



WP6 Transferability of methodological framework

Task 6.2 Report on gaps and opportunities regarding
transferability to other countries



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2 Executive Summary

Background and Objectives

This report constitutes Deliverable 6.2 (D6.2) under Work Package 6 (WP6) of the BEST-COST project. It evaluates the gaps, opportunities, and key methodological determinants influencing the geographic transferability of health impact assessment frameworks across different regional scales and beyond the initial pilot countries. The overarching goal is to analyse the overall harmonization of environmental health models, including indicators for green space ensuring that exposure evaluations, economic valuations, and health inequality indices remain valid when applied across diverse territorial boundaries.

Key Findings & Methodological Gaps

The deliverable identifies several systemic challenges across the core data layers.

- **Geographical Resolution:** Transitioning assessments from national to small-area (city or sub-city) levels is hindered by missing health statistics. Summing micro-scale assessments frequently yields higher aggregate values than uniform national-level assessments. The establishment of the European Health Data Space can help.
- **Exposure Misclassification:** Quality of e.g., noise pollution layers still vary across nations. Environmental Noise Directive (END) maps remain structurally restricted to major infrastructure corridors and large agglomerations, introducing systematic underestimation risks. For stressors like, e.g., chemicals, exposure metrics do not cover the whole EU. Human biomonitoring with larger numbers of participants and larger coverage of EU regions by using innovative micro-sampling can be a successful approach to assess chemical exposure at large scale.
- **Exposure-Response Functions (ERFs):** The report explores the fundamental trade-off between the statistical robustness of global meta-analytical ERFs and the contextual precision of region-specific curves, which account for local pollutant mixtures (e.g., varying PM_{2.5} chemical composition) and unique population vulnerabilities.
- **Socioeconomic and Economic Equivalence:** Cross-border application of a standardized Multiple Deprivation Index (MDI) at the municipal level faces severe limitations because physical assets assess poverty differently across the EU. Similarly, economic transferability of Willingness-to-Pay (WTP) data for averted Disability-Adjusted Life Years (DALYs) requires precise scaling factors adjusting for income elasticity and cultural health-preference clusters.

Innovations in Green Space exposure indicators

To improve assessment of green space exposure and enhance human-centric urban design metric transferability, this deliverable operationalizes indicators for the 3+30+300 environmental framework across the EU. This framework proposes that every citizen should be able to see at least three trees from their home, school or workplace, that every neighbourhood should have at least 30% tree canopy cover, and that every citizen should have access to a public green space within 300 m. Proposed indicators:

- **Viewshed Greenness Visibility Index (VGVI):** Models eye-level urban vegetation visibility, demonstrating proof-of-concept calculations for Leuven, Belgium and Tallinn, Estonia, two BEST-COST countries.



- Neighbourhood Climate and Health Green in the framework of the One Health approach: Calculates localized green-blue infrastructure percentages, mapping the distinct sensitivities introduced by weight distributions and grid buffer dimensions.
- Public Green Space Accessibility: Maps pedestrian road-network proximity thresholds using OpenStreetMap (OSM) as a globally transferable alternative, highlighting completeness dependencies using a validation case study in Lusaka, Zambia.

Global Transferability (Going Beyond Europe)

As detailed in Chapter 8, the report expands the methodological evaluation to non-European and low- and middle-income country contexts. It outlines a strategic "win-win" partnership model with African research entities.

- Benefits for Africa: Collaborative projects accelerate local capacity building. They deliver advanced open-source modelling tools. This supports targeted environmental health policies.
- Benefits for the EU: European frameworks gain deeper knowledge of ERF behaviour. African cohorts face much higher exposure gradients. Studying these levels helps to reveal the true shape of the ERF. It clarifies exact mathematical slopes and exposure thresholds. This fills scientific gaps that lower European exposure levels cannot resolve.

Practice Guidelines and Policy Recommendations

This document establishes an operational framework to overcome transferability barriers through two core implementations:

The impact transferability checklist: A comprehensive matrix guiding practitioners through parameter alignment, data manipulation rules, and reporting standards.

Data Integration Standards: Systematic adoption of FAIR principles, leveraging international open standards (Open Geospatial Consortium, INSPIRE Directive) to correct geospatial scale misalignments and promote machine-readable documentation.

Based on these findings, Chapter 9 outlines key policy-oriented recommendations targeting European regulatory frameworks.

- Data standardization: The European Commission can prioritize the standardization and public release of environmental, demographic, and baseline health variables at fine spatial scales.
- Inequality analysis: Fine-scale socioeconomic adjustments should be systematically funded to capture local deprivation patterns, allowing environmental and social stressors to be analysed at sufficient detail to support targeted local policy.
- Cross-Border harmonization: national regulatory bodies should adopt unified green space tracking indicators within European epidemiological research to address green infrastructure inequalities EU-wide. The proposed green space indicators provide a starting point.
- The exposome concept of gathering high-resolution exposure data over lifespan will contribute to clarifying the share that environmental determinants have in affecting human health.
- The EU can invest in exposure monitoring, cohort studies, and capacity building in LMICs to improve the representativeness of global ERFs and reduce uncertainty.



3 List of abbreviations

ACS	American Cancer Society
BoD	Burden of Disease
CRA	Comparative Risk Assessment Approach
CRVS	Civil Registration and Vital Statistics
DALY	Disability Adjusted Life Year
DEM	Digital Elevation Model
DSM	Digital Surface Model
DTM	Digital Terrain Model
EBoD	Environmental Burden of Disease
EEA	European Environment Agency
EMAPEC	Estimation of Morbidity from Air Pollution and its Economic Costs
END	Environmental Noise Directive
EQ-5D-5L	EuroQol Five-Dimension Five-Level questionnaire
ERF	Exposure-response function
FABDEM	Forest And Buildings removed Copernicus DEM
FAIR	Findable, Accessible, Interoperable, Reusable
GBD	Global Burden of Disease
GDP	Gross Domestic Product
GNI	Gross National Income
HBM	Human biomonitoring
HIA	Health Impact Assessment
IDW	Inverse Distance Weighting
INC	Income
LAU	Local Administrative Unit
LiDAR	Light Detection and Ranging
LUR	Land Use Regression
LMIC	Low- and middle-income country
MAUP	Modifiable Areal Unit Problem
MDI	Multiple Deprivation Index
NDVI	Normalized Difference Vegetation Index
NUTS	Nomenclature of Territorial Units for Statistics (Nomenclature des Unités Territoriales Statistiques)
OGC	Open Geospatial Consortium
OSM	Open Street Map
PAF	Population Attributable Fraction
PCA	Principal Component Analysis
PPP	Purchasing Power Parities
SES	Socio-Economic Status
SMAP	SMall Area estimates for Policymakers
SSA	Sub-Saharan Africa
SGVI	View-based Green View Index
TMREL	Theoretical Minimum Risk Exposure Level
uEMEP	urban European Monitoring and Evaluation Programme
VGVI	Viewshed Greenness Visibility Index
WHO	World Health Organization
WRI	World Resources Institute
WTP	Willingness To Pay
YLD	Years Lived with Disability
YLL	Years of Life Lost
ZPA	Zero Pollution Ambition



4 Introduction

The Burden of Disease (BoD) concept is commonly used to harmonise the impact of disease and premature death worldwide (Murray, 2022). The part of the BoD attributable to environmental stressors is referred to as the environmental burden of disease (EBoD). Preliminary studies of the exposome indicate that the burden of chronic diseases is primarily related to environmental stressors and, to a lesser extent, to genetics (Vermeulen et al., 2025).

Indicators related to the EBoD are applied across different policy areas, such as health, transport, or infrastructure. For example, in the Zero Pollution Ambition (ZPA), the number of premature deaths related to air pollution is used. Accordingly, we are on track to reduce the number of premature deaths caused by air pollution by 55% in 2030 compared to 2005 (EC, 2026).

Commonly used metrics to express the BoD attributable to a risk factor include the attributable fraction, the attributable number of cases, Years of Life Lost (YLL), Years Lived with Disability (YLD), Disability Adjusted Life Years (DALYs), and related costs. In this context, the commonly used methodology for calculating EBoD is the Comparative Risk Assessment (CRA) approach (Devleesschauwer et al., 2015). CRA estimates the attributable burden by comparing the observed population exposure distribution with an alternative, no- or lower-risk counterfactual exposure distribution, which is often referred to as the theoretical minimum risk exposure level (TMREL). In most EBoD calculations, a top-down approach is used, starting with the available population exposure and the exposure-response function (ERF) (e.g., relative risk) to calculate the population attributable fraction (PAF), as illustrated in Figure 1. This PAF is then multiplied by the total disease-specific burden in the population (e.g., observed prevalence or incidence) to calculate the attributable burden (Figure 1).

For noise annoyance and cancer effects from, e.g., chemicals, a different approach is often used, based on an absolute or unit of risk, i.e., a bottom-up approach (Hänninen et al., 2014) (Figure 2). This choice of a bottom-up approach is primarily driven by the availability of data and the choice of the exposure-outcome pairs. Detailed information on the methodological aspects of these calculations can be found in the BEST-COST Deliverable 1.4¹.

As mentioned above, the following data are required in the CRA approach to calculate the EBoD: exposure data, population data, ERF, and total BoD data. However, more and better harmonised data are necessary to produce detailed EBoD estimates. The CRA framework is commonly used in studies of ambient air pollution (Kienzler et al., 2025) or indoor air (Asikainen et al., 2016) and was applied in BEST-COST WP5 across different case study countries for ambient air pollution and noise (Deliverable 5.1 in prep²). In contrast, regarding chemical pollution, the number of chemicals addressed in EBoD estimates remains limited. Similarly, regarding a lack of harmonized green space indicators, EBoD estimates are poor (BEST-COST Deliverable 6.1³).

¹ Methodological protocol for quantifying environmental burden of disease

² Report on case study results, including disease burden, cost, social inequalities and impact of interventions

³ Transferability to other stressors and health promoting factors linked to different policy domains

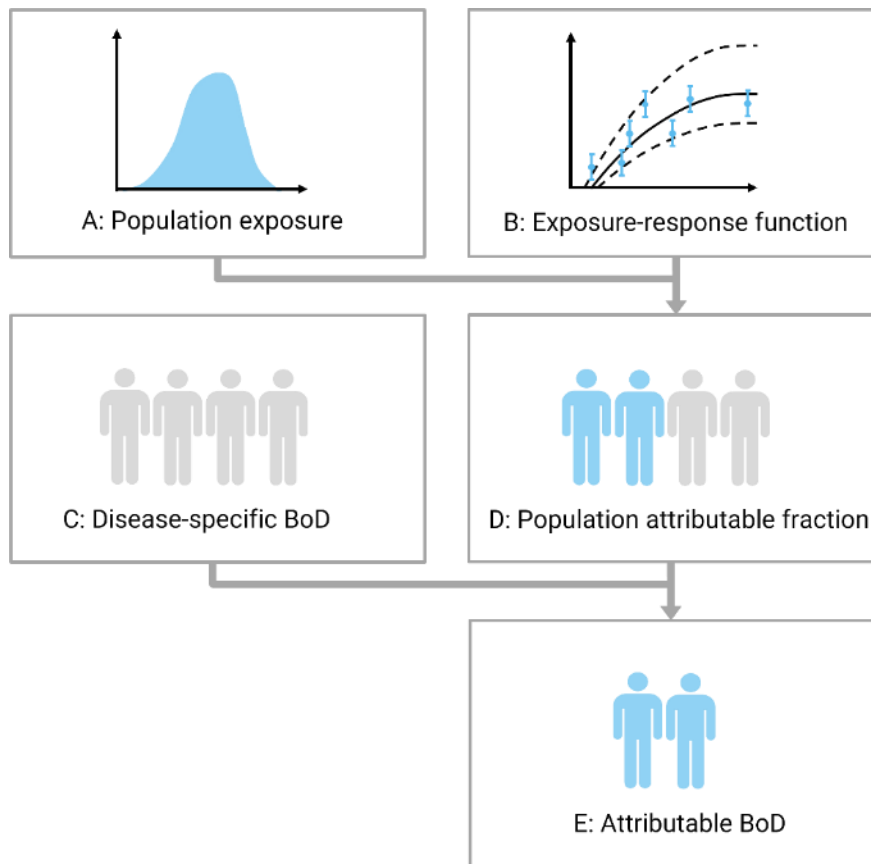


Figure 1. Schematic overview of the steps involved in calculating the **attributable** burden of disease for one exposure-outcome pair starting from an ERF based on a **relative** risk. One element of the illustration (person shape) originates from Wikimedia commons.

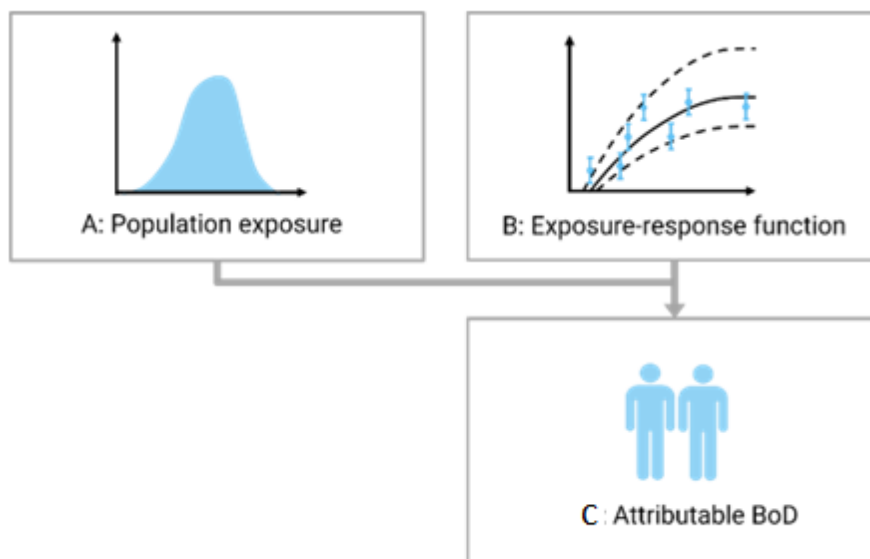


Figure 2. Schematic overview of the steps involved in calculating the **attributable** burden of disease for one exposure-outcome pair starting from an ERF based on an **absolute** risk. One element of the illustration (person shape) originates from Wikimedia commons.



Although EBoD and Health Impact Assessment (HIA) may seem comparable because both address health effects associated with environmental determinants, their purposes and analytics differ. HIA is primarily a prospective decision-support tool used to judge the potential health effects of a proposed policy, strategy, plan, programme or project, often with a strong emphasis on stakeholder engagement, distributional impacts and the appraisal of alternative scenarios. Quantitative or analytical HIAs are based on epidemiology and toxicology and tend towards quantification of the health impact. Both EBoD and HIA may use DALY as indicator (Rigaud et al., 2024).

Both EBoD and analytical HIA are influenced by the geographical level at which the calculations are performed. Issues may also arise when the methodology is transferred from one country to another. This will be further discussed in this Deliverable. The evaluation of geographic transferability within the EBoD concept will result in an overview of critical or key factors for transferability.

Furthermore, Deliverable 6.2 provides an in-depth discussion of the development of new green space indicators and their geographic transferability across the EU. Although environmental stressors such as air pollution have long benefited from mature, well-validated indicators, comparable metrics for green space remain underdeveloped. This gap limits our ability to quantify and compare the health benefits of green environments across regions. To address this, a broad and coherent set of health-relevant indicators is required. The indicators proposed here, grounded in the 3+30+300 rule, have been tested in case studies to evaluate their robustness and transferability across diverse European contexts.



5 Geographical resolution

5.1 Geographical resolution of an EBoD assessment

Environmental burden of disease (EBoD) calculations can be conducted at large study areas (e.g., national level) or at small ones (e.g., city or sub-city level).

For large study areas, a single representative estimation of population exposure can be applied to calculate the EBoD at, for example, the country level. The global approach offers the advantage that data on exposure and health outcomes are relatively easily to obtain.

In contrast, EBoD assessment in small areas can be feasible but faces important challenges (Pauwels et al., 2025a, 2025b). Spatial variation in exposure can be related to location-specific mortality and morbidity data, showing how EBoD varies across space and within the population and how it correlates with other variables (e.g., socioeconomic variables). Additionally, local results can be aggregated across wider areas and larger populations.

Small-area EBoD can pose some challenges. A first challenge relates to collecting data at a small scale. Generally, data availability decreases with increasing spatial resolution, especially for baseline morbidity data. Incidence data are usually unavailable at small areas, and the Global Burden of Disease (GBD) provides only modelled data at national and, in some cases, regional levels. To address this data gap, baseline health data can be downscaled (see Section 6.1). Furthermore, highly resolved (location-specific) baseline health data can lead to potential privacy and data protection challenges.

