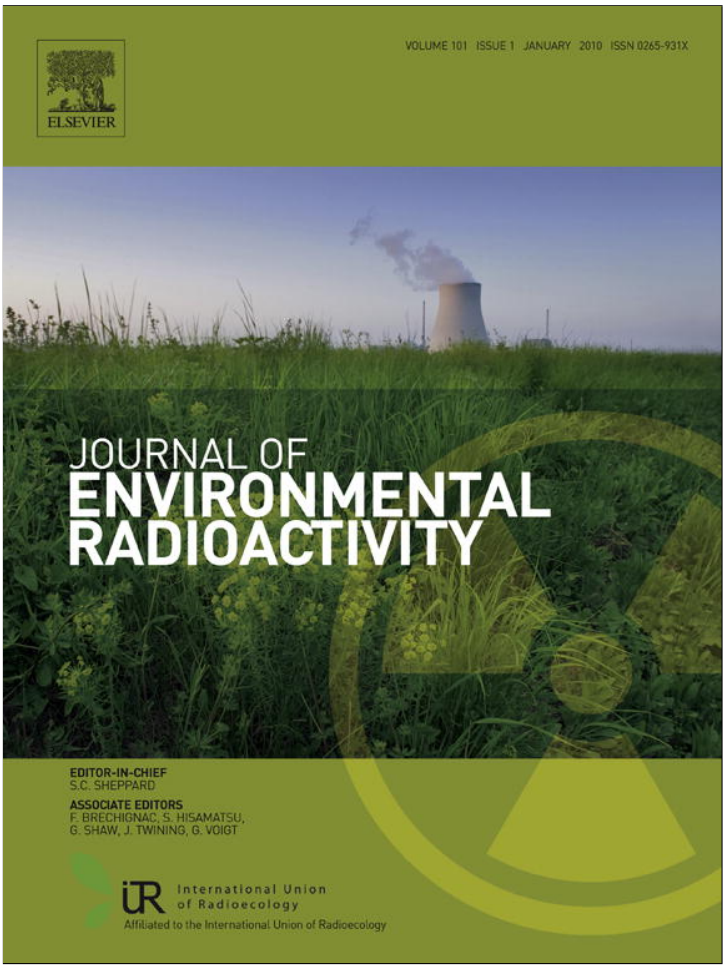

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Extension of sensitivity and uncertainty analysis for long term dose assessment of high level nuclear waste disposal sites to uncertainties in the human behaviour

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ABSTRACT

Biosphere dose conversion factors are computed for the French high-level geological waste disposal concept and to illustrate the combined probabilistic and deterministic approach. Both ^{135}Cs and ^{79}Se are used as examples. Probabilistic analyses of the system considering all parameters, as well as physical and societal parameters independently, allow quantification of their mutual impact on overall uncertainty. As physical parameter uncertainties decreased, for example with the availability of further experimental and field data, the societal uncertainties, which are less easily constrained, particularly for the long term, become more and more significant. One also has to distinguish uncertainties impacting the low dose portion of a distribution from those impacting the high dose range, the latter having logically a greater impact in an assessment situation. The use of cumulative probability curves allows us to quantify probability variations as a function of the dose estimate, with the ratio of the probability variation (slope of the curve) indicative of uncertainties of different radionuclides. In the case of ^{135}Cs with better constrained physical parameters, the uncertainty in human behaviour is more significant, even in the high dose range, where they increase the probability of higher doses. For both radionuclides, uncertainties impact more strongly in the intermediate than in the high dose range. In an assessment context, the focus will be on probabilities of higher dose values. The probabilistic approach can furthermore be used to construct critical groups based on a predefined probability level and to ensure that critical groups cover the expected range of uncertainty.

1. Introduction

Monte Carlo based probabilistic approaches have been used extensively to carry out error propagation and related uncertainty and sensitivity analyses. The Monte Carlo method (Metropolis, 1987), which relies essentially on the repeated sampling of input parameter values and repeated computational runs of a model code, has been extensively used in all fields spanning natural to social sciences and beyond (Doucet et al., 2001; Hora, 1997). In the environmental field, it has been applied to test the explanatory value of the model for contaminated sites (Gilbert et al., 1996) as well as a risk analysis tool (Eged et al., 2006; Gilbert et al., 1995; Wolt et al., 2001). For long-term risks, associated with high-level radioactive waste disposal, applications have also been widespread (Andersson et al., 2005; Avila et al., 2006; Bergström and Nordlinder, 1991; Ikonen, 2006; Jones et al., 2004; Schwarz and Hoffman, 1980). Specifically, the final component of the chain of calculations in a high-level radioactive waste safety assessment, the estimation of the dose to man as a consequence of the contamination of accessible ground water resources, is particularly characterised by uncertainty; mostly related to the fact that long-term evolution of the biosphere, including human behaviour, cannot be readily predicted. Generally the evolution of processes in the near field (e.g. dissolution of waste glass, corrosion of waste canisters, stability of engineered barriers) and in the geosphere (e.g. diffusive or advective transport in aquitards or aquifers) can be predicted via mathematical modelling of coupled chemical and transport processes for a period of several thousand years or beyond, whereas the evolution of processes at or near the surface, particularly if influenced by man and climate, are not open to such accurate physical and mathematical treatment. Simplified, so-called conservative models that tend to over-estimate the impact, have been developed to convert a defined concentration in an aquifer (usually in Bq per unit volume) to an effective dose rate for

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a defined critical group (given in Sv per year). This conversion rate is generally known as biosphere dose conversion factor, which can be multiplied by the time-dependent activity curve modelled on the basis of the geosphere transfer model, has also been used by other agencies for their feasibility and safety analyses of high-level geological nuclear waste disposal (EPRI, 2005; JNC, 2000; NAGRA, 2002; Nordlinder et al., 1999; Pinedo and Simón, 2001; Vieno and Nordman, 1996). This simplified biosphere conversion factor should not be confused with the more complex Landscape Dose Factor used in the Swedish and Finnish assessments (Avila et al., 2006).

These biosphere transfer and dose estimation models are based on two sets of parameters, those linked to physico-chemical, biophysical or transfer processes (physical parameters), such as sorption of radionuclides in the soil or uptake by plants from the soil or by animals due to the consumption of contaminated plants (Thiessen et al., 1999) and those linked to the behaviour of humans, such as their food consumption rates, the sources of their food or their daily living habits (societal parameters). Uncertainty and sensitivity analyses have been carried out by various modellers mostly for selected physical parameters with only a few exceptions (Bergström and Nordlinder, 1991; Davis et al., 1993) to the best of our knowledge.

The results simulated using a Monte Carlo probabilistic approach can be statistically treated to estimate the uncertainty of the final model result, based on the uncertainties of the input parameters (uncertainty analysis). They can furthermore be compared with input parameters in the search for possible correlations, "to ascertain how a given model depends on its input factors" (Saltelli et al., 1999) or to indicate the impact of the parametric uncertainty on the final result (sensitivity analysis).

Uncertainty and sensitivity analyses have been carried out for the biosphere transfers of a variety of pertinent radionuclides as part of the French feasibility study for high-level waste radioactive disposal (Andra, 2005a), but they were restricted to transfer parameters. The impact of the societal parameters has been treated on the basis of a series of different deterministic calculations for a small number of critical or reference groups (Klos and Albrecht, 2005). This approach of analysing a limited number of potential critical groups is also suggested by the French regulator (RFS, 1991). In this publication we describe a scientific approach that goes beyond this requirement; a combined sensitivity and uncertainty analysis based on the variability of both physical and societal parameters. This approach helps in validating the choice of the critical groups and allows us to verify that the use of individual critical groups covers the broad range of possible human behaviour. It can furthermore be used as a means to derive a more global evaluation of the overall uncertainty. This broader approach to the integration of uncertainties of physical and societal parameters further enables direct comparison of these unrelated uncertainties.

In this paper, we use two radionuclides, ^{135}Cs and ^{79}Se, to illustrate the impact of a combined investigation of societal and physical parameters in sensitivity and uncertainty analysis, after a review of the biosphere dose assessment model that has been applied and a description of the integration of societal parameters into a probabilistic approach. The two radionuclides were chosen because of their presence in significant quantities in the waste inventory, their long half lives and their different biogeochemical and physical transfer behaviour from well water to humans.

2. The biosphere transfer model

It is necessary to describe the biosphere transfer model to an adequate level since the model evidently bounds the outcome. It should none-the-less be stated that it is comparable with similar models either applicable to radioactive spills or to solid radioactive waste disposals, many described in published reports (Albrecht, 2007; Davis et al., 1993; Jones et al., 2004; Klos et al., 1996; Sheppard, 1992), but fewer in the open literature (Müller and Pröhl, 1993; Thiessen et al., 1999).

Such simplified transfer or dose assessment models are not intended to simulate a realistic situation yielding a result comparable to an actual dose, but to make sure that the resulting dose is higher than the dose that would be obtained by a more refined realistic modelling approach. This conservative approach allows significant simplification of both the conceptual and the mathematical models.

