

Dealing with uncertainties

The case of environmental burden of disease assessment

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Abstract

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Disability Adjusted Life Years (DALYs) aggregate the number of people affected by disease or mortality in a population and the duration and severity of their condition in one number. Such so-called environmental burden of disease estimates enable policy makers to evaluate, compare and prioritize dissimilar environmental health problems or interventions. The complexity and incomplete knowledge of the underlying issues, however, often compel assessors to make many assumptions about the underlying reality and to make use of incomplete information. Often, the resultant uncertainties are not completely (re)presented in the assessment results. Besides statistical uncertainty in input data and parameters – which is commonly addressed – a variety of other types of uncertainties may substantially influence the validity of assessments results. We have reviewed how different types of uncertainties manifest themselves in burden of disease assessments, and we give suggestions as to how researchers could deal with these uncertainties. We propose the use of an uncertainty typology that can help to identify and structure uncertainties for future assessments. Finally, we argue that uncertainties need to be properly identified, assessed, reported and interpreted in order for assessment results to sensibly support decision making.

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Key words : DALYs, environmental burden of disease, uncertainty characterization, uncertainties

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List of abbreviations

- 55 CI: Confidence Interval
- DALEs: Disability Adjusted Life Expectancy
- DALYs: Disability Adjusted Life Years
- eBOD: Environmental burden of disease
- HALEs: Health Adjusted Life Expectancy
- 60 HALYs: Health Adjusted Life Years
- PM: Particulate Matter
- QALYs: Quality Adjusted Life Years
- RR: Relative risk
- UV: Ultraviolet
- 65 WHO: World Health Organization

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95 **Introduction**

In environmental health research, focus has shifted from relatively simple to more complex and uncertain issues. Empirical single agent/single effect studies have been succeeded by research on systemic risks in which complex environmental health issues interact in varying
100 economic, cultural and political settings. Environmental health impact assessment has become a valuable tool for decision support. These types of assessments increasingly use so-called “*environmental burden of disease*” measures to express health impacts. The environmental burden of disease (eBOD) can be viewed as the gap - caused by environmental factors - between current health status and an ideal situation in which everyone lives into old age free
105 of disease and disability. Such burden of disease estimates enable comparison of diverse environmental health problems, which in turn enables policy makers to prioritize or evaluate the (potential) effectiveness of policies. However, eBOD assessments often have to rely on many assumptions about the underlying reality they attempt to describe, have to use incomplete knowledge and data, and are confronted with diverging perceptions about what
110 the salient aspects of a problem are. Assessments are often highly interdisciplinary, complex and multifaceted, and the overall uncertainty about results of such complex studies can therefore be significant [1]. This in turn may affect decision making based on these studies.

A 2005 comparison of 17 eBOD studies published between 1996 and 2005 (internal RIVM/
115 MNP publication by Knol and co-workers) showed that there are significant differences between eBOD estimates that concern – at first sight – similar issues. Smith and co-workers[2] for example estimate the fraction of the total global disease burden attributable to the environment to be 25-33%, whereas Melse and de Hollander[2;3] estimate this to be 7.5 to 11%. Such differences can sometimes not be fully explained by reading the reports, since

120 methods, assumptions and input data are often insufficiently reported, hampering
interpretation and comparability of results[4].

Even though it is never possible to completely reduce uncertainty to zero in these complex
assessments, there is significant room for improvement in dealing with uncertainty [1].

125 Various eBOD studies have addressed the need for uncertainty and sensitivity analysis
(a.o.[2;4-10]), but, as yet, most studies estimate overall uncertainty in the last phase of an
assessment and are based primarily on statistical uncertainty of some parameters and input
data. Other sources of uncertainty are often touched upon in the discussion sections of
publications, but usually not in a complete or systematic manner. However, many
130 environmental health issues are not so straightforward and are plagued by controversies and
uncertainties that cannot be captured in single numbers or limited probability intervals[11;12].
Only if both assessors and policy makers –the intended users of the assessment- realize the
extent of uncertainties and the way they may affect the assessment results, these assessments
can lead to truly informed policy making. In order to achieve this, a *typology* of different
135 types and dimensions of uncertainty can help to structure, assess and potentially reduce
uncertainties, and moreover improve the dialogue about uncertainties between scientists and
policy makers.

The present study explores the different types of uncertainty that may play a role in eBOD
140 studies (expressed in Disability Adjusted Life Years, DALYs), structured using such a
typology of uncertainty. The impact uncertainties can have on assessment results – and
thereby on decision making – will be illustrated using examples from existing eBOD
literature, drawn from the internal publication by Knol and co-workers Some suggestions are
given as to how to communicate uncertainties to policy makers in order to support well-
145 informed decisions (instead of “adding to the confusion”). This paper aims to create
awareness among environmental health impact assessors as well as policy makers about the

potential impact and importance of uncertainties, and to provide a practical approach and structure to deal with uncertainties in future assessments.

150

Environmental burden of disease

155 An increasingly popular metric to express the environmental burden of disease is the DALY
(Disability Adjusted Life Years). DALYs indicate the (potential) number of healthy life years
lost in a population (i.e. burden of disease). Not only life years lost due to mortality, but also
years spent with reduced quality of life due to diseases are included. For diseases, *severity*
weights (also commonly referred to as *disability weights*) are used to quantify and aggregate
160 the reduced quality of life or reduced ability to cope with the demands of everyday life. They
are developed by expert panels and range from 0 (complete health) to 1 (death); per year of
blindness for example the severity weight is 0,600; low birth weight is weighted at 0,291.
Additionally, DALY calculations can include the optional use of age weights and discounting
factors. Age weighting involves valuing life lost at a certain age more than life lost at other
165 ages. Discount factors (or time preference factors) value present years of life saved more than
future years (usual discount rate 3%). The use of both age weights and discount factors has
been discussed (and heavily debated) elsewhere (e.g.[13;14]).

Burden of disease calculations using DALYs were first published widely in the World
170 Development Report[15]. Subsequently, Murray and Lopez[16] used DALYs in their
extensive global burden of disease project in order to introduce morbidity in the
predominantly mortality-based health discussions. Since then, the World Health Organization
has endorsed the DALY approach, and it has been used in various studies on global, national
and regional levels. DALY (or similar) calculations are now increasingly being asked for in
175 order to develop, evaluate and prioritize (environmental) health related policy measures. Next
to DALYs, various other summary measures exist to express population health or disease
states, such as QALYs (Quality Adjusted Life Years), HALYs (Health Adjusted Life Years),
DALEs (Disability Adjusted Life Expectancy), HALEs (Health Adjusted Life Expectancy),

and various monetary valuation measures. Even though this paper focuses on the DALY,
180 most of the uncertainties identified play a similar role in these alternative indicators.

