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A review of uncertainty in environmental risk: characterising potential natures, locations, and levels.

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Abstract

Uncertainties, whether due to randomness or human or system errors, are inherent within any decision process. In order to improve the clarity and robustness of risk estimates and risk characterisations, environmental risk assessments (ERAs) should explicitly consider uncertainty. Typologies of uncertainty can help practitioners to understand and identify potential types of uncertainty within ERAs, but these tools have yet to be reviewed in earnest. Here we have systematically reviewed 30 distinct typologies and the uncertainties they communicate, and demonstrate that they: (i) use terminology that is often contradictory; (ii) differ in the frequencies and dimensions of uncertainties that they include; (iii) do not uniformly use systematic and robust methods to source information; and (iv) cannot be applied, on an individual basis, to the domain of ERA. On the basis of these observations we created a summary typology – consisting of seven locations (areas of occurrence) of uncertainty across five distinct levels (magnitude of uncertainty) – specifically for use with ERAs. This work highlights the potential for confusion given the many versions of uncertainty typologies which exist for closely related risk domains and, through the summary typology, provides environmental risk analysts with information to form a solid foundation for uncertainty analysis (based on improved understanding) to identify uncertainties within an ERA.

Keywords: uncertainty, typology, environmental, risk, assessment

1. Introduction

Uncertainty is a concept that is used inconsistently within the general literature, but is defined as limitations in knowledge about environmental impacts and the factors that influence them (which can range from randomness to human error; Defra 2011). There are many different types of uncertainties, some of which are context dependent. Uncertainties are inherent to environmental risk assessments (ERAs) and can lower confidence in the risk estimate, in turn weakening the basis for risk management actions (Verdonck *et al.* 2007). Risk analysts recognise that ERAs should explicitly consider uncertainty (Funtowicz and Ravetz 1990; Costanza *et al.* 1992; Handmer *et al.* 2001) by undergoing an uncertainty analysis. However, uncertainty analyses can fail to identify uncertainties within systems (Dale *et al.* 2007) and there are no formal processes which inform this analysis.

The identification of uncertainties within ERAs relies on expert judgement or risk analysts considering lists of potential uncertainties (typologies). These uncertainty typologies aim to define and communicate the important features of uncertainty within a specific domain. Uncertainty typologies are useful in helping practitioners better understand the associated concepts (Morgan and Henrion 1990), and also act as tools to aid uncertainty identification (Knol *et al.* 2009). Uncertainties cannot be managed if they are not identified, and they may not be identified if the potential types of uncertainty are not understood (Figure 1). As such, typologies play a pivotal role in uncertainty analysis, since an incomplete typology may lead to an incomplete uncertainty analysis and a misleading risk assessment. Therefore, the definitions and divisions within typologies should be comprehensive and applicable to the area in which they are to be used (e.g. ERAs; Knol *et al.* 2009).

[FIGURE 1 NEAR HERE]

Recent research has identified some of the issues associated with the use of uncertainty typologies, for example, that their creation can rely on potentially subjective expert judgement (Knol *et al*. 2009), that their successful implementation can depend on the skill and experience of the end-user (Gillund *et al.* 2008), and that no typology exists which "includes all of its meanings in a way that is clear, simple, and adequate for each potential use of such a typology" (Petersen 2006). However, the full extent of these problems and their potential impacts are not clear.

Significantly, uncertainty is interpreted differently by different people (Refsgaard *et al* 2007; Troldborg 2010). For example, protection and regulatory agencies often adopt brief high-level explanations (Fairman *et al.* 1998; US EPA 1998; DEFRA 2011). In reality, uncertainty is complex and in many cases the full concept is difficult to communicate or condense into one or two sentences. Early research into uncertainty focussed on characterising the physical flaws in acquiring experimental data (Veseley and Rasmuson 1984; Henrion and Fischoff 1986; Alcamo and Bartnicki 1987; Beck 1987). More recently, uncertainty has been investigated though its constituent dimensions (Walker *et al.* 2003), namely its: *nature*, describing how the uncertainty has come to exist, either due to the incompleteness of knowledge or the inherent variability of natural systems; *location*, where the uncertainty is manifest in the system of interest, for example in the data being recorded, the models utilised, or the decisions taken; and *level*, representing the significance of the uncertainty, ranging from deterministic understanding of the uncertainty at one end of the spectrum (a low level of uncertainty) to ignorance at the other end (a high level of uncertainty). If the different types of uncertainty within each dimension were understood by risk analysts it would then be more likely that they would be identified in applied scenarios. Uncertainty typologies are integral to this process.

In researching this topic, we note that many risk assessments fail to address uncertainty at all, which does undermine the quality of these assessments and the confidence placed in risk estimates. A robust uncertainty typology (non-domain specific) may help to address this oversight. Therefore there is a need to review and analyse the typologies available to environmental risk analysts, in order to ascertain whether they are comprehensive and applicable, and if not, to highlight the ways in which they could be improved.

2. Review considerations and methodology

When uncertainty typologies are used to aid uncertainty understanding and identification, some risk analysts use a single typology, but it is more likely that several will be used (van Asselt and Rotmans 2002). Whilst individual typologies should be comprehensive, ideally when combined the typologies should also be consistent in definition and identification. In order to examine the uncertainty typologies, we have systematically reviewed distinct versions – individually and as a group – and the uncertainties they communicate across a range of environmental risk domains, including integrated modelling, human and ecological risk assessment, and policy analysis. In doing so, we have: (i) explored the intra and inter-typology conflicts; (ii) examined their applicability to ERAs, drawing from uncertainties identified within existing assessments; (iii) provided a summary typology for use with ERAs and (iv) provided suggestions for ways in which we may be able to move uncertainty typologies, and therefore uncertainty analysis, forward.

We identified 30 uncertainty typologies (Table 1) that are either based in the domain of ‘environmental risk’ or that make reference to it. The typologies were published in peer-reviewed articles or books and were sourced using online academic search engines. A thorough check of the references provided by each source was also performed, which ensured the identification of relevant typologies not identified in the initial search. Some sources are not specifically labelled as typologies by their authors whilst others are presented as original typologies that are explained and justified in full. Unlabelled typologies were included in this research if it was believed that they played the role of a typology – e.g. provided systematic classification of types that have characteristics or traits in common. All relevant typologies have been included in this review article, to the best of the researchers' knowledge. Each typology was analysed for the types of uncertainties contained within it, the number of dimensions communicated, and their applicability to ERAs.

[TABLE 1 NEAR HERE]

3. Uncertainties communicated by existing typologies

3.1 The nature, location, and level of uncertainty in context

The nature of the uncertainty, which describes how the uncertainty has come to exist, dictates the degree to which it can be managed; knowledge-based (epistemic) uncertainties can be quantified, reduced, and potentially removed, whilst it may only be possible to quantify those uncertainties which are inherently random (known as aleatory). Separately, the location of the uncertainty, where the uncertainty occurs within an assessment, must be known to implement a management action. Finally, the level (or magnitude) of the uncertainty will inform the selection of the most appropriate management technique (Refsgaard *et al.* 2007). Therefore, in order to effectively manage uncertainty, it is essential that all dimensions are considered (Walker *et al.* 2003; Janssen *et al.* 2003; Refsgaard *et al.* 2007; Knol *et al.* 2009). The uncertainties that the 30 selected typologies communicate are described in the remainder of this section, and are organised according to these three dimensions of uncertainty with definitions and examples selected from the evidence base.

3.2 Nature of uncertainty

3.2.1 Aleatory uncertainty

Aleatory uncertainty (Bedford and Cooke 2001; Ascough II *et al.* 2008) represents the inherent randomness displayed in human and natural systems. It is also referred to as physical (Vesely and Rasmuson 1984), stochastic (Helton 1994), variability (Hoffman and Hammonds

1994; Janssen *et al.* 2003; Walker *et al.* 2003; Hayes 2006), random (Bevington and Robinson 2002; Regan *et al.* 2002), or ontic (Petersen 2006; Knol *et al.* 2009). Aleatory uncertainty cannot be reduced, although additional research may help to better understand the complexities of the system(s) of interest. Whilst such systems may actually be chaotic (i.e. epistemic) rather than random (i.e. aleatory; and are therefore in principle understandable; Regan *et al.* 2002), many risk analysts find it useful to treat the associated uncertainties as if they are random, primarily employing stochastic numerical techniques to quantify uncertainty. In mimicking nature, stochastic methods can produce results that are consistently more representative than their non-random counterparts (Hromkovic 2005), adding real value to the ERA process.