Risk assessors base their calculations on scenarios relating to the type of disposal facility, the geological setting, the release pathways and the evolution of the geosphere in time, essentially defined by up-stream models and regulatory requirements (RFS, 1991).

Here, we use a classical scenario, the well scenario, which supposes that a critical or reference group derives all of its water from a well in an aquifer located above the geological storage location taken to be in an aquitard (Marty et al., 2003). This water is used for drinking by humans and their livestock and for irrigation of soils (Fig. 1). The former contaminates man and animal products directly, the latter via soil contamination, plant uptake, and ingestion of soil and plants, and via external exposure and inhalation of resuspended soil.

Simplifications made considering contamination pathways (Fig. 1) are a consequence of the choice of radionuclides (^{135}Cs and ^{79}Se), the critical group (adult), and the scenario (deep well). Inhalation of resuspended soil, important for the actinides (Litaor, 1999) is insignificant for ^{135}Cs (pure β emitter) and ^{79}Se (high soil-to-plant uptake) (Andra, 2005a, Chapter 7, E6 and E9); ingestion of contaminated soil, sometimes important for dose assessments of infants and children is much less significant for adults (Sheppard, 1998). Significant contamination of a surface aquifer and surface water is – in the particular case of the French proposed high-level geological waste disposal site (Andra, 2005b) – unlikely. As a consequence, pasture or forest ecosystems, which are not irrigated in France, are not modelled as contaminated. The extent to which this conservative assumption simplifies the biosphere transfer part of the assessment calculations can be assessed on the basis of the Swedish and Finnish approaches, as these model, in detail, the transfers from a geosphere-biosphere interface zone to the sea via a variety of ecosystems, such as forests, mires, lakes and streams (Berglund et al., 2009; Ikonen, 2006).

Contamination of agricultural soil (C_{soil}, Bq/kg_{dry}), the only accumulation compartment in the model, is modelled as a dynamic process using a box model approach and first-order kinetics (Shukla, 1993). The first-order differential equation used for this dynamic compartment has an analytical solution for input parameters that are constant over each calculation step:

$$C_{soil}(t_j) = \frac{J}{k} + \left[\left(C_{soil}(t_i) - \frac{J}{k}\right)e^{-k(t_j - t_i)}\right] \quad (1)$$

J signifies the input rate and $k = \lambda_{lix} + \lambda_{exp} + \lambda_R$ the losses, the ratio J/k represents the soil concentration at equilibrium.

$$\frac{J}{k} = \frac{\frac{T_{irr}C_{irr}}{(1-p_{soil})\rho_p \cdot d}}{\lambda_{lix} + \lambda_{exp} + \lambda_R} = C^{\infty}_{soil} \quad (2)$$

It depends on the inputs constant (J) and the loss factors (k). The second part of the Eq. (1) depends essentially on the loss factor and determines the characteristic transition time of the system, i.e. the time needed to go from an initial concentration to a new equilibrium state. For assessment of high and intermediate level long-lived waste, a contamination period of 10 000 years is applied,

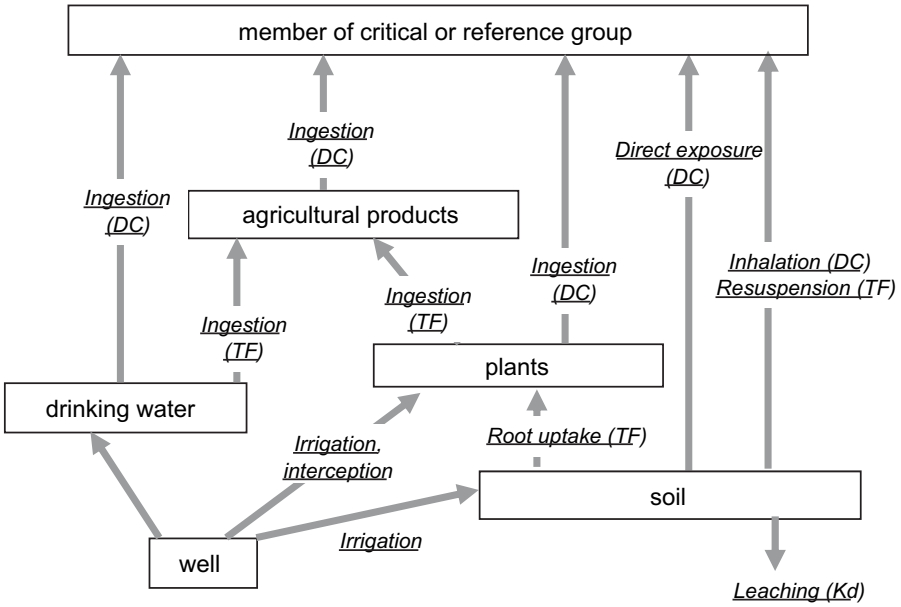

Fig. 1. Illustration of the contamination pathways considered in the well scenario, with transfer factors (TF) used to quantify inter-compartment transfers and dose coefficients (DC) for dose estimations.

which guarantees a steady state for most radionuclides. The activity in the irrigation water (C_{irr}) is set constant to unity (1 Bq L^{-1}) during the entire period.

The annualised rate of irrigation (T_{irr}) is a linear function of the precipitation (T_{rain}, both in L m^{-2} a^{-1}) and two fitted parameters based on local climate conditions ($C = -0.7724$, $D = 713.64$):

$$T_{irr} = C \cdot T_{rain} + D \tag{3}$$

Losses due to water percolating through the soil (λ_{lix}, a^{-1}) depend on the hydrologic soil balance (Hyd_bal $= T_{rain} + T_{irr} - ETP$), the sum of water input via precipitation and irrigation and the loss via evapotranspiration (ETP = 720 L m^{-2} a^{-1}), the radionuclide retardation factor ($R_s = 1 + (Kd \cdot (1 - p_{soil})\rho_p)/w_{soil} \cdot p_{soil}$), the solid-to-solution distribution coefficient (Kd, in m^3 kg^{-1}_{dry}) and the soil physical parameters ρ_p (particle density, kg m^{-3}), p_{soil} (soil porosity, –), w_{soil}, (the soil water content, –), and d (the homogenisation depth, m):

$$\lambda_{lix} = \frac{\text{Hyd\_bal}}{w_{soil} \cdot p_{soil} \cdot d \cdot R_s} \tag{4}$$

The hydrological soil balance is applicable for standard crop growth situations where irrigation maintains a specific soil moisture status and, therefore, forces the evapotranspiration to a specific value determined only by the predefined local annual variation in temperature.

Losses due to export of plants at harvest (λ_{exp}, a^{-1}) can be quantified using the rate of yield (r, in kg m^{-2} a^{-1}), a soil-to-plant transfer factor (FT_{sp}) and the soil physical parameters given before:

$$\lambda_{exp} = \frac{r \cdot FT_{sp}}{(1 - p_{soil})\rho_p \cdot d} \tag{5}$$

Finally losses via radioactive decay are considered based on the decay constant (λ_R, a^{-1}).

Contamination of plants can either be by interception of contaminated irrigation water by leaves ($F_{intercep}$) and subsequent translocation to edible parts (F_{trans}) (Colle et al., 2009) or by root uptake. The former ($C_{pp,intercept}$) is modelled using a semi-empirical approach (Müller and Pröhl, 1993) considering the contamination and amount of irrigation (C_{irr}, T_{irr}), the yield at harvest (r) and the loss rate by wash-off (λ_w):

$$C_{pp,intercept} = \frac{C_{irr} T_{irr} F_{trans} F_{intercep}}{r \cdot \lambda_w} \tag{6}$$

with the interception being a function of the leaf area index (LAI), the thickness of a water film on the leaf ($S = 0.5$ mm) and the height of a single irrigation event (R, in mm):

$$F_{intercep} = \frac{LAI \cdot S}{R}\left[1 - e^{\frac{-ln2}{35}R}\right] \tag{7}$$

Occurrences of non-physical values ($F_{intercep} > 1$) can be avoided in a probabilistic analysis using a logic statement; in the case of 10 000 runs 9 values were above 1 with an average of 1.07.

All additional transfers including soil-to-plant transfer via root uptake and further up the food chain are based on the assumption of steady-state conditions. Plant activities (primary products, $C_{pp,root}$, Bq kg^{-1}_{fresh}) based on root uptake are modelled by multiplying the soil activities with empirical concentration ratios for the plant under consideration (FT_{sp}, kg_{dry} kg^{-1}_{fresh}).

$$C_{pp,root} = C_{soil} \cdot FT_{sp} \tag{8}$$

The total plant activity is the sum of both contamination pathways $C_{pp} = C_{pp,root} + C_{pp,intercep}$.

