

CHAPTER 4

Ecotoxicology and Benefit-Cost Analysis:

The Role of Error Propagation

Introduction

An understandable desire exists on the part of policy makers to devise a set of procedures! an analytical approach, that can be used to guide policy. Such an approach would obviate the need **for** trusting to historical practice, or to the intuition of wise but inevitably fallible and probably biased Individuals, or to the awkward and time-consuming process of making every decision by plebiscite. It would "rationalize" policy making and, **if** the procedure were appropriately chosen, optimize the well-being of the affected sector of the public. Pollution abatement policy is **a** prime example, for it is here that a vigorous effort is underway to promote benefit-cost analysis as the appropriate analytical approach for determining proper emission levels (see U.S. Executive Order 12291).

Despite the advantages in efficiency of decision making, and possibly in enhancement of societal welfare, that may accrue to a society that employs the benefit-cost approach to set pollution emission levels, there are major pitfalls lurking that need to be identified and discussed. These pitfalls fall into two categories: limitations in the ability of ecologists to describe precisely the ecological consequences of pollutant emission rates, and limitations in the ability of economists to describe precisely the economic consequences of ecological changes.

Quite generally, the economic and ecological analyses that are required to characterize and quantify costs and benefits of particular pollutant abatement strategies consist of a sequence of steps. Table 1 shows what a typical sequence of steps would have to look like for a believable benefit-cost