3.2.2 Epistemic uncertainty

Epistemic uncertainty (Bedford and Cooke 2001; Walker *et al.* 2003; Petersen 2006; Ascough II *et al.* 2008; Knol *et al.* 2009) is the imperfection of knowledge concerning a system of interest. Epistemic uncertainty is also termed completeness (Vesely and Rasmuson 1984; Rowe 1994), subjective (Helton 1994), knowledge-based (Hoffman and Hammonds 1994; Janssen *et al.* 2003), or systematic (Bevington and Robinson 2002). In contrast to aleatory uncertainty, epistemic uncertainty can be quantified, reduced, and possibly eliminated, depending on the specific situation. However, additional information gathered to reduce uncertainty may instead reveal our true lack of knowledge thereby increasing the associated uncertainty (Janssen *et al.* 2003; van der Keur 2008).

3.2.3 Nature of uncertainty in environmental risk assessments

It can be difficult to distinguish between epistemic and aleatory uncertainty in applied ERAs, since the dividing line can be blurred by problem-specific features and the current level of subject knowledge (Janssen *et al.* 2003). This is important as it is increasingly recognised that (epistemic) uncertainty and (aleatory) variability need to be treated separately (Li *et al.* 2008; Kumar *et al.* 2009; Qin and Huang 2009), due to the differing degrees to which they can be managed.

Whether epistemic or aleatory, all uncertainties must also be considered in terms of their two other dimensions.

3.3 Location of uncertainty

3.3.1 System

This refers to the causes, processes, and effects within the investigated systems (or environment, identified prior to, or at the beginning of, the risk assessment). One or more conceptual models of a system should be developed in the initial stages of an ERA to help to identify the attributes that are unique to that system, (Defra 2011). In the conceptual model the analyst(s) must set boundaries that force the inclusion and exclusion of important features, potentially affecting the completeness of the assessment (Walker *et al.* 2003; Janssen *et al.* 2003). Within this process, problems can result from a lack of understanding about the system of interest (Rowe 1994) or, in some cases, from too much information leading to multiple frames of reference being used to understand a phenomenon (Dewulf *et al.* 2005). The associated uncertainties are termed contextual (Walker *et al.* 2003; Janssen *et al.* 2003; when the issue is ill-defined), conceptual (Rowe 1994; analysis of the issue), ambiguity (Dewulf *et al.* 2005; inexactness of data), and process (Ascough II *et al.* 2008). From either position (too much or too little information), the uncertainties reflect the limits of scientific understanding about the risk. Generally, where understanding is low, uncertainty will be high and vice-versa. System uncertainty can therefore impact ERAs wherever understanding is lacking. However, a field which develops rapidly, such as nanotechnology, can contain high levels of knowledge as well as system-related uncertainties, due largely to the unknowns associated with novel technologies. For example, the contribution of physical structure to a nanoparticle's toxicity (i.e. effect) may only be partly understood, whilst its relevance (i.e. exposure) to different receptors of interest may simply be unknown. (Zalk *et al.* 2009). Such system uncertainties can therefore impact the exposure and effects phases of ERAs.

3.3.2 Data

Whether empirical or experimental, all data carries a level of inherent confidence associated with its correctness. According to Morgan and Henrion (1990), the most common data uncertainty concerns errors in direct measurements. This type of uncertainty, either termed statistical (Morgan and Henrion 1990; Finkel 1990), random (Henrion and Fischoff 1986), or measurement (Regan *et al.* 2002), refers to the variation across multiple measurements of the same quantity. All measurable empirical quantities potentially contain this uncertainty (Morgan and Henrion 1990). The magnitude of this uncertainty can be quantified through statistical testing of the unexplained variation in measurements (Henrion and Fischoff 1986).

Systematic uncertainty (Henrion and Fischoff 1986; Finkel 1990; Morgan and Henrion 1990; Regan *et al.* 2002) is the difference between the true value of an item and the value to which the mean of the measurements converge as the sample size increases (Morgan and Henrion 1990; Regan *et al.* 2002), and can be much harder to quantify. This type of uncertainty is addressed by detecting errors in the experimental procedure, and generated data, and attempting to eliminate them. Separate data concerns arise from the analysis and interpretation of data (Regan *et al.* 2002; Maier *et al.* 2008), and from incomplete or unavailable data records (Maier *et al.* 2008).

In the context of ERAs, data uncertainties are most common in the analysis phase, where original experimental data is primarily used. For example, McColl *et al.* (2000) discuss the effect that a limited or erroneous data record can have when determining the dose-response levels for use in a contaminated site assessment, which may then be adopted in other assessments, potentially in different disciplines. The data uncertainties discussed should be managed because they directly impact on estimates of risk and, by extension, the quality of environmental decision-making (Faucheux and Froger 1995).

3.3.3 Model

Modelling, in the form of numerical or computational simulation, can be used to understand processes and provide evidence to support decision-making (Arhonditsis *et al.* 2007). The associated procedures routinely involve an initial conceptualisation stage (see Section 3.3.1), which is developed into a numerical and/or computational representation of the system under study (Stephens *et al.* 1993). Modelling relies heavily on data, primarily for input and validation purposes.

Parameter uncertainty (Alcamo and Bartnicki 1987; Beck 1987; Morgan and Henrion 1990; Bedford and Cooke 2001; Huijbregts *et al.* 2001; Janssen *et al.* 2003; Walker *et al.* 2003; Maier *et al.* 2008; Ascough II *et al.* 2008) is a reflection of the uncertainties associated with the data used to develop the model (see Section 3.3.2). The parameters are the unvarying constants within a model and may be exact (e.g. π), fixed (e.g. the gravitational constant g), measured *a priori*, or derived through calibration (Walker et al. 2003; Krayer von Kraus 2005). The data are collected from different locations, over different scales and time spans than the required input variables and parameters (Troldborg 2010), requiring the interpolation between and/or extrapolation beyond known values.

Computational and numerical models are simplified versions of real-world phenomena (Ascough II *et al.* 2008) and as such will include different uncertainties associated with their representativeness. These are termed model structure uncertainty (Alcamo and Bartnicki 1987; Beck 1987; Janssen *et al.* 2003; Walker *et al.* 2003), model uncertainty (Finkel 1990; Bedford and Cooke 2001, Huijbregts *et al.* 2001; Regan *et al.* 2002) or method uncertainty (Maier *et al.* 2008). These uncertainties may concern: the physical relationships between the variables and parameters used in the model (Ascough II *et al.* 2008; Knol *et al.* 2009); the interpretation of observations and theories and their subsequent implementation (Regan *et al*. 2002); approximations in numerical solution (van der Sluijs 1997); and the initial conceptual plans adopted (Alcamo and Bartnicki 1987; see Section 3.3.1). If a conceptual model presents an oversimplification of the scenario, the resulting numerical/computational model may fail to capture essential features, leading in turn to inadequate simulations. Conversely an undersimplification may yield a model that is too complex, and therefore expensive (or even prohibitive) to build and execute (El-Ghonemy *et al.* 2005).

The technical aspects of computational modelling, also contain uncertainties related to the software and hardware used (Rowe 1994; van der Sluijs 1997; Janssen *et al.* 2003; Walker *et al.* 2003; Ascough II *et al.* 2008). Software uncertainties arise from issues including errors in developer and operational platforms, poorly-designed algorithms, and mistakes in code (Walker *et al.* 2003). Hardware uncertainties arise, quite simply, from errors in the hardware, including processors, memory and storage devices (van der Sluijs 1997).

The parameter, structural, and technical uncertainties discussed all occur within models of physical systems and can limit their operational capability, ultimately leading to uncertainty in their output (Walker *et al.* 2003, Janssen *et al.* 2003; Ascough II *et al.* 2008). Even those models that are good representations of the real-world and provide consistently accurate results can never be completely exact.. Identifying and managing related uncertainties helps to ensure that the margin of model error is kept to a minimum.

Within ERAs, model uncertainties should be considered wherever numerical or computational models are used, which is principally during the analysis phase. For example, ApSimon *et al.* (2002) describe the model uncertainty associated with modelling complex atmospheric processes, such as particle deposition, within the exposure phase of a trans-boundary air pollution ERA. Furthermore, the output from the modelling process, which may be used to help formulate risk estimates, should be treated with due caution at the risk characterisation stage.

3.3.4 Human

Human uncertainties within ERAs are the unintentional, but potentially avoidable, human flaws that are not covered by system knowledge, models, and data uncertainties. The human uncertainties are generally more qualitative, reflective, and interpretive (Janssen *et al.* 2003). These include conflicts between individuals and/or small groups (disagreement uncertainty; Morgan and Henrion 1990), varying perspectives and values that are not easily reconciled (value diversity; Rowe 1994; van Asselt and Rotmans 2002), or the perceived societal importance of an individual, elevating their views above those of others (stakeholder uncertainty; Maier *et al.* 2008).

Human uncertainties can exist at any stage of ERAs, from unintentionally subjective actions at the problem formulation phase to stakeholder disagreements concerning tolerability thresholds during risk characterisation or evaluation. For example, in a multi-criteria approach for prioritising sites in sediment management Alvarez-Guerra *et al.* (2009) account for the unintentionally biased opinions, brought about by past experiences, when assigning weightings to different criteria. Human-based uncertainties are also strongly linked to the way in which we use language to communicate.

