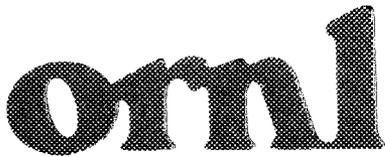




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# Review of Studies Related to Uncertainty in Risk Analysis

William R. Rish  
Ronald J. Marnicio

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Health and Safety Research Division

REVIEW OF STUDIES RELATED TO UNCERTAINTY  
IN RISK ANALYSIS

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## REVIEW OF STUDIES RELATED TO UNCERTAINTY IN RISK ANALYSIS\*

### ABSTRACT

The Environmental Protection Agency's Office of Radiation Programs (ORP) is responsible for regulating on a national level the risks associated with technological sources of ionizing radiation in the environment. A critical activity of the ORP is analyzing and evaluating risk. The ORP believes that the analysis of uncertainty should be an integral part of any risk assessment; therefore, the ORP has initiated a project to develop a framework for the treatment of uncertainty in risk analysis. Summaries of recent studies done in five areas of study are presented.

### 1. INTRODUCTION

The Environmental Protection Agency's Office of Radiation Programs is responsible for regulating on a national level the risks associated with technological sources of ionizing radiation in the environment. A critical activity at the ORP as part of developing regulatory policy is analyzing and evaluating risk. Those involved in the analysis of risk are often confronted with a formidable obstacle to producing reliable risk estimates -- uncertainties about the data, parameters, phenomena, models and methods involved.

The ORP believes that the analysis of uncertainty should be an integral part of any risk assessment. Accordingly, the ORP has initiated a project to develop a framework for the treatment of uncertainty in risk analysis. In order to begin the project, this review of the thoughts and work done by others on the problem of uncertainty in risk analysis was prepared. The following areas of study are included in this review:

1. philosophical discussions of uncertainty and its relationship to risk,
2. frameworks for the treatment of uncertainty in risk analysis,
3. methodologies for uncertainty analysis,
4. software available to facilitate uncertainty analysis, and
5. applications of uncertainty analysis methodologies.

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Summaries of recent studies done in each of these five areas are presented. Before proceeding to the next section, the author suggests that the reader examine the table of contents to this report. There is a logic represented by the organization of this report, as it proceeds from definitions and philosophy to structure (frameworks) to methods to applications to evaluations of usefulness (risk management considerations), that is useful to keep in mind when thinking about the problem of dealing with uncertainty in risk analysis.

An alternative logic, to be pursued later in the project, is to examine studies identifying the nature of uncertainties associated with each of the various processes that result in a potential hazard. Figure 1-1 is a conceptual framework for this logic, depicting the linkages from technological activity to transport, transformation and loss processes to exposure processes to dosimetry processes to effects processes. Each of these processes must be modeled as part of a risk analysis, and each has its associated inherent uncertainties. The sources and nature of these uncertainties in radiological risk analyses will be characterized later in the project, and the insights gained from the present review will be used to develop recommended treatments of these uncertainties.

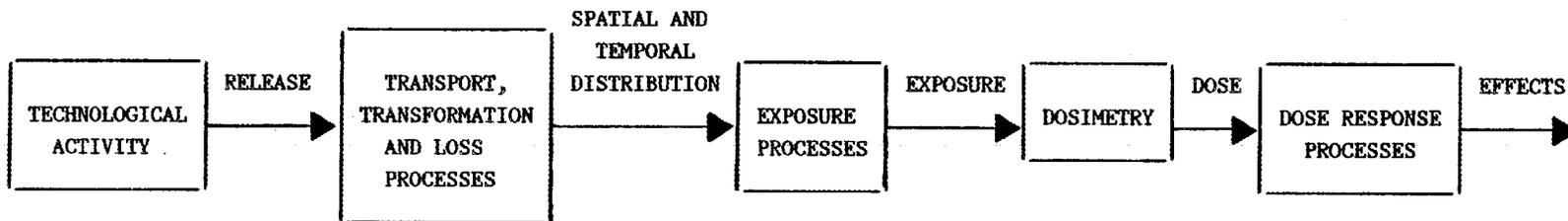


FIGURE 1-1: Framework Depicting Risk Processes and Their Linkages.

## 2. RISK AND UNCERTAINTY CONCEPTS

Very few papers have been devoted to discussing the fundamental concepts of risk, uncertainty, and their relationship to each other; however, a number of the papers included in this review contain some discussion of these concepts, usually as they relate to the particular topic or application involved. As a result, there is a great deal of inconsistency reflected in the literature regarding the concepts and terminology associated with risk and uncertainty. The ORP must establish internal consistency on these concepts as a starting point for developing an approach to uncertainty in risk analysis, especially since the choice of a particular interpretation can affect the analytical approach to be used. Accordingly, a glossary is being developed as part of this project, taking into consideration among other things the concepts reviewed in this section. The dictionary provides an introduction to the key concepts associated with risk and uncertainty. *Webster's Ninth New Collegiate Dictionary* [Merriam-Webster, 1985] defines risk in several ways as follows:

- possibility of loss or injury,
- the chance of loss,
- the degree of probability of loss, or
- a dangerous element or factor, where dangerous is defined as able or likely to inflict injury.

Two major concepts associated with risk are introduced by these definitions:

1. Risk involves a negative consequence (loss, injury).
2. Risk involves the potential for a negative consequence but not a certainty of it (possibility, chance, probability, able, likely). This implies that the existence of uncertainty is a requisite aspect of risk.

The *Random House Dictionary* [Random House, 1980] presents the following definition of risk: exposure to the chance of injury or loss.

This introduces a third concept: someone or something must be exposed to a potential for a negative consequence for risk to exist. Conversely, if someone or something is not exposed to the potential for a negative consequence then risk does not exist.

All of the papers included in this review incorporate these three risk concepts. The inconsistencies and controversies that appear in the literature are associated with attempts to develop measures for these concepts, especially a measure for the "potential." The problem seems to have evolved out of the need to perform quantitative analyses of risk and the subsequent need to establish a measurable definition of risk. For example, one of the first comprehensive risk analysis efforts in recent history, the *Reactor Safety Study* [NRC, 1975], includes a chapter on "The Meaning of Risk" (Chapter 2). The study points out that since "risk is a commonly used word that can convey a variety of meanings to different people," the investigators found it necessary to establish a "technical definition of risk," expressed as the following equations:

$$\text{Risk} \frac{(\text{Consequence})}{\text{unit time}} = \text{Frequency} \frac{(\text{Events})}{\text{unit time}} \times \text{Magnitude} \frac{(\text{Consequence})}{\text{event}}$$

Thus, in order to have a quantifiable measure of risk for this study the concept of potential for a negative consequence is defined as the statistical occurrence frequency of events that would result in a negative consequence should they occur. The terms frequency and probability are used interchangeably in the report. Uncertainty is not discussed in the chapter on the meaning of risk. Uncertainties about event frequencies are characterized by probability distributions (all assumed to be log-normal) that are propagated through calculations of system failure frequencies. The final results of the study take the form of "risk curves" plotting frequency of exceedance versus consequence level. One major criticism leveled against the study by the "Lewis Committee" [Lewis et al., 1978] is that it does not adequately represent risk since it does not present a family of risk curves representing uncertainty or confidence levels about the results. In fact, the *Reactor Safety Study* recommends on its risk

curves that "uncertainties can be accommodated by allowing variations in the average curve of factors of 1/3 and 6 in probability and 1/3 and 3 in consequence."

Later attempts to quantify the risks associated with nuclear power gave more rigorous treatment to the uncertainties involved.

Kaplan and his colleagues have provided several excellent treatises on the concepts behind the probabilistic risk analyses performed on the Indian Point and Zion nuclear plants, including detailed discussions on the relationship between uncertainty and risk [Consolidated Edison, 1982], [Commonwealth Edison, 1981], [Kaplan and Garrick, 1981], and [Kaplan et al., 1981].

They represent risk by the symbolic equation:

$$\text{Risk} = \text{Uncertainty} \times \text{Damage}$$

and observe that "there is no risk without uncertainty." The definitions of and distinctions between risk and hazard, probability and frequency, and probability and statistics are established and discussed in these studies. Risk is defined in two levels. The first level definition is as a set of triplets including a scenario description, the frequency of that scenario and the consequence measure of that scenario. Mathematical calculations of risk involve probabilities, consequences and models of the processes involved in the scenario. The position is taken that risk is properly represented as a family of risk curves plotting probability against consequence. That there is a family of curves is related to the second level definition of risk, which replaces single valued estimates of the frequencies of scenarios with probability density functions that represent uncertainty about the frequencies. This results in the concept of a family of risk curves, each having a different level of confidence corresponding to the confidence in the frequency estimates used.

A good discussion of the differences between the "frequentist" and "subjectivist" schools of thought on the meaning of probability is presented, and it is concluded that "probability is a numerical scale introduced to quantify states of confidence, states of knowledge, or degrees of belief." The concept and mathematics of Bayes' Theorem are introduced and adopted as the proper way to treat probability and uncertainty in risk analysis. In 1982, the NRC commissioned a team of top experts in probabilistic risk assessment (PRA) under the auspices of the

American Nuclear Society and the IEEE to prepare their *PRA Procedures Guide* [NRC, 1983]. Chapter 12 of this guide is devoted to uncertainty and sensitivity analysis and explains how the concept of uncertainty is viewed in nuclear power plant PRA. The guide states that "historically, in the context of PRAs, the term uncertainty has been used to describe two different concepts:

1. random variability in some parameter or measurable quantity; and
2. an imprecision in the analyst's knowledge about models, their parameters, or their predictions.

Making a distinction between these two concepts is important to decision-making because it indicates where, on the one hand, an increased effort in data gathering can improve the quality of decision-making by reducing uncertainty (concept 2) and, on the other hand, where it would be ineffective (concept 1). Furthermore, ... whether one is concerned with random variability or uncertainty affects the way in which the propagation of the relevant measures is performed."

The second concept above is adopted as the definition of uncertainty in the guide; however, it is pointed out that current PRA practice generally does not distinguish between the two concepts because of the complexity of the calculations involved. Three types of uncertainty in risk assessment are described: uncertainties in parameter values, uncertainties in modeling, and uncertainties in the degree of completeness. The distinction between the frequentist and subjectivist interpretation of probability is discussed, with neither being selected as a preferred interpretation for PRA purposes. A very important point made is that "the choice of a particular interpretation of probability and the associated theory of statistics affects the choice of analytical tools that will be used by the analyst." It is noted that "the subjectivist, with his interpretation of probability as a degree of belief, will in general find it easier to express the uncertainties quantitatively but since his assignment of probabilities is subjective, he may have difficulty in convincing others to accept his assignment."

In 1978, Morgan and his colleagues [Morgan et al., 1978a], building on a concept introduced by North and Merkhofer at a 1975 U.S. Senate hearing on air quality and emission controls [North and Merkhofer, 1976], observed that published population risk estimates for coal-fired power plants showed large diversity in magnitude and asserted that quantitative treatment of uncertainty is necessary to adequately characterize risk. Morgan, et al. have expressed for a number of years a strongly held belief that one of the characteristics of "good" policy and risk analysis is the adequate characterization and treatment of uncertainty [Morgan, 1978], [Morgan et al., 1982]. They observe that most risk-related policy studies do not deal explicitly with uncertainty,\* but rather involve single-valued deterministic calculations that rely on the professional judgment of experts. Morgan and Henrion are in the process of preparing a book on uncertainty in risk analysis. A preliminary rough draft of a section from the book is available, and contains discussions of ways to represent uncertainty, sources of uncertainty, types of models and ways to propagate uncertainty through a model [Henrion and Morgan, 1984]. The authors use the term "uncertainty" as "encompassing any kind of lack of information, vagueness, imprecision, about the true or appropriate functional form of a relationship." They express the point of view that "uncertainty is not inherent in a quantity, but in the eye of a beholder of the quantity."

Morgan has raised an important issue concerning the concept of uncertainty and risk analysis that has been the root of the problem of finding an appropriate manner to quantify uncertainty in risk analyses. As we have seen, early attempts at quantitative risk analysis were viewed as a scientific assessment; however, other than in hypothesis testing, the objective of science is the pursuit of truth and "good science does not engage in speculations. It waits for full understanding" [Morgan, 1978]. He believes that regulatory risk analysis is more properly considered part of the field of policy analysis than science. Unlike science, he observes, good policy analysis "recognizes that physical truth may be poorly or incompletely known. Its objective is to evaluate, order, and structure incomplete knowledge so as to allow decisions to be made with as

---

\* Exceptions noted are [NRC, 1975], [Howard et al., 1972], [North and Merkhofer, 1976], and [Rotty, 1977].

complete an understanding as possible of the current state of knowledge, its limitations, and its implications" [Morgan, 1978].

The EPA Office of Air Quality Planning and Standards (OAQPS) has adopted this viewpoint toward risk analysis and uncertainty. For example, Richmond expresses the following perspective [Richmond, 1981]:

"Those who view risk assessment as a scientific enterprise generally proceed on the premise that there is some "true risk" which one is trying to measure or estimate. Under this view risk is defined as the number of individuals actually affected in a specified time period divided by the population. Risk assessment, under this approach, is generally limited to extrapolative techniques using data from studies considered scientifically valid; conflicting evidence and/or preliminary results are generally ignored. Those pursuing the "scientific" approach to risk assessment emphasize the use of "objective" and reproducible statistical techniques. Probabilities are derived using the relative frequency interpretation of probability and uncertainty about the risk estimates is often dealt with by sensitivity analysis or by lower and upper bound risk estimates.

It is argued here that a more rational approach to regulatory risk assessment for environmental health and safety problems requires a different view of "risk" and a broader interpretation of probability than the relative frequency interpretation mentioned above. For purposes of regulatory risk assessment, *risk should be defined as the probability of a particular adverse event occurring in a given period of time based on the state of information at the time of decision making. To assess risk, one must therefore be concerned about major uncertainties which give rise to that risk.*

*... Risk from a regulatory decision making perspective, therefore, largely arises because of lack of knowledge at the time decisions are to be made. Since it is unlikely that we will ever know with certainty the precise location of health effect thresholds or the shape of dose-effect relationships for particularly susceptible populations, nor be able to predict meteorological variation with certainty, risk will always exist in this sense."*

This perspective is described in extensive detail in an OAQPS document on a *General Method for Assessing Health Risks Associated with Primary National Ambient Air Quality Standards*, along with a proposed approach to incorporating uncertainty into quantitative risk analyses that is consistent with the concepts presented [Feagans and Biller, 1981]. These concepts and approaches are currently being employed in the

development of air quality standards for ambient ozone and lead, efforts which are included in this review in the methodologies section [Whitfield and Wallsten, 1984 and Richmond and McCurdy, 1985].

In 1984, the EPA drafted an agency report on risk assessment and risk management [EPA, 1984a]. In this report the EPA states that "although health risk assessments are conducted by scientists, they are not, strictly speaking, science. Rather, they involve an analysis of scientific evidence to reach conclusions that are useful for regulatory purposes. Risk assessments are not pure science because their results -- for a variety of practical and ethical reasons -- are usually not empirically testable. The process involves judgment: no one should be misled into believing that results using present techniques have the status of scientific findings."

The report identifies the task of risk assessment as making "the most useful possible statements about" the relationship between certain diseases and certain substances, "reducing uncertainty as much as possible, and making explicit whatever uncertainty remains." This implies that the analyst must make decisions about whether to take steps to reduce uncertainties or to quantify them in the risk assessment.

In 1983 the National Research Council in its report on *Risk Assessment in the Federal Government: Managing the Process* [National Research Council, 1983] addressed the problem of terminology. The report indicates that no standard definitions of the concepts associated with risk assessment have been established, and the same concepts are encountered under different names. The study identifies its own set of terminology.

The 1984 annual meeting of the Society for Risk Analysis (SRA) was devoted to uncertainty in risk assessment, risk management, and decision making [SRA, 1984]. Several papers were presented at the meeting on risk and uncertainty concepts. Smith, et al. presented a *Taxonomy of Uncertainty* [Smith et al., 1984] that proposed a classification of types of uncertainty. According to the abstract for the paper:

Consideration of simple games of chance results in the identification of two major classes of uncertainty. The rest of these, which we call random uncertainty, is the uncertainty resulting from the underlying randomness of an event. Random uncertainty is uncertainty that cannot be further

reduced by additional sampling or analysis. The second class of uncertainty, which we call knowledge uncertainty, is the uncertainty resulting from incomplete information about a process. Knowledge uncertainty can generally be reduced by sampling or analysis, but normally this reduction entails some cost. A key issue in the area of uncertainty assessment, though it is rarely considered, is whether or not a given reduction in knowledge uncertainty (e.g., the "resolution of uncertainty") is worth the cost expended. Another important issue is the impact of uncertainty on various modes of decision making.

This paper presents the above classification of uncertainties, suggests further subdivisions based on resolvability, and applies the insights to several areas of uncertainty assessment including decision making in radioactive waste management, occupational health and safety, and power plant safety.

Lindley presented a paper claiming *The Only Measurement of Uncertainty is Probability* [Lindley, 1984]. According to Lindley:

A situation requiring action is risky if some features are uncertain. To study risk we therefore have to appreciate uncertainty. There is only one way to do this: by means of probability. This choice of measurement is not capricious: it can be proved that the only way judgments of uncertainty can be combined is by the rules of the probability calculus, the rules of coherence. The interpretation of probability is a statement of belief by the decision maker. The concept of utility as a measure of the worth of consequences follows immediately, as does the choice of act by maximizing expected utility.

Alternative methods are not allowable just because probability and utility are not understood. Risk analysts must educate their clients to think coherently. This will meet with considerable resistance because open statements of probability and utility expose the contradictions and true motivations that decision makers would often prefer to hide. Probability is an important tool in achieving government of the people, by the people, and for the people."

Apostolakis discussed *Uncertainties in Uncertainty Analysis* [Apostolakis, 1984]. In his paper he stated:

A problem that has plagued risk assessments for nuclear power plants is the inability of analysts to agree on a consistent approach to uncertainty. This may be explained by the reluctance of some assessors to bring into risk analysis the controversy between frequentist and Bayesian

statisticians, which, it is sometimes felt, has to do with philosophy and is irrelevant to real-world problems. As a result, one sees inconsistencies, misapplications of the theory, and confusion, which prove that the disagreement is of more than academic interest.

This paper addresses several statements found in risk assessments that reveal either misunderstandings or that, if followed, could lead to erroneous conclusions.

We believe that the Bayesian approach to uncertainty provides logically satisfying conclusions and removes much confusion and debate because uncertainties are not fundamentally different. A fundamental axiom of the Bayesian approach is that there is only one kind of uncertainty and that any two uncertain events are comparable. Uncertainties stemming from phenomenological considerations as well as from modeling concerns are quantifiable. We usually have to rely on expert opinion to quantify such modeling uncertainties, but there is nothing that would prevent such an effort from a theoretical standpoint. Because uncertainties are large does not mean they are unquantifiable. We argue that often data contain information that is ignored by "simple" methods, and this information may be important. Examples in which "point estimate" calculations have resulted in gross underestimates are given.

Finally, Gratt presented a proposal for consistent definitions of risk analysis, risk assessment and related terms [Gratt, 1984]. His paper forms the foundation for the development of an official glossary of the Society for Risk Analysis, an effort that is currently in progress. The paper is derived from an effort by a team of risk experts to develop a risk analysis/assessment glossary [Gratt et al., 1984]. In the glossary, the following definitions are proposed:

**Probability.** A probability assignment is a numerical encoding of a state of knowledge.

**Probability Error.** The magnitude of error which is estimated to have been made in determination of results.

**Risk.** The potential for realization of unwanted, adverse consequences to human life, health, property, or the environment; estimation of risk is usually based on the expected value of the conditional probability of the event occurring times the consequence of the event given that it has occurred.

**Risk Analysis.** A detailed examination performed to understand the nature of unwanted, negative consequences to human life, health, property, or the environment; and analytical process to provide information regarding undesirable events; the process of quantification of the probabilities and expected consequences for identified risks.

**Risk Assessment.** The process, including risk analysis, risk evaluation, and risk management alternatives, of establishing information regarding that risk and levels of risk for an individual, group, society, or the environment.

**Risk Estimation.** The scientific determination of the characteristics of risks, usually in as quantitative a way as possible. These include the magnitude, spatial scale, duration and intensity of adverse consequences and their associated probabilities as well as a description of the cause and effect links.

**Risk Evaluation.** A component of risk assessment in which judgments are made about the significance and acceptability of risk.

**Risk Identification.** Recognizing that a hazard exists and trying to define its characteristics. Often risks exist and are even measured for some time before their adverse consequences are recognized. In other cases, risk identification is a deliberate procedure to review, and it is hoped, anticipate possible hazards.

**Uncertainty Analysis.** A detailed examination of the systematic and random errors of a measurement or estimate; an analytical process to provide information regarding the uncertainty.

Note that probability is presented as a measure of state of knowledge, thus incorporating uncertainty into its definition. This is consistent with the concepts stated by Lindley and summarized previously.

Albert Klee of the EPA Hazardous Waste Engineering Research Laboratory has created a computer-based system for analyzing uncertainty in modeling, called MOUSE (Modular Oriented Uncertainty System Emulator) [Klee, 1985]. Chapter One of the MOUSE manual discusses the concept of uncertainty in modeling. Uncertainty is not thought to be merely a statistical concept of variance, but rather as the entire probability distribution of a measure including the shape of the distribution. This distribution, it is pointed out, can be partly or entirely subjective. It is

further noted that certainty is not identical to accuracy ("One can be very certain about something but still be dead wrong!"). Klee states that "it is reasonable to assume that the more our estimate is based on subjective information, the greater is the chance that it will be inaccurate," and that "it is the quantity of good data that affects uncertainty." The consequences of the failure to deal with uncertainty are discussed, and problems with "traditional approaches" to uncertainty in modeling are explained.

In an internal corporate report, Rish describes *A Program for Technological Risk Management* [Rish, 1984]. The report notes that the traditional approach to risk analysis has been to use "accepted" models employing assumptions and parameters which are "conservative" or "best-estimates." As a result, different studies of the same problem can report widely different results and conclusions depending on the models, assumptions and parameters selected. The decision-maker who must use the results knows that judgments concerning uncertainties have been made in performing the risk analysis, but has no measure of the level of confidence which can be placed in the results.

A risk analysis approach is proposed that places a high level of emphasis on understanding and characterizing the uncertainties which are inherent to technological risk management problems. The claim is made that characterizing and analyzing what is *not* understood about a technological system and its associated risk processes is equally as important as modeling what is understood. Risk is viewed as probability and consequence, and uncertainty is considered to be an important source of risk, measurable in terms of probability. An observation made is that a risk analyst makes decisions about how to handle uncertainties throughout the analytical process, and an important objective should be to make these decisions and their rationale explicit.

North [1983] expresses the view that in order for an analysis to be useful for risk management it must deal with uncertainty, and he suggests that using probability to communicate judgment about uncertainty is an effective approach. He sees decision analysis as providing a formal theory for choosing among alternatives whose consequences are uncertain, and advocates the use of judgmental probability as an effective way to quantify uncertainty.

An important concept to the study and assessment of radiation as a cause of cancer is the "probability of causation." The recent *Report of the National Institutes of Health Ad Hoc Working Group to Develop Radioepidemiological Tables* [NIH, 1985] includes a chapter on the probability of causation (PC). The probability of causation is defined by the relationship:

$$PC(C, D;X) = Ex(C, D;X)/P(C, D;X)$$

where  $PC(C, D;X)$  is the probability of causation of event C by possible cause D conditional on characteristic X. For example, suppose event C is the occurrence of lung cancer and D is exposure of the lung to 20 rads of gamma radiation, while X represents the individual characteristic of being a cigarette smoker.  $PC(C, D;X)$  is then the probability of causation of lung cancer from 20 rad among smokers, and can be generally interpreted as the proportion of total risk of C to an individual resulting from possible cause D where the individual is in a class having characteristic X. The probability of causation that is calculated for an individual in that class will be more or less correct as his personal characteristics match or vary from the average in the class. Nevertheless, the procedure assigns the same PC to all members of the class. Also note that this is a "retrospective" concept in that it answers "supposing event C has occurred, what is the probability that D was the cause?." Incidence rates are used as the measures of probability, and uncertainties are expressed as an approximation to a 95% confidence interval for the PCs based on judgments about geometric standard deviations for key factors in the PR calculations.

### 3. FRAMEWORKS

The first phase of a risk analysis is the structure of the many complex interactions of factors involved. These factors include the nature of and linkages between risk-related processes and events, the nature and sources of important uncertainties, the variables that can be used to control risks, and the places in the analysis where inputs from models, measurements, and various scientific disciplines will be required. The concept of a risk assessment "framework" has been introduced as a means to structure these factors in a risk analysis. These frameworks can be quite useful for organizing and planning an approach to handling uncertainties in a risk analysis. Accordingly, several examples of these "structuring-types" frameworks are reviewed below.

Morgan presents a schematic diagram for conceptualizing environmental risk assessment as the modeling of a series of processes, as shown in Figure 3-1 [Morgan, 1977]. In his framework, some human activity creates an environmental loading or emission; the emission is propagated, dispersed and transformed in the environment; objects and lifeforms in the environment are exposed; these exposures lead to effects that are valued by society as damages or benefits. Morgan notes that each of the processes in the boxes in Figure 3-1 must be evaluated in an environmental risk assessment; however, scientists often do not understand the physics, chemistry, and biology involved in each process. This framework can be used to obtain a structured concept of where uncertainties enter into the assessment process and how they can propagate through the assessment.

More recently, Henrion and Morgan have used the concept of risk assessment as policy analysis (see Section 2) to develop a more generic framework for structuring uncertainty treatment in policy modeling based on type of model, type of uncertain quantity in the model, and source of uncertainty [Henrion and Morgan, 1984]. The type of model is classified by the following critical dimensions:

- predictive or optimizing,
- analytic or implicit,
- static or dynamic,
- spatial disaggregation,

- deterministic or stochastic, and
- size.

Sources of uncertainty are organized by determining from where they arise, including:

- the use of direct empirical data,
- the use of indirect empirical data and inferences,
- inherent randomness,
- imprecise parameter definitions,
- disagreement,
- model form, and
- approximations made in model implementation.

The types of uncertain quantities in models, and the recommended treatment of uncertainty for these types, are summarized in Figure 3-2, reproduced from the reference [Henrion and Morgan, 1984].

Building on the early Morgan conceptual framework shown in Figure 3-1, Rish has developed a generic framework for structuring risk assessment and risk management with accompanying "risk analysis flow diagrams" [Rish, 1982 and Rish, 1984]. The generic framework is shown in Figure 3-3, and it is described as follows:

Some technological activity, such as generating electricity or disposing of chemical by-products, results in a release of mass and energy to the environment. Examples of releases might be hot water to a river, sulfur dioxide to air or leachate migration from solid waste buried in landfills. Release of these substances are subject to transport transformation and loss processes which, in return, produce spatial and temporal distributions. Animate and inanimate objects receive various levels of exposure to the substances through environmental exposure pathways and processes. The exposures of doses could result in physical, chemical and biological effects, such as materials damage, morbidity/mortality or ecosystem disruptions. If the effects from the technological activity can be assessed, then they are valued as costs or benefits depending on human valuation processes. Then, the costs and benefits resulting from applying alternative strategies to control the risks associated with the activity are compared. Preferences and values are used to make the tradeoffs required for risk management decisions about proper control strategies to adopt.

Potentially important parameter uncertainties in a risk analysis are identified and structured by developing more detailed "risk analysis flow diagrams" based on the generic framework. Examples are shown in Figures 3-4 through 3-6. These diagrams are limited in that they do not address the "critical dimensions," "sources of uncertain," and "types of models" discussed by Henrion and Morgan [Henrion and Morgan, 1984], but these factors can be considered relative to such a framework.

In addition to the structuring-type frameworks discussed above, many of the frameworks presented in the literature are procedural in nature, that is, they present a procedure for risk assessment and uncertainty treatment.

The EPA proposes that there are four steps to a risk assessment [EPA, 1984a]:

1. hazard evaluation,
2. dose-response evaluation,
3. exposure evaluation, and
4. risk characterization.

The following types of uncertainty are stated to occur at each of the above steps:

1. weight of evidence problems in hazard evaluation;
2. threshold and extrapolation uncertainties in dose-response evaluation;
3. data and modeling uncertainties, lack of data on dosimetry and assumptions about human behavioral aspects in exposure evaluation; and
4. the contributions and combined uncertainties from the first three steps in performing risk characterization.

A similar procedural framework is proposed by the National Science Foundation [NSF, 1985a]. The NSF describes risk assessment as a five step process including:

1. Risk Identification: Designation of the nature of the risk, including source, mechanism of action (if known), and potential adverse consequences.

2. Risk-Source Characterization: Description of the characteristics of the risk source that have a potential for creating risk (e.g., types, amounts, timing, and probabilities of release of toxic substances and energies).
3. Exposure Assessment: Measurement or estimation of the intensity, frequency, and duration of human or environmental exposures to the risk agents that are produced by a source of risk.
4. Dose-Response Assessment: Characterization of the relationship between the dose of the risk agent received and the health and other consequences to exposed populations or to the environment.
5. Risk Estimation: The process of integrating a risk-source characterization with an exposure assessment and a dose-response assessment to produce overall summary measures of the level of the health, safety, or environmental risk being assessed.

A summary of the methods associated with steps 2 through 5 above are presented and are reproduced in Fig. 3-7. In addition, a framework to conceptualize the propagation of uncertainties through each step of the risk assessment is presented, and is reproduced in Fig. 3-8.

The EPA's *Proposed Guidelines for Exposure Assessment* [EPA, 1984b] present a "Decision Path for Exposure Assessment", which is reproduced in Fig. 3-9. This procedural framework for exposure assessment places an emphasis on the characterization of uncertainty, and includes a table summarizing methods for characterizing this uncertainty depending on the type and extent of data available, reproduced in Fig. 3-10. This table is based on a study done for the EPA on characterizing uncertainty in exposure assessment [Whitmore, 1984].

Several procedural frameworks for quantitative health risk assessment have been developed for the EPA Office of Air Quality Planning and Standards, with emphasis on uncertainty treatment.

Merkhofer [Merkhofer, 1981] conceptualizes risk assessment according to the classic Decision Analysis Cycle [Howard, 1968] as shown in Fig. 3-11. Critical uncertainties in the risk assessment process, including uncertainties about functional relationships in models, are handled by probability encoding techniques. These topics are discussed in detail by Merkhofer.

Winkler and Sarin [Winkler and Sarin, 1981] present the risk assessment procedure in six steps as follows:

1. establishment of the objective of the risk assessment task,
2. definition of input and output variables,
3. determination of an appropriate level of decomposition,
4. probability assessments,
5. determination of a probability distribution for the output variables,  
and
6. data analysis.

The treatment of uncertainties is integral to this procedural framework, and a detailed discussion of uncertainties and their treatment is provided.

The EPA OAQPS synthesized the advice of these and other risk analysis experts into a proposed *General Method for Assessing the Health Risks Associated with Primary National Ambient Air Quality Standards* [Feagans and Biller, 1981]. A framework that is both "structuring-type" and "procedural" is presented for the NAAQS risk assessment and standard-setting processes. A diagram depicting the risk assessment process is reproduced in Fig. 3-12. The process involves two types of risk models, "benchmark models" and "head count models," the difference being in assumptions made about exposure characteristics of the population. The approach to assessing "benchmark risk" involves taking into account uncertainty in the dose-response relationship and uncertainty in peak air pollutant concentrations. The approach to assessing "head count risk" involves accounting for uncertainty about the activities of the sensitive population and a more thorough accounting for the effect of location on the uncertainties in pollutant concentrations and more complete description of uncertainties in the dose-response relationship than in the "benchmark" assessment. A detailed description of the concepts, method and mathematics behind the OAQPS framework is provided in the report.

Rod presents a procedural framework for validation and uncertainty analysis of large models used in policy-making and regulation [Rod, 1984]. The procedure is outlined as follows:

## VALIDATION

1. Identify sources of uncertainty and error.
2. Identify key descriptive output parameters.
3. List inputs ("hard-wired" as well as operator-input initial conditions and boundary conditions).
4. Establish a validation matrix.
5. Assess nominal accuracy with respect to key outputs.

## UNCERTAINTY ANALYSIS

6. Set acceptance criteria for system-related controlling parameters (discretization, timesteps, etc).
7. Establish ranges (and possibly distributions) for input parameters.
8. Identify correlation among both input and output variables.
9. Perform preliminary (first-order) sensitivity assessment on outputs.
10. Delete output variables which are both highly correlated and less descriptive.
11. Delete least impacting inputs and "lesser" impacting inputs which are highly correlated.
12. Establish uncertainty analysis matrix.

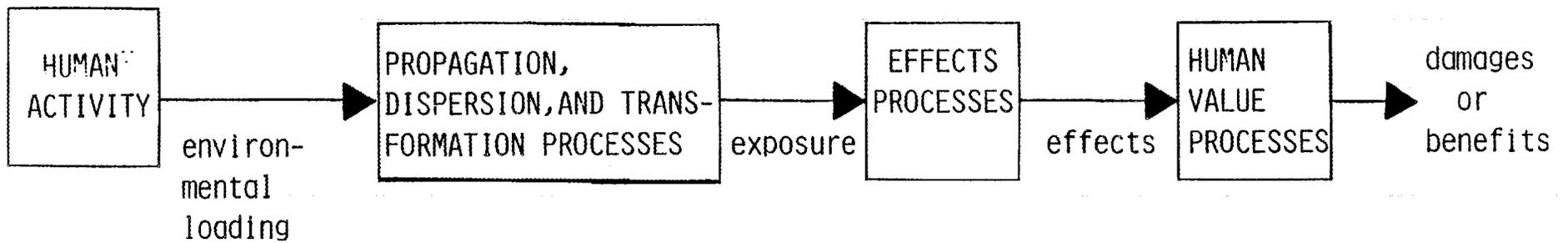
Rod also presents a draft matrix to aid in selecting appropriate methods for uncertainty treatment in modeling, reproduced in Fig. 3-13.

