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Assessment of data quality and uncertainty in disaster loss analysis

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1. Introduction

In recent years, disaster impact analysis methodologies have grown and their importance has gained worldwide recognition (Okuyama and Santos, 2014). Among other aspects of disaster analysis, the importance of estimating economic losses resulting from natural or man-made disasters is well known. Adequate accounts of disaster losses yield valuable information for governments and international organisations to make decisions about providing disaster relief assistance, e.g. how much, when, to whom and in what form. Reliable disaster loss accounts are also fundamental to establish loss trends and spatial patterns which are then used to measure the success and failure of global policies related to public health and safety. Disaster loss data is also particularly important for defining and setting priorities on what scientific research fields to fund and for evaluating the contribution and the effectiveness of scientific advances in overcoming the challenges our world is faced with. Furthermore, insurance companies also require reliable disaster loss accounts in their portfolios to guarantee their solvency or to undertake additional measures to alleviate the risk they may be faced with in case of a disaster (by issuing catastrophe bonds, for example).

Even though the importance of carrying out disaster loss analyses is unquestionable, the range of economic costs resulting from natural disasters is seen to be difficult to estimate, both in concept and in practice. For example, difficulties are usually found when trying to define objective spatial and temporal boundaries for a given loss analysis. Moreover, some of the more complex aspects of estimating disaster costs are related to the type and definition of losses in itself. Losses are conventionally classified as either direct or indirect losses. These categories can then be further subdivided into tangibles and intangibles losses, according to whether or not such losses can be valued in monetary terms. Quantifying these loss components is a challenge, especially those of indirect and intangible nature. However, the fact that multiple procedures are available to estimate some of these loss components (e.g. see (EMA, 2002), (ECLAC, 2003), (Hiete et al., 2012), (Koedam, 2012)) also complicates their unbiased quantification.

Standardized approaches are therefore required for loss quantification methodologies and loss data collection systems (i.e. databases). Defining such standards has the fundamental purpose of obtaining loss estimates with the highest possible level of reliability in order to provide adequate support for the higher-level strategic objectives of disaster loss analyses. Achieving a high level of reliability in disaster loss estimates is seen to depend on two essential factors: the reliability of the type of procedure used for the quantification of a given loss component and the availability of adequate and sufficient data to perform such quantification. Both factors can be associated to a characteristic generally termed as *quality*. There are no specific criteria that data or processes must possess to have *quality*. Instead, *quality* is measured according to the ability of that datum or process to fulfil a certain need or objective (ASQ, 2014). This lack of ability to fulfil needs or objectives is found to be the result of the existing *uncertainty* of the data or processes that are used. *Uncertainty* in these components is therefore a source of inaccuracy, errors, subjectivity and leads to failure in achieving a high level of *quality*. Hence, before grading a certain component of a disaster loss assessment framework in terms of its *quality*, a characterization and quantification of the sources of *uncertainty* that are involved must be performed.

2. Uncertainty: what is it?

Although the importance of uncertainty has been acknowledged throughout human history, its systematic analysis only started in the twentieth century. Numerous research studies across various fields and disciplines such as philosophy, physics, statistics, economics, finance, insurance, psychology, sociology, engineering or information science addressed the issue of uncertainty over the years (Van Asselt, 2000). As such, uncertainty can be seen to be a term used to account for many concepts (Morgan and Henrion, 1990). However, a simple and unified definition of what is uncertainty was never established. Epistemological differences between research fields added to this difficulty and, instead, several definitions of uncertainty have been proposed that bear some relation to the field where it has been analysed. To further complicate this scenario, different lexicons use different names for the same thing, and, in some cases, even the same name for different things. Therefore, scientific literature can be seen to contain many definitions, descriptions and typologies of uncertainty. Existing classifications and their (sometimes) confusing nomenclature reflect the existing differences between disciplines and research fields which are inevitably driven by their different objectives and their differences in terms of data availability.

