Uncertainty and WG7

The activities of EMRAS will focus on areas where uncertainties remain in the predictive capability of environmental models, notably in relation to the consequences of releases of radionuclides to particular types of environment

Last Questionnaire:

6. What is the robustness (uncertainty) accepted by your organization or regulatory body when modelling accidental tritium releases?

To be conservative is the requirement, but with no details on how to control the robustness. Some participants replayed simpler NO IDEA

In the PAST, uncertainty of models have been discussed in VAMP, BIOMOVSII, BIOMASS and also EMRAS I. More recently we have some news.

RELEVANT LITERATURE

- IAEA (1989). Evaluating the reliability of predictions made using environmental transfer models. Safety Series 100, IAEA, Vienna, Austria.
- Guidelines for Uncertainty Analysis,BIOMIOVS II Technical Report 11 July 1993
- Beven K (2002). Towards a coherent philosophy for modelling the environment. Proceedings: *Mathematical, Physical & Engineering Sciences*, **458** (2026), 2465-2484(20). The Royal Society.

National Dose Assessment Working Group (UK)

- An Overview of Uncertainty in Radiological Assessments *NDAWG/1/2005*
- Overview of Radiological Assessment Models -Key Gaps and Uncertainties *NDAWG/2/2006*
- **EPA> Guidance on the Development, Evaluation, and Application of Environmental Models, EPA/100/K-09/003 | March 2009**

Model evaluation is the process for generating information over the life cycle of the project that helps determine whether a model and its analytical results are of sufficient quality to serve as the basis for a decision. Model quality is an attribute that is meaningful only within the context of a specific model application. In simple terms, model evaluation provides information to help answer the following questions: (a) How have the principles of sound science been addressed during model development? (b) How is the choice of model supported by the quantity and quality of available data? (c) How closely does the model approximate the real system of interest? (d) How well does the model approximate the real system of interest? (d) How well does the model perform the specified task while meeting the objectives set by quality assurance project planning?

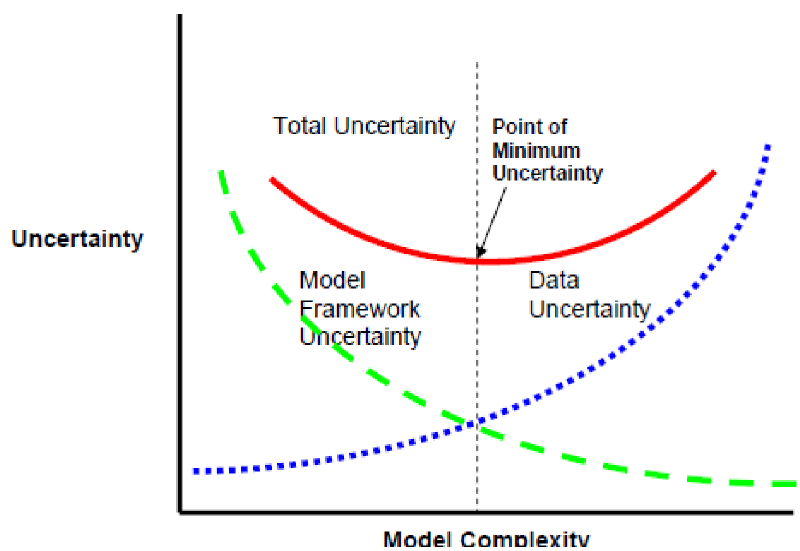
Sensitivity analysis: Sensitivity analysis is the study of the effect of changes in input values on the output from a model. This can be done by either varying a single parameter at a time to see the effect on the output or by varying a suite of input parameters simultaneously. It enables the user to identify the parameter or groups of parameters to which the model is most sensitive and, as such, can be used to direct research programmes.

Uncertainty: Uncertainty measures the lack of knowledge of the system under investigation, which in radiation dose assessment terms will relate to how well doses of interest can be estimated. For example, how well are the parameter values in a calculation of dose known? If further investigations can reduce the uncertainty in these parameter values by increasing the accuracy and precision with which they are known then this is epistemic or so called Type B uncertainty (IAEA, 1989). This is applicable to a parameter that is thought to have a well-defined value, but due to inevitable experimental difficulties there is some uncertainty about that value. In many dose assessment applications, a detailed knowledge of the processes involved is not required and a simpler parametric representation can be employed that captures the essential details. This adds modelling uncertainty by simplifying relationships but allows the average parameter value to represent the process adequately. For example, the transfer coefficient for a radionuclide between cow's intake and milk is uncertain and is determined by a multiplicity of physiological processes, but a single average value could be determined by a suitable experiment. In principle, carrying out further investigations to improve knowledge can reduce uncertainties. However, uncertainty is not simply the absence of knowledge. Uncertainty can still prevail in situations where further information becomes available. Also, new information can either decrease or increase perceived uncertainty by revealing the presence of complexities previously unknown or poorly understood. In other words, more knowledge does not necessarily imply less uncertainty. Though it may reveal uncertainties that were previously hidden, it may not help to resolve them.

