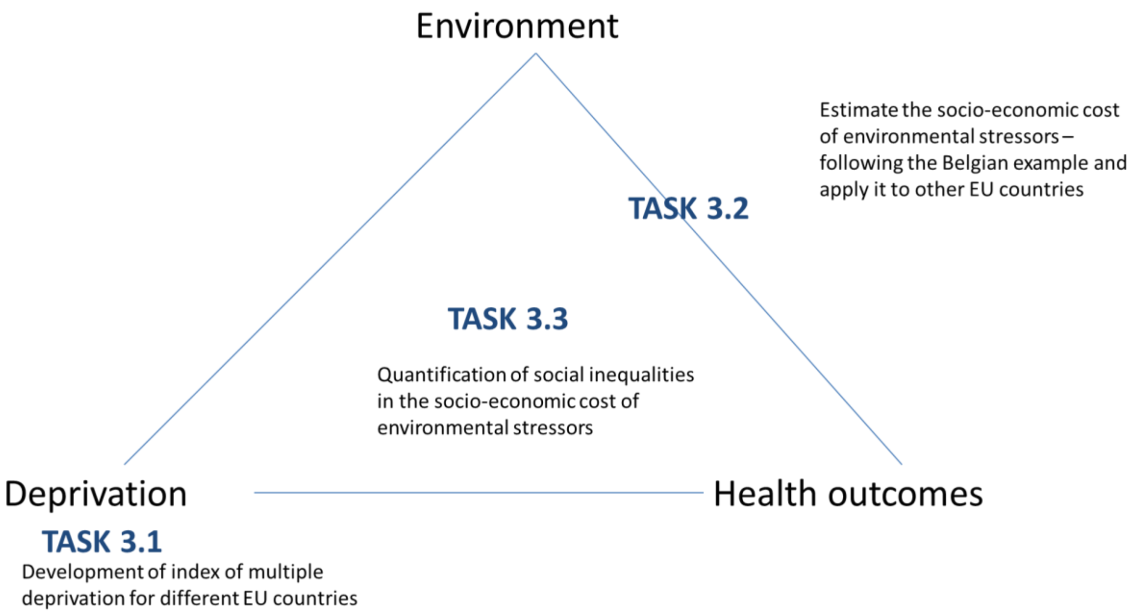

Figure 2.1: *Visual representation of WP3 tasks.*

2.3 Purpose and structure of this methodological protocol

This methodological protocol aims to describe the steps in the proposed framework for assessing social inequalities in the health impact of ambient air pollution and noise. The protocol further provides recommendations on implementing the proposed framework in the BEST-COST R package (WP4) and case studies (WP5), as well as in other study settings.

The protocol first describes the framework for a common index of multiple deprivation for European countries at a small geographical level, i.e. the data requirements, methodological choices, and steps to create the BEST-COST index of multiple deprivation. Then, input data requirements and the proposed methodology for combining the three dimensions of deprivation, exposure, and health outcomes are described. The health outcomes relevant to BEST-COST are detailed in Annex 2 - Definition of diseases using ICD10 codes. Finally, the protocol addresses the cartographic mapping of the targeted statistics. As an Annex to this protocol, a checklist of required data inputs and assumptions is given that can serve as a reporting guideline for studies implementing this methodology.

Funded by the European Union
BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

3 Framework for the development of a European index of multiple deprivation at small geographical level

In the report for BEST-COST Task 3.1 (Deliverable 3.1), we proposed a methodological framework for developing a Multiple Deprivation Index (MDI) for the BEST-COST project. MDI is a composite measure designed to capture various dimensions of socio-economic and material deprivation at the area level, making it particularly useful in studies of health and environmental inequalities. Unlike single indicators, such as income or education level, which focus on one aspect of socio-economic position, MDIs provide a more comprehensive, multidimensional view of deprivation within a specific geographic area, like a neighbourhood or district. Developed originally in the UK in the 1970s, MDIs are supposed to help allocate resources to regions in need by representing the complex, accumulated disadvantages that can impact health and social outcomes.

3.1 Summary of BEST-COST Task 3.1

We proposed a methodological framework for developing an MDI to quantify material and social deprivation. Based on a scoping review of existing European MDIs, this framework describes the methodological decisions taken from the review to the final selection of indicators and proposed construction of the BEST-COST MDI. The BEST-COST project targets the smallest possible geographical units to capture local variations in deprivation. Local Administrative Units (LAU), which are comprised of municipalities and communes within the European Union, are commonly used for this purpose. The following step-by-step approach was developed to achieve this aim:

- A summary of data collected through the scoping review was conducted to make informative decisions on the development of a standardised MDI,
- Benefits and shortcomings of methodological decisions were considered (e.g. the application of indicator weights, the temporal and geographical validity of specific indicators, the availability of data at small geographical areas, and others),
- To provide final recommendations, including the advantages and disadvantages, for the construction and computation of the composite score of the European MDI to be used and recommended by BEST-COST,
- To calculate the MDI for five European case study countries selected within BEST-COST: Belgium, Estonia, France, Norway, and Portugal.

Overall, an MDI tailored for the BEST-COST project should prioritise **feasibility**, ensuring that the necessary data for its construction are obtainable from all five case study countries at a minimum, with the aspiration for data availability across the entire European region. These data should be accessible at a **small-area level,** defined as granular enough to capture localised variations in deprivation, environmental stressors, and disease burden. Furthermore, the MDI should embrace a **multidimensional concept of deprivation**, encompassing both material and social dimensions. However, the index should deliberately exclude domains associated with exposure to environmental stressors and outcomes, such as health, to ensure the MDI does not confound estimates from environmental burden assessments. Notably, the

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

MDI design should aim for simplicity and ease of implementation to facilitate practical usage across diverse settings.

3.2 Scoping Review and Input data

After screening three databases, 163 articles met the inclusion criteria. Background information was initially collected, followed by a second extraction focusing on MDIs, including details on indicators, weighting methods, and geographical scales. Additional articles using the same MDI were reviewed to verify consistency and determine whether the MDIs were applied to health-related phenomena. A total of 18 MDIs and 156 individual indicators were identified. For a full description of the scoping review, please consult Chapter 4 of the D3.1 Report on the EU Index of Multiple Deprivation Methodology (8).

The first step in creating the MDI and collecting the input data was selecting the indicators. Our selection began with the scoping review to extract those commonly used in the literature, followed by an assessment of their availability in the five case study countries and at the European level. Subsequently, we prioritised indicators that were measured at least at the municipality level (i.e., LAU 2). To ensure a comprehensive set of indicators, we then categorised them thematically into higher-order domains.

Each indicator was then evaluated based on three criteria:

- Redundancy: We assessed whether the indicator was unique or overlapped with another similar concept.
- Cultural validity: We assessed the relevance and meaningfulness of the indicator within the European cultural context.
- Temporal validity: We evaluated the indicator's continued relevance for Europe in 2024 and beyond.

Indicators that fulfilled all the above criteria and comprised the final BEST-COST MDI are listed in Figure 3.1, whereas Table 3.1 summarises the availability of indicators and geographical scale between the five case study countries and across Europe.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

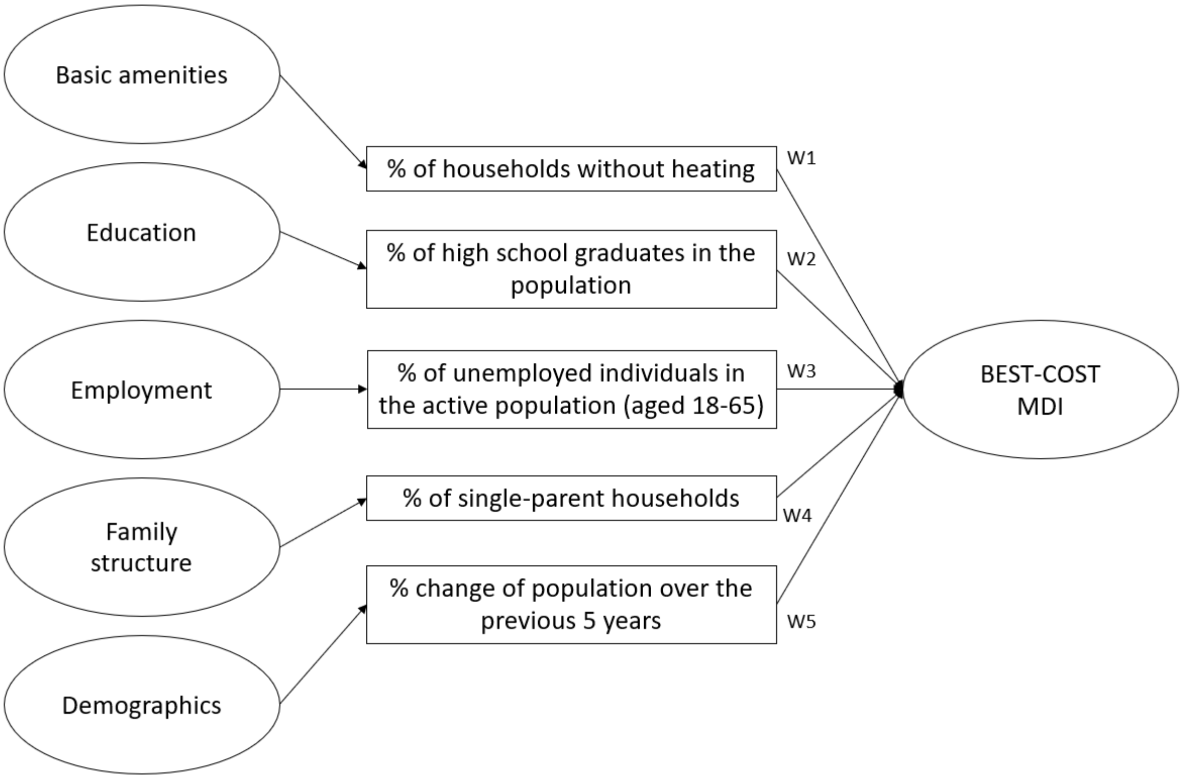

Figure 3.1: *Domains and indicators that comprise the BEST-COST MDI.*

The indicators were available across all countries except for central heating, which has not been collected in Norway for the past two decades due to a ceiling effect (all households meet the criteria). Despite this, central heating was retained as it represents the basic amenities domain, and no suitable alternative was available across all case study countries. Sensitivity and uncertainty analyses should assess the impact of this indicator's inclusion and its exclusion on the MDI's performance in Norway compared to other countries.