3.3.5 Language

Language uncertainties relate to how information is communicated. The uncertainties associated with language arise for a number of reasons, but stem primarily from a lack of clarity (Morgan and Henrion 1990). Language can be controlled; therefore, theoretically, the associated uncertainties can be eliminated. Linguistic variables may be: ambiguous (Bedford and Cooke 2001; Regan *et al.* 2002; Ascough II *et al.* 2008), where more than one meaning can be drawn and it is not clear which meaning is intended; underspecific (Regan *et al.* 2002; Ascough II *et al.* 2008), where terms do not provide the level of precision required; or vague (Regan *et al.* 2002; Ascough II *et al.* 2008), where there is a blurring of distinctions between terms. The use of a single field-specific term may carry these three linguistic uncertainties (Acosta *et al*. 2010). In addition to these, two further linguistic uncertainties have been suggested: context dependence (Regan *et al.* 2002), where there is a failure to properly convey the context in which a term is to be understood; and indeterminacy of linguistic terms (Regan *et al.* 2002), encompassing unknown future developments of languages and the resulting effects on incorporated terms.

Language, in the context of ERAs, is not phase-specific. As such, the associated uncertainties should exist in many locations throughout the process, from basic definitions to the communication of risk levels (Keiter *et al*. 2009). For example, language uncertainties exist within the expert elicitation exercises that are often used for information gathering, evidence-checking, or results validation (Acosta *et al*. 2010).

3.3.6 Variability

Variability uncertainty is concerned with the randomness within systems. Human variability (Rowe 1994; van Asselt and Rotmans 2002), the opposite of the controllable human uncertainties (see Section 3.3.4), occurs from intentionally biased and subjective human actions (Khan *et al.* 2002), which, from the viewpoint of the risk analyst, are uncontrollable. Humans invariably display bias when they have something to gain, and display subjectivity when they believe their own views to be more correct than those of others (Chen *et al.* 2007). Human variability can be exhibited by those with close links to ERAs (e.g. decision-makers, stakeholders, and scientists), as well as those with a lower vested interest (e.g. short-term employees such as laboratory technicians or computer modellers; Croke *et al.* 2007).

Conversely, natural randomness may be considered unexpected but free from intentional bias (Jørgensen *et al.* 2009). The associated uncertainty, termed natural variability (Finkel 1990; Rowe 1994; van Asselt and Rotmans 2002; Huijbregts *et al.* 2001; Regan *et al.* 2002; Ascough II *et al.* 2008) relates to the unpredictable quality of natural processes (Ascough II *et al.* 2008; Regan *et al.* 2002), which can vary across both spatial and temporal scales (Rowe 1994; Huijbregts *et al.* 2001; Regan *et al.* 2002). Since natural variability is intrinsic to nature, it is also intrinsic to the corresponding aspects within ERAs; from factors affecting the fate and transport of a stressor in exposure assessment (Schwartz *et al.* 2000), the difference in responses shown by receptors of the same species during effects assessment (Borsuk *et al*. 2006), to the variability in determining appropriate tolerance thresholds in risk characterisation (Chen and Ma 2007).

Two further categories of variability are also identified from the evidence base. Technological variability (van Asselt and Rotmans 2002; Ascough II *et al.* 2008) refers to unexpected issues that result from technological developments. Institutional variability (Funtowicz and Ravetz 1990; van Asselt and Rotmans 2002; Ascough II *et al.* 2008) is where human variability is exhibited throughout large groups (e.g. societies), and includes aspects such as social values, economic principles, and cultural dynamics (van Asselt and Rotmans 2002). With respect to ERAs, technological variability can occur wherever such systems are in place, and institutional variability is most likely to exist in assessments at the community or population scale (e.g. epidemiological studies).

3.3.7 Decision

Decision uncertainty (Finkel 1990; Ascough II *et al.* 2008), also termed volitional (Bedford and Cooke 2001) or choice-laden uncertainty (Huijbregts *et al.* 2001), exists when there is doubt about the optimal course of action. This often occurs where there are differing objectives (Finkel 1990). These uncertainties exist within the ERA process, principally at the risk characterisation phase, but also in a wider risk management context. For example, management of ecological and environmental resources requires decision-makers to evaluate multiple and often conflicting strategies, whilst balancing objectives of productivity and sustainability (Ducey and Larson 1999). Such decisions can also contain any or all of the other outlined uncertainties (Ascough II *et al.* 2008).

3.3.8 Location of uncertainty in environmental risk assessments

The location in which uncertainty manifests depends on the different aspects of the system being explored. For example, an ERA of a novel technology (e.g. engineered nanomaterials) in an open, natural, environment can potentially contain all of the wide range of uncertainties discussed above. In cases where certain aspects do not feature, such as modelling processes, the related uncertainties will not be an issue. However, whilst uncertainties can manifest individually several are likely to exist, meaning that the full range should be considered (Refsgaard *et al.* 2007).

In addition to the nature and location, one further dimension must be considered, which is discussed in the following sub-section.

3.4 Level of uncertainty

3.4.1 Assessing the level of uncertainty

Humans exhibit a variety of distinct levels of knowledge, ranging from determinism (perfect knowledge) to indeterminacy (lack of knowledge; Wynne 1992). The further we move from a deterministic understanding of a system, the more severe the uncertainty becomes (Walker *et al.* 2003; Figure 2). The level of uncertainty is specifically described according to two factors, namely the degree of confidence attached to the likelihood of an event occurring and the degree of confidence attached to the severity of the potential outcomes (Wynne 1992; Stirling 1999). These metrics are used to convey the level of understanding and the level of the associated uncertainty.

[FIGURE 2 NEAR HERE]

3.4.2 State 1: knowing a lot

At the deterministic end of the spectrum (here termed state 1) the uncertainty is low. This state, first described by Funtowicz and Ravetz (1990; and later by van der Sluijs 1997 and van Asselt and Rotmans 2002) as inexactness, refers to the specified events for which we "roughly know" the likelihoods and outcomes, and where significant digits and error bars are the representations of choice (Funtowicz and Ravetz 1990). Due to the applicability of common risk assessment tools (e.g. frequency distributions) in addressing this level of uncertainty, the term risk has also been applied (Wynne 1992; Stirling 1999). Other proposed terms include probabilistic (Beer 2006), statistical (Brouwer and Blois 2008; Knol *et al.* 2009) and certainty (Faucheux and Froger 1995).

3.4.3 State 2: knowing the probabilities

After deterministic understanding, we come to the state where we can confidently assign probabilities to events but have little understanding of the ramifications of the events (state 2). Termed ambiguity (Stirling 1999), conflicting evidence (van Asselt and Rotmans 2002), statistical (Walker *et al.* 2003; Janssen *et al.* 2003; Petersen 2006), incertitude (Beer 2006), or qualitative (Brouwer and Blois 2008), this level of uncertainty refers to a situation in which "we don't know what we know" (van Asselt and Rotmans 2002). Statistical measures can be used to constrain likelihoods (i.e. probability distributions; Janssen *et al.* 2003) with techniques such as sensitivity analysis and fuzzy logic used to better understand the outcomes (Stirling 1999).

3.4.4 State 3: knowing the outcomes

The third level of uncertainty is where there is confidence about the outcomes but not likelihoods of an event (i.e. the reverse of state 2). Termed unreliability (Funtowicz and Ravetz 1990; van der Sluijs 1997), uncertainty (Wynne 1992; Stirling 1999), practically immeasurable (van Asselt and Rotmans 1999), or ambiguity (Beer 2006), it refers to the position in which "we know what we do not know" (van Asselt and Rotmans 1999). The term scenario is also used when referring to this state (Walker *et al.* 2003; Janssen *et al.* 2003; Brouwer and Blois 2008; Knol *et al.* 2009), because of a reliance on the analysis of scenarios when attempting to resolve unknown probabilities.

3.4.5 State 4: knowing a little

If it is not possible to define probabilities or a complete set of outcomes, we move into a state of ignorance (state 4; Wynne 1992; Faucheux and Froger 1995; Stirling 1999; van Asselt and Rotmans 2002; Brown 2004; Beer 2006), and it becomes necessary to proceed with due caution (Stirling 1999). The terms borderline ignorance (Funtowicz and Ravetz

1990; van der Sluijs 1997) and recognised ignorance (Walker *et al.* 2003; Janssen *et al.* 2003; Brouwer and Blois 2008; Knol *et al.* 2009) are also used, since, by definition, "we cannot say anything useful about that of which we are ignorant". The ideal solution is to increase knowledge of the problem, thus reducing uncertainty, and move back towards determinism (Walker *et al.* 2003).

3.4.6 State 5: not knowing

The inverse of deterministic knowledge is indeterminacy (state 5; Wynne 1992; van Asselt and Rotmans 2002; Brown 2004), the most important form of uncertainty since it is the uncertainty of which we know nothing and to which we are completely ignorant (Walker *et al.* 2003). Only when an event occurs will we be in a position to observe its origins and effects, and move ourselves into a state of awareness.

