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Uncertainty in integrated assessment modelling: A labyrinthic path

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1. Introduction

Integrated Assessment is the practice of combining different strands of knowledge to accurately represent and analyse real word problems of interest to decision-makers. Since these problems rarely observe disciplinary boundaries, Integrated Assessment usually involves interdisciplinary research. However, what distinguishes Integrated Assessment from interdisciplinary research is its policy dimension, aiming to inform decision-makers on the complexity of real world problems.

Unfortunately, the body of existing disciplinary knowledge is often insufficient for the construction of an accurate representation of real world problems. Integrated Assessment offers a systematic approach to identification of the gaps in disciplinary knowledge that have often frustrated policy analysis in the past. Thus, Integrated Assessment has increasingly been the source of critical questions and new directions of research in the disciplinary sciences.

Integrated Assessment is particularly useful for analysis of real world problems that are complex, operate at different levels in time and space, are immersed in uncertainty and for which the stakes are high. Because there are no simple solutions to these complex problems facing humankind, Integrated Assessment aims at conveying innovative and sometimes counterintuitive insights into the issues at hand rather than ready-made solutions.

Portraying and translating real world problems can be done from a plurality of perspectives. There is no one "right" way to represent and analyse the world, therefore a diversity of methods and approaches to Integrated Assessment are needed, ranging from model-based methods to participatory methods [22,29]. Generally, these methods are, in varying degrees, in their relative infancy. The currently most widely used method of performing Integrated Assessment is modelling. Integrated Assessment models are frameworks to organize and structure various pieces of recent scientific disciplinary knowledge.

A key issue in Integrated Assessment (IA) modelling is uncertainty due to various reasons. First of all IA modelling is confronted with the inherent uncertainty and lack of knowledge that the disciplinary sciences face. Secondly, IA models have to deal with a variety of types and sources of uncertainty that have to be structured and combined in one way or another. And finally, IA models are prone to a cumulation of uncertainties, because of their ambition to cover the whole cause–effect chain of a particular real world problem.

This all makes uncertainty one of the most problematic but also one of the most challenging issues in the field of IA modelling. This paper therefore focuses on the laborious relation between uncertainty and IA modelling. After a description of what IA models are and where they can be used for, the issue of uncertainty is raised and how IA models struggle with it. One possible way out is presented in terms of a pluralistic approach towards the management of uncertainties in IA modelling.

2. What are IA models?

Integrated Assessment models are frameworks to organise and structure various strands of recent scientific knowledge. Most frameworks are computer simulation models that describe a specific problem and the cross-linkages and interactions with other problems in terms of specifying cause–effect relationships. This causal description can be done in a qualitative sense, through conceptual models, and in a quantitative sense, through formal computer models. The latter group is by far the most widely used, and can be distinguished according to the dominating modelling paradigm in optimization models and systems-based simulation models, both deterministic and stochastic.

In general, IA models attempt to portray the social, economic, environmental and institutional dimensions of a problem in question, as depicted in figure 1. The social dimension aims at describing the social behaviour of people in terms of demographics, consumption behaviour, migra-

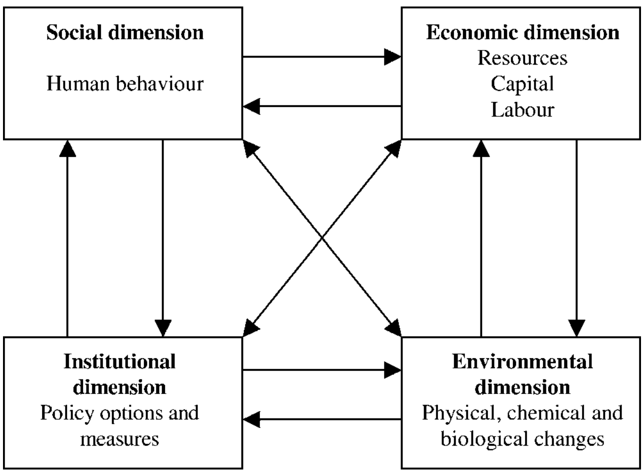

Figure 1. Template of an IA model.

tion and urbanisation. The economic dimension focuses on the production and consumption of resources, capital and labour. The environmental dimension deals with the physical, biological and chemical transformation of substances, and their penetration in the natural environment. Finally, the institutional dimension involves the palette of policy options and measures in terms of financial measures, legislative measures, education and R&D programmes.

Incorporating the above four dimensions in one and the same framework is a challenging but precarious undertaking. The essential problem in linking up these four dimensions is that there is no overall integrated paradigm based on a unifying theory how to do this. So physical, biogeochemical, financial, information and policy processes can be structured and linked in one modelling framework in many different ways. This leads to a manifold of possible integration routes, and thus to multiple integration strategies, of which two will be discussed briefly.

The first integration strategy is to link existing disciplinary models on an input–output basis. The advantage is that models can be linked easily in this way, but the disadvantage is that this may lead to an inextricable tangle of models and processes, which hampers insight into the dynamic behaviour of the overall system. Further, this strategy is based on linking subsystems rather than integrating them, which does not allow for inclusion of many interactions and feedbacks.

The second strategy is to develop a suite of simplified models, called metamodels or reduced form models. These metamodels are reformulated, simpler versions of the more complex or expert models. The price to pay for this strategy is that of simplification, but the advantage is that of harmonization of scale and aggregation level, based on one conceptual model which often stems from systems analysis.

The first strategy may lead to a complicated model, but not necessarily to a complex model. This means that their dynamic behaviour is almost linear, i.e., incremental changes in input lead to incremental changes in output. (Un)fortunately, the world does not function in such a simple, linear way, but shows strongly nonlinear, variable and chaotic behaviour. This implies that incremental changes in input may lead to considerable changes in the overall output, which may not be predicted beforehand.

The second strategy leads to a complex model, because the complexity arises from the many interactions and feedbacks between the metamodels. The system behaviour of the metamodels, however, can be relatively simple. The metamodel strategy is to be preferred in most cases, because it enables the inclusion of linkages, interactions and feedbacks at each possible level, which leads to a more advanced form of integration. However, the art is to keep the balance between simplicity and adequacy in terms of scientific representation of knowledge.