		Description of the indicator	Geographical resolution	Description of the indicator	Geographical resolution	Description of the indicator	Geographical resolution
Domain	**Indicator**	**Belgium**		**Estonia**		**France**	
Basic amenities	Heating	Percentage of households without central heating	Province (NUTS 2)	Percentage of households without central heating	County (LAU 1)	Percentage of main residences without central or electric heating	IRIS (<LAU2)
Education	School graduates	Percentage of high school graduates in the population	Statistical sector (<LAU2)	Percentage of high school graduates in the population	Municipality (LAU 2)	Percentage of out-of-school people aged 15 and over with at least a CAP-BEP diploma (ISCED 3)	IRIS (<LAU2)
	University graduates	Percentage of population with post-secondary diploma	Statistical sector (<LAU2)	Percentage of population with post-secondary diploma	Municipality (LAU 2)	Number of unschooled people aged 15 or over with different levels of education	IRIS (<LAU2)
Employment	Unemployment	Percentage of unemployed individuals in the active population (aged 18-65)	Statistical sector (<LAU2)	Percentage of unemployed individuals in the active population (aged 16–60)	Municipality (LAU 2)	Percentage of unemployed people aged 15-64	IRIS (<LAU2)
Family structure	Single-parent household	Percentage of a single-parent households	Statistical sector (<LAU2)	Percentage of a single-parent households	Municipality (LAU 2)	Percentage of single-parent households	IRIS (<LAU2)
Demographics	Change in population	Percentage change of population over the previous 5 years	Municipality (LAU 2)	Percentage change of population over the previous 5 years	Municipality (LAU 2)	Percentage of population change between 2015 and 2021	Municipality (LAU 2)

Domain	**Indicator**	**Norway**		**Portugal**		**Europe**	
Basic amenities	Heating	Not available		Private households (No.) in conventional dwellings of usual residence by place of residence (at	Parish (LAU 2)	Percentage of households without central heating	NUTS 2
Education	School graduates	Percentage of high school graduates in the population	Municipality (LAU 2)	Percentage of high school graduates in the population	Parish (LAU 2)	Percentage of high school graduates in the population	NUTS 2
	University graduates	Percentage of population with post-secondary diploma	Municipality (LAU 2)	Proportion of resident population with higher education completed (%) by Place of residence at Census date	Parish (LAU 2)	Percentage of population with post-secondary diploma	NUTS 2
Employment	Unemployment	Percentage of unemployed individuals in the active population (aged 16-60)	Municipality (LAU 2)	Unemployement rate (%) in the population aged 16-89	Parish (LAU 2)	Percentage of unemployed individuals in the active population (aged 16–60)	NUTS 2
Family structure	Single-parent household	Percentage of single-parent households	Municipality (LAU 2)	Proportion of monoparental family nuclei (%)	Parish (LAU 2)	Percentage of a single-parent households	NUTS 3
Demographics	Change in population	Percentage change of population over the previous 5 years	Municipality (LAU 2)	Resident population by Place of residence	Administrative regions (NUTS 2)	Percentage change of population over the previous 5 years	NUTS 2

Table 3.1: *Data mapping and geographical scale between the five case study countries and across Europe.*

Note : NUTS2 (Nomenclature of Territorial Units for Statistics, level 2, typically corresponding to regions), NUTS3 (Nomenclature of Territorial Units for Statistics, level 3, typically corresponding to smaller regions or counties), LAU2 (Local Administrative Units, level 2, often corresponding to municipalities), Statistical sector (the smallest census unit in some countries), and IRIS (Ilots Regroupés pour l'Information Statistique, the smallest statistical unit in France, typically smaller than municipalities).

3.3 Methodological choices

3.3.1 Weighting the indicators and dimensions

Indicator weights are typically used when the indicators are considered to have varying levels of importance in determining the overall composite score. Common methods for weighting include simply assigning equal weights to each indicator, using expert opinion to assign weights, or using data-driven approaches, such as Principal Component Analysis (PCA) or Factor Analysis (FA). If weights are used, they can either be created at the country level, reflecting the relative importance of the indicator to that country, or at the European level (universal weights).

Given the significant challenges of establishing culturally valid and temporally consistent weights for an MDI within the BEST-COST study, which aims to create a methodological framework across the European region and into the future, there is an argument that utilising equal weights may be more robust and advantageous than employing differential weights. This argument arises from the concern that European-wide differential weights constructed at a certain time and place may not be transferable to other countries or at later points in time. The use of weights was discussed with experts (25 Oct 2024) in the field of composite measures at an online workshop, and a consensus was reached to apply equal weights. While equal weighting might seem simplistic, it is often a pragmatic choice. Expert opinions and statistical methods can produce vastly different weights, which might be challenging to justify (8). Moreover, composite indicators often show less sensitivity to changes in indicator weights than one might expect, meaning that altering the weights of individual indicators does not significantly affect the overall composite score (8).

3.3.2 Development of a composite score

The methods for creating the composite score have been guided by the European Commission's *Handbook on Constructing Composite Indicators: Methodology and User Guide* (COIN). Following the selection of the indicators, we suggest the following steps to create the composite score:

3.3.2.1 Data Collection and Preparation

Indicator data, expressed as percentages of the population or specific age groups (e.g., employment rates), are collected for each case study country at available geographical levels (e.g., LAU 2 [municipality-level], NUTS2/3 [regional/county-level]) for a specified year (e.g., 2021). Efforts are made to harmonise the indicators using consistent definitions, such as defining education based on the International Standard Classification of Education (ISCED) level 3 or higher. However, some cross-country differences may persist due to variations in data collection practices, such as differing definitions of working-age populations set by national statistical agencies.

Data should be formatted with each row representing a geographical unit (e.g., LAU 2) and each column an indicator. Additional variables include country <country>, geographical level <geo_level>, code <geo_code>, and name <geo_name>. If the data is only available as raw counts, then the denominator (e.g., population of the municipality) is also required to calculate the percentage. **Figure 3.2** provides an example of Belgium in terms of data structure.

country	geo_level	geo_name	geo_code	noheating	edu	unemployed	single_parent_hh	population_change
Belgium	LAU2	Aartselaar	11001	2.4151528	55.730259	3.6817551	10.388239	1.64
Belgium	LAU2	Anvers	11002	8.8811769	40.218582	8.8436832	14.664978	1.71
Belgium	LAU2	Boechout	11004	4.5584908	56.333492	3.6236572	10.750898	4.79
Belgium	LAU2	Boom	11005	14.31027	41.339928	5.9042654	12.877903	5.68
Belgium	LAU2	Borsbeek	11007	5.4095826	48.976192	6.5500793	13.342851	4.68

Figure 3.2: *An example of data formatting for calculating the MDI.*

Missing data are assessed and, if classified as missing completely at random (MCAR) or missing at random (MAR), imputed using single regression or multiple imputation methods (9).

3.3.2.2 Normalisation

Indicators are then normalized to account for varying scales and associations:

- **Direction Alignment**: Indicators are aligned to have a consistent positive correlation with deprivation.
- **Transformation**: Indicators should be assessed for normality using visual inspection or statistical tests (e.g., Doornik-Hansen test). Non-normal indicators are transformed using a square root (moderate skew) with the following formula for a positively skewed distribution:

  $$x' = \sqrt{x} \qquad (1)$$

  Where x' is the transformed value; and x is the original value. Or for negatively skewed distributions:

  $$x' = \sqrt{k - x} \quad (2)$$

  Where k is a constant greater than the maximum value of x.

- Or natural log (severe skew) for positively skewed distributions:

  $$x' = ln[x + c] \quad (3)$$

  Where x' is the transformed value; and x is the original value; and c is the constant added to handle zeros (e.g., c = 1 or a fraction like 0.01). Or for negatively skewed distributions:

  $$x' = ln[k - x] \; (4)$$

  Where k is a constant greater than the maximum value of x.

- Outliers may be addressed by replacing extreme values with the next highest value, though log transformation and z-score normalisation often mitigates outlier effects.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

- **Normalisation Methods**: Two methods were considered:
  - **Min-Max Transformation**: Rescales indicators to a fixed range (e.g., 0 to 100):

$$\bar{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \times 10$$

  - **Z-Score Transformation**: Standardises values based on standard deviation (σ) of one and mean (μ) of zero:

$$z = \frac{x - \mu}{\sigma}$$

- While z-scores are less sensitive to outliers, they may result in negative values, which can complicate interpretation. Min-max transformation is preferred for simplicity but is more sensitive to outliers. Both methods should be tested for robustness.

3.3.2.3 Aggregation

Normalised indicators are aggregated using an arithmetic mean, assuming equal weights, using the following formula:

$$C_i = \frac{1}{m}\sum_{j=1}^{m} z_{ij}$$

Where C_i is the composite score for geographical unit i; m is the total number of indicators; z_{ij} is the normalised value of indicator j for geographical unit i.

3.3.2.4 Quantile Ranks

The final composite scores are transformed into quantile ranks by dividing geographical units into ten equal groups, ranging from the lowest to highest levels of deprivation. The decile for a given geographical unit is calculated as:

$$D = \left(\frac{R \times 10}{n}\right)$$

Where D is the decile score; R is the rank of the unit's composite score, sorted from lowest to highest; *n* is the total number of geographical units. For certain analyses quintiles or quartiles may be preferred, especially if working with small numbers of geographical units. However, the default will be creating deciles. Calculating deciles from the composite score ensures equal distribution of geographical units across deciles, allowing for intuitive visualisation and comparative analysis. For circumstances in which there are few geographical units (e.g., assessing NUTS level 2

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

in a small country), then quartiles can be computed instead of quintiles. This may also aid in simplifying pairwise comparisons of deprivation ranks.

It should be noted that individual indicators may still be of use in further analysis, and that we recommend that BEST-COST calculates both an overall composite score and deciles as well as individual indicators and associated deciles. Individual indicators do not need to be normalised, and, therefore, decile ranks for each geographical unit can simply be created from the raw score.

3.3.3 Assess validity and reliability

To assess the MDI's validity and reliability:

- **Internal reliability and scale fit:** Pearson correlations, Cronbach's alpha (>0.70), and item-total correlations will be calculated for each county. This measures the strength of the relationship between an individual item and the total score of the other items in a scale, reflecting how well the item contributes to the overall construct being measured.
- **Construct validity and dimensionality:** Principal Component Analysis (PCA), as well as biplots will be used to examine eigenvalues and component scores.
- **Test-retest reliability:** Correlation between two years, e.g. 2011 and 2021, will be assessed.

To validate the MDI:

- **Comparative validity:** The MDI will be compared to established MDIs (e.g., European MDI, Belgian MDI).
- **Predictive validity:** Regression analysis will be used to assess the MDI's ability to predict health outcomes (e.g., premature mortality) while controlling for area-level, age, and sex factors.

Preliminary analysis of the Belgian MDI revealed poor internal reliability and construct validity for population change and central heating indicators. Removing these indicators may improve the MDI's overall correlation with external factors. A final decision on indicator inclusion will be based on the results of the full analysis.

3.3.4 Assess the impact of uncertainties

To assess the robustness of the BEST-COST MDI, uncertainty analysis (UA) and sensitivity analysis (SA) are recommended after data collection and country-specific MDI development. UA evaluates how input choices (e.g., outlier handling, transformations) impact the final index score. SA measures the variance attributable to these uncertainties. Tools like the R package COINr can facilitate this assessment (10).

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

4 Quantification of social inequalities in the health impacts of environmental stressors

4.1 Summary of BEST-COST Task 3.2 and 3.3

A first step into the quantification of social inequalities in the health burden of environmental stressors was to assess the data availability of (1) exposure to environmental stressors, (2) health outcomes in terms of mortality and morbidity and (3) socioeconomic deprivation data in Europe and the case countries. In particular, the BEST-COST project targets the highest geographical resolution possible to capture local variations of these three components. A key challenge identified in this task was the variability in data availability and geographic resolution across countries, which hindered the initial goal of producing high-resolution burden estimates for the entire European Union. To address this, two recommendations were made: (1) researchers need to decide whether to focus on specific outcomes (e.g. mortality) or limit the analysis to one country in order to achieve a higher resolution, and (2) use low-resolution data when comparing multiple countries or regions to avoid information loss. For countries studied in the BEST-COST project (BE, EE, FR, NO, PT), it was feasible to calculate the socioeconomic burden of environmental stressors at the NUTS2 level. The second part of this chapter addresses the cartographic mapping of the targeted statistics. The key objective here was to develop a methodological framework that can be applied generically on various indicators or combinations to help produce maps that provide spatial insight into these data and their interrelations. A total of five data availability scenarios were included in this framework to help researchers and analysts produce clear and meaningful maps of the socioeconomic burden of environmental stressors.

4.2 Input data – data requirements and catalogue of available data

The data captured consisted of three different parts: deprivation, concentrations of environmental stressors, and disease prevalence/incidence and mortality.