A second challenge relates to methodological issues linked with the use of small population sizes. Estimating the PAF and attributable burden relies on the general statistical relationships of the ERF, which is often representative of a large, diverse population. Local groups might show a distribution of relevant confounders that is skewed compared to the general population, in which case applying these relationships as ERF would result in biased estimates. A possible remediation for the local result bias is to aggregate data (exposure, health) to some larger areas and populations. In doing so, the individual biases tend to cancel out (especially as the number of areas increases), thereby improving the accuracy of the aggregated estimate (Pauwels et al., 2025a).

A third challenge is that the attributable burden estimated in EBoD calculations for small areas (city- or sub-city-level) is often small due to small populations and limited numbers of disease cases. In some cases, the number of attributable cases may be less than 0.5, and, when rounded, may be reported as 0 cases. This can make effective communication of results challenging and increase the risk that the results might not be taken seriously (they might be "belittled").

A final challenge comes when the small-scale attributable burdens are summed to a larger geographical scale. Practical examples show that the sum of small-scale EBoDs (e.g. from a group of cities) yields higher numbers than a single EBoD at the larger scale (e.g., national). In Colorado, US, deSouza et al. (2024) demonstrated that the use of country-level NO₂ and PM_{2.5} estimates resulted in 50% and 10% decreases in attributable mortality, respectively. The use



of more detailed exposure data and block-level baseline mortality rates, instead of country-level data, yielded a 10% higher estimated annual mortality attributable to PM_{2.5} and NO₂ (deSouza et al., 2024; Williams et al., 2026). Similar observations were made in Finland (Korhonen et al., 2019). This phenomenon is well known in the fields of geography and public health and is referred to as the “Modifiable Areal Unit Problem (MAUP)” (Tessema et al., 2023). To overcome this barrier, i.e., minimising the MAUP effect, the GBD Study decided to perform the EBoD at the grid cell level (applying the exposure-response at the grid cell level) and sum then for the national results instead of performing the EBoD for the whole country (GBD 2019 Risk Factors Collaborators, 2020). Alternatively, a top-down proportional scaling can be applied to match the sum with the national envelope (“squeezing or ratio benchmarking”) (Rao and Molina, 2015; RIVM, 2025a).

Overall, it is necessary to gather high-resolution exposure, demographic and health data, and researchers should prioritise exploring associations at multiple spatial scales (Jaikumar et al., 2025). The incorporation of fine-scale spatial exposure data can help to identify hotspots, uncover environmental inequalities, and allow prioritisation of local interventions (Mitsakou et al., 2019). When examining multiple exposures, spatial scale should also be considered, as these may be measured or modelled with varying precision, potentially leading to an increased transfer of effect⁴ (Williams et al., 2026).

Integrating these diverse data sources across scales remains a key challenge but also an important opportunity to improve the robustness and policy relevance of EBoD assessments.

5.2 Geographical resolution in the derivation of exposure-response functions

Spatial scale is a key methodological determinant in the derivation of ERFs. Empirical evidence consistently shows that epidemiological analyses are sensitive to the spatial resolution at which exposure is assessed. Analyses using finer-scale exposure estimates generally yield larger effect estimates and reduced bias compared with those relying on coarse, spatially aggregated metrics. This scale dependence is primarily explained by exposure misclassification. When exposures are assigned using central-site measurements or area-wide averages at coarse spatial scales (e.g., city, regional, or national level), substantial within-area variability in exposure is obscured. In spatially heterogeneous environments, exposure levels can vary considerably over short distances due to local sources, land-use patterns, environmental conditions and built-environment characteristics (Marshall et al., 2008; Lu and Kwan, 2026). As a result, individuals with different real-life exposures may be assigned similar values, introducing non-differential measurement error that biases epidemiological associations toward the null and, therefore, attenuates ERFs.

To address these limitations, a growing number of studies have adopted high-resolution exposure assessment approaches, including spatially explicit modelling techniques, gridded

⁴ the ‘transfer of effect’ may occur when 2 pollutants are highly correlated and where one is measured or modelled with more error than the other



exposure surfaces, and hybrid methods that combine multiple data sources (Clark et al., 2025). These approaches better preserve local exposure contrasts and more accurately reflect spatial variability in environmental stressors (Kazakos et al., 2020; Ma et al., 2024). For example, studies using fine-scale air pollution estimates (e.g. 1 km x 1 km grids) have reported stronger associations with health outcomes compared to those using coarser spatial resolutions (Crouse et al., 2020; deSouza et al., 2024). Similar patterns have been observed for transportation noise and green space exposure, where higher-resolution modelling approaches (e.g. façade-level noise estimates or high-resolution vegetation metrics) improve the ability to detect exposure-response relationships (Vienneau et al., 2019; Wang et al., 2024). These findings indicate that geographical resolution is not merely a technical detail of exposure assessment, but a fundamental part of the magnitude and validity of estimated ERFs, as using coarse exposure proxies for ERF estimation are likely to underestimate the true health response per unit exposure.

Besides spatial resolution, spatiotemporal simplifications in exposure assessment further contribute to bias. Traditional epidemiological approaches frequently assume that exposure at the residential location is an adequate proxy for total individual exposure. However, individual total exposure reflects a combination of multiple environments and activities, shaped by different environments, mobility patterns and interactions with different microenvironments (e.g. indoor and outdoor settings) (Vermeulen et al., 2020). Ignoring this complexity compresses exposure distributions and can further weaken estimated exposure-response relationships (Kazakos et al., 2020; deSouza et al., 2024). While some evidence suggests that population-level biases resulting from residential-based exposure assessment may be modest in certain contexts, these effects are highly context-dependent and may vary across pollutants, environments and population groups (Hoek et al., 2024).

Spatial aggregation also limits the ability of epidemiological models to capture effect modification and adequately control for confounding by contextual factors such as socioeconomic status, housing characteristics, baseline health status and access to healthcare. Aggregated exposure estimates may average out important gradients in both exposure and vulnerability, thereby reducing the capacity to identify heterogeneity in susceptibility across populations and locations (Abed Al Ahad et al., 2023; deSouza et al., 2024). This has implications for both ERF transferability (see Section 6.1.3) and for the analysis of environmental health inequalities, which are often a key objective of small-area EBoD studies.

At the same time, increasing geographical resolution introduces methodological trade-offs. High-resolution exposure modelling can introduce additional uncertainty, particularly in data-sparse regions where monitoring data are limited. Fine-scale analyses may also involve smaller population units, reducing statistical power and increasing variability in effect estimates. These trade-offs highlight the need for transparency in reporting the spatial scale, exposure definition and modelling assumptions under which ERFs are derived to avoid mismatches between the scale of ERF derivation and that of EBoD application.

Overall, geographical resolution constitutes a fundamental methodological dimension in the derivation of ERFs. The growing body of evidence supports the use of high-resolution, spatio-temporally resolved exposure estimates to reduce misclassification, preserve meaningful exposure contrasts and better reflect real-world exposure patterns (Mitsakou et al., 2019; Jaikumar et al., 2025; Williams et al., 2026). Importantly, the validity and applicability of ERFs depend not only on their statistical robustness, but also on their conceptual and spatial



alignment with the exposure data and population context to which they are applied. Mismatches between the scale and definition of exposure in ERF derivation and in EBoD applications can introduce internal inconsistencies and bias burden estimates. These considerations are closely linked to broader questions of ERF transferability across regions and contexts, as further discussed in Section 6.1.3.



6 General transferability

6.1 Transferability of baseline health data

The availability of baseline health data is a key determinant of the feasibility and accuracy of EBoD assessments, yet such data are frequently absent or incomplete at the national and subnational levels.

In cases where health data are not available for a country, extrapolating national data across countries may be necessary and may lead to errors and uncertainties, as countries may have different health care systems (NEEDS, 2007). The GBD study, therefore, combines Gaussian process regression and Bayesian meta-regression to generate internally consistent estimates of incidence, prevalence, and mortality, borrowing statistical strength across age groups, time periods, and locations (Hrzic et al., 2026).

At smaller geographical levels, baseline health data (mortality and morbidity) are often lacking, representing a significant limiting factor for conducting EBoD assessments at the local level. To overcome this barrier, baseline health data can be downscaled from higher geographical levels (e.g., national) to lower geographical levels (e.g., municipality) using a population-weighted approach, adjusted for age and sex, following the steps described below (Khomenko et al., 2021).

1. Collect baseline health data at the higher geographical level (e.g. national) by age group and sex. Modelled estimates can be obtained from the GBD Results Tool, which provides data for all countries and selected regions (IHME, 2025).
2. Collect population data by the same age groups and sex strata at both higher (e.g., national) and lower geographical levels (e.g., city level, municipality).
3. Obtain the proportion of the population at the lower geographical level compared to the higher level for each age group and sex by dividing the population at the lower geographical level by the population at the higher level (collected in step 2).
4. Apply the proportion obtained in the last step to the baseline health estimates collected in step 1, yielding disaggregated health data at the lower geographical level for each age and sex stratum.

This approach has been used in BEST-COST WP5 to perform the EBoD calculations in local case studies i.e., downscaling from the country level to the capital and/or metropolitan area. The downscaling from country to smaller administrative units is more complex (BEST-COST Deliverables 5.1⁵ and 5.2⁶, in prep.). Additionally, a calibration factor (weight) could be applied. For instance, if mortality data are available at both higher and lower geographical levels and the missing data are for morbidity (e.g. incidence), then the proportion of deaths by age group at the lower level relative to the higher level could be multiplied by the results of the downscale. However, such adjustments should be interpreted with caution, as mortality and incidence reflect different underlying processes and may not share the same spatial patterns. Using

⁵ Report on case study results, including disease burden, cost, social inequalities and impact of Interventions

⁶ Report on the applicability of the BEST-COST methodology in HIA



mortality data to scale morbidity may also introduce bias (double counting) (Hussein et al., 2022). This occurs because mortality already reflects local exposure differences. The larger the difference in exposure between the higher and lower geographical levels, the larger the potential bias.

The assumption behind the above-mentioned age (and sex) stratified downscale of baseline health data is that the number of deaths or disease cases only depends on population (and sex). However, the number of deaths and disease cases depends on many more factors (e.g., lifestyle, occupational exposure, socioeconomic factors etc.). Therefore, the downscale must be seen as a proxy and used transparently, acknowledging the limitations.

Further, RIVM has developed a model to calculate health estimates at the district and neighbourhood level: SMAP-model (SMall Area estimates for Policymakers). In the Neighbourhood Atlas dashboard (Buurtatlas), data about health and health-related topics are published at the district and neighbourhood levels (VZinfo, 2026). The indicators on health status, lifestyle, and (perception of) the living environment are based on the Health Monitor for adults and older people conducted by the Public Health Services (GGD), Statistics Netherlands (CBS), and the National Institute for Public Health and the Environment (RIVM). Even though this is a huge data set, it still doesn't have enough respondents to calculate figures for all districts and neighbourhoods in the Netherlands using the traditional weighting method. Since there is a demand for data at this small scale, a model (using XGBoost) has been used to relate health and lifestyle data to background characteristics of the Health Monitor respondents. Through this relationship, it is then possible to calculate the expected health and lifestyle-estimates for all adults. The results are then averaged over the relevant district or neighbourhoods. These small area estimates should be used with some caution though. The model tries to reflect reality as best as possible, but the numbers are still estimates of reality (Volksgezondheid en Zorg, 2026). For areas with less than 100 inhabitants no estimates are presented.

6.2 Transferability of exposure

6.2.1 Air pollution

The measurements of PM_{2.5}, PM₁₀, NO₂ and O₃ are standardised across the EU to ensure comparability, quality, and compliance with health-based limits (e.g. Directive 2008/50/EC; EN 12341:2014; EN 14211:2012). Air pollutant measurements from various sources are integrated using modelling approaches to produce high-resolution maps, which are then used to estimate the EBoD and assess health risks at country level.

There are different approaches to air pollution modelling (e.g., dispersion models vs land-use regression models), and they may result in different estimated concentrations. Some air pollution models are available at the European level and at high resolution, such as the one developed by the EU project EXPANSE with a resolution 25 x 25 m (Shen et al., 2022). Additionally, each country (and maybe even region or city) may develop its own air pollution model. Consequently, when conducting an EBoD assessment in which multiple air pollution models exist for the same local study area, a choice must be made.



Furthermore, when estimates are made at a finer level, regional available data and models are often applied. High-geographical resolution models are especially suited for EBoD assessments at smaller scales.

The exposure models used in BEST-COST WP5 were uEMEP (Mu et al., 2022), models applied by GBD (van Donkelaar et al., 2016; Larkin et al., 2017), and EEA (EEA, 2025a). Urban EMEP (uEMEP), developed at the Norwegian Meteorological Institute, can achieve high-resolution air quality modelling down to 100 m for entire countries (Denby et al., 2020). Unfortunately, the same quality of high-resolution emission data that is available in Norway is not directly available for all of Europe. Many countries have suitable high-resolution data, but these are not readily accessible for use. In order to implement uEMEP for all of Europe, proxy data that can be used to redistribute emissions to fine scales are required (Mu et al., 2022). However, transferring local exposure assessment methods across regions should be considered an indirect approach and used transparently, with explicit acknowledgement of the assumptions and uncertainties introduced, as modelling frameworks may not capture the underlying determinants of exposure, which can differ between locations.

6.2.2 Noise

Comparing European noise maps between countries remains difficult due to “technical challenges”.

EBoD estimates based on the END (Environmental Noise Directive) strategic noise maps consider only agglomerations and major noise sources (major roads, railways and airports). Therefore, they may underestimate the overall effect of noise on health (EEA, 2025b). Article 3 in the END obligations is vague on defining spatial entities. An urban agglomeration is a delimited territory *“having a population in excess of 100,000 persons and a population density such that the Member State considers it to be an urbanized area”*. This results in variability in how urban areas are delimited (Staab et al., 2025).

For noise pollution, the strategic noise maps developed under the END differ substantially across countries due to differing exposure assessments methods and variations in input data. This results in many values being of low quality which influences impact assessment (Khomenko et al., 2022; Williams et al., 2026). Further efforts to standardise noise data are needed, along with increased data availability and quality (Staab et al., 2025).

Because of some countries' incomplete reporting of noise exposure data, gap filling may be necessary to complete missing information and ensure a complete assessment of environmental noise in Europe (Blanes et al., 2024). Detailed information on the gap-filling methodology can be found in Blanes et al (2023).

In order to estimate the health risks attributable to environmental noise in the European area, an extrapolation of the number of people affected by noise at levels below the END thresholds is needed, as effects are observed at lower exposure levels (Engelmann et al., 2023).



6.2.3 Other

For stressors like, e.g., chemicals, exposure metrics do not cover the whole EU. Imputation techniques are, in some cases, appropriate when exposure data is lacking. Incomplete data are a common problem in EBoD research. Different techniques exist for filling data gaps at the exposure level, including Inverse Distance Weighting (IDW), Land Use Regression (LUR), Kriging, or Bayesian methods (Allotey and Harel, 2019).

IDW is a deterministic spatial interpolation method that estimates the value at an unsampled location by computing a distance-weighted average of surrounding observations, assigning higher weights to nearer points and progressively lower weights to more distant ones (Lu and Wong, 2008). LUR is a multiple linear regression approach that relates measured concentrations to spatial predictors describing land-use and land-cover characteristics, traffic intensity, population density, and other relevant geographic features (Hoek et al., 2008). Kriging is a geostatistical interpolation technique that estimates values at unsampled locations by exploiting the spatial covariance structure inferred from observed data (Cressie, 2015). A Bayesian geostatistical model fills spatial gaps by combining covariate information with a Gaussian-process representation of spatial autocorrelation, allowing predictions at unsampled locations. Because the model is estimated within a Bayesian framework, it provides full uncertainty quantification for these predictions, which can be propagated into subsequent analyses (Banerjee et al., 2014).

Furthermore, spatio-temporal data can be applied in life course epidemiology to approach the potential of the “exposome” and the quest to identify stressors affecting the onset and progression of disease, which can then be used in EBoD analysis (Sahu, 2022, Batterman et al., 2025). For green space, there is a need to develop new indicators (Deliverable 6.1⁷; Section 7).

Transferability of green space indicators is further explored in Chapter 7.

6.3 Transferability of exposure response function

ERFs are a central component of both EBoD and HIA, as they quantify how changes in environmental exposure translate to changes in health outcomes. However, their transferability across geographical regions and contexts remains subject to ongoing scientific debate. This debate is often framed as a trade-off between statistical robustness, achieved by pooling evidence across a wide range of studies and regions, and contextual relevance, which favours ERFs derived from populations and exposure settings similar to those under assessment.