- *Many large IA models consist of linked subsystems which are not fully integrated. This means that these IA models are complicated but not complex, as a result of which their dynamic behaviour is almost linear and does not adequately reflect real world dynamics.*

A related problem is that various modelling paradigms can be used for each of the four dimensions sketched above. In describing the economic dimension still neo-classical economics is often used, based on an efficient resource allocation, resulting in one general equilibrium. Alternative paradigms form the input-output approach and the evolutionary economics approach. However, the social and ecological dimensions are often described using transitionary modelling paradigms, considering multiple equilibria, in the form of a transition from one equilibrium to another, such as, for instance, the demographic transition.

A final problem is that of aggregation versus disaggregation. The level of aggregation refers to the spatial and temporal resolution and the level of complexity used in the Integrated Assessment model. Social, economic, environmental and institutional processes operate on different scales, and differ in complexity. With regard to the temporal scale, economic processes and the related pace of technological change are to a large extent governed by the relatively short lifetime of the invested capital. Demographic processes operate on a longer time scale of at least one generation, whereas environmental processes are embedded in the much slower ecological dynamics which may cover hundreds of years.

The same variety holds for the spatial scale level. While atmospheric processes are often transnational, regional or even global, many land and water use processes operate on a smaller, local scale. By definition, IA models have to operate on different scale levels, so there is no optimal spatial and temporal scale level. This also means that higher scale processes and models have to be connected with lower scale ones. In the field of climate change modelling downscaling techniques are often used to bridge the gap between the relatively coarse climate change patterns derived from General Circulation Models and the ecosystem impact models that require a finer resolution [32]. Downscaling or upscaling the spatial level of modelling has profound consequences. This is related to the question to what extent the processes considered are generic, or distinctly spatially bound in character. In other words: does a relationship hold at a higher or lower scale level? In this context, Root and Schneider [18] propose an iterative scaling procedure which can be used as validation method for IA models.

3. What is the function of IA models?

Essentially, Integrated Assessment models are bridge-building tools. An IA model could in particular serve as a bridge between scientists and policymakers. Nevertheless, IA models could also help in bridging gaps between different disciplinary sciences. But here we will focus on the bridging function of IA models between the scientific arena and the policy arena. The goal of an IA model is to capture relevant and essential aspects of a particular societal problem in a comprehensive framework that allows for calculation of robust solutions, analysing the various stages in the policy life cycle.

Taking a variant of the policy life cycle of Winsemius [33] as starting point, various functions of IA models can be demarcated and set out against the various stages of the policy life cycle. In the very first stage of the policy life cycle, the recognition stage, problems have to be identified and set on the political agenda. This could be done directly by influencing policy-makers, or indirectly by exciting the public conscience. IA models could play an important role in this stage, as has been demonstrated by the IMAGE model [19], which had an early warning signalling function for the global climate change problem [31]. This *early warning function* is an important role for IA models, because at a time when a specific problem is emerging, IA models are able to capture the immature but available knowledge in one framework. This helps policy-makers to identify the potential scope of a problem and to frame the issue and its potential consequences, which could at least influence the current or future policy agenda.

In the second stage, the strategic policy-making phase, IA models could make an important contribution in different appearances. In the first place IA models could be used as *policy evaluation tools*, enabling rapid and flexible calculation and evaluation of future development pathways. For example, the IMAGE 2.1 model has been used for scenario exercises within the EC-context and the IPCC-context [1]. Secondly, IA models could be used as *frameworks for structuring knowledge*, in particular in identifying, illuminating and clarifying *uncertainties*. Examples of the latter IA model are the TARGETS model [21] and the ICAM model [6].

In the third stage, the function of IA models is more that of *negotiation tool*. The only IA model that has fulfilled this potential and has achieved this ambitious goal has been the RAINS model [10]. Tuinstra et al. [26] examine the role of the RAINS model in the negotiations over the second sulfur protocol to the Convention on Long-Range Transboundary Air Pollution (LRTAP), which was signed in 1994. This effort was unique in the sense that the negotiators worked closely with the model developers.

In the fourth stage of the policy life cycle, there is a need for detailed, sectoral models rather than IA models. So there is no particular need for IA models in this implementation phase. IA models have already quite a history, and are rooted in the global Earth models from the early seventies [14]. Nowadays, a diversity of IA models exists, ranging from simple to complex, from local to global, and from relatively short-term to long-term. Current IA models span a whole range of problems, from acidification to climate change, and from land use to water use, and from urban planning to sustainable development [22]. Although currently used IA models are relatively immature, IA models are often fully aware of the deficiencies and limitations of their models [20]. In spite of these limitations and deficiencies, so far IA models have been quite successful in influencing the policy arena, although it is hard to measure the degree of success.

- *In spite of the many deficiencies, IA models have unmistakably proven to be valuable tools in the decision-supportive arena, in particular in the field of global change, climate change and acidification.*

However, it should be noted that IA models often dance around the policy arena, but seldom dance within the policy arena. The reason is that it takes two to tango, and that each of the dancers has its own rationality: the scientific rationality is quite different from the political rationality. This makes that the direct use and application of IA models in the policy arena has been rarely realised successfully, which has often been frustrating, both for policy-makers and IA-model developers, but especially for the latter. This has been experienced earlier for scientific models in general within a policy context [8]. Previous research into model–client relations shows that if the model structure and the problem conceptualisation of the client are not in concordance with each other, it is very difficult for the client to understand or trust the model [17]. If this holds, it follows that that IA models have to be custom-designed in order to be used in the policy arena. This necessitates the involvement of clients to establish the model's credibility and authority during its development.

Numerous factors can be mentioned that account for the mismatch between IA-models and policy-makers, among which are: lack of transparency, complexity, policy irrelevance, and improper treatment of uncertainties. But in general terms the mismatch-explaining factors could be aggregated to the postulation that the IA-modelling rationality and the policy rationality only converge if the two are brought together in one process. In such a participatory process IA models are developed in close conjunction with potential clients, i.e., policy makers. This means in practice that, already in its conceptual phase, the IA model should be co-designed by policy-makers. This means early involvement of policy-makers to establish the model's credibility and authority during its development. Involvement includes discussions on the model's inputs and outputs, the temporal and spatial scale level used, the level of aggregation (detail) needed for developing policy strategies, issues and processes to be included or left out, and presentation of the model set-up and model results in terms of transparency. This culminates in a so-called user model, which helps tailor the model to the user's needs [27]. Since this is a continuing and iterative process, an intermediary layer of project managers may be established between the group of modelers and clients.

