Treatment of Risk in Environmental Impact Assessment

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ABSTRACT / Risk assessment and environmental impact assessment have developed as separate traditions. While environmental impact assessment is a broad field that includes all activities that attempt to analyze and evaluate the effects of human and related actions on the environment, risk assessment has been concerned with the relatively well-defined regulatory problems and employs formal quantitative analysis of the probability of specific undesired events, such as cancer. Risk analytic approaches, particularly the explicit treatment of uncertainty, can significantly contribute to environmental assessments. This article discusses the type and sources of uncertainty in environmental assessments, techniques for their quantification, and ways to use uncertainty estimates to calculate probabilities of effects or probabilities of exceeding environmental standards and to determine the need for mitigation or additional research.

Environmental impact assessment is a broad field that includes all activities that attempt to analyze and evaluate the effects of human actions on natural and anthropogenic environments. As is indicated in a number of reviews, the field considers the full range of human actions and includes identification and prioritization of issues, prediction and comparison of effects, consideration of acceptability, and translation of conclusions into policy recommendations (Munn 1975, Beanlands and Duinker 1983, and Westman 1985).

Risk assessment, as it has evolved since the mid 1970s, is much narrower and more tightly focused than environmental impact assessment. Risk assessments are associated with regulatory legislation such as the Pure Food and Drug Act and the Federal Insecticide, Fungicide and Rodenticide Act. Risk is most often defined as the uncertainty concerning an undesired event where uncertainty is expressed as the probability of occurrence (Rowe 1977, Whyte and Burton 1980, ASTM 1985). However, the term *risk assessment* is applied more generally to the process of characterizing the potential adverse effects of exposure to environmental hazards (National Research Council 1983). Although most risk assessments to date have addressed human health concerns, environmental concerns must now be addressed in the same terms (Gilford 1985). The characterization and quantification of uncertainty have been identified as major components of risk assessment (Ruckelshaus 1983). We believe that the emphasis on uncertainty in risk assessment represents a significant conceptual advance over conventional approaches to environmental impact assessment. This article discusses the nature and sources of uncertainty considered in risk assessment and shows how the probabilistic results of risk assessments can be interpreted and used.

KEY WORDS: Environmental impact assessment; Risk; Uncertainty; Analysis

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Types of Uncertainty

The following taxonomy of uncertainty (Figure 1), although original with the authors, is an adaptation of risk analysis terminology (for example, Rowe 1977, Fairley 1975) to environmental problems. Defined uncertainty is uncertainty about the state of the world; undefined uncertainty is uncertainty concerning one's actual level of ignorance. Undefined uncertainty is inherently unknowable and cannot be explicitly incorporated in risk assessment, but an awareness of its existence contributes a wholesome humility. It is referred to in engineering as the *unknown unknowns*.

The two fundamentally different types of defined uncertainty that can contribute to risk are identity uncertainty and analytical uncertainty (Figure 1). Identify uncertainty, the uncertainty concerning the identity of future victims, is the fundamental unknown in studies of human risks. For example, an insurance actuary may know rather precisely the annual probability of death among a particular class of people, but a new insurance company could be bankrupted by the untimely death of its first client, hence the uncertainty. Similarly, a person living adjacent to a facility that will cause cancer in 0.01% of the community may agree