Air pollution provides a key illustrative example. Historically, much of the evidence base for PM_{2.5}-related mortality has relied heavily on large North American cohort studies, particularly the American Cancer Society (ACS) studies, which sampled a wide range of metropolitan areas

⁷ Transferability to other stressors and health promoting factors linked to different policy domains



across the US with varying $PM_{2.5}$ concentrations and compositions. These ACS studies supported the derivation of relatively stable and widely used ERFs. At the time, it was generally assumed that it was unlikely that a different composition of $PM_{2.5}$ in Europe compared to the US would affect the ERF for premature mortality derived from these studies (NEEDS, 2007). This assumption, combined with the limited availability of large long-term European cohort studies at the time, supported the widespread use of US-derived ERFs in European impact assessments, including early WHO air quality guidelines (WHO, 2006) and the Clean Air Programme for Europe (EC, 2013).

More recently, however, growing evidence challenges the assumption of spatiotemporal homogeneity of air pollution mixtures. The toxicity of $PM_{2.5}$ is not just a matter of mass concentration, but also of its chemical composition, which varies across regions due to differences in emission sources, fuel use, traffic composition and agricultural practices (McDuffie et al., 2021). Moreover, temporal changes, such as shifts in energy production, emission control policies and climate-related events (e.g. wildfires and dust storms), can alter pollutant mixtures over time (Wang et al., 2025; Zhang et al., 2025). Consequently, air pollution mixtures and thus population exposure cannot be assumed to be uniform across time or space, and ERFs derived in one context may not be directly applicable in another.

These differences raise concerns about geographical transferability. Applying ERFs derived across regions may introduce bias if pollutant mixtures, exposure levels or population susceptibilities differ (Koolen and Rothenberg, 2019). Moreover, transferring ERFs across regions may be inappropriate when demographic and socioeconomic profiles diverge substantially, as variations in age structure, baseline health status or vulnerability can modify the observed effect size and lead to biased burden estimates. Temporal heterogeneity further complicates this, as exposure-response relationships may evolve alongside changing environmental conditions as illustrated by documented changes in $PM_{2.5}$ composition in the US over time (2006-2020) due to coal-to-gas transitions and stricter emission control policies (Cheng et al., 2024).

At the same time, transferability is not solely a geographical origin. As discussed in Section 5.1.2, ERFs are highly sensitive to methodological choices in exposure assessment, including spatial resolution, exposure definition and modelling approach. ERFs derived using coarse exposure metrics may already be attenuated due to exposure misclassification, and their applicability to high-resolution exposure fields can introduce internal inconsistencies in EBoD estimates (Katsouyanni and Evangelopoulos, 2022). Transferability should therefore be understood as a multidimensional concept encompassing not only population and environmental differences, but also the alignment of methodological characteristics between ERF derivation and application.

In response to these concerns, some researchers advocate the preferential use of Europe-specific ERFs for European EBoD assessments, arguing that these better reflect European demographics, air quality and exposure patterns, healthcare systems and baseline mortality and morbidity rates. This approach is also reflected in policy practices where regionally relevant evidence is prioritised, such as the policy assessment for the review of the National Ambient Air Quality Standards in the United States (Hoffmann et al., 2022). However, restricting analyses to regional evidence may reduce statistical power and limit generalisability, particularly for outcomes or exposures with limited evidence base.



In contrast, international initiatives such as the WHO projects HRAPIE-2 and EMAPEC (Estimation of Morbidity from Air Pollution and its Economic Costs) recommend using global ERFs estimates based on studies from around the world. This approach prioritises statistical robustness, as global meta-analyses include a larger number of studies and yield more stable estimates with narrower uncertainty intervals (EMAPEC, 2024, WHO, 2025). These initiatives emphasise the value of maximising statistical power and consistency for comparative assessments across countries. Moreover, global ERFs are particularly valuable in contexts where local epidemiological evidence is sparse or unavailable. However, their application requires careful consideration of underlying assumptions regarding exposure comparability and effect homogeneity (Forastiere et al., 2024).

Overall, the choice between global and region-specific ERFs should be considered as a context-dependent choice rather than a binary decision between global and regional estimates. Key considerations include geographical relevance, exposure characteristics, population context and methodological consistency (Williams et al., 2026). Transparent reporting of ERF provenance, exposure definition, spatial resolution and underlying study population is therefore essential.

Finally, the close link between transferability and exposure assessment underscores the importance of coherence across the entire EBoD framework. Aligning the spatial resolution, exposure definition and population characteristics used in ERF derivation with those used in EBoD application is important to minimise bias and improve consistency. Where uncertainty remains, sensitivity analyses using alternative ERFs (reflecting different regions, exposure definitions or modelling approaches) can help to characterise uncertainty and improve the robustness and credibility of EBoD results.

6.4 Lessons learnt from WP3 on transferability issues: MDI at municipality level

A core task of work package 3 was to measure small-area socioeconomic inequalities. This allows monitoring of how environmental exposures contribute to disease burden in vulnerable populations. To meet this goal, BEST-COST developed a cross-national Multiple Deprivation Index (MDI) at the municipality level. However, the index poses several challenges related to geographic scale and conceptual equivalence. Because the five case countries that were investigated in the BEST-COST project (Belgium, Estonia, France, Norway, and Portugal) define "municipalities" differently, population sizes and land areas vary widely, making direct comparisons difficult. For example, France has tens of thousands of municipalities, while Estonia has 79. This large difference in sample sizes affects the statistical precision of comparisons between countries. Furthermore, even within a single country, municipality populations vary widely. Large cities like Paris, Oslo, or Brussels have hundreds of thousands of residents and function almost like regions, while remote rural municipalities may have fewer than 1,000 people. Such extreme variation creates a high risk of small-number bias when estimating socioeconomic indicators as well as disease burden. Furthermore, data protection rules also constrain geographic resolution. For example, in France, mortality data were not



available at the finest level (Local Administrative Unit⁸ 2 or LAU2). Similarly, for Portugal, data was available at LAU1 rather than LAU2. This approach relies on assumptions that may affect local precision.

A further challenge is that the same socioeconomic indicator can mean different things across countries. Educational attainment was relatively universal. Other indicators, such as household heating, are likely not uniform. In warmer climates like Portugal, central heating may signal higher socioeconomic status (luxury). Whereas, in the cold climates of Estonia and Norway, lacking adequate heating is a basic sign of household deprivation. However, infrastructure differences also have an impact. In Estonia, centralised heating is not evenly available, so heating status is a useful marker of poverty. In Norway, almost all households have access to subsidised energy, making heating data less informative at the municipal level. As a result, heating data was only available for larger NUTS-2 regions.

Labour market indicators depend on each country's welfare system, not just on economic status. Norway and Belgium have generous welfare systems, so low unemployment rates can hide many people on disability or sick leave—people who might be classed as unemployed elsewhere. In countries with high long-term unemployment, the "jobless" measure means something different. It is not equivalent to the inactive population in countries with stronger welfare safety nets. These differences in definitions and the spatial scale at which data are available explain why a "one-size-fits-all" multiple deprivation index is not suitable for European comparisons.

Eurostat (under the European Commission) and its partner agencies in non-EU EEA countries already provide several harmonised and standardised socioeconomic indices. These are valuable public resources, but they are generally available only at the NUTS-2 level. Closing the remaining research gaps requires similar measures at finer spatial scales, such as LAU1 or LAU2 municipalities. Making harmonised socioeconomic data publicly available at these small-area levels would greatly improve the modelling of health inequalities. In addition, where national contexts differ substantially, these small-area indices could be further refined by applying country-specific PCA (Principal Component Analysis) adjustments to better capture local deprivation patterns. We therefore recommend that the European Commission prioritise the standardisation and public release of socioeconomic variables at the municipal level. This would allow environmental and social stressors to be analysed at sufficient detail to support targeted local policy.

⁸ <https://ec.europa.eu/eurostat/web/nuts/local-administrative-units>



6.5 Lessons learnt from WP2 on transferability of monetization

One of the WP2 aims was to estimate the monetary value of averted DALYs using willingness-to-pay (WTP) surveys. Transferability of economic evaluations is essential considering how strongly context-dependent they are, including on population preferences.

The monetary value placed on population preferences is determined by multiple factors, including culture, income, purchasing power (PP), risk perception, trust in institutions, and national norms regarding the valuation of health in public decision-making. When primary data cannot be collected, one common multi-country value (for example a 'joint' WTP EU value) may be considered an attractive solution. However, the risk of using common EU values may reduce local validity. Likely, a 'one-size-fits-all' approach risks overestimating benefits in lower-income settings and underestimating them in higher-income settings, depending on the adjustment method used. Furthermore, while improving contextual relevance, using country-specific WTP may require primary data, which is often hard to collect, and comes at the cost of cross-country comparability. This trade-off may be eased by determining the best-fitting transferability solutions to allow WTP per averted DALY estimated in one country to be transferred from one 'survey context' to another country's 'policy context' (Brouwer and Bateman, 2005).

The first practical task is therefore to identify which factors must be adapted when values move between geographical contexts. Three main categories stand out.

1. The first concerns the economic context, with income constituting the central determinant: typically, a WTP value is scaled from a source to a target country using the ratio of incomes raised to an income-elasticity term (OECD, 2025):

$$WTP \times DALY_{tr} = WTP \times DALY_b \times \left(\frac{INC_{tr}}{INC_b} \right)^\epsilon$$

Where:

WTP × DALY_{tr} is the WTP × DALY of the country to which the value is transferred

WTP × DALY_b is the WTP × DALY of the base country

INC_{tr} is the income of the country to which the value is transferred

INC_b is the income of the base country

Epsilon is the income elasticity value

Here, two methodological choices need to be made: the income indicator to be used (for example GDP, gross domestic product or GNI gross national income per capita, at PPP, purchasing power parities) and that of the elasticity. The income elasticity value (ϵ) can be drawn from the literature: guidelines are widespread and usually suggest setting the value below one among high-income countries and equal or above 1 in others (Robinson and Hammitt, 2011).

Meanwhile, benefit function transfer applies an estimated relationship between WTP and multiple country characteristics, into which the target country's own values are entered. This option - generally preferred as it allows for including more information than a single value - is also the approach made possible by BEST-COST's multi-country



design: estimating the relationship across the four surveyed countries (France, Ireland, Portugal, the Netherlands) allows coefficients to be derived for respondent characteristics that can also be obtained for the remaining member states. Candidate variables include income, age structure, sex, and educational attainment, all of which are routinely published by Eurostat. Which of these are retained in the final function depends on the analysis, since a characteristic is only useful for transfer if it both influences WTP and varies across countries.

2. The second group - population preferences - contains values, social norms, risk perception and institutional trust that have no scaling factor and can only be addressed by transferring values from countries that are similar in these respects. This is the rationale behind the selection of the four countries selected for WP2 (France, Ireland, Portugal, and the Netherlands), each representative of one of the EU preference clusters from four of the five EU health-preference clusters identified by the study by Pinheiro et al. (2025), which groups countries by their EQ-5D-5L (EuroQol Five-Dimension Five-Level questionnaire) value sets rather than by geography. Transfer to a non-surveyed country can proceed by assigning it to its cluster and drawing on the WTP evidence from the surveyed country that represents that cluster, rather than by entering a value into a function.
3. The health-state component, which is carried unchanged by the universal DALY weights.

In conclusion, the geographic transferability of BEST-COST's monetised health estimates is achievable yet cannot rely on a single process: each group of determinants follows its own route: an income-adjusted value or benefit function for the economic component, a cluster-based source selection for population preferences, and no adjustment at all for the health-state component, which is carried unchanged by the universal DALY weights. The principal asset of BEST-COST in this respect is its four-country design, which allows the income elasticity and the value function to be derived from primary data rather than borrowed from the literature, while ensuring that the surveyed countries span the main axes of European health-preference heterogeneity. Moreover, while health-state valuation is usually among the factors to be transferred across countries (Roudijk et al., 2019), no transfer method must be applied in the case of the WTP values elicited for BEST-COST, as the differences that would typically need adjusting are neutralised by construction. This is because WTP is elicited for averted DALYs, whose disability weights are drawn from the IHME Global Burden of Disease study and applied uniformly across countries.

6.6 FAIR data

The spatial transferability of EBoD models is frequently hindered by localised variations in environmental exposure metrics, baseline health distributions, and administrative reporting scales. When transferring an ERF calculated in one region to a different target geography, researchers encounter fragmented and heterogeneous data landscapes. Without unified data management, combining these inconsistent environmental layers results in significant spatial misalignment.



FAIR (Findable, Accessible, Interoperable, Reusable) principles help to overcome spatial transferability barriers. Applying the FAIR data principles systematically corrects these geographic distortions by embedding standardised spatial semantics and reproducible workflows directly into data architectures (Wilkinson et al., 2016). Interoperability plays a crucial role by mandating that geospatial data layers adhere to non-proprietary international frameworks, such as the Open Geospatial Consortium (OGC) standards (<https://www.ogc.org/>) or the European Union's INSPIRE Directive (2007/2), which establishes an infrastructure for spatial information in Europe. These frameworks dictate uniform grid projections, resolutions, and geographic coordinate references, allowing disparate computational models to automatically reconcile conflicting spatial scales.

Concurrently, reusability should ensure that the underlying provenance of an EBoD model, including its boundary definitions, statistical assumptions, and exposure-response limits, is clearly documented via machine-readable metadata. This allows researchers to quickly determine if an EBoD model can be safely calibrated to a target region or if the baseline spatial attributes demand local parameter adaptation.

6.7 Checklist EBoD transferability

Table 1 presents a checklist of how geographic transferability issues should be addressed in EBoD assessments. The table is based on observations made in previous sections.

Table 1 Checklist with geographic transferability issues to be accounted for in EBoD estimates

Item	Description	Reference
Definition	Clearly state the definition of exposure, health, geographical entities applied. Differences in definition lead to inconsistencies in spatial transferability and comparability.	(Katsouyanni and Evangelopoulos, 2022; Khomenko et al., 2022; Staab et al., 2025)
Geographical location EBoD application	Provide detailed information on the location at which the EBoD will be performed	
Reference period	Give details on the period for which the calculation will be done	
Study population	Describe the study population and account for characteristics available for the ERF that will be applied	
Health effect	Clearly describe the considered health effect (ICD-10; hospitalisation data; etc.)	
Data source	Data availability and gaps: Handle data availability and gaps transparently	(Blanes et al., 2024)
	Requirements for data FAIRification: The use of FAIR data is increasingly stimulated to ensure that exposure, health, and demographic datasets are findable, accessible, interoperable, and reusable across geographic contexts	
Methodological design	ERF selection: Consider - geographical relevance - study population - health effect - spatial resolution - (non)-linearity - threshold - date ERF was derived Describe the alignment of methodological characteristics between ERF and application	(Katsouyanni and Evangelopoulos, 2022)
	Define the exposure model applied and spatial resolution	(Mu et al., 2022; EEA, 2025a)
	Consider possible exposure misclassification	(Wei et al., 2022)
	Consider possible MAUP (Modifiable Areal Unit Problem)	(Tessema et al., 2023; deSouza et al., 2024; Williams et al., 2026)
	Mention possible confounding	(Vermeulen et al., 2020; Abed Al Ahad et al., 2023; Batterman et al., 2025)
	For multiple exposure: consider increased transfer of effect	(Williams et al., 2026)

Item	Description	Reference
	<i>Others</i>	
Data manipulation	Verify if downscaling is used	(Hussein et al., 2022)
	Report on imputation techniques (borrowing strength, multiple imputation, Kriging etc.)	(Hoek et al., 2008; Banerjee et al., 2014; Cressie, 2015; Allotey and Harel, 2019; Hrzic et al., 2026)
	<i>Others</i>	
Strength and limitations	Describe the topic geographical transferability (if applied) in the strength and limitations Report on possible over- and underestimation	(Katsouyanni and Evangelopoulos, 2022; Hoffmann et al., 2022; Pauwels et al., 2025b; Jaikumar et al., 2025)
Reporting	Transparency in spatial scales: Report clearly the spatial scales applied in all steps of the EBoD calculation Start designing a metadata-infosheet based on FAIR data principle for the EBoD calculation	

7 Transferability of new green space indicators

7.1 Green space indicators

Contact with natural environments (i.e. green and blue space) has been associated with a range of positive health effects, including a.o. increased physical activity, improved mental health, increased social contacts, reduction of health stress and enhanced overall well-being (Barton and Pretty, 2010; Gianfredi et al., 2021; Houlden et al., 2018; Deliverable 6.1). More detailed information on health effects and mechanistic information, including the effect of confounding, is described in Deliverable 6.1. In environmental health research, there is therefore a growing need for precise and nuanced indicators that capture how people are exposed to urban green and blue space. Traditional greenness indicators, such as the Normalized Difference Vegetation Index (NDVI), are widely used because they can be calculated relatively easily from satellite imagery and applied over large spatial extents. NDVI is useful for assessing the general presence of vegetation, but it also has important limitations. It does not distinguish between different types of green space, such as tree cover, grassland or heathland. Further, it does not account for blue spaces such as water bodies, and it provides no information on whether green space is visible, accessible or functional for use.