The involvement of policy-makers in the developing process of IA models is, however, more easily said than done. Having clients involved in the IA model design and building process is desirable indeed, but may lead to high expectations that cannot be fulfilled. Therefore, model builders and scientists need to make clear to clients the difficulty of attaining unrealistic goals. For example, policy-makers want to have geographically explicit impacts, which has lead many research groups to eschew accurate characterisation of what may be projected in favour of a precise characterisation with a much higher uncertainty. Under these circumstances, the modellers need to communicate to policy-makers the difficulty of attaining such lofty goals. Failing that, they should make clear the magnitude of uncertainties in geographically explicit projections.

- *IA modelling has to turn into a more demand-driven activity. However, having policy-makers as early stakeholders in the IA development process may lead to irresistible pressure on modelers toward unattainable goals, eschewing an accurate characterisation of uncertainties*

4. Uncertainty in IA models

Uncertainty is a key issue in IA modelling because of two reasons. First because IA models do cover a wide variety of uncertainties that originate from a range of different types and sources. And secondly, because IA models intend to capture an entire set of cause–effect relations involved in a specific problem, they are prone to accumulate uncertainties.

What type and sources of uncertainty play a role in IA modelling? A typology of uncertainties would help to differentiate between different types and sources of uncertainty and to communicate uncertainties in a more constructive manner. Realising that there is not one overall typology that satisfactorily covers all sorts of uncertainties, but that there are many possible typologies, we use here a typology of uncertainties developed by van Asselt [30] that is based upon an extensive screening of the scholarly literature. At the highest level of aggregation this typology distinguishes between the following two sources of uncertainty:

- *Variability*. The system/process under consideration can behave in different ways or is valued differently. Variability is an attribute of reality. Different sources of variability can be distinguished, i.e.: *inherent randomness of nature, value diversity, human behaviour, societal randomness*, and *technological surprises*.
  Variability as defined by the above sources goes beyond established seasonalities. Due to variability, reality inhibits inherent uncertainty and unpredictability. As such, it contributes to lack of knowledge, because due to variability perfect, certain knowledge is anyhow unattainable. Variability can thus be considered as a source of uncertainty due to lack of knowledge.
- *Lack of knowledge*. Lack of knowledge partly results out of variability, but knowledge with regard to deterministic processes can also be incomplete and uncertain. There are different degrees of lack of knowledge. A continuum can be described that ranges from: *inexactness, lack of observations/measurements, practically immeasurable, conflicting evidence, ignorance*, to *indeterminacy*.
  The first three degrees of lack of knowledge (i.e., inexactness, lack of measurements and practically immeasurable) are also referred to as unreliability [7]. The latter three degrees of uncertainty are also referred to as structural or systematic uncertainty [9,15].

Uncertainty thus has both an ontological (variability: concerning the general properties of objects) and an epistemological (lack of knowledge: concerning the human ability to know) dimension. Uncertainty is thus not simply the absence of knowledge. Uncertainty can still prevail in situations where a lot of information is available. Furthermore, new information can either decrease or increase uncertainty. New knowledge on complex processes may reveal the pres-

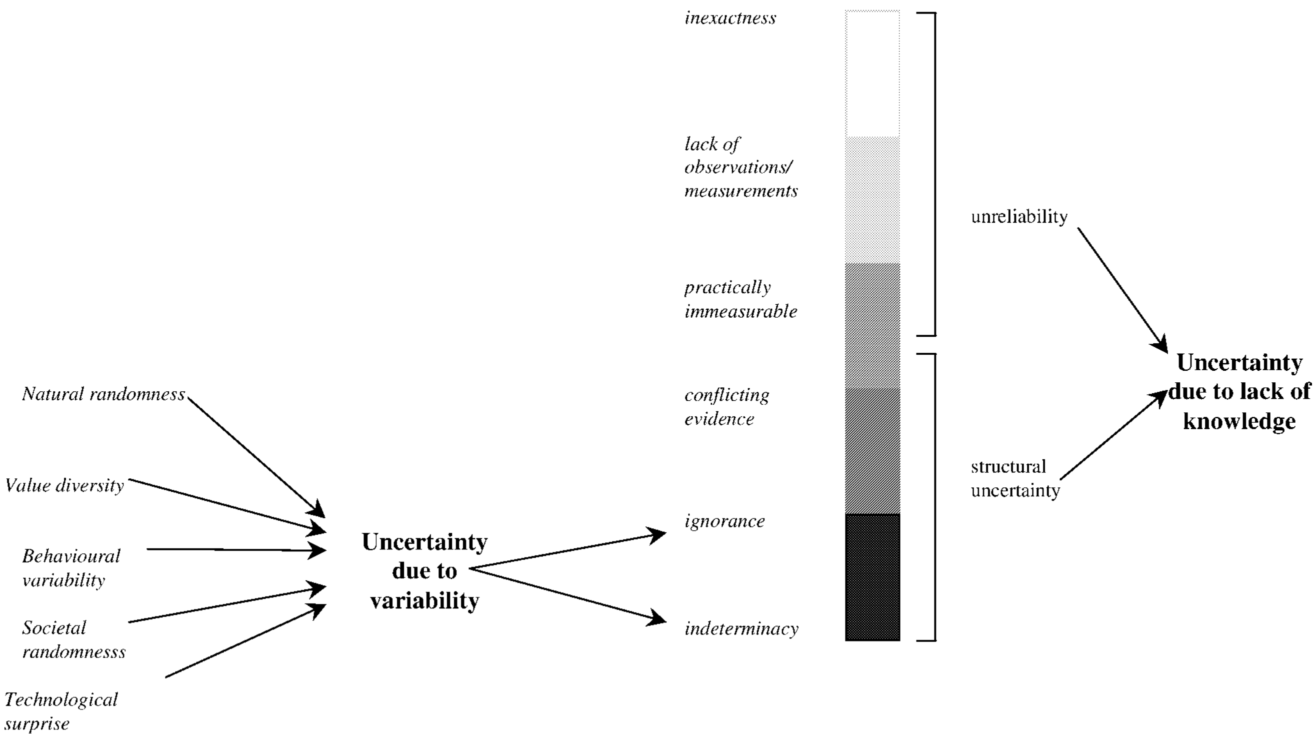

Figure 2. Sources of uncertainty [30].

ence of uncertainties that were previously unknown or were understated. In this way, more knowledge illuminates that our understanding is more limited or that processes are more complex than thought before. In other words, more knowledge does not imply less uncertainty and vice versa.