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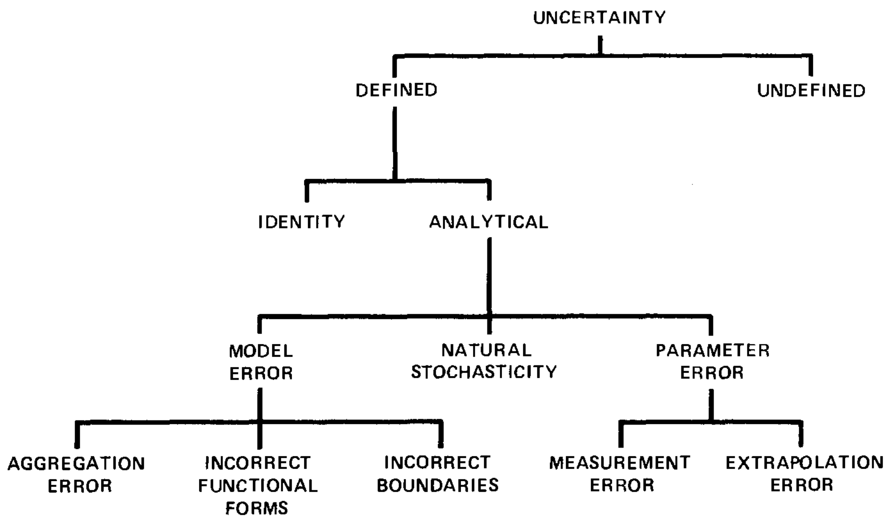

Figure 1. A taxonomy of uncertainty.

that the facility is acceptable to the society as a whole and yet move his family to another location. In contrast, the identity of the victim is irrelevant in ecological risk analysis. Therefore, the statement that a particular facility will kill 30% of the fish in a receiving river is a deterministic statement of hazard or impact and does not constitute a statement of risk.

The other type of defined uncertainty in risk analysis is analytical uncertainty (Figure 1). Because of the uncertainty in estimating the level or frequency of effects, there is a risk that an effect will be greater than expected. The probability density function for the predicted level of effect can be used to calculate the probability (that is, risk) that a certain level of effect will occur, given the total uncertainty in the analysis. For example, due to the uncertainty in ecological risk analysis, a pollutant may pose a risk of 0.2 of causing a 50% or greater reduction in gamefish biomass (an effect that may be both measurable and significant), even though the expected reduction in gamefish biomass is only 10% (an unmeasurable and probably insignificant effect).

While the availability of actuarial and epidemiological data makes analytical uncertainty a minor component of some human risk analysis, such uncertainty is invariably large in ecological analysis. There are no coroner's records for fish or birds. In addition, the millions of species of nonhuman biota exist in a web of food chain and competitive relationships that determine population sizes and affect toxic responses in largely unknown ways. Absolute predictions of the future state of ecological systems are not credible (Goldstein and Ricci 1981). The consideration of analytical uncertainty, which has been treated as an option in human risk analyses (for example, Hamilton 1980, Feagans and Biller 1981), is a necessity in ecological risk analyses.

Sources of Uncertainty

The analytical uncertainty associated with predicting environmental effects of stress has independent components that affect the calculation of risk in qualitatively different ways. These components also vary in the extent to which they can be reduced by additional information. We distinguish three sources of uncertainty: errors resulting from our conceptualizations (models) of the world, stochasticity in the natural world, and uncertainties associated with measuring model parameters. Model error corresponds to Rowe's (1977) descriptive uncertainty, and stochasticity and parameter uncertainty correspond to Rowe's measurement uncertainty, but the definitions used here are broader.

Model Error

Computing a risk estimate necessarily involves the use of some sort of mathematical or statistical model. A reducible source of uncertainty is the lack of correspondence between the model and reality. Major types of model error that have been studied are (a) using a small number of variables to represent a large number of complex phenomena [defined as aggregation error, (O'Neill 1973)], (b) choosing incorrect functional forms for interactions among variables, and (c) setting inappropriate boundaries for the components of the world to be included in the model. Because the complexity of the natural world greatly exceeds our ability to model it, model errors can never be completely eliminated. The most serious problem associated with model error is that the errors frequently involve biases whose magnitudes and directions may be difficult to determine.