As a response to the need for more policy-relevant and human-centred green indicators, the 3+30+300 framework was developed by Cecil Konijnendijk (2023) and is now applied in national, regional and local policies in several countries, e.g. in the Netherlands, Belgium, Finland etc.. This framework proposes that every citizen should be able to see at least three trees from their home, school or workplace, that every neighbourhood should have at least 30% tree canopy cover, and that every citizen should have access to a public green space within 300 m, corresponding to approximately a 5- to 10-minute walking distance. Together, these three indicators aim to capture different dimensions of human contact with urban nature: visible greenness, neighbourhood-level green cover and proximity to accessible public green space.

We derived three indicators that are a proxy for this 3+30+300 rule of thumb: the Viewshed Greenness Visibility Index (VGVI), the proportion of climate green within neighbourhoods and the accessibility to public green (and blue) spaces, and evaluated their geographic transferability within and outside the EU. While the original 3+30+300 rule of thumb considered only high vegetation (i.e. trees) for the 3 and 30 indicators, and green spaces for the 300 indicators, the indicators presented here allow blue spaces (e.g. rivers, waterbodies and shorelines) and different types of green elements to be incorporated in all three indicators.



7.2 Viewshed Greenness Visibility Index (VGVI)

7.2.1 Background and definition of the indicator

The original 3+30+300 rule of thumb states that “every resident in a city, town, or even village should be able to see at least three trees from their home, school, or place of work” (Konijnendijk, 2023). The specific number ‘3’ is, however, not supported by scientific evidence and is used as a proxy indicator for the visible green space.

A range of indices has been developed to assess the level of visible green space. Traditional, top-down greenness exposure metrics, such as Normalised Differential Vegetation Index (NDVI) and a Street View-based Green View Index (SGVI), do not fully capture all of the pathways through which humans experience nature (Labib et al., 2020; Wang et al., 2020). Alternatively, eye-level greenness visibility exposure can be modelled at high spatial resolution through the Viewshed Greenness Visibility Index (VGVI) (Labib et al., 2021). VGVI is particularly relevant for operationalising the “3 trees” component of the 3+30+300 framework, because it focuses on visible greenery from an eye-level perspective. Unlike NDVI or conventional canopy cover indicators, which describe the presence or amount of vegetation from a top-down perspective, VGVI estimates which green elements are actually visible from a given observer location. This makes the indicator more closely aligned with how people experience green space in daily life, e.g. from streets, buildings, schools or workplaces which can be relevant for mental health. In this sense, VGVI provides a more direct proxy for visible greenness than indicators that only quantify the amount of vegetation surrounding a location.

An important advantage of a viewshed-based approach is that it also accounts for visual obstruction. In urban environments, the presence of greenery does not necessarily mean that this greenery is visible. Buildings, walls and other built structures can block lines of sight, especially in dense urban areas. A tree may therefore be located close to an observer but still not be visible because it is hidden behind buildings. For this reason, the quality of the Digital Surface Model is crucial for VGVI calculations. The VGVI uses the digital surface model (DSM) to represent both building heights and vegetation heights, so that the model can distinguish between visible green elements and those that are obstructed from view.

The methodology of Labib et al. (2021) has been enhanced with technical improvements that significantly increased computational efficiency, enabling its application to larger regions such as Flanders, Belgium (Vervoort et al., 2024). Further, the index was designed to allow different weights to be assigned to different types of green space. Blue space can also be incorporated into the index, with the option to adjust the weight of the blue space in the index as well. Blue space visibility is a plausible and empirically supported marker of better psychological wellbeing, but the expected effect is context-dependent. Greater residential blue-space visibility has been associated with lower psychological distress (Nutsford et al., 2016) and an increased likelihood of residents reporting a good general health (Garrett et al., 2019).

The methodology combines high-resolution landcover-, vegetation- and elevation data to quantify the visibility of greenery from eye level. It requires multiple spatial datasets at high resolution:

- a map indicating the location of vegetated (green) and blue space areas;



- a Digital Terrain Model (DTM), containing data on terrain elevation;
- a Digital Surface Model (DSM) providing data on surface heights, including natural and built features.

7.2.2 Input data: Local datasets

Possible datasets that can be used include local topographic datasets indicating the location of high-resolution vegetation and freshwater bodies and rivers, land cover maps, and very high-resolution Digital Terrain Models (DTMs) and Digital Surface Models (DSMs) derived from LiDAR data. When available, these datasets provide highly detailed spatial information, allowing for accurate modelling of visible green space at fine spatial resolutions. However, several limitations should be considered. Local datasets may differ in format, classification systems, spatial resolution, and temporal coverage across regions, requiring substantial preprocessing to ensure consistency and comparability among regions. In addition, some datasets may already be outdated and do not reflect recent land use changes or vegetation dynamics (e.g. the tree cover map of Norway (nibio, 2020)). Further, access to high-quality datasets is not always freely available. Lastly, accounting for blue space in the VGVI using local datasets may prove challenging in some regions, as the required DEM and DTM might not always be available under landcover classified as water. This is, for example, the case in the Netherlands.

7.2.3 European and global datasets as transferable alternatives

Alternatively, European and global datasets can be used to derive the VGVI, enabling a more harmonised methodology and ensuring geographic transferability of the VGVI. Vegetated areas can be located using a combination of global and European land cover and canopy datasets. High vegetation can be derived from the High-Resolution Canopy Height Maps developed by WRI and Meta, based on 2017–2020 data at approximately 1.2 m resolution (Meta and World Resources Institute (WRI), 2024). By aggregating this data to 10 m resolution and creating a binary classification to distinguish tall vegetation (e.g. canopy height > 6 m) from lower vegetation, tree cover (including solitary trees) can be identified. The disadvantage of this global dataset is that there is no time series, it is only one product aggregated over several years. Alternatively, the Copernicus Tree Cover Density product at 10 m resolution (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023a) has a time series, but is less suitable for identifying individual trees. Other green elements, including water bodies, low vegetation, and agricultural land, can be derived from the Copernicus CLCplus Backbone dataset (2023) at 10 m resolution (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023b).

For modelling surface heights and vegetation elevation (DSM), the Copernicus Digital Elevation Model (DEM) (European Space Agency (ESA), 2024) can be used, providing European coverage at 10 m resolution and global coverage at 30 m resolution. To represent terrain elevation (DTM), the Continental Europe Digital Terrain Model at 30 m resolution (Hengl et al., 2020) can be applied and resampled to 10 m resolution for consistency with other datasets. An alternative global dataset is FABDEM (Forest And Buildings removed Copernicus DEM) (Uhe



et al., 2022), which reduces biases caused by buildings and vegetation in the Copernicus GLO-30 DEM.

While these European and global datasets allow for large-scale and cross-border applications, their coarser spatial resolution compared to local datasets may reduce the accuracy of visibility estimates, particularly in dense urban environments or for small-scale green features such as individual street trees.

7.2.4 Parameter choices and weighting of visible green

The VGV I requires a set of key parameters that need to be defined. It analyses for each potential observer location, represented by a grid cell, multiple lines of sight in all directions within a 360° field of view, up to a predefined maximum distance. This maximum distance, as well as the assumed observer height, needs to be defined. The choice of the maximum viewing distance involves an important trade-off between realism and computational feasibility: larger viewing distances increase the computational intensity of the analysis and may therefore limit the spatial extent for which the index can be calculated.

Further, a clear classification and selection of green elements is required, distinguishing, for example, between high vegetation, low vegetation, agricultural land, and water. Depending on the study objective, different weights can be assigned to these classes to reflect their relative contribution to perceived greenness. These weighting choices are not universal and should depend on the purpose of the indicator. If the aim is to assess visible trees, high vegetation can be given most (or all) weight. If the aim is to represent visible nature more broadly, low vegetation and water bodies can also be included (Vilcins et al., 2024; De Nocker et al., 2025). From a health perspective, it is reasonable to assign a higher weight to trees and other high vegetation than to low vegetation. The available evidence for health benefits is stronger for forests, trees and tree canopy (Chi et al., 2022; Yi et al., 2025), whereas low vegetation has rarely been studied separately (Lee et al., 2026). However, this does not mean that low vegetation should be excluded, as there is no scientific basis for assuming that it does not contribute to health benefits (Beute et al., 2023; WHO, 2021a) and some evidence even suggests that visual exposure to grass may reduce stress more than viewing tree canopies in certain settings (Huang et al., 2020). Different types of green and blue space can be accounted for with identical or different weights in the indicator. Further research is needed to determine appropriate weights for different types of green and blue spaces from a health perspective. Moreover, optimal weighting may depend on the health outcome of interest, as different weights may be appropriate for, for example, physical versus mental well-being.

7.2.5 Examples of VGV I derived for European cities

We derived the VGV I for Leuven, Belgium (Figure 3) and Tallinn, Estonia (Figure 4), both included in BEST-COST, at 10 m resolution using the updated methodology of Vervoort et al. (2024). The maximum viewing distance was set at 200 m and the observer height at 1.7 m. The following weights were assigned to different green types:



- trees above 6 m height (derived from High Resolution Canopy Height Maps (Meta and World Resources Institute (WRI), 2024)) and water: 100%;
- other trees (derived from CLCplus Backbone (2023) (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023b), low-growing woody plants, permanent herbaceous landcover, Lichens and mosses: 50%;
- agriculture: 0%.

The height threshold for trees derived from the High-Resolution Canopy Height Maps is a parameter that can be adjusted if needed. The datasets used as input for the VGVI framework are listed in Table 2.

Table 2. Input datasets used to derive VGVI in Figure 3 and Figure 4.

Data type	Source	Resolution
Landcover	CLCplus Backbone (2023) (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023b)	10 m
Canopy height	High Resolution Canopy Height Maps developed by WRI and Meta (based on 2017–2020 data) (Meta and World Resources Institute (WRI), 2024)	ca 1.2 m
Digital Elevation Model (DEM)	Copernicus Digital Elevation Model (DEM) (European Space Agency (ESA), 2024)	10 m
Digital Terrain model (DTM)	Continental Europe Digital Terrain Model (DTM) (Hengl et al., 2020)	30 m

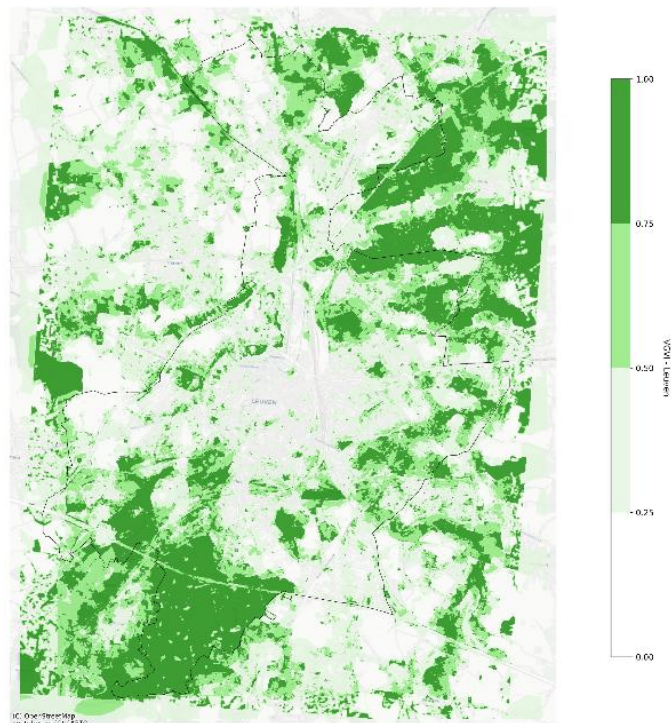


Figure 3. VGVI derived for the city of Leuven, Belgium using the following weights for green types: trees above 6 m height (derived from High Resolution Canopy Height Maps (Meta and World Resources Institute (WRI), 2024)) and water: 100%; other trees (derived from CLCplus Backbone (2023) (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023b), low-growing woody plants, permanent herbaceous landcover, Lichens and mosses: 50%; agriculture: 0%.

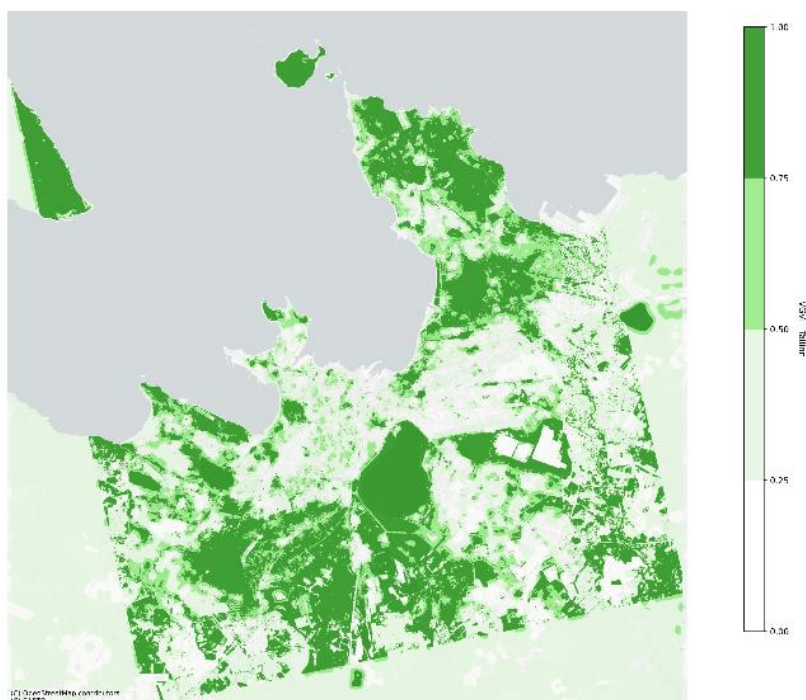


Figure 4. VGVI derived for the city of Tallinn, Estonia using the following weights for green types: trees above 6 m height (derived from High Resolution Canopy Height Maps (Meta and World Resources Institute (WRI), 2024)) and water: 100%; other trees (derived from CLCplus Backbone (2023) (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023b), low-growing woody plants, permanent herbaceous landcover, Lichens and mosses: 50%; agriculture: 0%.

In the Netherlands, the VGVI was derived by RIVM for the centre of Maastricht (Figure 5). In this specific example agricultural areas were considered as green but not water. As discussed above, accounting for blue space in the VGVI using local datasets may prove challenging in some regions, as the required DEM and DTM might not always be available under landcover classified as water.

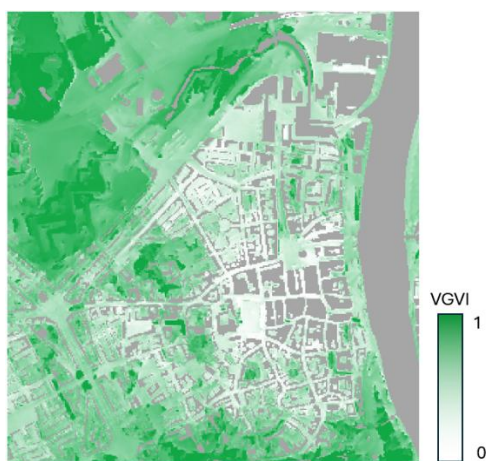


Figure 5. VGVI derived for the centre of Maastricht, the Netherlands. Grey areas are water bodies and buildings. Using national aerial imagery for green detection (Beeldmateriaal, 2025), Algemeen Hoogtebestand Nederland for DSM/DTMA. Agricultural areas are also considered green (through Basisregistratie Gewaspercelen 2025 dataset), but water is not considered as green space.



7.2.6 Limitations

The VGVI should be interpreted as a modelled approximation of visible greenness, rather than as a direct measure of how green space is experienced from homes, schools or workplaces. The results depend on the selected observer locations, the spatial resolution of the input data and the quality of the available height information. In addition, the analysis is done using a fixed observer height, for example 1.7 m, representing visibility from street level. This means that the indicator does not account for differences in visibility from upper floors of buildings, where residents may have a wider or different view of surrounding green space.

The accuracy of the VGVI also depends on the quality of the datasets used to represent vegetation and land cover. For example, canopy height estimates may be affected by cloud cover. In regions with persistent cloud cover, canopy height may be underestimated or even recorded as zero, even when trees are actually present (Earth Blox, 2024). In addition, land-cover datasets such as CLCplus Backbone contain classification uncertainties. Although the dataset reports an overall thematic accuracy of 90%, with omission and commission errors generally below 15% per class, these thresholds may be exceeded regionally for more difficult classes, such as low-growing woody plants and lichens and mosses (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2025). These uncertainties can affect which green elements are included in the VGVI calculation and how strongly they contribute to the final indicator value.