The typology of sources of uncertainty is visualized in figure 2. As a consequence of our limited understanding of the current state of any complex system under concern and our limited predictive capability in terms of the future states of that system, we are confronted with various types of uncertainty. Following Funtowicz and Ravetz [7] we distinguish three types of uncertainty in Integrated Assessment:

- technical uncertainties;
- methodological uncertainties;
- epistemological uncertainties.

Technical uncertainties arise from the quality of appropriateness of the data used to describe the system, from aggregation (temporal and spatial) and simplification as well as from lack of data and approximation. *Methodological uncertainties* arise from lack of knowledge and refer to questions as: what analytical tools and methods are appropriate? How to model causal relationships in view of incomplete understanding of the processes? What is and adequate frame to structure what we know and what is uncertain? How to interpret the uncertainties? And finally *epistemological uncertainties* concern the conception of a phenomenon. This type of uncertainty arises from structural uncertainty and variability. The key question with regard to this type of uncertainty is whether the description/theory/model relates to the real, variable world.

Using this typology of uncertainties in the context of IA modelling we can demonstrate which sources and types of uncertainty play a role in various stages of the IA modelling process. In IA modelling, technical, methodological and epistemological uncertainties materialise respectively as uncertainties in model quantities, uncertainty about model form and uncertainty about model completeness/adequacy of the IA model, see figure 3. Parameters, inputs and initial states are uncertain model quantities (technical uncertainties). Uncertainty about model form comprises uncertainty pertaining to model structure, uncertainties about the functional relationships and uncertainties with regard to the choice of algorithms (methodological uncertainties). Uncertainty about model completeness is the most fundamental and crucial for the quality of the IA model (epistemological uncertainties), and is often addressed in the model validation phase. However, complete validation is impossible in case of complex systems due to inherent uncertainty (especially due to ignorance and indeterminacy) [16]. To express the limits to validation exercises, model validation is also referred to as testing model performance. A fourth type of uncertainty relevant includes so-called model operation uncertainties. These uncertainties occur partly due to the hidden flaws in the technical equipment (especially numerical errors and bugs in hard- and software), but above all due to accumulation of uncertainties propagated through the model [3,28].

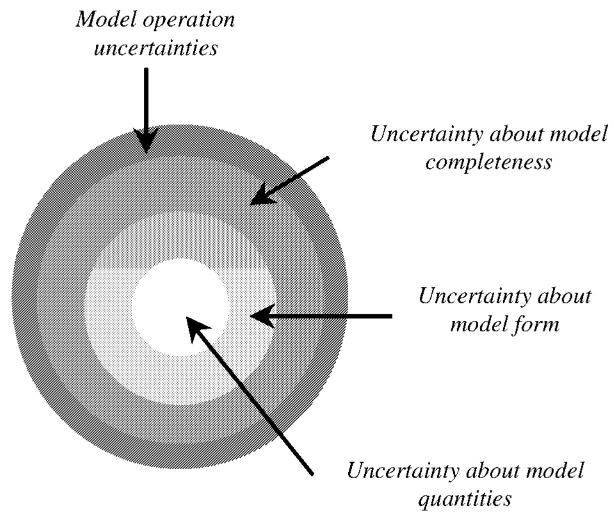

Figure 3. Types of uncertainty in IA-modelling.

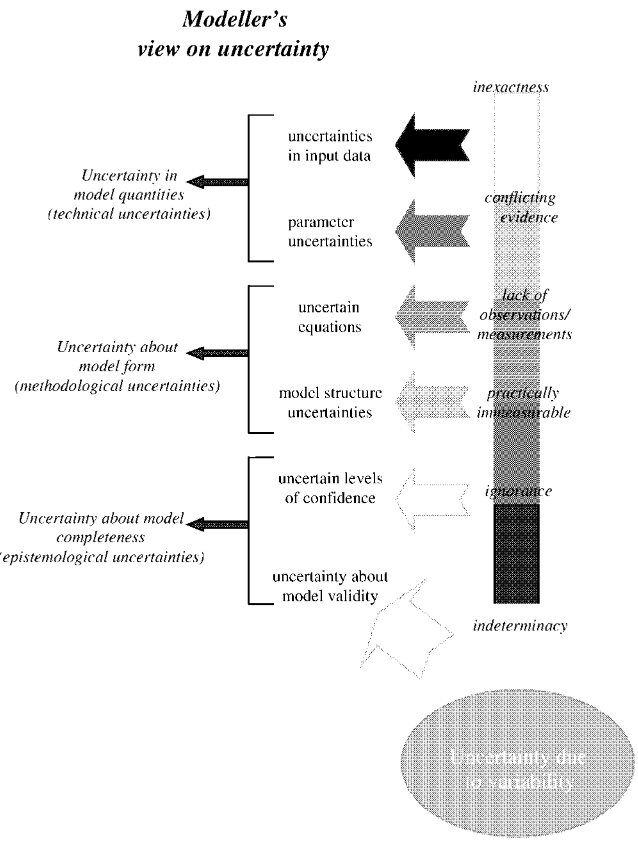

Figure 4. Integrated typology of sources and types of uncertainty in IA modelling.

Figure 4 synthesizes the characterizations of the sources and types of uncertainty in Integrated Assessment modelling.

5. Uncertainty management in IA modelling

In view of the above, a logical next question is then "how is uncertainty managed in Integrated Assessment modelling?" The aim of current uncertainty analysis in IA modelling is to evaluate to what extent particular uncertainties impact upon the conclusions. The standard practice is that uncertainty analysis is performed as a final step in the model cycle. The following approaches are currently used for uncertainty analysis in Integrated Assessment modelling [12,30]:

- sensitivity analysis,
- probability-based methods,
- formal scenario analysis,
- hedging-oriented methods,
- validation,
- the NUSAP approach.

The different approaches will be briefly discussed below, especially in relation to the various types and sources of uncertainty. For a more elaborate treatment of the different approaches is referred to van Asselt [30].

5.1. Sensitivity analysis

Sensitivity analysis is the study of the influence of variations in model parameters and initial values on model outcomes. In order to determine whether these variables have a significant effect on the model output, and to determine their relative importance, statistical techniques are usually applied in sensitivity analysis. Some methods for sensitivity analysis are individual parameter variation, differential sensitivity analysis, response-surface method (see [11]) and meta-modelling (e.g., [4]). Standard software packages, employing these methods, are widely available.