Similarly, activities in agricultural animal products (C_{ap}, Bq kg^{-1}_{fresh}) are based on the activities of ingested primary products, soil and water (assumed identical to irrigation water), the food (in_{pp}), soil (in_{soil}) and water (in_W) intake and the related transfer factor (F_{accu}, day kg^{-1}_{fresh}) with k types of primary products considered:

$$C_{ap} = \left(\sum_{n=1}^{k} in_{pp,n} \cdot C_{pp,n} + in_{soil} C_{soil} + in_w C_{irr}\right) \cdot F_{accu} \tag{9}$$

The total ingestion dose (in Sv a^{-1}) by a member of the critical group is a function of the intake of all k contaminated products ($C_{all,n}$), considering water, primary and agricultural products, the

consumption rate (H, $kg_{fresh}\,a^{-1}$), the autarky factor, indicating the fraction of the food item which was produced within the contaminated area (AH_n), and the dose factor for ingestion (FD_{ing}):

$$D_{ingest} = \sum_{n=1}^{k} FD_{ing} \cdot C_{all,n} \cdot H_n \cdot AH_n \quad (10)$$

The dose via direct exposure is estimated by multiplication of the soil concentration (C_{soil}), the dose factor for direct exposure (FD_{dir_exp}) and the time the member of the critical group spends on the contaminated soil (TPS_{soil}):

$$D_{dir\_exp} = FD_{dir\_exp} \cdot C_{soil} \cdot TPS_{soil} \quad (11)$$

The dose by inhalation is a function of the activity concentration in air (C_{air}, in $Bq\,m^{-3}$), the inhalation rate (I, in $m^3\,h^{-1}$), the time spent on the contaminated land (TPS, in $h.a^{-1}$) and the dose factor for inhalation (FDdir_exp, in $Sv\,Bq^{-1}$):

$$D_{inh} = C_{air} \cdot I \cdot FD_{inh} \cdot TPS, \quad (12)$$

with $C_{air} = susp \cdot d \cdot p_{soil} \cdot C_{soil}$, the product of the soil resuspension factor (m^{-1}), the homogenisation depth (m) and the soil density ($kg\,m^{-3}$) and soil activity (C_{soil}) (Garger et al., 1999).

The final dose (D_{sum}, in $Sv\,Bq^{-1}$) is given by the sum of direct exposure, the ingestion and the inhalation doses. It is a function of a number of parameters which can be classified into physical or transfer parameters, such as solid-to-solution distribution coefficients or soil-to-plant transfers, and societal parameters of which food consumption and living habits are some examples.

3. Application of the Monte Carlo method

3.1. Brief introduction to the software used

Andra developed, in co-operation with Digit Système Informatique, a program, called Model Management (MoM) that allows integration of the above equations to evaluate the transfer of radioactive or toxic substances in the biosphere. The tool combines implementation of mathematical equations with the handling of databases for both deterministic and stochastic model approaches. Some technical information, validation and qualification issues and application examples have been presented previously (Albrecht and Bonafos, 2004). MoM uses three independent templates for the definition of (1) mathematical equations (models), (2) element-specific and (3) site-specific parameters. All templates are available for manipulation and parameterisation, while maintaining the integrity of the core program. For each project, a model can be chosen from a list of available models (i.e. multi-element models for radionuclides or toxic chemical substances to calculate dose rates, or element-specific models such as those developed for ^{3}H, ^{14}C and ^{36}Cl). The software was formerly called Aquabios, which is the name of the biosphere transfer model used at Andra for assessing individual effective doses as a consequence of the release of "non-specific" radionuclides from a nuclear waste repository. The term "non-specific" is used to differentiate the model from alternative models for specific radionuclides, such as ^{3}H, ^{14}C (Penfold and Watkins, 1998) or ^{36}Cl (Limer et al., 2008; Sheppard, 2001) or for models considering toxic chemicals (Côme et al., 2004). Attached to each model is a choice of element- and site-specific parameter databases. Within the template for model definition, dynamic compartments and radioactive decay calculations can be defined by implementation of analytical solutions of the differential equations. Both deterministic and stochastic calculations are carried out step-wise allowing all parameters to be changed as a function of time with intermediate results managed by flexible intrinsic functions. An integrated function allows random and hypercube sampling of parameter values using a variety of statistical distributions (e.g. linear, normal, log-normal, and triangular). Reliability checks on these sampling features were made by comparing statistics of the parameter value sample that was created with the input specification. In the stochastic mode, MoM performs a large number of calculations for a single element with a defined number of time-steps. For each activated parameter (both physical and societal parameters can be activated), a predefined statistical distribution has to be defined. MoM supplies a list of parameter values and the associated results, which can be imported into a statistics program package for further analysis. Verification of the core calculator and other integrated functions has been carried out by comparison with spreadsheet or statistical tools. Limited validation of the integrated models has been accomplished by intercomparison with other models (Albrecht et al., 2005; Côme et al., 2004; Klos et al., 1999; Limer et al., 2008), though we are aware that validation of "numerical models of natural systems" has been argued to be "impossible" (Oreskes et al., 1994).

3.2. The choice of distributions and parameterisation

It is important that all parameters used in Monte Carlo probabilistic analysis are independent and can be described by probability density functions (pdf). It should also be mentioned that a Bayesian approach, not applied here, has also been used successfully, which adopts a degree-of-belief interpretation of probability, expert judgement or conditional probability (Bonano and Apostolakis, 1991). Expert judgements, as we will see, are included in the form of judgemental aspects, whether explicitly as in the Bayesian method or implicitly, as in the classical probabilistic approach used here. Significant effort is needed to derive the statistical distribution of parameter input values (Stephens et al., 1993). Ideally these pdf's would be derived from an existing database, but the lack of site- and radionuclide-specific data does not always permit this approach. In the case of Cs (mostly for the short-lived ^{134}Cs or ^{137}Cs but also applicable for the long-lived ^{135}Cs), pdf's can be derived from published data (Sheppard and Thibault, 1990), but in many cases data are insufficient to construct distributions. For such cases it had been proposed to assign a value of 3 times the mean for the maximum value (Coomes et al., 1982). This approximation originally derived for consumption data has been extended to physical parameters and is supported by more recent survey data (IAEA, 2003).

There has been some discussion in the literature about the application of normal or log-normal distributions to product parameters (*Kd*, soil-to-plant transfer) (Sheppard and Evenden, 1997) and the comparison with observed data (Sheppard and Evenden, 1990). In earlier approaches it was simply proposed to use log-normal distributions in cases where parameters were expected to vary by more than one order of magnitude (Hoffman et al., 1982). Attempts have been made to move from such expert judgements to empirical observations to mathematical explanations. The existence of well-defined distribution laws for variables allows construction of distribution laws for their sums and products (e.g. the use of log-normal distributions for product parameters). For parameters following log-normal distribution, the mean and the standard deviation need to be given. The values indicated in Table 1 are those used for the Andra 2005 feasibility report for the disposal of medium- and high-level long-lived radioactive waste and is based on a concise literature review (Andra, 2005a, Chapter 7; Gallerand and Leclerc-Cessac, 2003).

Table 1
Average values and standard deviations defining the log-normal statistical distributions as well as minima, maxima and highest probability values for triangular distributions, used for caesium and selenium radionuclide-specific parameters.

Parameter	Meaning	Cs average	Cs standard deviation	Se average	Se standard deviation
Food chain accumulation factors (day kg^{-1})					
FTlamb	Lamb	0.49	0.38	1.40	4.52
FTbeef	Beef	0.05	0.005	0.007	0.023
FTmilk	Milk	0.008	0.007	0.016	0.062
FTegg	Egg	0.40	0.53	9.03	28.5
FTmilkp	Milk products	0.047	0.038	0.003	0.01
FTpork	Pork	0.24	0.28	0.32	1.01
FT_chick	Chicken	3.00	2.37	9.03	28.4
Soil-to-plant transfer factors for ($kg_{dry}\ kg^{-1}_{fresh}$)					
FTs_cer	Cereal	0.007	0.023	0.449	0.58
FTs_leafy	Leafy vegetables	0.003	0.006	0.139	0.04
FTs_fruit	Fruit	0.000	0.000	0.020	0.01
FTs_pot	Potatoes	0.006	0.015	0.080	0.54
FTs_root	Root vegetables	0.004	0.013	0.070	0.40
Solid-to-liquid distribution coefficient ($m^3\ kg^{-1}_{dry}$)					
Kd	Soil *Kd*	18.0	25.8	0.020	0.033

Translocation factors Cs and Se for vegetables (–)

Triangular distribution		Minimum	Maximum	Value of highest probability
Ftrans_leaf	Leafy	0.4	0.6	0.5
Ftrans_plant	Others	0.006	0.6	0.11

3.3. Specific treatment of societal parameters

Societal parameters allow quantifying (1) human consumption and (2) the daily time budgets. To avoid consideration of extreme habits, a specific sampling treatment is applied. Parameter values for all food items describing human consumption, including the total consumption (N_{tot}) are drawn randomly using their specified distributions. For each run, the sum of the individual consumptions is quantified (N_{rand}). In the next step we calculate the ratio (rat*N*) between a sampled total consumption and N_{rand}:

$$\mathrm{rat}N = \frac{N_{tot}}{N_{rand}} \tag{13}$$

Each randomly drawn consumption value is then normalised by multiplication with ratN. This guarantees a constant sum for all food items if the total consumption is kept constant. In case of the total consumption varying according to a defined distribution law, total consumption itself will vary within this range. We would like to add that normalisation to a caloric intake as carried out in the Canadian programme (Davis et al., 1993) may be more realistic that the use of masses.