Despite the referred complexities, proposals, such as those in the following, have been made in pursuit of an ideal unified definition of uncertainty:

- A state of incomplete knowledge (Cullen and Frey, 1999)
- Any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system (Walker et al., 2003)
- Incomplete information about a particular subject (Ascough II et al., 2008)
- Lack of confidence in knowledge related to a specific question (Sigel et al., 2010)

These definitions can be seen to associate uncertainty to a certain state of knowledge or lack thereof. But uncertainty is not simply the absence of knowledge since it can occur in scenarios where there is no shortage of information (Van Asselt, 2000). One can picture scenarios where having additional information can either decrease or increase the uncertainty level. Additional knowledge regarding a certain process can reveal the presence of uncertainties that were previously unknown or disregarded. Therefore, having additional knowledge can point out the limitations in our understanding of a given process and increase the uncertainty about it. Nevertheless, knowledge and knowledge-related issues are seen to be decisive concepts that must be involved when defining a certain type of uncertainty which is often termed *epistemic* uncertainty. In different research fields, this type of uncertainty has also been addressed using terms such as incertitude (Carey and Burgman, 2008) or epistemological uncertainty (Gillund et al., 2008), or even simply as "uncertainty" (Frey and Burmaster, 1999; McCann et al., 2006). A simple form of illustrating the general concept of *epistemic* uncertainty is by recognising that, for a given person with a certain level of knowledge at a given time, a statement about any given fact can either be true, false or uncertain.

Aside from the referred knowledge-related aspects, uncertainty can also be the result of another category of factors which are generally found to be associated with randomness. This type of uncertainty, often termed *aleatoric* uncertainty, represents the intrinsic random nature of a certain phenomenon. In different research fields, this type of uncertainty has also been addressed using terms such as irreducible uncertainty (Tucker and Ferson, 2003), random variability (Bolker, 2008) or ontological uncertainty (Gillund et al., 2008). The time between the consecutive occurrence of disasters such as earthquakes and storms of a given intensity is an example of an uncertain and random phenomenon. However, when estimating the economic losses of disasters, such randomness is no longer important since losses are assessed after the actual occurrence of this particular random phenomenon. Nevertheless, there are other sources of *aleatoric* uncertainty that can affect disaster loss accounts. The variation in the number of people in a certain area over a certain period of time is often referred as being an example of *aleatoric* uncertainty (Aven, 2008). Therefore, accounting for such uncertainty is fundamental when estimating the size and characteristics of population affected by a disaster. Another source of *aleatoric* uncertainty is related with observation and/or evaluation errors that may occur when collecting loss data (Gardi et al., 2011). These errors fall within the general category of human errors which have been found to be inherently random (Cuschieri, 2006; Der Kiureghian and Ditlevsen, 2009).

Most contexts where the scientific research analysis and treatment of uncertainty is addressed assume that uncertainty can be expressed using numerically quantifiable metrics (e.g. see Beck, 1987; Smith and Shugart, 1994; Pate-Cornell, 1996; Charles, 1998; Walker et al., 2003). However, there are cases where such numerical quantification of uncertainty is not possible, namely when problems are ill-defined, when information is only partial or not quantifiable. Under such conditions, only qualitative descriptions can be established to express uncertainty. Qualitative descriptions involve language-based terminology which, in most cases, is imprecise such as our use of it. For example, vague and context-dependent terms or expressions can impair our understanding about what is being described. As a result of this lack of accuracy, an additional type of uncertainty then arises, termed *linguistic* uncertainty. *Linguistic* uncertainty differs from *aleatoric* and *epistemic* uncertainties since it is not a property of the data under analysis and it is not created by processing available data. Instead, *linguistic* uncertainty is created when attempting to express information using non-quantitative metrics.

For completeness, a final category of uncertainty is also briefly addressed herein. This fourth category of uncertainty occurs in a decision-making process that is based on the interpretation of results that were expressed and communicated following a given analysis. Since different individuals can have different interpretations of the same data due to subjective judgment or differences in values, beliefs and preferences, such variety of interpretation outcomes is an additional source of uncertainty. This type of uncertainty has been defined by Finkel (1990) who termed it *decision* uncertainty. However, it has also been addressed using terms such as value uncertainty (Morgan and Henrion, 1990), volitional uncertainty (Bedford and Cooke, 2001), decision-making uncertainty (Ascough II et al., 2008), human uncertainty (Maier et al., 2008) or human decision uncertainty (Kujala et al., 2013). This type of uncertainty has also been termed ambiguity by Kwakkel et al. (2010), following the terminology introduced by (Brugnach et al., 2008) when addressing the fact that different individuals may use different frames of reference to interpret the dame data. The use of the term ambiguity in this context must not be mistaken with the same term being used in a later Section of the current report to define one of the components of *linguistic* uncertainty, following the terminology introduced by Regan et al. (2002). Since *decision* uncertainty only appears in the context of decision making processes after data have been analysed and results have been expressed, additional details regarding its treatment and representation are not addressed herein as it falls outside the scope of the current report.