7.2.7 Geographic transferability of the indicator

The VGVI methodology is geographically transferable in the sense that the same viewshed-based modelling framework can be applied to different cities, regions or countries. The indicator requires spatial information on vegetated areas, terrain elevation and surface heights, combined with a set of methodological parameters such as observer height, maximum viewing distance and the classification and weighting of visible green elements. When high-resolution local datasets are available, the VGVI can be calculated with a high level of spatial detail and can better represent small-scale urban features such as individual street trees, building edges and local vegetation structures. However, using local datasets makes transferability more challenging, as datasets may differ between regions in terms of spatial resolution, classification systems, temporal coverage, height definitions and data accessibility. These differences require preprocessing and harmonisation before results can be compared across study areas. Further, even the updated VGVI framework from Vervoort et al. (2024) is computationally intensive. Using local datasets at a high resolution slows down calculations significantly.

European and global datasets provide a more transferable alternative, because they offer more consistent spatial coverage and more harmonised input layers across regions. Datasets such as global canopy height maps, CLCplus Backbone, Copernicus DEM and continental or global terrain models make it possible to apply the VGVI methodology over larger areas and across national borders, although at reduced spatial detail. Further, even when harmonised datasets are used, methodological choices remain necessary, including which types of green and blue



elements are included, how they are weighted, which vegetation-height threshold is used to define high vegetation, and which maximum viewing distance is applied. The VGVI can therefore be transferred geographically, but results should always be interpreted in relation to the spatial resolution and quality of the input datasets and the parameter choices used in the analysis.

Looking at nature has a calming effect with improvement of mood and stress reduction (see Deliverable 6.1). It was already shown in 1984 that patients recovering from gallbladder surgery recovered faster when having a view on green than those who looked at a brick wall (Ulrich, 1984; Nute and Chen, 2026). In the meanwhile more evidence is available for the effect of seeing nature on health (a.o. Fleming et al., 2024; Soga and Gaston, 2025). Recent technological advances have made it possible to move beyond self-reported wellbeing to record objective physiological responses showing how green positively affects our health in real world conditions even under heat stress (Kang and Yoon, 2026). Therefore, it is time to map “visible green” in a harmonized way across the EU and to consider this indicator more in epidemiological research.

7.3 Climate and health green within neighbourhoods

7.3.1 Background, standards and definition of the indicator

According to the original 3+30+300 rule of thumb, every city should strive to have at least 30% canopy cover. This 30% should be reached at the neighbourhood level, not at the city level, as this might, e.g., lead to tree inequity (Konijnendijk, 2023). These trees within a neighbourhood provide a multitude of functions, such as temperature regulation, flood risk mitigation, and air pollution reduction (Ettinger et al., 2024; Gillerot et al., 2024; Livesley et al., 2016). They influence climate and health. Within the One Health approach there are deeply interconnected.

However, canopy cover is not the only form of urban nature that contributes to these ecosystem services. Other green-blue infrastructures such as grass swales, rain gardens, wetlands, and other vegetation can also support the regulation of temperature, management of stormwater, and reduction in pollution exposure. The magnitude of these effects depends strongly on the type of green-blue infrastructure, its design, spatial configuration and local context.

For example, water bodies can substantially reduce land surface temperatures, in some studies even more than vegetated areas (Tan et al., 2021). However, these cooling effects are generally localised and depend strongly on water body size and surrounding urban morphology (Chen et al., 2026; Jandaghian and Colombo, 2024). For reducing human heat exposure, particularly at the pedestrian level, urban tree canopy is generally considered one of the most effective forms of nature-based infrastructure because it provides both shading and evapotranspiration (Alonzo et al., 2025; Nasrollahi et al., 2020). In addition, just like tree cover, grass in an urban context has been associated with lower air pollution exposure (reduced NO₂ concentrations) and better psychological well-being (Wang et al., 2020). Other types of urban nature may also contribute to health benefits: Jarvis et al. (2020) found that exposure to water, shrubs, and grass-herbs within 1,000 m was associated with lower odds of reporting poor or



fair general health and better mental health outcomes. Therefore, while tree canopy should remain a key component of healthy urban environments, other forms of green-blue infrastructure can provide complementary climate-regulating and health benefits and should also be considered in urban planning.

Our green-cover-within-a-neighbourhood indicator calculates the percentage of green-blue infrastructure within a predefined neighbourhood for every pixel in the study region. Different weights can be assigned to different types of green-blue infrastructure, reflecting their varying contributions to ecosystem services and health benefits. For this case study, weights were related to climate regulation. The weights can be adjusted depending on the local context and the intended purpose of the indicator, based on scientific evidence on the services provided by different types of green-blue spaces, as well as on policy priorities. In addition, the buffer distance used to define the neighbourhood can be adjusted, allowing the indicator to be adapted to different spatial scales and local planning contexts.

7.3.2 Input data

The data required for this indicator is a landcover dataset that makes it possible to distinguish between different types of green-blue infrastructure. This can either be one single dataset with multiple landcover classes or a combination of datasets representing the percentage cover of individual landcover classes within each pixel. Various data sources can be used to assess the amount and composition of green-blue infrastructure within a neighbourhood. Local datasets are often available at a much more detailed resolution than datasets at the European or global scale. Further, using local datasets ensures that the derived indicator is consistent with other policy applications that use the same input datasets. Examples include the land cover map of the Netherlands (Landelijk Grondgebruik Nederland (LGN)), available at 5 m resolution for 2024 (Hazeu et al., 2026) and the land cover map of Flanders (Bodembedekkingskaart (BBK)), available at 1 m resolution for 2021 (agentschap Digitaal Vlaanderen, 2024). To identify individual trees within urban areas, it is, however, preferable to use datasets specifically designed to represent tree cover. In an urban context, trees are often combined with other landcover types within one single pixel. These trees might not always be represented in these datasets in cases where they are not the dominant landcover type within a pixel. Dedicated green type datasets can therefore provide more accurate information. Examples include the Groenkaart in Flanders (Agentschap Natuur & Bos, 2022), the Groenkaart in the Netherlands (RIVM, 2022) or Skogressurskart – kronedekning in Norway (nibio, 2020).

However, using local datasets makes it more difficult to transfer the methodology to other countries or to compare results across regions. First, the available data and spatial resolution may differ between countries. Second, land-cover classes are not always defined in the same way. For example, the definition of a tree is not unambiguous. In Flanders, a tree, or high vegetation object, is defined as a green object higher than 3 m (Agentschap Natuur & Bos, 2022) whereas in the Netherlands this threshold is set at 2.5 m (RIVM, 2022).

Datasets at the European or global scale can provide a meaningful alternative, especially when the aim is to apply the methodology across multiple countries or to compare results between regions. Although these datasets generally have a coarser spatial resolution than local datasets, they offer more consistent spatial coverage and harmonised definitions. Further,



they are often updated regularly and may therefore be available for more recent years than some local datasets.

For high vegetation or tree cover, available datasets include the Copernicus High Resolution Layer Tree Cover Density product (Copernicus Land Monitoring Service, 2023), which is available at European scale at 10 m resolution for multiple reference years, including 2012, 2015, 2017-2023. Another example is the global forest cover dataset (Bourgoin et al., 2025), which provides tree cover information at approximately 10 m resolution for 2020.

For other types of green and blue infrastructure, the pan-European CLCplus Backbone product from the Copernicus Land Monitoring Service can be used (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023b). This dataset is available at 10 m resolution for 2018, 2021 and 2023, and distinguishes between classes such as sealed surfaces, woody vegetation, low-growing woody plants, herbaceous vegetation and water. A global alternative is the Copernicus Global Land Cover dataset (Copernicus Land Monitoring Service, 2020). This dataset is planned to become available for reference years up to 2026, but at present it is only available for 2020. These European and global datasets are particularly useful when consistency and transferability are important.

7.3.3 Impact of weighting choices

The choices made when translating different green-blue infrastructure types into a single indicator can substantially influence the results. In particular, the assigned weights may have a large effect on the estimated share of neighbourhoods that meet the target. For example, in Tallinn, Estonia, we calculated the percentage of climate green within a neighbourhood of 400 m using the Copernicus High Resolution Layer Tree Cover Density product (Copernicus Land Monitoring Service, 2023) to define tree cover and the CLCplus Backbone product from the Copernicus Land Monitoring Service (European Environment Agency (EEA) / Copernicus Land Monitoring Service, 2023b) for other green-blue infrastructure (Figure 6 and Figure 7). When fresh water bodies, including coastal seawater, are assigned a weight of 0.5 (open seawater was assigned a weight of 0), 63% of the surface area meets the criterion of at least 30% climate green within the neighbourhood (Figure 6, B). When water was excluded from the indicator, this share decreases to 53% (Figure 7, B). This illustrates that weighting decisions should be made transparently and should be based on the intended purpose of the indicator, scientific evidence on the services provided by different green-blue infrastructure types, and local policy priorities.

While the use of weighting factor increases the flexibility of the indicator, using different weights for different green-blue infrastructure types and including blue space might however decrease the interpretability of the indicator. This trade-off should be considered when selecting which land cover types to include in the indicator and determining their respective weights.

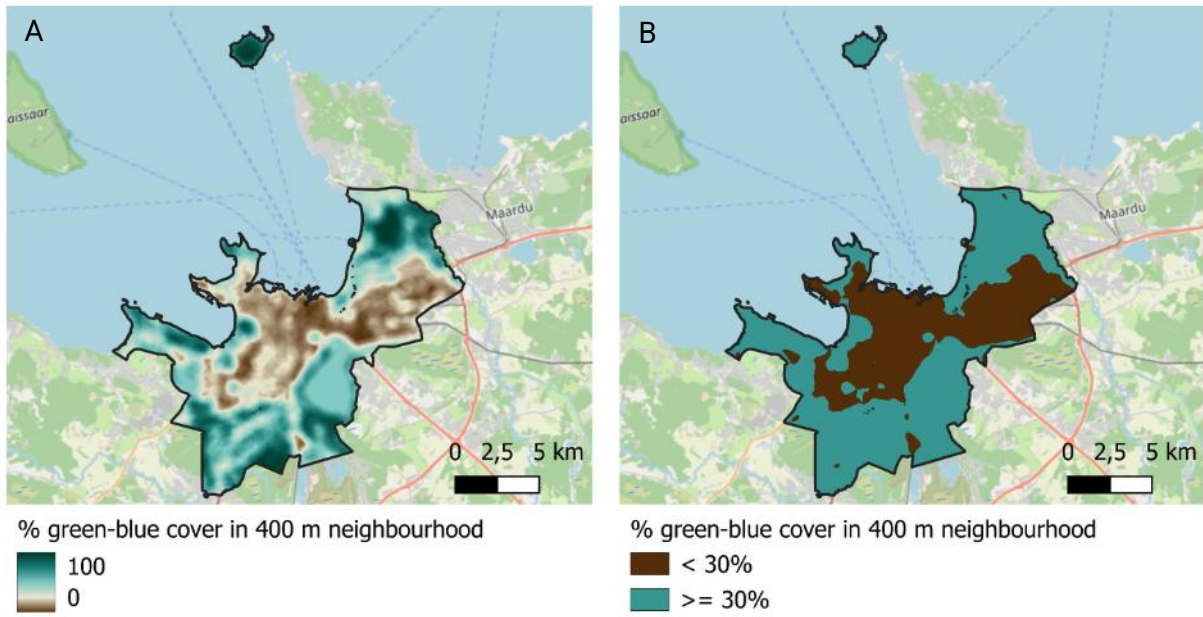


Figure 6. Percentage green-blue cover in a 400 m neighbourhood in Tallinn, Estonia. Land cover class trees was assigned a weight of 1. Land cover classes low vegetation, permanent herbaceous, lichens and mosses, water and coastal seawater were assigned a weight of 0.5. Panel A continuous scale, panel B categorical scale.

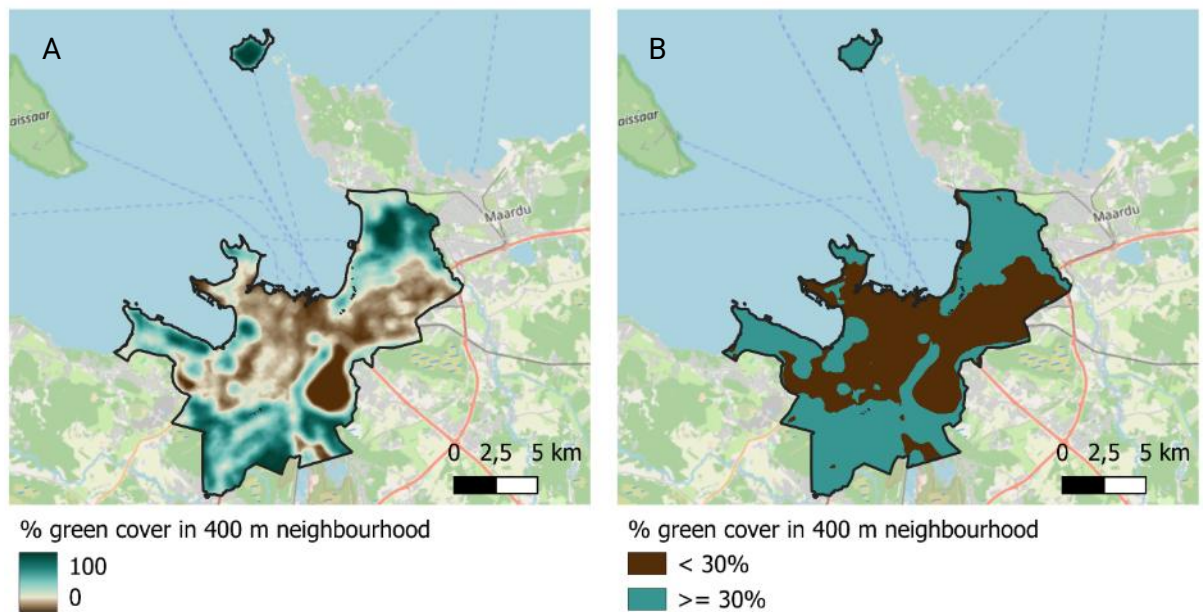


Figure 7. Percentage green-blue cover in a 400 m neighbourhood in Tallinn, Estonia. Land cover class trees was assigned a weight of 1. Land cover classes low vegetation, permanent herbaceous, and lichens and mosses were assigned a weight of 0.5. Land cover classes water and coastal seawater were assigned a weight of 0. Panel A continuous scale, Panel B categorical scale.



7.3.4 Impact of neighbourhood buffer size

The buffer size used to define the neighbourhood around each pixel also affects the results, particularly in urban areas surrounded by landcover types that differ from the composition in the immediate vicinity of the pixel. For example, the urban area of the municipality of Lillehammer, Norway, is largely surrounded by forest and open water. Using a larger neighbourhood buffer will therefore increase the proportion of climate green calculated around urban pixels, especially near the urban fringe. This is illustrated in Figure 8 and Figure 9. When a 400 m neighbourhood is considered, 61% of the surface area meets the criterion of at least 30% climate green within the neighbourhood (Figure 8, B). When the neighbourhood buffer is increased to 1000 m, this share increases to 78% (Figure 9, B). The additional areas meeting the criterion are indeed mainly located along the outer boundaries of Lillehammer's urban area.

The opposite effect can also occur. When the area surrounding an urban zone is dominated by landcover types that are not classified as green-blue infrastructure (e.g. agricultural land or sealed surfaces), increasing the neighbourhood buffer may reduce the calculated proportion of climate green in the neighbourhood. This effect is expected to be most pronounced along the urban fringe, where the larger buffer starts to include more of the surrounding non-green-blue landscape. The effect is also clearly observed around urban parks, where an expanding buffer increasingly encompasses the surrounding built-up environment. As a result, the neighbourhood may no longer meet the threshold value, even though the park itself with a smaller buffer size does.