A similar approach has been adopted for the randomisation of the daily time budget. The sum of the sampled individual daily occupations (time spent on the contaminated agricultural fields, on grass land, inside the house or outside the contaminated zone) is normalised to 24 h (rat*T*), which then allows normalisation of all sampled occupation data by multiplication with this ratio.

3.4. Summary of deterministic and stochastic input data

Parameters depending on the radionuclide represent the first set to consider. They include the food chain transfer factors, the soil-to-plant concentration ratios and the solid-to-liquid distribution coefficients (Table 1). For these parameters a log-normal distribution is chosen as representative. The mean value is identical to the value used in deterministic calculations; it is also called the best estimate or the phenomenological value. The standard deviation is calculated using the assumption that the difference between the maximum found in the literature and the phenomenological value is comparable to two standard deviations. All parameter values have been constructed based on published results (Colle et al., 2009; IAEA, 1994; Ng, 1982; Nisbet and Woodman, 2000; Sheppard and Thibault, 1990; Thorne, 2003; Voigt et al., 1993) and, in the case of Se, partly using analogies with sulphur (see Gallerand and Leclerc-Cessac, 2003 for further details).

The second set of parameters depends entirely on the biosphere and the chosen scenario (Andra, 2005a) (Table 2); they are either of physical origin or characterise the human behaviour (societal parameters). For these parameters triangular distributions have been chosen. Minimum and maximum values are either known extreme values or those measured or derived from census data, whereas the

Table 2
Minimum, maximum and the highest probability value defining the triangular statistical distributions used for physical and societal biosphere-dependent parameters.

Parameter	Meaning	Minimum	Maximum	Value of highest probability
Physical parameters				
Leaf area index for (–)				
LAI_cer	Cereals	2	7	4
LAI_leafy	Leafy vegetables	2	7	4
LAI_fruit	Fruit	2	7	4
LAI_pot	Potatoes	2	7	4
LAI_root	Root vegetables	2	7	4
Lamda_w	Leaf wash-off (an^{-1})	10	20	17
Rirr	Height per irrigation (mm)	1	25	3
T_{rain}	Precipitation ($L\,m^{-2}\,an^{-1}$)	553	1106	830
Human behaviour				
	Time spent ($h\,day^{-1}$)			
TPSCultu	On cultivated soil	1	7	4
TPShorszone	Off-zone	0	11	9
TPSMaison	Indoors	8	11	10
TPSPra	On prairie soils	0	4	1
Food consumption ($kg\,an^{-1}$; $L\,an^{-1}$)				
Hbeef	Beef	0	36	18
Hcer	Cereals	0	120	60
Hchick	Chicken	0	40	20
Heau	Water	440	880	440
Hegg	Eggs	0	29	11
Hfruit	Fruit	0	124	62
Hlamb	Lamb	0	6	2
Hleafy	Leafy vegetables	0	54	24
Hmilk	Milk	0	250	101
Hmilkp	Milk products	0	60	33
Hpork	Pork	0	60	29
Hpot	Potatoes	0	107	47
Hroot	Root vegetables	0	33	11
Hnour_tot	Total	291	583	437
Autarky levels for (–)				
AHbeef	Beef	0	1	0
AHcer	Cereals	0	1	0
AHchick	Chicken	0	1	1
AHeau	Water	0	1	1
AHegg	Eggs	0	1	1
AHfruit	Fruit	0	1	0.42
AHlamb	Lamb	0	1	1
AHleafy	Leafy vegetables	0	1	0.81
AHmilk	Milk	0	1	1
AHmilkp	Milk products	0	1	0.04
AHpork	Pork	0	1	0.26
AHpot	Potatoes	0	1	1
AHroot	Root vegetables	0	1	0.74

value at the highest probability density is mostly based on expert judgement. An example is the autarky level; minima (0) and maxima (1) are easily chosen, the value of highest probability density is based on census data. The latter has some validity for today's ecosystem, but is of course quite uncertain for a future situation.

3.5. The number of runs

To define the number of runs, we propose a relationship linking it to a risk limit, or a probability of detection. For each parameter we use a Latin hypercube range of samples composed of a sufficient number of runs. We choose for illustration a number of runs high enough in order to ensure that a phenomenon of probability 1/1000 will be detected. We would then deal with a space decomposed into 1000 boxes of equal probability 1/1000. The probability for one run not to be in the box S_1 is:

$$\overline{P}(S_1) = 1 - \frac{1}{1000} = 0.999. \quad (14)$$

The probability for N runs not to be in S_1 is:

$$\overline{P_N}(S_1) = \left(1 - \frac{1}{1000}\right)^N \quad (15)$$

So the probability for one of the N runs to be in the box S_1 is :

$$P_N(S_1) = 1 - \left(1 - \frac{1}{1000}\right)^N \quad (16)$$

The number of runs is adequate if $P_N(S_1)$ is close to 1. With $N = 10\,000$, we get:

$$P_{10,000}(S_1) = 1 - \left(1 - \frac{1}{1000}\right)^{10,000} \approx 0.999955 \quad (17)$$

So this computation shows that the probability to detect a situation is extremely high (0.999955), even if this situation happens rarely (up to the probability 1/1000). Therefore, we will work with $N = 10\,000$. The above-given argument depends of course on the assumption that low probability high consequence runs are of little relevance. However, if the consequence increases more rapidly than the probability decreases, then the argument necessarily fails as the risk (defined as probability multiplied by consequence) is determined by the most extreme small element of the parameter space. To test this we will carry out an uncertainty analysis with N varying between 200 and 100 000 runs.

4. Results and discussion

Before considering the outcome of the probabilistic analyses, we briefly indicate some results of a deterministic calculation for both radionuclides under consideration, ^{135}Cs and ^{79}Se. Deterministic calculation for the total dose yields 1.8×10^{-5} and 1.0×10^{-5} Sv/a per Bq/L for ^{135}Cs and ^{79}Se, respectively. Detailed analysis clearly indicates the impact of multiple ingestion pathways (Fig. 2). For both radionuclides, the ingestion pathway is the only pathway that needs consideration. For ^{135}Cs there is a small contribution from inhalation and external exposure, but it represents only 0.2% of the total dose.

The results shown in Fig. 2 can be used to interpret the probabilistic results, the relative importance of potatoes and leafy vegetable consumption for ^{135}Cs and fruit, chicken and root vegetable consumption for ^{79}Se will have some impact, but it needs to be kept in mind that certain decisions for deterministic parameter values will have to be considered. An example is the assumption that bread is not produced based on local cereal production; the autarky level for cereals is thus 0 and the cereal ingestion pathway thus does not appear as a pathway for the deterministic calculation. In the probabilistic calculation a uniform distribution between 0 and 1 is used; the impact of cereal consumption thus becomes apparent.

4.1. Uncertainty analysis

4.1.1. Caesium-135

We shall first use a full uncertainty analysis to illustrate some of the concepts used throughout the presentation of the results and the discussion. The model radionuclide is ^{135}Cs with a constant contamination of 1 Bq/L in the abstracted water for 10 000 years. The probability distribution shown in Fig. 3 is the result of a statistical treatment of 50 000 results obtained with 26 physical and 27 societal parameters varied according to defined distributions (Tables 1 and 2). There is a maximum probability density for dose values ranging between 5 and 10 μSv/a per Bq/L. For higher dose values probabilities decrease approximately monotonically. Fifty-two runs yielded dose values larger 70 μSv/a par Bq/L, with a maximum value 140 μSv/a per Bq/L. For reasons of illustration they are not shown here. The probability of these 52 occurrences is only 0.0010.

The black bar shown in Fig. 3 indicates the deterministic dose conversion factor of 17.7 μSv/a per Bq/L for the so-called reference biosphere (RB). It is based on a set of parameter values that are considered slightly cautious but reasonable (Andra, 2005a). The critical group is a so-called reference farmer with consumption rates set to median values. The grey bars indicates the mean value (M) of the 50 000 individual runs (13.7 μSv/a per Bq/L), as well as the mean plus 1 and 2 standard deviations (23.5 and 33.2 μSv/a per Bq/L) respectively.