Models have two fundamental types of uncertainty:

- Model framework uncertainty, which is a function of the soundness of the model's underlying scientific foundations.
- Data uncertainty, which arises from measurement errors, analytical imprecision, and limited sample size during collection and treatment of the data used to characterize the model parameters.

These two types of uncertainty have a reciprocal relationship, with one increasing as the other decreases.



Because different models contain different types and ranges of uncertainty, it can useful to conduct sensitivity analysis early in the model development phase to identify the relative importance of model parameters

Model complexity can be constrained by eliminating parameters when sensitivity analyses show that they do not significantly affect the outputs and when there is no process-based rationale for including them. **However, a variable of little significance in one application of a model may be more important in a different application**. Hence**, it is important to identify the existing data and and/or field collection efforts that are needed to adequately parameterize the model framework and support the application of a model.** The NRC Committee on Models in the Regulatory Decision Process recommended that models used in the regulatory process should be no more complicated than is necessary to inform regulatory decision and that it is often preferable to omit capabilities that do not substantially improve model performance

Qualitative assessments: Some of the uncertainty in model predictions may arise from sources whose uncertainty cannot be quantified. Examples are uncertainties about the theory underlying the model, the manner in which that theory is mathematically expressed to represent the environmental components, and the theory being modeled. Subjective evaluation of experts may be needed to determine appropriate values for model parameters and inputs that cannot be directly observed or measured. Qualitative assessments are needed for these sources of uncertainty. These assessments may involve expert elicitation regarding the system's behavior and comparison with model forecasts.

Quantitative assessments: The uncertainty in some sources — such as some model parameters and some input data — can be estimated through quantitative assessments involving statistical uncertainty and sensitivity analyses. These types of analyses can also be used to quantitatively describe how model estimates of current conditions may be expected to differ from comparable field observations. However, since model predictions are not directly observed, special care is needed when quantitatively comparing model predictions with field data.

Peer review provides the main mechanism for independent evaluation and review of environmental models. Peer review provides an independent, expert review of the evaluation; therefore, its purpose is two-fold:

. To evaluate whether the assumptions, methods, and conclusions derived from environmental models are based on sound scientific principles.

.To check the scientific appropriateness of a model for informing a specific regulatory decision. (The latter objective is particularly important for secondary applications of existing models.)

The management of uncertainty is not just a technical exercise. It is difficult to quantify uncertainty and in most cases the quantification of uncertainty is itself uncertain.

Uncertainty is, in part, socially constructed and its assessment includes subjective judgements. Those carrying out such assessments should consider a number of issues before commencing:

• Who is the assessment being carried out for?
• What decisions will be made based on the assessment? Will inclusion of uncertainty and variability improve those decisions?
• Will incorporation of uncertainty and variability improve the assessment?
• What are the major sources of uncertainty and variability? How will these be kept separate in the analysis?
• What are the time and resource implications of including uncertainty and variability? Is this effort justified?
• Are the necessary skills and experience available?

• What methods of incorporating uncertainty and variability are to be used? Have the strengths and weaknesses of those methods and other methods that could potentially be used been evaluated and compared?
• How will the results be communicated to the public and decision-makers?

The sources of uncertainty in the predictions from models can be grouped into broad categories as illustrated in figure and outlined here:

• Measurement uncertainty. This is the uncertainty in the field or laboratory data on which models are based, eg, lack of precision, inaccuracy, sampling and analysis errors.

• Parameter value uncertainty. This is caused by not knowing the most appropriate values to select for the various parameters of a model. Lack of data that could have been collected but have not, or data that may be practically immeasurable (too expensive and resource intensive). There may be conflicting evidence or different data sets available. Parameter value uncertainty can also arise when the parameters of a model are not closely related to measurable quantities, as this can result in ambiguities of interpretation of available data.