Typology of uncertainty

Uncertainties in assessments about a complex versatile world can take many forms and affect
185 assessments results in various ways. A typology of uncertainty can help to identify and
structure these different types of uncertainties, thereby gaining transparency and
understanding, and supporting the identification of useful methods to deal with various
uncertainties. We have adjusted an existing line of uncertainty typologies [17-24] to fit our
purpose of identifying, further characterizing and dealing with the uncertainties that arise in
190 eBOD assessments. Our typology (Table 1) distinguishes between ‘location’, ‘nature’,
‘range’, ‘recognized ignorance’, ‘methodological unreliability’ and ‘value diversity among
analysts’ as six characteristics of uncertainty (which can apply simultaneously to the same
piece of uncertain information). It is not claimed that this is the ‘best’ typology (cf.[21]); for
other purposes, other typologies might be more useful. The six uncertainty characteristics will
195 be explained below (for a more detailed introduction, the reader is referred to [21;22]).

First, the *location* of uncertainty indicates where the uncertainty manifests itself among the
main elements of assessment practices (distinction is made here between ‘context’, ‘model
structure’, ‘parameters’ and ‘input data’). These locations will be further described below.
200

Second, the *nature* of uncertainty expresses whether uncertainty is primarily a consequence of
the incompleteness and fallibility of knowledge (*epistemic uncertainty*) or primarily due to
intrinsic properties of the system under study (*ontic uncertainty*; ‘ontic’ meaning ‘pertaining
to the object’, that is, the system itself.). The ‘system’ in the case of eBOD calculations
205 comprises human populations. Within this population, the people vary in terms of their

susceptibility to environmental health impacts – which gives rise to an ‘ontic’ uncertainty in assessments. The present study distinguishes between two types of ontic uncertainty: *process variability* (indeterminacy and/or variability in natural and social processes) and *normative uncertainty* (related to the existence of a fundamental plurality of socio-ethico-normative considerations). An example of the latter is that individuals have different views on ‘wellbeing’ and the severity of their own or other’s illnesses.

Third, the *range of uncertainty* embodies a quantitative estimate of the uncertainty, either as a *statistical uncertainty* or as a *scenario uncertainty*. A ‘statistical uncertainty’ range can be given if uncertainties can be adequately expressed in statistical terms, e.g., as a range with associated probability (confidence interval). However, ‘deeper’ forms of uncertainty are often at play. These cannot be expressed statistically but can sometimes be expressed by a range. Such a range is then called a ‘scenario uncertainty’ range. Scenario uncertainties cannot be adequately depicted in terms of chances or probabilities, but can only be specified in terms of (a range of) equally plausible events. To specify a degree of probability or belief for such uncertainties is meaningless, since the mechanisms which lead to the events are not sufficiently known. Scenario uncertainties are often construed in terms of ‘what-if’ statements.

Fourth, *recognized ignorance* concerns those aspects of uncertainty for which we cannot establish any useful estimate, e.g., due to limits of ‘knowability’ or due to unknown processes. Unrecognized ignorance does not count as ‘uncertainty’, since it concerns ‘pure ignorance’ about which we cannot say anything knowledgeable: we don’t know what we don’t know. However, experts making a claim may acknowledge that they are ignorant about particular sources of uncertainty.

Fifth, the *methodological unreliability* of an (element of an) assessment reflects weaknesses in methodological quality. It is often not possible to establish the accuracy of a model or to

quantitatively assess the impacts of different sources of uncertainty. In those cases, one may
235 have recourse to qualitative judgments of the relevant procedures instead. Scientists can judge
the methodological rigour of the scientific procedure followed. The methodological rigour
can, for instance, be determined by looking at the theoretical and empirical basis, the
reproducibility of the assessment and its acceptance in the peer community.

240 And sixth, there is *value diversity among analysts* in scientific practice, which is reflected in
the existence of alternatives for the assumptions made in the assessment. Assessors often have
considerable freedom in making choices, and the choices actually made may be influenced by
different underlying epistemic, socio-cultural and practical values held by the assessors. An
example of a possible influence by a socio-cultural value is to base the assessment on ‘worst-
245 case’ assumptions (e.g., safety factors that may often remain implicit).

The different categories of *location* of uncertainty are used to structure this paper. The other
characteristics are discussed in each of the sections. The various types of uncertainty will be
illustrated using examples from the eBOD literature. Some of such illustrations (referred to
250 with “(Table 2, #)” in the remainder of the manuscript) have been characterized according to
the uncertainty typology in Table 1 and are summarized in Table 2. We will point towards
methods that can be used to deal with different types of uncertainties.

Table 1: Typology of uncertainty

255

Table 2: Examples of characterizations of uncertainties in eBOD assessments

Context uncertainty

260 ‘Context uncertainty’ stems from choices made about system boundaries and definitions used in an assessment. In eBOD studies, the definition of the environmental factor (s), the associated health outcomes, the links between these, and the scenarios used in the study (including the study area, affected population, and time frame) have to be agreed upon.

265 **Examples of context uncertainty in environmental burden of disease assessments**

Defining ‘environment’

Defining ‘environment’ is not straightforward. Whereas single risk factor assessments can generally define exposure relatively easy, broader multiple factor analyses (about e.g. ‘transport’, ‘agriculture’ or ‘total environment’) need to define these boundaries more
270 carefully (see Figure 1).

‘Environment’ has been defined to *exclude* genetics, diet and smoking behavior, but *include* for instance effects of the natural environment such as dust exposure and natural disasters [2]; *include* physical, chemical and biological human made or influenced exposures, but *exclude*
275 occupational health and safety, the majority of traffic, war, and life-style factors [3]; *include* all the physical, chemical and biological factors external to the human host and all related behaviors, but *exclude* those natural environments that cannot reasonably be modified [5;25;26], etc. These definitions can have significant influence on the outcome. This context uncertainty (Table 2, 1), has an *epistemic* component (because we can not yet gauge the
280 complete extent of the environment) and *normative* component (because different researchers hold different normative views on what the environment consists of).

Defining ‘health’

The domains of health range from each of the senses, to pain, to mobility and cognition, and finally to complex health-related functions and social interactions [27]. Many assessments
285 define health quite clinically, including only negative health effects that have a medical diagnosis. However, a broader definition – such as defined by WHO[6] stating that health is ‘a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity’ – also includes ‘soft’ health outcomes. For instance, the burden of disease related to noise varies significantly depending on whether noise annoyance and sleep
290 disturbance (‘soft’ health outcomes) are considered health effects.