3.4.7 Level of uncertainty in environmental risk assessments

Determining the level of uncertainty helps to focus attention toward the features of ERAs that are most uncertain, and, when approached with the nature and location, allows selection of the most appropriate managing tool(s). Resolving the level also allows the uncertainty to be described in an appropriate manner. For example, using statistical measures to describe uncertainties closest to the indeterminacy end of the spectrum is inappropriate because we know nothing of the associated statistical distributions (Krayer von Krauss 2005).

Uncertainty typologies should be analysed for the presence of the three dimensions (location, nature, level), since they strongly influence uncertainty management, as well as for the definitions and frequencies of the uncertainties that they communicate.

4. Analysis of existing uncertainty typologies

4.1 Comparison of uncertainty terms used

Contradictions between terms used in different uncertainty typologies can cause confusion and, if definitions are inappropriate, potentially lead to management issues. Contradictions either exist where one term is used for a range of different uncertainties (the same term has multiple definitions; Table 2), or where several distinct terms are used to describe the same uncertainty (different terms have the same definition; Table 3). We have identified a number of different discrepancies between the 30 uncertainty typologies.

[TABLE 2 NEAR HERE]

[TABLE 3 NEAR HERE]

When the level of the uncertainty is described, the term ‘statistical’ is used to represent both the state of determinism (state 1; Brouwer and Blois 2008; Knol *et al.* 2009) and the state in which probabilities can be defined but outcomes remain unclear (state 2; Janssen *et al.* 2003; Walker *et al.* 2003; Petersen 2006; Table 2). Similarly, the term ‘ambiguity’ is used to refer to state 2 (Stirling 1999), and also state 3 where outcomes can be defined but associated probabilities remain unresolved (Beer 2006). Furthermore, Beer (2006) makes use of the term ‘incertitude’ to describe a single level of uncertainty (state 2), while Stirling (1999) uses the same term to describe the uncertainties across all levels.

The term ‘ambiguity’ is also used when describing the location in which the uncertainties occur, with specific reference to system-related uncertainty (Dewulf *et al.* 2005) and language-related uncertainty (Bedford and Cooke 2001; Regan *et al.* 2002; Ascough II *et al.* 2008). Indeed, within our data set this term was identified to have four separate meanings across the six typologies in which it features (see Table 2). Similarly, the term ‘statistical’ is also used to represent a form of data uncertainty (Morgan and Henrion 1990; Finkel 1990), resulting in three different definitions across seven typologies within our data set. Alternate interpretations are also presented for the terms ‘indeterminacy’, ‘random’, ‘variability’, and ‘systematic’, with very different meanings attached to each.

There are similarities between the studied typologies. For example, ‘parameter uncertainty’ is listed by nine typologies out of the 30 identified, with all nine agreeing on its use. The uncertainty relating to the inherent variability of natural systems also has a single associated term, ‘natural variability’, which is adopted by five typologies. However, the use of competing terms to describe the same uncertainties is commonplace. Parameter and natural variability are the only terms in the selected typologies which are used consistently. Epistemic, used to describe knowledge-based failings, is used in five separate cases with another six competing terms used by eight other typologies, resulting in the use of seven terms over 13 typologies that describe the same type of uncertainty (Table 3). A similar pattern is observed for the terms associated with aleatory uncertainty, with six separate terms used across 14 typologies.

Of the 188 (non-distinct) uncertainties communicated by the 30 studied typologies, 98 (52%) are contained within eight of the typologies (Rowe 1994; van Asselt and Rotmans 2002; Walker *et al.* 2003; Janssen *et al.* 2003; Petersen 2006; Maier *et al.* 2008; Ascough II *et al.* 2008; Knol *et al.* 2009). Within these eight typologies, 14 terms (occurring 38 times out of 98 recorded) are used to describe the same form of uncertainty in more than one typology. Therefore, there are 60 instances in which the terminology differs – either different terms are used to refer to the same uncertainty or the same terms are used to refer to different uncertainties. In either case, the terminology used in these eight main typologies differs 61% of the time, which may lead to confusion..

4.2 Comparison of the number of types of uncertainties within typologies

The existence of multiple typologies in closely related subject domains can cause confusion with each having distinct methods, processes, concerns, and ultimately different uncertainties. Similar domains may be are expected to have similar uncertainty typologies. However, we have identified that this is rarely the case (Table 4). For example, the studied typologies that focus on computational modelling procedures vary in the number of different types of uncertainties that they list, ranging from four (Brouwer and Blois 2008) to 13 (Walker *et al.* 2003). In this domain there was also variation in the dimensions of uncertainty considered in the typology: Maier *et al.* (2008) describe 11 uncertainties, all related to the location dimension, while Petersen (2006) documents eight, which relate to location, level, and nature. If one of these typologies is considered comprehensive then the other must either be incomplete or excessive.

[TABLE 4 NEAR HERE]

The amount of information within the studied uncertainty typologies varied considerably. Some typologies (e.g. Helton 1994; Hoffman and Hammonds 1994; Bevington and Robinson 2002; Hayes 2006) only include a small number of uncertainties. This may mean that analysts consult additional typologies to provide a more complete analysis of uncertainty, and leads to the possibility that the terminology and definitions used in the different typologies are not complimentary, or that only unique or unusual types of uncertainty are explicitly listed. For example, although the levels of uncertainty are underexplored, Regan *et al.* (2002) provide a wealth of information on language-based uncertainties. The definitions and examples provided are clear, concise, thorough, and applicable to all subject domains.

The 30 studied uncertainty typologies contained examples of typologies that considered one dimension of uncertainty (16 out of 30), but the remaining 14 typologies covered two (7 out of 30) or three dimensions (7 out of 30) (Table 4). For a typology to be complete (in the context of this article) it should communicate all three dimensions (nature, location and level) effectively and in particular provide accurate descriptions of all relevant location-based uncertainties, which will allow practitioners to identify the specific issues in their own assessments. On this basis, only seven of the typologies identified in this work were considered to meet these criteria. However, six of the seven typologies that did consider the three dimensions did not include language-based uncertainties in their definitions, with the exception of Ascough II *et al.* (2008).

4.3 Comparison of evidence used to develop typologies

Each of the 30 identified typologies that we investigated used a limited body of evidence which was sourced by expert elicitation, small scale literature review or a combination of research areas (Table 1). Most commonly, the views and opinions of a relatively small number of researchers were used to develop the typology, but this method can introduce additional uncertainties including subjectivity, intentional bias, and the ability of researcher(s) to communicate effectively. Secondly, small-scale literature reviews (compared to the available relevant body of evidence) were conducted across a relatively restricted topic. In such cases, the selection of inappropriate materials or a lack of quality sources may result in an incomplete typology. Furthermore, the content may only be applicable to the subject domain of the literature (e.g. atmospheric modelling, habitat conservation, or toxicology assessments), and may reduce the accuracy when applying the typology to other domains. Finally, existing typologies were combined from related but non-identical research domains. The most comprehensive and robust typology presented here (Ascough II *et al.* 2008, on the basis of the criteria laid out in this discussion) is sourced in this way. Whilst this ensures that a large body of relevant research is taken into consideration, the reliability of the output relies on the accuracy of the input. In this sense, combining existing information can mean that shortcomings are transferred into the new typology which may impact on its use.

5. Uncertainty in environmental risk assessments

5.1 Assessment of existing uncertainty typologies for environmental risk assessments

The uncertainties discussed in this review have, through the use of examples, been shown to exist in published ERAs, yet it is not clear whether the compilers of the ERAs used uncertainty typologies to identify the uncertainties. The 30 identified typologies largely focus on specific aspects of the environmental management process, such as modelling, decision-making, or policy setting and do not cover all of the processes within an ERAs nor their associated uncertainties. Ten of the studied typologies are based in either ERA or environmental risk management (incorporating ERA). Of these ten, three provide extensive descriptions of potential uncertainties across all three dimensions (nature, location and level). However, of these three, two do not communicate language uncertainties (Janssen *et al.* 2003; Knol *et al.* 2009), and the other does not include a comprehensive description of modelling uncertainties (Regan *et al.* 2002). Therefore, we were not able to identify an individual typology which we believe depicts the full range of potential uncertainties within ERAs.

5.2 A summary uncertainty typology for environmental risk assessments

The current lack of a single comprehensive typology for ERAs suggests a significant knowledge gap in uncertainty analysis. Derived from the analysis in this review, we have integrated common attributes (identified from the 30 studied typologies) to represent the uncertainties that can occur within different parts of ERAs (Figure 3; see Section 3 for definitions and descriptions of the contained uncertainties and their relevance to the different phases of ERAs).