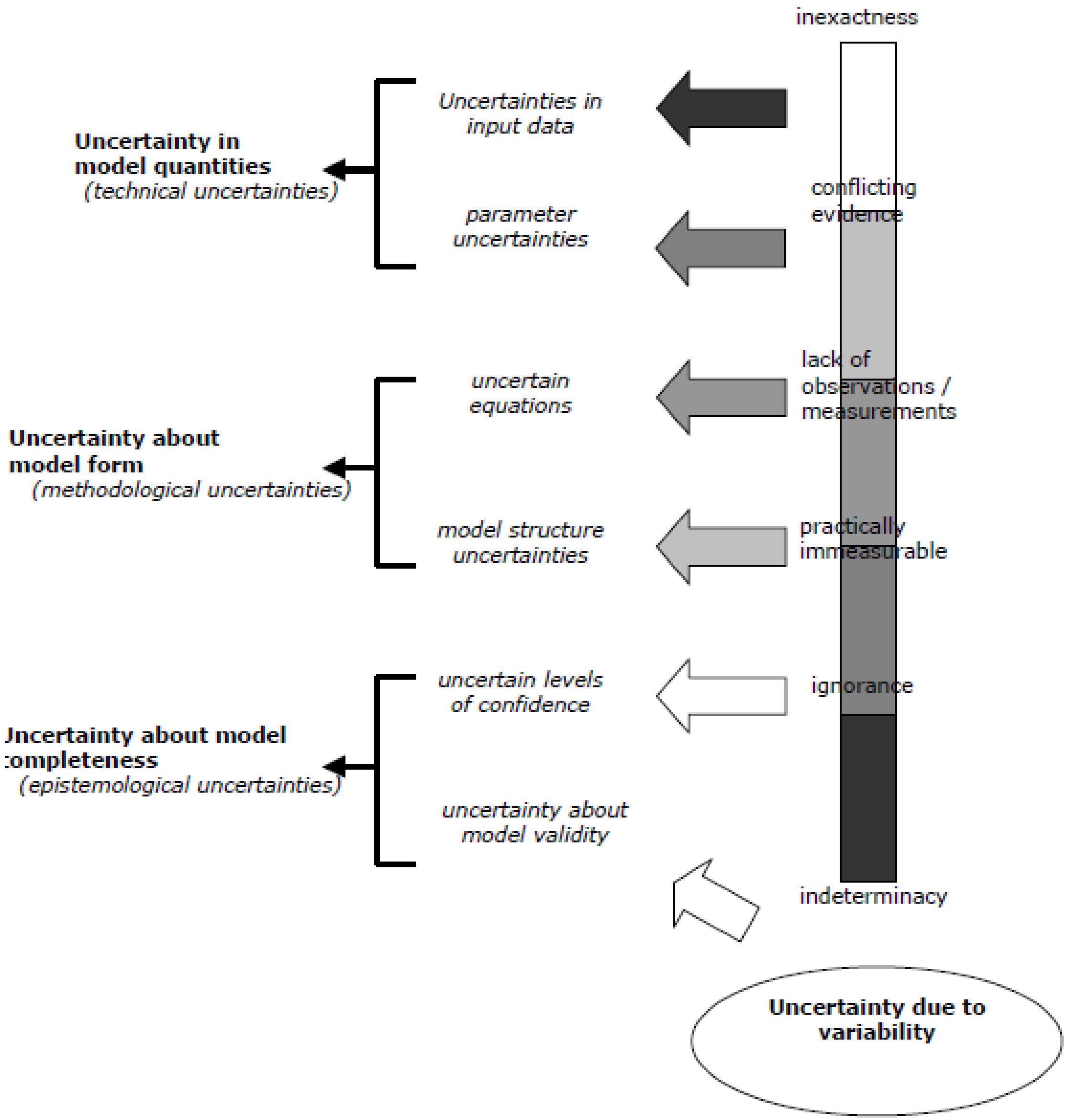
• Conceptual modelling uncertainty. This is the uncertainty associated with forming a coherent representation of the processes involved in the system being modeled based on the available data. General considerations of simplicity, adequacy and underlying physical principles will govern the selection of an appropriate model where a choice might exist. Model structural error is often overlooked when performing uncertainty analysis with the implicit assumption that the model is a good 'fit' to the environment that it purports to represent. Many environmental models perform badly against observations (Beven, 2002).

• Computational uncertainty. This arises from the representation of the selected model in computational terms. It includes the use of simplifying assumptions, discretisation and numerical methods of solution.