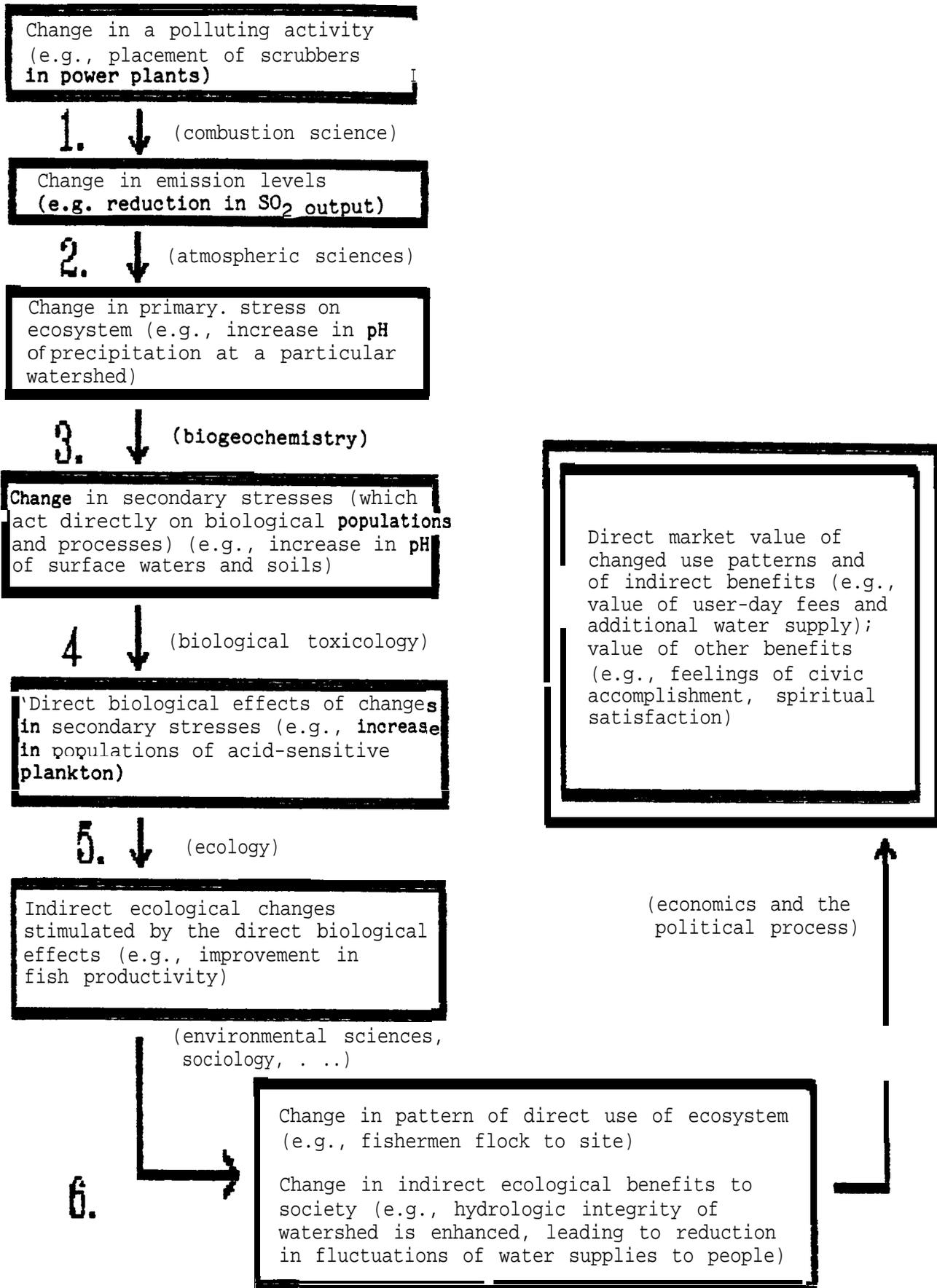


Table 1. The stages of ecosystem impact assessment

analysis, with the example of acid rain used to provide specificity. The information that must be used to quantify any given step in the sequence must come from analysis at the preceding stage. Thus the possibility exists that error may propagate through the sequence to the point where the final output--for example, the economic benefit of a particular level of pollution abatement--is so uncertain as to be of little or no use in a benefit-cost analysis or related procedure.

Whether or not this occurs will depend in part on the degree to which ecologists and other environmental scientists can characterize the uncertainty in a manner that can be used by economists. To take a simple example, consider the statement that the decrease in fish mortality following pollution abatement in a particular lake is uncertain. This statement may mean that the decrease **in** mortality cannot be predicted accurately but that the odds of any specified degree of decrease in mortality are known (from some combination of measurement and modeling). Or it may mean that only the range of uncertainty is known but that the probabilities of any particular value of mortality within that range are not known. In the former case, economists may be able to estimate an expected value of benefit of any particular degree of abatement (using methods such as those described elsewhere **in** this report), whereas in the latter case the opportunity to characterize the benefit of any particular degree of abatement is considerably more limited.

In the remainder of this chapter we discuss in a systematic and general manner the subject of error propagation in environmental impact assessment, with an emphasis on impacts involving ecosystems. We deduce some general results about error propagation that are Independent of the method of analysis. One key result is that error tends to **"biomagnify"** in ecological food chains, so that a small degree **of** uncertainty about the effect of a pollutant on the lowest **trophic** level **is** likely to translate into much more

substantial uncertainty about the effects on higher **trophic** levels, **in** which we are often more interested. **We** also explore the origin of some of the most refractory types of error in impact assessment. To relate the analysis to the specific concerns of practitioners of economic evaluation we also show how the relevant issue is not merely one of the magnitude of the range of uncertainty but also of the type of uncertainty; this is because economic analysis, which must begin where ecological analysis leaves off, can cope with some kinds of uncertainties better than others. Of particular concern in the context of benefit-cost analysis is the degree to which sources of ecological uncertainties can be characterized in ways that will be of use to economists. The overall dimensions and a few critical elements of this problem are discussed here, but it will be shown that considerable work on the part of ecologists will be necessary to bridge the gap between what is now known and what needs to be known to provide a plausible underpinning for the successful application of benefit-cost methods of decision-making.

Uncertainty in Impact Assessment: an Example

Examples of error propagation in environmental science abound. Consider the acid rain example from Table 1. Analysts have attempted to establish the existence and **valuse** of a threshold level of precipitation pH, below which lakes would become acidic and above which the natural restorative capacity of lakes and surrounding soils would afford protection. The existence of such a threshold would make the task of setting standards easier because such a threshold would provide a natural level to aim for--tightening the standard beyond the threshold would lead to diminishing returns.