The role of sensitivity analysis in the context of uncertainty analysis is to estimate the relative importance of uncertain parameters and initial values on the model output. However, one has to realise that there is not a one-to-one mapping possible from the degree of sensitivity to the salience of the uncertainty. Sensitivity analysis does nothing more, and nothing less, than providing insights into the role of uncertain parameters and initial values in model runs.

5.2. Probability-based methods

In economics, engineering and psychology, the probability concept is advanced as the formal representation of uncertainty that can be dealt with in a mathematical manner. Probability is not uniquely defined. The most frequently used probabilistic approach in IA modelling is the Bayesian approach, in which probabilities are interpreted as subjective “degrees of beliefs”. The information required to apply probability calculus are distributions for uncertain inputs/parameters, which express how likely the analyst or group of experts considers a particular value for that variable. The uncertainty expressed in this way is propagated through the model, so that the output variables also feature probability distributions or statistical measures as the 95-percentile. Usually, “intelligent” sampling techniques, generally Monte Carlo techniques, are applied to reduce computing requirements.

Probability-based methods thus give an indication of the likelihood of outputs dependent on the (subjective) likelihood attached to uncertain model inputs/parameters. However, probability-based methods solely address uncertainty in model quantities and ignore uncertainty in model structure. In case of lack of knowledge beyond the level of inexactness, it is questionable whether probability distributions can cover the range of possibilities.

5.3. Formal scenario analysis

Formal scenario analysis involves assessing sets of different assumptions of possible future states, which are parameterised in the model. Scenario analysis thus implies performing model runs for sets of parameter values and/or time-series, and comparing the results. Scenario analysis aims to investigate interesting, meaningful and varied future states. In that way in terms of uncertainty analysis, it has a considerable advantage above random sampling methods. In performing scenario analysis, IA modellers implicitly or explicitly draw the distinction between scientific uncertainties occurring in the environmental system, and the socio-economic uncertainties occurring in the human system. Many scenario exercises merely address uncertainties in model inputs, focusing on socio-economic variables. This implies that scenarios assess the consequences of socio-economic uncertainties on projections for the environmental system, but they neglect the scientific uncertainties in the environmental system itself. Further, scenario-analysis exercises quite often fall in the attractive pitfall to classify one of the scenarios as the most likely or best-guess scenario. In this way the output of scenario analysis then masks inherent uncertainty which was originally the starting-point of the analysis.

5.4. Hedging-oriented methods

This class of method is the most recent approach for dealing with uncertainty in IA models. Hedging can be viewed as building contingency plans and responding to opportunities and risks as they become apparent. Hedging-oriented methods aim to identify strategies, which balance the risks of waiting with premature action. In this type of modelling, the value of decision-variables in the model is determined based on a joint distribution on the possible outcomes that may occur in the next period. This approach does not assume that uncertainty is completely resolved at a certain point in time, but rather that due to progress in knowledge a probability distribution is adjusted. In this approach, the adjustment of probability distributions of the outcomes is central. Such distributions can either be inspired by probability-based methods or subjectively determined by the analysts. By using outputs derived from probability-based methods, hedging-oriented exercises inherit the disadvantage of solely addressing uncertainties in model inputs. However, hedging-oriented techniques are slightly more sophisticated than the previous methods for quantitative uncertainty analysis, because they do not only address uncertainty in the model, but they try to keep uncertainties within bounds of credibility for decision-makers. In other words, these techniques are not just about analysing uncertainty, they are about bounding uncertainty.

5.5. Validation

It is unusual to place validation approaches under the heading of uncertainty analysis. Validation implies testing model performance. With validation techniques, modellers aim to assess to what extent the model is an adequate representation of reality, and as a derivative to what extent it is in accordance with empirical observations and theoretical insights. In terms of our typology of uncertainty, validation is the analysis of uncertainty on model completeness, which type of uncertainty is caused by ignorance, indeterminacy and variability. In this broader perspective it is therefore legitimate to consider validation as uncertainty analysis.

A qualified validation exercise should yield insights in how well the IA model matches observations and hypotheses. It aims to confirm the model by demonstrating agreement between observations and the model "predictions", but such a confirmation is anyhow inherently partial. That does not necessarily imply that the model is complete enough or whether it is an adequate representation of reality. Models can only be evaluated in relative terms. Validation exercises, which in principle address the epistemological dimension, are not systematically used to assess and discuss radical uncertainties. The results of validation are generally solely used to "sell" the model as being scientifically credible.

5.6. The NUSAP method

Funtowicz and Ravetz [7] developed the NUSAP method as a scheme that would enable evaluation of uncertainties in such a way that both the quantitative and the qualitative aspects are addressed. NUSAP stands for Numeral, Unit, Spread, Assessment and Pedigree. The idea is to characterise each part of the analysis in these terms. Numerical, unit and spread are rather familiar concepts and enable to characterise estimate in quantitative terms. Assessment and Pedigree represent levels of uncertainty that go beyond technical uncertainties. They are the most qualitative categories in the scheme.

The advantage of the NUSAP method is that it enables to characterise both the quantitative and the qualitative, subjective aspects of uncertainty in a formal way. The disadvantage is that it concentrates on uncertainty in variables and it does not address uncertainty in relationships between different variables. Furthermore, notwithstanding its usefulness to roughly characterise salient uncertainties, performing a comprehensive NUSAP is probably a rather time-consuming effort. Finally, interpreting the results of a NUSAP analysis is difficult and ambiguous. NUSAP produces a judgement of the analysis in terms of how uncertain the underlying sources are. But does this imply that an IA model that uses "hard" data and equations is better than an IA model that uses "soft" data and equations?

Table 1
Potential of discussed methods in addressing different sources of uncertainty.

Source	Method
Lack of knowledge	
Inexactness	• Probability-based methods • Formal scenario-analysis
Lack of observations/ measurements	• Probability-based methods • Formal scenario-analysis • Hedging-oriented methods
Practically immeasurable	• Probability-based methods • Formal scenario analysis • Hedging-oriented methods
Conflicting evidence	• Formal scenario-analysis • Hedging-oriented methods
Ignorance	• Validation • Scenario approaches
Indeterminacy	• Scenario approaches
Variability	
Natural randomness	• Stochastic modelling*
Value diversity	• *No methods*
Behavioural variability	• Scenario-approaches
Societal randomness	• Scenario-approaches
Technological surprise	• *No methods*

*Not discussed in detail in this paper; it can be considered as belonging to probability-based methods.