Natural Stochasticity

Although philosophers may argue whether the natural world is ultimately deterministic or stochastic, the question is of little practical interest. At all scales of resolution, spatial heterogeneity and temporal variability are characteristic of natural systems. For example, the concentration of a contaminant in air or water varies unpredictably in space and time because of essentially unpredictable variations in meteorological parameters such as precipitation and wind direction. The spatial and temporal distributions and the sensitivities to stress of organisms in nature are similarly variable. Limits on the precision with which variable properties of the environment can be quantified define the upper limit of the precision with which it is possible to predict the ecological effects of a stressor. Out of the universe of similar environmental systems, a given percentage would be expected to show an effect. This percentage translates directly into an estimate of risk.

Parameter Uncertainty

Errors in parameter estimates introduce additional uncertainties into ecological risk estimates. Laboratory measurements of both the chemical and biological properties of hazardous chemicals are subject to frequently unreported errors. Many ecological variables are extraordinarily difficult to measure and can be estimated to only order-of-magnitude precision. Parameter values of interest may have to be estimated from structure–activity relationships (regression models that relate an often unknown parameter to one that is usually known, for example, Kenaga and Goring 1980, Veith and others 1983) or taxonomic correlations (for example, Suter and others 1983 and 1986, Calabrese 1984).

Quantifying Uncertainty

To varying degrees, it is possible to quantify all three types of uncertainty. Since stochasticity can be estimated from historic frequencies, it can be quantified for many characteristics of the physical environment. Long-term meteorological and hydrological records can be used to estimate probability distributions of wind speeds, streamflow rates, and so on. Other variable aspects of the environment, including distributions, abundances, and sensitivities of organisms, are in principle quantifiable, although the necessary data are difficult and expensive to collect. As in all risk analyses, expert opinion can be employed where data are insufficient.

Parameter uncertainties are also relatively easy to address. Parameter errors usually take the form of statistical distributions rather than biases. The parameters of these distributions can frequently be either directly calculated or realistically bounded, if proper data collection and reporting procedures have been followed. For experimentally measured parameters, such as median lethal concentrations (LC_{50}s) and degradation rates, a complete accounting of measurement error would include the variance between replications of an experiment within a laboratory, between laboratories using the same protocol, and, if appropriate, between protocols. Information concerning the magnitudes of these variances is increasingly available from the protocol development and evaluation activities of the US Environmental Protection Agency, the Organization of Economic Cooperation and Development, and the American Society for Testing and Materials (for example, Lemke 1981). This information has been incorporated in risk analysis methods (Suter and others 1986).

Parameter uncertainty also results from the use of regressions to extrapolate between available data and needed parameter values. Suter and others (1983 and 1986) used a regression analysis to estimate the errors associated with the extrapolation of acute LC_{50} values between species of fish and invertebrates and extrapolation of chronic toxic effects threshold levels from LC_{50}s. Similar analyses are possible for extrapolations among chemicals based on structure–activity relationships.

Model errors constitute the least tractable source of uncertainty in risk analysis. The most straightforward method is to test the model against independent field data (Miller and Little 1982). However, the data necessary to perform such tests are exceedingly difficult to collect, and when collected, are difficult to interpret. No matter how well a model performs for one set of environmental conditions, it is never possible to determine with certainty its applicability to a new set of conditions.

Although crucial in the long run for improving the models used in risk analysis (Mankin and others 1975, National Research Council 1981), empirical testing is clearly unsuitable as a routine method of assessing model errors. However, it is possible to assess how assumptions alter model output by comparing models that utilize different sets of assumptions (Gardner and others 1980). Although this procedure does not ensure that model results will correspond to effects in the field, it can be used to distinguish between predictions that are robust to model assumptions and predictions that are highly sensitive to model assumptions and hence susceptible to serious model errors (Gardner and others 1980, Levins 1966).

Implications of Uncertainty

Relationships among the components of risk are illustrated in Figure 2. Suppose we are interested in estimating the risk that the environmental concentration of a toxic contaminant will cause a valued species to fall below a specified threshold abundance. The dashed curve (Figure 2a) is the true density function, determined on the basis of the intrinsic hazard of the contaminant and the stochasticity of the environment. The solid curve is the density function, estimated using a risk model. The curve shifts and its variance increases because of model and parameter error.