All data concerning air pollution concentrations and noise levels on a European scale are available from the EEA website (https://www.eea.europa.eu/en/analysis/indicators). Atmospheric pollutant concentrations of $PM_{2.5}$ (µg/m³), O_3 (ppb) and NO_2 (µg/m³) are available for 38 countries on a very small geographical scale (1km x 1km). For road traffic, railway and aircraft noise, emissions are calculated using Lden (day–evening–night noise level) or Lnight (night-time noise), both in dB. Noise data are also available for 38 countries at agglomeration, regional or national level, depending on the country. Most countries use the annual average concentration to estimate air pollutant concentration levels, and Lden or Lnight to measure noise exposure. Geographical resolution for air pollutants data varies from country to country, ranging, e.g., from 10m*10m in Belgium to municipality level in Norway and Portugal. For noise exposure, the geographical resolution is smaller, generally representing exposure at major traffic arteries and cities or at a regional level.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

At the European scale, case country data on the prevalence and incidence of selected diseases are available at the NUTS2 level. All data concerning the prevalence, incidence and mortality of the diseases selected at the European level come from Eurostat databases (https://ec.europa.eu/eurostat/data/database). However, some health outcome data are unavailable, as is the case for sleep disturbance, annoyance, cognitive impairment, overweight and obesity, disorders of bone density and structure, disorders of newborns, disturbance and attention and kidney malignant neoplasms. Mortality on specific types of strokes, heart failure, disorders of newborns and skin cancer malignant neoplasms were not publicly available through the Eurostat databases.

If we look at the data by case country, the prevalence and/or incidence and mortality of selected diseases are available at a higher geographical resolution (department, municipality, county, parish, statistical sector). For the countries studied in BEST-COST WP3, prevalence, incidence and mortality data for the selected diseases were available from different sources depending on the country, such as (cancer) registers, hospital discharge data, hospitalization and patient admission data, health interview surveys, healthcare reimbursement data, medical bills, diagnosis records and mortality registers. **Table 4.1** below summarizes the highest geographical resolution for which data is available for each case study country and at the European level. More details and tables on the data collected can be found in BEST-COST Project Deliverable 3.2.

Table 4.1: Summary table for pollutant exposure and disease outcome considering the highest geographical resolution available for each country studied in the BEST-COST WP3 (BE, EE, FR, NO and PT) and the EU.

	Pollutant exposure		Outcome		
	Air pollutant	Noise pollutant	Disease prevalence/incidence	Disease mortality	Deprivation
Belgium	10m * 10m	NUTS 1	NUTS 1 / NUTS 2	Statistical sector	NUTS2
France	4km * 4km	-	NUTS 3	NUT3	LAU2
Estonia	-	NUTS 1	LAU 2	LAU 2	LAU1
Norway	6km * 6km	LAU 2	NUTS 3	NUTS 3	LAU2
Portugal	8km * 8km	NUTS 3	LAU 2	LAU 1	NUTS2
EU	1km * 1km	Country	NUTS 2	NUTS 2	NUTS2

NUTS = Nomenclature of territorial units for statistics, LAU = Local administrative units

To compute the inequalities in the burden attributable to environmental stressors, all three dimensions need to be at the same geographical resolution. In case of differences, the data need to be scaled up to the smallest possible geographical area.

Depending on the desired visualization, the data for the maps can be at different geographical resolutions – see Section 4.3.2 for the different visualization scenarios. A lower resolution was defined here as a minimum of NUTS1 (major socioeconomic regions), and a higher resolution conversely as a geographical maximum of NUTS2 (basic regions) based on the most common geographic resolutions encountered in the statistics on our key topics.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

4.3 Methodological choices

4.3.1 Proposed methodology for the combination of the three dimensions (deprivation, exposure, health outcomes)

Estimating the inequalities in the burden attributable to environmental stressors will require the following two main steps (11). First, the burden of disease attributable to environmental stressors will be computed and expressed in the pre-determined indicator or health metric (e.g. disability-adjusted life years [DALYs], mortality, prevalence). These calculations should be conducted for each pre-determined geographical unit (e.g. municipalities, regions, etc.), and disease-specific causes (or all-cause mortality). See WP1 methodologies for guidance on how to compute the burden attributable to environmental stressors. Below is an example of a possible dataset containing information regarding total all-cause mortality, all-cause mortality attributable to $PM_{2.5}$ and premature attributable mortality (i.e. mortality before the age of 70) – see **Figure 4.1**: Initial dataset**Figure 4.1**. For each geographical unit (e.g. municipality identified by the “NIS number”), the MDI score, index and mortality outcomes are available; if possible, stratified by age and sex.

NIS	MDI_SCORE	MDI_INDEX	REGION	SEX	AGE	POPULATION	MORTALITY_TOTAL	MORTALITY_ATTR	PREM_MORTALITY_ATTR
11001	-4.4677100	1	FL	F	[0,5)	297	0	0	0
11002	2.3811014	8	FL	F	[0,5)	17721	16	0	0
11004	-5.7852325	1	FL	F	[0,5)	308	0	0	0
11005	-0.4836578	6	FL	F	[0,5)	562	1	0	0
11007	-2.5229807	3	FL	F	[0,5)	320	0	0	0
11008	-2.8972957	2	FL	F	[0,5)	787	1	0	0

Figure 4.1: Initial dataset

Second, the same geographical units will be ranked using the BEST-COST MDI score into quantiles - preferably deciles, if the data allows. Thus, the estimated burden attributable to environmental stressors is available for each quantile/decile of the MDI across the areas of interest and can be compared to assess disparities in disease burden between levels of area-level deprivation. An example of the aggregated dataset is given in **Figure 4.2**.

SEX	AGE	MDI_INDEX	POPULATION	MORTALITY_TOTAL	MORTALITY_ATTR	PREM_MORTALITY_ATTR
F	[0,5)	1	21782	14	0	0
F	[0,5)	2	26358	13	0	0
F	[0,5)	3	23093	12	0	0
F	[0,5)	4	18935	7	0	0
F	[0,5)	5	22317	9	0	0
F	[0,5)	6	30596	17	0	0

Figure 4.2: Aggregation of all-cause mortality by sex, age and MDI index.

Funded by the European Union

BEST-COST is funded by the European Union’s Horizon Europe programme under Grant Agreement No.101095408

Health inequalities can be measured using various methods, each offering unique insights into the inequality gap (12-13). Over the following paragraphs, we outline several commonly used groups of health inequality measures, highlighting their advantages and disadvantages. While all these measures give an indication of the health inequality gap and are widely applied in ecological studies (12-13), they generally fall into three methodological categories: ranges, regression-based indices, and population-attributable risk. To account for the population size and the age structure of the geographical units, we suggest using age-standardized rates when computing any of the health inequality gap indicators presented below. **Figure 4.3** shows an example of the age-standardized rates for total all-cause mortality and attributable all-cause mortality stratified by sex and MDI index.

SEX	MDI_INDEX	MORT_TOT_RT_STD_ESP	MORT_ATT_RT_STD_ESP	PREM_MORT_ATT_RT_STD_ESP
F	1	690.2504	77.50682	12.08504
M	1	999.4546	112.21743	21.32377
F	2	709.7612	83.09122	15.60359
M	2	1049.1532	122.71914	22.96410
F	3	700.5963	79.88322	14.04067
M	3	1042.6527	119.96591	22.62804
F	4	733.7958	82.56854	15.87597
M	4	1117.5285	125.92576	25.59128
F	5	716.8773	76.26595	14.26372
M	5	1094.0244	117.02864	22.44527

Figure 4.3: Age-standardized rates for total mortality, premature and total mortality attributable to PM2.5 (European standard population)

4.3.1.1 Ranges

Ranges quantify the difference between the values of the most and least deprived areas, based on the quantile rank. It is usually an unweighted type of measure, which means that it does not consider the size of the population of each group. Nevertheless, by using age-standardized rates, we can consider the population size and the age structure of each geographical unit. At the same time, we compute ranges stratified by sex to control for it. Ranges can be expressed in absolute and relative terms:

Absolute range: Burden in the most deprived areas minus the burden in the least deprived areas

$$Absolute\ Range = B_{Q_k} - B_{Q_1}$$

Where: B_{Qk} is the burden in the most deprived quantile, and B_{Q_1} is the burden in the least deprived quantile.

Relative range: Burden in the most deprived areas divided by the burden in the least deprived area

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

$$Relative\ range = \frac{B_{Q_k}}{B_{Q_1}}$$

Where: B_{Qk} is the burden in the most deprived quantile, and B_{Q_1} is the burden in the least deprived quantile. Results from the example are given in **Figure 4.4**.

RANGE	SEX	MORT_ATT_RT_STD_ESP	PREM_MORT_ATT_RT_STD_ESP
ABS	F	9.79	8.63
ABS	M	23.85	16.22
REL	F	1.13	1.71
REL	M	1.21	1.76

Figure 4.4: Absolute and relative ranges for age-standardized rate by sex

Ranges compare the situation in two quantiles of the MDI (e.g., decile 1 vs decile 10). They are considered simple measures (13) that are straightforward to explain and understand and a starting point in assessing inequalities. On the other hand, ranges typically compare the minimum and maximum values of deprivation, generally ignoring intermediate groups (although these can be calculated separately). Health inequalities quantified with this type of measure will have larger values if the population ranking measure is more disaggregated, and vice versa. In addition, this type of measure does not account directly for confounding at the level of the analysis, as covariates cannot be adjusted for in the simple arithmetic calculation. They represent a purely descriptive metric and are less suitable for comparative analyses.

4.3.1.2 Population attributable risk and fraction

The Population Attributable Risk (PAR) is an absolute measure of health inequality that quantifies the potential health outcome changes of the average population if all considered areas had the same level of socio-economic deprivation as a reference group. This reference group is often set to the least deprived area, assuming that health outcome differences with other areas are attributable to socio-economic inequalities. PAR is calculated as the difference between the estimated health outcome for the reference group (y_{ref}) and the population average (μ) estimated health outcome.

$$PAR_{\text{deprivation}} = \mu - y_{ref}$$

Population Attributable Fraction (PAF) is obtained by dividing PAR by the population average estimated health outcome (13). This calculation differs from the one used to calculate the initial burden attributable to the exposure of interest (i.e. PAF of mortality attributable to $PM_{2.5}$). The PAF described below indicates the attributable burden that could be explained by inequalities.

$$PAF_{\text{deprivation}} = (PAR\ /\ \mu) * 100$$

See below the calculation of the PAR and PAF for the age-standardized mortality rates attributable to $PM_{2.5}$. These can be interpreted as: if the whole female population had the level of social deprivation as the highest quantile, 4.76% of the PM2.5 attributable mortality could be avoided. The results from the example are shown in **Figure 4.5**.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

VALUE	SEX	MORT_ATT_RT_STD_ESP	PREM_MORT_ATT_RT_STD_ESP
PAR	F	3.87	4.03
PAR	M	12.33	6.29
PAF	F	4.76%	25%
PAF	M	9.9%	22.77%

Figure 4.5: Population attributable risk and fraction for inequalities (based on the BEST-COST MDI) of attributable all-cause mortality age-standardized rates by sex.

One of the biggest advantages of this measure is its ease of interpretation and the fact that it can be used to monitor improvements or deteriorations, which are key elements in the BEST-COST project (12-15). The PAR/PAF also considers the whole range of inequalities and does not focus only on the least and most deprived quantiles (in contrast to the ranges). Like other inequality indicators, PAR/PAF cannot be interpreted as an indicator of causal relationships. Inequalities represent a very complex phenomenon that is difficult to disentangle from other causes of health burden. These measures should be interpreted as an indication of heterogeneity, and not as a causal explanation of why the differences exist.

