A graphical representation of uncertainty in complex decision making

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Abstract

The analysis of types of uncertainty and how they affect decision making in complex settings can be considerably simplified by addressing three core questions: how uncertain we are, how aware we are of uncertainty and how context and perception affect uncertainty. The continuum nature of the answers to these questions leads naturally to represent uncertainty in a 3D level-awareness-perception plot. This representation can help monitoring and assessing the dynamics of knowledge and uncertainty generation during a project and how it affects decision making. Of particular importance are how the level of unresolved uncertainty at the moment of decision making is represented in the decision itself and how the objective codification of both knowledge and the decision impact the events following a project. This leads to highlighting a further type of uncertainty which can be generated by the decision making itself and by its representation in the form of codified knowledge.

1 Introduction

A considerable amount of research in complex system science aims to provide advice for policy initiatives (Meadows, 1972; Holling, 1978; Walters, 1986; de la Mare, 1996; Brunner, 1999; Pielke, 2003; Adams, 2004; Walters and Martell, 2004; Allan and Stankey, 2009; 2009; Rockström *et al.*, 2009; Likens, 2010). This follows naturally from the realisation of the inherent complexity of many real world problems at the intersection of organisational, ecological and economic issues, as well as of the need for both scientific and public input in the political decision making processes (Butterworth and Punt, 1999; Lee, 1999; Morgan and Morrison, 1999; Doak *et al.*, 2008; Allan and Stankey, 2009; Allan and Stankey, 2009; Ivanović and Freer, 2009; Chapman, 2011).

Ideally, we would like scientific research to produce exact knowledge. However, given that in complex problems this is never achievable, a more realistic goal is that of reducing uncertainty. Reduced uncertainty can then feed into decision making within the balances and trade-off of negotiation for policy decisions (Ackerman and Heinzerling, 2004; Adams, 2004).

In the physical sciences uncertainty is reasonably well understood and at least from a pragmatic perspective practitioners are provided with established statistical and mathematical tools to describe it and process it. However, decision and policy making occur in the social, not physical sciences, arena; here, knowledge and uncertainty take several forms (Dorner, 1996; Cross *et al.*, 2001; Duckitt *et al.*, 2002; Pielke, 2003; Kolb and Kolb, 2005; Lewandowsky *et al.*, 2005; Joshi *et al.*, 2007; Brugnach *et al.*, 2008) and which scientific approach and instrument is best suited for these different types is not immediately clear (Stanovich, 1999; Syme *et al.*, 2006; Sterman and Sweeney, 2007).

In this work, I discuss a number of classifications of types of uncertainty and knowledge commonly found in the literature and propose a simple visual representation of their relations. I also endorse a dynamic view according to which knowledge and uncertainty, as well as ignorance, are created both during a research project and after decision making and propose the use of this visual representation as a means to map the process.

2 Types of uncertainty

Uncertainty is widely recognised to take several forms. Within the physical science a distinction is usually made between ontological and epistemic uncertainty (Walker *et al.*, 2003; Tannert *et al.*, 2007). The former refers to processes which are inherently stochastic, whose uncertainty cannot be reduced by further investigation. A typical example is given by several gambling games; in principle (dismissing microscopic dynamics occurring, say, in the rolling of a dice or in the throwing of a roulette ball), we can formally describe the full process via simple mathematical equations, which however do not allow us to reduce the inherent uncertainty in short-tem predictions. This generalises to any closed (i.e., with no interaction with the outside world) stochastic process for which full formal description is available. Epistemic uncertainty refers to processes which are in principle knowable, but for which our current understanding is limited; these are the problems for which better data collection and structural understanding may lead to reduced uncertainty. (Pielke, 2003) makes a similar distinction between uncertainty arising from closed vs open systems.

Within the epistemic uncertainty, researchers and practitioner often differentiate structural from data-driven uncertainty (Walker *et al.*, 2003). The first refers to our lack of knowledge of the processes and casual links at play while the second refers to lack of data which prevents us from fitting a structural model to a specific problem. Broadly speaking, in the latter case, we have a model of the process and we need to tune it, in the former case we need to develop, or we are unsure of, the model. A similar distinction is made between state, effect and response uncertainty in (Milliken, 1987).