The use of 50 000 individual runs was for illustrational purposes. A test series of Monte Carlo calculations with 200–100 000 individual runs (N) shows that 10 000 runs yield the same results (Table 3). The arithmetic mean and the 95th percentile

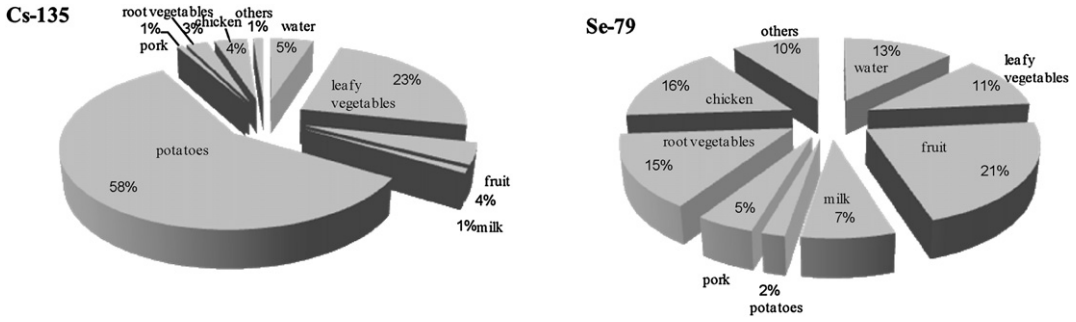

Fig. 2. Contribution of the individual ingestion pathways to the total biosphere dose conversion factor for the deterministic (best estimate) case.

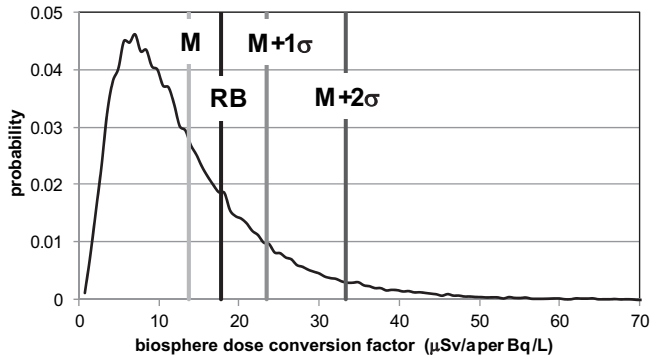

Fig. 3. Probability distribution for the ^{135}Cs biosphere dose conversion factor based on 50 000 samples with consideration of uncertainties of both physical (26) and societal (27) parameters (RB = reference biosphere; M = mean of probabilistic analysis; σ represents the standard deviation; abscissa interval width = 69.66 μSv/a per Bq/L).

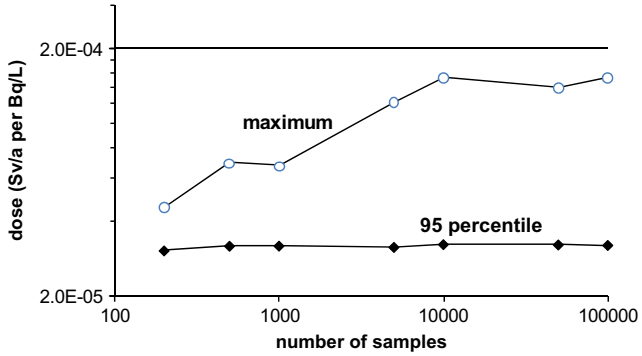

Fig. 4. Variation of the maximum value and the 95th percentile of the biosphere dose conversion factor for stochastic runs with different numbers of samples.

stabilise rapidly; with increasing sample number, the minimum values decrease and the maximum values increase (Fig. 4), indicating the sampling of low probability domains; but this has little impact on both averages and the median values.

To be able to appreciate the impact of uncertainties related to physical versus societal parameters, two stochastic calculations have been carried out, one with varying physical, one with varying societal parameters. Both runs compute the dose as a consequence of a 1 Bq/L constant ^{135}Cs contamination; both are based on 10 000 individual samples (Fig. 5). The probability distribution based on the uncertainties of societal parameters is centred and symmetric; a consequence of the fact that all parameter uncertainties are described by uniform or triangular distributions (Table 2). The probability distribution based on physical parameter uncertainties is asymmetric with a long tail towards higher dose factors, mostly a consequence of the large spread in uncertainties of the input parameters (Table 1). It is interesting to note that the uncertainty associated with societal parameters yields a higher mean dose factor than uncertainties related to physical parameter uncertainty. This has to do with the choice of the deterministic parameter values that are kept constant in the two probabilistic exercises. The autarky value for cereals (the plant with the highest soil-to-plant transfer factor for Cs, Table 1), in the deterministic case and during the physical parameter probabilistic exercise, is defined as 0, as people in France do not produce bread locally from a constrained source of cereals. All dose factors based on this assumption will thus be lower than factors obtained on the basis of a probabilistic exercise where the autarky value is varied between 0 and 1. Nonetheless for a dose factor calculated using both physical and societal parameter uncertainties, the lower part of the curve is dominated by physical parameter uncertainty. This is a consequence of the hypercube sampling procedure used for all parameter values and the random association of the sampled parameters to a complete parameter set. This means that the influence of high consumption or high autarky parameter values is generally compensated by lower physical parameter values. Only for dose factors higher than 2.8×10^{-5} Sv/a per Bq/L do the societal parameters significantly impact the probability curve, by pulling it to slightly higher values.

Probability analysis can also be used to define critical groups or to validate their choice. When the choice of critical groups is not based on a parallel probabilistic analysis, it cannot be shown that these critical groups cover the behavioural diversity given by the uncertainty distribution shown in Table 2. To illustrate this approach we use the cumulative probability distribution together with deterministic biosphere dose conversion factors for preselected critical groups (Fig. 6). Critical groups can be defined as "existing persons, or a future group of persons" who will be exposed at a higher level than the general population. When an actual group cannot be defined, a hypothetical group or representative individual should be considered who, due to location and time, would receive the greatest dose. The habits and characteristics of the group should be based upon present knowledge using cautious, but reasonable, assumptions" (ICRP 46 in IAEA, 2003, p. 149). The groups for which biosphere dose coefficients are given in Fig. 6 are those defined by Klos and Albrecht (2005), with slight modifications based on more recent consumption data.

For a defined zone in the vicinity of a contaminated source it seems possible to construct a constrained number of critical groups based on today's local behaviour. But the quantification of this behaviour is not simple, because data on consumption are mostly available for larger areas, with downscaling to local behaviour rather uncertain. Information on the autarky level or the origin of the food is even sparser. Transposing this information into the far future explains the uncertainty in human behaviour quantification (Table 2). The use of a probabilistic approach, with all parameters fluctuating, gives the overall uncertainty that can be used as a milestone to justify the choice of critical groups. For the example given in Fig. 6 the exercise is rather satisfactory. The deterministic dose calculated for the reference group (RG) compares well with

Table 3
Statistics of biosphere dose conversion factors (Sv/a per Bq/L) for a ^{135}Cs and ^{79}Se well water contamination with varying number of samples (*N*) for ^{137}Cs.

RN-Valid N	Arithmetic mean	Geometric mean	Median	Minimum	Maximum	5 Percentile	95 Percentile	Std. Dev.
^{135}Cs-200	1.35E-05	1.10E-05	1.11E-05	1.79E-06	4.57E-05	3.03E-06	3.06E-05	8.78E-06
^{135}Cs-500	1.37E-05	1.10E-05	1.10E-05	1.13E-06	6.90E-05	3.57E-06	3.20E-05	9.63E-06
^{135}Cs-1000	1.37E-05	1.11E-05	1.08E-05	1.28E-06	6.71E-05	3.54E-06	3.20E-05	9.50E-06
^{135}Cs-5 000	1.37E-05	1.11E-05	1.13E-05	9.78E-07	1.22E-04	3.62E-06	3.16E-05	9.50E-06
^{135}Cs-10 000	1.37E-05	1.10E-05	1.11E-05	7.05E-07	1.53E-04	3.60E-06	3.25E-05	9.75E-06
^{135}Cs-50 000	1.37E-05	1.10E-05	1.12E-05	7.56E-07	1.40E-04	3.59E-06	3.24E-05	9.60E-06
^{135}Cs-100 000	1.37E-05	1.10E-05	1.13E-05	7.49E-07	1.54E-04	3.56E-06	3.22E-05	9.54E-06
^{79}Sr-10 000	5.78E-06	4.24E-06	3.80E-06	5.51E-07	1.55E-04	1.64E-06	1.61E-05	7.13E-06

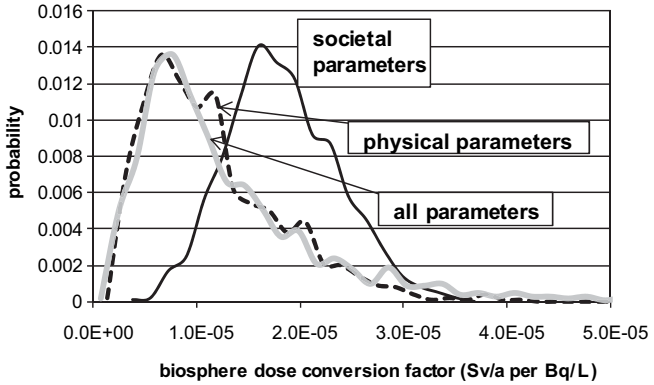

Fig. 5. Comparison of uncertainties of the biosphere dose conversion factor for ^{135}Cs related to uncertainties of physical (dashed line) and societal parameters (continuous black line); the distribution with all parameters considered (grey line) is shown for comparison (abscissa interval width = 9.82×10^{-7} Sv/a per Bq/L).

the 3 critical groups (CG) "dairy" and "cereal" farmer and the "country man". The reference group dose value plus 2 standard deviations based on the probabilistic approach is slightly above the 3 critical groups "sheep", "poultry" and "pig" farmer. The higher dose values given by the probabilistic approach are thus close to the deterministic values obtained for at least some of the critical groups. The uncertainty indicated on the basis of the different critical groups is therefore comparable to the uncertainty based on a complete uncertainty analysis.