A pragmatic (and normative) approach to define which diseases should be considered has been employed by Smith and co-workers[2], who included only disease categories that cause at least 1% of the global burden of disease (Table 2, 2). Other cut-off percentages could also
295 have been adopted, making this source of uncertainty a form of *scenario* uncertainty with a pragmatic *normative* nature and subject to a degree of *value diversity* among specialists. Since it is known which diseases are excluded and why, *recognized ignorance* and *methodological unreliability* do not play a substantial role. If the definition of the relevant health outcomes is not a thorough and informed process or is not communicated properly, this may bias studies
300 and limit the generalizability of the results [1].

Dealing with context uncertainty

Results of an assessment can be very sensitive to the definitions and system boundaries chosen. Although harmonization is important to make burden of disease studies comparable,
305 unfortunately most of these definitions cannot be harmonized across assessments, because they are dependent upon the purpose of a specific assessment[28]. Even though there is not one single way to deal with context uncertainties, a few general guidelines can be given. In summary, the chosen definitions and boundaries need to be identified, carefully discussed,

consistently used and adequately reported[2;29]. Problem definition and identification and
310 discussion of system boundaries may often need to involve relevant stakeholders. Even
though stakeholder discussions may not reduce these uncertainties, they at least help to reveal
them [1]. If more than one *sensible* definition of any of the elements can be made (thus
leaving room for *value diversity*), multiple analyses can be run using different sets of
definitions and system boundaries (scenario analysis). This is especially useful when there is
315 controversy about which definition is most appropriate, when the differences between
definitions are considerable, or when the scenarios in the assessment are likely to be affected
differently by the alternative definition. Sensitivity and decision analysis can help to identify
which sources of uncertainty mostly affect the results.

320

Model structure uncertainty

‘Model structure uncertainty’ relates to uncertainty about the (causal) structure of the modeled
system: uncertainty *within* the boundaries chosen. Various interpretations might prevail about
325 the dominant variables and their causal relationships and interactions represented in a model.
Because of the many difficulties in studying the large scale low exposure environmental
health risks that are so typical of the modern (Western) world, different views about the
model structure often exist.

330 Examples of model structure uncertainty in environmental burden of disease assessments

Even when the definitions of the contexts are valid and agreed upon, that does not
automatically mean that all relevant variables are included in the assessment. For example,

335 climate change may affect health in ways that are as yet unexpected, and therefore these health effects are not included in assessments [30]. Model structure uncertainty can also relate to the applicability and form of exposure-response relationships (for instance, threshold versus no threshold, or linear versus nonlinear) describing the causal relationships (Table 2, 3)[31;32]. Evidence for causality may not always be available or in agreement (Table 2, 4).
340 An example of this specific type of uncertainty is the inconclusiveness of the evidence for an association between noise exposure and cardiovascular impacts: some reviewers find the evidence for this relationship ‘sufficient’, whereas others state that it is ‘limited’[33]. A similar debate runs for the long-term health impacts of air pollution, of which the potential impact is as yet rather uncertain. Since different decisions can be made about whether
345 ‘sufficient evidence for causality’ exists[34;35], such uncertainty is characterized as *scenario* uncertainty. For example, a WHO eBOD study[36] based their estimate of the asthma-related burden of disease for children on a relative risk that Smith[37] considered not sufficiently robust. The *recognized ignorance* about the existence of causality, which is partly due to *methodological unreliability*, could be reduced by further research, which indicates its
350 *epistemic* nature.

Similar examples of model structure uncertainty relate to knowledge about e.g. the use of proxies, the development of the health effects, patho-physiological mechanisms, potential latency times, vulnerable groups, co-morbidity and multi-causality. Multiple risk factors can
355 simultaneously affect multiple hazards. Risk factors can lead to health effects through intermediate factors. There may be other correlated risk factors with common social and behavioral determinants[7;38-40]. Risk factors can be additive (separate effects added), synergistic (separate effects multiplied), or agonistic (separate effects reduced)[41]. For example, incomplete understanding of the joint effect of smoking and radon with regard to
360 lung cancer remains a key uncertainty in assessing the risk of indoor radon[42] (Table 2, 5).

Dealing with model structure uncertainty

Model structure uncertainty mainly stems from different interpretations about how ‘the system works’. Model structure uncertainty is often predominantly epistemic – relating to
365 incomplete or contradicting knowledge – and more research can increase understanding and possibly reduce uncertainty.

Refsgaard and co-workers[43] reviewed strategies for assessing model structure uncertainty and presented a framework for assessing predictive model structure uncertainties. It involves
370 the use of multiple conceptual models, assessment of their pedigree and reflection on the extent to which the sampled models adequately represent the space of plausible models. Furthermore, sensitivity and decision analyses can provide information about the relative importance of variation between different alternative assumptions. Another widely used technique is the use of Bayesian belief networks, that can cope with multiple model structures
375 [44;45].

Resources however often limit the possibility to run a large amount of alternative calculations, and pragmatic choices need to be made. Most important is therefore to document the assumed conceptual and technical model structure in a transparent way, to explore and document which limitations or other viewpoints exist, and reflect on what this means for the robustness
380 of the results. A graphical representation of the model showing which variables and linkage are included (and excluded) increases the understanding of the model structure[46]).

Standardization of the way such diagrams are presented (all using the same convention for what certain shapes of boxes and types of arrows in a causal diagram precisely mean) is recommendable.

385

Parameter uncertainty

Parameters are constants in functions that describe the relationships between variables of a modeled system. Parameters can be *descriptive* (e.g. relative risks, duration estimates, or attributable fractions) or *normative* (e.g. ‘maximum life expectancy’, severity weights, policy norms, age weights and discount factors).

Examples of parameter uncertainty in environmental burden of disease assessments

Relative risks and attributable fractions

The most common descriptive parameter used in eBOD calculations is the relative risk (RR), which indicates the ratio of the risk of a disease or death among those exposed to the specified risk to those not exposed. The RR is usually derived from epidemiological research or meta-analyses of various studies, and subsequently applied to the specific study context. The epidemiological study from which the RR stems can in itself form a source of uncertainty (Table 2, 7). Even though the epidemiological methods to derive RRs are fairly common (this limits *value diversity*, at least among epidemiologists), uncertainty can relate to e.g. differences in study design, measurement errors, etc [1] (*methodological unreliability*). For some environmental risks, especially new and emerging risks (e.g. electromagnetic fields or genetically modified foods), RR estimates are not or only limitedly available. Depending on the assessment context, it can often be debated whether specific relative risks can be extrapolated to other regions, time periods, substance mixtures, sub-populations or age groups[7;31;47]. An example is the use of exposure response relations for the long-term effects of PM₁₀, which are currently only available from studies in the United States. The validity of the use of such relative risks in burden of disease studies for e.g. the Netherlands is disputable, since e.g. air pollution mixtures (for which PM₁₀ is an indicator) and average population susceptibility vary between the countries (Table 2, 8)[11;48]. Similarly, in

assessing the health impacts of climate change, problems have been encountered when long-term effects had to be extrapolated from short-term associations [30].