Figure 2b presents the cumulative risk distributions for the density functions in Figure 2a. When the model distributions is shifted to the left, as shown in the figure, the model is conservative, predicting higher probabilities of risk than does the true density function. Unfortunately, it is often difficult or impossible to guarantee that the model distribution will be shift to the left rather than the right. In Figure 2c we show the cumulative risk distributions when the risk model is conservative but the parameter error is very large. In this case, the risk model overestimates risk at low concentrations and underestimates risk at high concentrations. This result has real practical importance because increasing the complexity of a model is often viewed as a desirable goal. However, both disaggregating the variables and increasing the complexity of process functions increase the number of model parameters and the potential for parameter error. Therefore, increasing model complexity may increase the chance that the model will underestimate the risk associated with high contaminant concentrations.

The relationship between model complexity and uncertainty is referred to by Rowe (1977) as the *information paradox.* The more complex one's model becomes (that is, the more one knows about the structure of the world), the greater one's uncertainty will be, because of the greater number of parameters to be estimated and because of the greater number of stochastic processes and model functions that must be included. In general, the number of model parameters will increase exponentially with the number of environmental components explicitly included in the model. As model complexity increases, either the costs of testing and parameter measurement or the total uncertainty will quickly become excessive (Suter and others 1985).

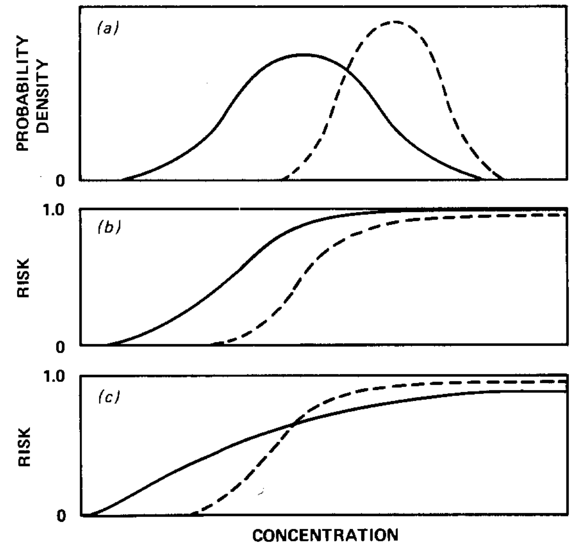

Figure 2. Relationships between true risk (– – –) and estimated risk (——), as functions of concentration, for a hypothetical environmental contaminant. Relative to true risk, the estimated risk density function *a* is shifted and its variance is increased because of model biases and parameter errors. Depending on the relative magnitudes of biases and errors, the cumulative estimated risk function corresponding to the density function in *a* may either overestimate true risk at all concentrations *b* or may overestimate true risk at low concentrations and underestimate it at high concentrations *c*.

One conclusion that can be drawn from this is that assessment models should be as simple as possible while also including the critical components and processes (Barnthouse and others 1984). When a simplification that biases the results is necessary, it should be designed to be conservative. Assessments should not be conservative simply for the sake of being cautious or describing a worst case. Rather, if one cannot describe the full set of components and interactions with a reasonable degree of uncertainty, then reduce the scope of the model in a way that will still protect the assessment endpoints. For example, models used to assess effects of power plants on fish populations typically ignore density-dependent mortality that may compensate for power-plant-induced mortality (Barnthouse and others 1986). The degree of compensation may be substantial or negligible, and no practical methods exist for measuring it.

Similarly, most simplifications of chemical fate models are conservative because they ignore removal processes, such as biodegradation or photodegradation, for which rates are typically unknown. However, it is not always possible to simplify assessment models in such a way as to be conservative. For example, models of acid rain effects on fish cannot ignore cation leaching from watersheds. In any case, these simplified models must be recognized for what they are: models of a reduced world. For example, output from a chemical fate model without removal processes should be explicitly described as "concentration due to dilution."