To analyse the quality of results obtained from a disaster loss assessment, the relevant types of uncertainty are those related with the available data and with data processing operations. Based on the previously described types of uncertainty, *epistemic* and *aleatoric* uncertainties are the general categories found to be the more significant. Still, if these uncertainties need to be expressed in qualitative terms, *linguistic* uncertainty must also be considered relevant. From a practical standpoint, it is also important to categorize these uncertainties according to their potential for being reduced or eliminated. Given its random nature, eliminating *aleatoric* uncertainty is not feasible (although in some cases it can be reduced in the statistical sense of obtaining a lower variance). At best, this type of uncertainty can be described by a statistical model. On the contrary, since *epistemic* uncertainty is presumably caused by having an inadequate level of knowledge, it can be reduced or even eliminated by improving the existing knowledge. With respect to *linguistic* uncertainty, Regan et al. (2002) suggest several ways to reduce this type of uncertainty, namely by providing precise numerical definitions for vague terms, and carefully specifying the context of terms and their meaning when these terms are ambiguous. Establishing precise numerical definitions for terms such as “low”, “medium” and “high” is a popular form of reducing vagueness when expressing uncertainty. This approach, however, may impose a level of precision that analysts find difficult to work with. Patt and Dessai (2005) and Budescu et al. (2009), for example, have shown that scientists and policy makers interpret terms such as “likely” or “very unlikely” in very different ways and continue to do so even after they have read a set of numerical definitions for these terms.

To express *aleatoric* and *epistemic* uncertainties using quantitative or qualitative approaches, it is helpful to subdivide these categories of uncertainties into more detailed classes. Several research studies attempted to establish such classes over the years. For example, MacEachren et al. (2005) published a review of models of information uncertainty and imperfect knowledge in the field of geography, while Thomson et al. (2005) proposed a typology of categories of uncertainty for intelligence information analysis. Another taxonomy for the treatment of uncertainty was also proposed by Regan et al. (2002) for ecology and conservation biology. In the field of health care, Han et al. (2011) proposed a three-dimensional taxonomy that characterizes uncertainty according to its fundamental sources, issues, and locus. Another example can be found in the domain of decision support and policy making for which Walker et al. (2003) proposed a framework to express the uncertainty in a model for decision makers. Following some concerns expressed by Norton et al. (2006) about this framework, Kwakkel et al. (2010) proposed a revised and extended version of this uncertainty classification system. With respect to attempts to express uncertainty in a common way across several domains, the taxonomy proposed by Smithson (1989), and later reviewed by Bammer and Smithson (2008), is useful for distinguishing between different kinds of uncertainty and for demonstrating how different disciplines and practice areas focus on different aspects of uncertainty. Reference is also made to Gerdon (1998) who developed a taxonomy of imperfect information and also to the more recent empirical classification proposed by Skeels et al. (2010) for the purpose of information visualisation. With respect to *linguistic* uncertainty, although it has been addressed and analysed by many different researchers (e.g. see (Cleaves, 1995), (Burgman, 2005), (Auger and Roy, 2008), (Carey and Burgman, 2008)), the taxonomy proposed by Regan et al. (2002) remains a standard reference.

Given the characteristics of the cross-domain approach proposed by Skeels et al. (2010), it is adopted herein to define an uncertainty classification framework suitable for disaster loss assessment data. Still, this classification is extended in order to include a particular uncertainty component that is not covered by the original proposal. With respect to *linguistic* uncertainty, the taxonomy proposed by Regan et al. (2002) is also adopted for the cases where uncertainty needs to be expressed using qualitative terms. A review of these frameworks is presented in the following, highlighting their most important features.