415 ***Severity weight factors, age weights and discounting***

Normative parameters such as severity weights for diseases or age weights and discounting factors for future health gains are generally based on the judgments of clinicians and economists respectively, and are therefore subjective interpretations of a number for which no ‘true value’ exists[49] (Table 2, 10). Different parameter values will prevail depending on
420 who is being asked, their age, gender, occupation, socio-economic status, cultural background and education level. This raises the question of transferability of weights to other individuals, cultures, population subgroups, age groups, similar diseases or time periods. Estimates of severity weight factors also depend on the way health states are presented to the persons who are asked to value, the range of health states to be valued in the same session, and the
425 valuation methods [27]. As an extreme example, the severity weight for severe noise-related sleep disturbance has been estimated at 0.01 (as e.g. used in [50;51]) up to as high as 0.12 [50]. Alternative but realistic assumptions for all normative parameters mentioned above (severity weights, age weights and discounting) can lead to up to quadrupling of DALYs[49].

430 **Dealing with parameter uncertainty**

Parameter uncertainty (together with input data uncertainty, discussed next) is commonly quantitatively assessed in eBOD studies, using statistical analyses. Confidence intervals (CI) of parameters, such as presented together with RR estimates, are used to calculate overall CIs
435 for DALYs. This approach is only suitable for *statistical uncertainty*. However, *scenario uncertainty* (Table 2, examples 8 and 11) on issues for which various interpretations exist (*value diversity*) is more difficult to cover in CIs. For these uncertainties, similar methods as

described for context and model structure uncertainty can be applied (further research, sensitivity and decision analyses, transparent reporting and interpretation, etc). Alternatively, parameters can be ‘frozen’ for a certain time period (e.g. monetary value of a statistical life) in order to allow for consistent assessment and policy making.

Input data uncertainty

Uncertainty in input data may relate to e.g. a lack of (good quality) data, inaccurate measurements, or extrapolated data, and is often statistically expressed. Exposure data and disease data (incidence, prevalence and/or mortality, by age and sex) are the most common input data sets needed for eBOD calculations.

Examples of input data uncertainty in environmental burden of disease assessments

The greatest source of uncertainty pertaining to exposure data in risk assessments generally relates to a lack of assessment-specific measurements. For many risk factors, data on exposure distributions are available for only a limited number of years, regions, countries or demographic groups[5]. In climate change research, for example, impacts relate to future exposures which cannot be measured [30]. If no (further) monitoring can take place, assessors often model the missing data or extrapolate non-assessment specific data (Table 2, 11). Prüss-Üstün[5], for example, used a combination of survey data, model data and expert judgment data in order to estimate solid fuel use across 181 countries. Whether such extrapolated or modeled data can still be meaningfully used can be judged differently by various stakeholders (*value diversity*). Overall, Prüss-Üstün et al[5] concluded that only for three environmental risk factors (water sanitation and hygiene; solid fuel use; and outdoor air pollution) the

necessary methodology and enough exposure data were available to make sensible global
465 estimates.

Even when exposure can be measured, different methods can lead to uncertainty in exposure
estimates (Table 2, 12). An example of such a *range* is e.g. the measurement of noise
exposure levels, which can differ up to 10 dB (A) depending on the methodologies used [52].
470 In studies related to UV radiation and skin cancer, sun exposure of many years before is
usually estimated using recalled sunburns or time spent in the sun. Such exposure
measurement can lead to results that differ significantly from e.g. ecological studies, which
use measurement data of ambient UV radiation levels[32].

475 Similar issues play a role for background morbidity and mortality data, which are needed to
calculate the estimated number of attributable cases. Such data should ideally stem from
empirical research or adequate monitoring in the target population[53]. However, these data
are often fragmented, partial, incomparable, or diagnostically uncertain[5;31]. Research
shows that indicative *uncertainty ranges* for regional prevalence rates of 16 important
480 diseases ranged from +/-10 percent to +/-90 percent in various countries[31]. The common
solution – modeling missing data or extrapolating data of one country to another country
where population dynamics and exposure to other determinants might be different – yields
further *epistemic uncertainty*.

485

Dealing with input data uncertainty

Whether input data are suitable for the intended purpose can be evaluated in a data quality
assessment (DQA), described by the Environmental Protection Agency[54] as the scientific
490 and statistical evaluation of data to determine whether they meet the objectives of the project,

and thus are of the right type, quality, and quantity to support their intended use. Other methods to assess data quality include pedigree analysis[55;56], data quality indicators[57], and data attribute rating system[58].

495 For morbidity data, models can be employed to calculate missing data and check for consistency in existing incomplete or low-quality datasets. However, past trends in incidence and data inaccuracies can lead to large discrepancies between measurements and calculations in such models, and their use requires both caution and expert knowledge[39;53;59].

500 **Using the uncertainty typology in practice**

In the preceding paragraphs we have outlined ways to deal with various types of uncertainties. In practice, eBOD assessments do not only have to deal with uncertainties, but also with time and budget constraints. It might often not be possible to employ all these presented methods for each uncertainty identified. Therefore, it is necessary to prioritize uncertainties and the work needed to assess or reduce them. Here we shortly describe how to 1. identify and characterize sources of uncertainty; 2. prioritize sources of uncertainties; and 3. select (and apply) methods for dealing with uncertainties, and the analyze the implications of uncertainty for decision-making. Subsequent communication of the results to policy makers will be discussed in the next paragraph. In all these steps, the typology for uncertainty can be used to support the process.

505
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1. In the first step, the different sources of uncertainty are identified. The generation of this so-called “grosslist” of uncertainty sources should be done using two different approaches: 1) by analyzing each conceptualization and calculation step of the eBOD assessment at hand and subsequently characterize each source according to the typology, and 2) by considering each possible type from the uncertainty typology and discuss where

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in the assessment this type of uncertainty may occur. Reasoning from both angles helps to minimize the chance that uncertainty sources are overlooked. The resulting list of uncertainties need to be further characterized using the uncertainty typology. This may be done either quantitatively or qualitatively.