[FIGURE 3 NEAR HERE]

The summary typology (Figure 3) consists of two types of uncertainty within the nature dimension (epistemic and aleatory), seven main kinds of location-based uncertainty (system processes, data, model, human, language, variability, and decision), and five levels of uncertainty (determinacy, statistical, scenario, ignorance, and indeterminacy). The majority of the uncertainties within the typology are well understood however we have modified the inclusion and organisation of the categories and sub-categories to aid the identification of uncertainties. Language uncertainties, for example, are often treated as a standalone group (Morgan and Henrion 1990; Regan *et al*. 2002; Ascough II *et al*. 2008), but are here considered differently. Since language, and its use, is theoretically controllable, the related uncertainties are similar to others that are epistemic in nature. Whilst not always achievable, it is possible to quantify, reduce or remove the effect that language has on different aspects within ERAs, using techniques such as fuzzy logic (Acosta *et al*. 2010). Furthermore, since language can manifest in many functions and tasks across ERAs, the associated uncertainties can be labelled as specific location-based concerns.

The distinction between potential human uncertainties has not been made by a single typology. Within ERAs, human actions are either controllable or uncontrollable: the former must, by definition, belong to the epistemic set, whilst the latter must reside within the aleatory set. Within ERAs, human uncertainties are of concern only where there is human input or influence. They are not a continual concern, and need not be evaluated in the same manner as the nature or level of uncertainty. For these reasons, two types of location-based human uncertainty are considered within the summary typology, segregated by their different natures.

Within the aleatory uncertainties, the variability sub-set (in the nature dimension) identifies four potential locations of uncertainty that share the same irreducible variable qualities: human; natural; institutional; and technological. It should be noted that these four locations could be considered direct subsets of the aleatory category, but that a grouping according to their common attribute of variability is also pertinent.

This presented summary typology has been developed from the outputs of the 30 studied typologies and as such can aid uncertainty identification and characterisation in ERAs, but should be framed with the same caveats as discussed previously (in Section 4.3) concerning information sourcing. Further work should concentrate on the characterisation and identification of uncertainties within case studies to enable generic definitions and characteristics to be elucidated. The summary typology (Figure 3) and uncertainty descriptions (Section 3) provide analysts with a more complete understanding of uncertainty in ERAs than typically exists at present, potentially aiding the uncertainty identification process (Figure 1). Once identified, and depending on the mix of the three dimensions, the uncertainties can be managed using one (or more) of a number of existing uncertainty management techniques, ranging from Monte-Carlo simulation to uncertainty factors to adaptive management. Many articles discuss the appropriateness of such techniques with respect to different uncertainties (e.g. van der Sluijs *et al.* 2005; Refsgaard *et al.* 2007; Knol *et al.* 2009), a topic that is beyond the extent of this review. However, we are aware that much more could be done to improve both uncertainty typologies and the guidance related to their implementation, in the context of ERAs and uncertainty analysis in general.

6. Identified knowledge gaps for uncertainty typologies

6.1 Using the evidence base

Basing the content of typologies on researcher views, small-scale literature reviews, or existing typologies has implicit problems, as previously discussed. There exists a large evidence base of peer-reviewed environmental risk-based research. A structured interrogation of this evidence base, which spans a number of approaches (e.g. modelling, assessments, and management) and environmental concerns, would enable a more comprehensive characterisation of potential uncertainties. Specifically, the analysis of information from competing (but related) research domains will ensure that the full scope of uncertainties are identified. Additionally, such a typology would be able to point to individual occurrences within the evidence base, making it defensible and transparent.

6.2 Factors influencing uncertainty

Extending the traditional typology format to include a system for direct identification of uncertainties would help to minimise any intentional or unintentional bias on the part of the analyst. By analysing the evidence base for any relationships that exist between identified uncertainties and other aspects (e.g. sources, pathways, receptors, the evidence utilised), key associations can be established and statistically evaluated through bivariate analysis. Strong relationships, if deemed to be transferrable, may then form the basis of such an identification system.

6.3 Structuring uncertainty typologies

Uncertainty identification requires a level of subjectivity on the part of the practitioner – even when typologies are adopted – and can be further influenced by a lack of familiarity with concepts (Gillund *et al.* 2008). Structuring the typology for the risk domain in which it is intended to be used (e.g. ERA) may prove beneficial. Relating the unfamiliar abstract concepts of uncertainty to more familiar processes (e.g. within problem formulation, exposure/effects assessment, and risk characterisation) may make the typology more intuitive to analysts, making it more robust and ultimately more useful during uncertainty identification.

7. Conclusion

Uncertainty typologies should be well-defined, defensible, and, most importantly, accurate. This paper provides the first major review and analysis of these tools, which are integral to the identification of uncertainty within environmental risk systems. We have shown that existing uncertainty typologies across environmental risk domains:

(i) use terminology that is often contradictory;

(ii) communicate varying frequencies and dimensions of uncertainties;

(iii) source information from limited data sets; and

(iv) cannot be applied, on an individual basis, to ERAs in order to characterise the wide range of potential uncertainties.

To attempt to address these issues, we have integrated the salient attributes of environmental uncertainty, identified in this review, into a summary uncertainty typology – consisting of seven locations of uncertainty across five distinct levels - that is specifically for use with ERAs.

This review has highlighted the need to use existing uncertainty typologies with caution. We believe that this research will be of benefit to environmental risk analysts in their attempts to better qualify uncertainties, and thus statements about risk, within ERAs.

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References

Acosta, H., D. Wu, and B. Forrest. 2010. Fuzzy experts on recreational vessels, a risk modelling approach for marine invasions. *Ecological Modelling* 221(5): 850-863.

Alcamo, J. and J. Bartnicki. 1987. A framework for error analysis of a long-range transport model with emphasis on parameter uncertainty. *Atmospheric Environment (1967)* 21(10): 2121-2131.

Alvarez-Guerra, M., J. Viguri, and N. Voulvoulis. 2009. A multicriteria-based methodology for site prioritisation in sediment management. *Environment International* 35(6): 920-930.

ApSimon, H.M., R.F. Warren, and S. Kayin, S. 2002. Addressing uncertainty in environmental modelling: a case study of integrated assessment of strategies to combat long-range transboundary air pollution. *Atmospheric Environment* 36: 5417-5426.

Arhonditsis, G., S. Qian, C. Stow, E. Lamon, and K. Reckhow. 2007. Eutrophication risk assessment using Bayesian calibration of process-based models: Application to a mesotrophic lake. *Ecological modelling* 208(2-4): 215-229.

Ascough II, J., H. Maier, J. Ravalico, and M. Strudley. 2008. Future research challenges for incorporation of uncertainty in environmental and ecological decision-making. *Ecological modelling* 219(3-4): 383-399.

van Asselt, M. and J. Rotmans. 2002. Uncertainty in integrated assessment modelling. *Climatic Change* 54(1): 75-105.

Beck, M. 1987. Water quality modeling: a review of the analysis of uncertainty. *Water Resources Research* 23(8): 1393-1442.

Bedford, T. and R. Cooke. 2001.*Probabilistic risk analysis: foundations and methods*. Cambridge: Cambridge University Press.

Beer, T. 2006. Ecological risk assessment and quantitative consequence analysis. *Human and Ecological Risk Assessment* 12(1): 51-65.

Bevington, P. and D. Robinson. 2002.*Data reduction and error analysis for the physical sciences*, Vol. 336. New York: McGraw-Hill.

Borsuk, M.E., P. Reichert, A. Peter, E. Schager, and P. Burkhardt-Holm. Assessing the decline of brown trout (*Salmo trutta*) in Swiss rivers using a Bayesian probability network. *Ecological Modelling* 192: 224-244.

Bowden, R. 2004. Building confidence in geological models. *Geological Society, London, Special Publications* 239(1): 157.

Brouwer, R. and C. De Blois. 2008. Integrated modelling of risk and uncertainty underlying the cost and effectiveness of water quality measures. *Environmental Modelling & Software* 23(7): 922-937.

Brown, J. 2004. Knowledge, uncertainty and physical geography: towards the development of methodologies for questioning belief. *Transactions of the Institute of British Geographers* 29(3): 367-381.

Chen, C., H. Ma, and K. Reckhow. 2007. Assessment of water quality management with a systematic qualitative uncertainty analysis. *Science of the total environment* 374(1): 13-25.

Chen, Y.C. and H.W. Ma. 2007. Combining the cost of reducing uncertainty with the selection of risk assessment models for remediation decision of site contamination. *Journal of Hazardous Materials* 14: 17-26.

Costanza, R., S. Funtowicz, and J. Ravetz. 1992. Assessing and communicating data quality in policy-relevant research. *Environmental Management* 16(1): 121-131.

Croke, B., J. Ticehurst, R. Letcher, J. Norton, L. Newham, and A. Jakeman. 2007. Integrated assessment of water resources: Australian experiences. *Water resources management* 21(1): 351-373.

Dale, V., G. Biddinger, M. Newman, J. Oris, G. Suter, T. Thompson, T. Armitage, J. Meyer, R. Allen-King, G. Burton, and others. 2008. Enhancing the ecological risk assessment process. *Integrated environmental assessment and management* 4(3): 306-313.