3. A classification framework for measuring and expressing uncertainty of disaster loss data

3.1 The Skeels et al. (2010) framework for aleatoric and epistemic uncertainties and its extension

The classification framework proposed by Skeels et al. (2010) is not developed using the general categories of *aleatoric* and *epistemic* uncertainties as a basis. Instead, it establishes a hierarchy and connectivity between five types of uncertainty that can be related to factors that are *aleatoric* and/or *epistemic* in nature. The five uncertainty types that Skeels et al. (2010) propose are:

- Measurement Precision
- Completeness
- Inference
- Disagreement
- Credibility

The classification proposed by Skeels et al. (2010) also establishes that, in a given process (e.g. a disaster loss assessment), uncertainty can exist in different stages of that process. In this context, the framework developed by Skeels et al. (2010) characterizes a process using three stages, where each one is associated to a more advanced state of data processing. The three stages can be generally defined as:

- Stage 1 - Gathering and collecting data
- Stage 2 - Sorting and manipulating data
- Stage 3 - Transforming data to reach the objectives of the process

According to the framework of Skeels et al. (2010), each stage is associated to one of the five types of uncertainty. Stage 1 is associated to Measurement Precision, Stage 2 is associated to Completeness, and Stage 3 is associated to Inferences. The remaining two types of uncertainty (Disagreement and Credibility) are said to span across all three stages. In addition, it is also found that Disagreement sometimes increases the Credibility uncertainty (Skeels et al., 2010). After a detailed analysis of this classification, it is possible to detect its inability to account for certain mechanisms related to human error. Therefore, the classification framework adopted herein includes a sixth type of uncertainty termed Human Error that is added to the original framework proposed by Skeels et al. (2010). As Disagreement and Credibility, Human Error also spans across all three previously referred stages. Furthermore, in some occasions, Human Error also leads to an increase of Disagreement and/or Credibility uncertainties. The hierarchy and connectivity between the types of uncertainty covered by the framework adopted herein are illustrated in Figure 1. To understand more clearly the role of each component of this framework in defining the global uncertainty of a process, a detailed description of each type of uncertainty is presented in the following.

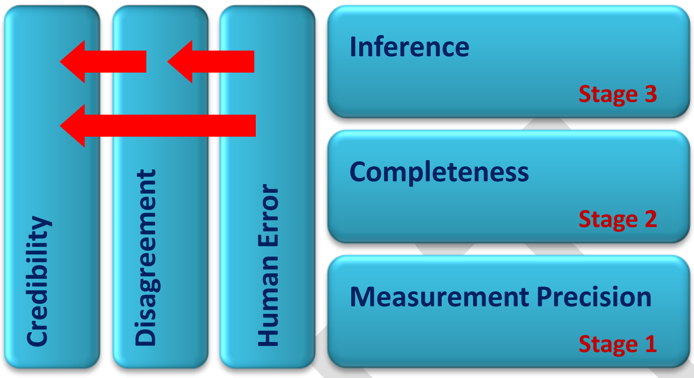

Figure 1. Hierarchy and connectivity between types of uncertainty.

3.1.1 Measurement precision – Stage 1

This category of uncertainty covers variations, imperfections and precision limitations in any type of measurement that produces quantitative data. Since the description proposed by Skeels et al. (2010) is not entirely explicit in terms of what type of factors may cause this type of uncertainty, it is detailed herein to increase its clarity. Therefore, it is referred that, in some cases, this imprecision might be due to limitations in the measurement technique being used, while in others, this imprecision might be the result of expected random variations in the actual phenomena being measured. Based on this description, this type of uncertainty is seen to account for factors of *aleatoric* and/or *epistemic* nature. This imprecision can, sometimes, be explicitly expressed by a statistical model or by a range where the true value is probably in, for example using a confidence interval. However, this uncertainty is often not able to be represented since only the measured data that is known to be imprecise is available.

3.1.2 Completeness – Stage 2

According to the description from Skeels et al. (2010), this category is represented by three sub-categories of uncertainty: sampling, missing values and aggregation. Sampling is a strategy where a subset of individuals from a statistical population is selected in order to estimate characteristics of the whole population. Therefore, completeness uncertainty will inevitably exist when generalizing these estimates to the whole population. Such uncertainty is *aleatoric* if the sample (i.e. the subset of the whole population) is randomly selected. However, if a specific sample is selected instead (e.g. based on a set of pre-defined criteria) the selection procedure may introduce *epistemic* uncertainty due to the potential inadequacy of the criteria. For example, this particular issue can occur when selecting parameters or variables to measure a particular phenomenon that will later be used for analysis (i.e. inference). If the selected parameters are inadequate, an incomplete sample of data will be obtained that will introduce *epistemic* uncertainty into the later analyses.