Because uncertainty is multi-dimensional, it is unlikely that a single approach will suffice to capture all the salient forces of uncertainty. Different approaches address different types and sources of uncertainty in different ways. If we use the above classification of types of uncertainty in IA modelling, table 1 indicates which sources of uncertainty can be addressed by the above approaches, while table 2 summarises which types of uncertainty are analysed by the discussed methods. We make the reservation that not all methods in any application are currently used to such a full extent. In table 1 the NUSAP method is not mentioned, because it is actually a method to articulate sources of uncertainty and the degree of uncertainty in the components of the analysis.

A complementary use of various methods is needed in order to be able to provide a comprehensive insight into the extent and the scope of uncertainty. Such combinations of uncertainty analysis methods are applied in IA modelling. For example, as follows from the description above, hedging-oriented methods are combined with probability-based methods. Sensitivity analysis is quite often used to filter out those uncertain parameters that will be subjected to probability-based uncertainty analysis. Exploratory modelling is an example of an approach that explicitly aims to incorporate a combination of the above methods in order to address uncertainty explicitly. In its general form it combines sensitivity analysis with both quantitative and qualitative scenario approaches and it is usually applied in a participatory set-up [2,13].

However, even if the available methods for uncertainty analysis are combined in a systematic manner, crucial types and sources of uncertainty are ignored as becomes apparent in tables 1 and 2. Current methods suffer from the fact

Table 2
Methods of uncertainty analysis in terms of types of uncertainty.

Uncertainty		Method	Output
Uncertainty in model quantities	Uncertainties in input data	• Sensitivity analysis	• role of uncertainties in input data in model runs
		• Probability-based methods	• propagation of probabilities in input data to outcomes
		• Formal scenario-analysis	• effects from uncertain socio-economic inputs on outcomes
		• Hedging-oriented methods	• assessing effects of uncertainty reduction in input data
		• NUSAP	• insight in the qualitative and quantitative nature of the uncertainty in the inputs
	Parameter uncertainties	• Sensitivity analysis	• role of uncertainties in parameters in model runs
		• Probability-based methods	• propagation of probabilities in parameters to outcomes
		• Hedging-oriented methods	• assessing effects of uncertainty reduction in parameters
		• NUSAP	• insight in the qualitative and quantitative nature of the uncertainty in the parameters
Uncertainty about model form	Uncertain equations	• Sensitivity analysis in the form of meta-modelling	• insights into crucial equations
	Model structure uncertainties	*No methods*	*No methods*
Uncertainty on model completeness	Uncertain levels of confidence	• NUSAP	• insight in the level of confidence in terms of the quality of the underlying sources
	Uncertainty about model validity	• Validation	• insights in model performance

that they address only uncertainties in model quantities and neglect the structure of the model itself. In doing so, significant uncertainties are "exogenised" and thereby become invisible [34]. As a consequence, such uncertainty analyses merely involve evaluation of the impacts of "certain uncertainties", i.e., uncertainties for which estimates or (often questionable) probability distributions are available. The more fundamental, and probably the most salient, uncertainties are ignored. Current uncertainty analysis techniques thus merely address technical uncertainties, in a sense hiding inherent uncertainty. Furthermore, sources of variability are difficult to address with the current methods. Scenario approaches in principle allow for inclusion of behavioural variability and societal randomness, however, in practice this is seldom the case. As can be concluded from table 1, there are no methods available yet to deal with value diversity and technological surprise in IA modelling.

At the moment, uncertainty is not at the heart of Integrated Assessment. Notwithstanding modeller's claims, in the practice of IA modelling, uncertainty is treated as a marginal issue that could unfortunately not be resolved yet. Uncertainty is treated as if it were an additional physical variable, as a mathematical artefact. By attaching deterministic intervals or stochastic probability distribution functions to uncertain model parameters, it is suggested that variations in parameter values do yield estimates of the uncertainties in the model outcome. However, that may be true in the mathematical sense (although only partly), but it does not reflect the nature and source of the real world uncertainties. One may compare one type of uncertainty with the other in mathematical terms, but in physical terms that could lead to comparing apples and pears. It is not allowed to simply compare the uncertainty of the climate sensitivity (representing uncertainties in geophysical feedbacks) with the uncertainty of the fertility rate (representing uncertainties in triggering factors behind fertility behaviour). While the geophysical uncertainty might be reduced by future research, the demographic uncertainty might be structural in the sense that it cannot be reduced in the longer term.

To illustrate this, in table 3 we present an overview of the various uncertainties in IA models of climate change. This overview is not exhaustive, but just meant to indicate that but the formal uncertainty analysis techniques applied originate from principles that are incompatible with this recognition of inherent uncertainty. The available formal techniques do not allow to address inherent uncertainty adequately. The use of qualitative methods for uncertainty analysis in IA modelling is relatively rare. The present situation in IA modelling can

Table 3
Sources of uncertainty in modeling climate change.

Uncertainty due to lack of knowledge	Examples of climate change uncertainties
Inexactness	Life-times of greenhouse gasses
Lack of observations/measurements	Temperature feedbacks
Practically immeasurable	Indirect effects of aerosols
Conflicting evidence	CO_2-fertilisation effect
Ignorance	Geophysical feedbacks
Role of sun spots	
Natural randomness	Ocean dynamics
Climate risk aversive versus economic risk aversive	
Behavioural variety	Energy use (consumption patterns)
Societal randomness	Effectiveness of policy agreements (such as Kyoto)
Technological randomness	Renewable energy

therefore be described by the tension between objectivity and truth as guiding principles for actual uncertainty analysis on the one hand, and the recognition of the inevitable uncertainty on the other hand.

So to date, there is no alternative crystallized portfolio of methods that enables integrated assessors to deal adequately with inherent uncertainty in their daily practice. There is no ready-made kit of tools, recipes, techniques and models available. The above evaluation teaches us that as uncertain situations become more imminent, the ability to analyse uncertainty decreases. In sum, from the state-of-the-art in Integrated Assessment modelling we conclude that [30]:

- *Uncertainty analysis lacks a tool-kit that enables to address salient technical, methodological and epistemological uncertainties in an adequate manner as central activity in Integrated Assessment Modelling.*

6. Towards a pluralistic approach of uncertainty management in IA modelling

If we do not change the way uncertainty is treated in IA modelling, uncertainty is a problem that has the potential to sap the role IA models may play in facilitating decision-making processes. Uncertainty should then no longer be treated as a marginal issue or a closing entry in IA modelling, but it should be at the heart of the IA modelling process. In the following, we aim to provide concrete suggestions for a more adequate form of uncertainty management in IA modelling.