In a study of suitable methods for risk assessment of biotechnology [NSF, 1985b], the National Science Foundation presents a general diagram that indicates the applicability of five possible risk assessment approaches depending on "the *degree of uncertainty* about the system being investigated and the *degree of precision* that is being investigated and the *degree of precision* that is desired in the analytic results." The diagram is reproduced in Fig. 3-14. It is further pointed out that the methods shown on the diagram can be classified into three categories:

mathematical models (e.g., dispersion model, ecosystem structural models), physical simulations (e.g., microcosm or mesocosm tests), and real-world empirical methods (e.g., detection and monitoring, laboratory experiments, field studies). As the risk assessment focus shifts from most likely outcomes

to low-probability outcomes, empirically-based or physical simulation methods become less useful. For example, it is unlikely that low-probability outcomes would be observed in microcosm tests or realistic field trials, although they might appear plausible, based on predictive modeling studies.

Finally, Decision Focus Incorporated has developed and applied risk and decision frameworks for environmental and technology assessment problems for a number of years [North et al., 1985, Balson and Barrager, 1979, and Amaral et al., 1985]. The basic approach to these frameworks is the same for the problems to which they have been applied, and a good example to illustrate the frameworks is provided by North in his acid rain work [North and Balson, 1985]. North points out that the predominant EPA approach to assessing the potential health impacts of chemicals suspected of inducing cancer in man is to develop plausible upper-bound estimates of impacts. He sees this method as being useful "when the plausible upper-bound estimates of risk are relatively low . . .," but not "helpful when there is a potential for large impacts but a high likelihood that the large impacts will not occur." North proposes a framework based on decision analysis, with the key idea being the use of judgmental probability as a way to quantify uncertainty. Based on the principal that the purpose of risk assessment is to summarize available scientific information including characterization of uncertainties, the decision framework includes a set of scenarios with associated probabilities that span the range of scientific judgment on key uncertain relationships among processes and parameters associated with the potential risk. An overview of the decision framework is reproduced in Figure 3-15. Uncertainties are characterized in the framework by decision trees showing alternative risk process outcomes and derived from probability distributions for key uncertainties obtained from expert judgment. The decision process is then represented as dependent upon the state of and possible resolution of these uncertainties as a function of time and time constraints. Note that this type of framework serves both a structuring and procedural function because the decision tree approach provides a structured model of the risk assessment and decision process while having an inherent formal procedure associated with it. There are, however, alternative procedures and treatments of uncertainty available that may be more appropriate depending on the particular problem being addressed.



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FIGURE 3-1: Diagram for conceptualizing environmental risk assessment -- from [Morgan, 1977].

Quantity type	Examples	Defined as certain	Treat only parametrically	Treat either parametrically or probabilistically	Depends on how input variables are treated	Rational for treatment
<b>INPUT PARAMETERS:</b>						
Empirical parameters	Thermal efficiency, oxidation rate, price, toxicity.			●		There exists a "correct value" which is not precisely known and must be estimated.
Defined constants	Atomic weight of O, Joules per kWh.	●				The value is fixed by definition and is not empirical.
Value parameters	Investment rate to prevent mortality discount rate, risk aversion.		●			If one is uncertain about what one's values are the impact of alternative value assumptions should be systematically explored.
Model domain parameters	Size of base case plant, time horizon, geographic domain.		●			A set of fixed domain and form parameters specify a model. The implications of alternative models can be explored through parametric analysis of domain and form parameters.
Model form parameters	Order of exponent in a power law model, index across a function space.		●			
<b>MODEL VARIABLES:</b>						
Index variables	Time, spatial location.	●				Allows implementation of a model. May change if domain or form parameters are varied parametrically.
State variables	Minimum set of variables needed to predict all future values of a model's variables.				●	The value of state variables depend upon the value of input parameters.
Decision variables	Air quality standard (for EPA), plant size and type (for utility).		●			The decision-maker controls the value of this variable. As with value parameter, if he is uncertain he should systematically explore the implications of alternative choices.
<b>OUTCOME VARIABLES:</b>						
Outcome variables	Estimated excess deaths per year, expected net present value.				●	The value of outcome variable depend upon the value of input parameters and state variables.

Note: As explained in the text, a given quantity such as "plant size" or "investment rate to prevent mortality" may be classified as different quantity types depending upon the model context and the decision-maker.

[ Reproduced with authors' permission ]

FIGURE 3-2: Summary of different types of parameters and variables that enter into policy modeling and recommended treatment of uncertainty [Henrion and Morgan, 1984].

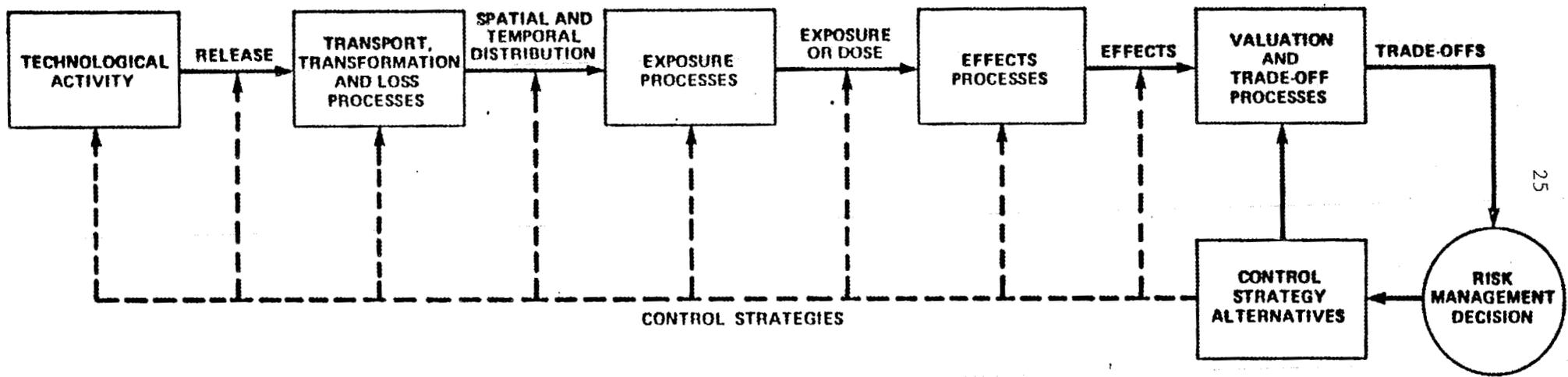


FIGURE 3-3: Framework for technological risk assessment and management--from [Rish, 1984].

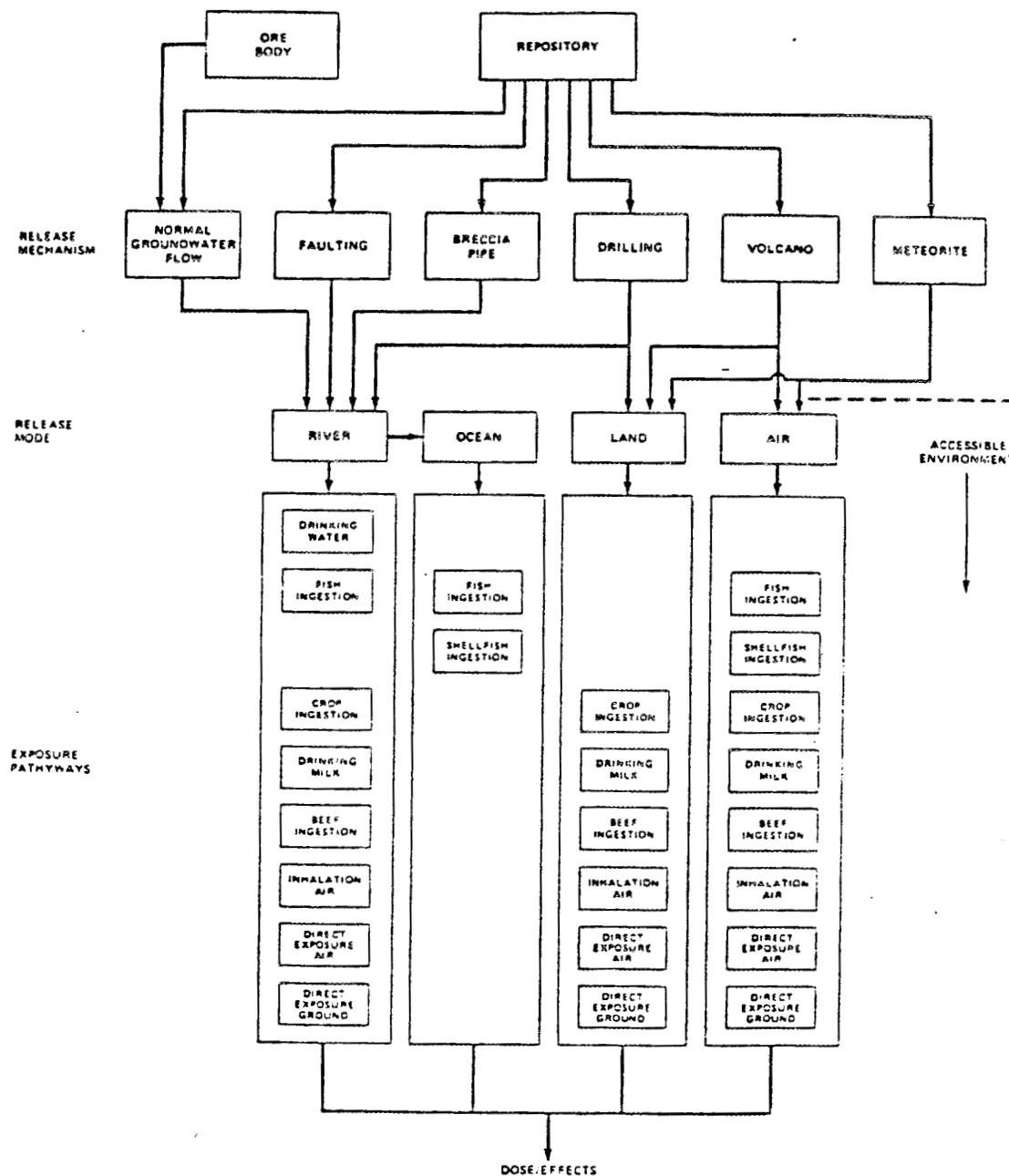


FIGURE 3-4: Diagram showing the basic structure of the EPA assessment methodology for estimating health effects from ore body and geologic repository releases--from [Rish et al., 1983].

## STRUCTURE OF EPA MODEL AND KEY UNCERTAIN PARAMETERS

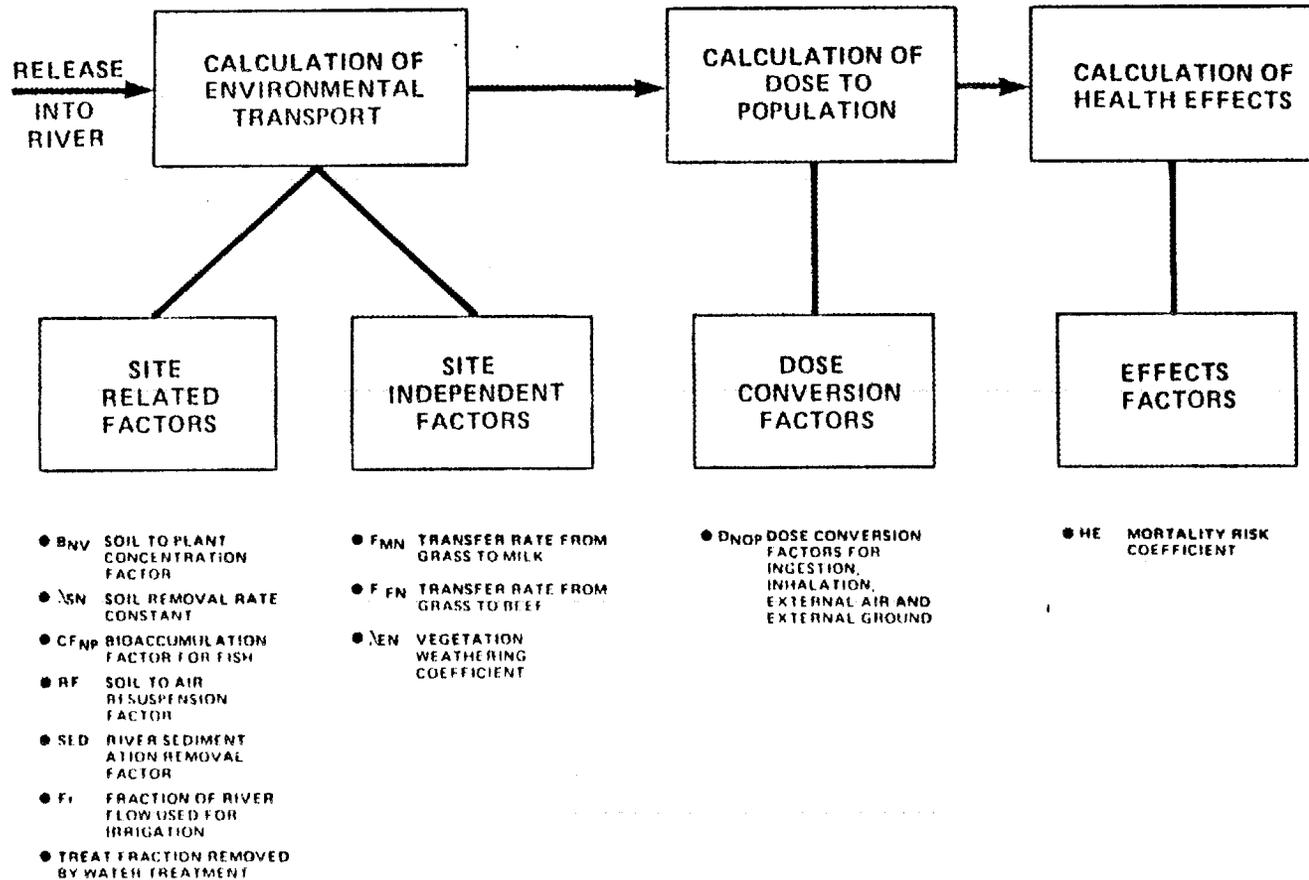


FIGURE 3-5: Detailed risk analysis flow diagram for river release portion of Figure 3-4--from [Rish et al., 1983].

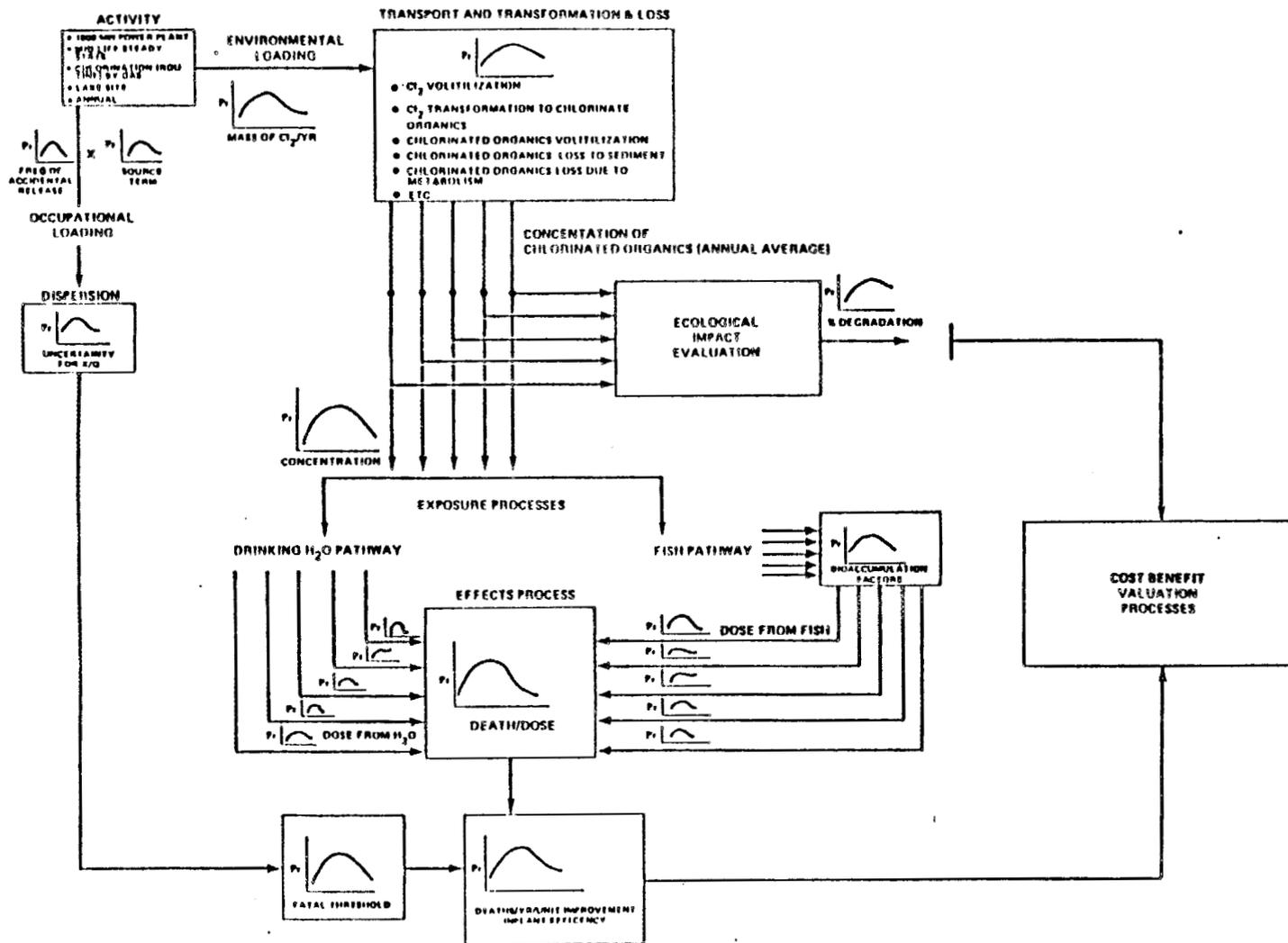


FIGURE 3-6: Preliminary risk analysis diagram for impact from gaseous chlorination--from [Envirosphere, 1983]

Methods Directed At

RISK-SOURCE CHARACTERIZATION (measuring the degree of danger associated with the source of risk)	EXPOSURE ASSESSMENT (Estimating the intensity, frequency, duration, etc. of human and other exposures to the risk agent)	DOSE-RESPONSE ASSESSMENT (Characterizing the relationship between the dose of risk agent received and health and other consequences to exposed populations)	RISK ESTIMATION (Developing overall measures of the level of risk)
Monitoring -equipment monitoring -environmental status monitoring Performance testing	Monitoring for exposure assess. -biologic monitoring food crops, livestock, fish wild animals, indigenous vegetation, etc. -Remote geologic monitoring aerial photography, multi-spectral overhead imagery -media contamination (site dose monitoring) Air, surface water, sediment soil, groundwater	Short-term test  Molecular structure analysis  Tests on humans  Animal bioassay	Statistical analysis
Accident investigation	-individual dose monitoring dosimeters, film badges	Epidemiology -cohort vs case-control -retrospective vs prospective	
Statistical methods for risk-source characterization -statistical sampling -component failure analysis -extreme value theory	Calculation of dose -based on exposure time -coexisting or decay substances -material deposition in tissue	Pharmacokinetics	
Codified engineering methods	Exposure modeling -air analytic models, trajectory models, transformation models -surface water dissolved oxygen models, etc. -groundwater absorption models travel time models -food chain chemical migration models	Low-dose extrapolation models  Animal to human extrapolation  Ecological effect models	Worst-case analysis  Sensitivity analysis  Confidence bounds  Probability distrib. -Monte Carlo analysis -event tree analysis -probability tree analysis
Modeling methods for risk-source characterization -engineering failure analysis -simulation models logic trees, event trees, fault trees -analytic models industrial effluents, biological models for pests, containment models	Population at risk models -census, sensitive groups, population estimation, trip generation models, etc.		

Fig. 3-7. Summary of risk assessment methods--from [NSF, 1985a].

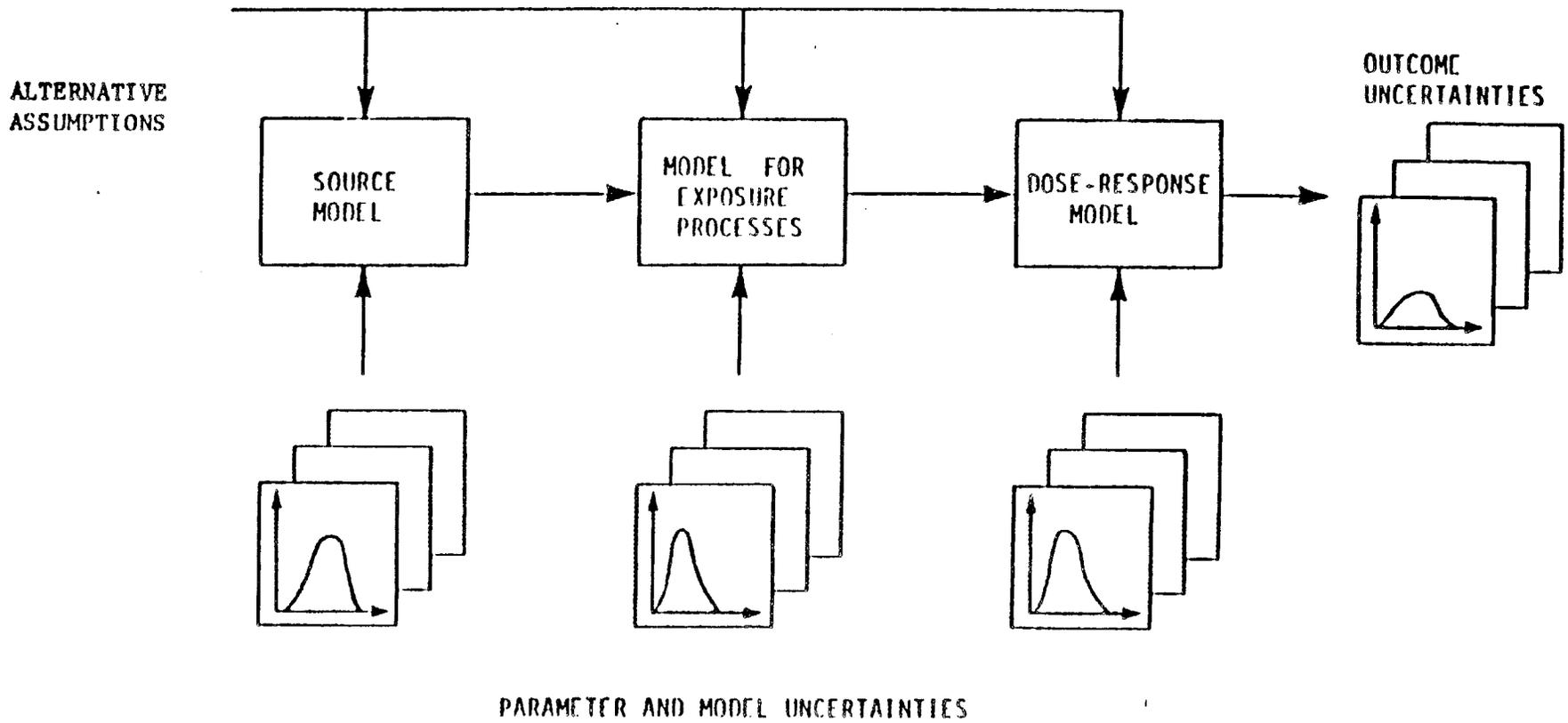


FIGURE 3-8: NSF concept of uncertainty treatment in risk analysis--from [NSF, 1985a]

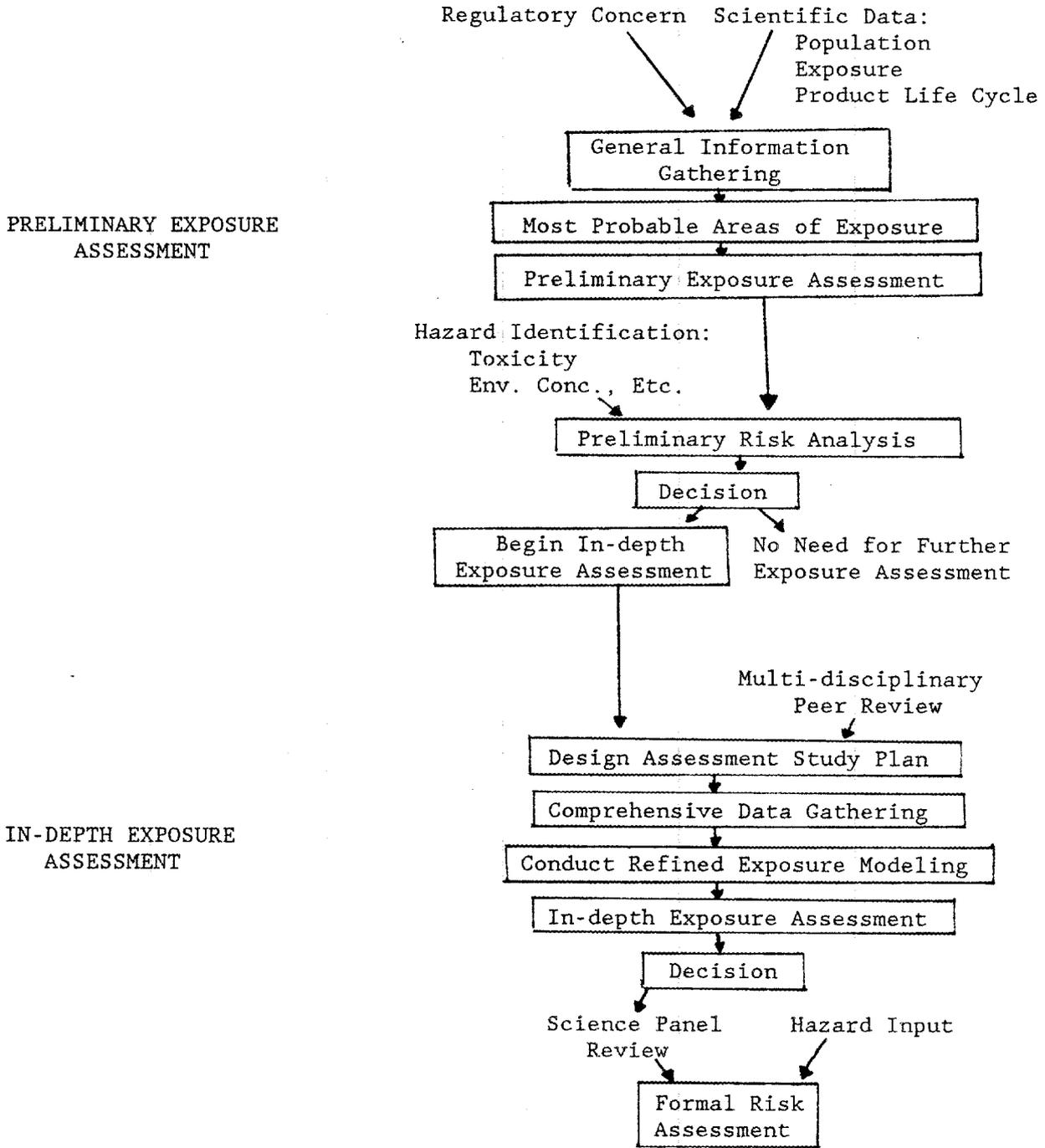


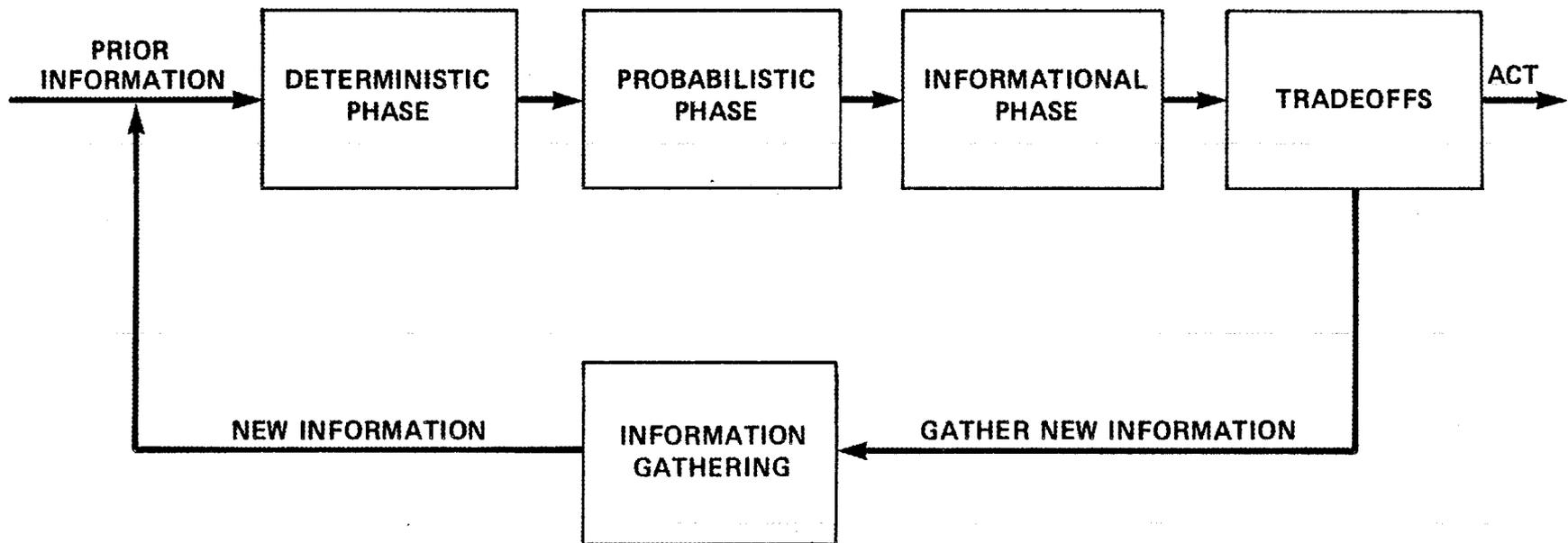
Fig 3-9. Decision path for exposure assessment--from [EPA, 1984a].

Table 2. Summary of Primary Methods for Characterizing Uncertainty for Exposure Assessments

Type and extent of data	Population characteristic being estimated	Primary methods for characterizing uncertainty	
		Qualitative methods	Quantitative methods
Measured exposures for a large sample of population members	Distribution of exposure	1. Limitations of the survey design and measurement techniques	1. Confidence interval estimates for percentiles of the exposure distribution 2. Goodness of fit for exposure models, if any have been postulated
Measured exposures for a small sample of population members	Summary parameter(s) of the exposure distribution, e.g. mean or a percentile	1. Limitations of the survey design and measurement techniques	1. Confidence interval estimates for the summary parameter(s) 2. Goodness of fit for exposure models, if any have been postulated
Measured model input variables for a large sample of population	Distribution of exposure	1. Limitations of the survey design and measurement techniques 2. Validity of the exposure model	1. Confidence interval estimates for percentiles of the exposure distribution 2. Goodness of fit for input variable distribution functions if any have been postulated 3. Estimated distribution of exposure based upon alternative models
Estimated distributors of model input variables	Distribution of exposure	1. Validity of the exposure model 2. Limitations of the data or other basis for the input variable distribution	1. Confidence interval estimates for percentiles of the exposure distribution 2. Goodness of fit for input distributions, if input variable data are available 3. Estimated distribution of exposure based upon alternative models
Limited data for model input variables	Minimum, maximum, and range of the exposure distribution	1. Limitations of the data 2. Validity of the exposure model	If input variable data are very limited e.g. some extant data collected for other purposes, quantitative characterization of uncertainty may not be possible

Fig. 3-10. Table of uncertainty methods for exposure assessment--from [EPA, 1984a].

FIGURE 3-11: **CLASSIC DECISION ANALYSIS CYCLE**



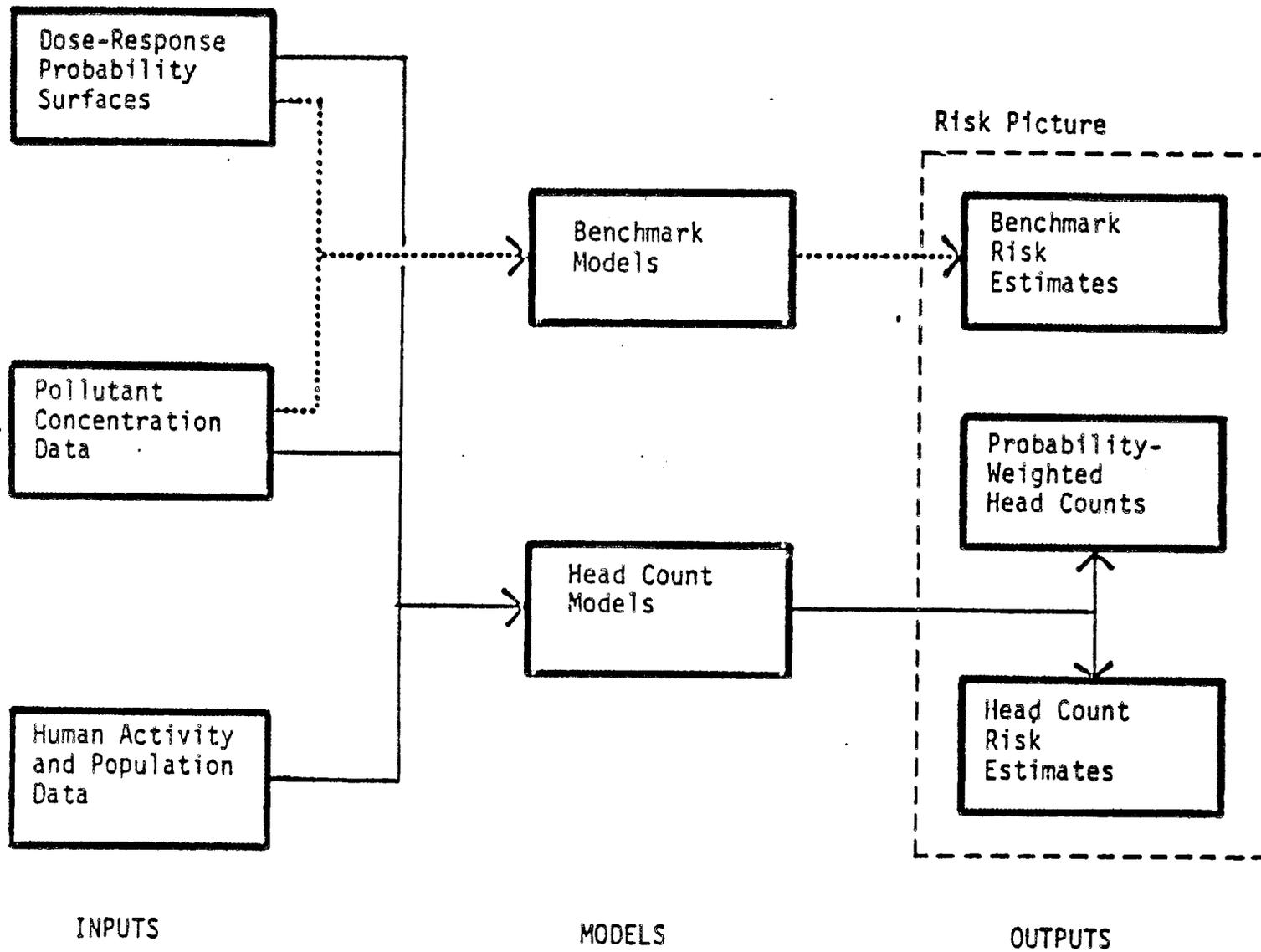


Fig. 3-12. EPA National Ambient Air Quality Standards risk assessment process--from [Feagans and Biller, 1981].