However, uncertainties in impact assessment render the threshold notion a highly dubious one in this context. It is likely, in fact, that **one's**

perception of the location of the threshold for a particular class of lakes depends on how long one has been observing those lakes under various levels of **exposure**; whereas precipitation with a **pH** of, say, **4.5** might acidify the lakes **in** 10 years, precipitation with a higher **pH** of, say, **4.9** might acidify the lakes in 30 years, a period longer than anyone has had the opportunity to observe. Thus the threshold concept is time-dependent and intrinsic uncertainty characterizes **its** evaluation

The threshold value for one class of lakes might not be of much use for others. For example, in eastern North America it has been pointed out that over several decades, the period over which observations have been made, lakes receiving precipitation with a **pH** of less than about **4.7** have had their chemistry altered by the precipitation. Even if we accept this relatively short time-frame for that particular group of lakes, there is still uncertainty as to the value of this "threshold" in other areas. In the mountains of the western United States, for example, the susceptibility of lakes to acidification appears to be greater than in watersheds of the northeastern U.S. (Roth et al, 1985). A more complete discussion of uncertainties plaguing the use of the threshold concept in **ecotoxicology** is found in Cairns and Harte (1985).

Even if we had confidence in the location of a **pH** threshold, we would still not know exactly what the effect on precipitation **pH** would be for any specified emissions reduction plan. Here the uncertainty stems from the complexity of the source-receptor relation.

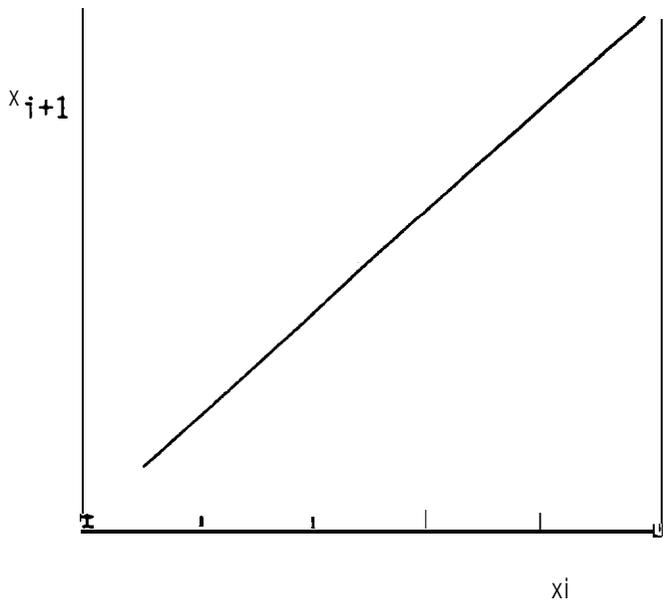
The uncertainty in deducing the effect of a particular level of emissions reduction on precipitation **pH** must be combined with the further uncertainty in deducing the effect of a reduction in precipitation **pH** on surface water acidity. By combining these two uncertainties, the overall uncertainty in steps 2 to 4 of Table 1 can be determined. At the other stages in the impact

assessment further opportunity for error arises. The combined error is almost invariably sufficiently large to make it difficult to obtain a precise characterization of the ecological benefits from a particular **emissions-reduction** plan.

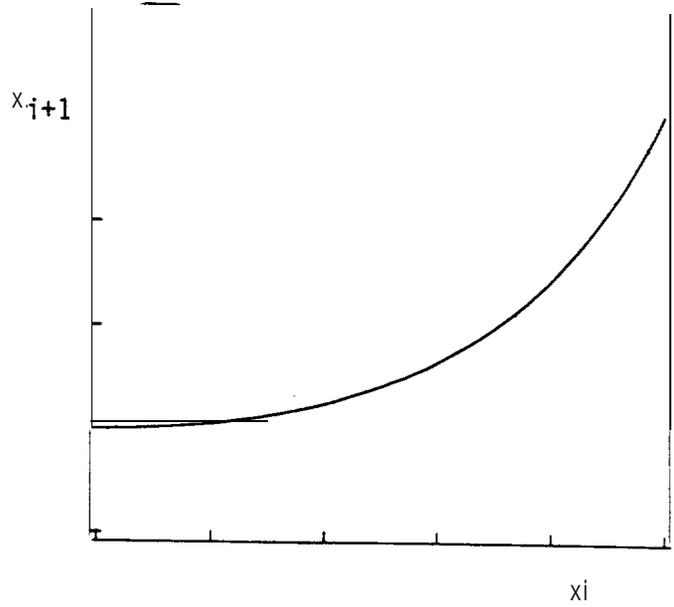
The fact that one cannot precisely characterize the benefits of a pollution-abatement policy should not be taken to mean that the policy is unwarranted. Even though an economic analysis might not produce a reliable cost-benefit ratio, **it** can lead to a range of uncertainty in that ratio, which can then be evaluated through the political process to determine what policy action is warranted. The first step, however, must be to have a systematic approach to the analysis of uncertainty; this is discussed in the following section.