Dale, V., J. Meyer, and United States Environmental Protection Agency Science Advisory Board. 2007. *Advice to EPA on advancing the science and application of ecological risk assessment in environmental decision making: a report of the U.S. EPA Science Advisory Board*. Washington: United States Environmental Protection Agency, Office of the Administrator.

Department for Environment, Food and Rural Affairs. 2011. Guidelines for environmental risk assessment and management: Green Leaves III. HMSO, London. Available at: http://www.defra.gov.uk/publications/files/pb13670-green-leaves-iii-1111071.pdf.

Dewulf, A., M. Craps, R. Bouwen, T. Taillieu, C. Pahl-Wostl, and M. Krayer von Krauss. 2005. Integrated management of natural resources: dealing with ambiguous issues, multiple actors and diverging frames. *Water science and technology* 52(6): 115-124.

Ducey, M. and B. Larson. 1999. A fuzzy set approach to the problem of sustainability. *Forest Ecology and Management* 115(1): 29-40.

El-Ghonemy, H., L. Watts, and L. Fowler. 2005. Treatment of uncertainty and developing conceptual models for environmental risk assessments and radioactive waste disposal safety cases. *Environment international* 31(1): 89-97.

Environmental Protection Act. 1990.*Environmental Protection Act: chapter 43, section 1*. London: The Stationery Office.

Fairman, R., C. Mead, W. Williams, and A. de Medio Ambiente. 1998.*Environmental risk* *assessment: approaches, experiences and information sources*. Luxembourg: Office for Official Publications of the European Communities.

Faucheux, S. and G. Froger. 1995. Decision-making under environmental uncertainty. *Ecological Economics* 15(1): 29-42.

Finkel, A. 1990. *Confronting Uncertainty in Risk Management: A Guide for Decision–Makers*. Washington: Center for Risk Management, Resources for the Future.

Funtowicz, S. and J. Ravetz. 1990.*Uncertainty and quality in science for policy*, Vol. 15. Dordrecht: Kluwer.

Gillund, F., K. Kjшlberg, M. Krayer von Krauss, and A. Myhr. 2008. Do uncertainty analyses reveal uncertainties? Using the introduction of DNA vaccines to aquaculture as a case. *Science of the Total Environment* 407(1): 185-196.

Griffin, S., P. Goodrum, G. Diamond, W. Meylan, W. Brattin, and J. Hassett. 1999. Application of a probabilistic risk assessment methodology to a lead smelter site. *Human and Ecological Risk Assessment* 5(4): 845-868.

Hacking, I. 1984. The emergence of probability: a philosophical study of early ideas about probability, induction and statistical inference. Cambridge: Cambridge University Press.

Handmer, J., T. Norton, and S. Dovers. 2001.*Ecology, Uncertainty and Policy: managing ecosystems for sustainability*. Harlow: Prentice Hall.

Hayes, K., H. Regan, M. Burgman, R. Devlin, A. Kapuscinski, and J. Dambacher. 2006. Methods to address uncertainty in ecological risk assessment of Genetically Modified Organisms, *in* 'Ninth International Symposium on Biosafety of Genetically Modified Organisms Biosafety Research and Environmental Risk Assessment', September 24-29, Jeju Island, South Korea.

Helton, J. 1994. Treatment of uncertainty in performance assessments for complex systems.

Risk Analysis 14(4): 483-511.

Henrion, M. and B. Fischhoff, B. 1986. Assessing uncertainty in physical constants. *American Journal of Physics* 54: 791.

Hoffman, F. and J. Hammonds, J. 1994. Propagation of uncertainty in risk assessments: the need to distinguish between uncertainty due to lack of knowledge and uncertainty due to variability. *Risk Analysis* 14(5): 707-712.

Hromkovic, J. 2005.*Design and analysis of randomized algorithms: introduction to design paradigms*. New York: Springer-Verlag New York Inc.

Huijbregts, M., G. Norris, R. Bretz, A. Ciroth, B. Maurice, B. von Bahr, B. Weidema, and A. de Beaufort. 2001. Framework for modelling data uncertainty in life cycle inventories. *The International Journal of Life Cycle Assessment* 6(3): 127-132.

Janssen, P., A. Petersen, J. van der Sluijs, J. Risbey, and J. Ravetz. 2003. RIVM/MNP guidance for uncertainty assessment and communication: Quickscan hints & actions list. *RIVM/MNP Guidance for Uncertainty Assessment and Communication Series* 2.

Jorgensen, R., T. Hauser, T. D'Hertefeldt, N. Andersen, and D. Hooftman. 2009. The variability of processes involved in transgene dispersal - case studies from Brassica and related genera. *Environmental Science and Pollution Research* 16(4): 389-395.

Keiter, S., T. Braunbeck, S. Heise, S. Pudenz, W. Manz, and H. Hollert. 2009. A fuzzy logic-classification of sediments based on data from in vitro biotests. *Journal of Soils and Sediments* 9: 168–179.

van der Keur, P., H. Henriksen, J. Refsgaard, M. Brugnach, C. Pahl-Wostl, A. Dewulf, and H. Buiteveld. 2008. Identification of major sources of uncertainty in current IWRM practice. Illustrated for the Rhine basin. *Water resources management* 22(11): 1677-1708.

Khan, F., R. Sadiq, and T. Husain. 2002. GreenPro-I: a risk-based life cycle assessment and decision-making methodology for process plant design. *Environmental Modelling & Software* 17(8): 669-692.

Knol, A., A. Petersen, J. van der Sluijs, and E. Lebret. 2009. Dealing with uncertainties in environmental burden of disease assessment. *Environmental Health: A Global Access Science Source* 8(21).

Krayer von Krauss, M. 2005. *Uncertainty in policy relevant sciences*. PhD thesis, Technical University of Denmark.

Kumar, V., M. Mari, M. Schuhmacher, and J. Domingo. 2009. Partitioning total variance in risk assessment: Application to a municipal solid waste incinerator. *Environmental Modelling & Software* 24(2): 247-261.

Li, H., G. Huang, and Y. Zou. 2008. An integrated fuzzy-stochastic modeling approach for assessing health-impact risk from air pollution. *Stochastic Environmental Research and Risk Assessment* 22(6): 789-803.

Li, J., G. Huang, G. Zeng, I. Maqsood, and Y. Huang. 2007. An integrated fuzzy-stochastic modeling approach for risk assessment of groundwater contamination. *Journal of environmental management* 82(2): 173-188.

Linkov, I., D. Loney, S. Cormier, F. Satterstrom, and T. Bridges. 2009. Weight-of-evidence evaluation in environmental assessment: Review of qualitative and quantitative approaches. *Science of the Total Environment* 407(19): 5199-5205.

Maier, H., J. Ascough II, M. Wattenbach, C. Renschler, W. Labiosa, and J. Ravalico. 2008. Chapter Five - Uncertainty in Environmental Decision Making: Issues, Challenges and Future Directions. *Developments in Integrated Environmental Assessment* 3: 69-85.

McColl, S., J. Hicks, L. Craig, and J. Shortreed. 2000. *Environmental Health Risk*

Management: A Primer for Canadians. University of Waterloo, Institute for Risk Research.

Morgan, M. and M. Henrion. 1990. *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis*. Cambridge: Cambridge University Press.

Petersen, A. 2006. *Simulating nature: a philosophical study of computer-simulation uncertainties and their role in climate science and policy advice*. Amsterdam: Aksant Academic Publishers.

Pollard, S. 2001. An overview of the use of risk assessment for environmental regulation in the UK - key drivers and regulatory initiatives. *Risk Decision and Policy* 6(1): 33-46.

Qin, X. and G. Huang. 2009. Characterizing uncertainties associated with contaminant transport modeling through a coupled fuzzy-stochastic approach. *Water, Air, & Soil Pollution* 197(1): 331-348.

Refsgaard, J., J. van Der Sluijs, A. Hojberg, and P. Vanrolleghem. 2007. Uncertainty in the environmental modelling process - A framework and guidance. *Environmental Modelling & Software* 22(11): 1543-1556.

Regan, H., M. Colyvan, and M. Burgman. 2002. A taxonomy and treatment of uncertainty for ecology and conservation biology. *Ecological applications* 12(2): 618-628.

Rowe, W. 1994. Understanding uncertainty. *Risk Analysis* 14(5): 743-750.

Schwartz, S., V. Berding, and M. Matthies. 2000. Aquatic fate assessment of the polycyclic musk fragrance HHCB. Scenario and variability analysis in accordance with the EU risk assessment guidelines. *Chemosphere* 41: 671–679.

van der Sluijs, J., M. Craye, S. Funtowicz, P. Kloprogge, J. Ravetz, and J. Risbey. 2005. Combining quantitative and qualitative measures of uncertainty in model-based environmental assessment: The NUSAP system. *Risk Analysis* 25(2): 481-492.

van der Sluijs, J. 1997. *Anchoring amid uncertainty, On the management of uncertainties in* *risk assessment of anthropogenic climate change*. PhD thesis, Utrecht University.