Suggested key:  
 1 - Excellent  
 2 - Good  
 3 - Average  
 4 - Poor  
 5 - Terrible  
 ? - Don't know.  
 N - Not applicable

Methods:	Criteria:	Pragmatic issues: Implementation effort	Computational effort	Availability of software	Representation issues: Accuracy for non-linear models	Knowledge of accuracy	Conceptual issues: Conceptual clarity of method	Ease of formulating problem	Ease of attributing uncertainty among inputs	Ease of explaining results	Others (please specify)
Scenario analysis											
Probability/decision trees											
Analytic methods											
Method of moments											
Discrete probability method											
Crude Monte Carlo											
Latin Hypercube Sampling											
Differential sensitivity theory											
Response surfaces											
Non-probabilistic inference											
Others (please specify)											

FIGURE 3-13: Aid to selecting appropriate treatment of uncertainty in modeling--from [Rod, 1984].

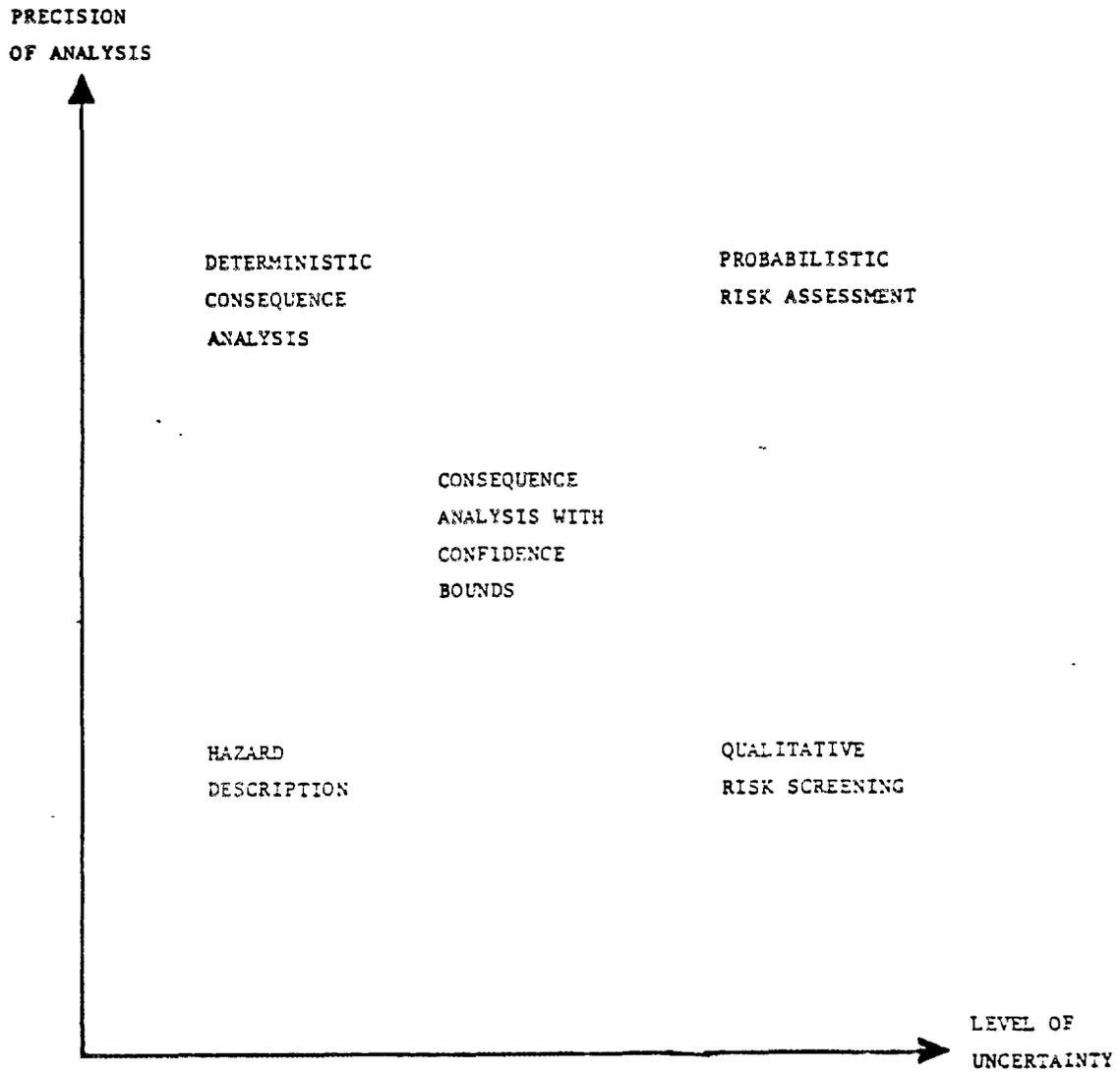


Fig. 3-14. Alternative risk analysis approaches--from [NSF, 1985b].

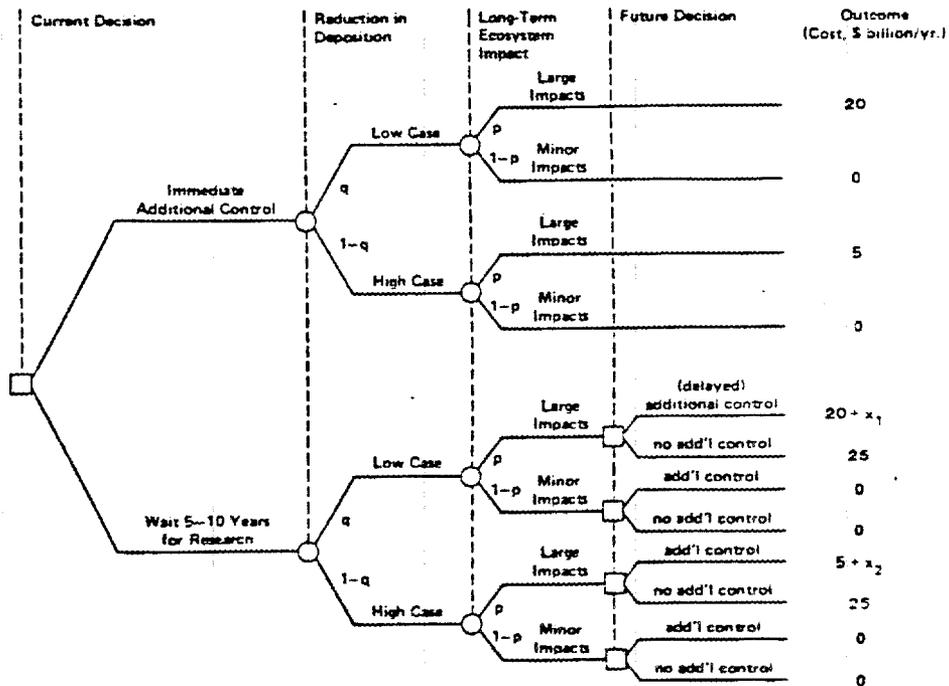
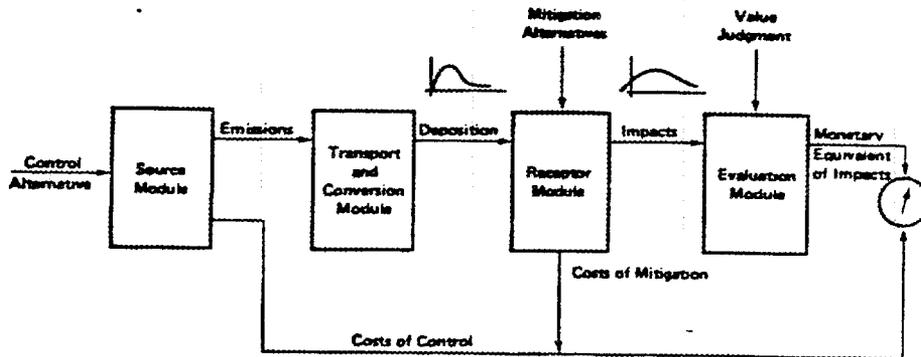


FIGURE 3-15. Acid deposition risk framework and decision tree-- from [North and Balson, 1985]. Sections of decision tree correspond to decisions (squares) or uncertainties (circles) associated with portions of risk framework. For example, uncertainty in predicted reductions in deposition for alternative regulatory strategies is depicted as low reduction or high reduction with associated probabilities. Branch magnitudes and probabilities are developed by discretizing the subjective probability distributions of uncertain factors.

#### 4. METHODOLOGIES

There are more papers available on methodologies for uncertainty treatment than in any other area reviewed. Three categories of papers are reviewed below: surveys of techniques for uncertainty analysis in modeling, papers discussing ways to characterize uncertainties in model inputs and outputs, and papers discussing how to deal with uncertainty about the validity of the model itself.

##### 4.1 SURVEYS

Rod (Carnegie-Mellon University) describes and compares methods for uncertainty analysis of large computer codes used in policy-making and regulation [Rod, 1984]. Methods summarized include the following input parameter screening techniques, designed "to identify and retain for analysis only those which have a significant impact on the output variables of interest:"

- one-at-a-time sampling,
- factorial designs,
- stepwise regression,
- differential analysis.

Also summarized are techniques for analyzing uncertainties inherent in the input parameters of large computer models, including:

- linear and non-linear regression,
- response surface methods,
- Monte Carlo techniques,
- Fourier analysis,
- method of moments,
- differential sensitivity theory (adjoint).

The advantages and disadvantages of the techniques are outlined, and depend on the particular application.

Henrion and Morgan (Carnegie-Mellon University) present a *Survey of Techniques for Uncertainty Analysis* in rough draft form [Henrion and Morgan, 1984]. As was mentioned in Sect. 3, the authors first discuss how to classify a modeling problem by types of quantities involved, sources of uncertainty, and type of model. This classification is viewed as useful and necessary for selecting appropriate methods for treating uncertainty in a given problem. Next the authors summarize various techniques for propagating uncertainty through a model, and briefly "assess their relative advantages and disadvantages with consideration of the different kinds of model to which they may be applied." The techniques described are:

- scenario analysis,
- discrete probability distributions,
- exact analytic methods,
- approximate analysis and method of moments,
- Monte Carlo simulation,
- variance reduction techniques,
- response surface methods,
- methods for attributing sources of uncertainty, and
- methods for expressing correlations and probabilistic dependencies among uncertain parameters.

Three papers are available that provide a good overview of uncertainty considerations in probabilistic risk assessment (PRA). Vesely and Rasmuson [1984] identify the different types of uncertainties in a PRA and describe their implications. Two major types of uncertainty in a risk analysis are differentiated: uncertainty due to physical variability, and uncertainty due to lack of knowledge. Three types of uncertainty encountered in a PRA are identified as: parameter uncertainties, modeling uncertainties, and completeness uncertainties. The authors summarize the uncertainty analyses that have been performed in current PRAs for each of these types of uncertainty. Conclusions are drawn regarding interpretations of uncertainties, areas having largest uncertainties, and needs which exist in uncertainty analysis.

In a complementary paper, Cox and Baybutt [1981] present a survey and comparative evaluation of methods which have been developed for determination of uncertainties in accident consequences and probabilities for use in probabilistic risk assessment. While discussed in the context of PRA, the discussions presented are relevant to risk analysis in general. The methods considered are: analytic techniques, Monte Carlo simulation, response surface approaches, differential sensitivity techniques, and evaluation of classical statistical confidence bounds. It is concluded that only the response surface and differential sensitivity approaches are sufficiently general and flexible for use as overall methods of uncertainty analysis in probabilistic risk assessment. The other methods considered, however, are concluded to be very useful in particular problems. According to the authors: "Analytic techniques are applicable to the uncertainty analysis of fault trees, and can also be used in support of response surface approaches. The Monte Carlo method can be applied when output is not too expensive to evaluate, and partitioning of output uncertainty is not needed. Classical approaches are important when the system model is known precisely, and statistical sampling variability is a dominant source of uncertainty." A table is presented in the paper, showing the advantages and disadvantages of the various methods examined.

Martz et al. [1983] present a comparative evaluation of several methods for propagating uncertainties in actual coupled nuclear power plant safety system fault tree models. The methods considered are Monte Carlo simulation, the method of moments, a discrete distribution combination method, and a bootstrap method. The Monte Carlo method is found to be superior. Each of the methods are described in the context of their use in fault tree analysis, but if one views the fault tree model as an algebraic expression then these descriptions are relevant to algebraic models in general and the comparisons are relevant to similar algebraic expressions.

The sensitivity of the model output probability distribution to the choice of input parameter distributions is also investigated. The output distribution is especially sensitive to the choice of symmetric versus asymmetric input distributions. Gamma, log gamma, log normal, and log uniform distributions produce quite similar results, except that the output distribution corresponding to log normal distributions has a heavier

right-hand tail. Log Cauchy input distributions yield an output distribution with an extremely heavy right-hand tail. It is concluded to be impossible to identify an unequivocal "best" universal family of input distributions to use in reactor probabilistic risk assessment fault tree uncertainty analyses.

In a study prepared for the NRC, Iman and Helton [1985] compare several widely used techniques for performing uncertainty and sensitivity analyses on computer models [Iman and Helton, 1985]. As the paper's abstract explains:

The objective of the study is to compare several widely used techniques on three models having large uncertainties and varying degrees of complexity in order to highlight some of the problem areas that must be addressed in actual applications. The following approaches to uncertainty and sensitivity analysis are considered: (1) response surface methodology based on input determined from a fractional factorial design; (2) Latin hypercube sampling with and without regression analysis; and (3) differential analysis. These techniques are compared on the basis of: (1) ease of implementation, (2) flexibility, (3) estimation of the cumulative distribution function of the output, and (4) adaptability to different methods of sensitivity analysis. With respect to these criteria, the technique using Latin hypercube sampling and regression analysis gives the best results overall. The models used in the comparisons are well documented, thus making it possible for researchers to make comparisons of other techniques with the results in this study.

The three models used are: an environmental radionuclide pathways model, a model for multicomponent aerosol dynamics, and a model for salt dissolution in bedded salt formations. Each of the three uncertainty and sensitivity analysis approaches are summarized with source references provided. Note that Iman is a key member of a group of researchers at Sandia National Laboratories who have been doing a significant amount of methodological development work in the uncertainty and risk analysis areas.

The NRC's *PRA Procedures Guide* [NRC, 1983] contains a chapter on uncertainty and sensitivity analysis (Chapter 12) that summarized methods for qualitative and quantitative uncertainty analysis. While discussed in the context of nuclear power plant PRA, the summaries are relevant to data and model uncertainties in general.

The qualitative uncertainty analysis approach outlined is actually partially quantitative. Two hierarchical levels of qualitative analysis are proposed, a detailed level supported by a local limited sensitivity analysis to rank the uncertainties and a higher level supported by a global (overall) limited sensitivity analysis to assess the impact of the uncertainties on the final PRA results.

The survey of quantitative uncertainty analysis includes discussion of:

- commonly used measures of uncertainty and random variability;
- the quantifiability of uncertainties encountered in risk modeling;
- approaches to quantification of parameter and modeling uncertainties;
- methods for evaluating model output uncertainty when the input uncertainties are expressed as probability distributions (Bayesian framework);
- methods for evaluating model output uncertainty when data-based estimates of input uncertainties are available (Classical framework); and
- methods of displaying uncertainties in risk analysis results.

In an introductory chapter to the EPA's *MOUSE Manual* [Klee, 1985], Klee briefly describes and critiques what he calls the traditional approaches to uncertainty in mathematical models including: the best value approach, the conservative approach, and sensitivity analysis. Three alternative approaches are described: direct or complete enumeration, probability calculus, and a form of Monte Carlo simulation called model sampling. The Monte Carlo simulation approach is selected as the basis for MOUSE, a computerized uncertainty analysis system. Sensitivity and uncertainty analysis are compared, and a means to use them in a complementary manner is proposed.

Cranwell [1985] presents a survey of the current methods for treating uncertainties in modeling the performance of geologic repositories for high-level radioactive waste. A great deal of methodological and applications work is occurring in this area. Methods for treating computer code and model uncertainty, parameter uncertainty, risk scenario uncertainty and sensitivity analysis are discussed. The following methods are discussed for each of these topics:

- Computer code/model uncertainty: validation, determining computational limits, and quality assurance of codes.
- Parameter uncertainty: deterministic models with statistical sampling, stochastic models, kriging, and the geostatistical approach.
- Risk scenario uncertainty: methods to address "completeness," methods to address truncation of the set of scenarios considered.
- Sensitivity analysis: stepwise regression and adjoint sensitivity methods.

Whitmore [1984], in a study done for the EPA, critically discusses methodologies for characterizing uncertainty in exposure assessments for various stages of information availability. These stages include:

- assessments based upon limited initial data for directly measured exposures and for model input variables;
- assessments based upon estimation of input variable distributions;
- assessments based upon data for model input variables when distributions are known and unknown; and
- assessments based upon data for exposure.

Also discussed are methods for combining uncertainties over sources, pathways, routes of exposure and subpopulations. A hypothetical example is provided.

Seiler [1983a and 1983b] discusses analytical methods available for error propagation in mathematical models. He points out that analytical calculations of error propagation are usually restricted to small relative errors, whereas numerical methods cover both small and large errors. In biology and related disciplines such as risk assessment, errors are often large and uncertain. It is shown in his paper that even for large errors, an analytical treatment is possible in many cases. These instances can be identified by an analysis of the overall algebraic structure of the calculation. Error propagation formulae for the general and some special cases are derived and their properties discussed. Explicit formulae for some simple algebraic structures that often occur in risk assessments are derived and applied to practical problems.

## 4.2 CHARACTERIZING UNCERTAINTY

Papers discussed under this category address how to characterize the uncertainty about a quantity or aspect of an analysis in order to obtain a meaningful measure of that uncertainty.

Generally speaking, uncertainty can be characterized in any of the following ways [based on Henrion and Morgan, 1984]:

- Simply acknowledge the uncertainty in qualitative terms.
- Specify a range of two or more alternative values for the quantity, for example a low, nominal and high value.
- Specify a standard error, confidence interval, or uncertainty factor about a nominal value.
- Specify a discrete probability distribution over a finite set of alternative values.
- Specify a complete continuous distribution either as a uniform, normal, beta, or other standard parametric distribution, or as a point on an arbitrary density function or cumulative probability distribution.
- Specify a non-probabilistic quantitative representation of uncertainty, employing fuzzy sets, certainty factors, Dempster-Shafer representation, or others.

According to Lindley [1984], "the only measurement of uncertainty is probability." While this statement by no means represents a consensus opinion, there seems to be a growing movement among risk analysts to use probabilistic measures of uncertainty. There is, however, disagreement about whether such probabilistic characterizations should be developed strictly from data using classical statistical methods for variability and error analysis, or should have a subjective element to them provided by encodings of expert judgments and governed by the principles of Bayesian statistics. It has been this reviewer's observation that investigators who are primarily involved in scientific research that is removed from the policy area tend to rely on classical methods, while those who are involved in research at the interface of policy making feel more comfortable using judgmental inputs. In fact, this latter group often is required to rely on judgments from a practical standpoint, because the

time constraints and pressures of the decision process that their work supports will not allow them to wait for better data or understanding. In any case, methods from both schools of thought are useful depending on the information available and the purpose of the analysis.

Easterling [1984], in a presentation of work being done for the NRC by Sandia National Laboratories, makes the distinction between two sources of uncertainty in risk analyses: random variation and parameter estimate uncertainty. This paper addresses the necessity of distinguishing between random variables and parameters in an uncertainty assessment, whether that assessment is data-based or data-free. For example, an earthquake risk model may include a parameter such as average soil property for a site. This property may be estimated from random soil samples. In an uncertainty analysis, the appropriate uncertainty to be considered is the variance of the parameter-estimate,  $\sigma^2/n$ , where  $n$  is the number of samples, not the variance of individual soil samples,  $\sigma^2$ . A similar example is the need to estimate an average human error probability across different people and conditions and thus to consider uncertainty of that estimated average, rather than the variability among individuals. This distinction, which has not always been recognized, and its impact on an uncertainty assessment is illustrated via a simple model,  $Y = X + \theta$ , where  $X$  is a random variable,  $\theta$  is a parameter, and the problem is to estimate the parameter  $\eta = \text{Prob}(Y > y_0)$ .

In the introductory chapter to the Indian Point Probabilistic Safety Study, Kaplan presents a tutorial on risk, probability, and uncertainty concepts and mathematics [Consolidated Edison, 1982]. As part of this discussion, some of the basic concepts and mathematics of probability distributions are presented. Also, the distinction between the classical (frequentist) and the Bayesian (subjectivist) characterizations of uncertainty, and the mathematics of each, is discussed. An excellent applications-oriented discussion of the use of Bayes' Theorem for developing and updating probability distributions as measures of uncertainty is included.

Fields [1982] describes the techniques behind a computer code (TERPED) developed at Oak Ridge National Laboratory for determining with what confidence a parameter set may be considered to have a normal or log-normal frequency distribution. Several measures to test the distribution

hypothesis are described including: the chi-square statistic, the Kolmogoroo-Smirnov non-parametric statistic, and Pearson's correlation coefficient.

Two widely used texts dealing with the characterization and treatment of experimental uncertainty using classical techniques are the works of Beers [1957] and Bevington [1969].

A majority of the risk analysis community at this time predominantly use subjective probability distributions to characterize uncertainties encountered in modeling, especially for model parameter uncertainties. Bayes' Theorum provides the theoretical foundation for these characterizations [de Finetti, 1968]. The methods used to develop these distributions involve eliciting expert judgments about uncertainties in the form of encoded "prior probability distributions," which are then updated using Bayes' Theorum with subsequent new data on the uncertain measure.

Several reviews are available on this topic. Hampton et al. [1973] survey and comment on the subjective probability assessment literature. Hogarth [1975] presents an extensive review of the probability encoding literature. Wallsten and Budescu [1983] present a review and discussion of the empirical literature on subjective probability encoding from a psychological and psychometric perspective. Henrion [1980] reviews current techniques for assessing subjective probabilities, the psychological considerations of probability assessment, shortcomings of assessment techniques, and possible ways to alleviate those shortcomings.

Two seminal papers on this topic are presented by de Finetti and Tversky and Kahneman. The interpretation of probabilities, particularly subjective probabilities, are discussed by de Finetti [1968]. The subjective probability that a person attaches to an event is said to measure that person's "degree of belief" or "state of information" about the event. If assessed properly, these probabilities will conform to the axioms of mathematical probability theory.

Tversky and Kahneman [1974] summarize the various modes of judgment commonly used to assign probabilities including "representativeness," "availability," and "anchoring and adjustment." Kahneman and Tversky argue that "representativeness" is one of the methods that people use to make probability assessments by assigning a probability to an event based on the degree to which that event is representative of the major

characteristic of the process or population from which it originated. They also observe the assignment of the probability of an event based upon the "availability" of information about that event. "Anchoring and adjustment" is a mode of judgment whereby assessments are made by starting with an initial guess or anchor and representing uncertainty about this point by adjustments about the anchor. It is argued that these various heuristics introduce biases to uncertainty/probability characterizations, and in a more recent paper these authors suggest approaches to reduce these biases [Kahneman and Tversky, 1982]. The state-of-the-art in the area of heuristics and biases in judgments under uncertainty is reviewed in a book on the topic edited by Kahneman, Slovic, and Tversky [Kahneman et al., 1982].

A number of techniques are described for eliciting or "encoding" expert judgments about uncertain factors as probability distributions or as discrete probabilities.

Winkler [1962] discusses a variety of probability encoding techniques for the assessment of prior distributions in Bayesian analysis. Spetzler and von Holstein [1975] discuss biases affecting subjective probability assessments, and a variety of encoding techniques and their applicability are discussed. These techniques are used during an interview with the expert. The interview process has five phases as follows:

1. Motivating. Rapport with the subject is established and possible motivational biases are explored.
2. Structuring. The structure of the uncertain quantity is defined.
3. Conditioning. The subject is conditioned to think fundamentally about his judgment and to avoid cognitive biases.
4. Encoding. The subject's judgment is quantified in probabilistic terms.
5. Verifying. The responses obtained in the encoding are checked for consistency.

These five steps constitute the Stanford Research Institute (SRI) probability encoding method, which has been used in many applications and is in the same form today [SRI, 1979].

Wallsten and Whitfield, as part of their work for the EPA Office of Air Quality Planning and Standards on ambient lead standard-setting, have developed an encoding protocol. In a recent paper [Whitfield and Wallsten, 1984], this protocol is summarized, and a method for combining the judgments with exposure estimates is described. The method for estimating risks does not merge the experts' judgments into a single or average judgment, but rather estimates a range of risks based on a range of judgments.

Martz et al. raise the possibility that expert opinions on uncertainties may be correlated and discuss the problems created by this possibility. Techniques for dealing with this dependency problem are briefly discussed [Martz et al., 1985].

Boyd and Regulinski [1979] summarize the psychology of probability encoding and present a procedure for characterizing the uncertainty in technology cost and performance.

#### 4.3 MODEL UNCERTAINTY

The papers reviewed so far have mainly considered uncertainty about the values of parameters used in risk models. Often, there is also significant uncertainty about the validity of the model itself: conceptual, mathematical and computer code. A conceptual model of a risk-related process is a simplification of the real world, and as such, all aspects of the process being modeled might not be included. Also, alternative concepts are often plausible. Converting conceptual models to mathematical expressions and then to computer codes involves using assumptions, truncations and approximations, and the possibility for human error is present. All of these factors contribute to the existence of what is generally called "model uncertainty."

Model uncertainty has not been given nearly as much attention as parameter uncertainty. Recently, a need to develop methods to address model uncertainty has been recognized, especially since there are "dangers inherent in trying to quantify model parameter uncertainty when the model itself is uncertain [Dudney and Jones, 1984]." In their survey, Henrion and Morgan [1984] discuss uncertainty about model form and uncertainty introduced by approximations made in model implementation. General

approaches to characterizing and reducing these types of uncertainty are suggested. One interesting approach is described as follows:

Given a number of alternative functional forms, in many cases it is possible to reformulate them as a single form with an extra parameter that can make the model equivalent to each of the original forms according to the value chosen. For example, it is possible to define a dose-response function with a threshold parameter and dose exponent parameter, which will also reproduce non-threshold models (if the threshold parameter is zero) and linear models (if the exponent is one). Thus uncertainty about the model form can be converted into uncertainty about parameter values. This often simplifies the analysis, especially if one wants to compare the impact of uncertainty about the model form with other uncertainties.

Cranwell [1985] discusses approaches to the problems of "completeness" and "truncation" associated with the selection and screening of risk scenarios for analysis of the risks from a geologic radioactive waste repository. The issue of "completeness" in risk modeling is one often raised. This is uncertainty about whether all significant events and processes that might result in risk have been included in the analysis. "Truncation" is a similar issue, being uncertainty introduced by judgments made about which of a number of coexisting events and processes are significant contributors to risk and which can be truncated from the analysis.

An approach to "completeness" uncertainty that uses Boolean logic (e.g., OR and AND) is suggested by Najafi [1984]. Fault tree-type Boolean algebra is used to include in the analysis the probability that alternative events, processes, or models are appropriate (or that combinations of these are necessary to yield the risk). This is the same basic approach used in risk analysis approaches employing decision tree frameworks (see [North and Balson, 1985] for example).

Rish [1982] suggests that where alternative plausible models are postulated, the sensitivity of risk analysis results to these alternative formulations should be examined. He elicits model structures and assumptions, as well as parameter uncertainties, during expert interviews.

Cox [1982] introduces the concept of "artifactual uncertainty" as "uncertainty on the part of the analyst about what procedures to use in converting raw data into final estimates." He states that "uncertainty of

this type" arises "from artifacts in data selection, processing, or interpretation ..." Cox argues that artifactual uncertainty requires conceptual advances for their resolution and interfere with the determination of risk that is "attributable" to the technological activity being regulated. Important and unresolved methodological (artifactual) sources of uncertainty that arise in the construction of risk estimates are itemized and explained.

Wong [1984] discusses the implications of model uncertainty in making extrapolations from animal experiments for the assessment of carcinogenic potentials of low levels of environmental carcinogens. Three implications of model uncertainty to risk assessors are: (1) there is a need to use a rich model in risk analysis for valid inferences; (2) it is necessary to include both the model and the sampling uncertainties in the indicator of uncertainty in the extrapolations from risk analysis; and (3) experimental design needs to be investigated under rich model and realistic sample size assumptions. Based on the first two implications, an inference procedure is proposed. The procedure has a wider scope of applicability, includes a goodness of fit test for the model, and provides a better description and confidence interval for the extrapolation than the traditional approach. Based on the third implication, experimental design is examined with a design criterion that allows for both the model and the sampling uncertainties. Issues on how best to reduce the total uncertainty and the trade-offs between the model and the sampling uncertainties are examined.

## 5. SOFTWARE SYSTEMS

There is a range of software systems available to facilitate the analysis of uncertainty, depending on the particular aspect of the analysis being addressed. There are of course many standard statistical packages available; however, for the purposes of this review these were omitted, and only those systems more directly relevant to the types of frameworks and methodologies described in the previous sections are included here.

MOUSE (Modular Oriented Uncertainty System Emulator) is a general purpose interactive uncertainty software system developed at the EPA by Albert Klee [Klee, 1985]. MOUSE deals with the problem of uncertainties in models that consist of one or more algebraic equations. It was designed to be used by those with little or no knowledge of computer languages or programming. It is compact (and thus can run on almost any digital computer), easy and fast to learn, and has most of the features needed for substantive uncertainty analysis including: built-in probability distribution, plotting and graphing capabilities, sensitivity analysis, interest functions for cost analyses, correlation among variables, aid to deriving probability distributions, and Monte Carlo propagation.

MOUSE has been used within EPA for uncertainty analysis on: a facilities design cost model to construct and close a surface impoundment or landfill facility, a waste pile costing model required to construct and close a waste pile facility, the use of engineering fault tree analysis in failure analysis of RCRA land disposal facilities, cost models for systems for the incineration of hazardous wastes, and an investigation of a model to determine an appropriate level for regulating organic toxicants in hazardous wastes.

Max Henrion at Carnegie-Mellon University has developed another general purpose uncertainty analysis system called DEMOS (Decision Modeling System) [Henrion, 1979]. It is an interactive environment for structuring, analyzing, and communicating probabilistic models. It provides general mathematical modeling facilities, but it was designed primarily for policy-related modeling using techniques from cost-benefit analysis,

engineering-economics, risk assessment and decision analysis. Some typical applications have been studies of:

- integrated assessments of acid deposition;
- regulatory strategies for controlling the health impact of air pollution;
- the effect of office automation on net energy use in the office;
- a comparison of the cost-effectiveness and net benefits of seat belts, air bags, and other restraint systems for car occupants;
- lifecycle costs of electric power plants for third world countries;
- comparison of environmental and socio-economic impact of alternative sites and technologies for a synfuels plant; and
- uncertainty about the risk analysis used to develop the EPA's environmental release limits for radioactivity from high-level waste geologic repositories (40 CFR 191).

DEMOS has convenient facilities for representing uncertainty about each parameter, either as a range of alternative values or as a probability distribution, and supports several methods for deterministic and probabilistic sensitivity analysis. Both data values and model structure may be defined and modified interactively, and alternative versions of a model can be constructed and compared. Models may contain considerable documentary text integrated with the mathematical structure. This is intended to aid communication between model authors and to facilitate understanding of the assumptions and implications of the model by reviewers and clients.

Inman and Shortencarier [1984] of Sandia National Laboratory have developed a computer program for the generation of Latin Hypercube and random samples for propagating uncertainties through computer codes. The program is relatively portable and can be used as the mechanism to convert a deterministic model into one that propagates input parameters probabilistically. Sampling can be done from standard or user-defined distributions and from empirical data. Correlation among input parameters can be treated. A companion program is available for calculating partial correlation and standard regression coefficients for a data set [Inman et al., 1985].

Goldstein [1983] describes a software system that he developed at MITRE for performing calculations in which one or more of the variables are probabilistic. The objective is to enable analysts to systematically and explicitly incorporate uncertainty into their calculations with a minimum of set-up overhead. Eleven continuous and five discrete probability distributions are included. Also, there are easily invoked routines to portray the results of the calculations statistically and graphically. The software is coded in the APL computer language. It runs interactively on the MITRE Washington Computer Center's IBM mainframe.

Bonner and Moore Associates [1980] offer a commercial FORTRAN-based software package for probabilistic calculations through Boeing Computer Services. Calculations are performed with Monte Carlo simulation techniques. The system is called PAUS (Planning and Analysis of Uncertain Situations). PAUS is intended for a variety of business applications; however, it also appears adaptable to engineering and risk analysis applications.

Vausio [1984] describes two codes available from Argonne National Laboratory for sensitivity and uncertainty analysis. The purpose of the SCREEN code is to identify a group of most important input variables of a code that has many (tens, hundreds) input variables with uncertainties, and do this without relying on judgment or exhaustive sensitivity studies. The purpose of the PROSA-2 code is to propagate uncertainties and calculate the distributions of interesting output variable(s) of a safety analysis code using response surface techniques, based on the same runs used for screening. Several applications are discussed, but the codes are generic, not tailored to any specific safety application code. They are compatible in terms of input/output requirements but also independent of each other (e.g., PROSA-2 can be used without first using SCREEN if a set of important input variables has first been selected by other methods). Also, although Screen can select cases to be run (by random sampling), a user can select cases by other methods, if he so prefers, and still use the rest of SCREEN for identifying important input variables.