2. The relative importance of each source should subsequently be weighted, depending on its impact on the outcome of the eBOD assessment in question. Where some form of quantification is possible, the relative importance can be assessed by means of sensitivity analysis[8-10]. However, for many sources of uncertainty, quantification is not feasible. In that case, the relative importance can be assessed using expert judgment. Two possible approaches include *coding* and *card sorting*. In the coding approach [60], experts are asked to go over the grosslist of uncertainty sources and code each source as being either of a) crucial importance; b) of importance; or c) of medium importance. This is a “quick and dirty” technique and, to avoid errors and biases, several experts should do this independently and discuss potential differences in their judgments. The card sorting approach (used by e.g. [61;62]) is more advanced and involves organizing an expert workshop. Any missing or incorrectly characterized uncertainty sources on the gross-list can be addressed during such a workshop. Experts are asked to independently select the top 20% (or another percentage) sources of uncertainty that they consider most important in view of their impact on the eBOD calculation at hand, and sort these according to importance. The uncertainties are displayed on cards to facilitate the sorting – hence the name. Results from individual experts are combined to arrive at a group ranking of the items on the gross-list. Arguments used by the experts to defend their ranking should be documented and special attention should be given to reasons for any substantial disagreement on the importance of a particular uncertainty source on the gross-list.

3. Once the prioritization has been done, appropriate tools can be selected for further analysis of the key uncertainties identified. Each uncertainty type requires another method

to best address it, and to gauge its impact on decision-making. The uncertainty tool catalogue by Van der Sluijs et al [63] provides guidance to select appropriate methods based on the typology of uncertainties. Additionally, Refsgaard and co-workers[64] distinguish methods according to their purpose within the process of dealing with
550 uncertainties.

It may not be possible to correctly identify, characterize and prioritize all sources of uncertainty right in the beginning of the project. The typology may thus be reassessed throughout the project: new sources of uncertainty may be added or their weights may be
555 adjusted. The uncertainty typology should therefore be used interactively during the process of an eBOD assessment. A such, it also provides a framework to keep track of all sources of uncertainty during the assessment process, so that sources identified early in the project – especially those that cannot be quantified - are not forgotten at the end of the study, when the uncertainties are typically quantified.

560

Communicating uncertain results to policy makers

Most policy makers will feel more comfortable to make decisions based on single, undisputed numbers with small uncertainty ranges than on ambiguous, uncertain and controversial
565 estimates and different scenario analyses. However, unfortunately that is not the way complex processes can be described. On the other hand, giving policy makers a 100+ paged report listing all the possible uncertainties won't lead to informed policy making either. Scientists can help policy makers by assessing which uncertainties are most policy relevant, and identifying and prioritizing policy options that are robust given these uncertainties. If no
570 single best policy option for all scenarios can be determined, the conditional robustness can be analyzed and options can be discussed in a democratic process including scientists,

stakeholders, policy makers and politicians[65]. As the communication needs of all these parties can vary greatly, one mode of risk communication is rarely sufficient.

575 Uncertainties can be communicated linguistically, numerically, or graphically. Confidence intervals can be provided reflecting uncertainty in parameters and input data. For uncertainties that cannot be expressed in statistical intervals, other characterizations of likelihood can be used to communicate uncertainty at a level appropriate to existing scientific understanding. Risbey and co-workers[66] distinguish different expressions for different levels of precision, 580 ranging from full well defended probability density functions; to well defended percentile bounds; first order estimates; expected signs or trends; ambiguous signs or trends and finally to effective ignorance. Many of the uncertainties identified in our study cannot be captured quantitatively, but some can be expressed in these latter characterizations of precision. In presenting summary measures, the assumptions being made and the definitions being used 585 need to be explicit. The reader disagreeing with the assumptions should then be able to recalculate any estimates using his/her own assumptions [67]. Providing a graphical representation of the underlying causal web in a standardized way can support further understanding of the assessment context and model structure.

590 In order not to overwhelm the user of the assessment results with uncertainties, the concept of 'progressive disclosure of information' can be employed[68;69], in which information about uncertainty is gradually provided in various custom-made layers. In the 'outer layers' – used in e.g. a press release or a project summary – policy relevant uncertainties should be integrated in the main messages, emphasizing their implications and policy or societal 595 relevance, but without any technical details. More 'inner' layers of communication contain specific, detailed and balanced information about all uncertainties, with emphasis on nature, extent and sources of uncertainties. A policy maker using an eBOD assessment will therefore not be directly confronted with a typology of all uncertainties, but will be provided with policy-critical uncertainty information and the proper interpretation and context of the results.

600 Writers should be aware that the time spent on reading reports is often limited, and most
attention will be paid to primary sections of the report such as the summary, conclusions and
recommendations. In that light, it is important to make sure all critical uncertainties are being
clearly and credibly addressed and properly framed in all these primary sections[69]. The
report should present all calculation methods, assumptions, parameters and input data, thereby
605 providing maximum transparency of the assessment approach. Even though DALYs are made
to reduce complex information to single numbers, it is essential to allow readers to unravel the
DALYs and, when desired, reproduce them[11;49]. Fox-Rushby and Hanson[4] show that 9
out of 16 papers on burden of disease published between 1993 and 2000 do not state which
assumptions are adopted.

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The assertion that burden of disease figures can only be properly interpreted when presented
with assessment-specific, informative and complete background information leads to a second
consideration related to the usability of assessment results. These results can only be used for
the specific purpose (policy question) they were derived for, and cannot just simply be used in
615 other assessments or for other policy purposes.

Conclusions and suggestions for further research

620 Disability Adjusted Life Years – or other forms of aggregated health measures – can be very
attractive indicators for policy makers. The measure combines information about the
magnitude, severity and duration of negative health responses in one number, thereby
providing a means to compare otherwise incomparable environmental health problems. This
simplification of the complex underlying reality is both the advantage as well as the pitfall of
625 the measure. We have shown that various sources of uncertainty can influence environmental
burden of disease (eBOD) assessments and their output, thereby potentially influencing policy

decisions based on these assessments. Statistically quantifiable uncertainty in parameters and input data – the type of uncertainty that is usually communicated in eBOD assessments – is far from the only type of uncertainty. Variations in definitions of the environment and health factors and scenarios to be assessed, unknown impacts of e.g. multi-causality and co-morbidity, lacking consensus about causality, controversial views about model structures, etc.: these issues affect many eBOD assessments, but cannot be easily quantified, and are usually not fully addressed.

Increased awareness of the issue of uncertainty and a well-structured approach towards assessing and communicating uncertainties can help to bring about a more balanced interpretation of the results of eBOD assessments. A typology of uncertainties such as presented in this paper can be used to systematically identify and map key uncertainties – both quantitative and qualitative. It supports the identification of all relevant sources of uncertainty and a prioritization based on a qualitative assessment of their importance. The use of the typology may facilitate a structured dialogue between scientists and stakeholders on possible sources and types of uncertainty. This helps the key actors to achieve a common understanding on the uncertainties and their importance. The main limitation of the typology is that it strongly relies on expert judgment and mainly yields qualitative insight. However, ‘dealing’ with uncertainties does not necessarily have to mean ‘reducing’ them. Most of the time, mere identification and proper communication of uncertainties along with systematic reflection on the policy implications of these uncertainties is most important, or – more practically – the only feasible thing to do. Ideally, policies should be robust under the uncertainties identified.