Once a model is available to study a problem, other technical issues affect how certain we are of the answers they provide. Much work in computer science is devoted to understand whether a problem requires polynomial vs exponential increase in resource (time and memory) as its size increase. For example, it is important to know how more complex a problem becomes when we double the number of parameters used in the model descriptions, which technically refers to, for example, whether a problem is P or NP-hard (Cheeseman *et al.*, 1991). This has considerably practical implications: finding the best scheduling for a large set of interdependent tasks or the fastest route to visit several locations in a sequences are all examples of problems which increase exponentially with size. The result is that using these models with large parameterisation soon becomes intractable in practise and we can no longer be certain of whether the answer we obtain is optimal. Other technical issues arise when we ask whether an answer to a problem can be achieved via logical or computation processes and we dive into issues on completeness and incompatibility in logical systems (Chaitin, 1997; Boschetti and Gray, 2007)

A broader understanding of uncertainty arises by including the social and psychological dimension of decision making. Within a social context, (Brugnach *et al.*, 2008) differentiates knowing 'too little' from knowing 'too differently'; this refers to cases in which the same problem, seen via the lens of different actors, may be perceived differently. Different actors may use different 'frames' to define the same problem, leading to multiple, diverging views of how the problem should be addressed. (Brugnach *et al.*, 2008) define a frame as a 'sense-making device' or as representations of the external world, which may be biased when compared with accurate, decision-theoretical representations. In this case, scientific evidence, model development and data collection may not be enough to address the problem, unless a common framework for discussion is first achieved (Lee, 1999; Brugnach *et al.*, 2008; Allan and Stankey, 2009; Allan and Stankey, 2009; Chapman, 2011). Uncertainty, in this case, is a result of a problem's context dependency (Busemeyer *et al.*, 2009; Lambert Mogiliansky *et al.*, 2009; Yukalov and Sornette, 2009).

Together with the social dimension, a number of authors consider the cognitive dimensions (Dorner, 1996; Stanovich, 1999; Sorrentino and Roney, 2000; Moldoveanu and Langer, 2001; Cronin *et al.*, 2009). A problem may be rationally well defined, but may appear different to different individuals because of cognitive or emotionally reasons. Here for 'rationally well defined' I mean that the problem may be amenable to complete description, so that each individual has access to the same, full information; still, different individuals may reach different conclusions. It may be so for cognitive limitations, which lead some individuals to draw rationally fallacious conclusions (Tversky and Kahneman, 1974; 1983; Sweeney and Sterman, 2000; Sterman and Sweeney, 2002; Halford *et al.*, 2005; Sterman and Sweeney, 2007; Sweeney and Sterman, 2007; Sterman, 2008); it may be the conclusions appear rationally fallacious, but hold heuristic or evolutionary value (Stanovich, 1999); it may be that a 'correct' or rational answer is not available (Campbell and Sowden, 1985); or it may be that the problem is actually context dependent despite the experimenters think otherwise (Moldoveanu and Langer, 2001) .

An ethical dimension to the analysis of uncertainty is provided by (Walker *et al.*, 2003; Tannert *et al.*, 2007) who include subjective uncertainty. Certain problems are morally ambiguous either because it is not clear to the individual which moral rule, among many, should apply, or because a problem may be novel and no moral rule may be available. In this case, the individual is left to his/her own moral devises to make a decision whose outcome becomes uncertain.

With the exception of ontological uncertainty, ambiguity is a common feature of all other types of uncertainty; in the absence of a satisfactory knowledge of a problem, understanding can be achieved via multiple models, multiple realisations of the same model, multiple frames, multiple deductive or inductive paths (some possibly logically incorrect) or multiple moral reasoning.

So far, the discussion has assumed that the individual is aware of his/her state of knowledge or uncertainty, but this needs not be the case. In a famous press interview in 2002, the former US Defence Secretary Donald Rumsfeld popularised the concept of 'unknown unknowns' as a component of a classification of uncertainty types into 'things we know that we know', 'things we know that we do not know' and 'things we do not know that we do not know'. This classification was already established in engineering and military sciences, which emphasise the risks implicit in the 'unknown unknowns', and in the field of logics which studies the decision-making and modelling implications of these classes of knowledge (Fagin and Halpern, 1987; Samet, 1990; Modica and Rustichini, 1994; Modica and Rustichini, 1999). While the 'unknown unknowns' have attracted much on the popular attention, as well as considerable work in the ecological and environmental literature (Doak *et al.*, 2008; Wintle *et al.*, 2010), two other concepts in this classification are of interest. The first is that it is easier to discuss knowledge and uncertainty if we are aware of them and that awareness is necessary to rationalise and communicate why a decision has been taken (Pronin and Kugler, 2010). The second concept is that the classification implies the existence, at least in principle, of 'unknown knowns': things we know without being aware of. This idea fits nicely the discussion on different types (Joshi *et al.*, 2007) and dimensions (Cross *et al.*, 2001) of knowledge (Syme *et al.*, 2009).