Astolfi and Lisanti [1983] describes three codes for uncertainty propagation, experimental design and stratified random sampling techniques. MUP (Monte Carlo Uncertainty Propagation) is a code for uncertainty analysis by Monte Carlo simulation, including correlation analysis,

extreme value identification, and study of selected ranges of the variable space. CEC-DES (Central Composite Design) is a code for building experimental matrices according to the principles of central composite and factorial experimental designs. STRADE (Stratified Random Design) is a code for experimental designs based on Latin Hypercube sampling techniques. Note that these codes were published by the Commission of the European Communities Joint Research Center, which also published a program for the systematic combination of random variables (called SCORE) based on discrete probability distribution techniques [Colombo and Jaarsma, 1980].

## 6. APPLICATIONS

The application of techniques to analyze uncertainty in environmental risk assessment began in the early 1970s. This was a time when two concurrent events occurred that probably were the driving force for this applications work: (1) a set of environmental statutes were promulgated (National Environmental Policy Act in 1970, Clean Air Act in 1970, Clean Water Act in 1972, and Federal Water Pollution Control Act in 1972); and (2) high-speed computer capabilities became significantly more available and affordable. These environmental statutes required modeling of environmental risks to be done to show compliance in an adjudicatory and adversarial setting. As experience with such modeling increased, especially subject to the type of regulatory review it was receiving, it was logical that concerns about uncertainty developed. Available and affordable high-speed computers made techniques such as simulation modeling and Monte Carlo sampling viable.

R. V. O'Neill at Oak Ridge National Laboratory (ORNL) developed and applied stochastic modeling techniques to analyze "errors" in ecological models [O'Neill, 1971a and b]. Methods to analyze uncertainty in hydrological models also began to be applied around that time [Ibbit, 1972, Cornell, 1972, Warren and Price, 1961, and Warren and Skiba, 1964]. Also at that time, in the relatively new field of applied decision analysis, R. A. Howard and his associates at Stanford University did a pioneering study on a decision to seed hurricanes [Howard et al., 1972] that involved encoding expert opinions about uncertain events and outcomes and using these in decision tree models of risk.

Since those early studies, three major environmental issues seem to have driven much of the applications work involving the treatment of uncertainty in environmental risk assessment: nuclear fuel cycle risks, air pollution and (more recently) hazardous waste disposal.

The publications of the AEC sponsored study of the safety of nuclear power reactors [AEC, 1973] and the NRC sponsored *Reactor Safety Study* [NRC, 1975] began an era of significant uncertainty analysis development and application in the nuclear power plant safety assessment area, known as probabilistic risk assessment (PRA). The *Reactor Safety Study* contains an underemphasized analysis of uncertainty in event frequencies and

diurnal meteorological variability, done with an associated computer code for Monte Carlo uncertainty propagation in fault trees called SAMPLE. The so-called Lewis Committee criticized the study for inadequate consideration of uncertainty [Lewis et al., 1978]. As shown in Figs. 6-1 and 6-2, reproduced from the study, uncertainties in the results are represented by "error bars" on the histograms (Fig. 6-1) and by recommended probability and consequence "error bars" on the risk curves (footnote to Fig. 6-2).

After the Reactor Safety Study, development and applications of computer-based techniques for analyzing uncertainty in fault tree analysis continued to grow. Lee and Apostolakis [1976] developed a code based on the method of moments, and shortly after, Lee and Salem [1978] introduced a Monte Carlo-based code. Numerous other codes have been developed and applied to nuclear plant fault trees using Monte Carlo methods [Kalli and Lanore, 1977 and Matthews, 1977], the method of moments [Cox and Miller, 1978], and discrete probability distributions [Kaplan, 1981].

The probabilistic risk assessment process is depicted by the diagram in Fig. 6-3 [NRC, 1984]. In the past, uncertainty analyses in PRAs were done as part of the plant systems analysis and not as part of the environmental transport and consequence modeling. The uncertainty ranges that were estimated for core-melt frequencies and risks in past PRAs included, with very few exceptions, those due to uncertainties in the data (i.e., those due to imprecisions in statistical estimation), uncertainties in data extrapolation, and unit-to-unit variations. In earlier studies, uncertainties attributable to modeling and assumptions were usually not included in the PRA uncertainty analyses; sometimes, however, their impacts were considered separately in sensitivity analyses, to some extent. Many of the later studies include subjective estimates of the uncertainty contribution due to modeling assumptions. Uncertainties in the data and uncertainties arising from modeling assumptions are propagated through the analysis to estimate the uncertainties in the PRA results.

Two good examples of uncertainty treatment in PRA plant systems analysis are found in the Indian Point and Zion Probabilistic Safety Studies done by Pickard, Lowe and Garrick [Consolidated Edison, 1982 and Commonwealth Edison, 1981]. The results of the PRAs are presented as "risk curves," which are basically complementary cumulative distribution

functions (CCDFs) based on a set of accident scenarios and their respective frequencies and consequence levels. An example of a risk curve is shown in Fig. 6-4a. When uncertainties are propagated through the PRA the result is a family of such curves, as shown in Fig. 6-4b, with each curve representing a different confidence level about the risk from the plant. This family of curves can be "cut" at a specific damage level, as shown in Fig. 6-4c, to express the state of certainty about the frequency with which a given consequence level or greater occurs. Note that uncertainties in these (Zion, Indian Point) studies was propagated using a discrete probability distribution (DPD) technique [Kaplan, 1981].

The environmental transport and consequence modeling portions of nuclear plant PRAs are done using a computer code called CRAC2 (Calculation of Reactor Accident Consequences). Over the past few years a group of scientists at ORNL have been developing and applying probabilistic methods to analyze uncertainties in the CRAC2 modeling. They have examined the sensitivity of cancer fatality and economic cost predictions to: uncertainties in aerosol particle size and respiratory passage solubility of radionuclides for the inhalation pathway; uncertainties in estimated human intakes or radionuclides for terrestrial foodchain pathways; and alternative models for wet deposition and plume rise [Kocher et al., 1985]. In addition to this work, a group at Sandia National Laboratory have used their Latin Hypercube Sampling code [Iman and Shortencarier, 1984] to examine uncertainty in CRAC2 model parameters (with correlation) [Alpert et al., 1985].

Rish and Mauro present an analysis of offsite doses and mortality risks due to routine airborne emissions from a nuclear power plant wherein key uncertain model parameters are represented by probability distributions that are propagated through the analysis by Monte Carlo simulation [Rish and Mauro, 1982]. Their work is directed at dealing with uncertainties in showing compliance with the NRC's proposed PRA-based quantitative safety goals. Parameters treated as uncertain are:

- the average annual radionuclide release rates (Ci/yr);
- the atmospheric dilution (CHI/Q) and deposition (D/Q) factors;
- the transfer rates of radionuclides from soil to vegetation to milk;

- the inhalation and ingestion whole body equivalent dose conversion factors (rems/micro Ci); and
- the radiation exposure risk coefficient (fatalities per person-rem).

Judgmental probability distributions representing uncertainties about each of these parameters were developed as inputs to the simulation in order to obtain probability distributions representing uncertainty about estimated doses and fatalities. Figs. 6-5a and b and 6-6a and b, reproduced from their study, show the results as cumulative probability distributions (CDFs) representing uncertainty about individual and population whole body doses and mortality risks.

In addition to the nuclear power plant safety (PRA) area, consideration of potential impacts associated with radionuclide releases from other parts of the nuclear fuel cycle have also led to applications of uncertainty analysis. Barr [1974] discusses qualitatively the sensitivity of dose and health effects estimates to uncertainties in the risk analysis for release of transuranium elements to the atmosphere as fine particles from the Liquid Metal Fast Breeder Reactor. Inhalation and ingestion pathways are evaluated.

McKone and Layton [1984] examine the relative magnitude of uncertainty associated with estimating the radiological consequences of routine tritium releases by a generic fusion technology. This paper presents a compartment model that includes information of the distribution of tritium in typical ecosystems and information of the uptake of loose and bound tritium in human metabolism. This information is used to carry out an uncertainty analysis on the radiological consequences of first-generation fusion energy systems. In this analysis, the authors first determine the parameters to which the final results are most sensitive. These parameters, represented by a probability distribution in the form of a histogram, are then propagated through the models to obtain a distribution of the consequences.

In a general investigation of uncertainty treatment in modeling, Gardner et al. [1981] examine the uncertainties of a variety of models of different mathematical forms, including: an atmospheric carbon dioxide model, a marsh hydrology model, a model of plutonium movement in a forested watershed, and a model of food chain transport of iodine [Gardner

et al., 1981]. The authors conclude that: (1) the relative contribution of a parameter to model uncertainty may not be reflected by sensitivity analysis; (2) the mathematical formulation of the model is critical with simpler models often having lower uncertainties; (3) deterministic solutions often give biased predictions, especially when stochastic effects are present; and (4) the models are relatively insensitive to assumptions regarding statistical frequency distributions for uncertain model parameters. Note that a Monte Carlo technique is used to propagate parameter uncertainties in the models examined.

Several studies analyze uncertainty about predictions of food chain transport and dosimetry for radionuclides using a method based on the means and variances of model parameters [Hoffman and Baes, 1979, Dunning and Schwarz, 1980, and Shaeffer, 1981]. The technique used estimates a conservative upper limit for the model output as follows:

"If, say, the parameter of interest  $X$  (e.g., the dose to man) is calculated as the product of radioecological or technical parameters  $X_i$ ,

$$X = X_1 * \dots * X_n ,$$

then first logarithms are taken and

$$X = \exp(Y_1 + \dots + Y_n)$$

with  $Y_i = \log X_i$ . The mean  $m_i$  and the variance  $v_i$  of the log-transformed variables  $Y_i$  are calculated from the observations, and the value

$$\exp(m + 2.326 * v)$$

with  $m = m_1 + \dots + m_n$ ,  $v = v_1 + \dots + v_n$  is presented as a conservative estimate for  $X$ , where the constant 2.326 appearing in the formula is taken from the table of the standard normal distribution." [Sawitzki, 1984]

Sawitzki argues that this procedure is unreliable because it requires assuming a distribution for the input parameter uncertainties, which introduces a systematic bias of under estimation [Sawitzki, 1984]. For nuclear regulatory decisions, Sawitzki recommends a distribution-free approach based on ranks. The results of applying this approach to data on radionuclide pathway model parameters provided in the much-utilized Hoffman and Baes [1979] report are presented in a set of tables.

A great deal of uncertainty analyses are being performed as part of the federal high-level radioactive waste repository program. The problem of predicting the performance of a geologic repository in containing and isolating radioactive waste for tens of thousands of years involves numerous and significant uncertainties. Both the NRC and EPA are requiring in their regulations that repository license applications include explicit consideration of uncertainty about the predicted performance of the geologic repository and its interaction with the environment.

A number of statistically-based sensitivity and uncertainty analysis techniques for repository computer codes have been developed and applied at Sandia National Laboratory. For documentation of the methodological development, see: [Iman et al., 1978, Iman and Conover, 1980, Iman et al., 1980, Iman, 1977, Iman and Shortencarier, 1984, [McKay et al., 1976, and Cranwell and Helton, 1981].

The Sandia group apply these methodologies in a review and evaluation done for the NRC of the then draft EPA Standard 40 CFR Part 191 [Sandia, 1983]. Analyses of hypothetical repositories in three candidate rock media are performed to address the issues of interpretation, achievability, uncertainty, and compliance with respect to the requirements of the draft Standard. An analysis investigating the health effects associated with unit radionuclide releases is performed to ascertain the release limits of the draft Standard and their relationship to the assumed health effects. Calculations of health effects per curie of release are carried out for the purpose of showing the effects of uncertainty in defining the release limits. The release limits in 40 CFR Part 191 are derived by EPA using single point values for the input parameters or variables that are known to have uncertainties. The effect of these uncertainties is evaluated in the Sandia study by performing

calculations in which ranges and distributions are assigned to the distribution coefficients ( $R_d$ ), river discharge, regional erosion rates, and exchange factor between the surface water and soil compartments. These probability distributions (all uniform or lognormal) are propagated through models using Latin Hypercube Sampling simulation. A sample comparison with the EPA calculation is presented in Fig. 6-7, which shows the health effects associated with one curie of a given radionuclide when the ingestion pathways are considered.

In addition to uncertainties about the key model parameters described above, uncertainty in the frequency of occurrence of radionuclide release scenarios are also analyzed. The flow chart in Fig. 6-8 depicts the procedure used to include scenario frequency uncertainty in the repository risk analysis [Ortiz et al., 1984]. This analysis results in a family of "risk curves" (complementary cumulative distribution functions) representing uncertainty about the ratio of predicted releases to the draft EPA release limits (called a "release ratio"), as shown in Fig. 6-9.

The investigators conclude that a practical approach that can take into account uncertainties is available for repository risk analysis; however, the more significant problem is to assign meaningful ranges and distributions to uncertain factors.

In a study done for the Department of Energy and supplemented by the EPA, Rish et al. perform an uncertainty and sensitivity analysis of the river pathways model used by the EPA to derive the 40 CFR Part 191 radionuclide release limits [Rish et al., 1983 and Rish et al., 1985]. Uncertainties about important river pathways exposure model parameters are characterized by probability distributions and these distributions were propagated through the models using a simulation technique. This produced uncertainty distributions for estimates of dose and risk per curie of radionuclide released to a river. In addition, an analysis is performed to determine the sensitivity of dose and risk uncertainty results to the uncertainties about key model input parameters and groups of parameters.

The diagram shown in Fig. 6-10 depicts the structure of the pathways model used by the EPA in support of the standard. The authors review the model and identify the key uncertain input parameters in each portion of the model. These uncertain parameters are listed on Fig. 6-10 under the portion of the model in which they appear.

The uncertainty about each parameter listed in Figure 6-10 is characterized by a probability distribution based on a review of pertinent literature, discussions with experts, and informed judgment. These uncertainty distributions are then propagated through the model using simulation techniques. This uncertainty analysis results in probability distributions representing the overall uncertainty about population dose and mortality risk estimates from the model. An example of these results is shown in Fig. 6-11, which shows uncertainty distributions for the mortality risk per curie of radium-226 released to a river. Similar results are developed for the other radionuclides specified in draft 40CFR191. These results can be used to assess the level of certainty one can have that proposed release limits will result in a specified mortality risk goal. To do this, one simply multiplies the horizontal axis by the curies of interest to convert to associated mortality effects.

In addition to the uncertainty analysis, a number of model sensitivity analyses are performed. These included sensitivity of the model results to: the sampling technique and sample size used, the type of input parameter uncertainty distributions assumed, a range change in the input parameters, and small changes to the input parameters within their uncertainty ranges (elasticity).

Unlike Gardner et al., the authors find that uncertainty analysis results can be rather sensitive to alternative assumptions about the type of probability distribution which best represents the uncertainty about an input parameter. This is illustrated by the results shown in Fig. 6-12, comparing mortality effects uncertainty results for neptunium-237, assuming two different distributions representing uncertainty about the appropriate ingestion dose conversion factor to use in the model. Note that the only difference between the distributions is that for one, it is assumed that in addition to knowing the upper and lower bounds on the parameter there is enough understanding and information to also specify a median value (or "best estimate"); yet, there is a significant difference revealed in the results. It is concluded that this example highlights the need to assure high quality in developing parameter uncertainty distributions for this type of analysis.

In addition to the deterministic sensitivity analyses described above, a probabilistic analysis is done to assess the sensitivity of the dose and effects uncertainty distribution outputs to eliminating uncertainties about individual input parameters and groups of parameters. The purpose of this uncertainty sensitivity analysis is to determine the relative contributions of important input parameter uncertainties to the overall uncertainty in dose and risk estimates from the model. Fig. 6-13 shows results for neptunium-237 which illustrate the method used. Each key uncertain input parameter is fixed at this median value, and, keeping all other uncertain parameters as distributions, the simulation is run. The results, when compared to the simulation results obtained with all parameters input as uncertainty distributions, indicate the reduction in overall model output uncertainty from eliminating the uncertainty in the particular input parameter being analyzed. Thus, Fig. 6-13 shows the reduction in overall mortality effects uncertainty from eliminating the uncertainty about the ingestion dose conversion factor for neptunium-237.

One important conclusion of the study is that it is important to assure high quality in the input parameter uncertainty distributions used in an uncertainty analysis. The validity of the results depends directly on the quality of the input uncertainty characterizations and the results are quite sensitive to the type of distributions assumed. Careful consideration must be given to the implications of using a particular probability distribution to represent a state of knowledge. The authors recommend that the process of developing the input uncertainty distributions should include at least one expert in the technical aspects of the model and its parameters, an analyst experienced in the techniques and problems of characterizing uncertainties and independent expert review. Giuffre et al. [1980] also employ a Monte Carlo-type propagation approach to examine the effect of parameter uncertainty on predictive modeling of the performance of a hypothetical geologic repository for high-level radioactive waste in bedded salt rock. A potentially significant waste release scenario and a selection of parameters likely to have an effect on repository performance are chosen for analysis. Two "case studies" are developed to describe a poorly-characterized repository with wide uncertainty bounds and the same repository with the regional hydrology better known. A comparison of the results from the case studies

is used to provide information on the effect that the state of knowledge of the regional hydrology barrier has on the uncertainty of repository performance.

Lognormal probability distributions are assumed to represent uncertainty in all important uncertain model parameters. The output measures examined are:

- Peak 50-yr individual dose (rem)
- Time of peak 50-yr individual dose (yr)
- Peak population dose (man-rem/yr)
- Time of peak population dose (yr)
- Integrated population dose (man-rem)
- Peak Flow rate of radioactivity (Ci/yr)
- Time of peak flow rate of radioactivity (yr)

The summary statistics of the outputs for each case are calculated and are presented in Figure 6-14. The "interquartile spread" is one-half the difference between the 75<sup>th</sup> and 25<sup>th</sup> percentile values.

Several other studies are available that examine the effect of input parameter uncertainties on model output uncertainty for high-level waste repository performance models. Giuffre and Nalbandian evaluate several Monte Carlo and numerical analytic techniques to estimate system uncertainty for predicted groundwater flow times. Each technique was constrained to use only about 200 system evaluations because in repository analyses these evaluations are often quite costly. The results show that the Monte Carlo techniques yield reasonable estimate of system uncertainty. The numerical analytic techniques failed because of the severely "spiked" integrands that must be evaluated. Figure 6-15 shows the results for the Monte Carlo propagation technique examined.

Kocher et al. [1981] summarize estimates of potential uncertainties in the separate components of a calculation of long-term population dose and health effects resulting from a known release of plutonium to a freshwater surface-water system. The components discussed include: (1) radionuclide concentrations in the surface waters; (2) intake by an exposed individual per unit concentration in surface waters; (3) dose to an individual per unit intake; (4) size of the exposed population and its age distribution; and (5) the incremental cancer risk per unit population

dose. For each component the authors discuss an uncertainty based on the range of possible values indicated by available data and an uncertainty based on an expected distribution of values about the mean for the exposed population. The analysis emphasizes significant uncertainties in the fraction of ingested plutonium absorbed into blood from the gastrointestinal tract and the risk factor for induction of bone cancer by alpha-particle irradiation.

The analysis emphasizes estimates of the potential uncertainty in each of the five separate components listed above for the purpose of identifying those components whose uncertainty contributes significantly to the overall uncertainty in the number of health effects per unit release. No attempt is made, however, to rigorously combine the separate uncertainties to obtain a proper estimate of the uncertainty in health effects. Rather, the largest uncertainties in the separate components are used to provide semi-quantitative estimates of potential uncertainties in population dose and health effects.

Two different types of uncertainties are discussed in this paper. For the first, the uncertainty is described by the range of possible parameter values obtained from available data. The authors state that this type of uncertainty is appropriate if the primary concern is estimation of any potential effects which might be experienced by any exposed individual. They point out, however, that the range tends to emphasize extreme parameter values which may occur only with very low probability in an exposed population, particularly if the data on which the range is based are extensive. The authors also consider a second type of uncertainty described by the distribution of values about the mean experienced by the exposed population, e.g., the standard deviation. They stated that this measure of uncertainty is appropriate if the primary concern is estimation of collective dose and health effects. Figure 6-16 shows the results for estimated uncertainties in separate components of the health effects calculation for plutonium.

Another approach to examining uncertainties in repository modeling, that of doing parametric analyses of uncertain parameters, is presented by Parker and Ichel [Parker and Ichel, 1981].

A simplified mathematical model is developed to screen potential mined geological repository sites taking into account the uncertainty in the input data. Initial input data that are assumed constant are: inventory of radioactive wastes, number and size of canisters, size of repository, and the groundwater flow area. Though there is some uncertainty in these data, by far the greatest uncertainty pertained to leach rate of the waste form and canister, ground water velocity, retardation rates of nuclides relative to ground water, distance to the biosphere, and flow rate in the receiving waters in the biosphere. These are varied over realistic ranges from one to four orders of magnitude. The results show that there are a wide variety of combinations of these parameters that allow a waste repository to be sited without exceeding the maximum permissible concentrations of isotopes in drinking water. It is concluded that for the artificially-created nuclides it is the intermediate time period, greater than 1,000 years and less than 1 million years, that poses the greatest problem. Examples of the results for predicted Pu-239 and I-129 concentrations in groundwater are shown in Figs. 6-17 and 6-18.

Sutcliffe et al. [1981] analyze uncertainties in repository models in yet another manner, by a combination of parametric analysis and propagation by a discrete probability distribution-type method. Discrete probability type method involves the following steps:

- associating probability distributions with the model parameters;
- computing probability distributions of the performance variables by using the system model; and
- perturbing the distributions and observing the effect on the performance distributions.

The probability distributions were computed by:

- dividing the input and output variable spaces into finite intervals;
- computing the output values for every combination of input values (each variable interval is given a representative value); and
- summing the probabilities of input variable combinations to the appropriate output variable interval.

The discretizing process used is depicted in Fig. 6-19. Results of the propagation using these discretized distributions are shown in Fig. 6-20.

The Office of Nuclear Waste Isolation (ONWI) at Battelle Memorial Institute is using a number of statistical techniques to analyze (1) the uncertainty inherent in data collected on potential repository sites and (2) the important sensitivities and uncertainties in repository performance models [ONWI, 1985]. A geostatistical technique called "Kriging" is being applied to analyze spatial uncertainty in hydrologic data. Kriging uses the spatial correlation structure of data collected, modeling the structure by visual fit, to derive the means and standard deviations of parameters distributed in space. This is necessary due to uncertainties resulting from limitations on measurements that can be obtained spatially at a site (measurements such as stratigraphic parameters and pressure heads).

Important uncertain model parameters are being identified by subjecting performance models to an "adjoint sensitivity analysis" [INTERA, 1983]. The adjoint technique, facilitated by the computer code GRESS [Oblow, 1983], involves deriving the partial derivatives of model output to model inputs. This results in a response surface showing dynamic sensitivities with correlation. A limitation of this approach is that the partial derivatives are valid around minor perturbations to the specified design case analyzed, especially where model response is non-linear to input parameter changes. Once a set of adjoint equations are derived for a comprehensive set of critical design cases, then Taylor series expansions can be used to obtain estimates of model uncertainty. ONWI intends to use a Latin Hypercube Sampling (LHS) simulation technique to propagate important input parameter uncertainties through repository performance models, where important uncertainties will be identified by the adjoint sensitivity analyses. Input parameter uncertainty distributions will be developed by combining statistical analyses of measured data supplemented with elicited expert judgments. A comparison of the LHS approach to the adjoint sensitivity approach as applied to a model of radionuclide releases from a borehole into the repository is available [Harper and Gupta, 1983].

Finally, in the high-level waste repository area, Rockwell International is involved in applications of probability encoding of expert opinions on uncertainty in hydrologic parameters for basalt rock [Runchal et al., 1984], and in propagating model parameter uncertainties through groundwater travel time models [Clifton, 1985]. The Stanford Research Institute technique for expert probability encoding of uncertainties [SRI, 1979] is used to elicit probability distributions representing expert opinions on hydrologic parameter uncertainties for basalt rock [Runchal et al., 1984]. Results for effective porosity and anisotropy ratio parameters are reproduced in Figs. 6-21 and 6-22. Comparisons of "internal" Rockwell experts and "external" independent experts are shown.

Uncertainty about predicted groundwater travel time in basalt rock is quantified in another study [Clifton, 1985] by propagating probability distributions for model input parameter uncertainties using a Monte Carlo technique. The uncertainty analyses are combined with parametric analyses on key assumptions about parameter correlations and on model geometry. Example results from the study are reproduced in Figs. 6-23 and 6-24.

Assessing and regulating the environmental and human health risks associated with air pollution is another area where a significant amount of application of uncertainty analysis has been done.

North and Merkhofer [1976] present a methodology for analyzing emission control strategies for sulfur oxide emissions from coal-fired electric power plants. Alternative strategies for controlling sulfur oxide emissions from representative coal-fired electric power plants are evaluated both in terms of their economic and environmental impacts. A framework is provided for converting environmental impacts to human health, ecological, aesthetic, and material damage costs borne by society. A comparison of these costs to the costs of pollution control provides the basis for choice among available strategies. Existing uncertainties in health effects and SO atmospheric transport and conversion are explicitly represented. These uncertainties are shown to be crucial to the decision among control strategies. Computations show the resolution of these uncertainties to be worth hundreds of millions of dollars per year.

The authors subjectively estimate the extreme high and low values for a number of parameters governing the prediction of ambient sulfate levels, exposures and health costs resulting from sulfur oxide emissions. They assume that these extreme values represent approximately the 5% and 95% points on cumulative probability distributions for uncertainty in the parameters. These distributions are propagated through the analysis to produce cumulative probability distributions for uncertainty in ambient sulfate concentrations (reproduced in Fig. 6-25) and health cost per unit increase in sulfate concentration (reproduced in Fig. 6-26).

Since the mid-1970s, a group of researchers at Carnegie-Mellon University and Brookhaven National Laboratory (BNL) have been developing and applying methods for analyzing uncertainty to estimating the health risks of sulfur air pollution from coal-fired power plants. In the mid-1970s, Morgan et al. [1978a and b] performed an analysis of uncertainty in the local health impacts of sulfur air pollution from coal-fired power plants using self-developed subjective probability distributions based on a careful reading of the literature to characterize the uncertainty in model coefficients. The authors employ Monte Carlo simulation to propagate this uncertainty through to the model output. Subjective probability distributions reflecting present knowledge of the value of each parameter are used with a model that assumes Gaussian plume dispersion, linear chemistry, and a linear functional relationship between air pollution levels and health damage. A stochastic simulation is employed to generate the probability density functions for excess mortalities and person-years lost per year of plant operation, for four hypothetical but realistic coal-fired electric power plants located in the Ohio River Valley. Example results from the study are reproduced in Figs. 6-27 and 6-28. This work had considerable impact, particularly within the health impact assessment programs of DOE [Morgan et al., 1983 and DOE, 1983], where it began to be used by the DOE in their Health and Environmental Risk Assessment Program. The investigators, however, recognize several limitations in the study. These include the fact that it uses a local impact model which does not consider long-range transport, that by 1979 some of the subjective probability distributions used had become out of date, and that the models do not allow one to easily explore the implications of the range of existing expert opinions [Morgan et al., 1982].

In 1979, Morgan et al. [1981] ran a small invitational workshop at BNL on "problems and research needs in eliciting and using expert judgments for policy analysis involving energy and environmental systems." On the basis of this workshop, they developed a protocol for eliciting quantitative expert judgments about uncertain technical factors in an analysis [Morgan et al., 1982].

In follow-on work, Morgan et al. conduct interviews with a set of leading atmospheric scientists to obtain their conceptual models for plume sulfur transport and chemistry, and to elicit the necessary subjective probability distributions for uncertain model parameters. These models and distributions are used to analyze uncertainty in estimates of sulfur mass balance associated with a power plant plume as a function of time [Rish, 1982 and Morgan et al., 1982]. Fig. 6-29, reproduced from the work, shows probability density functions of the fraction of sulfur present as  $\text{SO}$  and  $\text{SO}^{\text{---}}$  as a function of flight time for one atmospheric expert. The model is also run to estimate the total sulfur mass balance as a function of flight time. When this is done for each expert, the results allow a direct comparison of the conclusions and uncertainties associated with each expert's opinions, as can be seen in Fig. 6-30.

The authors extend this mass balance uncertainty analysis by eliciting models and uncertainty distributions from a set of leading air pollution health experts, then coupling the mass balance model with an exposure and health effects model to quantify uncertainty about health risks. Fig. 6-31, reproduced from a recent overview of the work [Morgan et al., 1984], summarizes the final results obtained. The authors conclude that "from that one can set a fairly high upper bound on the possible health impacts of chronic exposure to low-level sulfate air pollution. Between this bound and the lower limit of no effect, there is no agreement across the set of air pollution health effects experts about the likely health impacts of sulfate. Within this group one can get almost any answer, including the answer that with 100 percent probability there are no adverse health impacts, depending upon which expert one talks to."

In 1978, the EPA Office of Air Quality Planning and Standards (OAQPS) began an ongoing program to incorporate uncertainty analysis into their ambient air quality standard-setting process. Nelson [1979] describes two

approaches to evaluating uncertainties in adverse health effects from exposures to sulfates and photochemical oxidants--one qualitative approach and one quantitative. In his qualitative approach, he organizes in tables the state of information available from epidemiological, clinical, and toxicologic studies on adverse health effects attributable to exposures. He also organizes in a table the current beliefs about some key characteristics of the damage function for the pollutant.

Nelson also describes a quantitative approach to uncertainty about the health effects of ozone being applied by the EPA OAQPS in their risk assessments for ambient ozone standard-setting [EPA, 1978]. The approach involves eliciting from health experts probabilities of various health effects for different levels of ozone concentration. The effects evaluated are:

1. reduction in pulmonary function,
2. increased cough, chest discomfort and mucous membrane irritation, and
3. aggravation of asthma, emphysema, and chronic bronchitis.

Examples of the elicited probability distributions are shown in Fig. 6-32.

The OAQPS continue to develop their approach to incorporating uncertainty in air pollution exposure and risk assessment as part of the National Ambient Air Quality Standards (NAAQS) program by presenting, in 1981, a general method for assessing health risks that involves a concerted effort to quantitatively treat uncertainties in the assessment and standard-setting processes [Feagans and Biller, 1981]. Uncertainties in pollutant concentrations in space and time, human migration patterns and subsequent exposures, and dose-response relationships are being treated. Subjective probability distributions are being elicited from experts about key uncertain factors in the risk analysis. For example, Fig. 6-33 shows a cumulative probability distribution for uncertainty about an indoor-to-outdoor multiplication factor, developed from the literature [Richmond and McCurdy, 1985]. EPA has already relied on exposure estimates generated as a result of this program in its review of the carbon monoxide and sulfur dioxide NAAQS [Johnson and Paul, 1983, Paul and Johnson, 1985, and Biller et al., 1984]. EPA's first on-line application of the risk assessment approach for NAAQS is currently underway for the lead (Pb) NAAQS review through an interagency agreement

with Argonne National Laboratory [Wallsten and Whitfield, 1985]. The Clean Air Scientific Advisory Committee (CASAC), part of EPA's independent Science Advisory Board, has been involved in the review of EPA's lead risk assessment efforts. The EPA is currently using the approach in reviewing the ozone ambient air quality standard [Richmond and McCurdy, 1985]. The CASAC will also play an important role in reviewing and advising OAQPS on the ozone exposure and risk assessment projects now underway.

As an example of the type of uncertainty treatment being done as part of this program, a technique for encoding expert subjective probabilities regarding dose-response functions has been developed, and experts on ozone and lead health effects have been elicited [Wallsten et al., 1983 and Wallsten and Whitfield, 1985].

As part of the technical support for their "Proposed Guidelines for Exposure Assessment" [EPA, 1984b] the EPA Office of Health and Environmental Assessment commissioned Whitmore to develop a methodological approach to characterizing uncertainty in exposure assessments [Whitmore, 1984]. The methodology recommended depends on the underlying parameters being estimated, the type and extent of data available, and the estimation procedures used. Methods for uncertainty characterization are presented for the following categories:

- ASSESSMENTS BASED UPON LIMITED INITIAL DATA
  - Limited Data for Directly measured Exposures
  - Limited Data for Model Input Variables
- ASSESSMENTS BASED UPON ESTIMATION OF INPUT VARIABLE DISTRIBUTIONS
  - Estimation of Input Variable Distributions
  - Limiting Distributional Results
- ASSESSMENTS BASED UPON DATA FOR MODEL INPUT VARIABLES
  - Interval Estimates of Exposure Percentiles - Input Variable Distributions Not Known
  - Interval Estimates of Exposure Percentiles - Input Variable Distributions Known
- COMBINING OVER SOURCES, PATHWAYS, AND/OR ROUTES FOR A SUBPOPULATION
  - Combining Estimated Exposure Distributions
  - Limiting Distributional Results
- COMBINING OVER SUBPOPULATIONS.

The study provides a simple hypothetical example of a sequence of exposure assessments with a characterization of uncertainty for each. The sequence begins with an assessment based upon limited initial data and ends with an assessment based on sufficient monitoring data to validate and/or empirically estimate a model.

The example is an assessment of human exposure via soil ingestion of TCDD (specifically 2,3,7,8-TCDD) resulting from TCDD contaminated soil located in an unsecure disposal site such as a sanitary landfill. Figs. 6-34 and 6-35 are examples of results from this case study.

Several recent applications of uncertainty analysis to human dose-response modeling are available. Morris et al. [1984] present a probabilistic approach to dealing with uncertainties encountered when interpreting and extrapolating the results from animal experiments to man in cancer risk estimation. An example is provided: estimating human cancer risk from an average exposure to benzo-a-pyrene (BAP). Examples are given showing distributions of effects from different models combining data from four studies of BAP.

Strom and Crawford-Brown [1984] characterize probabilistically the uncertainties in using in-vivo lung counting and urinalysis bioassays to assign radiation doses to workers. They also develop characterizations of uncertainty when air monitoring data are used to estimate dose.

Mauskopf and Curtis-Powell [1985] present a methodology designed to estimate the health damages attributable to unregulated disposal of toxic chemicals and illustrate the use of this methodology on three waste streams: one containing a carcinogenic chemical and two containing other toxic chemicals. An uncertainty analysis of the result is also presented.

The adverse health effects for a carcinogenic chemical are estimated assuming a linear, no threshold dose-response relationship and dose-response constants derived from estimates of the Very Safe Dose (VSD) for the chemical. A life table model is used to estimate the expected number of excess cancer cases attributable to the chemical exposure and the timing of these cases relative to onset of exposure. For the non-carcinogens, the adverse health effects are quantified simply as the number of person years of exposure at various levels above the Acceptable Daily Intake (ADI). An uncertainty analysis is performed for each waste stream using the Modular Uncertainty System Emulator (MOUSE) computerized system.