The potential extent of uncertainties presented here should not be interpreted as criticism towards to the DALY approach as such, or as argumentation for not using the method. Instead, for some assessments, DALYs can be a very valuable way of presenting the possible extent of environmental health effects to policy makers. Uncertainties do not halt impact

655 assessments, but do affect the assessment process and the interpretation and communication
of its results. Scientists have the responsibility to assess and communicate risk assessments in
such a way that underlying uncertainties are reflected in the outcomes. Results should not be
presented as being more robust than can be inferred from the underlying knowledge base.
And policy makers, for their part, have the responsibility to take uncertainty information
660 seriously and deal with it sensibly[70].

In the meantime, on a meta-level, the methodology for calculating the eBOD and dealing with
uncertainties needs to be improved[27]. For example, the disproportional way in which
uncertainty in small severity weights affects overall assessment uncertainty should be studied,
665 with solutions perhaps lying in normalizing this weighting factor. Further research on
summary measures can perhaps in the future lead to better measures than DALYs, an area
already explored by Murray[27]. It is not possible to harmonize the use of methods and
knowledge or to standardize datasets, since these are highly assessment specific (and should
stay that way). However, the criteria used for deliberating which methods and dataset could
670 be used should be harmonized to the extent possible. Besides, further effort should be
invested in monitoring and improving environment and health data sets.

Competing interests

675 No competing interests

Authors' contributions

ABK initiated the research and studied the environmental burden of disease literature. ACP
and JPS designed and described the uncertainty typology. All authors discussed the

680 application of the uncertainty typology to the case of environmental burden of disease
assessment. ABK drafted the main manuscript using detailed input from ACP, JPS and EL.
All authors read and approved the final manuscript.

685 **References**

1. Briggs DJ, Sabel CE, Lee K. Uncertainty in epidemiology and health risk and impact assessment. *Environ.Geochem.Health* 2008;DOI 10.1007/s10653-008-9214-5.
- 690 2. Smith KR, Corvalan CF, Kjellstrom T. How much global ill health is attributable to environmental factors? *Epidemiology* 1999;10(5):573-84.
3. Melse, J. M. and de Hollander, A. E. M. Environment and health within the OECD region: lost health, lost money. Background document to the OECD Environment Outlook. 402101.001. 2001. Bilthoven, the Netherlands, RIVM.
- 695 4. Fox-Rushby JA, Hanson K. Calculating and presenting disability adjusted life years (DALYs) in cost-effectiveness analysis. *Health Policy Plan.* 2001;16(3):326-31.
5. Prüss-Ustün A, Bonjour S, Corvalán C. The impact of the environment on health by country: a meta-synthesis. *Environ.Health* 2008;7:7.
- 700 6. WHO. Preamble to the Constitution of the World Health Organization as adopted by the International Health Conference, New York, 19-22 June. signed on 22 July 1946 by the representatives of 61 States (Official Records of the World Health Organization, no. 2, p. 100) and entered into force on 7 April 1948. 1946.
- 705 7. Murray CJ, Ezzati M, Lopez AD, Rodgers A, van der Hoorn S. Comparative quantification of health risks conceptual framework and methodological issues. *Popul.Health Metr.* 2003;1(1):1.
8. Saltelli A, Chan K, Scorr E. *Sensitivity Analysis: Gauging the Worth of Scientific Models.* John Wiley and Sons Ltd; 2000.
- 710 9. Saltelli A, Tarantola S, Campolongo F, Ratto M. *Sensitivity Analysis in Practice. A Guide to Assessing Scientific Models.* John Wiley & Sons Ltd.; 2004.
10. Saltelli A, Ratto M, Andres T. *Global Sensitivity Analysis - The Primer.* John Wiley and Sons Ltd; 2008.
- 715 11. Nurminen M, Nurminen T, Corvalan CF. Methodologic issues in epidemiologic risk assessment. *Epidemiology* 1999;10(5):585-93.
12. van der Sluijs JP, Petersen AC, Janssen PHM, Risbey JS, Ravetz JR. Exploring the quality of evidence for complex and contested policy decisions. *Environmental Research Letters* 2008;DOI:10.1088/1748-9326/3/2/024008(024008 (9pp)).
13. Anand S, Hanson K. Disability-adjusted life years: a critical review. *J Health Econ.* 1997;16(6):685-702.
- 720 14. Arnesen T, Nord E. The value of DALY life: problems with ethics and validity of disability adjusted life years. *BMJ* 1999;319(7222):1423-5.
15. World Bank. *World Development Report 1993: Investing in Health.* 1993.

- 725 16. Murray CJ, Lopez AD. *The Global Burden of Disease*. Cambridge, MA: Harvard University Press; 1996.
17. Funtowicz S, Ravetz J. *Uncertainty and quality in science for policy*. Dordrecht, the Netherlands: Kluwer Academic Publishers; 1990.
- 730 18. van der Sluijs JP. *Anchoring amid uncertainty; On the management of uncertainties in risk assessment of anthropogenic climate change [PhD Thesis]*. [dissertation]. Utrecht University; 1997.
19. Walker WE, Harremoes P, Rotmans J, van der Sluijs JP, van Asselt MBA, Janssen PH et al. Defining uncertainty. A conceptual basis for uncertainty management in model-based decision support. *Integr Assessment* 2003;4:5-17.
- 735 20. Janssen PHM, Petersen AC, van der Sluijs JP, Risbey JS, Ravetz JR. A guidance for assessing and communicating uncertainties. *Water Sci.Technol.* 2005;52(6):125-31.
21. Petersen AC. *Simulating nature: A philosophical study of computer-simulation uncertainties and their role in climate science and policy advice*. Available at: <http://hdl.handle.net/1871/11385> [dissertation]. Apeldoorn and Antwerp: Het Spinhuis Publishers; 2006.
- 740 22. Petersen AC. A typology of uncertainty in scientific simulation. (submitted) 2008.
23. Kraye von Krauss MP. Response to "To what extent, and how, might uncertainty be defined" by Norton, Brown, and Mysiak. *Integrated Assessment* 2006;6(1):89-94.
- 745 24. Norton J. To what extent, and how, might uncertainty be defined? Comments engendered by "Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support": Walker et al., *Integrated Assessment* 4: 1, 2003. *Integrated Assessment* 2006;6(1):83-8.
25. Prüss-Ustün A, Corvalán C. How much disease burden can be prevented by environmental interventions? *Epidemiology* 2007;18(1):167-78.
- 750 26. Prüss-Ustün, A. and Corvalán, C. Preventing disease through healthy environments. Towards an estimate of the environmental burden of disease. 2006. WHO.
27. Murray CJ, Salomon JA, Mathers C. A critical examination of summary measures of population health. *Bull.World Health Organ* 2000;78(8):981-94.
28. Mont D. Measuring health and disability. *Lancet* 2007;369(9573):1658-63.
- 755 29. Saracci R, Vineis P. Disease proportions attributable to environment. *Environ.Health* 2007;6:38.
30. Kovats RS, Campbell-Lendrum D, Matthies F. Climate change and human health: estimating avoidable deaths and disease. *Risk Anal.* 2005;25(6):1409-18.
- 760 31. Mathers CD, Salomon J, Ezzati M, Begg S, van der Hoorn S, Lopez AD. Sensitivity and uncertainty analyses for burden of disease and riskfactors estimates. In: Lopez AD, Mathers CD, Ezzati M, Jamison DT, Murray JLM, editors. *Global burden of disease and risk factors*. New York: Oxford University Press; 2006. p. 399-426.