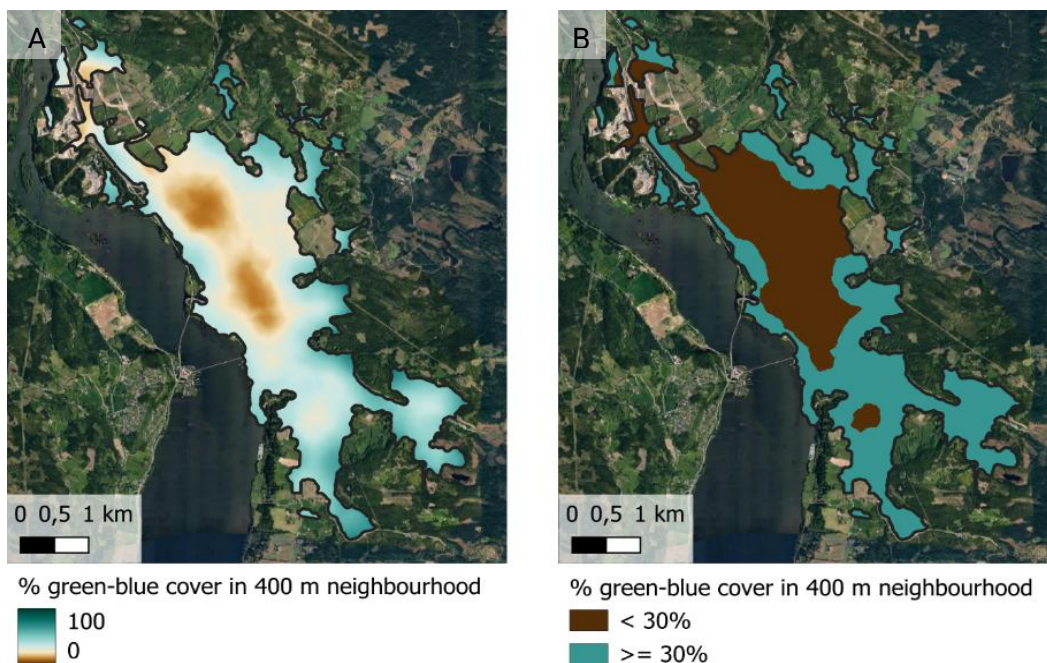


Figure 8. Percentage green-blue cover in a **400 m** radius neighbourhood in the urban area of Lillehammer, Norway. Land cover class trees was assigned a weight of 1. Land cover classes low vegetation, permanent herbaceous, lichens and mosses, water and coastal seawater were assigned a weight of 0.5.

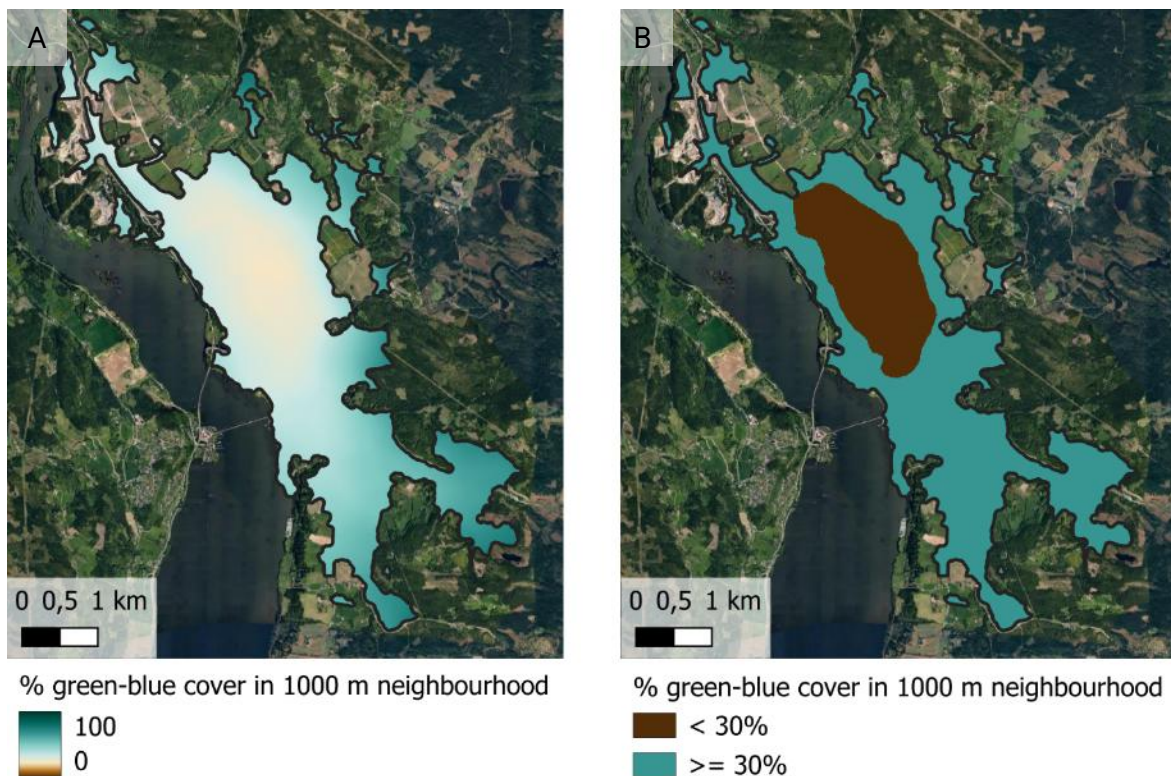


Figure 9. Percentage green-blue cover in a **1000 m** radius neighbourhood in the urban area of Lillehammer, Norway. Land cover class trees was assigned a weight of 1. Land cover classes low vegetation, permanent herbaceous, lichens and mosses, water and coastal seawater were assigned a weight of 0.5.

7.3.5 Geographic transferability of the indicator

The methodology behind the indicator can be transferred to other cities, regions or countries, but the ease of transfer depends strongly on the input data used. When local datasets are used, the indicator can often be calculated at a higher spatial resolution and with land-cover classes that are better aligned with local policy contexts. However, this also makes transferability more challenging. Suitable local datasets need to be identified for each study area, and differences in classification systems and definitions of green-blue infrastructure types need to be harmonised before results can be compared across regions.

When European or global datasets are used, the methodology is easier to transfer geographically, because these datasets provide consistent spatial coverage and harmonised land-cover definitions. This makes them particularly useful for cross-country applications and comparative analyses.

Further, while the 30% threshold provides a relatively simple and transferable benchmark, the interpretation of what counts towards this threshold is less universal. Therefore, even when using harmonised datasets, methodological choices remain necessary. These include deciding which green-blue infrastructure types are included in the indicator, whether different types should be weighted differently, and which buffer distance should be used to define the neighbourhood around each pixel. These choices should be aligned with the intended purpose of the indicator, the local planning context and the ecosystem services or the health benefits that the indicator aims to represent. A tree canopy-based interpretation may be appropriate



when the focus is on shade and cooling benefits, whereas a broader climate-green and health-impact interpretation may also include shrubs, herbaceous vegetation, wetlands or water bodies. It was already shown in a meta-analysis that the percentage green surrounding us, influences our health (Liu et al., 2023). For robust application in epidemiological research and transferability, applying the indicator in different geographic context requires a clear definition of the green-blue infrastructure types included in the calculation and the weightings and buffer sizes applied.

7.4 Accessibility to public green spaces

7.4.1 Background, standards and definition of the indicator

The original 3+30+**300** rule of thumb recommends that “*every citizen should have a large public green space within 300 m, approximately a 5-min walk or so, from their home*” (Konijnendijk, 2023). The threshold of 300 m was based on a review of the evidence by the European Regional Office of the World Health Organization (WHO, 2017). Such proximity is considered important because it encourages the recreational use of green space, with potential positive impacts on both physical and mental health (Konijnendijk, 2023; BEST-COST Deliverable 6.1). Locations without an accessible green space within this distance are therefore considered not to meet this criterion. However, this 300 m criterion does not explicitly capture the potential importance of smaller pockets of greenery located closer to the home. Such spaces may be particularly relevant for population groups with a more limited walking range, such as young children, older people, or people with reduced mobility. Therefore, a smaller distance threshold could also be considered.

Standards for the distance to and size of accessible green spaces differ between countries, regions and cities. In Flanders, for example, Van Herzele and Wiedemann (2003) refer to the availability of e.g. small residential green spaces within 150 m, neighbourhood green spaces of at least 1 ha within 400 m, and larger green areas of at least 200 ha within 5 km (RIVM, 2025b, 2026). In the United Kingdom, considerable work has also been carried out on proximity standards. Natural England (2003) recommended that everyone should have access to a natural green space of at least 2 ha within 300 m of their residence.

Besides the distance and area, the quality, accessibility and function of green space are important aspects to consider. Konijnendijk (2023) highlights that public green spaces can take many different forms. For example, in Mediterranean cities, tree-lined walking avenues or ramblas function as green spaces, regardless of whether they are also traffic corridors. This shows that the definition of green space is context-dependent and may be subject to discussion. The definition of green types to include as accessible green spaces impacts the resulting indicator values significantly (Smith et al., 2017). Potential categories include, among others, parks, forests, gardens, grasslands, heathlands, dunes, recreation areas, playgrounds, nature reserves, wetlands and other semi-natural vegetation types. Other categories are less straightforward and require methodological and/or policy choices, such as whether to include water bodies or tree rows. Including or excluding blue spaces, for example, may strongly influence results in urban areas with a dense network of canals or water bodies, such as the



centre of Amsterdam, the Netherlands, as illustrated in Figure 10 and Figure 11. While blue space is often less accessible for recreational purposes than green space, there are still health benefits linked to access to blue space. For example, psychological benefits of visiting natural environments were reported in the context of an urban river ecological restoration project (de Bell, 2017). Larger amounts of blue space in the surrounding area can be associated with higher physical activity and restoration (Georgiou et al., 2021). It must however be noted that also quality of the blue space impacts the associations found with health impacts. A river section with concrete walls could for example be viewed as a sewage-like environment (de Bell, 2017).

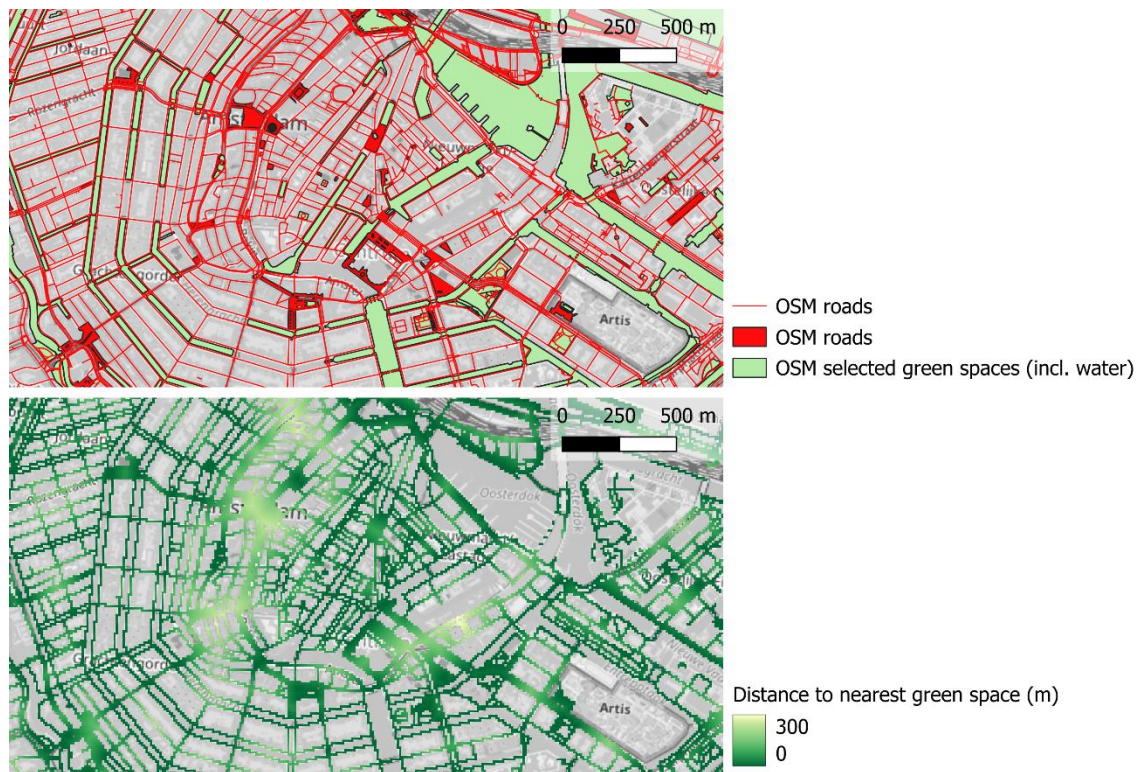


Figure 10. Green areas (*incl. water*) and roads selected from OSM data and the resulting distance to the nearest green area with a distance threshold of 300 m considered, within the city of Amsterdam, the Netherlands.

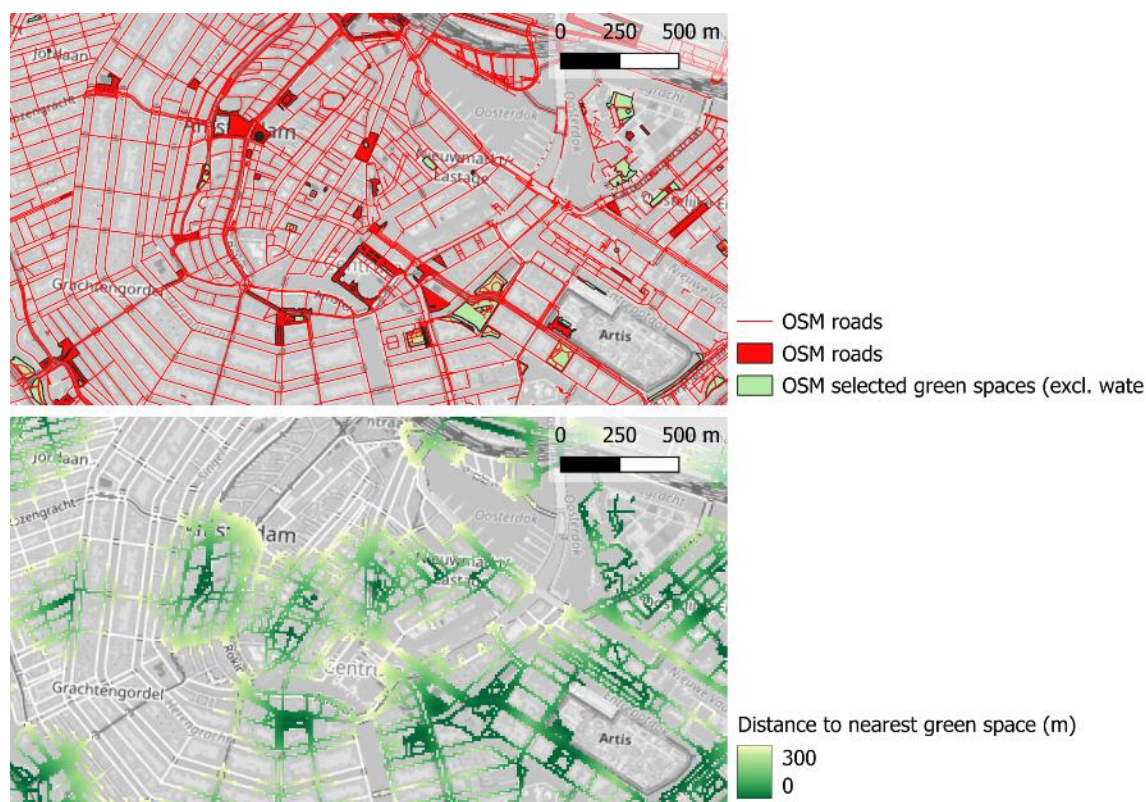


Figure 11. Green areas (excl. water) and roads selected from OSM data and the resulting distance to the nearest green area with a distance threshold of 300 m considered, within the city of Amsterdam, the Netherlands.

Therefore, this indicator should not just be interpreted as a technical distance measure. It reflects premade methodological choices influenced by local policy choices regarding which green, and potentially blue, spaces are considered relevant, accessible and functional for use.

7.4.2 Framework to assess accessibility to public green spaces

The methodology we developed identifies roads and paths that intersect with green space polygons. The required input data include an up-to-date road network (preferably with information on permitted access) and a spatial dataset containing the green space types considered relevant, accessible and functional for use. An area threshold can be set for a green space to be considered relevant (e.g. 0.2 ha). The distance along the road network to the nearest accessible green space is then calculated at raster level, using a 10 m resolution. To limit the calculation, a maximum distance threshold is applied. This threshold corresponds to the maximum distance within which access to green space is considered relevant for the indicator. Pixels located beyond this threshold are therefore not assigned an exact network distance, as they already fall outside the defined accessibility range.



7.4.2.1 Input data – local datasets

Local datasets on roads and green space categories can be used for this purpose. However, a disadvantage of relying on local datasets is that they may not be uniform across study areas. Some datasets include a broad range of road types, including bicycle lanes, roads for motorised traffic, footpaths and informal trails, whereas others may only include paved roads. This has an impact on the identification of accessible green spaces, as relevant access routes may be missing from datasets with a more limited scope. Furthermore, specific paths may be absent from the available data, as illustrated in Figure 12.