• Scenario uncertainty. This concerns uncertainties which cannot be adequately depicted in terms of chances or probabilities, but which can only be specified in terms of (a range of) possible outcomes. In dose assessment this source of uncertainty includes the need to make assumptions about the habits of animals in the food chain and human behaviour.

• Ignorance. Although not a manageable category of uncertainty, the recognition of ignorance allows for the fact that "we don't know what we don't know" and that there are inherent limitations to the reduction of uncertainty.

Type III modeling error: NEGLECT of processes because a lack of understanding of how the system works
K. Beven Hydrol Earth Syst Sci 11 (2007) 460



Standard for determining acceptability of model uncertainty

12 There are no clear international standards to determine the acceptability of models. Such acceptability is usually defined by user acceptance criteria and demonstrated by model validation. Although, in some specialised contexts, there is a movement toward the development of more physically based models, radiological impact assessment models have relied, and will continue substantially to rely, on large databases of empirical parameter values or distributions. Thus, many of the data that might be used for validation are already incorporated in the underlying databases. The issue of how new datasets could be generated for validation purposes and the identification of appropriate techniques for carrying out such validation studies are not addressed in this paper, but are potential

topics for future consideration by the NDAWG.

13 In general, the adequacy of models can only be assessed in relation to how well they predict environmental measurements. The National Dose Assessment Working Group considers that models which are generally within a factor of 3 of environmental measurements may be regarded as adequate for prospective radiological assessments. Models which differ from environmental measurements by a factor of more than 10 may be considered as inadequate.

Definition of criteria for significance of uncertainty

14 The NDAWG modelling sub-group defined the following scoring criteria for determining the significance of uncertainty:
• Uncertainty – Score of 1 if less than about factor of 3, score of 3 if greater than about a factor of 10, otherwise a score of 2.

• Dose – Score of 1 if dose from any permitted radioactive substance release is <20 μSv/y, score of 3 if dose is >100 μSv/y.

15 The dose score is intended to be a measure of the highest prospective critical group dose which may be received from discharges of a radionuclide at its limit specified in any RSA 93 authorisation in the UK.

16 These two scores were multiplied together to give a combined score and given the following priority rating (see Figure):
• High priority (red) – score of 6 or 9.
• Medium priority (yellow) – score of 4 or 3 (where uncertainty score = 3 and dose score = 1)
• Low priority (white) – score of 1, 2 or 3 (where uncertainty score = 1 and dose score = 3 – low uncertainty so little need to improve modelling despite high dose)

			Dose score		
			<20 μSv/y	20-100 μSv/y	>100 μSv/y
			1	2	3
Uncertainty score	> Factor of 10	3	3	6	9
	Factor of 3 – 10	2	2	4	6
	< Factor of 3	1	1	2	3

Releases to air

• Develop models for transfer of organically bound tritium (OBT) from air/soil to food

Releases to freshwater

Examine transfer of OBT and phosphorus isotopes to freshwater fish (may need to consider chemical speciation).

Releases to estuary / coastal waters

Examine concentration factors for transfer to fish for OBT and Eu-154

Releases to sewer

Continue and broaden research on transfer of radionuclides in sludge to soil and on into the foodchain, in particular for H-3 and C-14

Releases to air – Short Term

Transfer to food score is 9

General Time dependence leads to more uncertainty than for continuous releases. Seasonality is a major factor.

Effect of agricultural practices and season of the year important for short term releases.

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WHAT TO DO WITH ACCIDENTAL TRITIUM

Tritium is a life element, his transfer into the biosphere is subject to environmental conditions, season and time of the day, as well as genotype, adaptation to soil and climate etc. LARGE NATURAL VARIABILITY

To test the full model, we must have a data base of past accidents with coherent description.

FORTUNATELY there were few accidental emissions of tritium and UNFORTUNATELY there are not well documented for our purposes

(See Ch Murphy for SRS, R Peterson for LLNL)