What and how we know have been two topics of philosophical enquiring since antiquity. Here we focus on aspects of the discussion which pertain to scientific advice for decision making. In this case, it is often assumed (although it does not need to be) that information is provided in a codified form. That is, it should be represented by numbers which can be processed or interpreted by cognitive or logical analysis or be condensed into numerical models which can be employed to obtain projections, predictions and other numerical estimates. One problem with this assumption is that knowledge is not a homogenous entity, but come in several types. (Joshi *et al.*, 2007) proposes to consider encoded, tacit, embodied, embrained, procedural and embedded knowledge. To quote (Joshi *et al.*, 2007): "Tacit knowledge refers to the type of knowledge that is difficult to explicate or articulate. Embodied knowledge can be partially articulated and results from physical presence (i.e. from interpersonal communication). Encoded knowledge is the knowledge that refers to the knowledge residing in text books and in data banks. Embrained knowledge refers to the cognitive ability of understanding underlying patterns of a given phenomenon (e.g. double loop learning). Procedural knowledge refers to knowledge about the processes. Finally, embedded knowledge refers to knowledge that is contained within a variety of contextual factor and is not pre given".

It is clear that all these knowledge types are pertinent to our analysis when decisions need to be taken by multiple actors via negotiation. Because decision makers and stakeholders have different roles and relate to one another within social networks, it is also clear that the different types of knowledge may require alternative structures to disseminate effectively (Reagans and Zuckerman, 2001). For example, codified knowledge travels naturally over greater distances in a network than other forms, while tacit knowledge appears to be transferred more effectively between actors sharing similar roles and background. In this context, (Cross *et al.*, 2001) propose a classification in terms of dimensions of knowledge, which include: knowing what another person knows, being able to gain timely access to that person, the willingness of the person sought out to engage and the degree of safety in the relationship that promotes learning and creativity. So while the types of knowledge highlight what form information is hold in a social group, the dimensions of knowledge address how and under what conditions knowledge can be exchanged.

The above discussion is obviously not exhaustive, but already includes more than 15 types. We can achieve a considerable simplification by noticing that they address three core questions: 1) how uncertain we are, 2) how aware we are of uncertainty and 3) how context and perception affect uncertainty. It is important to notice that this simplification is useful not only because it summarises the above discussion, but also because it highlights some conceptual relations between different types. For example, ontological and epistemic uncertainty both address the question of how uncertain we are; however, within the scope of this work, their difference is less significant than it may appear. Rarely real world decision making needs to face ontological uncertainty, since rarely, if ever, we have a full understanding of a real world problem; the vast majority of problems of real interest fall into the epistemic class. Furthermore, the technical distinction between the two is also less clear than it may appear: chaotic processes are in principle knowable and predictable (given an infinite amount of information) but empirically inaccessible, so it is not clear in which class they should fall. In most real world problems, the distinction between structural and data-driven uncertainty is also fairly blurred for at last two reasons: first, we rarely, if ever, have the 'right' model. More often, we have a model, or a number of models, which represent our current understanding of a process. Which model we use is often a problem-dependent choice; once the model is chosen, data is sought for model tuning. Other times data itself may suggest which model should be used. Second, models may display different dynamical behaviours depending on input parameters (Boschetti, 2008) and thus the effective causal structure of the model may depend on parameters choices. For the applied scientist or the practitioner these types of uncertainty all collapse into the question of what type of model should be used, what data should be considered reliable, what tool should be employed to summarise the conclusions, how the information should be packaged for delivery and how the uncertainty should be communicated.

Similarly, types of uncertainty arising psychological, cognitive and social drivers can be grouped into a single category. It is so not just because of superficial similarities but, more important, because they are strongly correlated to one another. For example, a considerable literature highlights the strong casual connections between attitudes towards uncertainty and the worldviews people hold (Duckitt *et al.*, 2002; Unger, 2002; Jost *et al.*, 2003; Lewandowsky *et al.*, 2005; Heath and Gifford, 2006; Kahan *et al.*, 2007; Duckitt and Sibley, 2009; Leviston and Walker, 2010; Lewandowsky, 2010), which inevitably affect the perception of a situation which they bring into the negotiation table. These worldviews and attitudes towards uncertainty also affect thinking styles and cognitive attitudes (Dorner, 1996; Stanovich, 1999; Sorrentino and Roney, 2000) which determine how a complex problem is addressed, how much information is sough, how such information is processed and how likely it is to fall into fallacious conclusions. Because these attitudes also affect the perception of the role of the individual within the community and society at large, they also affects the way social dilemmas and thus the paradox of rationality, are addressed (Duckitt *et al.*, 2002; Jost *et al.*, 2003; Duckitt and Sibley, 2009).

It thus seems that some clarification on this subject can be obtained by considering three concepts: a) the *level* of uncertainty, b) the *awareness* of uncertainty, and c) the *framing* or *perception* of a problem. Neither of these are binary variables: in real world problems we are never either fully certainty or fully uncertain, never fully aware or fully unaware of uncertainty; similarly, how many frames are used to perceive a problem depends on the problem as well as on the number of actors affected by it. These concepts thus span a continuum and have the flavour of geometrical *dimensions*.

This leads quite naturally to represent these ideas graphically in 3D plot, in which each axis maps one of such dimensions.