4.3.1.3 Regression-based indices

4.3.1.3.1 Poisson/negative binominal regression

Relative inequalities in the attributable burden of disease metrics can be assessed using either Poisson regression or, if in the presence of overdispersion (i.e., standard deviation higher than mean), negative binomial regression can be used. These models are more appropriate than general linear models as the outcome variable is count data and should align with a Poisson distribution. Important covariates, such as the age structure of the area or centrality measures, can be added as covariates to the model to adjust the effects in an additional model. Other factors, such as sex and age, may be added either as covariates or aggregated on (i.e., separate models). The models should include robust standard errors. In the crude model (i.e., no adjustment for confounding), the attributable burden of disease metric is the outcome variable, with quantile ranks as the exposure variable. Incidence Rate Ratios (IRRs) should be requested with 95% confidence intervals (CIs), using the least deprived quantile (Q1) as a reference. Both crude and adjusted models should be presented to display levels of confounding. The IRR in the crude form should provide an identical value to calculating the relative range, although this measure also provides confidence intervals.

To account for the hierarchical structure of certain geographical analyses (e.g., municipalities nested within counties), it may be beneficial to investigate using larger geographical regions (e.g., counties) as a random intercept or slope, or both - in the regression model using a mixed-effects model. This approach captures unobserved heterogeneity at the larger geographical level and models variations in baseline disease burden across health regions while estimating the associations between quartiles/deciles of the MDI and disease burden within smaller geographical units. This is especially important if regional differences in the MDI are observed. However, this does require greater statistical power (i.e., a larger number of units per quantile category of the MDI). Further, if larger regional differences are not observed, including this would be unnecessary.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

An absolute difference between quantiles can also be calculated using post-estimation analysis following crude and adjusted regression models, such as marginal means. The crude model should provide the same estimate derived by calculating the absolute difference, but again with CIs. In the adjusted models, the absolute values are adjusted for covariates. The post-estimation analysis should specify that the distribution is based on a Poisson distribution rather than a normal (Gaussian) distribution, which is a common distinction in count data modelling.

Poisson or negative binomial regression models offer significant advantages to simple ranges by accounting for covariance, with mixed-effects models further addressing the geographical structure of the data. These models provide similar insights to those derived from range-based measures and are intuitive to interpret but offer additional benefits, including uncertainty estimates, statistical tests, and adjustments for confounding. When the MDI is used as a categorical exposure variable, incidence rate ratios (IRRs) are calculated for each level relative to a reference group. For quartiles, this results in three IRRs, and for deciles, nine, which is beneficial for assessing dose-response relationships but can generate many values. Simplifying the analysis by comparing only the most and least deprived groups reduces complexity but overlooks intermediate ranks. Alternatively, measures such as the Relative Index of Inequality (RII) and the Slope Index of Inequality (SII) (16) can be used, as they provide a single estimate while incorporating information from all levels of the MDI, although interpretation is not quite as straightforward.

4.3.1.3.2 The Relative Index of Inequality and Slope Index of Inequality

The Relative Index of Inequality (RII) and Slope Index of Inequality (SII) are respectively used to quantify the relative and absolute inequality gap by accounting for the distribution of the MDI in the samples (14). To estimate the RII and SII, first, the 'ridits' (transformation score) of the MDI need to be calculated, which are surrogates for the cumulative probabilities that would be observed if the response could be measured on a continuous scale. In the case of a decile rank, this is the middle value of each rank with a score between 0 and 1, so that decile 1= 0.05, decile 2=0.15, decile 3=0.25, decile 4=0.35…, decile 10=0.95. The RII is then calculated using a generalised linear model (GLM) with a log-family link. The RII is the exponential beta coefficient for the ridit-transformed MDI quartiles/deciles. As our outcome is based on count data, we should use a Poisson regression model. The RII can be interpreted as the relative risk of the outcome (e.g., COPD-specific DALYs attributable to $PM_{2.5}$), comparing hypothetical units (e.g., municipalities) with the lowest levels of deprivation with those with most of the deprivation hierarchy, accounting for the middle quantile rankings.

The SII is calculated similarly to the RII but with an identity link. The SII is the beta coefficient of the transformed education and income variables. The RII and SII represent the relative and absolute level of inequality in the estimated indicator values between the most deprived and the least deprived areas. However, RII and SII also consider the situation in other ranks by using a linear regression model. Subgroups are weighted according to their population share.

To calculate SII, the same Poisson regression equation is specified as used for the RII; however, rather than a log link, an identity link is used instead. The difference between the two estimated values (most deprived [v_1] and least deprived [v_0] generates the SII value:

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

$$SII = v_1 - v_0$$

The ratio of the estimated values generates the RII value.

$$RII = v_1 / v_0$$

The biggest improvement of regression-based indices compared to the use of ranges is their possibility of taking into consideration the population size of each group as well as the inequalities in the whole population. In addition, these indices can account for covariate adjustments and can be used to estimate the uncertainty around the estimates.

4.3.1.3.3 A note on confounding

As discussed, a key advantage of regression models is their ability to adjust for covariates. For BEST-COST, three major covariates—population size, age structure, and sex—must be considered when estimating the socio-economic impact of environmental stressors. Geographical units often vary significantly in population size, which can be partially addressed by using rates of the attributable disease burden. However, very small populations may produce noisy estimates, necessitating the consideration of smoothing techniques. Age can be adjusted in the outcome by calculating age-adjusted rates based on an appropriate standard population. However, this approach does not account for differences in age structure within the MDI. Including age groups as a covariate in the model, rather than relying solely on age-adjusted rates, allows for adjustment in both the exposure and outcome. While relative differences in sex may be less pronounced, absolute differences in disease burden are often substantial, with men typically showing higher rates of YLL and women higher rates of YLD. Sex can be incorporated as a covariate or used to stratify the analysis, depending on the study's objectives. Lastly, other covariates, such as rural-urban typology, may also be explored in such models as potential confounders or even effect modifiers using interaction terms.

4.3.1.3.4 An example

We assessed socio-economic inequalities in health across Belgian municipalities and sex groups. The primary objective was to examine relative and absolute differences in all-cause premature mortality (death rates in 70 years or younger) attributable to $PM_{2.5}$ between deciles of the BEST-COST MDI. We assessed 1) ranges, 2) negative binomial regression models, and 3) Relative Index of Inequality (RII) and Slope Index of Inequality (SII).

Each row of the dataset represented a municipality-sex combination (e.g., municipality A by sex A, municipality A by sex B) and included a variable for attributable mortality rates per 10,000 population (outcome), the BEST-COST MDI decile rank (exposure), and several covariates representing the proportion of the municipality's population by sex for each 10-year age group, as well as variables for sex and municipality, as exemplarily shown in **Figure 4.6** below.

	municipality_nr	sex	mortality...	rank	nis_age_...	nis_age_...	nis_age_...	nis_age_...	nis_age_...	nis_age_...	nis_age_...	nis_age_...	nis_age_...	nis_age_...
1	11001	F	.7343642	1	.0885742	.1013467	.0930168	.1053728	.1235596	.149521	.140497	.1181452	.0397057	.040261
2	11001	M	.8539059	1	.0990406	.1082111	.1083521	.1027088	.1248589	.155474	.128386	.1144187	.0345655	.0239842
3	11002	F	42.6929	8	.1325518	.1082081	.1414345	.1487315	.1203153	.1104782	.0960515	.0738296	.0310627	.0373369
4	11002	M	81.86356	8	.1378274	.1151263	.1415247	.1556331	.1358342	.1215471	.0915388	.0612756	.0210807	.0186121

Figure 4.6: Initial dataset for the analysis.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

The findings are presented below in **Table 4.2**.

Table 4.2: Overall findings and comparisons of relative and absolute inequalities in premature mortality comparing different models.

	Females	Males
Relative difference		
Range	1.48	1.49
Crude IRR (95% CI)	1.48 (1.30-1.69)	1.49 (1.36-1.64)
Adj. IRR (95% CI)	1.60 (1.37-1.85)	1.72 (1.53-1.94)
RII (95% CIs)	1.33 (1.02-1.73)	1.63 (1.32-2.00)
Absolute Difference		
Range per 10,000.	0.73	1.27
Adj. margins per 10,000.	0.73 (0.50-0.96)	1.28 (0.97-1.58)
SII (95% CIs) per 10,000.	0.47 (0.03-0.91)	1.27 (0.73-1.82, p<.001)

Note. IRR=Incidence rate ratio, CI=confidence intervals, RII=relative index of inequality, SII=slope index of inequality. Adj IRR= adjusted incidence rate ratio and margins using a negative binominal regression analysis, adjusted for age 10-year structure of each municipality.

The findings reveal substantial socioeconomic inequalities in $PM_{2.5}$-attributable premature mortality across Belgian municipalities, with higher deprivation, as measured by the BEST-COST MDI, significantly associated with increased mortality in both sexes (Figure 4.7). After adjusting for age structure, the relative risk of premature mortality was 1.60 times higher for females and 1.72 times higher for males in the most deprived municipalities compared to the least deprived, with absolute mortality rate differences of 0.73 (females) and 0.47 (males) per 10,000 population. Regression analyses confirmed these findings, with age adjustment slightly increasing the estimates. The RII indicated that premature mortality risk was 1.33 times higher for females and 1.63 times higher for males in the most deprived areas, while the SII showed an excess of 0.47 premature deaths per 10,000 females and 1.27 per 10,000 males. Although estimates from RII and SII were slightly lower than those from negative binomial regression, likely due to the influence of middle values, the results consistently highlight significant socio-economic disparities in $PM_{2.5}$-attributable premature mortality across municipalities.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

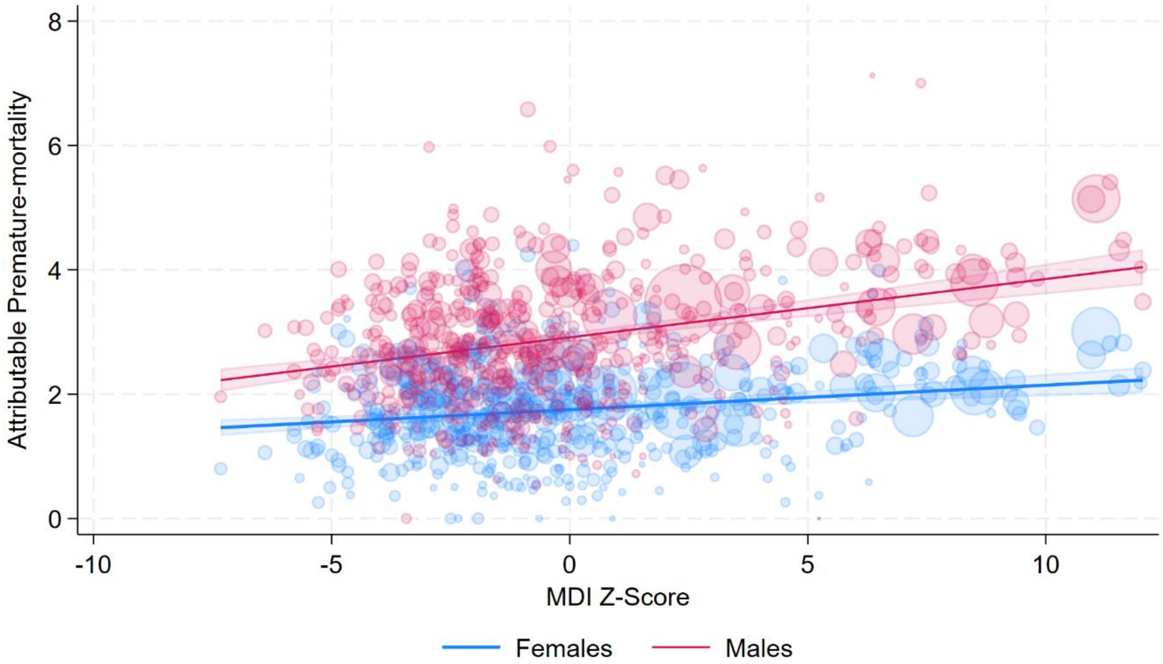

Figure 4.7: Two-way bubble plot illustrating the relationship between z-scores of the BEST-COST MDI (higher value=higher deprivation) and premature mortality attributable to $PM_{2.5}$ across Belgian municipalities (2021), aggregated by gender. Each data point represents a municipality with the size determined by the population, with separate linear fit-lines and 95% CI bands depicted for males and females.