SPECIFIC CAUSES OF UNCERTAINTY

A. MISSING COMMUNICATION

1. EXPERIMENTS AND OBT MODELING IN AECL UNDISCLOSED
2. CARDIFF CASE: EXPERIMENTS ORDERED BY GE HEALTHCARE UNDISCLOSED (BUT ENVIRONMENTAL AGENCY AND FSA REPORT AVAILABLE ON REQUEST)
3. MANY REPORTS, PHD THESIS DIFFICULT TO ACCESS, OR DELAY FOR UNRESTRICTED
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B. INCOMPLETE DOCUMENTATION –IGNORING PAST ACHIEVMENTS (BIOMOVS, EMRAS I, SELECTIVE UPTAKE OF DISSOLVED ORGANIC TRITIUM)
C. NO COMMON KNOWLEDGE DATA BASE DUE TO COPYRIGHT RESTRICTION
D. MISSING APPRECIATION – S STRACK CASE- LOST INFORMATION T IN WHEAT
E. LIMITS IN ALLOCATION OF TIME AND BUDGET
F. MISSING DEDICATION- ONLY A JOB
G. MISSING PEER REVIEW
H. INSUFFICIENT PARAMETER UNCERTAINTY

For a single process model (UFOTRI) and a single scenario (BIOMOVS) a parameter uncertainty was done in the past
Consider parameter range and probability distribution
(uniform, trianglular, norma, lognormal, etc)
Considers correlation between parameters
Apply LATIN HYPERCUBE SAMPLING and Standardized rank regression coefficients (see IAEA SS 100)

I. NEED OF INTERDISCIPLINARY APPROACH

We must develop submodels using basic research from life science, internationally agreed, plus a minimum of working hypothesis (justifiable). We must test the model with available tritium data
Collaboration with national research in agriculture and animal husbandry.

ANIMALS- Transfer factors- few nutrition and some H metabolism knowledge. Tested . Accepted by IAEA
ANIMALS, Dynamic
EXAMPLE MAGENTC
Use recent results from animal nutrition, metabolism and physiology
Make a single working hypothesis- with justification
Justification asked for expert judgment
Test the model with all available experimental data
P/O<3
ACCEPTED and used for cases without experimental data
Next step, use the model and simplify without significant loss of predictive power

J. LUMPED PARAMETERS and steady state approach

PLANTS

$C_{TFWT}=C_{\infty}(1-e^{-k\,t})$
k is the rate constant for HTO uptake (h^{-1})

K has a large variability- see Cecile Boyer review and new experimental results on lettuce

simplification of

$$\frac{dC}{dt} = \frac{V_{exc}}{M_w}(C_{air} - 0.91\rho_s C) + \frac{V_{exc}}{M_w}(\rho_s - \rho)C_s$$

Exchange velocity=1/(Ra+Rb+Rc)

- Aerodynamic resistance Ra, Boundary layer resistance Rb, Total surface resistance Rc can be split up into canopy and ground related resistance For HTO uptake to leaves only canopy resistance

Ra, Rb - affected by wind speed, crop height, leaf size, and atmospheric stability;
- decrease with increasing wind speed and crop height

CAN BE HANDELED WITH TODAY KNOWLEDGE (BIOMETOROLOGY, GIS, Remote Sensing) NEED COOPERATION

K Avoid calibration with a single experiment or a limited number of experiments

$$\frac{dC_{OBT}}{dt} = \upsilon C_{HTO}$$

where
_ C_{OBT} is the OBT concentration in the plant leaves (Bq L_1 of combustion water),
_ C_{HTO} is the tissue free-water tritium concentration (Bq L_1),
_ ν is the conversion rate from HTO to OBT (% h_1), NOT a plant dependent constant. **NOT A PARAMETER**

L. INCOMPLETE USE OF RECENT ADVANCES IN SOIL WATER-PLANT MODELING
Actual evaporation and transpiration
Rooting depth and distribution
Profile of HTO in soil
Water stress
Macropores
OPTIMISATION OF NUMERICAL GRID
REMAIN THE VARIABILITY OF SOIL PEDOFUNCTION (must be site specific but still variability in hydraulic conductivity)
EFFCTS ON FINAL UNCERTAINTY MUST BE EXERCISED
(LOT OF MODELS are available, including contaminants, must be adapted)

M. OBT (NE) définition, annalitical technique, bioavailability

N. Incomplete use of plant physiology and growth processes
(OBT formation, loss by respiration, partition to edible plant parts)
>> photosynthesis, select a practical model
>> use appropriate plant growth model

O. INCOMPLETE USE OF Carbon knowledge (common pathways)
Growth- tested with FACE data

Translocation, respiration , etc

MORE STEPS

1. Analyze model simplification without loss of predictive power, using sensitivity and uncertainty approach
2. run on a full year of meteorological data to observe consistency
3. test on different soils and climate
4. test with available data

PEER REVIEW

For operational application add land use, population distribution, production and habits
Consider an improved atmospheric model, site adapted