3 A geometrical representation of uncertainty types

In Figure 1 we give an example of such visualisation, in which we map some of the uncertainty types previously discussed ('known knows', 'unknown knows', 'known unknows', 'unknown unknows' and 'knowing too differently'). Other types should be understood as varying in degrees along the level and awareness axis (epistemic, structural, data-driven, model complexity, encoded, procedural, embrained and embedded).

This representation allows to better understand the meaning of the 'unknown knows'. In the bottom right-hand quadrant we find tacit and embodied knowledge. This includes the assumptions we hold about how certain processes work, about the beliefs and values we assume other people hold as well as the knowledge which is held by different actors but not shared by the overall team; the latter needs to made explicit via the different dimensions of knowledge described by (Cross *et al.*, 2001), before it can become part of the team awareness and can be easily discussed and processed.

A strength of this representation lies in allowing us to visualise the dynamics involved in a research project. Naturally, we expect the status of our knowledge and uncertainty to change during a project. Naively, we may also wish that the changes all point towards the same area in the 3D plot: if a research effort was to decrease the level of uncertainty, make us more aware of the available knowledge and reduce the number of frames involved, then decision making would be, at least, easier. In other words, naively, we may wish to move towards a single frame, known-knowns setting.

Reality is far more complex, of course; as immortalised by Socrates' famous statement, better knowledge also implies a better understanding of the known unknowns; fortunately, it also implies a better understanding of how to address them, for example via more and better data collection and modelling of those processes whose uncertainty have the largest impact on the problem. Similarly, while involving more parties into the problem solving exercises inevitably carries the risk of increasing the number of frames, it also may widen the pool of knowledge available as well as make us aware of aspect of uncertainty we had not previously considered. Since the knowledge required to address a real world problem is usually not homogenous, but includes several items (for example, it may require knowledge of physical, ecological, economic and political processes, each of which can have multiple facets), it is easy to imagine how a multidisciplinary research project may result in several aspects of uncertainty moving in different directions within the level-awareness-framing plot.

Abstract examples of the dynamics we can expect during a project are given in Figure 2. For sake of simplicity, it focuses on the 2D plane including level and awareness of uncertainty. Various items of knowledge are plotted at the location where they may lie at the end of a hypothetical project; the arrows lead back to the project beginning, when not only our knowledge, but also our awareness was still unquestioned. By the end of the project, we may be both less uncertainty and more aware of data available, the best model to use, the system behaviour, the most informative indicators to monitor, among other items. For what regards available strategies, team based knowledge and assumptions, some items may have moved from the known unknowns to the known knowns, while other specific items of knowledge may still be individually held, but not shared by the full team. Other items may have become more uncertain as a result of collected information, including the model parameterisation, or the potential occurrence of events which may need preparing but we had not previously considered. It may also happen that despite we have chosen a model to use, we have become aware that multiple models are needed to address all the aspects of the problem at hand.

As we mentioned above, knowledge is not a black and white state: we are never totally ignorant or fully knowledgeable of a complex problem. In practical terms, this leads to asking when we know enough or when is our knowledge good enough for decision making (Ascher, 1981; 1993; Brunner, 1999; Pielke, 2003). Within Figure 2, this equates to asking where the vertical axis should be located. Stereotypical judgements apply to this question; scientists are commonly prone to claim they do not know enough: for them the vertical axis lies far on the right hand side of Figure 2. Managers are prone to claim they know enough, for them the axis lies far to the left. Well established experimental work in cognitive science suggests that such polarisation is real, not necessarily between scientists and managers, but between people with different attitudes towards uncertainty (Sorrentino and Roney, 2000). Some people strive in uncertainty (Stanovich, 1999), others need certainty, preferring to take firm decisions even when little knowledge is available in order to achieve 'closure' on a problem (Jost *et al.*, 2003); both will likely be unaware of this and will find arguments to rationalise their attitudes. Being aware of this, as well as the role that people with specific attitudes have in the project, is important in order not to be trapped into apparently rational argumentation which in fact are a mirror for ideological differences.

The dynamics on the level-awareness-perception plot may be fairly complex and non-linear. Figure 3 shows a hypothetical dynamics in the awareness-perception 2D plane, where time runs along the line as indicated by the thin arrow. At project start, the team may hold a number of different frames, through which they perceive the problem at hand; however, the team itself may not be aware of this, since it is natural for each team member to assume their perspective is shared by others. During the project, interactions between parties may make the existence of the multiple frames explicit, raising the team awareness of the issue (Stage 2 in the plot). Negotiations, meetings and workshop may develop a temporary convergence of views (Stage 3), but it is also possible that further information may reverse the process (Stage 4). Hopefully, by the end of the project some final convergence has been achieved together with a better awareness of the differences. However, after the project is completed it is also possible that the interactions between the parties stop, which may lead both to divergence of opinions to re-occur and to our awareness of this to decrease (dashed line).