The model used to estimate the excess cancer cases attributable to 20 years unregulated disposal of the hazardous chemical is given by:

$$\text{Cancer cases} = \frac{\sum}{\text{AG}} \text{POP} \times \text{WT} \times \frac{(\sum \text{PRA} \times \text{EI})}{\text{T}}$$

where

- $\frac{\sum}{\text{AG}}$  = the sum over 9 population age groups, 0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80-89
- POP = the total number of people exposed
- WT = is the proportion of exposed persons in each age group
- $\frac{\sum}{\text{T}}$  = the sum over the remaining years of life for each age group
- PRA = the probability of being alive at each age
- EI = the excess bladder cancer incidence rate attributable to exposure to 3,3'-dichlorobenzidine

The excess cancer incidence rate for each year is estimated using the relationship:

$$\text{EI} = \text{IN} \times \sigma \times \alpha \times \text{TF}$$

where

- IN = the baseline bladder cancer incidence rate when there is no exposure to the hazardous chemical
- $\sigma$  = the dose response constant
- $\alpha$  = the concentration of the hazardous chemical 3,3'-dichlorobenzidine in the well water
- TF = the appropriate time factor as derived above

In their work to develop radioepidemiological tables, the NIH [1985] estimate the magnitudes of various sources of uncertainty and propagate them through calculations of probability of causation of various forms of cancer from radiation exposures [NIH, 1985]. Uncertainties are estimated as geometric standard deviations of assumed lognormally distributed

available data, or by subjectively assigning upper and lower bound estimates to a parameter then assuming this range to be the 95% confidence interval for a lognormally distributed distribution. Figure 6-36 shows a table from the report summarizing the uncertainty quantifications. Combining uncertainties is done by assuming the output uncertainty is also lognormally distributed and a product of K independent parameters, then using:

$$\ln^2 S = \ln^2 S_1 + \dots + \ln^2 S_K$$

Finally, an interesting project is ongoing at the Office of Science and Technology Policy that involves making explicit the scientific bases and data underlying the assumptions used in risk assessment by federal agencies [Scott, 1985]. Initially, the Federal agencies were asked to provide the assumptions most commonly used in their risk assessments. Those which had a common theme were melded to form a single statement. The resultant list has 16 assumptions. The second step has been to locate all the supporting databases which can be found in the earlier phase of the project and their own expertise in the field. Each assumption will be addressed by three or four reports. Panels drawn from experts in the field will be asked to synthesize a single paper from the several reports. This paper will be a consensus view of the quality and depth of the database underlying each assumption. In addition to providing a survey of the science behind the risk assessment process, the papers will point to areas where further research is needed.

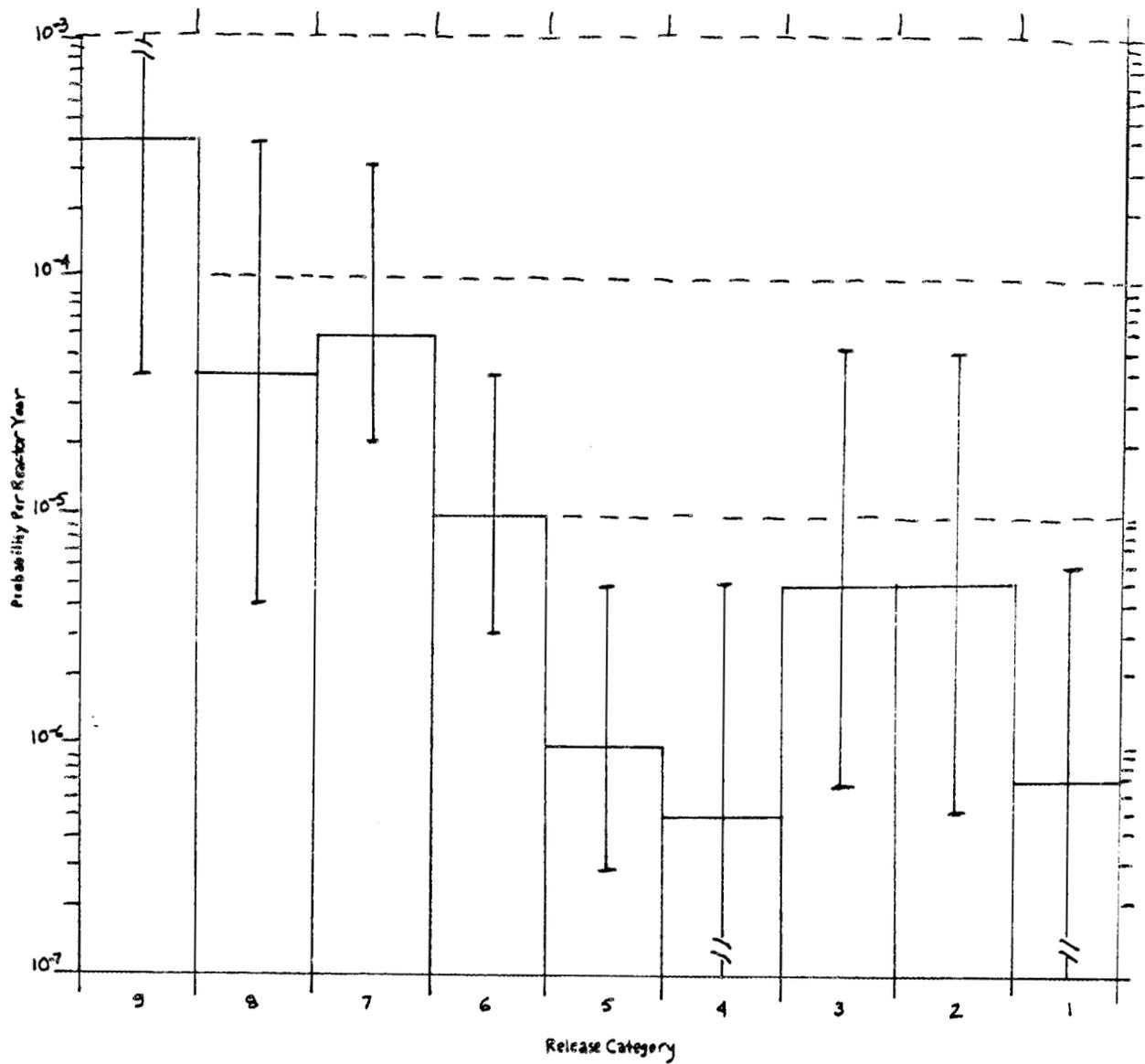
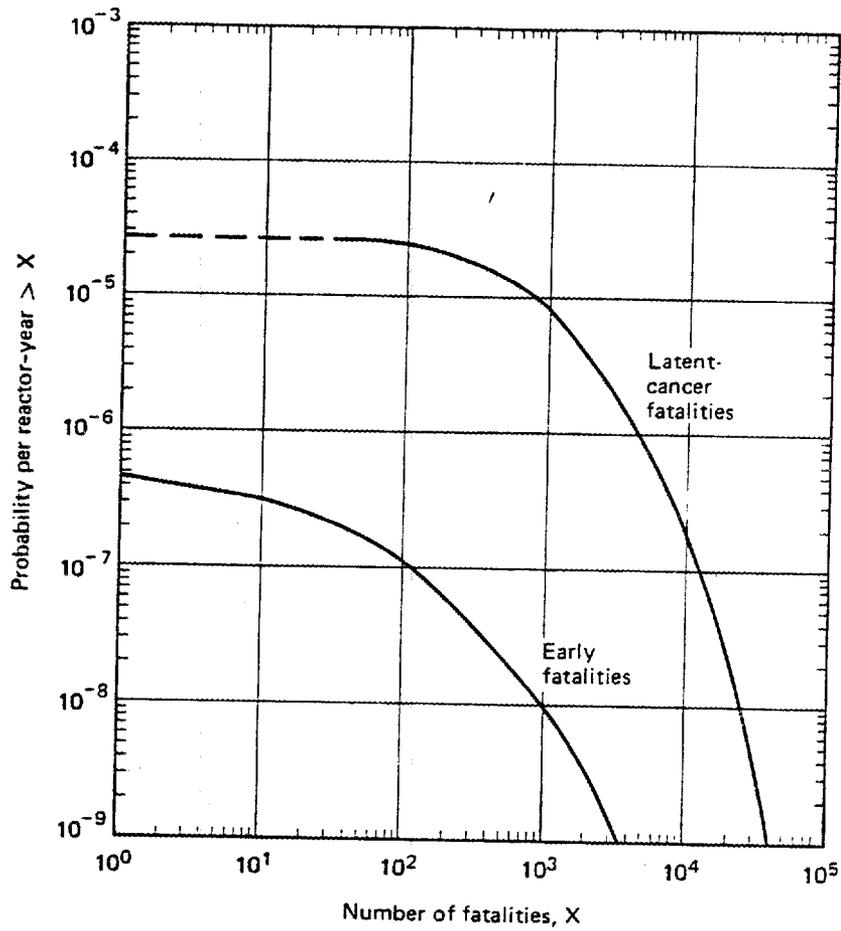


FIGURE 6-1: Histogram of PWR radioactive release probabilities showing uncertainty "bars" -- from [NRC, 1975].



Note: Approximate uncertainties are estimated to be represented by factors of 1/4 and 4 on consequence magnitudes and by factors of 1/5 and 5 on probabilities.

FIGURE 6-2: Risk curves for early and latent fatalities per reactor-year -- from [NRC, 1975].

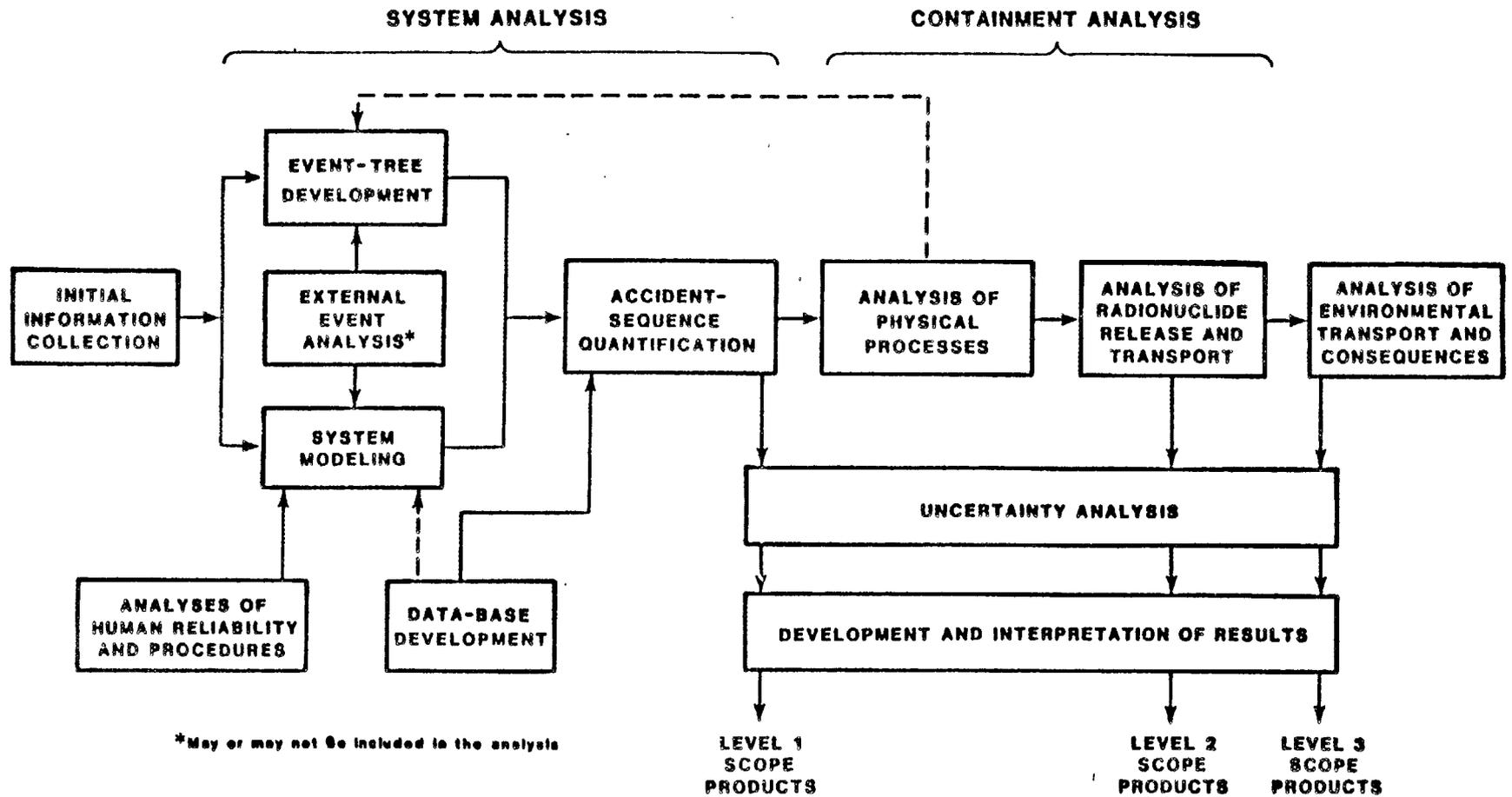


FIGURE 6-3: Diagram depicting probabilistic risk assessment (PRA) process--from [NRC, 1984].

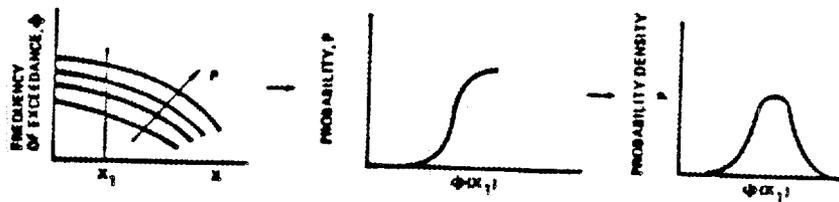
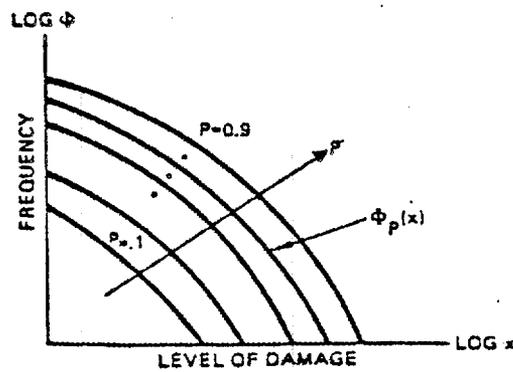
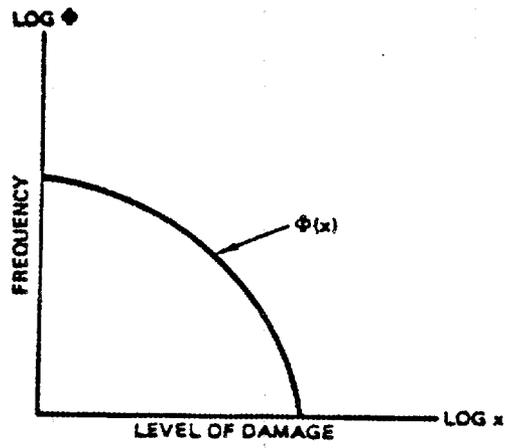
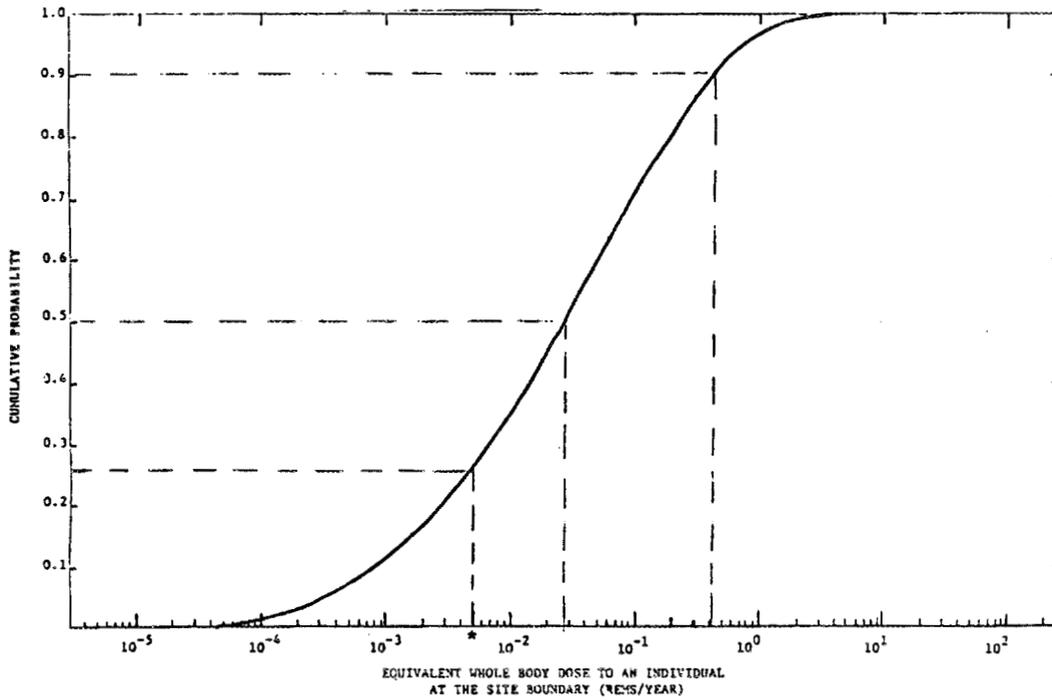


FIGURE 6-4: (a) risk curve, (b) family of curves showing uncertainty about risk, and (c) development of "cut curves" showing uncertainty about frequency at a specified damage level.

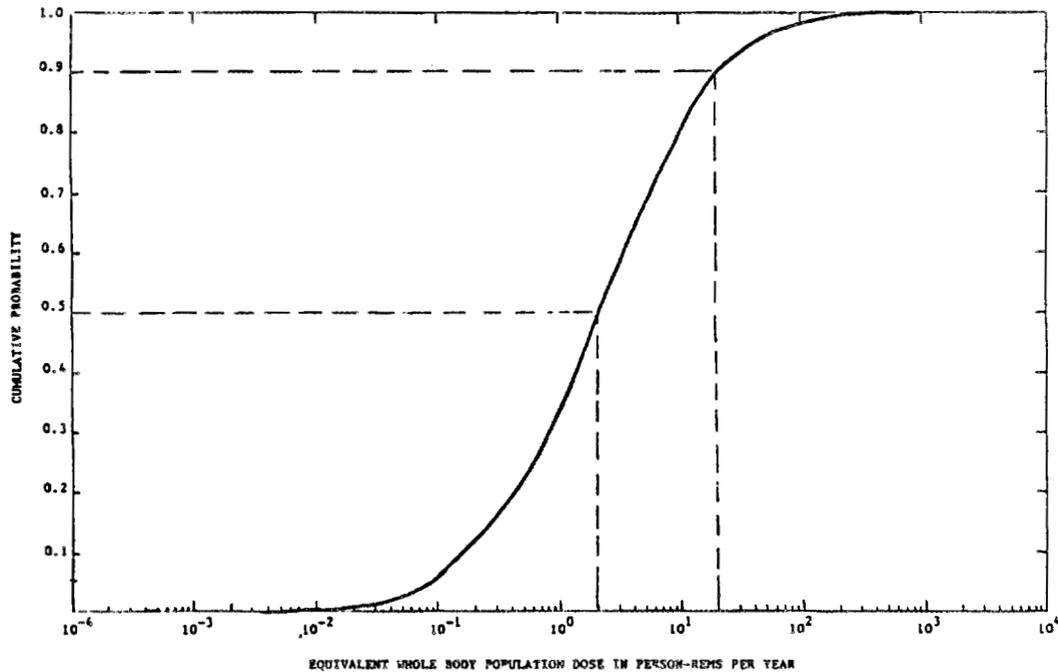
CUMULATIVE PROBABILITY DISTRIBUTION REPRESENTING UNCERTAINTY  
ABOUT THE ESTIMATED ANNUAL EQUIVALENT WHOLE BODY DOSE  
TO AN INDIVIDUAL AT THE SITE BOUNDARY



(A)

\*5 millirems/yr

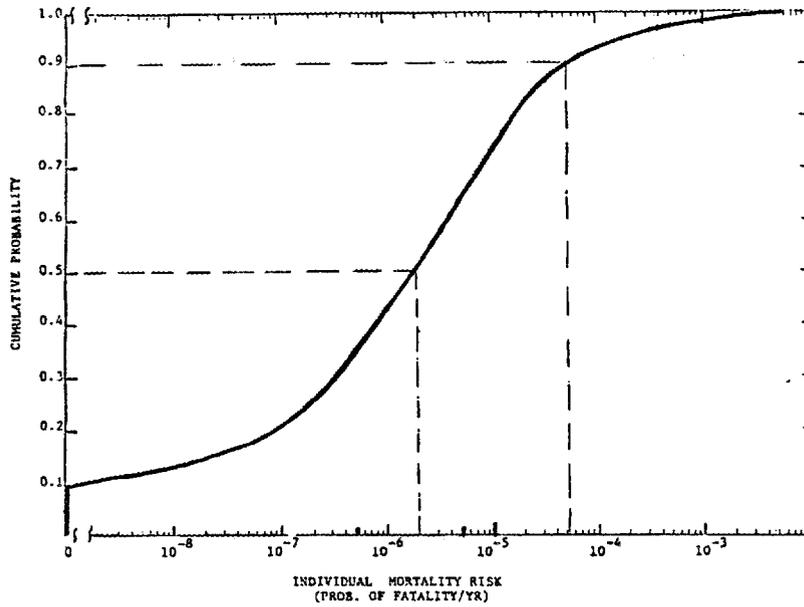
CUMULATIVE PROBABILITY DISTRIBUTION REPRESENTING UNCERTAINTY  
IN THE ESTIMATED ANNUAL EQUIVALENT WHOLE BODY DOSE  
TO THE POPULATION WITHIN 50 MILES



(B)

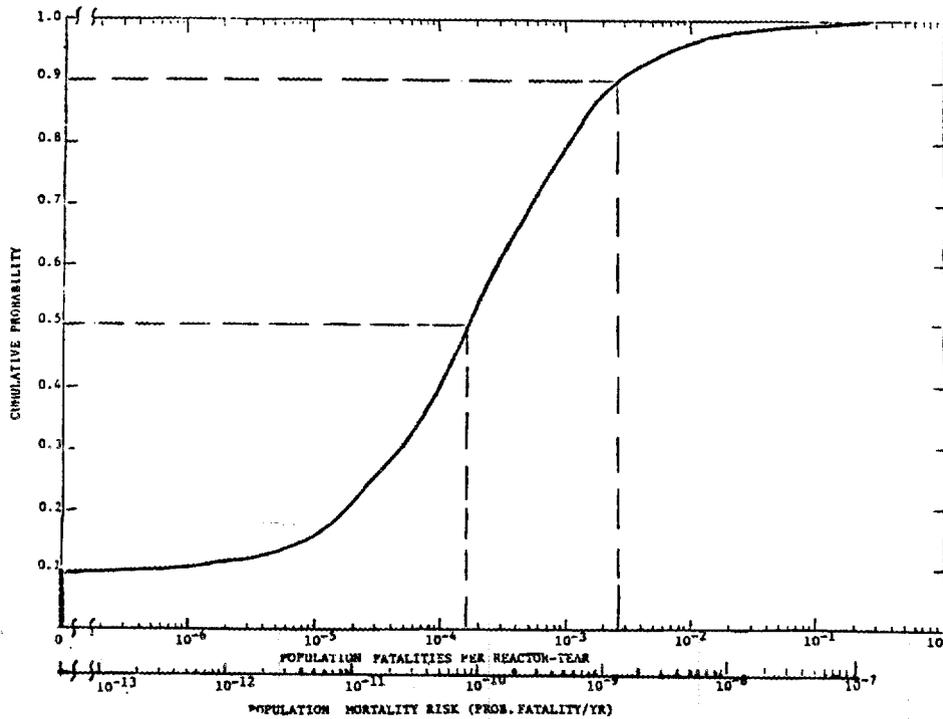
FIGURE 6-5: Probability distributions showing uncertainty in doses from routine PWR nuclear plant air emissions [Rish and Mauro, 1982].

UNCERTAINTY IN INDIVIDUAL ANNUAL MORTALITY RISK  
FOR ROUTINE AIRBORNE EMISSIONS FROM BASE CASE PWR



(A)

UNCERTAINTY IN POPULATION ANNUAL MORTALITY RISK  
FOR ROUTINE AIRBORNE EMISSIONS FROM BASE CASE PWR



(B)

FIGURE 6-6: Probability distributions showing uncertainty in mortality risks from routine PWR nuclear plant air emissions [Rish and Mauro, 1982].

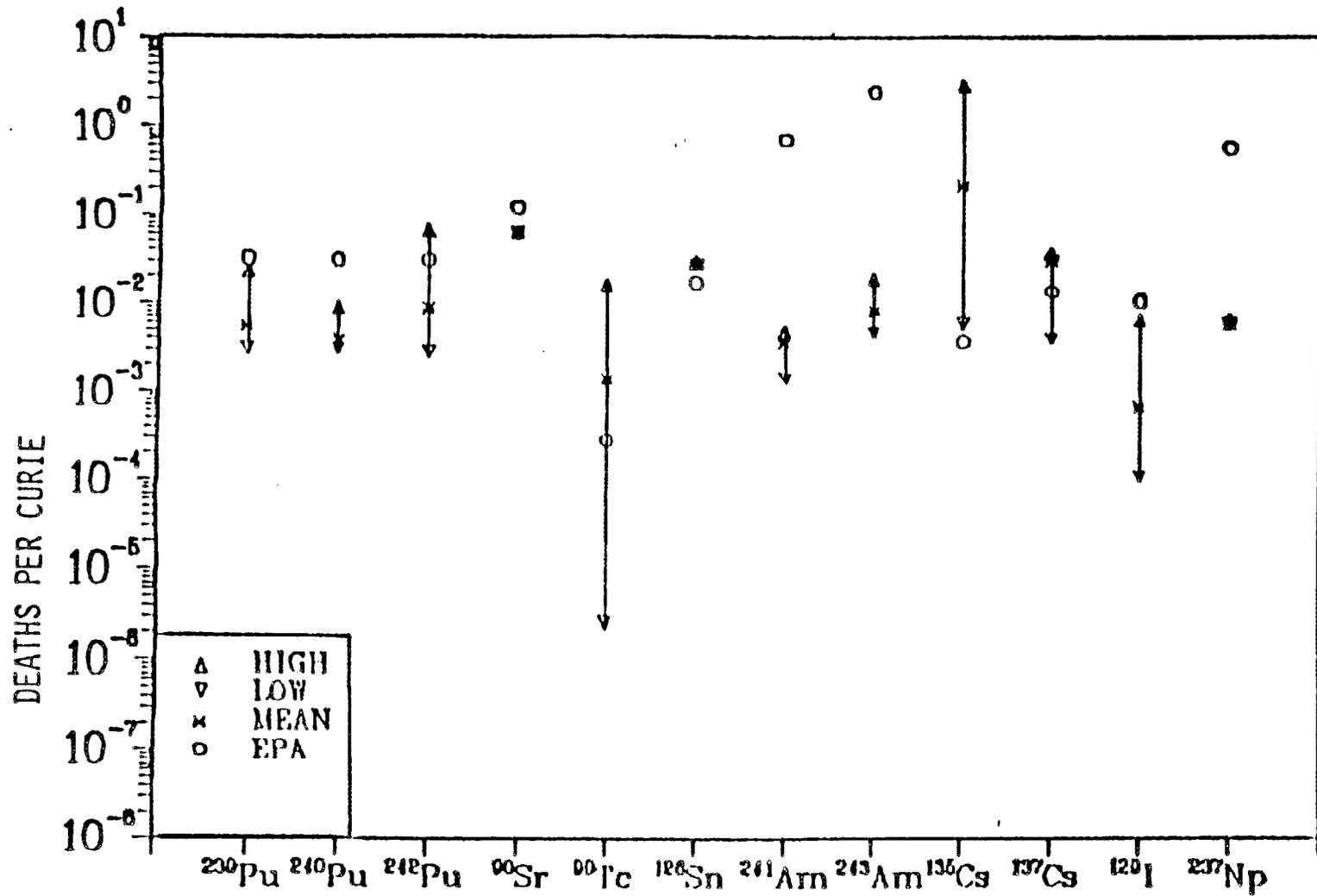


FIGURE 6-7. Mortality risk associated with one curie release for ingestion pathways model used by EPA to derive draft 40CFR191 release limits. Uncertainty bars are shown--from [Sandia, 1983].

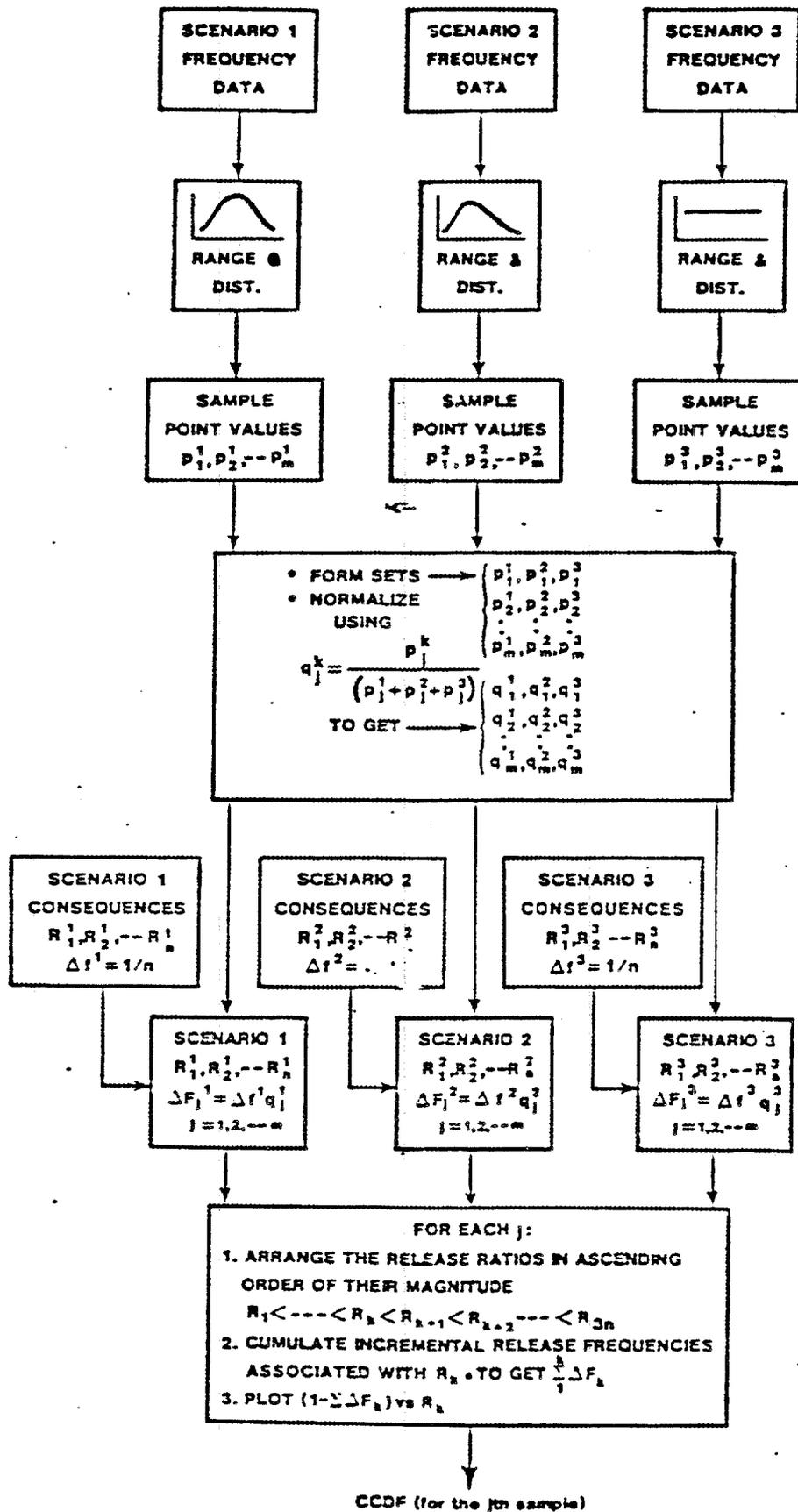


Fig. 6-8. Flow chart for CCDF (complementary cumulative distribution function) construction including uncertainty in scenario frequency--from [Ortiz et al, 1984]. Process used by Sandia in review of 40CFR191 modeling.

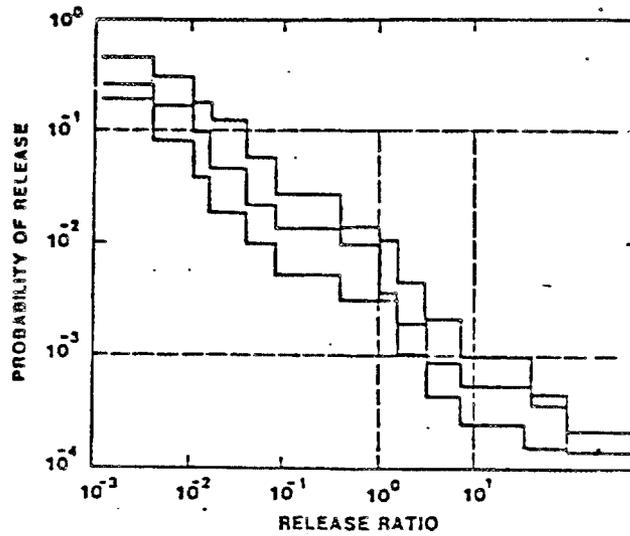


Fig. 6-9. Family of risk curves showing effect of uncertainty in scenario frequencies--from [Ortiz et al., 1984]. Sandia review of 40CFR191.