Uses of Risk Analysis

It is not usually possible to accurately predict the levels of environmental effects caused by human actions. However, even without predicting absolute magnitudes of effects, application of the concept of risk can lead to substantial improvements in environmental assessment and protection. Risk analysis can provide a more rational basis for decisions that may otherwise be highly subjective, by (a) emphasizing probabilities and frequencies of events and (b) explicitly quantifying uncertainty. For example, frequency distributions of ambient contaminant concentrations can be used to forecast impacts on water quality or compliance with standards.

For any given benchmark concentration (for example, an ambient-air or water-quality criterion) the probability of exceeding the benchmark can be read from the cumulative distribution function in Figure 3a. The presentation of such functions would enhance the quality of environmental impact assessments, which frequently are based on worst-case analyses in which the probability of occurrence of the worst case is not considered. Alternatively, the benchmark concentration might be the level above which contaminant discharge would not be permitted. In this case, something like Figure 3a might be used to estimate the frequency of days on which action would have to be taken. Probabilistic models would be used to generate the curves (Parkhurst and others 1981, Di Toro 1986, Barnthouse 1986). The models should include estimates of both variability in relevant environmental parameters and uncertainty in contaminant-specific parameters such as partition coefficients and degradation rates.

Risk analysis can also be used to set standards based on probabilities of exceeding effects thresholds. Suter and others (1983 and 1986) described a method for calculating probability distributions for toxicological benchmarks such as $LC_{50}s$ and chronic-effects thresholds. Such a distribution, plotted as a cumulative probability function, is presented in Figure 3b. The allowable ambient concentration might be set using this curve so that the risk of exceeding the threshold level

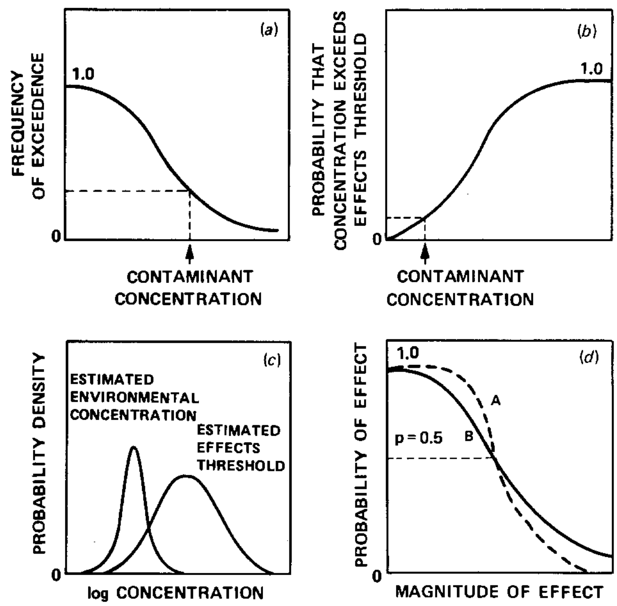

Figure 3. Four applications of ecological risk functions. **(a)** A cumulative frequency function is used to estimate the frequency with which the environmental concentration of a contaminant will exceed an "action" concentration. **(b)** A cumulative probability function for the effects threshold concentration of a hypothetical organism is used to select an action concentration with an X% chance of exceeding the true-effects threshold. **(c)** Probability density functions for two components of a risk estimate are compared to identify the component with the greater uncertainty. **(d)** The risks of adverse effects of different magnitudes are compared for two alternative facility designs. The expected effects of the two alternatives are the same, but alternative *B* presents greater risks of severe adverse effects.

is 5%. Figure 3b could also be used to decide whether the uncertainty is sufficient to justify additional testing when tiered testing schemes are used in hazard assessment.