Figure 4 highlights some of the processes which can be used to map the different areas in the level-awareness-perception plot into decision making. As discussed above, engagement is crucial both to make tacit and embedded knowledge available to the overall team and to address the uncertainty arising from multiple framing. Of course, much harder to address are the aspects on which uncertainty is very high. When a problem involves human, physical, ecological, economic and political processes, no matter how good the decision making process is, allowance for unexpected outcomes needs to be included. In the field of ecological management, for example, (Wintle *et al.*, 2010) recommends that long-term monitoring for unexpected events should be a part of any plan and several authors recommend adaptive management as the our best approach to prepare for unknown threats (Doak *et al.*, 2008; Allan and Stankey, 2009; Denny *et al.*, 2009; Lindenmayer *et al.*, 2009; Lindenmayer and Likens, 2009; Fulton *et al.*, 2010). Of course, as widely discussed in the media following Rumsfeld's famous interview and well known in the engineering and military establishment, by far the toughest challenges come from the bottom-left quadrant of the level-awareness-perception plot, the famous unknown unknowns. Naturally, by definition, nothing can be done to anticipate or prepare for this. But several authors suggest that adaptive management and careful monitoring at least provide a flexible framework for addressing unexpected events (Brugnach *et al.*, 2008; Wintle *et al.*, 2010). An considerable literature on futures studies and the role of scenario development, is dedicated to these issues (Bezold, 2010; Destatte, 2010; Miles, 2010; Ringland, 2010; Valaskakis, 2010).

Addressing the aspects which we are confident we know well 'enough', that is the single frame, known knowns quadrant, appears to be less problematic since it may include the knowledge which can feed directly into strategy formulation. This is also the domain which appears to be more pertinent to quantitative science, in terms of both generation of codified knowledge and codified measurement of uncertainty. And interesting question thus is to what extent codification reduces uncertainty, which I address in the next section.

4 Meaning and uncertainty in codified knowledge

We know that knowledge can increase uncertainty by making us aware of aspects of our ignorance. However, it is often assumed that codified knowledge reduces uncertainty, by generating information which is both objective and crisp. Here for 'crisp' I refer to values which can be unambiguously assigned to a set, as opposed to 'fuzzy' values which can have degrees of memberships (Zadeh, 1965). For example, we know that climate change is dangerous; this is not a piece of codified information, since the term 'dangerous' is fuzzy. Climate scientists also define the threshold of dangerous warming at 2^o (New *et al.*, 2011); this is a piece of codified information, since 2^o defines a crisp threshold. An important question is to what extent such codification reduces the uncertainty on how to address climate change. As mentioned above, in complex problems knowledge is never complete and in these cases scientific research helps detecting, explaining and quantifying uncertainty rather than certainty. In defining the threshold of dangerous warming at 2^o, for example, we can thus ask where the knowledge on the uncertainty of the impact of warming has gone.

There are two ways in which the uncertainty can be recovered. The first is to include an estimation of the uncertainty associated with the crisp value. Obviously, a crisp threshold including a pointer to uncertainty is no longer crisp and in policy making this requires that uncertainty is accepted and understood as positive information about the problem to address rather than as an obstruction to problem simplification. The second is that the *meaning* of scientific knowledge is understood as something broader and richer that the provision of the threshold.

Policy making by definition also requires a crisp outcome. It may be useful to think of policy making as a de-fuzzifying filter (Zrilic *et al.*, 2000; Lopez *et al.*, 2006) which takes fuzzy information as input and needs to produce crisp, clear regulation as output. In the framework of this discussion, all types of uncertainties discussed in Section 2 are naturally fuzzy, with the exception of codified information; this, most often, is provided by the natural sciences and economics and more rarely by the social sciences. The purpose of a policy is also often stated in broad fuzzy terms: for example, address global warming, improve the health system or ensure sustainability. Policy making however needs to define precisely what should be done, which implies a set of crisp instructions and of crisp performance indicators.

These examples can be seen as attempts to implement *meaning* (purpose of a policy, broad understanding of a natural process and its uncertainty) via *fixed rules* (regulations and codified information). This problem has been studied extensively in the field of artificial intelligence, cybernetics, mathematical logic and philosophy (Milner, 1993; Pattee, 1997; Kauffman, 2000; Rosen, 2001; Wiedermann and Leeuwen, 2002). From this literature we know that there is a relation among the meaning of 'law' in scientific knowledge, 'rule' in social behaviour and 'instruction' in computer science in the sense that they share three important features: they all imply inevitability, they apply only provided precise conditions are met and they cannot include specifications for their own modification (Rosen, 2001; Boschetti *et al.*, 2008; Boschetti, 2010).