Missing values in the data under analysis also lead to completeness uncertainty but their effect must be distinguished from those arising from sampling. Missing values are intended to be included but are not present in the data, while sampling implies deliberate extrapolation from a few values to cover a larger set of possible values. Datasets with information that is known to be erroneous should be considered incomplete since, after removing the incorrect values, a data subset with missing values is ultimately obtained. Since this type of uncertainty is related to having inadequate data to perform a given analysis, it is categorized as being of *epistemic* nature.

Aggregating (i.e. summarizing) data is an irreversible procedure also causing uncertainty. Once data have been aggregated, part of the information is lost and data are no longer complete. As for the previous case, this type of uncertainty is also related to having inadequate data to perform a given analysis. Therefore, it is categorized as being of *epistemic* nature.

3.1.3 Inference – Stage 3

Inference is connected with decision-making since it is inference that assigns meaning to the data and transforms it into decisions. According to the description from Skeels et al. (2010), inference is a broad category that also includes three sub-categories of uncertainty: modelling, prediction and extrapolation into the past. Modelling uncertainty is introduced when the model being considered is not an adequate representation of the data properties under analysis, i.e. if the model does not reflect the causal relations that produce the phenomenon being examined. This includes models of any kind such as physical models, probabilistic models, hypothesis-testing, diagnostic models or expert opinions.

Prediction involves inferring future events by creating a model for the causal relationship between current or past data and future occurrences. As for the previous case, uncertainty is introduced when the model being considered is not able to represent future outcomes of the phenomenon under analysis. Likewise, uncertainty from extrapolation into the past involves the use of data to reproduce or make inferences about past events. Again, uncertainty is introduced when the model being considered is not able to represent past outcomes of the phenomenon under analysis.

As can be seen, all three categories of uncertainty are directly related to the adequacy of the model being used to establish the required results. The difference between the three types of uncertainty is only at the level of what kind of inference is being performed with the model. Modelling uncertainty will occur when the inference being made is about the present (i.e. the model is used to reproduce the phenomenon under analysis using the existing data). On the other hand, prediction or extrapolation into the past uncertainties will occur when inference is about future or past outcomes of the phenomenon under analysis, respectively, for which there is no or not enough data. Since these types of uncertainty reflect the inability to reproduce a given phenomenon by lack of capacity or knowledge, there are found to be all of *epistemic* nature.

3.1.4 Human Error – All stages

Human error is a critical element of human activity and professional practice. As previously noted, human errors, as considered herein, are a source of *aleatoric* uncertainty and can occur in any activity of the previous three stages that involves people. Even though this uncertainty may be difficult to quantify (Kim and Bishu, 2006), its classification and analysis has been addressed using several different approaches (e.g. see reviews presented by Whittingham (2004) and Rausand (2011)). In order to express more clearly the uncertainty associated to human errors, it is helpful to describe them using a more detailed and categorized approach. Within the scope of the present framework, human errors are considered to be random events that are either unintentional or deliberate. In this context, the taxonomy proposed by Reason (1990) is found to be the more adequate approach to categorize human errors for the proposed uncertainty classification. According to Reason (1990), there are four categories of human errors. The first three categories reflect unintentional events while the last one reflects a deliberate event. These four categories are:

- Slip - An action that is carried out with the correct intention but a faulty execution.
- Lapse - A failure to execute an action because of a distraction or a lapse of memory.
- Mistake - A correct execution of an incorrect intention. A person may believe an action being carried out is correct when, in fact, it is wrong.
- Violation - A person intentionally applies a rule or a procedure that is different than what is known to be required. A violation may be executed with good or bad intention.