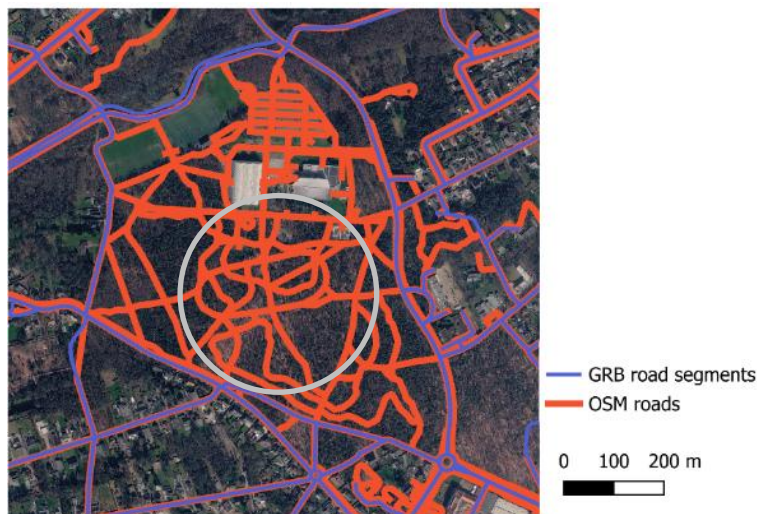


Figure 12. Woodchip running tracks (orange lines within the circle) near a sports complex in Genk, Belgium, missing in the official road dataset of Flanders (i.e. *grootchalig referentiebestand* (GRB) road segments). These paths are present in the OSM dataset.

7.4.2.2 OpenStreetMap as a globally available alternative

A globally available alternative to local datasets is the use of OpenStreetMap (OSM) data. OSM is an open geographic database maintained through collaborative contributions by a community of volunteers. This database includes road networks, but also different types of green land use such as forest, parks, natural grassland and tree rows. The database contains information on the accessibility of both road networks and land use polygons. We developed a methodology that selects OSM roads within the study region, including both line segments and polygons representing e.g. village squares, and uses their intersection with green space polygons to identify potentially accessible green spaces.

The information on accessibility is used in our analysis to discard roads or paths and green space polygons that are indicated to be inaccessible. Examples of such features include paths in nature reserves with restricted access and military domains. OSM data can either be downloaded directly within the processing script for a user-defined bounding box or obtained from regional extracts provided through e.g. the Geofabrik download server (<https://download.geofabrik.de>). The in-script download provides access to a broader range



of OSM feature. Further, it contains information on the accessibility of the OSM feature which is not available from Geofabrik extracts. However, it is only feasible for relatively small study areas, such as individual cities, and is not suitable for analyses at country level. For larger study areas, Geofabrik extracts therefore provide a more practical alternative. However, care is needed when using these extracts, as they do not contain all feature types that may be relevant for assessing accessible green space, such as village greens and tree rows. Moreover, roads are included only as line features, whereas road polygons are not provided. Consequently, public squares that have a road function are missing as well.

7.4.3 Limitations

An important limitation of OSM data is that its quality and completeness depend on the contributions of volunteers. As a result, the data may not always be fully accurate, consistent or complete across study areas. In the context of our methodology, this is particularly relevant as green areas are selected when intersected by roads or paths. Whether a green space is identified as accessible therefore depends not only on the actual situation on the ground, but also on how both the road network and the green space polygons have been digitised. If these features are not mapped precisely, a road and a green space may fail to intersect in the dataset even though access exists in reality. This is relevant as this intersection is used to select accessible green spaces in our methodology. Further, an intersection may be present in the data although the green space is not actually accessible, as illustrated in Figure 13.

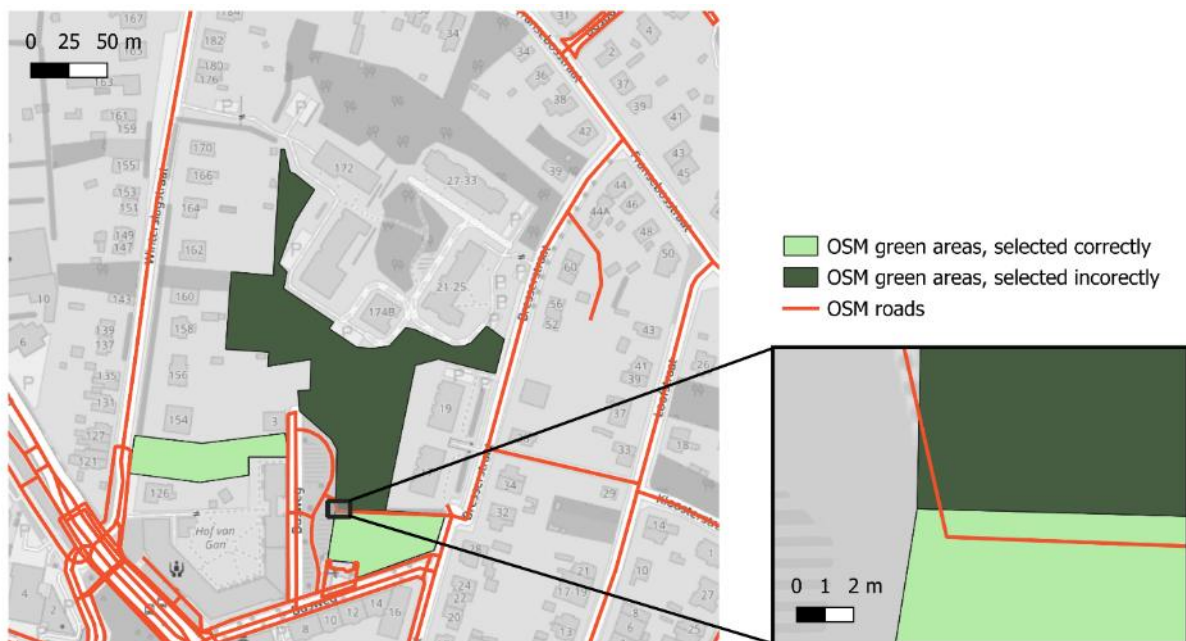


Figure 13. Non accessible forested land in Genk, Belgium, present in the OSM dataset intersected by a road segment part of the same OSM dataset that was not digitised accurately.

This issue is not specific to OSM, but represents a more general limitation of the methodology. Since only green spaces intersected by a road or path are selected, accessible green areas located directly next to a street may be excluded if no road or path segment overlaps the green



space polygon. For example, a park or play area adjacent to a street, but without a mapped path crossing the polygon, may be discarded, as illustrated in Figure 14.

This limitation is difficult to address in a fully automated and consistent way. Applying a buffer around roads or paths could help include green spaces that are located immediately adjacent to the road network. However, this approach may also result in the incorrect selection of green spaces that are not publicly accessible, such as fenced-off areas or school playgrounds. Additional information on accessibility, land ownership or barriers would therefore be required to further reduce such classification errors. This issue does not occur when streets, squares or quays are digitised as polygons rather than as line segments, as is the case for some features in OSM. Figure 15 shows an example where a quay is represented by a polygon and therefore intersects with a playground polygon and two grassland polygons, allowing these green areas to be identified as accessible



Figure 14. Accessible park in the city centre of Genk, Belgium. Although both the road network and the park are included in the OSM dataset, the roads do not actually intersect the green space polygons. As a result, the green space polygons are, therefore, not considered in the proximity analysis of accessible green spaces.



Figure 15. Playground and two grass areas on a quay in Tallinn, Estonia. Because the quay is digitised as a polygon rather than as a line segment, it intersects with the playground and grass polygons, allowing these areas to be identified as accessible green spaces.

Another limitation concerns the delineation of individual green space polygons. The results may be influenced by whether adjacent or overlapping green space polygons are dissolved into larger units or treated as separate polygons. In some cases, a continuous green space may be represented as multiple polygons due to differences in land-use classification, for example at the transition between a park and a forest. Similarly, a park polygon may be split into several smaller polygons when a road or path crosses the area.

However, separate polygons do not always represent artificial fragmentation in the dataset. In some cases, they can correspond to green space types that differ in their accessibility, such as a private garden adjacent to a public urban park, a nature reserve with restricted access next to an accessible forest, or a fenced-off playground on a school property next to a grass field. Whether such polygons should be combined therefore depends on the purpose of the analysis and on the extent to which the different green space types can be considered functionally connected and accessible as a single green space. Therefore, decisions on whether to merge adjacent polygons should ideally be assessed on a case-by-case basis using local knowledge. However, such an approach is not feasible when the analysis is carried out at a larger spatial scale.

A further limitation is that the completeness of OSM data can vary substantially between regions. This is particularly relevant when applying the indicator in areas where green spaces and footpaths are less consistently mapped. The example of Lusaka, Zambia, illustrates this limitation. Using the same methodology, only 320 green spaces were selected from the OSM dataset across the entire study area (Figure 16). A visual inspection of several locations showed that this number is likely an underestimation of the actual availability of accessible green spaces. For example, Libala Stage 2 Community Park (Figure 17) and Cherise Kids Park (Figure 18) could be identified from other sources, but were not present as green space polygons in the OSM dataset and were therefore not included in the analysis. In other cases, green space polygons were present in OSM but were still not selected by the methodology because the connecting paths were missing from the OSM road network. This was the case for e.g. Cheswa Park (Figure 19), where footpaths are visible on satellite imagery but are not



represented in OSM. As the methodology selects green spaces based on their intersection with mapped roads or paths, such omissions can lead to accessible green spaces being incorrectly excluded. Consequently, the resulting distance-to-green-space map may overestimate distances in areas where OSM green space polygons or access paths are incomplete. The example of Lusaka, Zambia highlights that the 'accessibility to green space' indicator is strongly dependent on the completeness of both green space and road/path data. Local knowledge is therefore needed to evaluate if the OSM data is sufficiently complete in a region, and in regions with less complete OSM coverage, results should be interpreted with caution or complemented with local datasets. Zambia serves as a practical example for this approach. We will expand on this in Chapter 8, which evaluates how methodologies related to indicators and their use for environmental burden of disease or positive health impact calculations can be transferred outside of the EU.

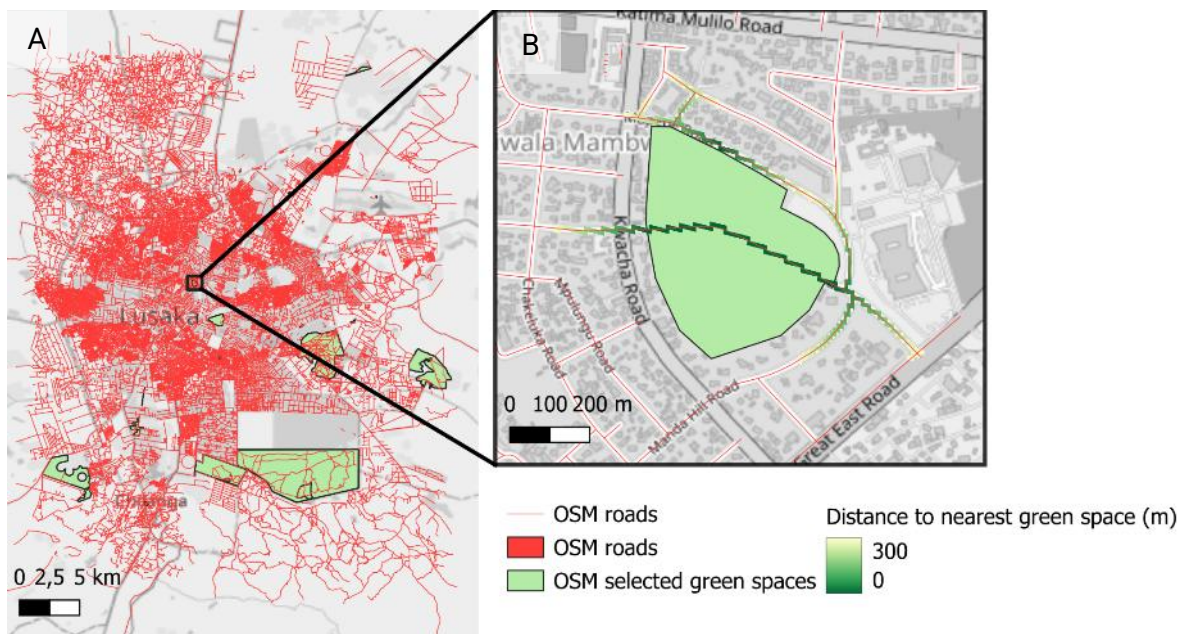


Figure 16. Selected OSM green spaces in Lusaka, Zambia (A) and example of resulting distance calculation to nearest green space (B).

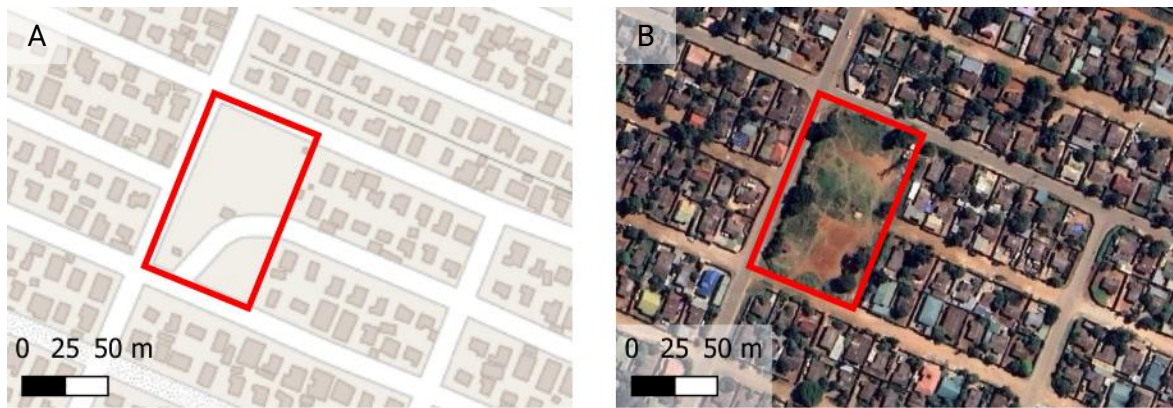


Figure 17. Location (red) of the Libala Stage 2 Community Park in Lusaka, Zambia, not present in the OSM data (A).

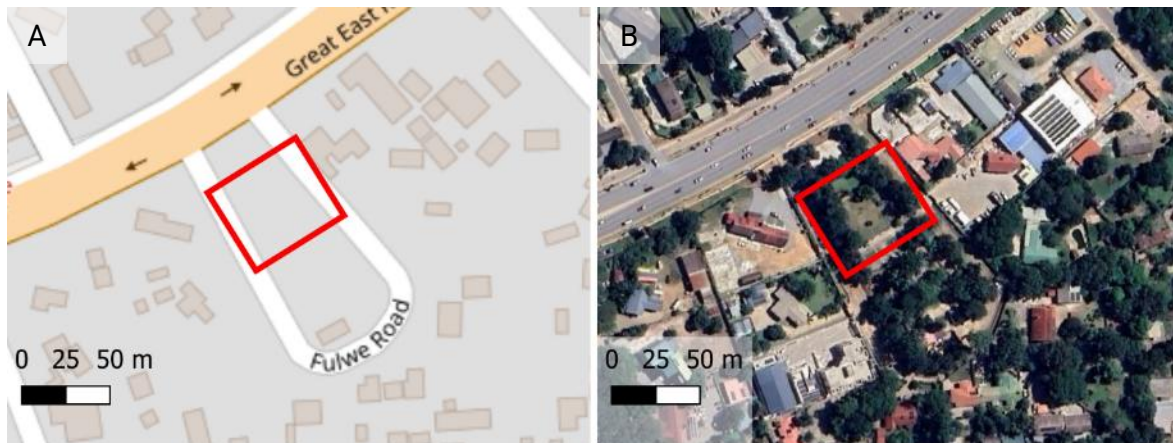


Figure 18. Location (red) of the Cherise Kids Park in Lusaka, Zambia, not present in the OSM data (A).



Figure 19. Park feature (Cheswa park) in Lusaka, Zambia, present in the OSM database (A) but not selected for the analysis due to footpaths that can be seen from satellite imagery (B) but that are missing in the OSM database (A).

In the presented methodology, the quality of the public green spaces is not considered while this might impact quantity and quality of the green space exposure. Research indicates that characteristics such as biodiversity and habitat diversity can contribute to psychological restoration and mental well-being (Cameron et al., 2020; Fuller et al., 2007; Thwaites et al.,



2024; Wood et al., 2018). Other relevant dimensions include naturalness, accessibility, amenities, perceived attractiveness and safety, as well as spatial structure and connectivity (Nguyen et al., 2021; Yang et al., 2026). However, the evidence varies considerably between quality dimensions, and there is currently no generally accepted method for combining these characteristics into a single health-related quality score.

7.4.4 Geographic transferability of the indicator

The ‘accessibility to public green spaces’ indicator is geographically transferable in the sense that the same methodological framework can be applied to different cities, regions and countries. The methodology only requires a spatial dataset of relevant green spaces, a road or path network, an area threshold above which a green space is considered relevant, and a predefined distance threshold within which access to green space is considered relevant. The use of OSM data further increases this transferability, as it provides a globally available and relatively uniform source of both green space polygons and road/path networks. The methodology can thus be applied in regions where local datasets are not available or where a consistent comparison between different study areas is required.