In terms of policy making, rules provide a way to codify desired human behaviour and regulate human interaction: if we wish to prevent people from stealing and we want this to apply fairly, uniformly and consistently within a large population, we need to specify what stealing means, under what conditions stealing will be persecuted and what penalties an offender will face. The purpose is thus for the rules to *actuate* the meaning. The crucial question for our discussion is whether rules can *replace* the meaning that is whether, once the proper rules are found, we can trust that an effective translation meaning↔rules has been achieved. Was this possible, we could in principle dispense with the fuzziness inherent in the meaning and proceed with the rules, which, being crisp, can be more easily processed logically or numerically and communicated in a network on actors with different background knowledge (Cross *et al.*, 2001) .

Centuries of legal litigation and extensive work in logics and computer science suggest that this is very unlikely to be achieved. As mentioned above, a rule requires that the conditions under which it applies need to be clearly defined; only under these conditions we can expect the rule to be effective by working as it was designed to. But, also as discussed above, much of the real world uncertainty we need to address via regulation lies in unknown unknowns. The result is that we can never be sure that the conditions required by the rule will be met in the future; under different conditions the rule may lead to unexpected results. In addition, the above discussion suggests that the only instrument available to address unknown unknowns is adaptation. But since rules cannot include specifications for their own modification, adaptation is precluded without human intervention (Boschetti *et al.*, 2008; Boschetti, 2010). Rule re-design cannot be achieved if the meaning has been lost or if the uncertainty related to the quantification has been forgotten, since both meaning and uncertainty are crucial to re-evaluate the decision making problem under novel conditions.

This does not suggest that the search for a suitable set of rules or regulations is futile or that setting the threshold for dangerous warming at 2^o is not useful; rather it suggests that the rules, once defined, still need to carry an associated meaning, as a pointer to the reasons why the rule was set, and an associate uncertainty assessment, as a pointer to their robustness. As an example, in (Ascher, 1993; Boschetti *et al.*, 2008; Boschetti *et al.*, 2010) it is suggested that an essential component of numerical modelling is the definition of the assumptions and parameterisation, without which the meaning of the model outcome cannot be properly assessed. Assumptions and parameterisation involve subjective choices by the modeller, which results in uncertainty which may be lost in the crispness of the numerical model output.

This issue is represented graphically in Figure 5, which describes a simplified flow-chart of a policy making process. The grey ovals with broken border represent fuzzy knowledge, which for complex problems includes scientific research. Grey rectangles represent the de-fuzzifying filters: the final decision making which defines the regulation and the scientific act of collapsing complex information into a hard number or a threshold. White rectangles represent crisp information. The left-hand side part of the figure, flowchart A, shows how science is often asked to contribute to policy making by providing a crisp piece of information which is then analysed together with the fuzzy information provided by other fields of knowledge. On the right-hand side, flowchart B shows an alternative flowchart in which scientific information is not de-fuzzified prior to decision making and, carrying its own inherent uncertainty, contributes to the decision making as a fuzzy entity on the same ground as other factors. In this framework, numerical economic information often is treated similarly to scientific advice.

Once the meaning and uncertainty of a crisp value contributing to a decision making or of the policy itself has been lost, both the value and the policy become de-contextualised. Then, when novel contexts arise (for example when different background events require a re-evaluation of the scientific advice and of the policy) it is possible that a new meaning is assigned to both value and policy. When multiple actors are involved in a problem, it is likely that multiple meanings and interpretations arise, which results in moving upward in the perception axis of the level-awareness-perception plot, as described in Figure 6. Codification and de-contextualisation can thus be seen as further drivers and causes of uncertainty which can act both during and after problem solving and decision making.

5 Conclusions

Many of the uncertainty types discussed in the literature can be understood in terms of three concepts: amount of uncertainty, level of awareness of uncertainty and multiple interpretations or perceptions of the same problem. Considering each of these concepts in terms of dimensions allows us to map the dynamics of knowledge and uncertainty generation during a project as well as after its completion. Projects however do not live in isolation, rather in a temporal continuum which includes both the background uncertainty and knowledge they inherit and the impact of the project outcomes on future events. The latter will inevitably be affected by novel events which may require re-addressing of some issues. Strict codification of knowledge can be particularly susceptive to changes in context which may in turn generate further uncertainty in terms of multiple interpretations of what was assumed to have been objectively de-fuzzyfied in the codification. This observation further highlights the dynamical processes underlying the determination, assessment and perception of uncertainty.