As the choice of critical groups or of the parameterisation of these groups is demanding and intricate, we propose the use of probabilistic analysis, capable to run thousands of test cases in little time, to define the critical groups. We agree that this can be interpreted as a rather direct and crude way to link a probabilistic to a deterministic analysis. Based on risk evaluation guidelines possibly set by a regulator (a probability or percentile limit) the modeller can use the set of input data of his probabilistic analysis to obtain a critical group whose behaviour will cause a dose exactly at the limit set by the regulator. As we will see when comparing results of ^{135}Cs with those of ^{79}Se and as was shown by Klos and Albrecht (2005), these results are valid only for the radionuclide under consideration. An at-the-limit-behaviour critical group is radionuclide specific.

The 95th percentile for the ^{135}Cs probabilistic dose calculation gave a value of 3.25×10^{-5} Sv a^{-1}. This value corresponds to the dose obtained for realisation number 391 of the Monte Carlo analysis. The parameter values for the social parameters of realisation 391 are summarised in Table 4; they can be used to construct a critical group. We are aware that many different combinations of parameter values would lead to a dose at the 95th percentile and that these parameter value vectors may be widely dispersed in sampling space, so the selection of one such vector to define a critical group may be arbitrary. One should also keep under consideration that sets of data from a probabilistic analysis have their strict validity as an ensemble and that picking one out may be considered as misleading. We none-the-less propose this procedure to help defining critical groups for assessments into the far future.

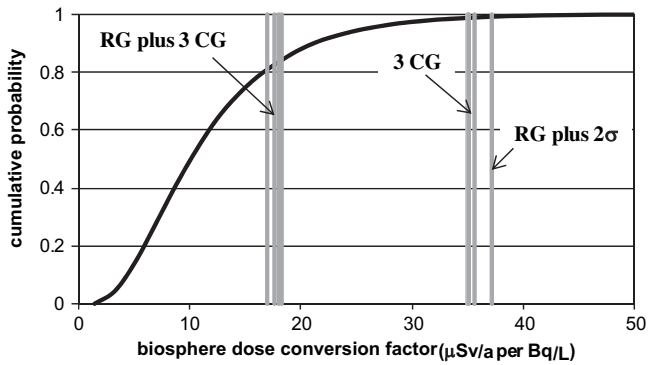

Fig. 6. Cumulative probability distribution for the dose coefficient of ^{135}Cs for the reference group (RG; including RG plus 2 standard deviations) compared with deterministic coefficients obtained for 6 defined critical groups (CG) (Klos and Albrecht, 2005), RG plus 3 CG means the reference case and three critical group cases.

4.1.2. Selenium-79

All probabilistic calculations for ^{79}Se were carried out for a set of 10,000 individual samples. To compare the impact of the uncertainty of physical versus societal parameters, we again carried out 3 independent analyses. The one considering both physical and societal parameter uncertainties indicates the total uncertainty of the biosphere dose conversion factor (Table 3). The mean of 5.8×10^{-6} Sv/a per Bq/L is below the deterministic reference value of 1.0×10^{-5} Sv/a per Bq/L, but the latter is well within the range of 2 standard deviations (2.0×10^{-5} Sv/a per Bq/L). In two further analyses physical or societal parameters were considered independently of each other, thus indicating the relative impact of both on the final result (Fig. 7). The curve indicated by "all parameters" is a graphical representation of the statistics given in Table 3. The 201 values larger than 25 μSv/a per Bq/L (including the maximum of 155 μSv/a per Bq/L, Table 3), contributing a probability of 0.02, are not shown.

Table 4
Parameter values for shot number 391/10 000 giving a dose identical to the 95th percentile of the Monte Carlo analysis.

Parameter	Meaning	Deterministic value
Time spent (h day^{-1})		
TPSCultu	On cultivated soil	6.12
TPShorszone	Off-zone	5.49
TPSMaison	Indoors	1.63
TPSPra	On prairie soils	10.05
Autarky levels for (–)		
AHbeef	Beef	0.97
AHcer	Cereals	0.27
AHchick	Chicken	0.99
AHeau	Water	0.45
AHegg	Eggs	0.87
AHfruit	Fruit	0.72
AHlamb	Lamb	0.93
AHleafy	Leafy vegetables	0.78
AHmilk	Milk	0.48
AHmilkp	Milk products	0.70
AHpork	Pork	0.30
AHpot	Potatoes	0.21
AHroot	Root vegetables	0.59
Food consumption (kg an$^{-1;}$ L an^{-1})		
Hbeef	Beef	17.0
Hcer	Cereals	46.7
Hchick	Chicken	19.1
Heau	Water	767.4
Hegg	Eggs	7.5
Hfruit	Fruit	24.8
Hlamb	Lamb	1.2
Hleafy	Leafy vegetables	13.9
Hmilk	Milk	85.7
Hmilk	Milk	23.2
Hpork	Pork	34.4
Hpot	Potatoes	57.4
Hroot	Root vegetables	4.9

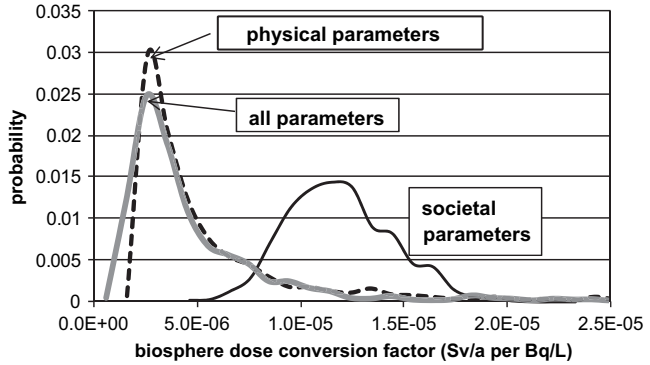

Fig. 7. Comparison of uncertainties of the biosphere dose conversion factor for ^{79}Se related to uncertainties of physical (grey line) and societal parameters (black line) together with the probability curve based on all parameters (grey line; abscissa interval width = 9.80×10^{-7} Sv/a per Bq/L).

As was the case for ^{135}Cs, the choice of parameter values for the societal parameters, compared with the deterministic calculation or the probabilistic exercise for physical parameters, generally yields higher dose factors, with a rather broad, symmetrical distribution. If only physical parameters are included in the probabilistic analysis, the probability distribution is much narrower with a long tail towards higher dose factors. The overall uncertainty of the biosphere dose conversion factor seems mostly a consequence of uncertainties in the physical parameterisation of the model. Uncertainties in human behaviour result in a change in slope on the low dose side and in a reduced probability maximum.

We have again carried out 6 additional deterministic calculations for different critical groups (Fig. 8). The uncertainty based on the use of multiple critical groups does not cover the range of uncertainty of the overall probabilistic approach. This is of course a consequence of the dominance of the physical parameters on the overall uncertainty (Fig. 7). In the case of a radionuclide such as ^{79}Se, for which the overall uncertainty is mostly dependent on uncertainties of physical parameter values, calculations for different critical groups is not a useful deterministic exercise in regard to illustrating overall uncertainties.

4.1.3. Comparison ^{135}Cs–^{79}Se

For radionuclides such as ^{135}Cs and ^{79}Se for which the ingestion pathway is clearly dominant and for which the drinking water pathway has a noteworthy impact (5% for Cs and 13% for Se), one can safely say that the uncertainties of site- and human-behaviour-specific parameters have roughly the same absolute impact. The differences in the uncertainties must be related to radionuclide-specific parameters and to specific combinations between physical and societal parameters.

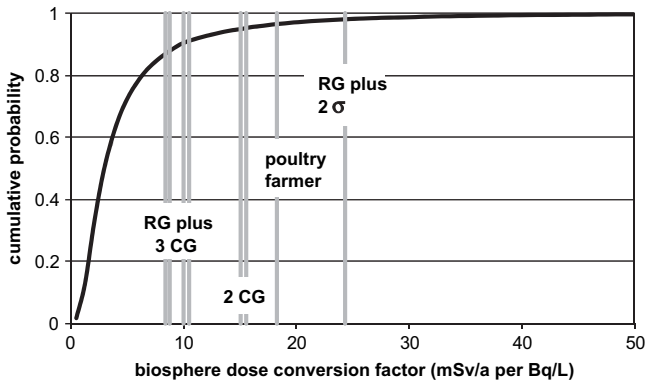

Fig. 8. Cumulative probability distribution for the dose coefficient of ^{79}Se for the reference group (RG; including RG plus 2 standard deviations) compared to deterministic coefficients obtained for 6 defined critical groups (CG) (Klos and Albrecht, 2005), RG plus 3 CG means the reference case and three critical group cases.