Stephens, M., B. Goodwin, and T. Andres. 1993. Deriving parameter probability density functions. *Reliability Engineering & System Safety*42(2-3): 271-291.

Stirling, A. 1998. Risk at a turning point? *Journal of Risk Research* 1(2): 97-109.

Troldborg, M. 2010. *Risk assessment models and uncertainty estimation of groundwater contamination from point sources*. PhD Thesis, Technical University of Denmark.

United States Environmental Protection Agency. 1998. *Guidelines for ecological risk assessment*. Washington: United States Environmental Protection Agency, Risk Assessment Forum.

Verdonck, F.A.M., A. Souren, M.B.A. van Asselt, P.A. Van Sprang, and P.A. Vanrolleghem. 2007. Improving uncertainty analysis in European Union risk assessment of chemicals. *Integrated Environmental Assessment and Management* 3: 333-343.

Vesely, W. and D. Rasmuson. 1984. Uncertainties in nuclear probabilistic risk analyses. *Risk Analysis* 4(4): 313-322.

Walker, W., P. Harremoes, J. Rotmans, J. van der Sluijs, M.van Asselt, P. Janssen, and M. Krayer von Krauss. 2003. Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment* 4(1): 5-17.

Wu, F. and Y. Tsang. 2004. Second-order Monte Carlo uncertainty/variability analysis using correlated model parameters: application to salmonid embryo survival risk assessment. *Ecological modelling* 177(3-4): 393-414.

Wynne, B. 1992. Uncertainty and environmental learning. Reconceiving science and policy in the preventive paradigm. *Global Environmental Change* 2(2): 111-127.

Zalk, D., S. Paik, and P. Swuste. 2009. Evaluating the Control Banding Nanotool: a qualitative risk assessment method for controlling nanoparticle exposures. *Journal of Nanoparticle Research* 11(7): 1685-1704.

Zhang, K.,Y. Pei, and C. Lin. 2010. An investigation of correlations between different environmental assessments and risk assessment. *Procedia Environmental Sciences* 2: 643-649.

Figure Captions

Figure 1 A basic overview of uncertainty analysis, including the stages of understanding, identifying, and managing uncertainty, as performed in environmental risk assessments.

Figure 2 Schematic showing the spectrum of uncertainty levels, defined through knowledge about likelihoods and knowledge about outcomes (after Walker *et al.* 2003 and Krayer von Kraus 2005).

Figure 3 A summary uncertainty typology for use with environmental risk assessments, derived from a review of 30 identified typologies. The inner segments represent the potential nature(s) and location(s) of the uncertainty. The outer ring depicts the level(s) of uncertainty and is such that any location of uncertainty can exist at any level of uncertainty. This typology is suggested as an aid to uncertainty understanding and identification as it can be applied to the components within the different phases of ERAs.

Table 1. Information about the 30 uncertainty typologies examined in this review, including the risk domains in which they are based, the methods for data sourcing, and the uncertainties that they contain.

Typology source	Risk research domain	Typology based on	Uncertainties considered
Vesely and Rasmuson (1984)	Environmental risk management	Empirical evidence (literature)	Data; model (understanding, approximation); completeness; physical variability
Henrion and Fischoff (1986)	Uncertainty analysis	Empirical evidence (literature)	Random; systematic
Alcamo and Bartnicki (1987)	Environmental modelling	Researcher opinion	Model (structure, parameters, forcing, initial state, operation)
Beck (1987)	Environmental modelling	Empirical evidence (literature)	Model (aggregation, structure, numerical, parameter); variability; errors
Morgan and Henrion (1990)	Environmental policy analysis	Researcher opinion	Statistical variation; systematic error; linguistic; variability; inherent randomness; disagreement; model (approximation, form)
Finkel (1990)	Environmental risk management	Empirical evidence (literature)	Model; parameter; decision; natural variability
Funtowicz and Ravetz (1990)	Environmental policy analysis	Researcher opinion	Inexactness; unreliability; border with ignorance
Wynne (1992)	Environmental policy analysis	Researcher opinion; Empirical evidence (literature)	Risk; uncertainty; ignorance; indeterminacy
Helton (1994)	Uncertainty analysis	Researcher opinion	Stochastic; subjective
Hoffman and Hammonds (1994)	Uncertainty analysis	Researcher opinion	Lack of knowledge; variability
Rowe (1994)	Uncertainty analysis	Researcher opinion	Temporal; structural; metrical; translational
Faucheux and Froger (1995)	Environmental decision-making	Empirical evidence (literature)	Ignorance; strong uncertainty; uncertainty; certainty

(*Continued*)

Table 1. (*Continued*).

Typology source	Risk research domain	Typology based on	Uncertainties considered
van der Sluijs (1997)	Environmental modelling	Researcher opinion; Empirical evidence (existing typologies)	Inexactness; unreliability; ignorance; model (input data, conceptual model structure, technical model structure, bugs, model completeness)
Stirling (1998)	Environmental policy analysis	Researcher opinion; Empirical evidence (literature)	Risk; uncertainty; ambiguity; ignorance
Bedford and Cooke (2001)	Environmental risk management	Researcher opinion	Aleatory; epistemic; parameter; data; model; ambiguity; volitional
Huijbregts et al. (2001)	Environmental risk management	Researcher opinion	Parameter; model; choices; variability (spatial, temporal, between source and object)
Bevington and Robinson (2002)	Uncertainty analysis	Researcher opinion	Systematic errors; random errors
Regan, Colyvan, and Burgman (2002)	Environmental risk management	Researcher opinion; Empirical evidence (literature)	Epistemic (measurement error, systematic error, natural variation, inherent randomness, model, subjective judgement); linguistic (vagueness, context dependence, ambiguity, underspecificity, indeterminacy of theoretical terms)
van Asselt and Rotmans (2002)	Environmental modelling	Empirical evidence (existing typologies)	Variability (nature, cognitive, behavioural, societal, technological); knowledge (inexactness, lack of measurements, practically immeasurable, conflicting evidence, ignorance, indeterminacy)
Janssen et al. (2003)	Environmental risk management	Researcher opinion; Empirical evidence (literature)	Statistical; scenario; recognised ignorance; knowledge-based; variability-based; context; expert judgement; model (structure, technical, parameters, input); data; outputs
Walker et al. (2003)	Environmental decision-making	Researcher opinion; Empirical evidence (literature)	Statistical; scenario; recognised ignorance; total ignorance; epistemic; variability; context; model (structure, technical, parameters, input, outputs)
Brown (2004)	Uncertainty analysis	Researcher opinion; Empirical evidence (literature)	Bounded uncertainty; unbounded uncertainty; indeterminacy; ignorance
Dewulf et al. (2005)	Environmental risk management	Empirical evidence (existing typologies)	Inherent nature of phenomena; lack of knowledge; ambiguity in system understanding

(*Continued*)

Table 1. (*Continued*).

Typology source	Risk research domain	Typology based on	Uncertainties considered
Beer (2006)	Environmental risk assessment	Empirical evidence (literature, existing typologies)	Probabilistic; ambiguity; incertitude; ignorance; indeterminacy
Petersen (2006)	Environmental modelling	Researcher opinion; Empirical evidence (literature, existing typologies)	Location; nature; range; recognised ignorance; methodological unreliability; value diversity
Hayes et al. (2006)	Environmental risk assessment	Researcher opinion; Empirical evidence (literature)	Linguistic; variability; incertitude
Maier et al. (2008)	Environmental decision-making	Researcher opinion; Empirical evidence (literature)	Data (measurement error, type of data, length of record, analysis); model (method, record quality, calibration, validation, experience); human (stakeholder, politics)
Ascough II et al. (2008)	Environmental decision-making	Empirical evidence (existing typologies)	Knowledge; variability; linguistic; process; model; variability; linguistic; decision
Brouwer and Blois (2008)	Environmental modelling	Empirical evidence (existing typologies)	Statistical; scenario; qualitative; recognised ignorance
Knol et al. (2009)	Environmental risk assessment	Researcher opinion; Empirical evidence (existing typologies)	Statistical; scenario; recognised ignorance; epistemic; ontic (process, normative); model (structure, parameters, input data); methodological; analyst uncertainty

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Table 2. Contradictions in terms (where the same single term is used to represent two or more distinct uncertainty types) between the 30 typologies, with regard to the location, level and nature of uncertainty, and featuring the terms ambiguity (as denoted by the symbol (1), indeterminacy (2), natural variability (3), parameter (4), random (5), statistical (6), systematic (7) and variability (8).