32. Lucas R. Environmental disease burden - the confused case of UVR exposure. *Environ.Health* 2007;6(38).
- 765 33. van Kempen, E. E. M. M., Staatsen, B. A. M., and van Kamp, I. Selection and evaluation of exposure-effect-relationships for health impact assessment in the field of noise and health . 630400001, 1-77. 2005. Bilthoven, RIVM.
- 770 34. Lipton R, Odegaard T. Causal thinking and causal language in epidemiology: it's in the details. *Epidemiol Perspect.Innov.* 2005;2:8.
35. Phillips CV, Goodman KJ. Causal criteria and counterfactuals; nothing more (or less) than scientific common sense. *Emerg.Themes.Epidemiol* 2006;3:5.
- 775 36. Valent F, Little D, Bertollini R, Nemer LE, Barbone F, Tamburlini G. Burden of disease attributable to selected environmental factors and injury among children and adolescents in Europe. *Lancet* 2004;363(9426):2032-9.
37. Smith KR. Inaugural article: national burden of disease in India from indoor air pollution. *Proc.Natl.Acad.Sci.U.S.A* 2000;97(24):13286-93.
- 780 38. Ezzati M, Hoorn SV, Rodgers A, Lopez AD, Mathers CD, Murray CJ. Estimates of global and regional potential health gains from reducing multiple major risk factors. *Lancet* 2003;362(9380):271-80.
39. Lopez AD, Mathers CD, Ezzati M, Jamison DT, Murray CJL. Measuring the global burden of disease and risk factors, 1990-2001. In: Lopez AD, Mathers CD, Ezzati M, Jamison DT, Murray JLM, editors. *Global burden of disease and risk factors*. New York: Oxford University Press; 2006. p. 1-13.
- 785 40. Ezzati M, van der Hoorn S, Lopez AD, Danaei G, Rodgers A, Mathers CD et al. Comparative quantification of mortality and burden of disease attributable to selected major risk factors. In: Lopez AD, Mathers CD, Ezzati M, Jamison DT, Murray CJ, editors. *Global burden of disease and risk factors*. New York: Oxford University Press; 2006. p. 241-68.
- 790 41. European Environment Agency. *An Approach to Multi-Causality in Environment & Health*. nog aanvullen 2003.
42. Health Council of the Netherlands (HCN). *Radon: Evaluation 'BEIR VI'*. publication no. 2000/05, 1-32. 2000. The Hague.
- 795 43. Refsgaard JC, van der Sluijs JP, Brown J, van der Keur P. A Framework For Dealing With Uncertainty Due To Model Structure Error. *Advances in Water Resources* 2006;29(11):1586-97.
44. Small MJ. Methods for assessing uncertainty in fundamental assumptions and associated models for cancer risk assessment. *Risk Anal.* 2008;28(5):1289-308.
- 800 45. Droguett EL, Mosleh A. Bayesian methodology for model uncertainty using model performance data. *Risk Anal.* 2008;28(5):1457-76.

46. Niemeijer D, de Groot R. Framing environmental indicators: moving from causal chains to causal networks. *Environment, Development and Sustainability* 2006;10(1):89-106.
- 805 47. Nilunger L, Diderichsen F, Burström B, Ostlin P. Using risk analysis in Health Impact Assessment: the impact of different relative risks for men and women in different socio-economic groups. *Health Policy* 2004;67(2):215-24.
48. Knol, A. B. and Staatsen, B. A. M. Trends in the environmental burden of disease in the Netherlands, 1980 - 2020. 500029001 . 2005. Bilthoven, the Netherlands, RIVM.
- 810 49. Arnesen T, Kapiriri L. Can the value choices in DALYs influence global priority-setting? *Health Policy* 2004;70(2):137-49.
50. van Kempen EEMM. Milieu-DALY's: zieketelast die wordt veroorzaakt door blootstelling aan milieufactoren. Ontwikkeling van wegingsfactoren voor verschillende effecten van milieuverontreiniging en een schatting van de omvang van deze effecten. [dissertation]. University of Maastricht; 1998.
- 815 51. de Hollander AE, Melse JM, Lebrecht E, Kramers PG. An aggregate public health indicator to represent the impact of multiple environmental exposures. *Epidemiology* 1999;10(5):606-17.
- 820 52. Nijland H, van Wee G. Traffic noise in Europe: a comparison of calculation methods, noise indices and noise standards for road and railroad traffic in Europe. *Transport Reviews* 2005;25(5):591-612.
53. Kruijshaar ME, Barendregt JJ, Hoeymans N. The use of models in the estimation of disease epidemiology. *Bull. World Health Organ* 2002;80(8):622-8.
- 825 54. EPA (U.S. Environmental Protection Agency). Data Quality Assessment: A reviewer's guide (QA/G-9R). Available: <http://www.epa.gov/quality/qs-docs/g9r-final.pdf> 2006.
55. van der Sluijs JP, Craye M, Funtowicz S, Kloprogge P, Ravetz J, Risbey J. Experiences with the NUSAP system for multidimensional uncertainty assessment in model based foresight studies. *Water Sci. Technol.* 2005;52:133-44.
- 830 56. van der Sluijs JP, Craye M, Funtowicz S, Kloprogge P, Ravetz J, Risbey J. Combining quantitative and qualitative measures of uncertainty in model-based environmental assessment: the NUSAP system. *Risk Anal.* 2005;25(2):481-92.
57. SETAC. Life-Cycle Assessment Data Quality: A Conceptual Framework. 1994. Pensacola, FL, Society of Environmental Toxicology and Chemistry and SETAC Foundation for Environmental Education.
- 835 58. Beck L, Wilson D. EPA's data attribute rating system. *Proc. Speciality Conf. on Emission Inventory: Planning for the future* 1997:176-89.
- 840 59. Mathers CD, Murray CJ, Lopez AD. Epidemiological evidence: improving validity through consistency analysis. *Bull. World Health Organ* 2002;80(8):611.