A Framework for Analysis

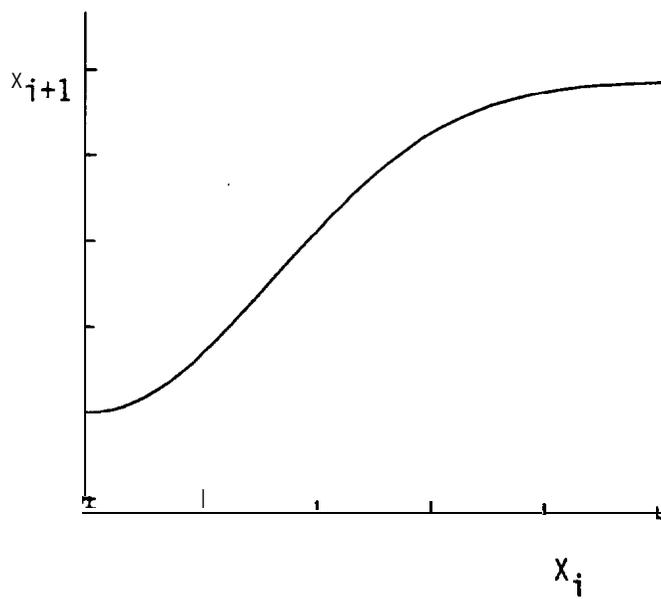
The sequence of steps in an environmental impact assessment as shown on the left hand side of Table 1 provides a convenient framework for **analysing** the propagation of error in such assessments. Generally, the relation between the i th and the **$i+1$ st** stage in the **sequence** is likely to look like one of the three graphs shown in figure 1. In each of the graphs, the horizontal axis represents the variable describing the i th stage and the vertical axis represents the subsequent one down the chain. The first of these three graphs illustrates a linear relation, in which the response, or output, at the subsequent stage is proportional to the input from the one before, as, for example, if the loss of organisms is proportional to the concentration of a pollutant. The second one illustrates a threshold process, in which an output is only weakly dependent on an input for small values of the input, but when the Input exceeds a critical value, then the output rises sharply. **The**



a.



b.



c.

Figure 1

Illustration of a **linear (a)**, a **threshold (b)**, and a **saturation (c) process** relating variables describing successive stages in the assessment chain.

third graph in Figure 1 illustrates a saturation process, in which an output ceases to be strongly dependent on input once the input exceeds a critical value.

These three basic types of relations between sequential stages in the impact chain can be modified or combined to describe, generically, most real processes. For example, the graphs can be turned upside down to describe processes in which an output **is** a decreasing function of input. Or graphs 1-b and 1-c can be combined to describe a process with a threshold at a relatively low value of the input and a saturation effect at a higher one.

If knowledge of the functional relation between two sequential stages in the chain were complete, and the Input data were known with perfect precision and accuracy* then a graph of the function describing the relation might, indeed, look something like one of the plots in Figure 1. But, **in** reality, there is always uncertainty in both knowledge of functional relations and **in** the data needed to substitute into those functions. These uncertainties will propagate down the impact chain, sometimes leading to a surprisingly high level of uncertainty at the end.

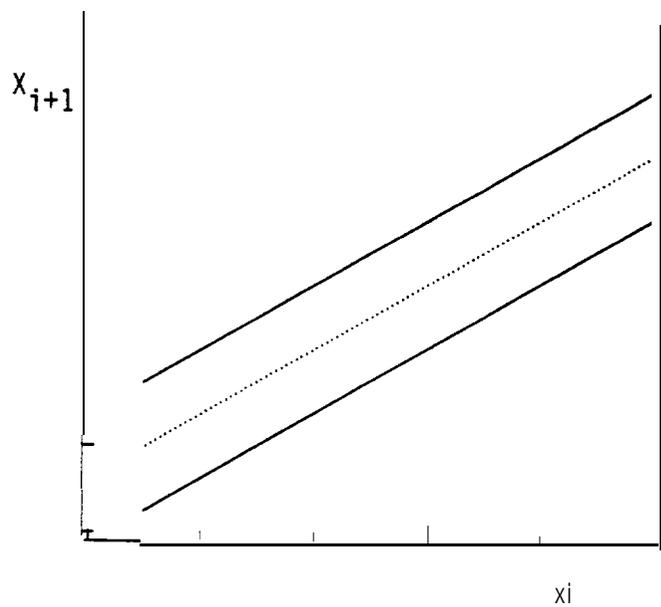
Two types of uncertainty were alluded to above. one results from poor knowledge of the dynamics of the **processes--i.e.** uncertainty in our understanding of the form of the relation between variables--and one results from **incertain** numerical values for data. For example, suppose that we are interested in estimating the uncertainty **in** our knowledge of the lessening of damage to plankton populations due to an expected decline in the rate of input of a pollutant to a lake. Because it is difficult to predict with high