Uncertainity Type	Location							Level					Nature	
Typology	System	Data	Model	Human	Language	Variability	Decision	State 1 (determinism)	State 2 (statistical)	State 3 (scenario)	State 4 (recognised ignorance)	State 5 (total ignorance)	Knowledge-based	Randomness-based
Vesely and Rasmuson (1984)														8
Alcamo and Bartnicki (1987)			4											
Beck (1987)			4											
Morgan and Henrion (1990)		6,7				8								
Finkel (1990)		6,7	4			3								
Wynne (1992)												2		
Hoffman and Hammonds (1994)														8
Rowe (1994)						3								
Stirling (1998)									1					
Bedford and Cooke (2001)			4		1									
Huijbregts et al. (2001)			4											
Bevington and Robinson (2002)													7	5
Regan, Colyvan, and Burgman (2002)		7			1,2	3								5
van Asselt and Rotmans (2002)						3,8						2		8
Janssen et al. (2003)			4						6					8
Walker et al. (2003)			4						6					8
Brown (2004)												2		
Dewulf et al. (2005)	1													
Petersen (2006)									6					
Hayes et al. (2006)														8
Ascough II et al. (2008)			4		1	3,8								
Brouwer and Blois (2008)								6						
Knol et al. (2009)			4					6						

Table 3. Identified contradictions in description terms between the 30 typologies where distinct terms are used to describe the same uncertainty type, with regard to the nature dimension (knowledge or randomness) of uncertainty.

Typology	Term describing knowledge uncertainty	Term describing random uncertainty
Vesely and Rasmuson (1984)	Completeness	Variability
Helton (1994)	Subjective	Stochastic
Hoffman and Hammonds (1994)	Knowledge	Variability
Rowe (1994)	Completeness	N/A
van Asselt and Rotmans (2002)	N/A	Variability
Bedford and Cooke (2001)	Epistemic	Aleatory
Bevington and Robinson (2002)	Systematic	Random
Regan, Colyvan, and Burgman (2002)	N/A	Random
Janssen et al. (2003)	Knowledge	Variability
Walker et al. (2003)	Epistemic	Variability
Dewulf et al. (2005)	Uncertainty	Indeterminacy
Petersen (2006)	Epistemic	Ontic
Hayes et al. (2006)	Incertitude	Variability
Ascough II et al. (2008)	Epistemic	Aleatory
Knol et al. (2009)	Epistemic	Ontic

Table 4. The number of distinct uncertainties and dimensions communicated by each of the 30 uncertainty typologies featured in this review.

Typology source	Risk research domain	Uncertainty frequency	Dimension frequency
Vesely and Rasmuson (1984)	Environmental risk management	5	2
Henrion and Fischoff (1986)	Uncertainty analysis	2	1
Alcamo and Bartnicki (1987)	Environmental modelling	5	1
Beck (1987)	Environmental modelling	6	2
Morgan and Henrion (1990)	Environmental policy analysis	8	2
Finkel (1990)	Environmental risk management	4	1
Funtowicz and Ravetz (1990)	Environmental policy analysis	3	1
Wynne (1992)	Environmental policy analysis	4	1
Helton (1994)	Uncertainty analysis	2	1
Hoffman and Hammonds (1994)	Uncertainty analysis	2	1
Rowe (1994)	Uncertainty analysis	9	3
Faucheux and Froger (1995)	Environmental decision-making	4	1
van der Sluijs (1997)	Environmental modelling	7	2
Stirling (1998)	Environmental policy analysis	4	1
Bedford and Cooke (2001)	Environmental risk management	11	3
Huijbregts et al. (2001)	Environmental risk management	7	2
Bevington and Robinson (2002)	Uncertainty analysis	6	1
Regan, Colyvan, and Burgman (2002)	Environmental risk management	2	1
van Asselt and Rotmans (2002)	Environmental modelling	11	2
Janssen et al. (2003)	Environmental risk management	13	3
Walker et al. (2003)	Environmental decision-making	10	3
Brown (2004)	Uncertainty analysis	4	1
Dewulf et al. (2005)	Environmental risk management	3	2
Beer (2006)	Environmental risk assessment	4	1
Petersen (2006)	Environmental modelling	8	3
Hayes et al. (2006)	Environmental risk assessment	3	1
Maier et al. (2008)	Environmental decision-making	11	1

(*Continued*)

Table 4. (*Continued*).

Typology source	Risk research domain	Uncertainty frequency	Dimension frequency
Ascough II et al. (2008)	Environmental decision-making	16	3
Brouwer and Blois (2008)	Environmental modelling	4	1
Knol et al. (2009)	Environmental risk assessment	10	3

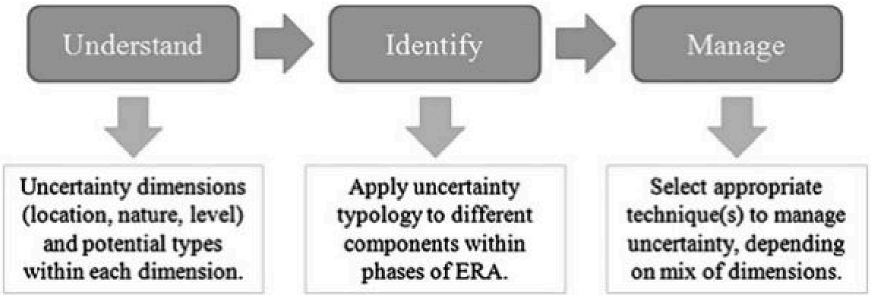

Figure 1. A basic overview of uncertainty analysis, including the stages of understanding, identifying and managing uncertainty, as performed in environmental risk assessments.

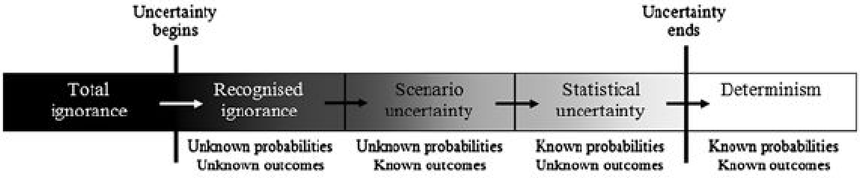

Figure 2. Schematic showing the spectrum of uncertainty levels, defined through knowledge about likelihoods and knowledge about outcomes (after Walker et al. 2003; Krayer von Kraus 2005).

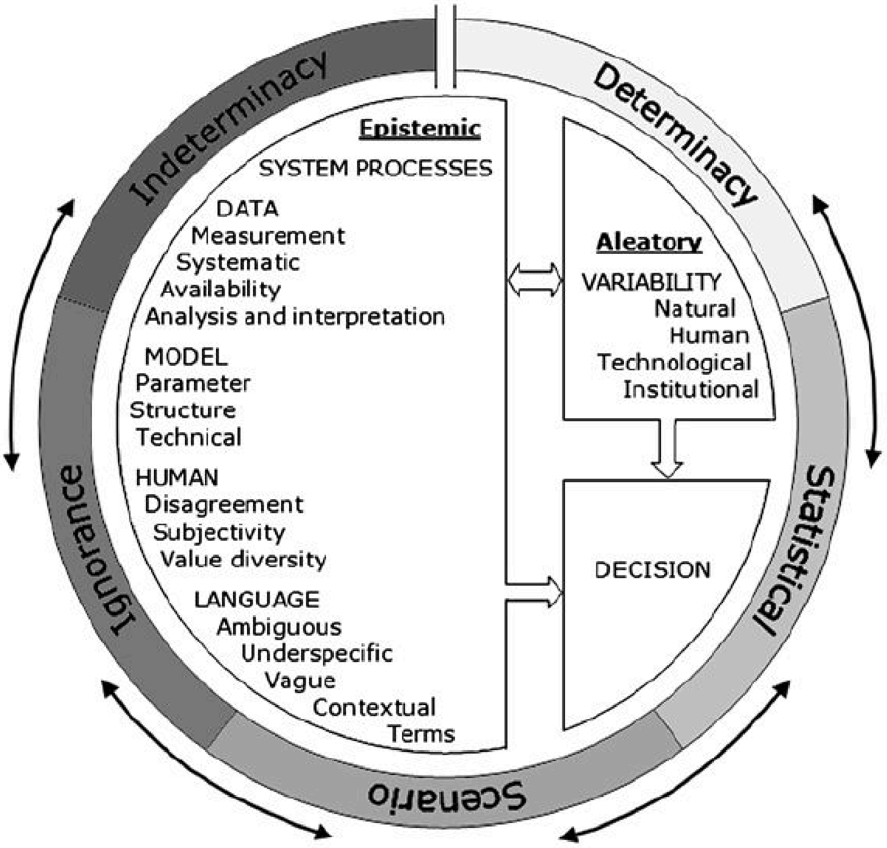

Figure 3. A summary uncertainty typology for use with environmental risk assessments, derived from a review of 30 identified typologies. The inner segments represent the potential nature(s) and location(s) of the uncertainty. The outer ring depicts the level(s) of uncertainty and is such that any location of uncertainty can exist at any level of uncertainty. This typology is suggested as an aid to uncertainty understanding and identification as it can be applied to the components within the different phases of ERAs.