In the first place uncertainty management in IA modelling should encompass the various types and sources of uncertainty in an adequate manner. More specifically, in terms of types of uncertainty, this means that methods have to be developed for addressing methodological and epistemological uncertainties. And in terms of sources of uncertainty, this means that methods have to be developed for analysing uncertainty due to variability. After having determined the dominating types and sources of uncertainty in the IA model, the most salient uncertainties, both as manifested in model quantities and in model structure, have to be selected. Checklists and heuristics have been proposed to rank uncertainties in terms of salience [5,30,31]. For instance, in earlier work we proposed to use magnitude (relative contribution to uncertainty), degree (range of uncertainty) and time-variability (fluctuating rate over time) as indicators of importance. The three indicators can be used to assess the components/variables of an IA model in a qualitative or semi-quantitative way.

However, we have to realise that due to the nature of uncertainty, ranking the most salient uncertainties is always a judgmental exercise, notwithstanding the usefulness of checklists and techniques for doing it in a systematic way.

The process of assessing and interpreting the most salient uncertainties, is often due to subjectivity and disagreement. Uncertainty management in IA modelling has therefore to be pluralistic, i.e., including multiple perspectives. Such a pluralistic approach, proposed by van Asselt and Rotmans [28] and van Asselt [30], implies that an IA model does not merely include one (hidden) perspective, but comprises a set of perspectives. This means in practise that the selected salient uncertainties in an IA model are estimated according to different perspectives. A perspective is then defined as a coherent and consistent description of the perceptual screen through which (groups of) people interpret or make sense to the world and its social dimensions, and which guide them in acting. A perspective thus comprises both a “world view” (i.e., how people interpret the world) and a “management style” (i.e., how they act upon it).

A typology of perspectives is then necessary to arrive at a limited set of perspective-based interpretations of uncertainties. The challenge is to find a typology of perspectives that sufficiently covers the pluralism in value-systems. Unfortunately, the social sciences do not provide a ready-to-hand, generally accepted typology that is independent of time and scale. Social sciences emphasize that people think and act on the basis of a “situation-logic”, and generic typologies would violate this broadly shared conviction. A typology of perspectives that could be used is that of the Cultural Theory [24,25]. We realise that its scheme is rigid and that it cannot fully take account of the real world variety of perspectives. The typology associated with the Cultural Theory is nothing more, but also nothing less, than an attempt to systematically address the complex issues of different perspectives at a rather general level. As any model, it is merely a limited and defective reflection of reality. However, in spite of the lacunae and inconsistencies, we did not find a typology that better satisfied the criteria mentioned above. In the context of our aims, it therefore seems legitimate and reasonable to use the types put forward in Cultural Theory to characterise the spectrum of perspectives and to use the associated typology. These perspectives, which each represent a different attitude (management style and world view) to nature and society, are typified as hierarchist, egalitarian, individualist and fatalist.

Using this framework of perspectives, the selected model uncertainties can be interpreted in multiple ways. This practically means that model inputs, quantities and relationships can be interpreted according to the qualitative description of the perspectives. By specifying alternative values for the selected model uncertainties, a chain of perspective-based model formulations is created, or so-called model routes [28]. These multiple model routes are alternative ways of looking at model inputs, parameters and relationships, taking into account the bias and preferences of a number of stereotypical perspectives.

The implemented and calibrated model routes allow for systematic experimentation. To this end, the distinction between world view and management style is relevant. Matching each perspective's management style to its respective world view is a technique used to assess the utopias. A utopia is a world in which a certain perspective is dominant and the world functions according to the reigning world view. In terms of our dichotomy, dystopias describe either what would happen to the world if reality proved not to resemble the adopted world view following adoption of the favoured strategy, or vice versa, i.e., where reality functions in line with one's favoured world view, but opposite strategies are applied. In IA modelling terms, dystopias are scenarios involving mismatches between world views and management style. Although we realise that the concept of "utopias" and "dystopias" is value-laden, and that use of the concept is controversial, we think the concept is useful within the context of IA modelling.

By systematically performing experiments with varying combinations of world views and management styles, a series of scenarios can be generated. Furthermore, one could also experiment with changes in perspectives over time in developing scenarios.

The result of performing utopian and dystopian model experiments is a flow of outputs representing various pathways into the future. There are different strategies for analysing these projections. One way is to evaluate whether the outcomes differ significantly from previous IA model studies. Another way to analyse the model experiments, is to concentrate on differences between the various utopias. Do they significantly differ and are the differences counter-intuitive? What do these differences teach us about possible futures? So by means of multiple model routes, we create a set of model runs that spans the space of possible arguments, constrained by what is known.

Preferably, the colouring of the selected salient uncertainties should be done in a participatory setting. Either by means of a group process or by a systematic analysis of individual perspective-based interpretations of uncertainty, the model routes can be created. These chains of model uncertainties need to be checked by scientists in terms of consistency. Also the model-based assessment needs to be participatory through "what-if" exercises, assessing the future in terms of utopias and dystopias.

The above steps of identification of uncertainties, selection of salient uncertainties, multiple model routes, exploring possible futures, and model-based assessment, form a framework for participatory and pluralistic uncertainty management in IA modelling. In this way, uncertainty is at the core of the IA modelling process. This pluralistic uncertainty management has been developed within the scope of RIVM's research project "Global Dynamics and Sustainable Development" that involved the development of the IA model TARGETS, which is an acronym for Tool to Assess Regional and Global Environmental and health Targets for Sustainability. In TARGETS the perspective-based model routes are "hard-wired" implemented. For an extensive description of the application of the method of perspective-based model routes the reader is referred to Rotmans and de Vries [21] and van Asselt [30]. The way perspective-based model routes were implemented was very science-oriented. We just allowed scientific interpretations of the selected salient uncertainties in the TARGETS model. However, many of the uncertainties involved in the analysis were transscientific and implicitly or explicitly deal with societal developments, human behaviour or value diversity. One of the major lessons that we learned from experiences with the TARGETS model is that such a transscientific exercise should be participatory in order to allow a mutual learning process in which those uncertainties are selected that are societally salient.