60. Janssen, P. H. M, Petersen, A. C., van der Sluijs, J. P., Risbey, J. S., and Ravetz, J. R. Guidance for uncertainty assessment and communication - Quicksan Hints & Actions List (appendix I). 2003. RIVM/MNP.
- 845 61. Kloprogge, P, van der Sluijs, J. P., and Petersen, A. C. A method for the analysis of assumptions in assessments. 550002010/2005. 2005. Copernicus Institute for Sustainable Development and Innovation.
- 850 62. Kloprogge P, van der Sluijs JP, Petersen AC. A method for the analysis of assumptions in model-based environmental assessments. Environmental Modelling & Software (submitted) 2009.
- 855 63. van der Sluijs, J. P., Janssen, P. H. M, Petersen, A. C., Kloprogge, P, Risbey, J. S., Tuinstra, W, and Ravetz, J. R. RIVM/MNP Guidance for Uncertainty Assessment and Communication: Tool Catalogue for Uncertainty Assessment. NWS-E-2004-37. 2004. Utrecht/Bilthoven, Copernicus Institute & RIVM.
64. Refsgaard JC, van der Sluijs JP, Hojberg j., Vanrolleghem PA. Uncertainty in the environmental modeling proces: A framewordk and guidance. Environmental Modeling& Software 2007(22):1543-56.
- 860 65. Pielke R. The Honest Broker: Making Sense of Science in Policy and Politics. Cambridge: Cambridge University Press; 2007.
66. Risbey JS, van der Sluijs JP, Kloprogge P, Ravetz J, Funtowicz S, Quintana CS. Application of a checklist for quality assistance in environmental modelling to an energy model. Environmental Modeling & Assessment 2005;10(1):63-79.
- 865 67. Soskolne C. Advancing methods for environmental burden of disease calculations. Environ.Health 2007;6(38).
68. Wardekker JA, van der Sluijs JP, Janssen PHM, Kloprogge P, Petersen AC. Uncertainty communication in environmental assessments: Views from the Dutch Science-Policy interface. Environmental Science Policy 2008(11):627-41.
- 870 69. Kloprogge, P, van der Sluijs, J. P., and Wardekker, J. A. Uncertainty communication: issues and good practice. NWS-E-2007-199, 1-60. 2007. Utrecht, Department of Science Technology and Society, Copernicus Institute, Utrecht University.
- 875 70. Petersen AC, van Asselt MBA. Conclusions and recommendations. In: Mathijssen J, Petersen AC, Besseling P, Rahman A, Don H, editors. Dealing with Uncertainty in Policymaking. PBL Report 550032011 ed. The Hague/Bilthoven/Leiden: CPB/PBL/Rand Europe; 2008.

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Figures and tables

885 (uploaded separately)

Figure 1: Possible boundaries of the definition of ‘environment’ [2]

Table 1: Typology of uncertainty

Uncertainty characterizations	Categories
Location: the location at which the uncertainty manifests itself in the assessment	Context : The definitions and boundaries of the assessment within the context of the underlying policy question
	Model structure: Structure and form of the relationships between model variables that describe the system
	Parameters: Constants in functions that define relationships in environmental health impact assessment models (relative risks, severity weights)
	Input data: Input data sets (concentrations, demographic data, prevalence, incidence)
Nature: the underlying cause of the uncertainty	Epistemic: resulting from incomplete knowledge
	Ontic
	Process variability, resulting from natural and social variability in the system Normative uncertainty, resulting from a plurality of socio-ethico-normative considerations within a society
Range: a quantitative estimate of the uncertainty	Statistical (range + chance) : specified probabilities and specified outcomes
	Scenario (range + “what if”) : specified outcomes, unspecified probabilities
Recognized ignorance: unknown outcomes, unknown probabilities – uncertainties are present, but no useful estimate can be given	
Methodological unreliability: Methodological quality of all different elements of the assessment; a qualitative judgment of the assessment process which can be based on e.g. its theoretical foundation, empirical basis, reproducibility and acceptance within the peer community	
Value diversity among analysts: Potential value-ladenness of assumptions which inevitably involve – to some degree – arbitrary judgments by the analysts.	

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Table 2: Illustrations of characterizations of uncertainties in environmental burden of disease assessments

CONTEXT UNCERTAINTY						
Source of uncertainty		<i>Nature</i> Epistemic / Ontic (Process Variability/ Normative Uncertainty)	<i>Range</i> Statistical/ Scenario	<i>Recognized ignorance</i>	<i>Methodo- logical unreliability</i>	<i>Value diversity among analysts</i>
1	Multiple ways of defining the 'total environment'	E/Nor	Sc	-	+	++
2	Only including diseases that cause at least 1% of the global burden of disease	Nor	Sc	--	--	+
MODEL STRUCTURE UNCERTAINTY						
3	Specific form of the exposure-response relationship is unknown	E	Sc	+	+	+
4	Evidence for causality (environmental factor leading to health effect) is weak and contradicting	E	Sc	++	++	+
5	Incomplete understanding of the joint effect of smoking and radon in relation to lung cancer	E	Sc	+	+	+
6	Accounting for susceptibility of the individual	Pro/ E	St	+	+	+
PARAMETER UNCERTAINTY						
7	Determining a relative risk (RR) for long-term exposure to PM ₁₀	E	St	+	+	-
8	Applying an American RR for PM ₁₀ to the Netherlands	E	Sc	++	+	+
9	Estimating the average duration of effects related to long-term exposures	E	St	+	+	+
10	Use of severity weights	Nor/ E	Sc	+	+	++
INPUT DATA UNCERTAINTY						
11	Extrapolating non-assessment-specific exposure measurements	E	Sc	++	+	+
12	Measuring population exposure	E	St	+	+	-

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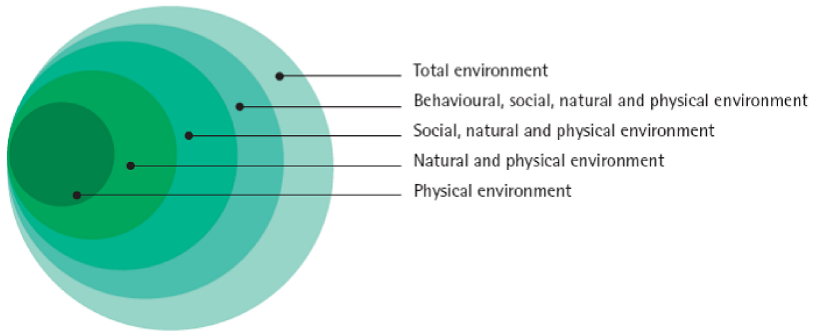


Figure 1