*'Precision' refers to the detail with which a number is expressed--the number of significant figures. "Accuracy" refers to how close the number is to the true, or real, value. Thus if I state my height **is** 3.47258 meters, I am being precise but inaccurate. Oftentimes authors will substitute precision for accuracy, providing more significant figures than the data deserve and giving the illusion that they are highly accurate.

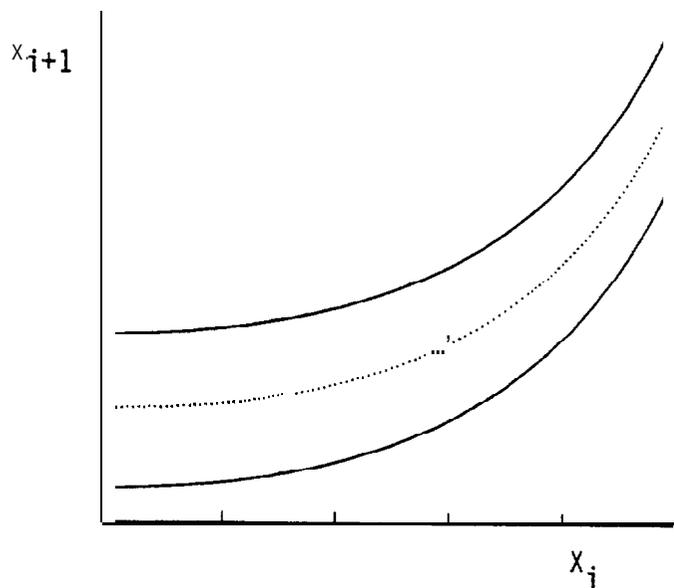
accuracy how the concentration of a pollutant in a lake will respond to a change in the input rate, there will be uncertainty in our knowledge of what the concentration of pollutant **in** the lakewater will be. On top of that we will have, at best, only partial knowledge of how the plankton population will respond to any precisely stated change in the pollutant concentration. In other **words**, even with perfectly accurate data describing the pollutant, our knowledge of the functional form of the relation between pollutant concentration and plankton survivability **is** uncertain.

Because of the uncertainty in our knowledge of functional relations, the graphs shown in Figure 1 must be modified as in Figure 2. Furthermore, because the input data (the horizontal axis variable) are likely to be uncertain, the output (the vertical axis variable) is also going to have an uncertainty that reflects the fuzziness of the input data. At each stage in the chain, the uncertainty may be amplified or damped as uncertainty **in** the output from one stage becomes uncertainty in the input to the next. Figure 3 provides a generic illustration of how the error will propagate down the chain. The range of uncertainty is shown to broaden **in** the figure, a result of the width and steepness of the functional forms assumed. If probability distributions characterizing the likelihood of the parameters taking on particular values within the range of uncertainty are known, then a more sophisticated analysis can be carried out; shown here is the simpler case in which only the propagation of the range of uncertainty is described.