6 Figures

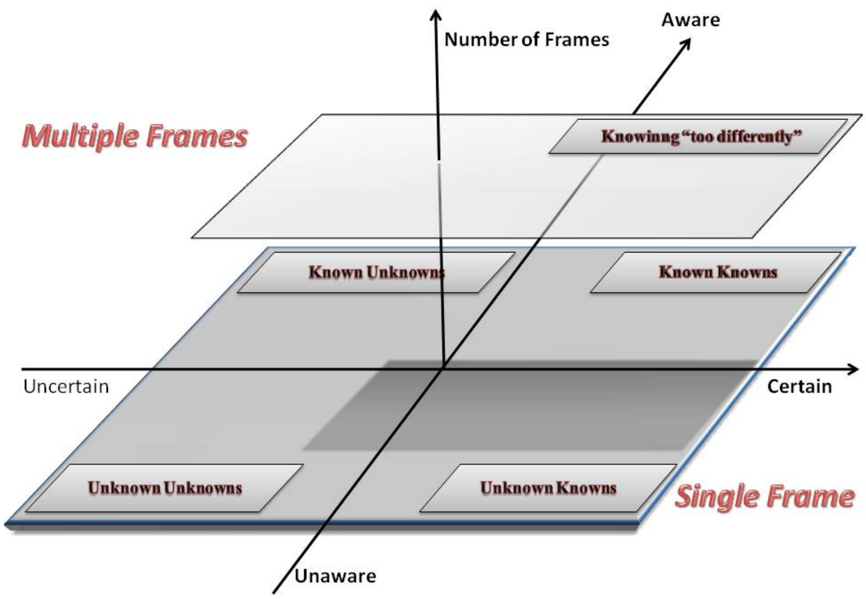

Figure 1. The level-awareness-perception plot. The X axis maps the level of uncertainty; the Y axis maps the awareness of uncertainty; the Z axis maps the number of different frames or interpretations of an issue, that is how ‘differently’ actors view the same problem.

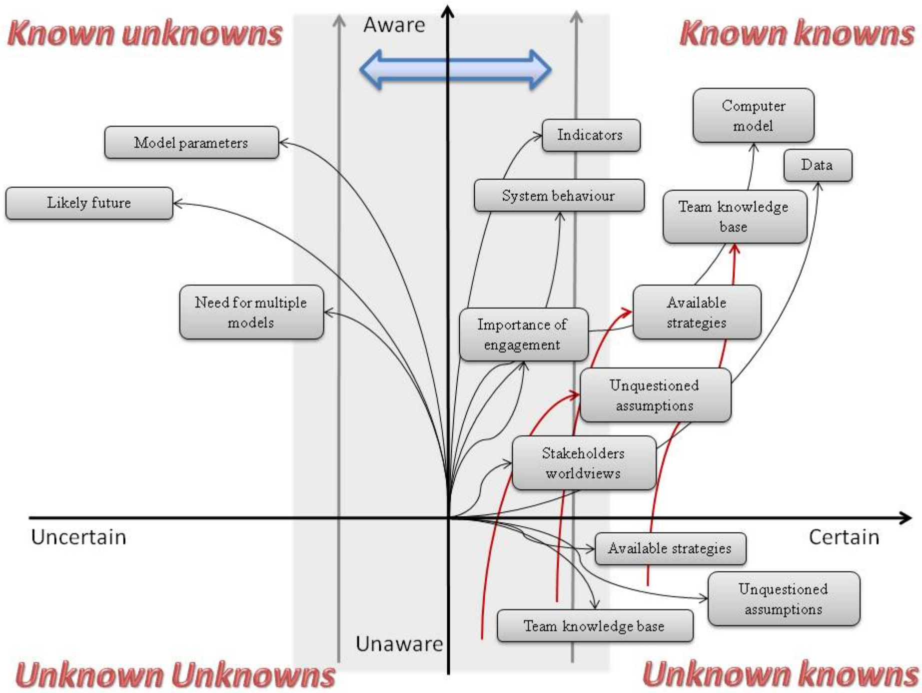

Figure 2. Example of mapping on the 2D level-awareness plane of the knowledge at the completion of a hypothetical project.

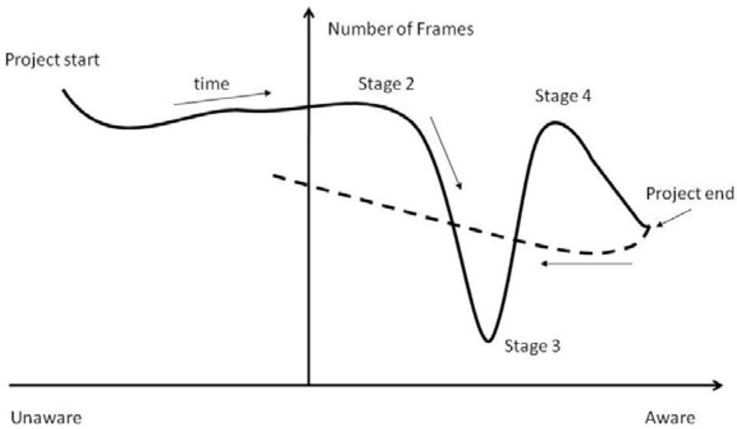

Figure 3. Example of mapping on the 2D awareness-perception plane of the dynamics during and after a hypothetical project. In the plot time runs along the line as indicated by the thin arrow.