The results are, however, not necessarily directly comparable between regions without considering local context and data quality. First, the definition of what is considered an accessible and functional green space may differ between countries, regions and cities. As described above, some standards focus on public green spaces within 300 m, while others make a distinction between small residential green spaces, neighbourhood green spaces and larger green areas. In addition, the types of green and potentially blue spaces that are considered relevant may differ depending on local policy choices and urban context. For example, water bodies may be considered relevant in some cities, while in Mediterranean cities, tree-lined walking avenues or ramblas may also function as green spaces. Therefore, the selection of green space types should ideally be adapted to the local definition of relevant, accessible and functional green space. A check is thus required to assess whether additional green typologies need to be included or discarded from the analysis when the methodology is applied in a different geographic context.

Further, geographic transferability is limited by the availability, completeness, accuracy and consistency of the input data. When local datasets are used, differences in their scope can affect the results. Some road datasets may include footpaths, bicycle lanes and informal trails, whereas others may only include paved roads or roads for motorised traffic. Similarly, local green space datasets may differ in the categories they include and in the level of detail at which green areas are mapped. Although OSM provides a globally available alternative, its completeness also varies substantially between regions because it depends on the contributions of volunteers. The Lusaka, Zambia, example illustrates that, in regions where green spaces or access paths are less consistently mapped, the indicator may underestimate the actual availability of accessible green spaces and overestimate the distance to the nearest green space.

The methodology can thus be transferred geographically, but the interpretation of the indicator should always consider local definitions, policy standards and data completeness. The indicator should therefore not be interpreted as a purely technical distance measure, but as the result of methodological choices regarding which green spaces are considered relevant,



accessible and functional for use. For applications at larger spatial scales or across multiple regions, a consistent methodological framework is needed, but this should be complemented with local knowledge and critical evaluation. In regions with less complete OSM coverage or limited local data, results should be interpreted with caution, and additional local datasets on accessibility, land ownership, barriers or informal paths may be required to improve the quality of the indicator.



8 Going beyond Europe

While previous sections have primarily focused on European applications of EBoD and HIA, there is a growing recognition of the need to extend these frameworks to low- and middle-income countries (LMICs). However, as highlighted in Sections 5.1.2 and 6.1.3, such an extension is not straightforward and raises important methodological and contextual challenges, particularly with regard to the transferability of EBoD approaches across different environmental risk factors and exposure settings.

Sub-Saharan Africa (SSA), in particular, is repeatedly identified as a priority region due to its disproportionately high environmental burden of disease and rapidly changing exposure patterns (Armstrong-Mensah et al., 2025). In this context, it is important to emphasise that EBoD assessments are inherently risk factor-based, rather than disease-based. Although the region is undergoing a rapid epidemiological transition characterised by a shift from disease-burden profiles dominated by communicable diseases and childhood illness towards an increasing prevalence of chronic, non-communicable diseases (Gouda et al., 2019), environmental risk factors remain central drivers of both disease groups. Environmental exposures such as air pollution, unsafe water and sanitation, chemical exposures and climate-related hazards contribute simultaneously to transmission and progression of infectious diseases and to the increasing burden of chronic conditions (Fisher et al., 2021; WHO, 2018). Environmental exposures in LMICs differ substantially from those typically observed in high-income settings, both in magnitude and composition. This is particularly evident for air pollution. Household air pollution remains a dominant risk factor for children and women due to the widespread reliance on solid fuels for cooking. At the same time, ambient air pollution is rising rapidly in urban areas due to population growth, traffic emissions, industrialisation and informal waste burning (Amegah and Agyei-Mensah, 2017; Okello et al., 2023a). Moreover, the chemical and biological composition of African aerosols may differ substantially from those typically observed in North America or Europe, with higher contributions from biomass burning, dust, polycyclic aromatic hydrocarbons and microbial components (Kalisa et al., 2019). These differences may influence toxicity and population responses and thus have direct implications for the transferability of ERFs as discussed in Section 6.1.3.

Beyond air pollution, other environmental risk factors further highlight the context-specific nature of exposures in LMICs. Chemical exposures represent an important and often insufficiently characterised risk category, including the use of pesticides that are restricted or banned in the European Union (Anaduaka et al., 2023), as well as emerging concerns related to microplastics and chemicals associated with waste imports and insufficient waste management infrastructure (Adeniran and Shakantu, 2022). Other environmental stressors, such as environmental noise, occupational exposure (e.g. in artisanal mining) and climate-related hazards, also contribute to the overall burden of disease (Chen et al., 2023; Santofimio et al., 2024; Bianco et al., 2024). These exposures often interact with broader structural vulnerabilities, including poverty, rapid urbanisation, demographic change, increased vulnerability to climate change and limited access to healthcare, reinforcing their public health impact (Liousse et al., 2014; WHO, 2018; Siiba et al., 2024).



Despite the high relevance of the above environmental risk factors, LMICs remain underrepresented in the epidemiological evidence base underpinning EBoD and HIA (Brauer et al., 2024). Large regions, including Africa, the Middle East and South Asia, are still poorly covered in cohort studies and meta-analyses, limiting our understanding of exposure-response relationships across diverse settings and particularly at high exposure levels. As a result, important drivers of geographical heterogeneity remain insufficiently characterised, and current ERFs may not adequately reflect health risks in these contexts (Leuenberger et al., 2019a; Winkler et al., 2019, 2020).

This lack of local epidemiological evidence is further compounded by persistent data and methodological constraints. Although improvements in data availability are being observed, important limitations persist. In several SSA countries, cause-specific mortality, incidence, and prevalence estimates remain sparse, incomplete or available only at aggregated national scales. These limitations are partly related to ongoing challenges in Civil Registration and Vital Statistics (CRVS) systems, although substantial progress has been made in recent years (WHO, 2021b). At the same time, environmental monitoring networks for air pollution, water quality and other hazards are characterised by limited spatial coverage and short or discontinuous time series (Okello et al., 2023b; Kassandros et al., 2026). Also, the use of human biomonitoring (HBM) is limited and scattered in most African countries, although there are some initiatives (Lehmann et al., 2018; Godebo et al., 2019). As highlighted in Section 5.1.2, limitations in data quality and spatial resolution can lead to exposure misclassification, obscure local variability and introduce bias in burden estimates.

In addition to these data gaps, exposure patterns in LMICs are often highly localised and shaped by context-specific sources, including solid fuel combustion, informal waste handling, artisanal mining and occupational exposures. These sources are typically not well captured by conventional monitoring approaches, further complicating exposure assessment (WHO, 2021c). This issue is particularly relevant for EBoD applications based on the CRA framework, where accurate characterisation of population exposure distribution is a key prerequisite for robust burden estimation.

Addressing these challenges requires methodological adaptation and innovation. Recent studies highlight the potential of hybrid exposure assessment approaches that combine satellite observations, land-use regression (LUR) models and low-cost sensor networks to improve spatial coverage in data-scarce regions (Clark et al., 2022; Brum et al., 2024). Such approaches can help better capture fine-scale spatial variability and context-specific exposure patterns, thereby reducing misclassification (see Section 5.1.2).

At the same time, there is a critical need for more epidemiological studies in LMICs to generate locally relevant ERFs and reduce reliance on evidence from high-income settings (Tonne, 2017; Rojas-Rueda et al., 2021; Chen et al., 2023). Strengthening the evidence base is essential to improve both the validity and the transferability of EBoD assessments.

Beyond technical and data-related challenges, institutional and structural factors also influence the applicability of EBoD and HIA approaches. In many LMIC contexts, health considerations are not yet consistently integrated into environmental assessment processes, and technical capacity for conducting comprehensive quantitative health assessments remains uneven (Leuenberger et al., 2019b). Consequently, applications of EBoD and HIA are often fragmented and applied in a project-specific manner, such as for a single mine or dam, rather than being used as a national policy-level decision tool (Knoblauch et al., 2018). In



addition, vulnerable populations, such as those living in informal settlements, may be underrepresented in available data due to gaps in monitoring and data collection, possibly exacerbating existing health inequities (Cai and Mustapha, 2023).

Exchanging knowledge on the environment and health and building partnerships with LMICs would be a win-win for several parties, with the knowledge gained from exposure to other mixtures than in the EU, higher exposure, and better characterisation of exposure-response relationships.

Overall, extending EBoD and HIA approaches to LMIC contexts requires more than the transfer of existing frameworks. In line with considerations discussed in Sections 5.1.2 and 6.1.3, careful attention must be paid to spatial resolution, exposure assessment and the contextual validity of ERFs. Strengthening local data systems, advancing exposure modelling approaches and investing in locally grounded epidemiological research are essential steps. More broadly, building sustainable research capacity and addressing structural inequities in the global research landscape will be critical to better capture geographical heterogeneity and ensure robust, policy-relevant assessments across diverse settings (Malekzadeh et al., 2020).



9 BEST-COST WP6 policy-oriented recommendations

Overall policy recommendations are described below.

1. Establish an EU-wide framework for harmonised high-resolution exposure and health data and support data collection (see Chapter 6 in general)

Takeaway:

The EU can mandate harmonised spatial data standards (grid resolution, coordinate systems, metadata) across Member States to reduce, e.g., MAUP (Modifiable Areal Unit Problem) effects and exposure misclassification for different determinants on health, including air pollution, noise, chemicals, and heat. This fits within the exposome concept of gathering “high-resolution” exposure data over lifespan and will contribute to clarifying the share that environmental determinants have on human health. These standards should align with other developments in the EU regarding e.g., the European Health Data Space (EDHS) and the Common Data Platform on Chemicals (CDPC).

Policy action:

Integration of Environmental Burden of Disease (EBoD) data requirements into the INSPIRE Directive revision (Greendata4all⁹). Support Member States in reporting exposure and baseline health data at harmonised grid levels (e.g. fine-resolution data).

Support national statistical offices to produce LAU-level (Local Administrative Unit level) morbidity and mortality datasets with GDPR-compliant anonymisation.

2. Help in the creation of an EU mechanism for exposure-response (ERF) validation and contextualisation (“ERF working group”) (see Section 6.1.3)

Takeaway:

ERFs for different stressors can be systematically evaluated for scientific robustness and for geographical, methodological and temporal transferability before use in EU policy assessments.

Policy action:

Help in establishing an expert group in collaboration with ECHA, EEA, WHO to review and provide counsel on ERFs for use in EBoD would be beneficial. At least the following criteria should be accounted for (not exhaustive):

- evidence rating,
- spatial resolution alignment,
- exposure definition,
- pollutant composition differences,
- population vulnerability and susceptibility

⁹ <https://www.europarl.europa.eu/legislative-train/theme-a-european-green-deal/file-revision-of-the-inspire-directive>



3. Strengthen EU-wide socioeconomic indicators at the municipal level to support inequality analyses (see section 6.1.4)

Takeaway:

The EU can develop harmonised LAU-level (Local Administrative Unit level) socioeconomic indicators to enable cross-country analysis of environmental inequalities.

Policy action:

Help Eurostat with producing harmonised LAU1/LAU2 socioeconomic datasets (education, income, labour market, housing) in alignment with the GDPR.

4. Costs (See section 6.1.5)

A remaining limitation concerns the coverage of European health-preference heterogeneity. The four surveyed countries represent four of the five EU preference clusters identified by Pinheiro et al. (2025), leaving the fifth, Eastern European cluster (Poland and Romania) unrepresented. In addition, because the monetary value per averted DALY (Disability Adjusted Life Year) strongly drives the resulting estimates, the choice of WTP (Willingness to Pay) value and income-elasticity assumption has a substantial influence on monetised results, and income-based adjustment produces lower values in lower-income settings.

Takeaway:

Monetised estimates of averted DALYs are transferable across the EU, but their accuracy depends on how well the source countries represent the target's health preferences and on the valuation assumptions applied. Coverage of the fifth cluster is currently missing, and the sensitivity of results to WTP and elasticity choices means monetary values should not be read in isolation.

Policy action:

In applications, test the sensitivity of monetised estimates to alternative WTP values and elasticity assumptions, and present monetised results alongside the underlying DALYs, so that lower-income contexts are not judged less policy-relevant simply because their income-adjusted values are lower.

5. Mandate FAIR-compliant environmental and health data infrastructures to support transferability (see Section 6.1.7)

Takeaway:

FAIR principles can become a legal requirement for environmental health reporting under EU legislation.

Policy action:

Require FAIR metadata for all exposure, health and demographic datasets used in EBoD/HIA under the Zero Pollution Action Plan.

Funding of Member States to adopt OGC-compliant (Open Geospatial Consortium) geospatial standards¹⁰ and machine-readable provenance documentation.

6. Green space (See chapter 7)

Takeaway:

¹⁰ <https://www.ogc.org/>



New harmonised green-space indicators can support EU-wide health assessments, but must account for local definitions, data quality and methodological choices.

Policy action: Transparent documentation of green-space definitions is needed, including the green and blue space types considered, weighting schemes and spatial thresholds. Investment is also needed in up-to-date, high-resolution and harmonised European datasets to reduce dependence on incomplete citizen-science data, while more systematic and complete registration of green spaces and access routes in open datasets should be encouraged. Further, it is desired that consistent time series for all input datasets should be developed using the same methodologies, so that observed changes can be attributed with confidence to actual changes in green space rather than to changes in the underlying data or classification methods. Experience with these new green space indicators and their application in epidemiological research should be communicated widely through networks like e.g. EIONET to foster knowledge exchange.

7. Support EU–LMIC (Low- and middle-income country) partnerships to improve transferability of ERFs and global environmental burden of disease (EBoD) relevance (see Chapter 8)

Takeaway:

The EU can invest in exposure monitoring, cohort studies and capacity building in LMICs to improve the representativeness of global ERFs and reduce uncertainty.

Policy action:

Funding of Horizon Europe partnerships with African and Asian research institutes to develop hybrid exposure assessment approaches: satellite + LUR (land use regression) models + low-cost sensors.

Support the establishment of longitudinal cohorts in LMICs to derive context-specific ERFs. Promote reciprocal knowledge exchange with respect to high-exposure settings to refine EU-relevant and improve OSOA chemical assessments.



10 Conclusions

This deliverable outlines a comprehensive path forward for establishing robust, geographically transferable frameworks to assess the health impact of environmental stressors and green space indicators both within and outside the EU.

Methodological Harmonization and Spatial Scale

Achieving valid cross-border models requires direct reconciliation of spatial scales and geographical definitions. Moving environmental risk calculations from national envelopes down to highly local municipal levels addresses localized vulnerabilities but presents distinct data-sparsity, privacy, and statistical scaling challenges. Systemic aggregation errors introduced by the Modifiable Areal Unit Problem (MAUP) require transparent downscaling proxies and proportional calibration tools to ensure that local health indices remain valid across varying administrative structures.

Overcoming Data Gaps and Exposure Misclassification

Significant discrepancies persist in European exposure monitoring datasets. Standardized metrics under the Environmental Noise Directive (END) remain restricted to major transport routes, which risks underestimating community-wide health impacts. Similarly, the lack of continuous pan-European tracking architectures for complex modern stressors—such as chemical pollutants—demands a broader use and integration of high-resolution tools. Expanding human biomonitoring (frequency and coverage) through micro-sampling and embedding spatial semantics into structural data architectures via FAIR data principles are critical to correcting fragmented data landscapes and automating cross-border model execution.

Human-Centric Environmental Indicators for Green

Operationalizing indicators to fulfil the 3+30+300 environmental design framework demonstrates that high-resolution top-down canopy data and eye-level vistas (such as the Viewshed Greenness Visibility Index - VGVI) can be effectively simulated across different cities, like Leuven, Belgium and Tallinn, Estonia. However, the sensitivity of these models to pixel weight distributions and grid buffer boundaries show that environmental indicators for green reflect methodological choices regarding the types of green-blue space included, their relative weighting, and the spatial context considered. Therefore, transparent technical documentation of parameter bounds is essential to prevent internal inconsistencies during epidemiological applications. The use of these new green space indicators in exposomics-supported epidemiological research is a prerequisite to come to better calculations of the positive impact of green on health. Therefore, we stress again the importance of these indicators and their use in future research.

Mutual Global Learning Models

Establishing institutional, bidirectional "win-win" partnerships with international research bodies creates mutual value. Low- and middle-income country partners should receive advanced capacity-building infrastructure and open-source planning tools. Concurrently, European modelling networks gain deeper knowledge of exposure-response functions (ERFs) by evaluating extreme, high-exposure gradients and distinct pollution profiles that are completely absent within contemporary Europe, revealing the true non-linear shapes and biological limits of global health curves.



11 Annex 1

Empty



12References

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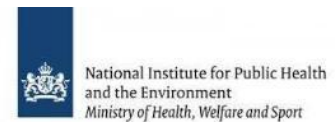
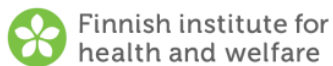
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