4.3.2 Proposed mapping framework

4.3.2.1 Outline of the framework

The proposed framework is underpinned by five mapping scenarios that both reflect and address the strongly variable availability and geographical detail that are characteristic of how these data are disseminated within the EU. In the absence of clear guidelines, this variable data availability may render mapping difficult. The mapping scenarios are also designed along the lines of typical research questions that may initially entail the assessment of single indicators but then escalate to bi- or even tri-variate inquiries to assess spatial relationships between multiple indicators. The proposed mapping scenarios handle the following five situations:

1. Mapping a single high-resolution indicator.
2. Mapping a single low-resolution indicator.
3. Mapping two equal resolution indicators.
4. Mapping a higher and lower resolution indicator.
5. Mapping three equal resolution indicators.

Besides the framework's focus on handling data availability and geographical resolution, another key methodological choice was to limit ourselves to "only" five scenarios, which, of course, never include all imaginable mapping requirements that may be encountered. At first,

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

we were planning to define additional and more advanced scenarios, e.g., to assess three indicators on various levels of geographic detail. However, while developing the mapping solutions for these situations, it became clear that the required techniques were too experimental and advanced to allow even a mixed scientific audience to grasp the meaning of the resulting maps easily. The line had to be drawn somewhere, but we believe that, especially with scenarios 3 to 5, we can already enable more elaborate analyses that may be of interest to the BEST-COST consortium.

In the subsequent paragraphs, we will first specify the spatial data and software requirements of the proposed mapping framework. Here, we will focus on how we have implemented this framework so far, allowing room for equivalent approaches and software that may also suit this purpose. A short paragraph will be dedicated to the preprocessing performed on the mapped spatial data. Next, we summarize the general map design guidelines to be followed. Finally, we will describe the protocols that can be used to reproduce or adapt the example maps and graphs developed for our framework.

4.3.2.2 Spatial data storage and format requirements

In Section 4.2 of this report and Section 4 of the report of Deliverable 3.3, we explain the geographically coded statistics on environmental stressors, health outcomes and socio-economic deprivation that are made available by the EU and the five selected case countries. We will not repeat this information here but will expand on how we propose to organise this large collection of geodata to facilitate comprehensible and reproducible workflows that can be leveraged for advanced mapping assignments. This will also fit into the software requirements covered in the next paragraph.

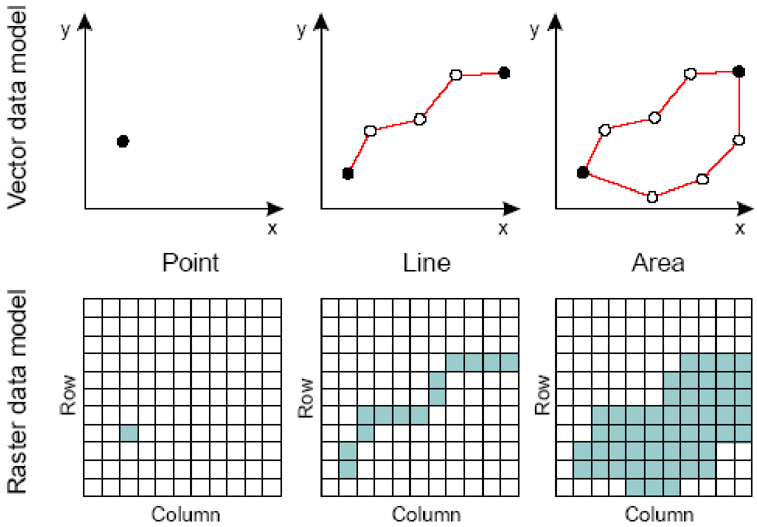

Figure 4.8: Illustration of the vector and raster data models that are used to represent real-word geographical objects, and to construct spatial data in GIS.[2]

Essentially, there are two ways to structure spatial data: vector format or raster format (**Figure 4.8**). Most geocoded statistics used in this study use a vector format, in which several textual,

[2] https://worldbank.github.io/OpenNightLights/_images/mod1-rastervector2.png

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

numerical, or other types of attributes are added to geographic objects such as municipalities, regions and countries. The spatial units used for this work are typically delineated by georeferenced polygon geometries, or areas, which may be stored and managed separately from the statistical data on the corresponding units. Apart from polygon or area geometries, line and point geometries are also possible. **Vector format** spatial data are organised as tables, containing at least one column with the feature geometries, and they are often distributed using file formats like shapefile, GeoPackage or GEOJSON. **Raster format** spatial data, on the other hand, are organised as georeferenced images or grids, in which each pixel or cell directly represents a rectangular patch of the Earth's surface, and the corresponding cell value a quality or quantity corresponding to that patch of land. A commonly used file format for raster spatial data is GeoTiff, but other common file formats include ASCII Grids and JPEG 2000. Typically, when raster data is mapped on geographical units containing many individual pixels, some form of raster-to-vector format conversion is performed on the involved data. The raster-vector conversion applied for our mapping workflow will be discussed further in the data preprocessing paragraph.

Figure 4.9: Illustration of the GeoPackage file format and one of its key features, i.e., the possibility to store many spatial layers within a single GeoPackage file.[3]

The earlier mentioned GeoPackage format has some particularly interesting qualities regarding our spatial data storage needs (**Figure 4.9**). GeoPackage is described as "*an open, standards-based, platform-independent, portable, self-describing, compact format for transferring geospatial information*"[4]. Each GeoPackage file is, in fact, an SQLite container that can hold many GIS layers which may be interlinked in a relational and/or geographical fashion. Seeing that we want to (**1.**) consolidate and share large volumes of vector spatial data (or raster data that can be converted to vector format) and (**2.**) combine, reorganize, and query these data in various ways depending on the mapping requirements at hand, the decision was made to include all these data layers in a single GeoPackage. As such, the GeoPackage became a sort of data warehouse that feeds input to and/or stores output from the mapping framework workflows. This GeoPackage produced for the mapping workflow can be accessed on the BEST-COST WP3 SharePoint via this link.

[2] https://kennis.hunzeenaas.nl/images/hunzeenaas/thumb/5/56/GeoPackage_layers.png/500px-GeoPackage_layers.png
[4] https://www.geopackage.org/

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

4.3.2.3 Software requirements

Following project guidelines and current trends, the decision was made to draw on free, open-source software to develop the workflows of the mapping framework. For the analysis and mapping of spatial data, we needed some form of **Geographic Information System (GIS)**. The most obvious choice here is **QGIS**, which provides functional polyvalent GIS software featuring a rich collection of add-ons and plugins, as well as a vibrant user community[5]. Seeing that, for this work, maximum system stability and performance are to be preferred over the availability of the most recent features, we advise using the Long-Term Release (LTR) version of QGIS rather than its current release.

Besides enabling the production of well-designed maps, QGIS also features a database connection interface that allows users to import (non-)spatial layers from various database systems (**Figure 4.10**), including GeoPackages. Data can be imported directly as a complete layer from a database or through customized **Structured Query Language (SQL)** scripts that may filter and combine data from several layers in the database. SQL is a programming language used to create, query, manipulate, and manage data in relational database systems. Seeing that we store our data in a GeoPackage file, essentially an SQLite container, the produced SQL scripts were written in the **SQLite dialect**[6].

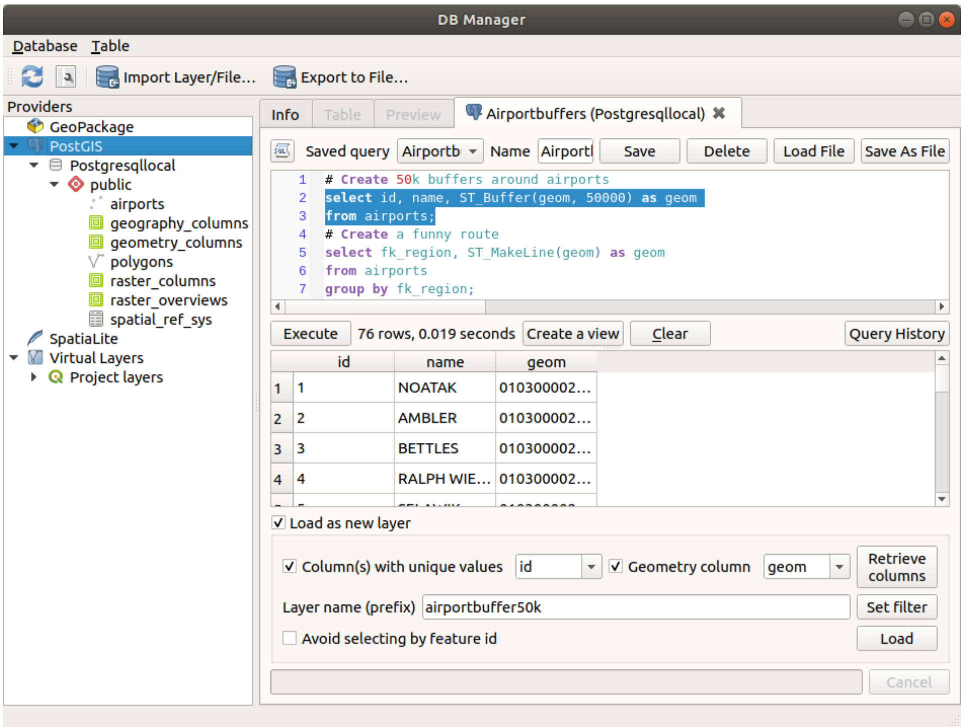

Figure 4.10: Example view of the DB Manager interface in QGIS.[7]

[5] https://www.qgis.org/
[6] https://www.sqlite.org
[7] https://docs.qgis.org/3.34/en/_images/db_manager_sql.png

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

Even though many of our processing and mapping requirements can be fulfilled by QGIS and SQL, some functionalities are not or only poorly covered by these technologies. For example, for the bulk processing and consolidation of GIS data, it may be more useful to draw on a scripting language instead. Also, QGIS only provides limited support for generating customised graphs and charts. Furthermore, for the generation of bivariate choropleth maps that are used in the earlier mentioned mapping scenarios 3 and 5, QGIS currently misses a stable plugin to produce correct bivariate legends. These specific requirements were addressed using **Python** (17). Python is a widely used general-purpose programming language with a strong ecosystem of GIS packages. Key GIS Python packages include **Geopandas**[8] for vector-GIS processing and **Rasterio**[9] for raster-GIS processing. Both these packages draw on the **Geospatial Data Abstraction Library** (GDAL)[10]. The **Matplotlib**[11] package was used to produce support graphs. To create programmable database interfaces in Python, we used the **SQLAlchemy**[12] package. The Python environment used to develop the mapping framework was created and managed with **Anaconda**[13]. Although Python scripts can be written in simple text editors and executed from the command line, typically, one would use an Integrated Development Environment (IDE) that provides additional support and functionalities. Examples of commonly used Python-supported IDEs that are free or have a free version are **PyCharm**[14] and **Visual Studio Code** (VSC)[15].

4.3.2.4 Data preprocessing

The georeferenced statistics used to illustrate our mapping framework are mainly distributed as spatially implicit vector-GIS data, i.e., tabular data (often provided as Excel or CSV files) containing an alphanumerical field to denote the corresponding NUTS region identifier. This is the case for population, health, and deprivation data. The main provider of these statistics on the EU level is EUROSTAT[16]. The spatial definitions of the various NUTS and LAU regions are distributed in shapefile and other vector-GIS formats by GISCO[17]. We only performed minor preprocessing on these data, seeing that they are already provided in an easy-to-map format. The main operation performed on these data is their consolidation in a GeoPackage file, which was done in Python. The corresponding Python script, called "*preprocessing_vector.py*", can be consulted on the BEST-COST GitHub page via this link.