Another experience with the TARGETS model is that it turned out to be difficult both for colleague IA modellers, for other scientists, for the policy audience and the public at large, to interpret the perspective-based results. This is mainly because it is such a fundamentally different way of dealing with uncertainty, that it takes time to understand both the principles and the outcomes, and to grasp how such insights can be used for decision-support. Again, participating in the process seems to enhance the capability to deal with the outcomes. However, even in case of a participatory set-up, not all intended users can participate in the development process, which necessitates transparent and understandable communication of the insights and the results. Obviously, this requires new ways of conveying counter-intuitive insights, because traditional representations are not suitable for communicating non-traditional outcomes.

In general, pluralistic uncertainty management has the potential to yield new and challenging insights on complex issues dealt within Integrated Assessment modelling. This approach has considerable advantages compared to existing approaches in uncertainty analysis:

- Pluralistic uncertainty management focuses on the most salient uncertainties.
- This approach is able to address sources of uncertainty that are not addressed by other methods for uncertainty management, especially conflicting evidence and uncertainty due to variability.
- Using the perspective-based model routes as ways to envisage coherent clusters of various interpretations of uncertainties in an IA model, differences in future projections can be motivated and explained, instead of merely arriving at minimum, maximum and "best-guess" values.
- Pluralistic uncertainty management makes subjectivity in IA models explicit, and enhances the reflexivity of integrated assessors.

So overall, this multiple perspective approach allows to take account of plurality in a rather consistent way. The resulting insights could be informative and relevant for societal decision-making.

However, notwithstanding its advantages pluralistic uncertainty management is not a panacea. Other methods of uncertainty analysis can serve as complementary tools to allow for a more comprehensive evaluation of uncertainty. The combination with sensitivity analysis, scenario approaches, or probability-based methods could enable to evaluate different types and sources of uncertainty with each other. A complementary use of various uncertainty methods is needed in order to be able to provide a comprehensive insight into the extent and the scope of uncertainty. The challenge is to develop procedures and protocols that allow smart and sensible combinations of the available methods in IA modelling endeavours. Systematic uncertainty research is needed in order to develop guidelines for good practice in uncertainty management in IA modelling.

7. Conclusions

Over the last decades Integrated Assessment models have proven to be valuable tools. Especially in the recognition phase and strategic policy-making phase of global problems like acidification and climate change IA models have been invaluable. Still, the potential of IA models outstretches by far the limited use and application thus far. An important reason for this gap between the potential and actual usage of IA models is the fact that the quality of most IA models does not meet yet the high expectations that surround them.

Illustrative for this is the way most IA models deal with the issue of uncertainty. At present they fail to make these uncertainties explicit, and to illuminate and explain the nature of the various types and sources of these uncertainties, let alone to communicate these uncertainties in sound and transparent way to decision-makers. In IA modelling uncertainties are often reduced to technical artefacts, by, for instance, attaching stochastic probability distribution functions to uncertain model parameters, thereby suggesting that variations in parameter values do yield estimates of the uncertainties in the model outcome. In IA models the sources and types of uncertainty is so diverse, that it is not allowed to simply compare one type of uncertainty with another, which would lead to comparing apples and pears. While the one type of uncertainty might be reduced by future research, the other might be structural in the sense that it cannot be reduced in the longer term.

In this article we have therefore advocated a more pluralistic form of uncertainty management in IA modelling. Pluralistic uncertainty management differs fundamentally from the classical methods for uncertainty analysis. In this approach uncertainty is "marked" and communicated by different interpretations according to different perspectives. In IA modelling terms this means that multiple perspectives are incorporated as a way to assess the most salient uncertainties, both as manifested in model quantities and in model structure. Such a pluralistic approach implies that an IA model does not merely include one (hidden) perspective, but comprises a set of perspectives. A perspective is reflected in choices concerning model inputs, parameter choices, model structure and model equations. In this way, experimenting with the model implies choosing among perspective-dependent options.

Our point of departure was an in-depth analysis of the concept of uncertainty in relation to IA models. This enabled us to make the abstract notion of uncertainty more concrete and tangible by means of a generic typology of the sources of uncertainty. This classification provided an evaluation scheme for reviewing current methods for uncertainty treatment in IA modelling. In this way, the strengths and weaknesses, as well as the added value and the complementary value of the various approaches could be explored in a systematic way. We hope to have demonstrated that pluralistic uncertainty management is a viable and sensible complementary method for qualified uncertainty treatment. Building upon a review of existing uncertainty methods, it was discussed that no single approach suffices to address all types and sources of uncertainty in IA modelling. Because uncertainty in IA modelling is multi-dimensional, it is unlikely that a single approach will suffice to capture all the salient forces of uncertainty. Different approaches address different types and sources of uncertainty in different ways. To that end, it is advocated not to rely on one method, but to use the available methods in a complementary manner. Although systematic fundamental uncertainty research is still needed in the context of IA modelling, we argue that significant profit in terms of quality terms can be gained by using the available tools in more sophisticated ways. Notwithstanding the limits and practical constraints associated with the individual approaches, the available methods, including pluralistic uncertainty management, enable IA modelers to do a better job than they usually do. This practically means that major improvements are already within any IA modeler's reach.

Pluralistic approaches are a valuable extension of the tool kit for uncertainty treatment in IA modelling, because it enables to address types and sources of uncertainty that are not addressed by existing methods. On the other hand, the evaluation of the various methods in terms of the types and sources of uncertainty clearly indicate that pluralistic uncertainty management is not a panacea, but that it ideally should be used in combination with other uncertainty analysis techniques.

An important issue that needs to be addressed is how the available IA methods for uncertainty treatment in IA modelling can be used in a participatory manner. Arousing the interest of potential clients such as policy-makers in a later stage of the IA model development turns out to be illusory and is doomed to fail. The only solution seems to involve policy-makers in the model development process from the onset, in particular with regard to uncertainty management. This is, however, a troublesome process that is demanding for both developers and potential clients, and requires a shift in the way people perceive IA models. This shift means that potential clients do not consider IA models as objective truth machines, generating definitive answers and predictions, but rather as subjective, heuristic tools that facilitate thinking about complex societal issues, generating insights rather than answers.

Overall, Integrated Assessment models face a prosperous future, because the world around us is becoming increasingly integrated in its social, economic, environmental and institutional activities. The complex dynamics of these strongly interacting processes force us to think and act in a more integrated manner, a process in which IA models are indispensable tools. However, much work remains to be done with regard to uncertainty management in IA models. The management of uncertainty in IA models needs to be enhanced, in order to communicate the intricate concept of uncertainty in a modern adequate manner to a wider community. Dealing with uncertainty in a more satisfactory manner is among the greatest challenges the IA modelling community faces.

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