## STRUCTURE OF EPA MODEL AND KEY UNCERTAIN PARAMETERS

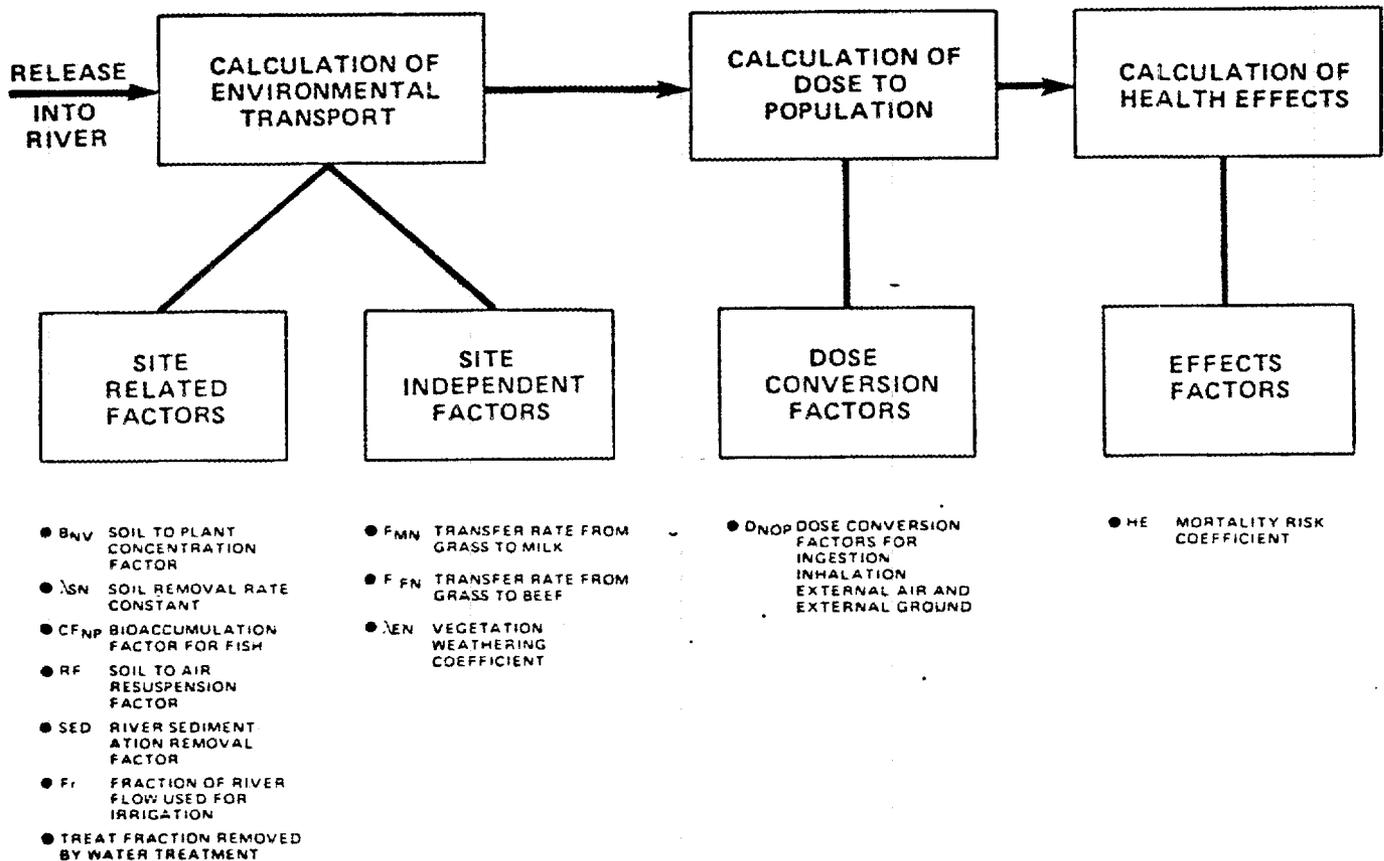
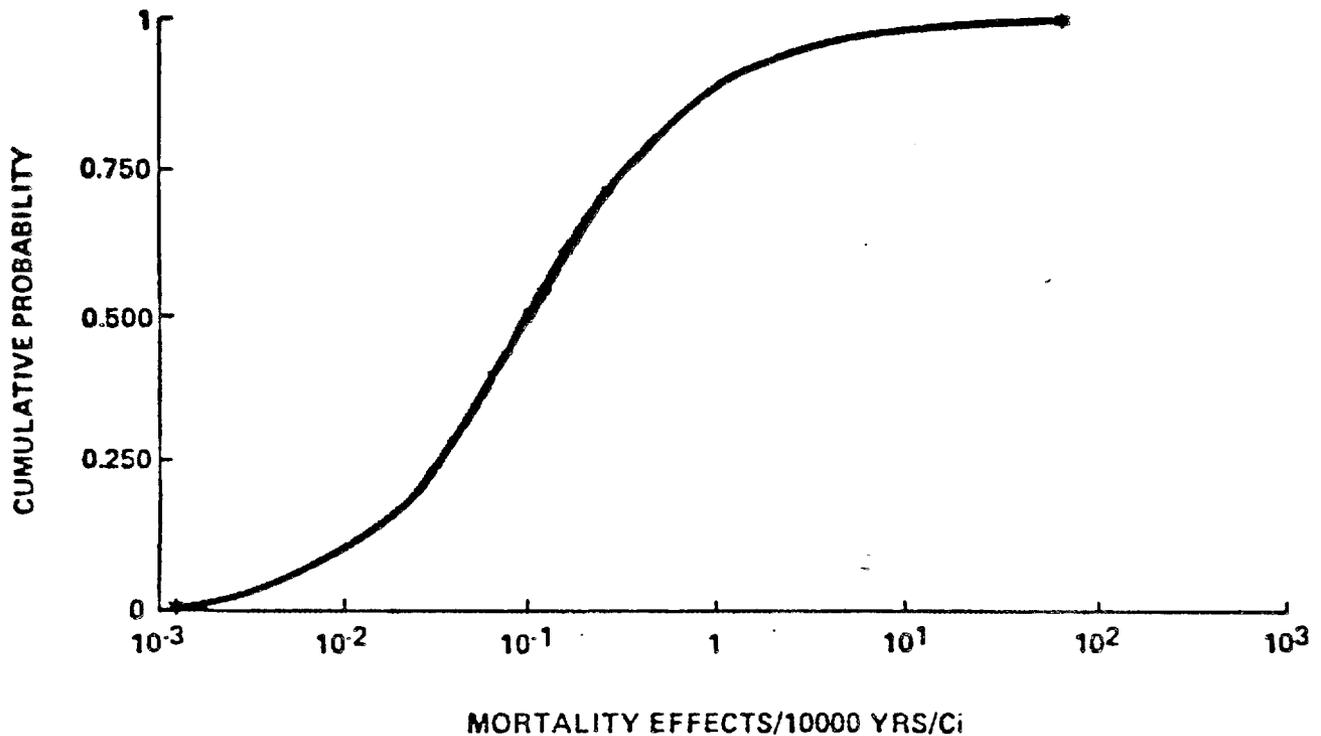


Fig. 6-10. Structure of EPA river release model used to derive 40CFR191 release limits--from [Rish et al., 1983]. Key uncertain parameters are shown.



RA-226 summary of uncertainty distributions  
used for exposure pathways model parameters

Parameter	Type of Distribution	Lower Bound	Median	Upper Bound	EPA Values
Drop - ingestion	Lognormal	1.4E6	1.3E6	1.3E8	6.2E6
Drop - inhalation	Lognormal	3.3E2	3.0E6	3.5E8	7.3E6
Drop - external ground	Lognormal	2.7E4	2.0E5	1.5E6	N.A.
Drop - external air	Lognormal	1.4E6	1.0E7	7.6E7	N.A.
B <sub>av</sub>	3 point subjective	2.0E-5	4.0E-2	6.0E-1	1.5E-2(veg) 6.4E-4(prod)
F <sub>mn</sub> (milk)	3 point subjective	1.0E-4	4.0E-4	7.0E-4	4.5E-4
F <sub>fn</sub> (beef)	3 point	0.0	5.0E-4	2.0E-3	5.0E-4
Bioaccumulation factor	Uniform	1.0E1	1.0E2	2.0E2	50
λ an	Lognormal	1.2E-3	1.0E-2	8.5E-2	1.8E-3
Sedimentation factor	Point	--	1.0	--	1.0

Fig. 6-11. Uncertainty in model inputs and resulting probability distribution showing uncertainty about mortality risk estimate from EPA 40CFR191 modeling of one curie RA-226 to river--from [Rish et al., 1985].

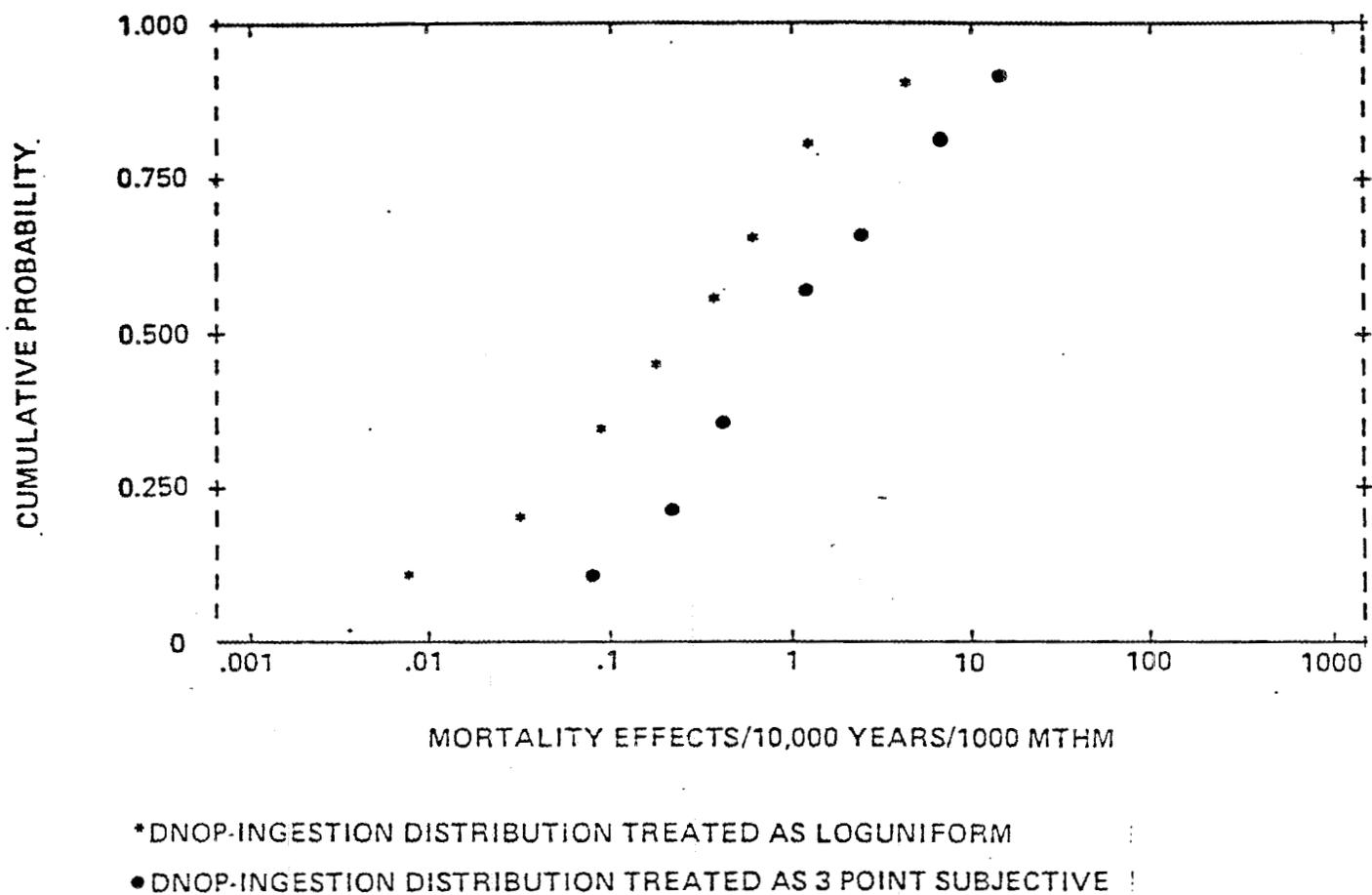


Fig. 6-12. Probability distributions showing uncertainty about mortality risk estimate from 1 curie of Np-237 released to a river-sensitivity to shape of DNOP-ingestion uncertainty distribution--from [Rish et al., 1983].

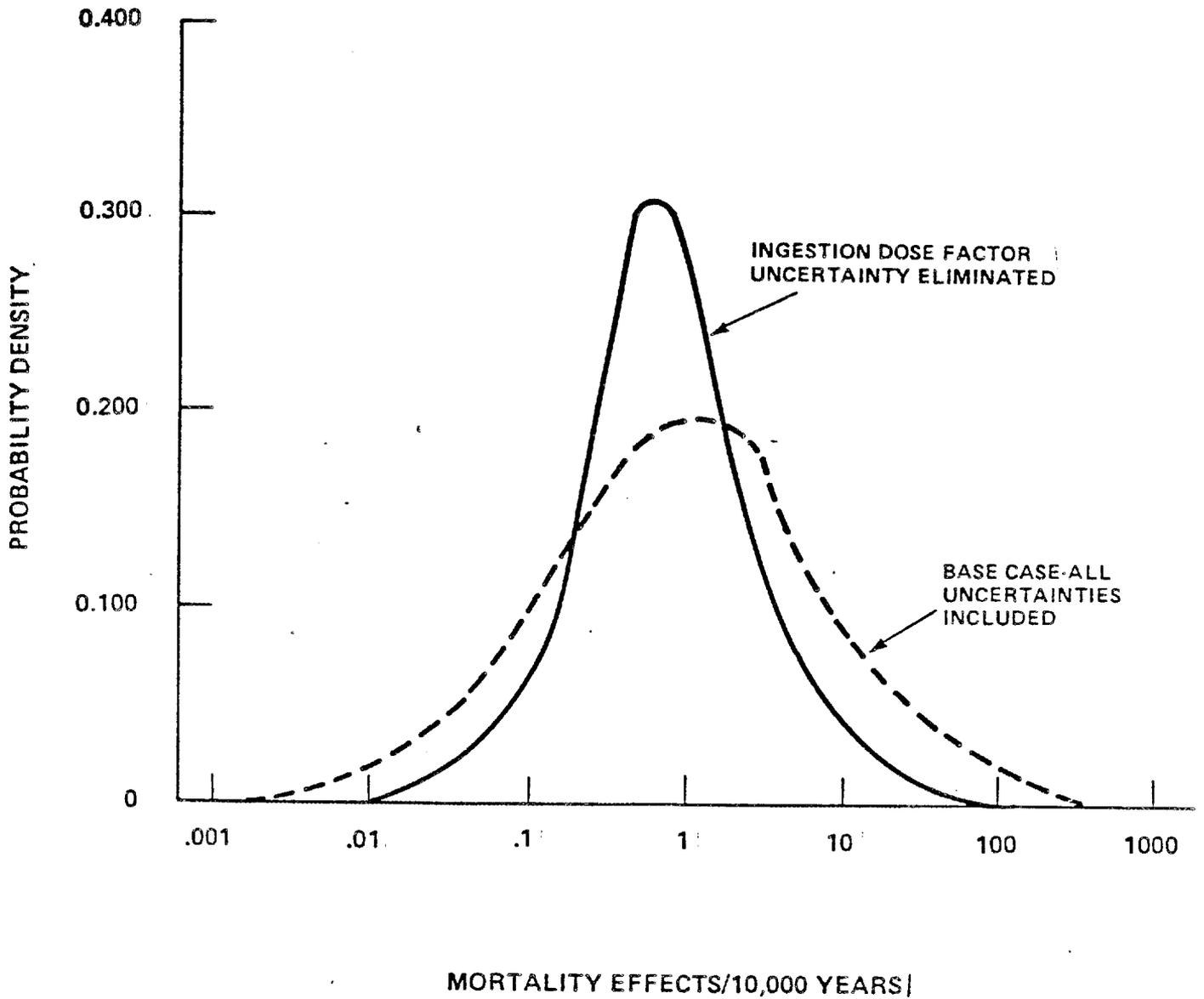


Fig. 6-13. Uncertainty sensitivity analysis example for Neptunium-237, effect of eliminating ingestion dose conversion factor uncertainty--from [Rish et al., 1983].

Variable	Baseline Value	Case	Mean	Standard Deviation	Median	Interquartile Spread
Peak 50-yr Dose (rem)	$5.9 \times 10^{-2}$	1	$1.2 \times 10^{-1}$	$4.6 \times 10^{-1}$	$2.3 \times 10^{-2}$	$2.6 \times 10^{-2}$
		2	$6.6 \times 10^{-2}$	$1.9 \times 10^{-1}$	$3.0 \times 10^{-2}$	$2.3 \times 10^{-2}$
Time of Peak 50-yr Dose (yr)	$5.9 \times 10^3$	1	$1.3 \times 10^5$	$4.9 \times 10^5$	$1.2 \times 10^4$	$1.6 \times 10^4$
		2	$2.4 \times 10^5$	$7.0 \times 10^5$	$9.4 \times 10^3$	$6.0 \times 10^3$
Peak Population Dose (man-rem/yr)	$2.3 \times 10^4$	1	$4.6 \times 10^4$	$1.9 \times 10^5$	$9.5 \times 10^3$	$1.0 \times 10^4$
		2	$2.5 \times 10^4$	$7.6 \times 10^4$	$1.2 \times 10^4$	$8.3 \times 10^3$
Time of Peak Population Dose (yr)	$5.9 \times 10^3$	1	$1.3 \times 10^5$	$4.9 \times 10^5$	$1.2 \times 10^4$	$1.6 \times 10^4$
		2	$2.5 \times 10^5$	$7.6 \times 10^5$	$7.6 \times 10^5$	$6.4 \times 10^3$
Integrated Population Dose (man-rem)	$2.1 \times 10^8$	1	$1.3 \times 10^{10}$	$4.2 \times 10^{10}$	$2.6 \times 10^8$	$1.3 \times 10^9$
		2	$9.0 \times 10^9$	$3.0 \times 10^{10}$	$2.9 \times 10^8$	$1.5 \times 10^9$
Peak Flow Rate (Ci/yr)	$2.9 \times 10^1$	1	$3.4 \times 10^1$	$7.0 \times 10^1$	$1.1 \times 10^1$	$1.2 \times 10^1$
		2	$2.7 \times 10^1$	$4.5 \times 10^1$	$1.3 \times 10^1$	$1.1 \times 10^1$
Time of Peak Flow Rate (yr)	$5.9 \times 10^3$	1	$2.3 \times 10^4$	$3.7 \times 10^4$	$1.0 \times 10^4$	$9.4 \times 10^3$
		2	$1.2 \times 10^4$	$1.2 \times 10^4$	$8.4 \times 10^3$	$4.9 \times 10^3$
Integrated Flow (Ci)	$1.1 \times 10^5$	1	$2.4 \times 10^5$	$3.7 \times 10^5$	$1.3 \times 10^5$	$2.4 \times 10^5$
		2	$2.2 \times 10^5$	$2.6 \times 10^5$	$1.4 \times 10^5$	$6.9 \times 10^4$

Fig.6-14. Table of summary statistics from Monte Carlo uncertainty analysis of HLW repository performance--from [Giuffre et al., 1980].

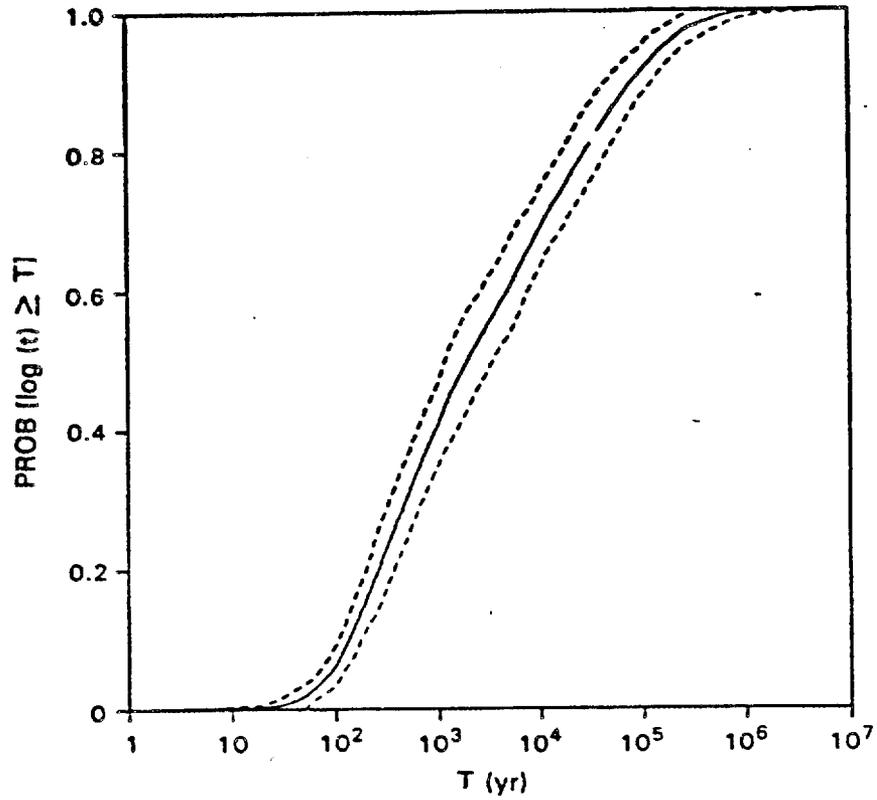


Fig. 6-15. Cumulative probability distribution showing uncertainty in logarithm of predicted groundwater flow time near a repository--from [Giuffre and Nalbandian, 1981]. Results are from Monte Carlo uncertainty propagation in groundwater flow model.

Component	Range (Orders-of-magnitude)	Uncertainty in mean (Orders-of-magnitude)
Environmental concentration	2	1
Individual intake	2	<1
Dose per unit intake	3	1-3
Population and age distribution	$\leq 2$	$\leq 2$
Cancer risk per unit dose	$\geq 4$	$\geq 1$

Fig. 6-16. Table showing estimated uncertainties in separate components of health effects calculation for plutonium--from [Kocher et al., 1981].

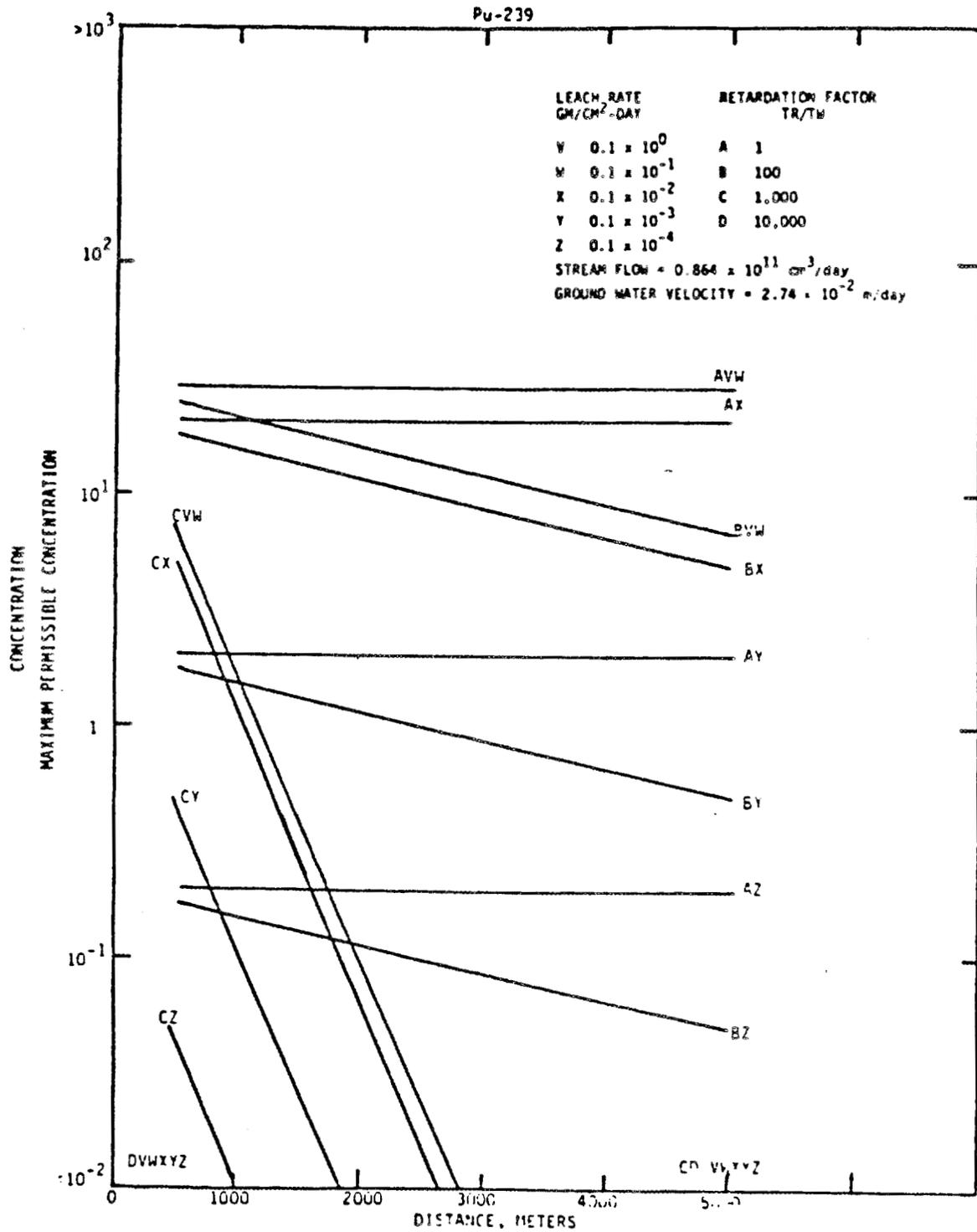


Fig. 6-17. Parametric analysis results for plutonium-239 concentration in groundwater--from [Parker and Ichel, 1981].

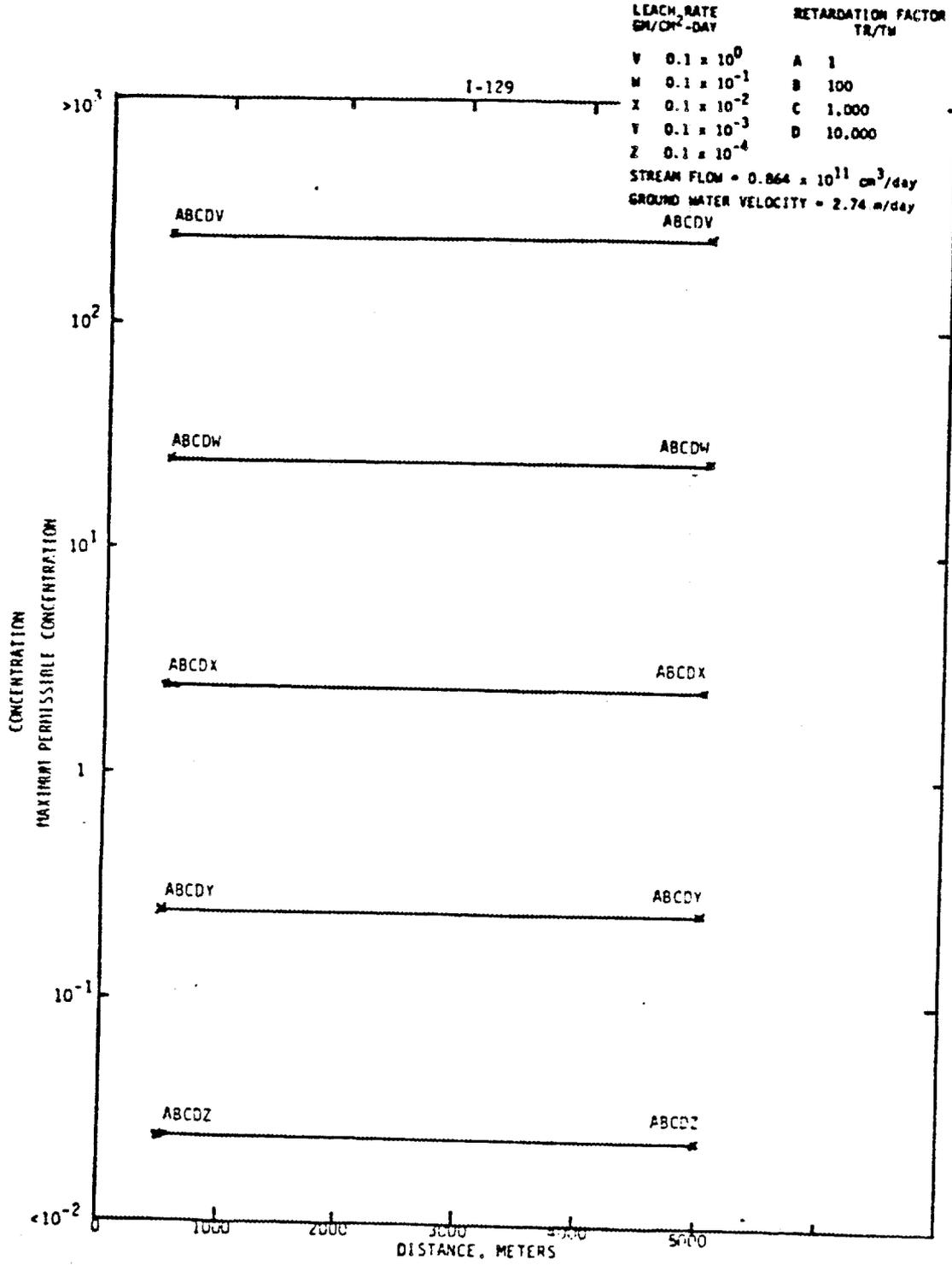


Fig. 6-18. Parametric analysis results for iodine-129 concentration in groundwater--from [Parker and Ichel, 1981].

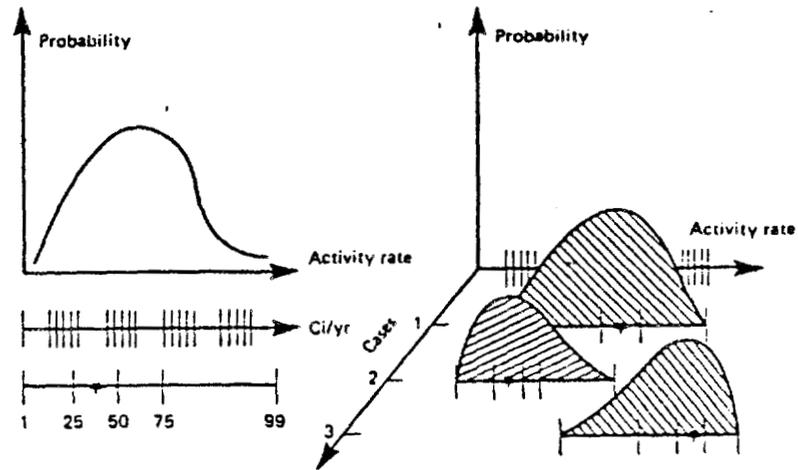
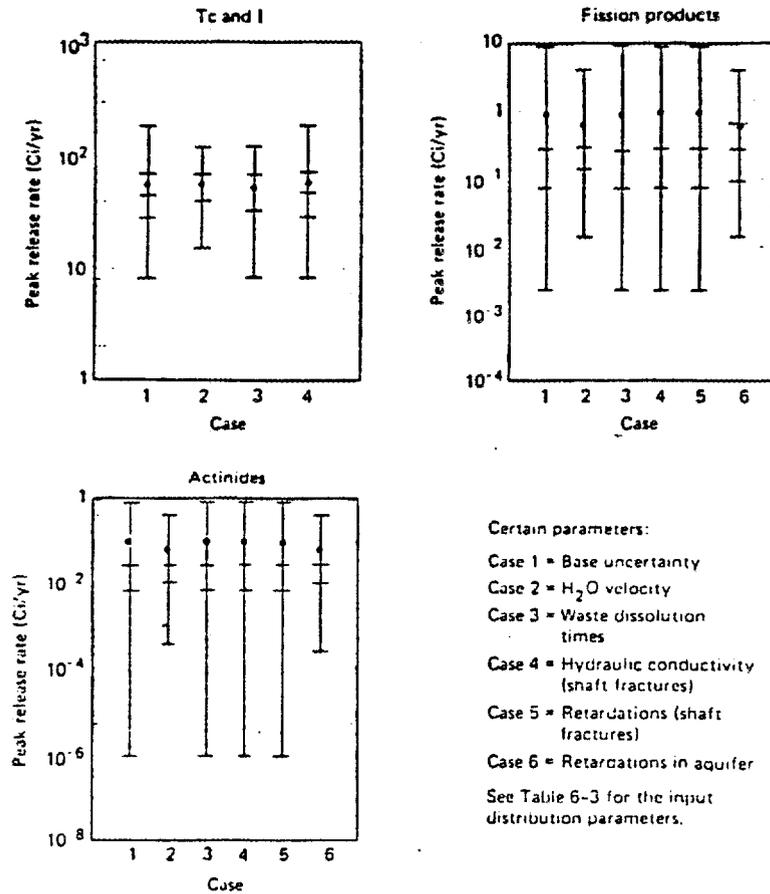


Fig. 6-19. Bar graph representation of a probability distribution--from [Sutcliffe et al., 1981].



Horizontal bars represent the 1st, 25th, 50th, 75th and 90th percentiles.  
 \* represents the mean value.

Fig. 6-20. Bar graph results from uncertainty analysis of repository release rates--from [Sutcliffe et al., 1981]. Different cases correspond to effect of treating different uncertain parameters as certain in the analysis.