EU-level environmental stressor data on noise and air pollution, as well as gridded population statistics, can be found as raster-GIS data in GeoTiff and other raster file formats. Census grid data are again provided by GISCO[18], and the environmental stressor data by the European

[8] https://geopandas.org/
[9] https://rasterio.readthedocs.io/
[10] https://gdal.org/en/latest/
[11] https://matplotlib.org/
[12] https://www.sqlalchemy.org/
[13] https://www.anaconda.com/
[14] https://www.jetbrains.com/pycharm/
[15] https://code.visualstudio.com/
[16] https://ec.europa.eu/eurostat/data/database
[17] https://ec.europa.eu/eurostat/web/gisco
[18] https://ec.europa.eu/eurostat/web/gisco/geodata/population-distribution/geostat

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

Environment Agency (EEA)[19]. Here we had to perform two operations to obtain exposure data in vector-GIS format, at the geographical level of the various NUTS regions. First, all raster layers were spatially resampled to a common raster grid with 1 by 1 km pixels using the bilinear resampling algorithm. To obtain the noise exposure per NUTS region, we then calculated the zonal mean of the population-weighted complement of the Quietness Suitability Index (QSI) (18):

$$E_j = \frac{\sum_i^N I_{i,j}\, P_i\, (1 - Q_i)}{\sum_i^N I_{i,j}\, P_i}$$

In this formula, E_j represents exposure to noise in NUTS region *j*, P_i the population in pixel *i,* Q_i the QSI value in pixel *i,* whose values range between 0 and 1, *N* the number of pixels in the raster grid, and $I_{i,j}$ an identity function that equals 1 if pixel *i* is in NUTS region *j*, and 0 otherwise. For air pollution we calculated per NUTS region the percentage of the population exposed to an average yearly concentration exceeding the WHO threshold value of the corresponding pollutant, above which exposure is considered detrimental to public health:

$$E_{p,j} = 100\, \frac{\sum_i^N I_{i,j}\, P_i\, T_{i,p}}{\sum_i^N I_{i,j}\, P_i}$$

In this formula, $E_{p,j}$ represents exposure to air pollutant *p* in NUTS region *j*, and $T_{i,p}$ a threshold function that equals 1 if the yearly average air concentration of pollutant *p* in pixel *i* exceeds the corresponding WHO threshold value, and 0 otherwise. For the example of NO_2 air pollution, the WHO guideline specifies a maximum yearly average concentration of 10 $\mu g/m^3$ (19). Finally, the obtained vectorized noise and air pollution exposure layers, now covering the NUTS regions, were also consolidated within the above mentioned GeoPackage file. The operations performed on the raster data can be consulted on the BEST-COST GitHub page, in the Python script called "*raster_preprocessing.py*" which can be accessed via this link.

4.3.2.5 General map design guidelines

When producing a series of maps that may cover one or several study sites, it is recommended first to make **map layout templates** that contain all the necessary placeholders and map frames with preset configurations and page layout. This can be done using the *Layout Manager* interface in QGIS. The map templates can then easily be duplicated and completed with the layers and specific map layouts required for each scenario, all while retaining a common format. In **Figure 4.11**, we illustrate the key elements included in each map with a completed EU-level example. Note that a North arrow was not deemed necessary, seeing that in its absence, by convention, the upper side of the map is assumed to be pointing towards the geographic North. Also note that, depending on the medium in which these maps will be shown, one could decide to provide horizontally oriented templates, which may be more suitable to display in a slideshow, and/or vertically oriented templates that are more apt for documents.

[19] https://www.eea.europa.eu/en/datahub

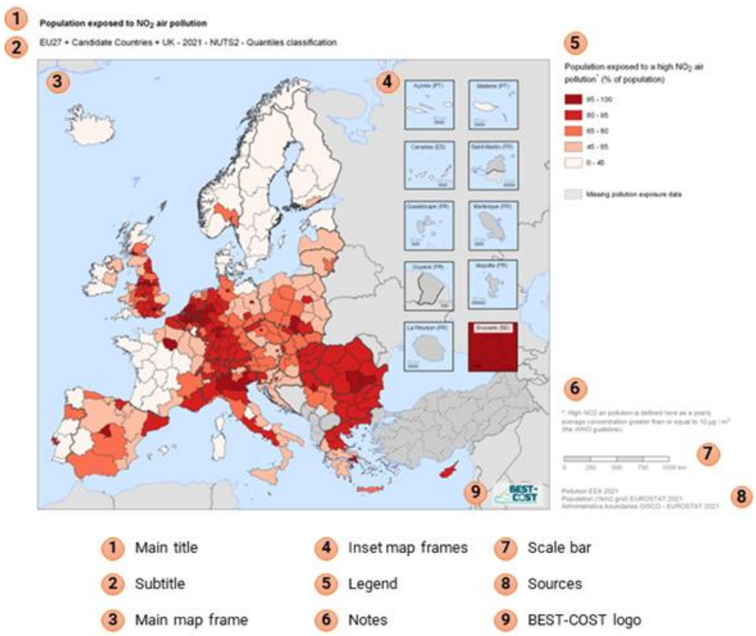

Figure 4.11: Key elements included in the map product generated in the frame of this work.

Cartographic design principles will not be covered in detail here as this would exceed the scope of this methodological protocol. For a thorough exploration of this topic, please consult Slocum et al. (2022) (20) and Leff et al. (2016) (21). As was mentioned in the Deliverable 3.2 report, we adhere to the principles of **visual balance** and **intellectual-visual hierarchy** to make the maps as self-explanatory and self-containing as possible. To the fullest extent possible, we use colourblind-friendly colour schemes or also provide colourblind-friendly alternatives. Preference should be given to the colour schemes defined by ColorBrewer[20], which are perceptually optimized and included by default both in QGIS and Matplotlib. For the map background, we recommend depicting oceans, seas, and major lakes with a light blue hue. Countries visible on the map but falling outside the area of interest should be depicted with neutral light grey. Coastlines should be mapped with a thin, darker blue hue to highlight land-sea borders better. If multiple hierarchies of administrative borders are shown on the same map, e.g., countries (NUTS0) and NUTS2 regions within countries, then the layout of the corresponding line geometries must be adapted to reflect this hierarchy, giving more visual weight to higher-order borders and vice versa.

[20] https://colorbrewer2.org/

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

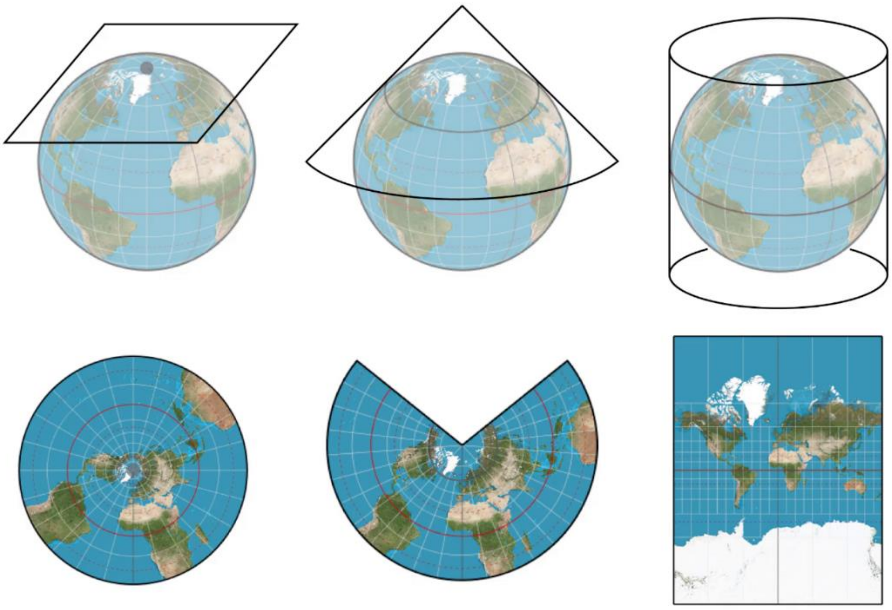

Figure 4.12: The three main types of map projections, each having their characteristic map distortions. From left to right: planar, conical, and cylindrical map projections.[21]

Another important concern when making maps is choosing the **Coordinate Reference System** (CRS) that will be used to display the spatial data. A CRS consists of a geodetic system and a **map projection.** Considering the 3D curvature of the Earth's surface and the fact that we are depicting (part of) it on a 2D surface, all map projections will entail some distortion of shape, area, distance and/or direction (**Figure 4.12**). That being said, standard CRS can be found that are adapted to facilitate mapping for a specific purpose and/or on a specific area, which may cover a country, region, continent or even the complete Earth's surface. For example, to make an EU-level map with or without its Candidate Countries, one would typically use the *European Terrestrial Reference System 1989 Lambert Azimuthal Equal Area* (ETRS89-LAEA)[22]. As another example, for the country of Belgium, one could either use the *Belgian Lambert 72* system (BD72)[23] or its newer counterpart, *Belgian Lambert 2008*[24]. Each country will typically have one or more national CRS that are optimized for producing maps of the corresponding country[25].

4.3.2.6 Mapping and support graph protocols

In the Annex of this document, we share the mapping and graph protocols, i.e., the steps to be taken to reproduce and possibly adapt the example maps and support graphs developed to illustrate our mapping framework. We only elaborated these protocols insofar that the provided scripts and preconfigured QGIS project file may be insufficient to reproduce our results. Two generalized protocols are provided, one for the mapping and one for graph generation, that can be adapted to the requirements of the five mapping scenarios included in

[21] https://mapscaping.com/understanding_map_projections/
[22] https://epsg.io/3035
[23] https://epsg.io/31370
[24] https://epsg.io/3812
[25] https://www.crs-geo.eu/crs-national.htm

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

our proposed framework, which were outlined earlier in Section 4.3.2.1. A more general explanation of the mapping scenarios and the underlying motivation for choosing their corresponding methodologies can be found in Section 5.3 of the Deliverable 3.2 report. The content of the Deliverable 3.2 report will not be repeated here.

All workflows developed for the mapping framework are documented in scripts that are made available on the BEST-COST GitHub repository. A copy of the **QGIS project file**, containing all map templates and elaborated layouts, can be downloaded via this link. The **SQL scripts** developed to select and reorganize example data for each mapping scenario are included directly in the QGIS project file (see *DB Manager*). However, separate copies of these queries have also been included as SQL text files in a folder within the BEST-COST GitHub repository that can be accessed via this link. Each query file name starts with the label "SC*x*", with *x* indicating the scenario number. Scenarios can have more than one SQL file, labelled "*A*", "*B*", "*C*", …, to facilitate alternative examples and/or multi-resolution maps and graphs. The generation of the support graphs was implemented with a **Python script** called "support_graphs.py", which can be accessed via this link. Note that the above SQL scripts are also used in this support graph script to obtain identical datasets that match the corresponding map.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

5 Strengths, limitations, and future perspectives

The purpose of this protocol was to provide guidelines for the future application of the WP3 methods rather than justify the choices made to establish these methods. To learn more about the underlying motivation for these methodologies, please consult the WP3 reports (WP3 INEQUALITIES). Here, we list some key considerations for the methods described in this report that may impact the interpretation of the corresponding results and their long-term use.