A third major application of risk analysis is in allocating research efforts to maximize the uncertainty reduction per dollar invested in research related to ecological hazards. If the contributions to total uncertainty of several different components of a risk estimate can be compared, then research efforts can be concentrated on the component(s) contributing the greatest uncertainty. For example, in Figure 3c, uncertainty about the environmental concentration of a toxic contaminant is compared with uncertainty about its effects threshold. The relative variances of the two distributions correspond roughly to the variances estimated by Suter and others (1983) for largemouth bass exposed to mercury released from a hypothetical indirect coal liquefaction plant. Additional relevant data would decrease the spread of these curves. The pre-

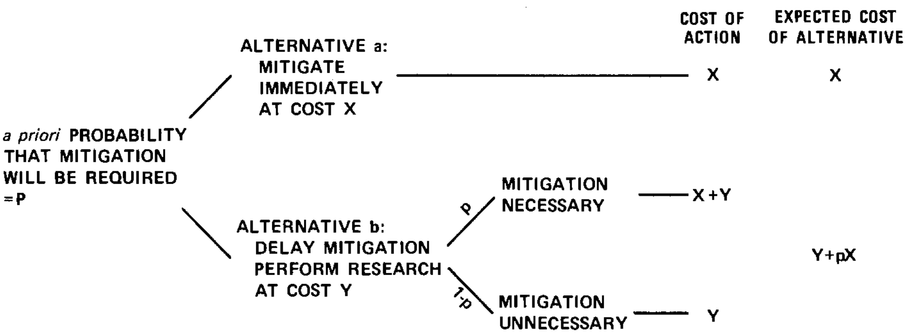

Figure 4. A risk estimate is used as a component of a decision analysis regarding a potential environmental impact. Whether or not it is economical to delay mitigation while performing research concerning the potential impact depends on the a priori probability (p), estimated using a risk model, that research will show mitigation to be necessary.

dicted reduction in overlap between the curves could be used as a measure of the value of the data.

Decisions concerning alternative plant sites and mitigating technologies can be facilitated using risk curves such as those shown in Figure 3d. Such curves provide information about both the expected effects of an action (such as building a plant or licensing a chemical) and about the risk of extremely large effects.

More sophisticated applications of risk analysis to environmental decision making are also possible. For example, Figure 4 presents a decision tree comparing two alternative courses of action for a decision maker confronted with a potential environmental problem. It has been estimated, using a risk model, that the probability is p that the environmental impact of some industrial facility is serious enough to require mitigation. The decision maker has a choice of ordering immediate mitigation, at cost X, or of delaying mitigation while a research program is performed, at cost Y, to eliminate the uncertainty about whether mitigation is necessary. Whether or not it would be economical to delay mitigation would depend on the cost of the research relative to the cost of mitigating and on the a priori probability p that, following research, mitigation would still be necessary.

Examples

Industrial Effluents

The effluents from the proposed synfuels industry present a particular challenge to environmental assessment because their composition is only roughly predictable but is expected to be highly complex. The US Environmental Protection Agency's Synfuels Risk Analysis Program developed risk assessment methods and applied them to the problem of setting research priorities for the anticipated industry (Barnthouse and others 1985, Suter and others 1984). Effluent streams and components were identified as needing additional research if they appeared to pose a significant hazard but their environmental behavior was in some way poorly specified. Risk assessment provided a means of simultaneously identifying the relative hazard and uncertainty associated with the effluent components.

Effluent compositions were defined in terms of chemical classes so as to minimize the effluent characterization problem and to reduce the assessment task to a manageable scale. The need to consider the effluent toxicities was established by using an additivity model to estimate the acute toxicity of the whole effluents based on the toxicities of their component chemical classes. Only one of the effluents was predicted to be acutely toxic, but all effluents had sufficiently high toxicity and uncertainty concerning their actual effects to justify additional research. Some specific research needs were immediately identifiable because no environmental toxicity data were available for certain classes of chemicals, such as nitroaromatics, which were expected to occur in the effluents. Some classes, such as ammonia and cadmium, contributed significantly to aquatic toxicity; but because these classes are well studied and narrowly defined, the uncertainty concerning their effects is relatively small. Of the classes for which there are some aquatic toxicity data, only the phenolics had both high apparent hazard and high uncertainty, which would justify additional research.