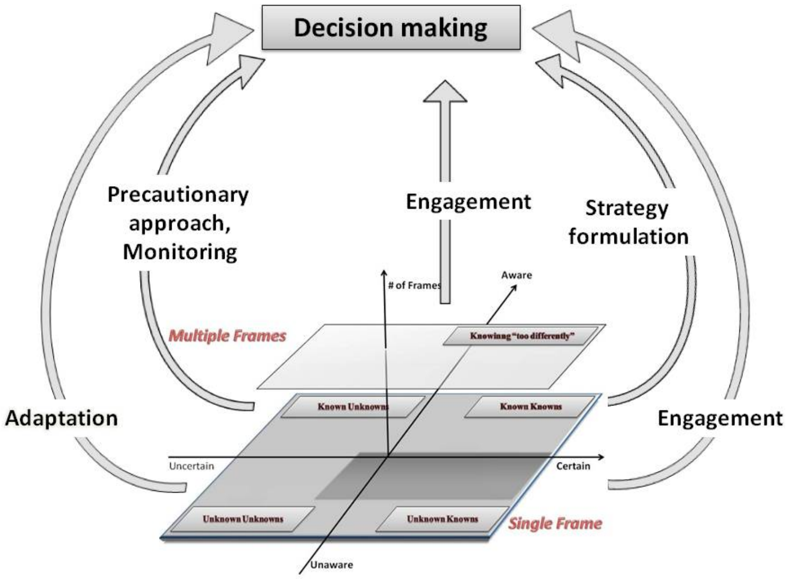

Figure 4. Summary of tools suitable to map items from different areas of the level-awareness-perception plot into decision making.

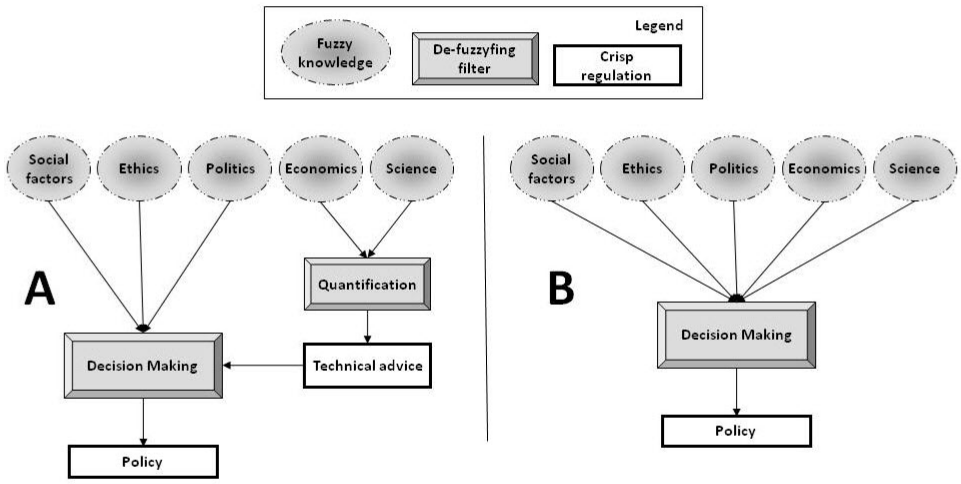

Figure 5. (A) Scientific advice contributes to decision making by first collapsing potentially fuzzy scientific information into crisp numerical information via quantification, which is then accounted for in the decision making process, along with other fuzzy contributing factors. (B) Scientific advice contributes to decision making at the same level as other fuzzy contributing factors.

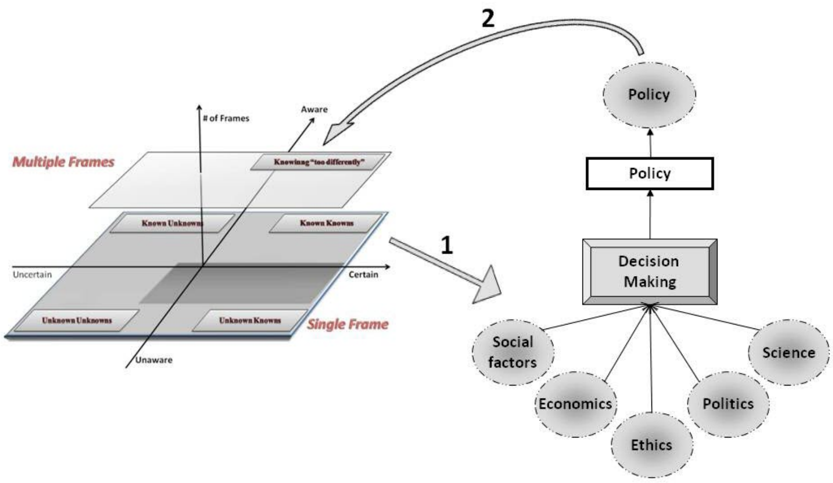

Figure 6. Loss of meaning and de-contextualisation of a crisp policy may given rise to new multiple interpretation and perception thus raising the level of perceptual uncertainty, .

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