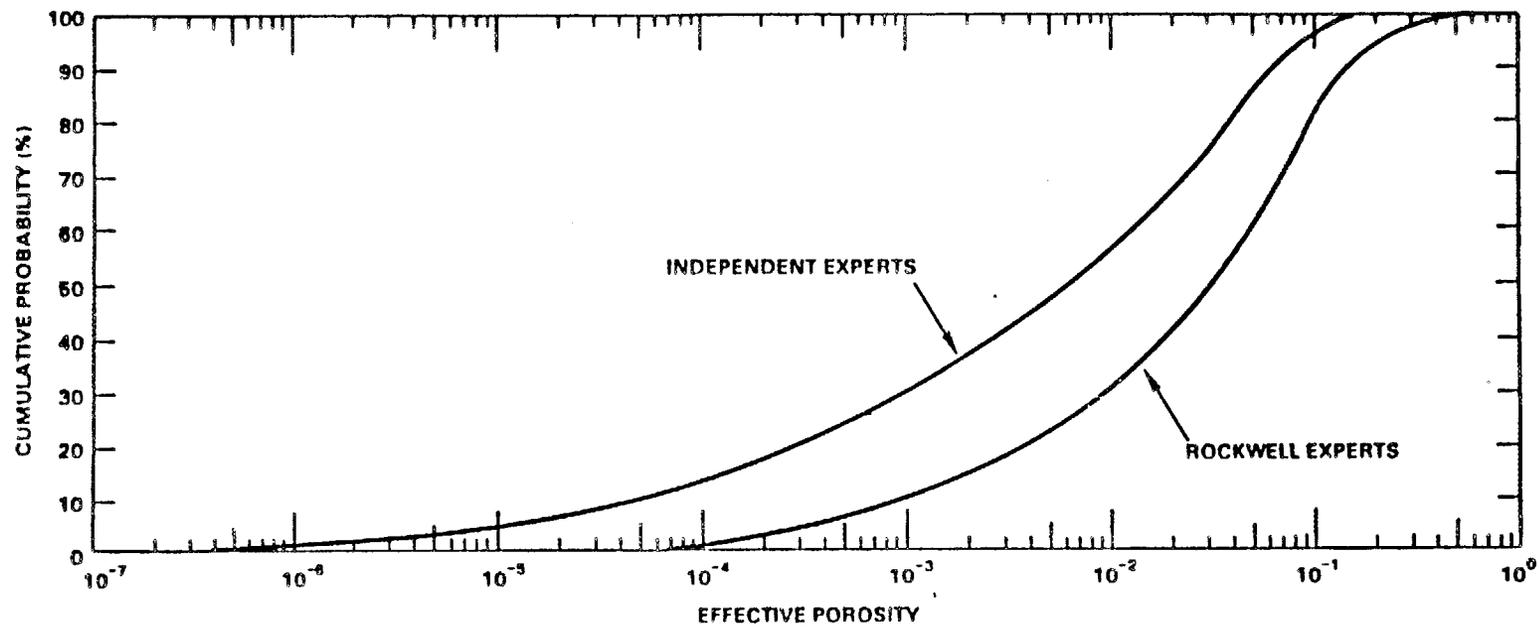


Fig. 6-21. Comparison of probability distributions for effective porosity in basalt elicited from experts--from [Runchal et al., 1984].

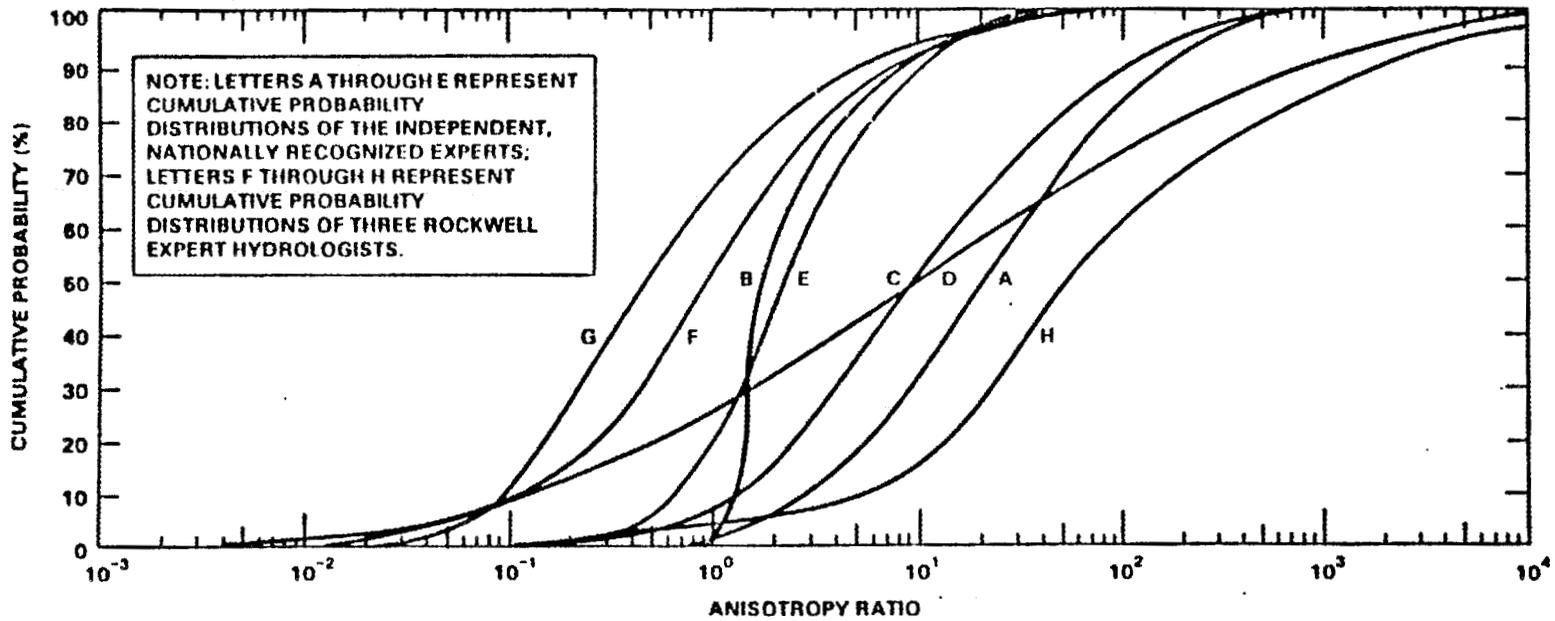


Fig. 6-22. Comparison of probability distributions for two groups of expert hydrologists representing their encoded uncertainties about the hydraulic conductivity anisotropy ratio in basalt-- from [Runchal et al., 1984].

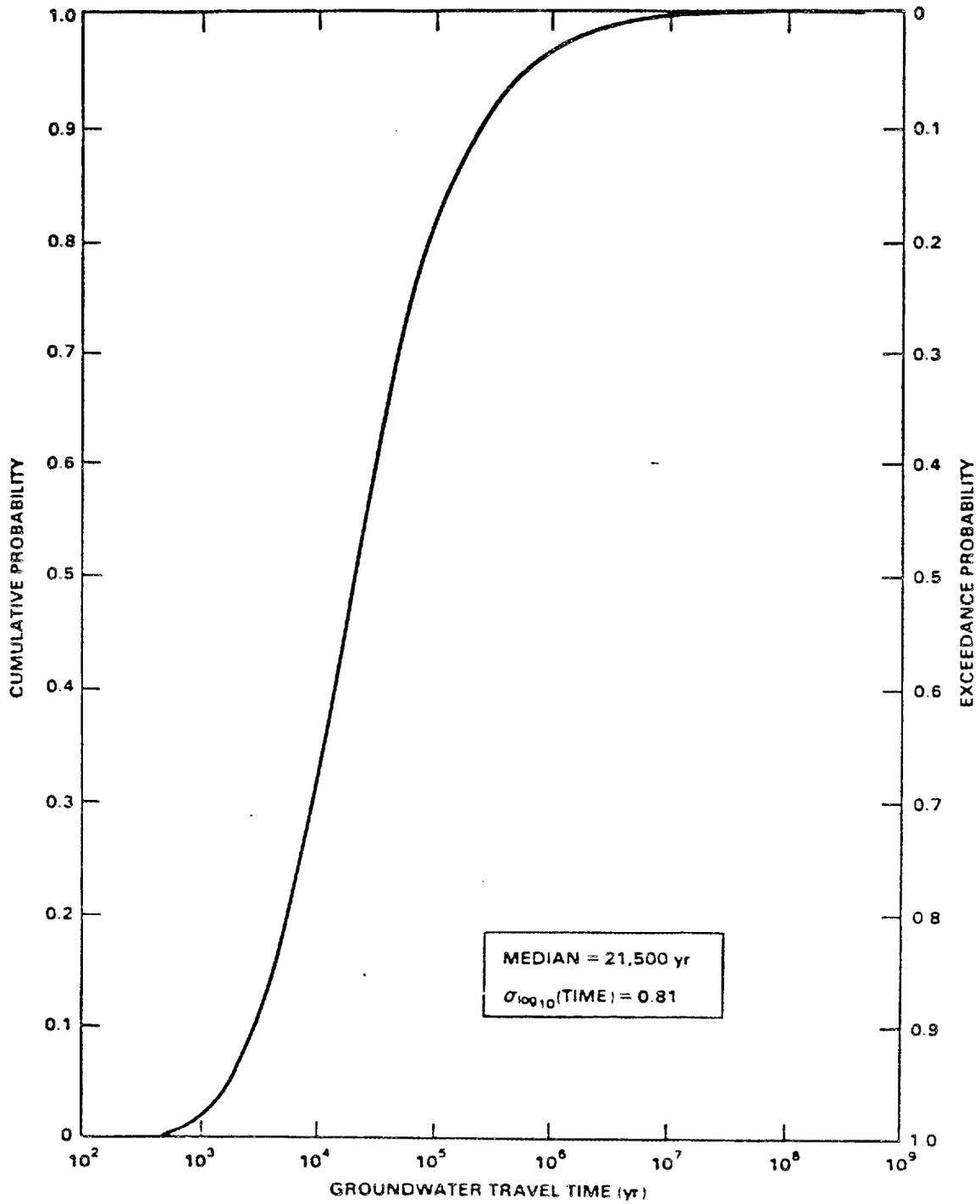


Fig. 6-23. Uncertainty in groundwater travel time prediction in basalt rock--from [Clifton, 1985].

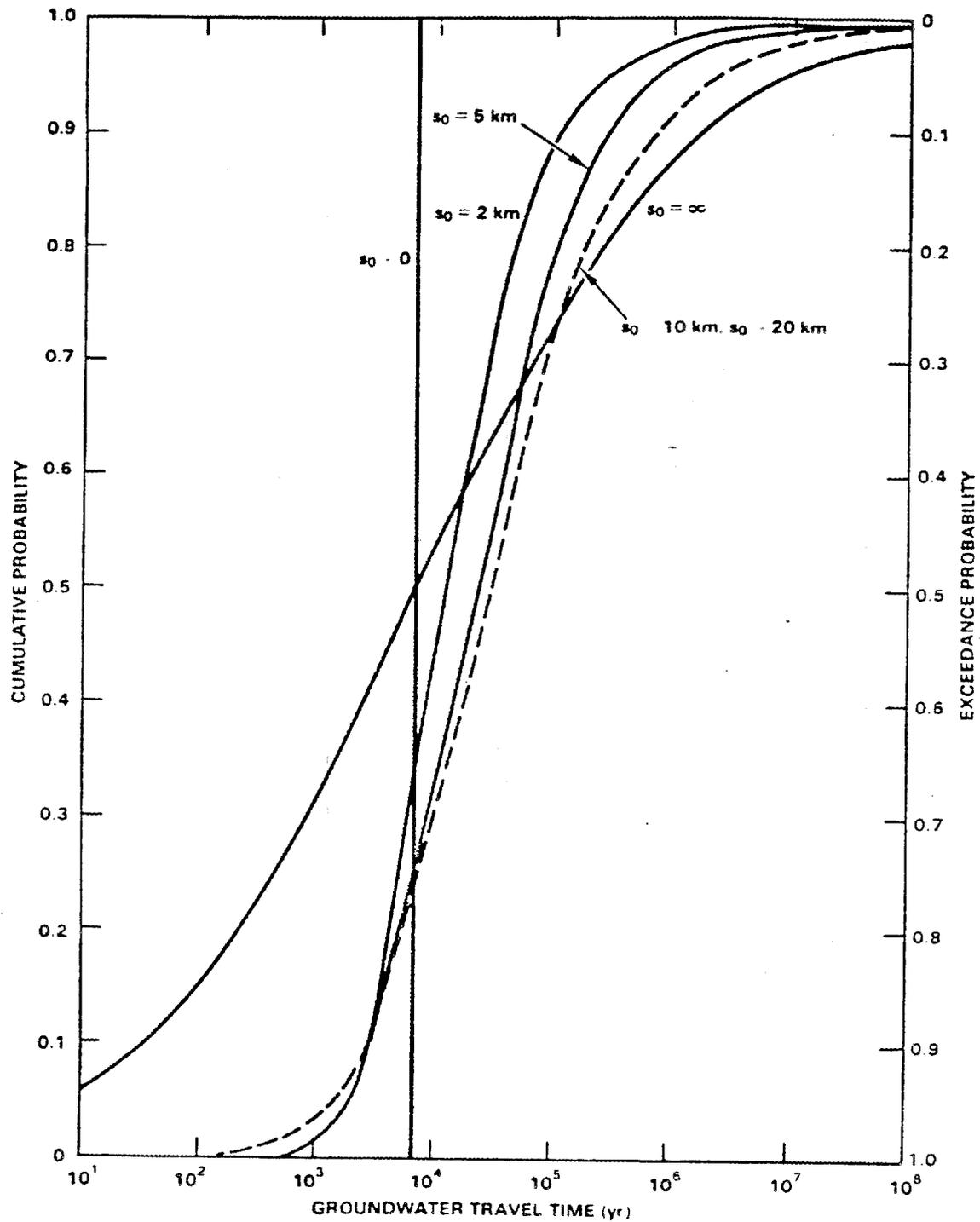


Fig. 6-24. Uncertainty in groundwater travel times from models with different log-transmissivity correlation ranges--from [Clifton, 1985].

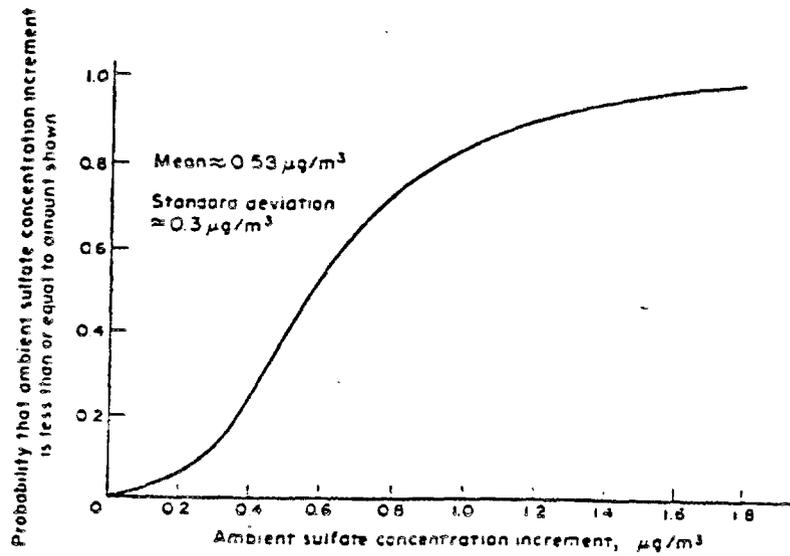


Fig. 6-25. Sketch of probability distribution illustrative of present uncertainty on increment of ambient sulfate concentration in urban area approximately 300 miles (500 km) downwind of rural power plant emitting  $10^4$  kg of sulfur oxide per hour--from [North and Merkhofer, 1976].

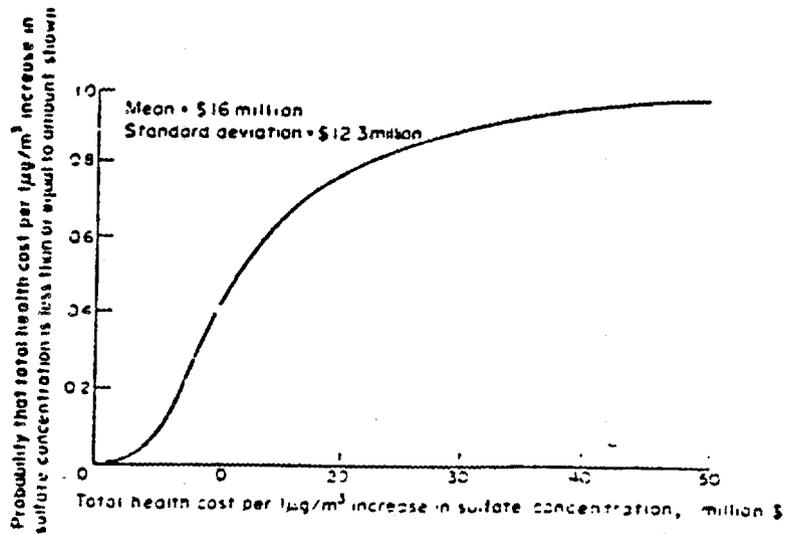


Fig. 6-26. Probability distribution of present uncertainty on total health cost due to a  $1 \mu\text{g}/\text{m}^3$  increase (from an ambient level of  $16 \mu\text{g}/\text{m}^3$ ) in annual average suspended sulfate concentration for the New York Metropolitan area. Population at risk: 11.5 million--from [North and Merkhofer, 1976].

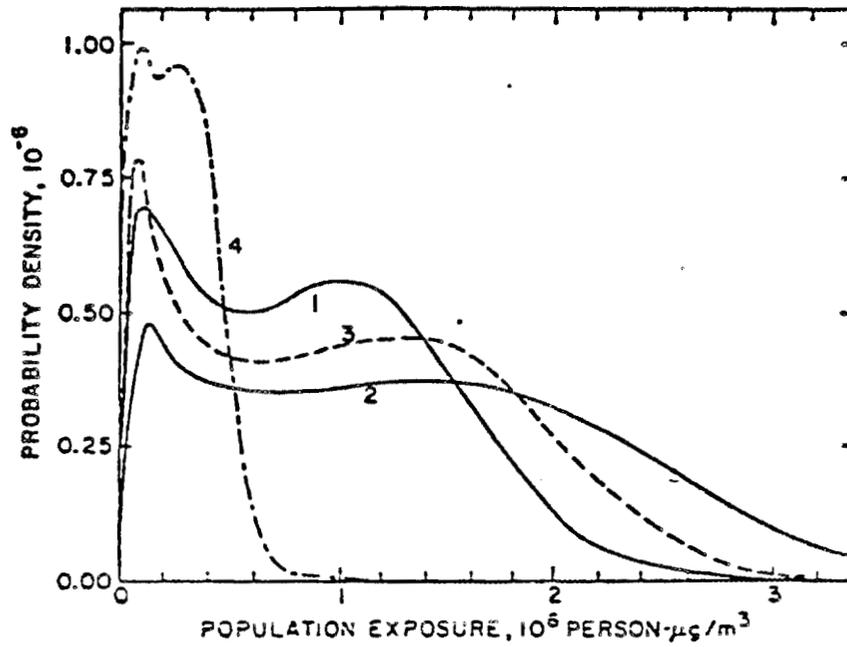


Fig. 6-27. Smoothed probability density functions that characterize total population exposure uncertainty for four identical hypothetical 1000-MW(e) coal-fired power plants--from [Morgan et al., 1978a].

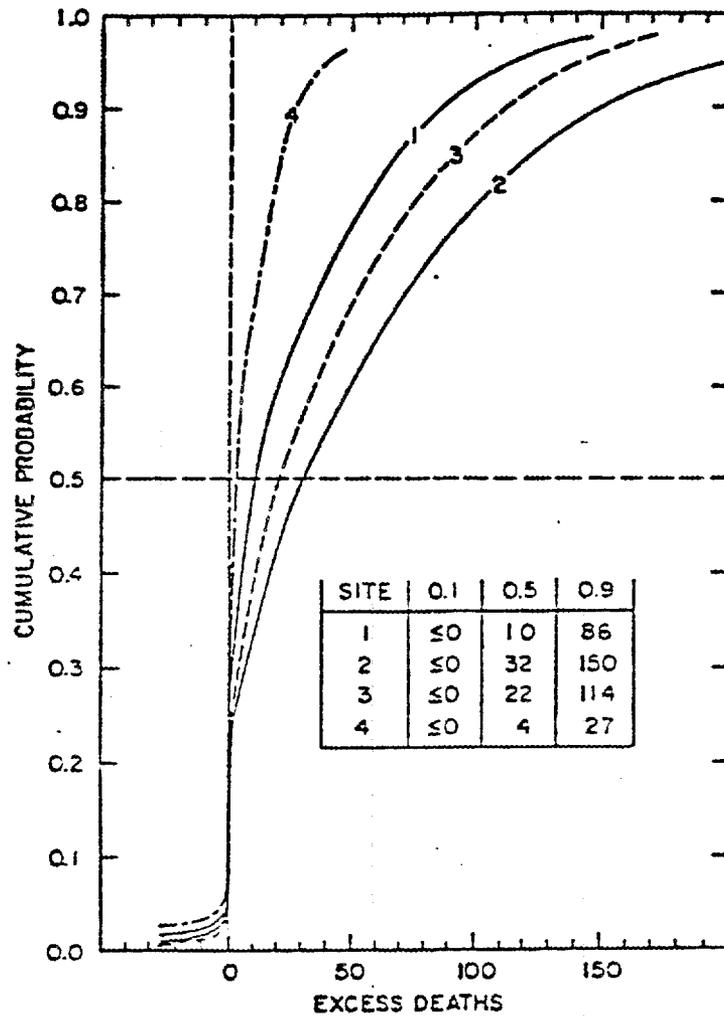


Fig. 6-28. Cumulative probability distributions representing uncertainty in annual excess deaths from sulfate aerosol exposures to a distance of 80 km around four hypothetical uncontrolled 1000 MW coal-fired power plants located in the Ohio River Valley-- from [Morgan et al., 1978a].

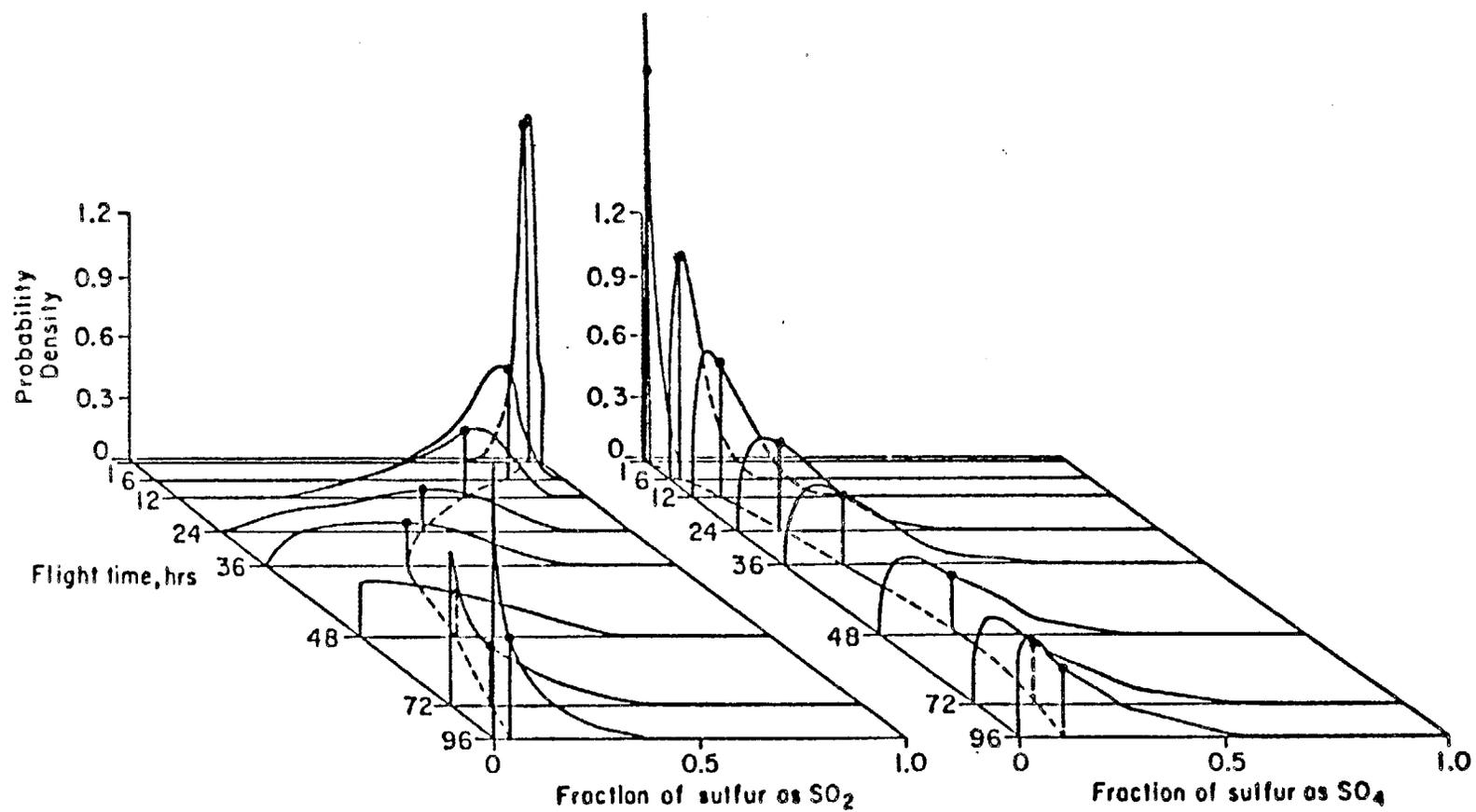
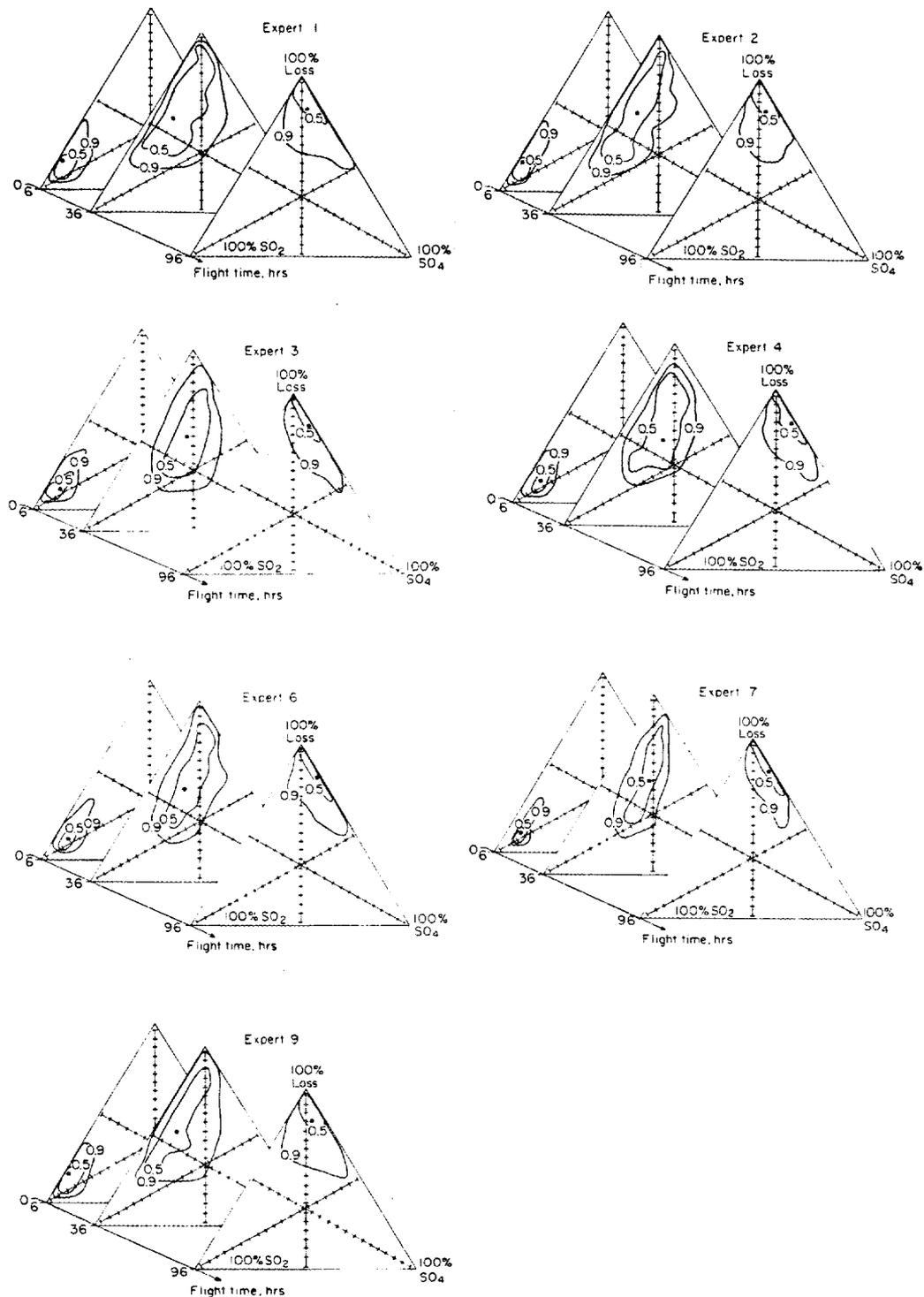


Fig. 6-29. Probability density functions for the total amount of sulfur emitted from a plant which is present as sulfur dioxide (left) and sulfate aerosol (right) as a function of flight time using the model specifications and subjective probability distributions provided by one expert--from [Morgan et al., 1982].



[ Reproduced with authors' permission ]

FIGURE 6-30: Probabilistic plots of mass balance as a function of plume flight time based on the models and subjective probability distributions provided by each of seven atmospheric science experts. Inner contours report the 50% confidence region. Outer contours report the 90% confidence region. [Morgan et al., 1982].

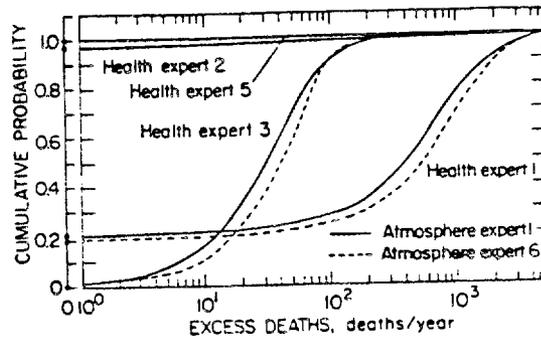


Fig. 6-31. Uncertainty in annual average excess deaths from exposure to sulfate air pollution from a new 1Gw FGD equipped coal-fired power plant for the health effects models and uncertainties of four health experts using the atmospheric models and uncertainties of two atmospheric experts who represent the range of views among atmospheric experts-- from [Morgan et al., 1984].

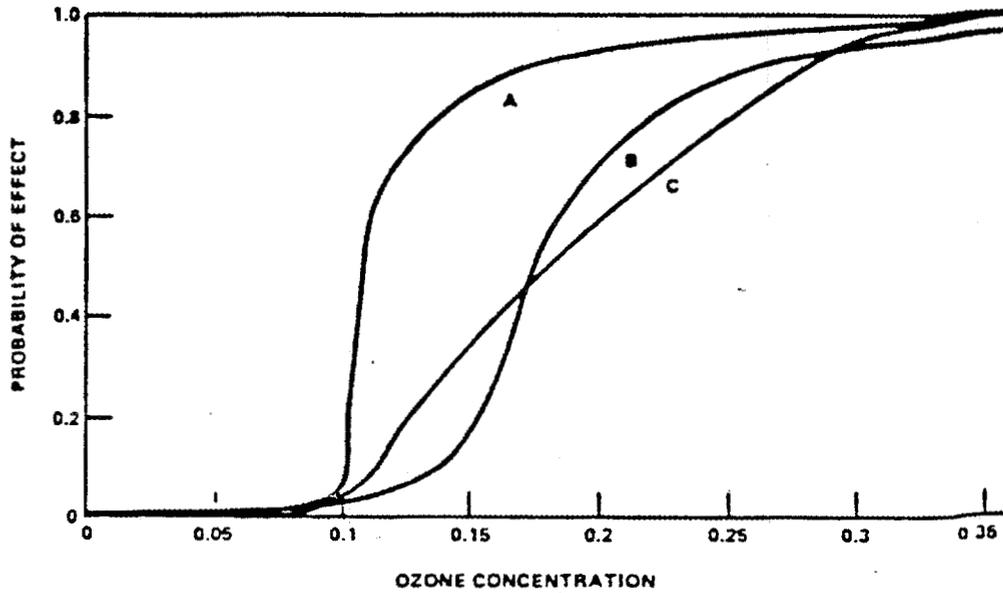


Fig. 6-32. Probability distributions elicited from three experts showing their uncertainty about the ozone concentration level at which reduction in pulmonary function occurs--from [Nelson, 1979].

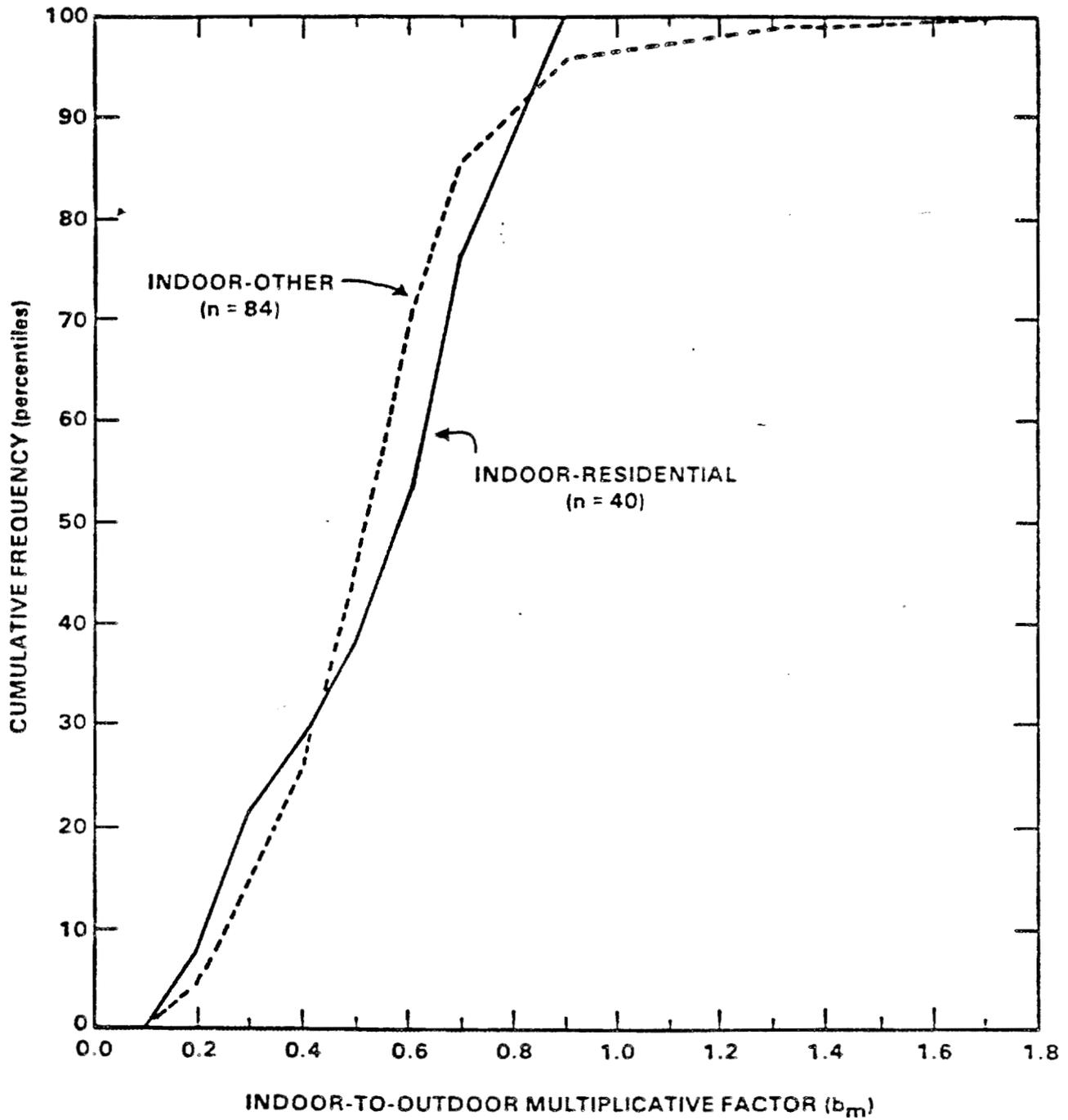


Fig.6-33. Cumulative probability distribution representing uncertainty in an indoor-to-outdoor multiplicative factor for adjusting exposure estimates (developed from the literature)--from [Richmond and McCurdy, 1985].