These differences cannot be explained simply on the basis of comparison of parameter uncertainties (Table 1, Fig. 2). For ^{135}Cs, we have available a very large database as a consequence of research carried out in relation to ^{137}Cs and ^{134}Cs released to the environment by atmospheric bomb testing and nuclear spills and accidents (Devell et al., 1986; Mück, 1996). For ^{79}Se, far fewer data were available, in spite of research on stable selenium in contaminated areas (Johnson et al., 2000). For certain transfer parameters, an analogy with sulphur was required, which increases somewhat parameter value uncertainties. This enhanced uncertainty regarding the physical transfer parameters for ^{79}Se is balanced by the extreme variability (uncertainty) of the soil *Kd* for ^{135}Cs. In a single study, Smolders et al. (1997) found the soil *Kd* varying between 0.120 and 1670 $m^3\,kg_{dry}^{-1}$, depending strongly on soil mineralogy not easily quantified into the far future.

These differences in the overall uncertainties can be quantified on the basis of one standard deviation compared with the arithmetic mean, which is 71% for ^{135}Cs and 123% for ^{79}Se (Table 3) or by taking the ratio of the maximum over the minimum value which is 217 for ^{135}Cs and 281 for ^{79}Se.

One can furthermore compare the probability curves for ^{135}Cs (Fig. 5) and ^{79}Se (Fig. 7) to see that the width of the curves for ^{135}Cs are larger than those for ^{79}Se, indicating higher uncertainty and that the relative impact of human behaviour uncertainty is somewhat lower for ^{79}Se relative to ^{135}Cs. Particularly, the higher dose factors for ^{135}Cs are impacted by societal parameter uncertainty. This explains why it is possible for ^{135}Cs to illustrate dose coefficient uncertainties using deterministic calculations for different critical groups, an exercise that makes less sense for ^{79}Se.

The difficulty to explain in detail variations in uncertainty distributions as those shown in Figs. 5 and 7 are related to parameter choices for the different radionuclides. For ^{135}Cs, the example of the deterministic choice of cereal autarky has already been given. For ^{79}Se, the chicken and egg pathways are particularly important because the transfer factors from animal food to chicken products are particularly high (9 day kg^{-1}, Table 1). As autarky values for both chicken products for deterministic calculations and for the physical parameter probabilistic exercise are set to unity (eggs and chicken meat considered to be entirely from local production based on contaminated primary agricultural products), the consideration of autarky values smaller than one for chicken meat and eggs in the all parameter or the societal parameter probabilistic exercises, will pull dose factors to lower values.

The cumulative probability distribution represents an additional tool for illustration and quantification of relative uncertainties. For both ^{135}Cs (Fig. 6) and ^{79}Se (Fig. 8) we can differentiate zones with different gradients in the variation of probabilities. The larger the variation of probability is in the chosen zone, the larger is the impact of uncertainty on the result. A first zone with a small gradient is located in the low dose range (visible for ^{135}Cs in the range below 4 μSv/a per Bq/L, Fig. 6), the second zone is in the intermediate dose range and is characterised by an increase in gradient. Finally the curve in the high dose range zone has again a lower gradient. We can safely ignore the low dose zone. To quantify the relative impact of uncertainties, we choose a point in zone 2, for example the median (A) and a point in zone 3, the mean plus two standard deviations (B) for illustration; both with defined values of the biosphere dose conversion factor. With ε being a small variation of the dose conversion factor ($\varepsilon = 0.5$), we can define variations of probabilities (local rate of change in the cumulative curve) around A $[A-\varepsilon; A+\varepsilon]$ and B $[B-\varepsilon; B+\varepsilon]$ and compare them

Table 5
Variation of probabilities as a function of dose and of radionuclide (all values are in μSv/a per Bq/L).

RN	A	$[A-\varepsilon; A+\varepsilon]$ slope near A	B	$[B-\varepsilon; B+\varepsilon]$ slope near B	ε	$[A-\varepsilon;A+\varepsilon]/[B-\varepsilon;B+\varepsilon]$ ratio of slopes
^{135}Cs	11.1	0.041	33.2	0.0087	0.5	4.7
^{79}Se	3.8	0.154	20.4	0.0036	0.5	42.6

between individual sections of the graph and between different radionuclides (Table 5). The probability variation around A is more important than it is around B. For both radionuclides a small change in dose near the median value (A) has a much higher impact on the probability than a small change near the higher dose value (B). The ratio of A over B is more pronounced for ^{79}Se, (42.6), than it is for ^{135}Cs (4.7), thus giving us a method for quantifying the difference in uncertainties of one radionuclide versus another. The fact that the ratio A/B is larger for ^{79}Se tells us that the bulk of uncertainty is near A, an intermediate value and that the uncertainty near the higher dose value of B is 42.6 times smaller. For ^{135}Cs this ratio is 4.7, which is significantly lower, indicating that the uncertainty of the dose factor for higher values has a higher probability impact. The probabilistic analysis thus gives us a tool to test for which dose values uncertainties will be most influential. In the case of both radionuclides, we can show that for the same difference of uncertainty on the dose coefficient, the probability difference is highest for intermediate dose values in the vicinity of the median. As a consequence, it is necessary to have a good precision on the input parameters that result in these factors. On the other hand, large uncertainties on input parameters leading to high dose coefficients will not have the same impact on the variation of probability. This conclusion is of importance for performance assessment. As a matter of fact, the critical cases are those with high biosphere dose conversion coefficients. For these cases it would be necessary to move from the theoretical approach given in terms of variability to a better quantification of actual occurrences the latter requiring site and experimental work. For a relatively large uncertainty the consequences in terms of probability will only be slightly modified.

4.2. Sensitivity analysis

The various probabilistic analyses carried out for the purpose of uncertainty analyses can also be used to quantify the impact of the uncertainty of each parameter on the overall result. This can be done by quantifying the linear correlation between the input parameters and the dose coefficient (Saltelli et al., 1999). In the case of the overall uncertainty analysis in which 53 parameters were varied according to their individual uncertainty, and where 5000, 10 000 or 50 000 sets of input parameters were sampled and used for dose coefficient calculations, these 5 000, 10 000 or 50 000 input sets can be compared with the related number of dose results.

We determine first the Pearson correlation (often simply called correlation) to quantify the extent to which values of the input variables are "proportional" to the dose conversion factor. The proportionalities or the linear relationships indicate to what extent the two parameters are related. If the correlation is high, it can be "summarized" by a straight line and the parameter will have a significant impact on the dose coefficient. The complete results of the sensitivity analysis of ^{135}Cs are shown in Table 6 for a Monte Carlo analyses based on 5000, 10 000 and 50 000 individual samples. Only those input parameters with correlation coefficients significant at the 0.05 level of confidence are indicated. There is again no significant difference between the correlation coefficients based on 5000, 10 000 or 50 000 samples. This reconfirms our theoretical hypothesis and its evaluation using the statistical distribution of biosphere dose coefficients (Table 3). Correlation coefficients with values larger 0.1 are of particular interest. Parameters defining the autarky and consumption behaviour and those parameters quantifying the transfer from soil-to-plant, and farther up the food chain, the soil solid-to-solution distribution and the precipitation have an important impact on the dose coefficients. The slope of most correlations is positive; higher *Kd*, higher consumption, higher use of locally produced contaminated food and higher soil-to-plant and plant-to-agricultural product transfer factors all increase the dose to man. Only the amount of precipitation has an inverse relationship with the dose coefficient, because increased yearly averaged precipitation reduces the need for irrigation and thus the amount of contaminant input to the soil.

Table 6
Pearson r and Spearman correlation coefficients for relations between individual input parameters and the calculated biosphere dose conversion factor for ^{135}Cs.

Parameter Based on data	$N=5000$	$N=10\,000$	$N=50\,000$	$N=10\,000$
	Raw (Pearson)			Ranked (Spearman)
Autarky				
Ahcer – cereals	0.17	0.17	0.21	0.19
Aheau – water	0.04	0.04	0.03	0.06
Ahfeuil – leafy vegetables	0.03	0.03	0.05	0.07
Ahpdt – potatoes	0.14	0.14	0.14	0.17
Ahplait – milk products	0.04	0.04	0.03	0.02
Ahporc – pork	0.10	0.10	0.08	0.05
Human consumption				
Hcer – cereals	0.05	0.05	0.07	0.07
Hfeuil – leafy vegetables	0.06	0.06	0.06	0.06
Hfruit – fruit	0.08	0.08	0.06	0.04
Hpdt – potatoes	0.18	0.18	0.17	0.17
Hporc – pork	0.06	0.06	0.06	0.05
Hrac – root vetetables	0.05	0.05	0.05	0.03
Transfer parameters				
Ftplait – milk products	0.05	0.05	0.04	0.04
Ftporc – pork	0.14	0.14	0.11	0.08
Ftsolcer – cereals	0.40	0.40	0.39	0.46
Ftsolfeuil – leafy vegetables	0.09	0.09	0.10	0.11
Ftsolpdt – potatoes	0.27	0.27	0.28	0.30
Ftsolrac – root vegetables	0.06	0.06	0.09	0.07
Ftvolail – chicken	0.04	0.04	0.05	0.05
Others				
Kdsol-soil Kd	0.27	0.27	0.27	0.43
Pluie – precipitation	−0.30	−0.30	−0.32	−0.34

For the sake of completeness, we consider the impact of data ranking. In the case of the Pearson analysis raw data were used. We assumed relationships to be linear input–output distributions, allowing the use of linear regression techniques, thus not requiring nonlinear distributions, with which only rank transformation statistics can cope (Spearman approach) (Saltelli and Sobol, 1995). The clear advantage of the Pearson approach is the possibility to draw conclusions made on the results back to the model (inverse modelling), which is not straightforward when using the Spearman approach. But the latter approach solves the problem sometimes associated to the frequency distribution.