3.1.5 Disagreement – All stages

Disagreement can create uncertainty in any of the previously defined three stages. At Stage 1, disagreement happens when a given parameter is measured multiple times or is obtained from different sources and the measurements are not the same (as a result of human error or any other cause). At Stage 2, disagreement may occur, for example, when several non-identical but partially overlapping datasets representing the same phenomenon are available. At Stage 3, disagreement can occur when two (or more) different conclusions are drawn from the same data. This can happen when two (or more) experts analyse a certain dataset and come to different conclusions (again, as a result of human error or other causes), or it can happen when different mathematical models are applied to a certain dataset to perform an inference. The *aleatoric* or *epistemic* nature of the disagreement uncertainty depends on the nature of the factors leading to such uncertainty. For example, if the source is related to human error uncertainty, which is *aleatoric*, the resulting disagreement uncertainty will also be of *aleatoric* nature. A similar reasoning can be established for the case of the measurement precision uncertainty of Stage 1 which can be of *aleatoric* and/or *epistemic* nature, thus leading to disagreement uncertainty of the same nature. A similar conclusion can be drawn with respect to the sampling uncertainty of Stage 2. On the other hand, since the remaining uncertainties of Stage 2 (missing values and aggregation) and the Stage 3 uncertainties are all of *epistemic* nature, the consequent disagreement uncertainty that may follow is also of *epistemic* nature.

3.1.6 Credibility – All stages

Credibility can also lead to uncertainty in any of the previously defined three stages. A source of information that produces data in conflict with other data, that produced unreliable data in the past, or is otherwise suspect for some reason (e.g. data with errors can lead to concerns about the correctness of other datasets coming from the same source) can lead to this type of uncertainty. Sources of information can be human (e.g. individuals or institutions) or non-human (e.g. machines, measurement tools, models) and credibility issues can be cast on both of them in different forms. For example, credibility could be questioned due to the methods used to get the data or concerns surrounding the biases or conflicts of interest with the creators of the data. A human source may also be considered untrustworthy based on past behaviour. Likewise, machines or measurement tools can also be considered untrustworthy based on past behaviour. In this case the credibility appears to be similar to measurement precision uncertainty. However, the difference is that credibility is a judgment made by the information user about the information source, rather than being a known precision limitation mathematically expressible by the information source itself. Furthermore, it is also noted that credibility and disagreement are often associated because as soon as disagreement occurs, whether among people or among measurements, credibility is often called into question. Likewise, when human error occurs, credibility issues are also usually cast.

3.2 The Regan et al. (2002) framework for linguistic uncertainty

The framework proposed by Regan et al. (2002) identifies the following five types of linguistic uncertainty:

- Vagueness - This type of uncertainty will occur because much of the words we use allow borderline cases. For example the words “low,” “remote,” and “endangered” establish a vague sense of quantification when used in the expressions “the chance of a ship collision is low,” “the risk of an earthquake turning into a disaster is remote,” and “the people are endangered.” Terms used to define likelihood and consequences categories in qualitative assessments are typically vague - words such as low, negligible, moderate, or frequent, large, etc. all permit borderline cases.
- Context dependence - This type of uncertainty will occur when the context in which a proposition is to be understood is not fully specified. For example describing an oil spill as “small” creates uncertainty - small for what? The occurrence of such an event in the open ocean or in a rather limited estuary will have consequences that are significantly different. Still, it is important to note that the term “small” is also vague and that this source of uncertainty will remain even if the context of the oil spill is fully specified.
- Ambiguity - This type of uncertainty is associated with the meaning of words. Words can have more than one meaning and it is often not clear what the meaning is. Inconsistent use of the same word can confound attempts to compare the results of apparently similar studies (Hayes and Barry, 2008).
- Under-specificity - This type of uncertainty is created by expressing information using an undesired generality. Undesired generality can occur in many ways and can lead to

many ways to interpret a statement. For example, does the statement “there is a 70% chance of rain” mean that it will it rain for 70% of the day, it will rain over 70% of an area, or that there is a 70% chance of at least some rain at a particular point? Unwanted generality can also occur through imprecise descriptions of locations (e.g. inland USA), processes (e.g. fishing), etc.

- Indeterminacy - This type of uncertainty is a subtle and insidious form of *linguistic* uncertainty. It arises because the future use of a term may not be completely fixed by its current use. This means that some terms although not currently ambiguous, have the potential for ambiguity in the future.