Acid Deposition

The issue of acid deposition involves a variety of complex processes operating at scales ranging from the organismal to the continental. The following example shows how, by broadly defining the problems and emphasizing uncertainty, the issue can be made more manageable.

Morgan and others (1985) considered the problem of health effects of sulfate aerosols. They independently elicited models and judgments concerning parameterization and uncertainty from experts on atmospheric processes and health effects. From these they generated probability density functions on estimated sulfate exposure and effects. They found that the uncertainty concerning exposure was relatively small, because atmospheric scientists have relatively well-developed models which were well supported. In contrast the health effects experts agreed little about models or assumptions. The results of this exercise provide estimates of effects from a single coal-fired plant that range from zero to a few thousand excess deaths per annum. More clearly, they indicate that further research in atmospheric science would contribute little to improving the estimates of health effects.

Genetically Engineered Organisms

Engineered organisms potentially constitute the most difficult problem facing environmental assessment. While some of the techniques developed for assessing toxic chemicals are also applicable to novel organisms, the fact that organisms reproduce, evolve, and have specific habitat requirements considerably complicates the problem of predicting their fate and effects. Because the field is new and the number of organisms to be assessed is small, assessments have not used risk analysis. Rather, they have relied on the informal judgments of expert panels. However, because of the overconfidence of experts (Fischhoff and others 1981), the inconsistency in ad hoc procedures, and the eventual need to assess hundreds or thousands of new organisms per year, formal assessment procedures must eventually be developed. Because of the less predictable behavior of organisms and the fact that their reproductive capability allows them to persist indefinitely, it is particularly important that assessments of organisms include the explicit treatment of uncertainty.

Suter (1985) has presented a conceptual framework for environmental risk analysis of engineered organisms. Major sources of uncertainty include the probabilities of movement between habitats, colonization of new habitats, pathogenicity by a nominally free-living organism, extension of a pathogen's host range to nontarget species, disruption of ecosystem processes, exchange of genetic material between organisms, and evolution that reduces constraints on the organisms' behavior. Because of the specificity of habitat requirements, it is difficult to generalize from tests of the persistence or effects of an organism in a particular system. A bacterium that goes extinct in one soil may proliferate in a soil 1 m away. Therefore, it would be naive to accept test results as being predictors of the environmental behavior of organisms, as is usually done for chemicals. A risk-based assessment strategy will provide a means to deal appropriately with these uncertainties.

Conclusions

Risk analysis, because of its explicit treatment of uncertainty, provides two significant benefits for environmental impact assessment. The first is that it eliminates the need for worst-case scenarios and analyses by providing probability densities on the expected effect that can be used to estimate the probability of any worse effect. Worst-case analyses are often unrealistic, and because there is no absolute worst case and no scale of badness, they should not be used to compare alternative actions. The second advantage is that it provides an objective means of deciding, based on reduction in uncertainty, which research would most improve the assessment.

Regardless of its intellectual appeal, environmental risk analysis will soon be forgotten unless the concepts can be translated into operational techniques. Steps in this direction have already been taken (Barnthouse and Suter 1986). Most of the necessary components of operational risk analysis methodologies (such as, air/water quality models, ecological effects models, and toxicological data bases) already exist. The only constraints on the usefulness of existing models and data are that (a) the models must be modified so that output can be expressed in probabilistic terms, and (b) error variances in experimental studies and in data extrapolations must be reported so that parameter uncertainties can be quantified.

As in other types of risk analyses, the most difficult problem facing the environmental risk analyst is that of demonstrating that his risk model provides reasonable estimates of ecological risks in the real world. At least for environmental contaminants, many of the same physical, chemical, and biological processes underlie both ecological and human health risks. Thus, progress made in one field can directly benefit the other.

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