We have tested the impact of a ranked data set on correlations. Both input parameters as well as the results were ranked. The results are shown in Table 6 for ^{135}Cs and in Table 7 for ^{79}Se. For ^{135}Cs all correlations are within the same range, with the exception of the soil *Kd* for which the Spearman approach yields a higher correlation (0.43) compared with the Pearson approach (0.27). The lower correlation calculated for the raw *Kd* values is a consequence of the very large variability of this parameter (Table 1), which is smoothed out using ranked data.

Table 7
Pearson r and Spearman correlation coefficients for quantification of relations between individual input parameters and the calculated biosphere dose conversion factor for ^{79}Se.

Parameter Based on data	$N = 10\,000$ Raw	$N = 10\,000$ Ranked
Autarky		
Ahcer – cereals	0.06	0.11
Aheau – water	0.07	0.20
Ahfeuil – leafy vegetables	0.02	0.05
Ahlait – milk	0.04	0.06
Ahoeuf – eggs	0.04	0.03
Ahpdt – potatoes	0.04	0.04
Ahporc – pork	0.05	0.07
Ahvola – chicken	0.04	0.05
Human consumption		
Hcer – cereals	0.04	0.06
Heau – water	0.04	0.08
Hfruit – fruits	0.02	0.01
Hlait – milk	0.03	0.06
Hoeuf – eggs	0.05	0.06
Hpdt – potatoes	0.03	0.05
Hporc – pork	0.05	0.05
Hvola – chicken	0.05	0.08
Transfer parameters		
Ftlait – milk	0.11	0.17
Ftoeuf – eggs	0.16	0.15
Ftporc – porc	0.19	0.14
Ftsolcer – cereals	0.33	0.38
Ftsolpdt – potatoes	0.09	0.11
Ftvolail – chicken	0.24	0.20
Others		
Kdsol – soil *Kd*	0.46	0.56
Pluie – precipitation	−0.23	−0.33

The correlations of ^{79}Se dose coefficients with input parameters are again rather insensitive to data ranking (Table 7). Some differences can be found for the autarky level of drinking water or for the rate of precipitation.

Regression analyses give valuable information about those parameters that contribute the most to uncertainty and variation in the biosphere dose conversion factor. They thus help to understand the model and its parameterisation and possible needs in terms of data acquisition or related research.

We do not wish to discuss each individual correlation; for some examples interpretation is straightforward. Both the rate of precipitation, which directly influences the irrigation need or the soil *Kd*, which constrains accumulation in the soil, show significant correlations for both radionuclides. For ^{135}Cs the particular importance of parameters relating to potatoes could have been anticipated, as potatoes represent 58% of the total ingestion pathways (Fig. 2). This importance of potatoes is a combined consequence of the high potato consumption (Table 2), and the soil-to-potato transfer factor, which is higher than that for most other agricultural plants (Table 1). For ^{79}Se, no individual agricultural product really dominates the ingestion dose, which is why transfer parameters of several products such as milk, eggs, pork, cereals or chicken turn out important in the sensitivity analysis. Eggs and chicken meat may strongly accumulate ^{79}Se (Table 1), but their yearly consumption is relatively low (Table 2).

It could be argued that some of the insights obtained from the application of probabilistic analysis in biosphere transfer modelling could just as well be gained through a careful study of the input parameters and the equations. This is definitely so in a backward interpretation when the results are known and the search for the cause can be initiated systematically. But without a systematic procedure, such as the one used for probabilistic analysis, there is no guarantee to obtain a complete understanding of the system and its related uncertainties.

5. Summary and conclusions

This publication recalls some of the advantages of the application of a probabilistic approach in the calculation of doses as a consequence of radionuclide release to the biosphere from a nuclear waste disposal site. Compared with a purely deterministic approach, with the advantage of single parameter values and a single result, more easily kept in mind and specified in procedures and requirements, the probabilistic calculation furnishes a large amount of results based on a continuum of input values. This allows studying in much greater detail the impact of input parameter variability on the final result. The probabilistic approach is complementary to the more practical deterministic approach. The probabilistic approach demands a larger involvement of the modeller with the parameterisation and mathematical coding of the system under investigation, a procedure that we have elucidated in some detail in the text. A first screening of equations and parameters permits simplifying the system by reducing the number of parameters. Those parameters, for example, that merely control the dynamic state of a system are not critical to dose assessment evaluation, as the latter is considered conservatively at equilibrium. The definition of probability density functions requires a thorough review of existing databases for parameter values and of available mathematical and statistical tools (i.e. Beauzamy, 2004). Some of the theoretical considerations have been used to specify the number of samples on the basis of a probability or to define statistical uncertainty distributions of combined parameters based on individual uncertainties.

The search for simplified relationships between varying input values and the range of output values, (i.e. linear or more complex) forms the basis of sensitivity analyses that bring about a more concise understanding of the mathematical behaviour of the system and its ability of representation of the "real", physical system. Having as a result a continuous representation in the form of a probability density function clearly gives the reader an impression of the overall uncertainty, but it requires a basic understanding of what probability means. Of course biosphere dose conversion factors larger than the mean or the 95th percentile are possible but their probability of occurrence decreases the higher the choice of cut-off percentile. The strength of the probability density function also lies in the quantification of variations of probability via computation of the slope of the curve. The higher the slope, the higher the variation of probability; thus the higher is the impact of uncertainty on the dose coefficient. Focus needs to be given on the high dose part of the curve (i.e. 95th percentile) relative to an intermediate dose part (i.e. median). The ratio between the slopes at the lower and the higher dose sections is significantly higher for ^{79}Se (42.6) than for ^{135}Cs (4.7) illustrating the lower relative impact of uncertainty on higher compared to lower dose values for ^{79}Se in comparison with ^{135}Cs.

After recalling these advantages of a complementary probabilistic approach and its application to the determination of the biosphere dose conversion coefficient for a high-level waste disposal facility in a claystone geological formation in the East of France, studied by Andra, we have pondered on the combined evaluation of both physical and societal parameters in an assessment calculation. The former describes the (bio)physical transfer of radionuclides from contaminated well water, via soil irrigation, plant- and agricultural product contamination to intake by humans, the latter deals essentially with human behaviour such as eating habits, not easily predicable for the far future. The uncertainty related to social parameters is independent of the

radionuclide contrary to the uncertainty in physical parameters, such as the soil Kd, which is strongly dependant on the radionuclide and the level of information available. For ^{135}Cs we have available a very large database compared with that for ^{79}Se, where for certain transfer parameters an analogy with sulphur was required. This increases parameter value uncertainties for ^{79}Se. This increased uncertainty regarding the physical transfer parameters for ^{79}Se is balanced by the extreme variability (uncertainty) of the soil *Kd* for ^{135}Cs. For ^{135}Cs and for ^{79}Se, physical parameter uncertainties influence the biosphere dose conversion factor more strongly than societal uncertainties. In case of ^{135}Cs the consideration of societal parameter uncertainty increases the probability of higher dose rates, whereas for ^{75}Se the probability curve is shifted in the low dose portion to lower values. Both are entirely dependent on the definition of autarky values for the deterministic calculations, which, in the French case vary strongly from one food item (cereal = 0) to another (chicken products = 1). The differing impact is a consequence of the fact that cereals impact significantly the dose factor for ^{135}Cs and chicken products for ^{79}Se. With time, when more site-specific experimental data on selenium and caesium become available, the relative impact of uncertainty of societal parameters will rise, as it is unlikely that better predictions of human behaviour for the far future will become available. This difference in uncertainty analysis of ^{79}Se versus ^{135}Cs can also be seen in the sensitivity analysis. For ^{135}Cs more parameters describing food consumption and food origin have above-significant correlations with the biosphere dose conversion factor than for ^{79}Se.

To be able to quantify uncertainty within the deterministic approach, a variety of critical groups with more penalising food consumption, assumptions on food autarky or time budgets have been applied (Klos and Albrecht, 2005). Here again the probabilistic approach is complementary; it can be used to test if the uncertainties based on the choice of different critical groups are broadly comparable with a full probabilistic analysis or such an analysis can be used to define and parameterise the critical groups.

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