The main strength of the approach presented here is the multisectoral nature of the outcome(s). Being able to quantify the deprivation inequalities in the burden attributable to environmental stressors represents a key element for lowering both inequalities and exposure to these stressors. To our knowledge, just a few scientific reports dealt with these outcomes simultaneously, highlighting the need for more guidelines (11, 22). Considering the complexity of combining three dimensions (i.e. health, exposure, and deprivation), another strength of the framework is the provision of workable solutions to map data. The framework provides the means to help tackle spatial research questions that may be of a univariate or multivariate nature. In addition to generating maps, we also invested effort in creating workflows to generate support graphs that provide an alternate and complementary view of the mapped data.

An important strength of the methodological framework developed is its validation internally to the BEST-COST project, which counts a consortium of partners from 10 European countries and the USA, and externally, thanks to the participation of international experts in the field. The access to such a broad consortium also helped with the data availability mapping. Seeing the variability of the resolutions on which these data are distributed within the EU and the selected case countries, the methodological framework (including the creation of maps) incorporates the possibility of working at different geographical resolutions. It should be noted that at the time of writing, the team does not have access to the ensemble of the data needed to test the framework. Nevertheless, these methods have been tested in country-specific efforts (23-24). In addition, the maps are run mainly for illustrative purposes, as the data currently used for them will not be the same as those used in the BEST-COST project.

It is important to highlight some limitations of the framework presented. One above all is the development of the MDI for the BEST-COST project. While the MDI represents a powerful and useful tool to describe deprivation in a multifaceted index, many of the decisions taken in the development of the MDI are closely related to the settings of the project itself. For example, the cultural validity of the indicators was mainly assessed for the case countries of the project, as were the indicators themselves, which were based on data availability in these countries. In addition, if the MDI is used for long-term future assessment of deprivation, one should further assess the temporal and cultural validity of the indicators included, as these may change over time. The project prioritised developing an MDI with uniform indicators across case countries to facilitate implementation and comparison. While acknowledging that cultural and socio-economic differences may influence the MDI's interpretation across countries, the selected indicators were deemed universally relevant. For instance, unemployment rates were included as a key indicator of deprivation, given their importance across all five case countries. With respect to the methods presented for the computation of the inequalities in the burden of environmental stressors, the author would like to acknowledge that many different approaches are possible. All of them have advantages and disadvantages (as presented in the text) and the choice of the methodology will depend mostly on the data available and the objectives of BEST-COST. Range measures can be calculated for all types of inequality dimensions and are easy to interpret. However, these measures ignore the situation between the most and least deprived subgroups. More complex measures, like SII/ and PAR/PAF, overcome this limitation. These are inherently more challenging to calculate and interpret. The authors of this protocol recommend using PAR/PAF to quantify the inequalities in the attributable burden, for its common use in the current literature to quantify changes in inequalities and for its easy interpretability. One of the main challenges to address in the BEST-COST project is the selection of suitable measures that would allow to effectively communicate the effect of interventions on the unequal burden of environmental stressors. Renard and colleagues (15) warn against using the SII/RII in monitoring health inequalities in the context of a change in the distribution of the inequalities in the population. On the other hand, PAR/PAF, albeit a simpler population-level inequality indicator, can translate an improvement in the distribution as a progress through a decrease of the indicator value.

The different types of measures here provided can give a different perspective on the data. In addition, both absolute and relative measures can be reported as they measure different aspects of inequality that complement each other (13).

Despite this documentation, the knowledge transfer to other WPs, that is needed to reproduce and adapt this exercise, may require more resources and effort. While implementing the methodological framework presented here, new or yet poorly understood needs might arise in the WP4 and WP5.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

6 Recommendations for the implementation in the BEST-COST R package (WP4) and case studies (WP5)

WP4

- Considering that the focus of the WP4 R package is the computation of the attributable burden, when it comes to the inclusion of deprivation in the estimation, we recommend having a preparatory R function that focuses on the computation of the MDI for the case countries (provided by NIPH, leader of Task 3.1). The output of this function can be sourced and used as an input for more general functions in the BEST-COST R package. Here, the index results will be used in the PAR/PAF formula, as advised by the current methodological framework.
- The mapping and support graph workflows presented in this document are underpinned by rather elaborate software requirements and processing chains, which may not be straightforward to implement exclusively using R or Python. For the work under WP3, the maps were created using QGIS, and the support graphs were created using Python. The possibility of making a QGIS plug-in that facilitates parts of the proposed mapping workflow could be investigated. Alternatively, these maps will be available for the collaborators of the BEST-COST project and external users with at least a basic understanding of GIS software.
- The framework presented here did not tackle the inclusion of uncertainty analysis in estimating the impact of deprivation on the burden attributable to environmental exposures. A suggestion could be the use of Monte Carlo simulations to sample outcomes by deprivation deciles; see, for example Otavova et al. (2022) (23) or Li et al. (2024) (25).

WP5

- WP3 recommends indicators for creating an MDI specific to the objectives of the BEST-COST project, as well as developing the methodological framework for constructing the composite score. Since the validity testing and assessment of uncertainties were not performed under WP3, these tasks will be transferred to WP5. Specifically, WP5 will construct and evaluate the MDI for the five case study countries and, if possible, extend the assessment across Europe at NUTS level 2, using Eurostat data.
- Considering the difference in data availability (mainly for the health outcomes), we suggest conducting an in-depth analysis using high-resolution data to select case countries. The choice of the countries will depend on the accessibility of the data needed.
- We recommend using maps for communication purposes, namely, to present the results of uni- or multivariate analysis to a non-scientific audience.
- As an Annex of this protocol, we provide a checklist aiming to help BEST-COST members, but also external users, to report the necessary information regarding data inputs, assumptions and processing steps for the computation of the burden of environmental stressors attributable to inequalities as well as for production of maps

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

and support graphs. It is good practice that these checklists are tested in the context of writing scientific publications, which means that the final checklist will be available after its piloting in the scientific publications derived from WP5.

7 References

(1) Targa J, Colina M, Banyuls L, González Ortiz A, Soares J. Status report of air quality in Europe for year 2023, using validated and up-to-date data. ETC-HE Report 2024/5; 2024.
(2) Boogaard H, Patton AP, Atkinson RW, Brook JR, Chang HH, Crouse DL, Fussell JC, Hoek G, Hoffmann B, Kappeler R, Kutlar Joss M, Ondras M, Sagiv SK, Samoli E, Shaikh R, Smargiassi A, Szpiro AA, Van Vliet EDS, Vienneau D, Weuve J, Lurmann FW, Forastiere F. Long-term exposure to traffic-related air pollution and selected health outcomes: A systematic review and meta-analysis. Environ Int. 2022;164:107262. doi: 10.1016/j.envint.2022.107262.
(3) Münzel T, Sørensen M, Daiber A. Transportation noise pollution and cardiovascular disease. Nat Rev Cardiol. 2021 Sep;18(9):619-636. doi: 10.1038/s41569-021-00532-5.
(4) Thurston GD, Kipen H, Annesi-Maesano I, Balmes J, Brook RD, Cromar K, De Matteis S, Forastiere F, Forsberg B, Frampton MW, Grigg J, Heederik D, Kelly FJ, Kuenzli N, Laumbach R, Peters A, Rajagopalan ST, Rich D, Ritz B, Samet JM, Sandstrom T, Sigsgaard T, Sunyer J, Brunekreef B. A joint ERS/ATS policy statement: what constitutes an adverse health effect of air pollution? An analytical framework. Eur Respir J. 2017;49(1):1600419. doi: 10.1183/13993003.00419-2016.
(5) Kaźmierczak, A., et al. Unequal Exposure and Unequal Impacts: Social Vulnerability to Air Pollution, Noise and Extreme Temperatures in Europe. European Environment Agency; 2019.
(6) Samoli E, Stergiopoulou A, Santana P, Rodopoulou S, Mitsakou C, Dimitroulopoulou C, Bauwelinck M, de Hoogh K, Costa C, Marí-Dell'Olmo M, Corman D, Vardoulakis S, Katsouyanni K; EURO-HEALTHY Consortium. Spatial variability in air pollution exposure in relation to socioeconomic indicators in nine European metropolitan areas: A study on environmental inequality. Environ Pollut. 2019;249:345-353. doi: 10.1016/j.envpol.2019.03.050.
(7) Barnes J, De Vito L, Hayes E, Guàrdia NB, Esteve JF, Van Kamp I. Qualitative assessment of links between exposure to noise and air pollution and socioeconomic status. WIT Transactions on Ecology and the Environment. 2018; 230, 15-25. doi: 10.2495/AIR180021.
(8) Nardo M, Saisana M, Saltelli A, Tarantola S, Hoffmann A, Giovannini E. Handbook on Constructing Composite Indicators: Methodology and User Guide. Paris (France): OECD publishing; 2008. JRC47008. https://knowledge4policy.ec.europa.eu/publication/handbook-constructing-composite-indicators-methodology-user-guide-0_en#:~:text=This%20Handbook%20aims%20to%20provide%20a%20guide%20to%20the%20construction. Last accessed: 31.01.2025
(9) Lijuan Ren, Tao Wang, Aicha Seklouli-Sekhari, Haiqing Zhang, Abdelaziz Bouras. A review on missing values for main challenges and methods. Information Systems, 2023, 119, pp.102268. https://doi.org/10.1016/j.is.2023.102268.
(10) Becker W, Caperna G, Del Sorbo M, Norlen H, Papadimitriou E, Saisana M. “COINr: An R package for developing composite indicators.” Journal of Open Source Software. 2022; 7(78), 4567. doi:10.21105/joss.04567
and https://bluefoxr.github.io/COINrDoc/aggregation.html#aggregation-in-coinr. Last accessed:

Funded by the European Union

BEST-COST is funded by the European Union’s Horizon Europe programme under Grant Agreement No.101095408

(11) Environmental Gradients and Health Inequalities in the Americas. Access to Water and Sanitation as Determinants of Health. 2016: https://iris.paho.org/handle/10665.2/31404. Last accessed: Last accessed: 31.01.2025
(12) ScotPHO. Measuring health inequalities. https://www.scotpho.org.uk/methods-and-data/measuring-health-inequalities/. Last accessed: Last accessed: 31.01.2025
(13) Schlotheuber A, Hosseinpoor AR. Summary Measures of Health Inequality: A Review of Existing Measures and Their Application. Int J Environ Res Public Health. 2022;19(6):3697. https://doi.org/10.3390/ijerph19063697.
(14) Mackenbach JP, Stirbu I, Roskam AJ, Schaap MM, Menvielle G, Leinsalu M, Kunst AE; European Union Working Group on Socioeconomic Inequalities in Health. Socioeconomic inequalities in health in 22 European countries. N Engl J Med. 2008;358(23):2468-81.
(15) Renard F, Devleesschauwer B, Speybroeck N, Deboosere P. Monitoring health inequalities when the socio-economic composition changes: are the slope and relative indices of inequality appropriate? Results of a simulation study. BMC Public Health. 2019;19:662. https://doi.org/10.1186/s12889-019-6980-1.
(16) Mackenbach JP, Kunst AE. Measuring the magnitude of socio-economic inequalities in health: an overview of available measures illustrated with two examples from Europe. Soc Sci Med. 1997;44(6):757–771. https://doi.org/10.1016/s0277-9536(96)00073-1.
(17) van Rossum, G. (1995). Python reference manual. Department of Computer Science [CS]. CWI.
(18) 'Quiet areas in Europe — The environment unaffected by noise pollution'. European Environment Agency, 2016. https://www.eea.europa.eu/publications/quiet-areas-in-europe. Last accessed: Aug 14, 2024.
(19) WHO global air quality guidelines: Particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide [Internet]. Geneva: World Health Organization; 2021. Available from: https://www.ncbi.nlm.nih.gov/books/NBK574594/.
(20) Slocum TA, McMaster RB, Kessler FC, Howard HH. Thematic Cartography and Geovisualization (4th ed.). CRC Press; 2022. https://doi.org/10.1201/9781003150527.
(21) Leff B, Davis-Holland A, Ducey E. Best Practices for Map Design – Introduction. 2016. https://proceedings.esri.com/library/userconf/fed16/papers/fed_86.pdf. Last accessed:
(22) Jakubowska A. The Burden of Air Pollution: A Perspective on Global Health Inequalities. Pollutants. 2023; 3(3):419-436. doi:10.3390/pollutants3030029.
(23) Otavova M, Faes C, Bouland C, De Clercq E, Vandeninden B, Eggerickx T, Sanderson JP, Devleesschauwer B, Masquelier B. Inequalities in mortality associated with housing conditions in Belgium between 1991 and 2020. BMC Public Health. 2022;22(1):2397. doi: 10.1186/s12889-022-14819-w.
(24) Otavova M, Masquelier B, Faes C, van den Borre L, Vandeninden B, de Clercq E, Devleesschauwer B. Trends in socioeconomic inequalities in cause-specific premature mortality in Belgium, 1998-2019. BMC Public Health. 2024;24(1):470. doi: 10.1186/s12889-024-17933-z.
(25) Li T, Dragomir AD, Luta G. A Comparison of Statistical Methods to Construct Confidence Intervals and Fiducial Intervals for Measures of Health Disparities. Int J Environ Res Public Health. 2024;21(2):208. doi: 10.3390/ijerph21020208.