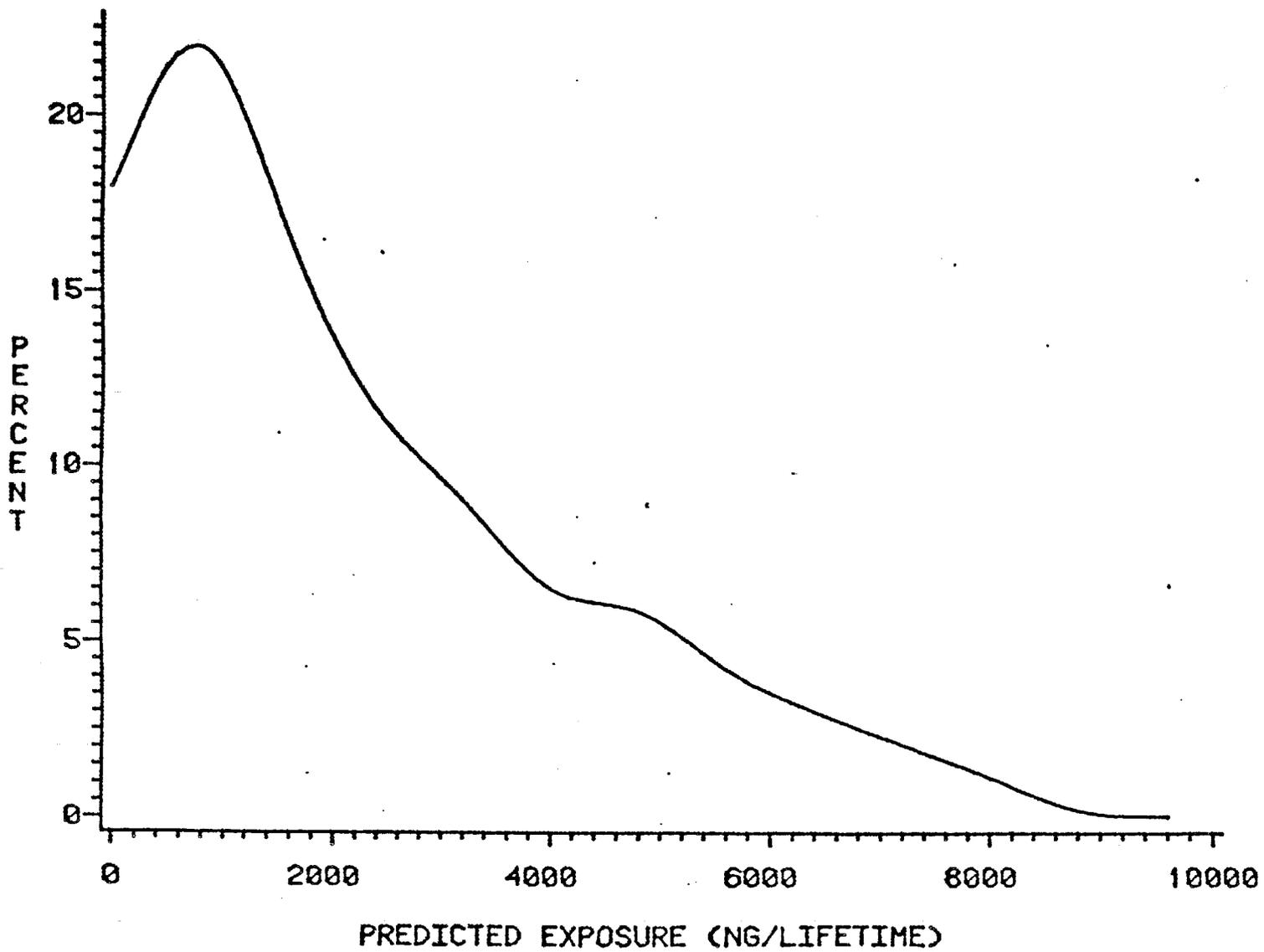


Fig. 6-34. Probability distribution of estimated exposures from TCDD contaminated soil at a hypothetical sanitary landfill--from [Whitmore, 1984]. The plot results from assuming equally likely input variable combinations from a range of variable values.

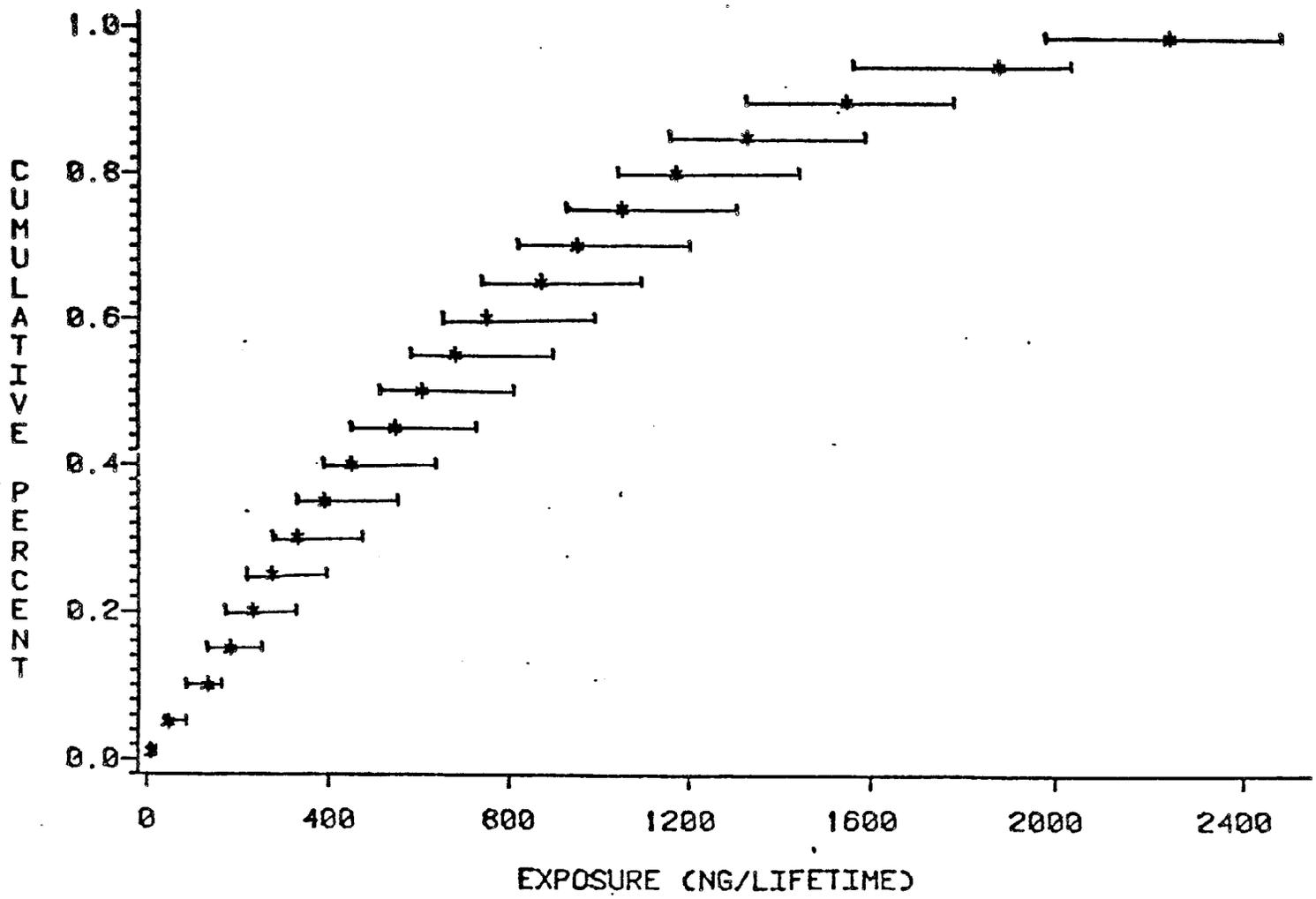


Fig. 6-35. 95% confidence interval band for selected percentiles of a TCDD exposure distribution for a hypothetical case--from [Whitmore, 1984]. Uncertainty in exposure duration is assumed to be beta distributed and uncertainty in ingestion rate is assumed to be uniformly distributed.

Source	G. S. D. (S <sub>i</sub> )
Baseline values	
Esophagus and liver cancer	1.53
Salivary glands, thyroid, lung & stomach cancers	1.36
All leukemia except chronic lymphatic	1.10
All other cancers	1.17
Effect of age at exposure	1.23
Time responses	
Leukemia & bone cancer	1.10
Other cancers	1.15
Ratio of the L to LQ linear coefficient (Except breast & thyroid cancer)	1.43
Latent period (years 5-14 after exposure only) (except leukemia and bone cancer) with bias correction factor = 0.71	1.19
Risk coefficients derived from A-bomb survivors Leukemia, cancers of esophagus, stomach, colon, lung, breast, kidney & bladder with bias correction factor = 1.62	1.17
Risk coefficients for other tabulated cancers	1.17

Fig. 6-36. Table summarizing uncertainty as geometric standard deviations (G.S.D.) of key radiation dose--response parameters--from [NIH, 1985].



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APPENDIX A

GLOSSARY OF RISK ASSESSMENT TERMINOLOGY



## GLOSSARY

This glossary was prepared by combining definitions presented in the following documents, as referenced by the bracketed numbers at the end of each definition.

- [1] U.S. Environmental Protection Agency, *High-Level and Transuranic Radioactive Wastes: Background Information Document for Final Rule*, Office of Radiation Programs, EPA 520/1-85-023 (August 1985).
- [2] U.S. Department of Health and Human Services, *Report of the National Institutes of Health Ad Hoc Working Group to Develop Radioepidemiological Tables*, NIH Publication No. 85-2748 (January 1985).
- [3] U.S. Energy Research and Development Administration, *Risk Management Guide*, EG & G Idaho, Inc., ERDA 76-45/11 (June 1977).
- [4] INTERA Environmental Consultants, *A Proposed Approach to Uncertainty Analysis*, ONWI-488 (July 1983).
- [5] Gratt, L. B., et al., *Risk Analysis/Assessment Glossary*, Rev. 1, IWG Corp., IWG-FR-003-04 (July 1984).
- [6] U.S. Department of Energy, *Environmental Assessment - Deaf Smith County Site, Texas: Volume II*, Office of Civilian Radioactive Waste Management, DOE/RW-0069 (May 1986).
- [7] Gratt, L. B. et al., *Risk Analysis/Assessment Glossary*, Rev. 2, IWG Corp. (June 1986).

**Abatement.** The reduction in degree or intensity of pollution. [7]

**Absolute Risk.** An expression of excess risk based on the assumption that the excess risk from radiation exposure adds to the underlying (base-line) risk by a constant increment dependent on dose; an absolute risk time - response model distributes the radiogenic risk after exposure independently of the underlying natural risk. [2]

**Accident.** An unwanted energy transfer (an accident) causing property damage and/or human injury. [3]

**Accident.** That occurrence in a sequence of events which usually produces unintended injury, death or property damage. [5]

**Accuracy.** The degree of agreement between a measured value and the true value; usually expressed at +/- percent of full scale. [5]

- Artificial Variability.** Variability induced by procedures used to convert raw data into model inputs; sources include data selection, processing, level of aggregation, ergodicity, and interpretation.
- Attributable Risk.** The rate of the disease in exposed individuals that can be attributed to the exposure. This measure is derived by subtracting the rate (usually incidence or mortality) of the disease among nonexposed persons from the corresponding rate among exposed individuals. [5]
- Bayesian Framework (Subjectivist Framework).** A school of thought on the meaning of probability which views probability as an expression of an internal state, that is a state of knowledge or confidence expressed subjectively. This school of thought is associated with the statistician Bayes, and its inherent logical reasoning is viewed as governed by Bayes' Theorem.
- Benefit.** The degree to which effects are judged desirable. [5]
- Best Available Control Technology.** An emission limitation (including a visible emission standard) based on the maximum degree of reduction for each pollutant subject to regulation under the act which would be emitted from any proposed major stationary source or major modification which the Administrator, on a case-by-case basis, taking into account energy, environmental, and economic impacts and other costs, determines is achievable for such source or modification through application of production processes or available methods, systems, and techniques, including fuel cleaning or treatment or innovative fuel combustion techniques for control of such pollutant. [5]
- Bias.** Any difference between the true value and that actually obtained due to all causes other than sampling variability. [5]
- Case-Fatality Rate.** A ratio of the number of deaths due to a disease to the number of cases of that disease in a specified period of time. It expresses the frequency with which affected individuals die of the disease. [7]
- Code.** A quantitative procedure to solve a particular mathematical abstract of the physical problem. [4]
- Code.** A mathematical and logical model that has been translated to computer language.
- Common Mode Failures.** Several errors in a technological system occurring simultaneously. [7]
- Classical Framework (Frequentist Framework).** A school of thought on the meaning of probability which views probability as something external which is a measure of the results of repetitive experiments. From this perspective, probability is a measurable quantity and the outcome of experiments involving repeated trials and observations.

**Comparative Risk.** An expression of the risks associated with two (or more) actions leading to the same goal; may be expressed quantitatively (a ratio of 1.5) or qualitatively (one risk greater than another risk). [5]

**Confidence Interval.** An interval estimate of a statistical parameter obtained as a particular function of observed values of one or more random variables whose joint distribution depends upon that parameter. The interval-valued function is so defined that, in an infinitely increasing number of independent replications of the experiment yielding the observed values of the random variables, the proportion of times that the interval contains the (unknown) parameter value converges to a number at least as large as some preset value, called the confidence level of the interval. [2]

**Confidence Interval.** A range of values ( $a_1 < a < a_2$ ) determined from a sample of definite rules so chosen that, in repeated random samples from the hypothesized population, an arbitrarily fixed proportion (1-E) of that range will include the true value,  $x$ , of an estimated parameter. The limits,  $a_1$ , and  $a_2$ , are called confidence limits; the relative frequency (1-E) with which these limits include  $a$  is called the confidence level. As with significance levels, confidence levels are commonly chosen as 0.05 or 0.01, the corresponding confidence coefficients being 0.95 and 0.99. Confidence intervals should not be interpreted as implying that the parameter itself has a range of values; it has only one value. On the other hand, the confidence limits ( $a_1, a_2$ ) being derived from a sample either do or do not include the true value  $a$  of the parameter. However, in repeated samples, a certain proportion (namely 1-E) of these intervals will include  $a$  provided that the actual population satisfied the initial hypothesis. [5]

**Confounding Factors.** Variables that may introduce differences between cases and controls which do not reflect differences in the variables of primary interest. [5]

**Cost-Benefit Analysis.** Cost-benefit analysis - A formal quantitative procedure comparing costs and benefits of a proposed project or act under a set of preestablished rules. To determine a rank ordering of projects to maximize rate of return when available funds are unlimited, the quotient of benefits divided by costs is the appropriate form; to maximize absolute return given limited resources, benefits-costs is the appropriate form. [5]

**Credibility Interval.** An analogue of confidence interval in terms of subjective probability. If one's information about the true value of an unknown parameter can be summarized by a probability distribution for that value, a credibility interval of a given probability level for the parameter is an interval such that the subjective probability distribution, integrated over the interval, is not less than the given probability level. [2]

**Damage.** Damage is the severity of injury or the physical, functional, or monetary loss that could result if control of a hazard is lost. [5]

**Danger.** Expresses a relative exposure to a hazard. A hazard may be present, but there may be little danger because of the precautions taken. [5]

**De Minimus Risk.** From the legal maxim "de minimus non curat lex" or "the law is not concerned with trifles." [5]

**Diversity.** Pertaining to the variety of species within a given association of organisms. Areas with low diversity are characterized by a few species; often relatively large numbers of individuals represent each species. [7]

**Dose.** The amount or concentration of undesired matter or energy deposited at the site of effect. [5]

**Dose-Effect.** The relationship between dose (usually an estimate of dose) and the gradation of the effect in a population, that is a biological change measured on a graded scale of severity, although at other times one may only be able to describe a qualitative effect that occurs within some range of exposure levels. [5]

**Dose-Effect (Dose-Response) Model.** A mathematical formulation of the way in which the effect, or response, depends on dose. [2]

**Dose-Response.** A correlation between a quantified exposure (dose) and the proportion of a population that demonstrates a specific effect (response). [5]

**Dose-Response Assessment.** The process of characterizing the relation between the dose of an agent administered or received and the incidence of an adverse health effect in exposed populations and estimating the incidence of an adverse as a function of human exposure to the agent. [5]

**Effect.** A biological change caused by an exposure. [5]

**Efficacy.** A measure of the probability and intensity of beneficial effects. [5]

**Environmental Pathway.** All routes of transport by which a toxicant can travel from its release site to human populations including air, food chain, and water. [7]

**Excess Deaths.** The excess over statistically expected deaths in a population within a given time interval. Attempts are made to relate excess deaths to specific causes. Note that since every person can (and must) die only once, there can be no excess deaths over all time. [5]

**Expected.** Assumed to be probable or certain on the basis of existing evidence and in the absence of significant evidence to the contrary. [6]

**Expected Deaths.** The number of deaths statistically expected in a population in a given time interval obtained by summing the product of age-, sex-, and race-specific mortality rates from a standard population and person-years in each age, sex, and race category in the study population. [5]

**Expected Loss.** The quantity obtained by multiplying the magnitude of health or environmental effect loss by the probability (or risk) of that loss and adding the products. The expected loss is the average loss over a large number of trials; one must reflect on the appropriateness of its use in cases for which there will be only one, or a few, trials. [5]

**Extrapolation.** In risk assessment, this process entails postulating a biologic reality based on observable responses and developing a mathematical model to describe this reality. The model may then be used to extrapolate to response levels which cannot be directly observed. [5]

**Failure Modes and Effects Analysis.** A tool to systematically analyze all contributing component failure modes and identify the resulting effects on the system. [5]

**False Negative Results.** Results which show no effect when one is there. [5]

**False Positive Results.** Results which show an effect when one is not there. [5]

**Fault Tree Analysis.** A technique by which many events that interact to produce other events can be related using simple logical relationships permitting a methodical building of a structure that represents the system. [5]

**Gaussian Distribution Model.** Where  $x$  is the mean, (XXXX) is the standard deviation. It is also called the normal distribution. For example, a Gaussian air dispersion model is one in which the pollution is assumed to spread in air according to such a distribution and described by the two parameters  $x$  and (XXXX) of the normal distribution. [5]

**Geometric Mean.** The geometric mean of a set of positive numbers is the exponential of the arithmetic mean of their logarithms. The geometric mean of a lognormal distribution is the exponential of the mean of the associated normal distribution. [2]

**Geometric Standard Deviation (GSD).** The geometric standard deviation of a lognormal distribution is the exponential of the standard deviation of the associated normal distribution. The geometric standard deviation is not standard for statistical terminology but is more commonly used by physicists. [2]

**Hazard.** A condition or physical situation with a potential for an undesirable consequence, such as harm to life or limb. [5]

- Hazard.** A source of risk or peril; the potential for an unwanted release of energy to result in personal injury or property damage. [3]
- Hazard Assessment.** An analysis and evaluation of the physical, chemical and biological properties of the hazard. [5]
- Hazard Identification.** The process of determining whether exposure to an agent can cause an increase in the incidence of a health condition. [5]
- Health Effect.** A deviation in the normal function of the human body. [5]
- Health Effect Assessment.** The component of risk assessment which determines the probability of a health effect given a particular level or range of exposure to a hazard. [5]
- Health Risk.** Risk in which an adverse event affects human health. [5]
- Hockey Stick Regression Function.** This means that for a suitable dose  $X_0$ ,  $f(X)$  remains constant for any  $X$  less than  $X_0$  and increases linearly as  $X$  increases for any  $X$  more than  $X_0$ . The dose  $X_0$  is considered as a physiological threshold value. [7]
- Impact.** The force of impression of one thing on another. [5]
- Incidence.** The number of new cases of a disease in a population over a period of time. [5]
- Incidence or Incidence Rate.** The rate of occurrence of a disease within a specified period of time, often expressed as number of cases per 100,000 individuals per year. [2]
- Individual Risk.** The risk to an individual rather than to a population. [5]
- Individual Susceptibility.** The marked variability in the manner in which individuals will respond to a given exposure to a toxic agent. [5]
- Linear (L) Model.** Also, linear dose-effect relationship; expresses the effect (e.g., mutation or cancer) as a direct (linear) function of dose. [2]
- Linear-Quadratic (LQ) Model.** Also, linear-quadratic dose-effect relationship; expresses the effect (e.g., mutation or cancer) as partly directly proportional to the dose (linear term) and partly proportional to the square of the dose (quadratic term). The linear term will predominate at lower doses, the quadratic term at higher doses. [2]
- Logit Model.** A dose-response model which, like the probit model, leads to an S-shaped dose-response curve, symmetrical about the 50% response curve. The logit model leads to lower "very safe doses" than the probit model even when both models are equally descriptive of the data in the observable range. [7]

**Lognormal Distribution.** A distribution of the frequency of a value plotted on a linear scale versus the value plotted on a logarithmic scale, which results in a bell-shaped curve. [1]

**Lognormal Distribution.** If the logarithms of a set of values are distributed according to a normal distribution they are said to have a lognormal distribution, or be distributed "lognormal." [2]

**Log-Probit Model.** A dose-response model which assumes that each animal has its own threshold dose, below which no response occurs and above which a tumor is produced by exposure to a chemical. [7]

**Maximally Exposed Individual.** A hypothetical person who is exposed to a release of radioactivity in such a way that he receives the maximum possible individual radiation dose or dose commitment. For instance, if the release is a puff of contaminated air, the maximally exposed individual is a person at the point of the largest ground-level concentration and stays there during the whole time the contaminated air cloud remains above. This term is not meant to imply that there really is such a person; it is used only to indicate the maximum exposure a person could receive. [6]

**Maximum Permissible Concentration.** The average concentration of a radionuclide in air or water to which a worker or member of the general population may be continuously exposed without exceeding regulatory limits on external or internal radiation doses. [6]

**Mitigation.** (1) Avoiding the impact altogether by not taking a certain action or parts of an action; (2) minimizing impacts by limiting the degree or magnitude of the action and its implementation; (3) rectifying the impact by repairing, rehabilitating, or restoring the affected environment; (4) reducing or eliminating the impact over time by preservation and maintenance operations during the life of the action; and (5) compensating for the impact by replacing or providing substitute resources or environments. [6]

**Model.** A conceptual description and the associated mathematical representation of a system, component, or condition. It is used to predict changes in the system, component, or condition in response to internal or external stimuli as well as changes over time and space. An example is a hydrologic model to predict groundwater travel or radionuclide transport from the waste emplacement area to the accessible environment. [6]

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**Model.** A simplified representation of some aspect of reality; either conceptual, visual, verbal, physical, mathematical, and/or logical.

**Morbidity.** A departure from a state of physical or mental wellbeing, resulting from disease or injury. Frequently used only if the affected individual is aware of the condition. Awareness itself connotes a degree of measurable impact. Frequently, but not always, there is a further restriction that some action has been taken such as restriction of activity, loss of work, seeking of medical advice, etc. (7)

**Mortality (rate).** The rate at which people die from a disease, e.g., a specific type of cancer, often expressed as number of deaths per 100,000 per year. [2]

**Mortality Rate.** The number of deaths that occur in a given population during a given time interval; usually deaths per  $10^3$  or  $10^5$  people per year. Can be age, sex, race, and cause specific. [7]

**Normal Distribution.** A random variable  $X$  is said to be normally distributed if, for some number  $\mu$  and some positive number  $\sigma$ ,  $Y=(X-\mu)/\sigma$  has a standard normal distribution with probability density function. [2]

**One-Hit Model.** The dose-response model based on the concept that a tumor can be induced by a single receptor that has been exposed to a single quantum or effective dose unit of a chemical. [7]

**Population at Risk.** A limited population that may be unique for a specific dose-effect relationship; the uniqueness may be with respect to susceptibility to the effect or with respect to the dose or exposure itself. [5]

**Population Dose (Population Exposure).** The summation of individual doses received by all those exposed to the source or event being considered. [7]

**Precision.** A measure of how exactly the result is determined without reference to any "true" value. [5]

**Precision.** A measure of how consistently the result is determined by repeated determinations without reference to any "true" value. [7]

**Premature Death.** A death that occurs before statistical expectation, usually attributable to a specific cause, and usually referring to deaths statistically estimated in a population rather than to individuals. [7]

**Prevalence.** The number of existing cases in a population who have the disease at a given point (or during a given period of time). [7]

**Probability.** A probability assignment is a numerical encoding of a state of knowledge. [5]

**Probable Error.** The magnitude of error which is estimated to have been made in determination of results. [5]

- Probit Analysis.** A statistical transformation which will make the cumulative normal distribution linear. In analysis of dose-response, when the data on response rate as a function of dose are given as probits, the linear regression line of these data yields the best estimate of the dose-response curve. The probit unit  $Y=5+Z(p)$ , where  $P$  = prevalence of response at each dose level and  $Z(p)$  = corresponding value of the standard cumulative normal distribution. [5]
- Proportionate Mortality Ratio (PMR).** The fraction of all deaths from a given cause in the study population divided by the same fraction from a standard population. A tool for investigating cause-specific risks when only data on deaths are available. If data on the population at risk are also available, SMRs are preferred. [7]
- Quality Assurance.** All the planned and systematic actions necessary to provide adequate confidence that a structure, system, or component is constructed to plans and specifications and will perform satisfactorily. [6]
- Quality Control.** Quality assurance actions that provide a means to control and measure the characteristics of an item, process, or facility to established requirements. [6]
- Random Error.** Indefiniteness of result due to finite precision of experiment. Measure of fluctuation in result after repeated experimentation. [5]
- Rate.** In epidemiologic usage, the frequency of a disease or characteristic expressed per unit of size of the population or group in which it is observed. The time at or during which the cases are observed is a further specification. [7]
- RAU.** Risk analysis unit. [7]
- Reasonably Achievable.** Mitigation measures or courses of action shown to be reasonable considering the costs and benefits in accordance with the National Environmental Policy Act of 1969. [6]
- Relative Risk.** The ratio of the rate of the disease (usually incidence or mortality) among those exposed to the rate among those not exposed. [5]
- Relative Risk.** An expression of excess risk relative to the underlying (baseline) risk; if the excess equals the baseline risk the relative risk is 2. [2]
- Release Limit.** A regulatory limit on the concentration or amount of radioactive material released to the environment. [6]
- Reliability.** The probability a system performs a specified function or mission under given conditions for a prescribed time.

- Residual Uncertainty.** Those inherent uncertainties in data, modeling, and assumed future conditions that cannot be eliminated. [6]
- Response.** The proportion or absolute size of a population that demonstrates a specific effect. May also refer to the nature of the effect. [7]
- Risk.** The potential for realization of unwanted, adverse consequences to human life, health, property, or the environment; estimation of risk is usually based on the expected value of the conditional probability of the event occurring times the consequence of the event given that it has occurred. [5]
- Risk.** Mathematically, expected loss; the probability of an accident multiplied by the consequence (loss converted into dollars) of the accident. [3]
- Risk Analysis.** A detailed examination performed to understand the nature of unwanted, negative consequences to human life, health, property, or the environment; an analytical process to provide information regarding undesirable events; the process of quantification of the probabilities and expected consequences for identified risks. [5]
- Risk Analysis.** The quantification of the degree of risk. [3]
- Risk Analysis.** An analysis that combines or uses an uncertainty analysis along with the probability that the state evaluated in the analysis (geologic, biologic, etc.) exists. Note that a risk analysis uses as an integral part an uncertainty analysis and an uncertainty analysis similarly contains a sensitivity analysis. [4]
- Risk Assessment.** The process, including risk analysis, risk evaluation, and risk management alternatives, of establishing information regarding that risk and levels of risk for an individual, group, society, or the environment. [5]
- Risk Assessment.** The combined functions of risk analysis and evaluation. [5]
- Risk Coefficient.** A fitted constant in an equation that describes how an effect depends on dose. [2]
- Risk Estimation.** The scientific determination of the characteristics of risks, usually in as quantitative a way as possible. These include the magnitude, spatial scale, duration and intensity of adverse consequences and their associated probabilities as well as a description of the cause and effect links. [5]
- Risk Estimate.** Absolute - risk estimate based on the assumption that there is some absolute number of deaths in a population exposed at a given age per unit of dose. Relative - risk estimate based on the assumption that the annual rate of radiation-induced excess cancer deaths is proportional to the ambient rate of occurrence of fatal cancer. [1]

- Risk Evaluation.** A component of risk assessment in which judgments are made about the significance and acceptability of risk. [5]
- Risk Evaluation.** The appraisal of the significance or consequences of a given quantitative measure of risk. [3]
- Risk Identification.** Recognizing that a hazard exists and trying to define its characteristics. Often risks exist and are even measured for some time before their adverse consequences are recognized. In other cases, risk identification is a deliberate procedure to review and, it is hoped, anticipate possible hazards. [5]
- Risk Management.** The process, derived through system safety principles, whereby management decisions are made concerning control and minimization of hazards and acceptance of residual risks. [3]
- Rulemaking.** Process of formulating specific regulations governing a particular matter. [6]
- Safety.** Relative protection from adverse consequences. [5]
- Scenario.** A particular chain of hypothetical circumstances often used in performance analysis to model possible events. [6]
- Scenario Analysis.** Analytical process that attempts to quantify the probabilities and consequences of a postulated sequence of events. [6]
- Sensitivity Analysis.** An analysis that defines quantitatively or semi-quantitatively the dependence of a selected performance assessment measure (or an intermediate variable) on a specific parameter or set of parameters. [4]
- Standard Deviation.** A measure of dispersion or variation, usually taken as the square root of the variance. [5]
- Standard Geometric Deviation.** Measure of dispersion of values about a geometric mean; the portion of the frequency distribution that is one standard geometric deviation to either side of the geometric mean; accounts for 68% of the total samples. [5]
- Standardized Mortality Ratio (SMR).** The ratio of observed deaths in a population to the expected number of deaths as derived from standard population rates with adjustment of age and possibly other factors such as sex or race. [7]
- Standard Normal Deviation.** Measure of dispersion of values about a mean value; the positive square root of the average of the squares of the individual deviations from the mean. [5]
- Statistical Significance.** The statistical significance determined by using appropriate standard techniques of multivariate analysis with results interpreted at the stated confidence level and based on data relating species which are present in sufficient numbers at control areas to permit a valid statistical comparison with the areas being tested. [5]

**Stochastic.** A stochastic process is one in which the system incorporates an element of randomness, as opposed to a deterministic system. For example, in radiobiology stochastic effects are those in which the probability of an effect occurring rather than its severity is a function of dose, without threshold. [2]

**Stochastic Model.** A model whose inputs are uncertain and whose outputs are therefore also uncertain and must be described by probability distributions. [6]

**Surrogate.** Something that serves as a substitute. In risk analysis, surrogates are often used when data on the item of interest (a chemical, an industry, an exposure, etc.) is lacking. As an example, underground mining of coal and hardrock minerals can be used as a surrogate for underground oil shale mining. [7]

**Systematic Error.** A reproducible inaccuracy introduced by faulty equipment, calibration, or technique. [5]

**Threshold.** A pollutant concentration below which no deleterious effect occurs. [7]

**Threshold Dose.** The minimum application of a given substance required to produce an observable effect. [7]

**To the Extent Practicable.** The degree to which an intended course of action is capable of being effected in a manner that is reasonable and feasible within a framework of constraints. [6]

**Uncertainty.** A lack of certainty about a quality, quantity, or model due to inherent randomness, artifactual variability, and/or incomplete knowledge.

**Uncertainty Analysis.** A detailed examination of the systematic and random errors of a measurement or estimate; an analytical process to provide information regarding the uncertainty. [5]

**Uncertainty Analysis.** The analysis that defines the dependence of a set of selected performance assessment measures on the set of uncertain input parameters. It includes the characterization of uncertainty in (1) the input parameters; (2) the evaluation methodology; and (3) the output performance assessment measures. [4]

**Uncertainty Assessment.** The process of identifying, characterizing, analyzing, and evaluating the implications of uncertainties that are inherent to risk analysis.

**Validation of Computer Codes and Models.** The process of obtaining assurance that a model as embodied in a computer program is a correct representation of the process or system for which it is intended. Ideally, validation is a comparison of predictions derived from the model with empirical observation. However, as this is frequently impractical or impossible owing to the large physical and time scales involved in HLW disposal, short term testing supported by other avenues such as peer review are used to obtain this assurance. [4]

**Verification of Computer Codes and Models.** Testing a code with analytical solutions for idealized boundary value problems. A computer code will be considered verified when it has been shown to solve the boundary value problems with sufficient accuracy. [6]

**Worst Case Analysis.** An analysis based on assumptions and input data selected to yield a "worst impact" statement. [6]

**Zero Order Analysis.** The simplest approach to quantification of a risk with a limited treatment of each risk component (e.g., source terms, transport, health effects, etc.). [7]



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