Linguistic uncertainty may be deliberate or not. People may use vague terms deliberately to avoid giving an impression of precision or because they lack communication skills. In either case, *linguistic* uncertainty creates problems when attempting to quantify certainty with terms such as “highly certain” or “medium confidence”. O’Hagan et al. (2006) and Morgan and Henrion (1990) emphasise that verbal expressions of uncertainty can mean different things to different people (a case particularly important with people that have different professional backgrounds) and, in some cases, can also mean different things to the same person in different contexts. Therefore, verbal expressions of certainty do not provide a consistent (e.g. between assessments or even between assessors) basis for uncertainty analysis.

4. Expressing uncertainty: an approach suitable for disaster loss data

Most standard statistical techniques that have been developed to handle uncertainty assume that it is due to variations in phenomena that can be precisely (i.e. numerically) measured. Such techniques usually consider that some sort of data distribution reflecting this uncertainty is available to allow the use of numerical simulation methods for uncertainty quantification and propagation. For this category of uncertainty analysis, it is, therefore, possible to use methods such as those based on Monte Carlo analysis, Latin Hypercube sampling, importance sampling, variance reduction techniques, perturbation analysis, sensitivity analysis, response surface-based approaches, the Fourier amplitude sensitivity test, the Sobol' variance decomposition or fast probability integration (e.g. see (Helton and Davis, 2003), (Saltelli et al., 2004), (Sudret, 2007), (Lemaire, 2009), (Smith, 2014)). In addition, methods using non-probabilistic approaches such as those based on interval analysis or fuzzy analysis (e.g. see (Ayyub and Klir, 2006), (Hayes, 2011)) are also available for this category of problems.

Even though the power and validity of these numerical methodologies is unquestionable, their use is, usually, only feasible in traditional science fields where sufficient hard data is available for numerical treatment. On the other hand, disaster loss data is often coarse and scattered, thus precluding the use of such refined mathematical manipulations. In other words, available data is frequently insufficient, thus unable to support the meaningful definition of adequate statistical descriptors suitable for mathematical treatment. In such cases, defining qualitative expressions of uncertainty is often the only available option. However, even though qualitative expressions of uncertainty are more difficult to define unequivocally, as well as more difficult to use in a numerical uncertainty propagation analysis, they have the potential to be more informative than statistical descriptors since they can include a large number of attributes (Norton et al., 2006).

A suitable methodology to characterize the uncertainty in disaster loss data must, therefore, be able to accommodate both quantitative and qualitative measures of the uncertainty in a certain datum. The methodology must be able to express this uncertainty it in a clear and meaningful way so that, in the end, a measure of how reliable and accurate the datum is for a given purpose can be established (i.e. to reflect the quality of the datum). Potentially fitting methodologies of this type have been analysed, for example, by van der Sluijs et al. (2004) and Refsgaard et al. (2007). Based on their descriptions and reviews, the NUSAP (Numeral Unit Spread Assessment Pedigree) method is adopted herein given the adequate features of this approach. NUSAP is a system proposed by Funtowicz and Ravetz (1990) originally developed to characterize and assess the multidimensional uncertainty in science for policy. Given its ability to capture both quantitative and qualitative dimensions of uncertainty and to represent them in a standardized and self-explanatory way, this system has also been successfully used and adapted in other research and science fields (van der Sluijs et al., 2005; Costanza, 2007; Boone et al., 2009; Colli et al., 2009; Boone et al., 2010; Durugbo et al., 2010; Lorenz et al., 2013; Matschewsky, 2013; Henriksson et al., 2014). In the end, NUSAP is able to provide a critical review of the knowledge base that is available for each component associated to the data, pinpointing specific weaknesses.

The NUSAP method involves five parameters that are used to characterize a certain datum. The five parameters are *Numeral*, *Unit*, *Spread*, *Assessment* and *Pedigree*. According to Funtowicz and Ravetz (1990), parameters *Numeral*, *Unit* and *Spread* address the quantitative aspects of the datum being analysed, while *Assessment* and *Pedigree* are assigned to describe its more qualitative components. Depending on the datum under analysis, *Numeral* can be defined using an ordinary number representing a mean value or a best estimate but, when appropriate, it can also be defined using a more general quantity such as an expression of a number (e.g. a million). Parameter *Unit* usually expresses the scale of *Numeral* by defining its unit of measurement, but it can also contain additional information such as the date of the evaluation. According to Funtowicz and Ravetz (1990), *Spread* is expected to represent the more quantifiable component of the uncertainty of the datum under analysis. Therefore, if sufficient data is available, *Spread* can be defined by the variance of the data, which could be determined by statistical methods such as those previously referred. However, data may often be insufficient to establish a meaningful statistic representing the variability of the datum. In some cases, available data may only allow the definition of an interval or a range of variation of the datum, which can be established using mathematical procedures or expert elicitation.