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

8 Annex 1 - Checklist of required data inputs, assumptions and processing steps

Item number	Domains and description of the recommended items	Reported on page number
Introduction		
1.1	Present background information on the study, its objective(s), its relevance to health policy or practice, and information on target diseases, environmental risk factors, deprivation and the potential association between these three elements.	
Study setting		
2.1	Report for which health outcome the burden was calculated (i.e. which diseases and which indicators). Provide a case definition, using an internationally recognized classification system such as the 10th Revision of the International Classification of Diseases and Related Health Problems (ICD-10). *In the BEST-COST project, these were: lung cancer (ICD10: C33, C34–C34.92, Z12.2, Z80.1-Z80.2, Z85.1-Z85.20), ischemic heart disease - divided in three categories : all IHD (I20-I25), myocardial infarction (I21-I23) and angina pectoris (I20), stroke - divided in four categories : all strokes, ischemic stroke (G45-G46.8, I63-I63.9, I65-I66.9, I67.2-I67.3, I67.5-I67.6, I69.3), intracerebral stroke (I61–I62, I62.1–I62.9, I68.1–I68.2, I69.1–I69.2) and subarachnoid stroke (I60–I60.9, I62.0, I67.0–I67.1, I69.0), type II diabetes (E11.2, E11.21, E11.22, E11.29), chronic obstructive pulmonary disease (J41, J42, J43, J44, and J47), asthma (J45 and J46), heart failure, unspecified (I50.9), disorders of newborn related to slow fetal growth and fetal malnutrition (P05.1), essential (primary) hypertension (I10), overweight, obesity and other hyperalimentation (E66.0), disorders of bone density and structure (M80, M81, M82), chronic kidney disease (N18), disturbance of activity and attention (F90.0), depressive episode (F32), malignant neoplasms, stated or presumed to be primary, of specified sites, except of lymphoid, haematopoietic and related tissue – divided in three categories : malignant neoplasm of bladder (C67), malignant neoplasm of kidney, except renal pelvis (C64) and skin cancer (non-melanoma, C44).*	
2.2	Report for which environmental risk factor the burden was calculated. *In the BEST-COST project, we considered air pollution ($PM_{2.5}$, NO_2, and O_3) and noise pollution (from roads, railways, and aircraft) as environmental risk factors.*	
2.3	Report the reference population used for the burden of disease assessment, including any stratification applied. This should detail the population for which the burden was calculated, including the geographical location (e.g., country, province, or state) and whether it pertains to the general population or a specific subgroup (e.g., females, adolescents aged 10–19 years, etc.). *For the BEST-COST project, the assessment considered the smallest possible geographical level to account for local variations.*	

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

2.4	Report the reference time period (e.g., year(s), month(s)) of the study. This refers to the time period to which the burden of disease estimates refer.	
Input data		
3.1	Report the source and stratification information of the input data for each selected country, including: • demographic data; • environmental data; • health outcome data - prevalence/incidence/mortality data; • deprivation data. It is good practice to make available directly in the manuscript or via sharable datasets the aggregated data.	
3.2	Report demographic data for each selected country, per geographical area, report corresponding LAU/NUTS level, number of units, population min/mean/max and surface area min/mean/max	
3.3	Report environmental data for each selected country. Per pollutant, report metric and unit, geographical resolution/area, geographical coverage, data type, data accessibility, data source and URL and stratification information	
3.4	Report health outcome prevalence/incidence data for each selected country. Per disease/health outcome, report geographical area, reference period, definition of disease, incidence or prevalence, data type, data accessibility, data source and URL and stratification information	
3.5	Report health outcome mortality data for each selected country. Per disease, report geographical area, reference period, definition of disease, data type, data accessibility, data source and URL and stratification information	
Multiple Deprivation Index methods		
4.1	Report the specific selected indicators, provide their specific definition, including the specific denominator population (e.g., working age population). *In the BEST-COST project, the selected indicators were: percentage of households without central heating, percentage of high school graduates in the population, percentage of unemployed individuals in the active population (aged 18-65 years), percentage of a single-parent households, and percentage change of population size over the previous 5 years.*	
4.2	Report whether weights were assigned to each indicator. If unequal weighting were chosen, specify the method for determining the weights for each indicator, such as statistically driven processes (e.g., Principal Component Analysis or Factor Analysis), or expert opinion. *In the BEST-COST project, equal weights were assigned to each indicator.*	
4.3	Report the calculation method for the index score, including steps such as normalization, aggregation, and quantile ranking. Refer to the European Commission ’ s Handbook on Constructing Composite Indicators: Methodology and User Guide (COIN) for details regarding the use of these methods. *In the BEST-COST project, these methods were: z-scores calculation, sum of the z-scores, ranking deciles based on min and max values.*	

Funded by the European Union

BEST-COST is funded by the European Union’s Horizon Europe programme under Grant Agreement No.101095408

4.4	Report the methods used to assess the validity and reliability of the index. These include internal reliability and scale fit.	
4.5	Report Pearson correlations, Cronbach's alpha, and item-total correlations.	
4.6	Report the results of the eigenvalues and component scores, as well as the test-retest reliability.	
4.7	Report the results of the comparative validity (correlation to other established MDIs)	
4.8	Report the source and stratification information of the input data: • demographic data (namely, the information on the population and surface of the geographical units); • deprivation indicators (including a description of the indicator, geographical resolution, year).	
Mapping protocol		
4.9	Report the software and packages used for the maps (QGIS, SQL, Python, Geopandas, Rasterio, Geospatial Data Abstraction Library (GDAL), Matplotlib, SQLAlchemy, Anaconda, PyCharm, Visual Studio Code (VSC)).	
4.10	Report the specific geographical resolution of the data used for the maps. Report if data aggregations were performed. *Within the BEST-COST project, five scenarios were developed in the mapping framework. Use these to guide your choice of map, based on the geographical resolution of your data. A QGIS project file can be downloaded from the BEST-COST GitHub repository.*	
4.11	Describe the symbology used in each layer of the maps to help readers with the interpretation of these. *Within the BEST-COST project, these were already preconfigured. The description of these can be find the project file.*	
Support graph protocol		
4.12	It is recommended to combine the maps with support graphs to help the reader to understand the implications of the different outcome and their combination. *In the BEST-COST project, a Python script was created for the support graphs. This can be found in the BEST-COST GitHub repository.*	
Quantification of social inequalities in the health impact cost of environmental stressors		
5.1	Report the method used to estimate the burden of disease attributable to environmental stressors for each quantile of deprivation. These can be ranges estimations, regression-based indices (Relative Index of Inequality [RII], Slope Index of Inequality [SII]) or population attributable risk or fraction. *In the BEST-COST project, the function in the R package allows to compute ranges and PAF.*	
Uncertainty analysis		

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

6.1	Describe any methods used to perform uncertainty and variable importance (sensitivity) analyses. If, for example, Monte Carlo simulations were used, report the number of iterations. Describe the methods used for each of the inputs. For the deprivation index, refer to the European Commission's Handbook on Constructing Composite Indicators: Methodology and User Guide (COIN) for details regarding the uncertainty analysis in the creation of an index.	
Results		
7.1	Report the point estimates and, if applicable, the uncertainty interval of the burden of disease estimates. Provide both absolute values, crude rates (optional), and age-standardized rates per 100,000 in a table or figures, if needed for each of the input values singularly and their combination (PAFs). *Considering the objectives of the BEST-COST project, country comparisons or other geographical units and trends over time might be included.*	
7.2	If applicable, report the results of the scenario analyses. Tables and/or figures illustrating findings on the scenario analyses are strongly recommended	
Discussion		
8.1	Discuss how the findings fit within current knowledge of the inequalities in the environmental burden of disease. Discuss potential implications for public health practice. Compare the results with those of other studies, and discuss methodological design differences, if relevant. *Considering the objectives of the BEST-COST project, it is particularly important to stress the applicability of the results in the implementation of health impact assessment exercises that can be used for generating evidence-based policies.*	
8.2	Discuss strengths and limitations, and the generalisability of the study findings. If applicable, discuss the results of the uncertainty and scenario analyses.	

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

9 Annex 2 - Definition of diseases using ICD10 codes

Disease level 2 (according to GBD)	Disease level 3 (according to GBD)	Disease level 4 (according to GBD)	ICD10 code
Neoplasm	Lung cancer		ICD10: C33, C34–C34.92, Z12.2, Z80.1-Z80.2, Z85.1-Z85.20
	Malignant neoplasm of bladder		ICD10: C67
	Malignant neoplasm of kidney, except renal pelvis		ICD10: C64
	Skin cancer (non-melanoma)		ICD10: C44
Cardiovascular diseases	Ischemic heart disease		ICD10: I20–I25
		Myocardial infarction	ICD10: I21–I23
		Angina Pectoris	ICD10: I20
	Stroke		ICD10: G45–G46.8, I60–I63.9, I65–I66.9, I67.0–I67.3, I67.5–I67.6, I68.1–I68.2, I69.0–I69.3
		Ischemic stroke	G45-G46.8, I63-I63.9, I65-I66.9, I67.2-I67.3, I67.5-I67.6, I69.3
		Intracerebral haemorrhage	I61–I62, I62.1–I62.9, I68.1–I68.2, I69.1–I69.2
		Subarachnoid haemorrhage	I60–I60.9, I62.0, I67.0–I67.1, I69.0
		Heart failure, unspecified	ICD10: I50. 9
/	Essential (primary) hypertension		ICD10: I10
Diabetes, urogenital, blood,	Type II Diabetes		ICD-10: E11.2, E11.21, E11.22, E11.29

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

and endocrine diseases	Chronic kidney disease		ICD10: N18
Chronic respiratory diseases	Chronic Obstructive Pulmonary Disease		ICD 10: J41, J42, J43, J44, and J47
	Asthma		ICD10: J45 and J46
Mental disorders	Depressive episode		ICD10: F32
Neonatal disorder	Disorders of newborn related to slow fetal growth and fetal malnutrition	Newborn small for gestational age	ICD10: P05.1
/	Overweight, obesity and other hyperalimentation	Obesity	ICD10: E66.0
/	Disorders of bone density and structure	Osteoporosis	ICD10: M80, M81, M82
/	Disturbance of activity and attention		ICD10: F90.0

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

Partners

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408

www.best-cost.eu

@BestCostEU

Funded by the European Union

BEST-COST is funded by the European Union's Horizon Europe programme under Grant Agreement No.101095408.