Assessment is the first parameter of NUSAP expressing qualitative judgments about the datum. Although *Assessment* can be used to represent different aspects of the datum, it can be used to establish a global measure of expert judgement about the overall goodness, reliability or level of confidence associated to the value in *Numeral* or, if desired, in *Spread* instead. For example, this qualitative grade can be defined using qualifiers such as "optimistic/pessimistic", "reliable/unreliable", "official/unofficial" or "exact/accurate/estimate/guess". Alternatively, in cases where there is sufficient data to carry out statistical analyses, the level of confidence can be defined by the statistical significance level used to derive the datum or its *Spread*. The final parameter of NUSAP, *Pedigree*, is a concept first introduced in uncertainty analysis by Funtowicz and Ravetz (1990) where a set of criteria is used to assess several aspects related to the information flow and the knowledge used to characterize the datum under analysis. *Pedigree* is a matrix where problem-specific criteria are graded according to a numerical scale. Since, for each of these criteria, a linguistic description is assigned to each value of the scale, the *Pedigree* matrix represents, thus, a tool suitable for the quantification of qualitative assessments associated to different components of the uncertainty involved in the object being analysed. The structure of the *Pedigree* matrix has no formal requirements since the rating scale as well as the number and type of criteria are selected according to the needs of the specific problem under analysis. After grading each criterion, a global average *Pedigree* score can also be established, which reflects the overall quality of the process that lead to the datum under analysis (Costanza, 2007). Nevertheless, it is noted that since the grading of each *Pedigree* criterion is based on qualitative descriptors, *linguistic* uncertainty may be involved, as well as subjective judgements from the person involved in the grading. To illustrate this component of NUSAP, Table 1 presents the *Pedigree* matrix considered by Ciroth (2009) for managing the uncertainty and quality of cost data.

Table 1. *Pedigree* matrix for the uncertainty and quality management of cost data (Ciroth, 2009).

Grade	Criterion				
	Reliability of source	Completeness	Temporal differences	Geographical differences	Further technological differences
5	Verified data based on measurements	Representative data from a sufficient sample of sites over an adequate period to even out normal fluctuations	Less than 0.5 years of difference to year of study	Data from area under study, same currency	Data from enterprises, processes, and materials under study
4	Verified data partly based on assumptions or non- verified data based on measurements periods	Representative data from a smaller number of sites but for adequate	Less than 2 years difference	Average data from larger area in which the area under study is included, same currency	Data from processes and materials under study from different enterprises, similar accounting systems
3	Non-verified data partly based on assumptions	Representative data from an adequate number of sites but from shorter periods	Less than 4 years difference	Data from area with slightly similar cost conditions, same currency, or with similar cost conditions, and similar currency	Data from processes and materials under study but from different technology, and/or different accounting systems
2	Qualified estimate (e.g. by industrial expert)	Representative data but from a smaller number of sites and shorter periods or incomplete data from an adequate number of sites and periods	Less than 8 years difference	Data from area with slightly similar cost conditions, different currency	Data on related processes or materials but same technology
1	Non-qualified estimate or unknown origin	Representativeness unknown or incomplete data from a smaller number of sites and/or from shorter periods	Age of data unknown or more than 8 years of difference	Data from unknown area or area with very different cost conditions	Data on related processes or materials but different technology

6. Final remarks

After reviewing and analysing different structures for the assessment of uncertainty, an existing methodology suitable for the characterization of uncertainty in disaster loss data was also addressed. Details about the practical implementation of this methodology must now be developed in order to address the specific type of loss data that need to be characterized, i.e. human losses and economic losses. An important part of this practical implementation process will need to establish *Pedigree* matrices suitable for each type of loss data that address the different sources of uncertainty involved in the previously proposed classification framework.

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