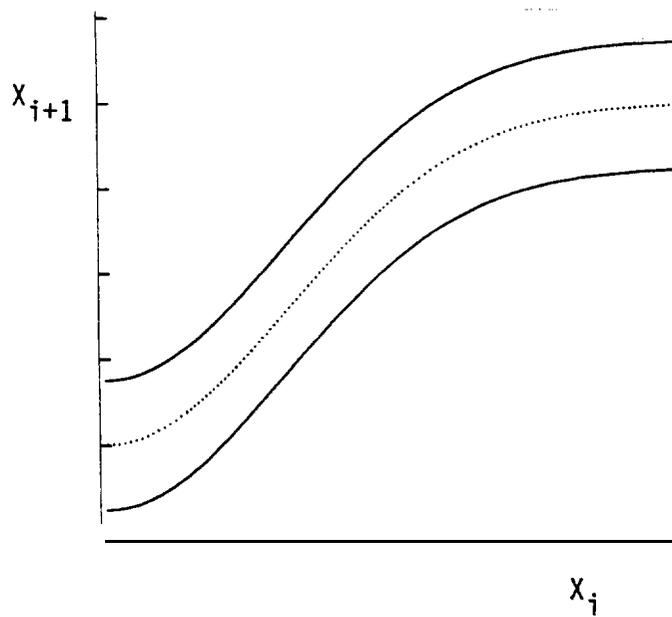
A useful analysis of the consequences for policy makers of this sort of error propagation is given in Reckhow (1984). In the following section, we discuss some general results about uncertainty that can be deduced from the above considerations.



a.



b.



c.

Figure 2

Examples of error bands in the curves shown in Figure 1.

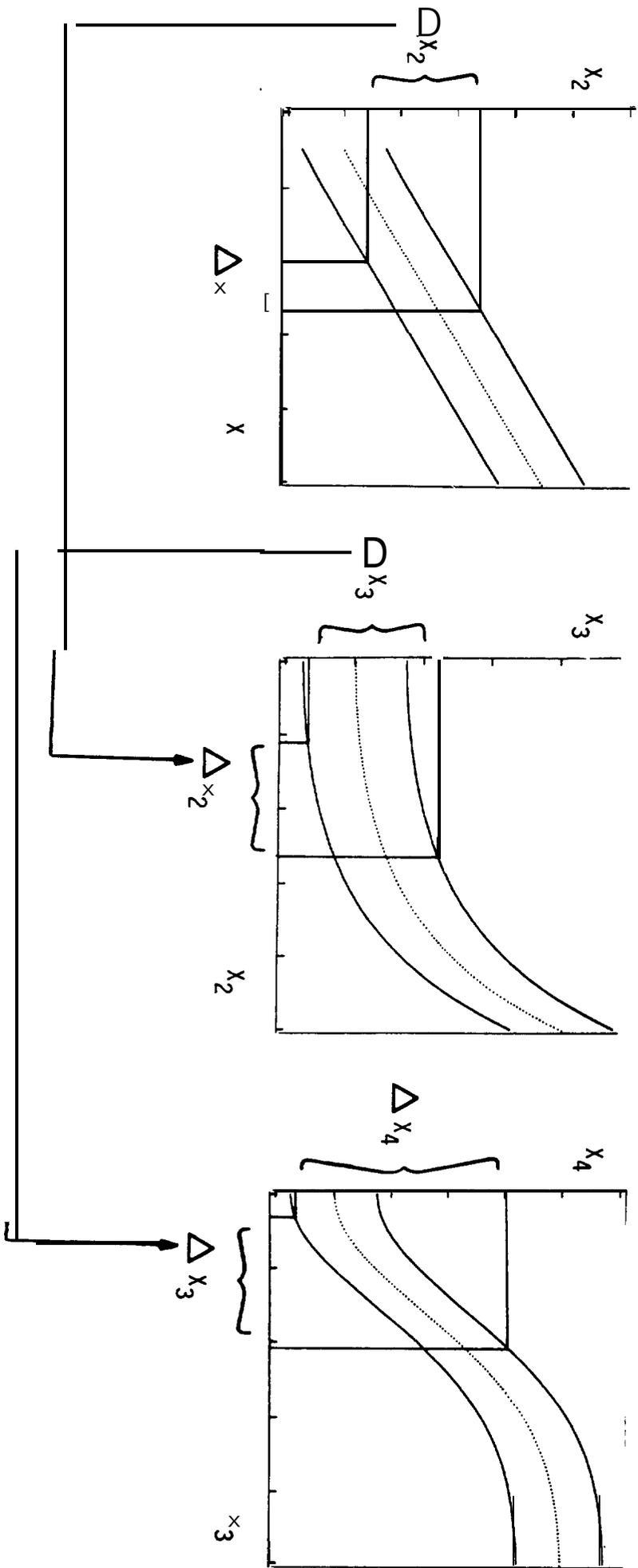


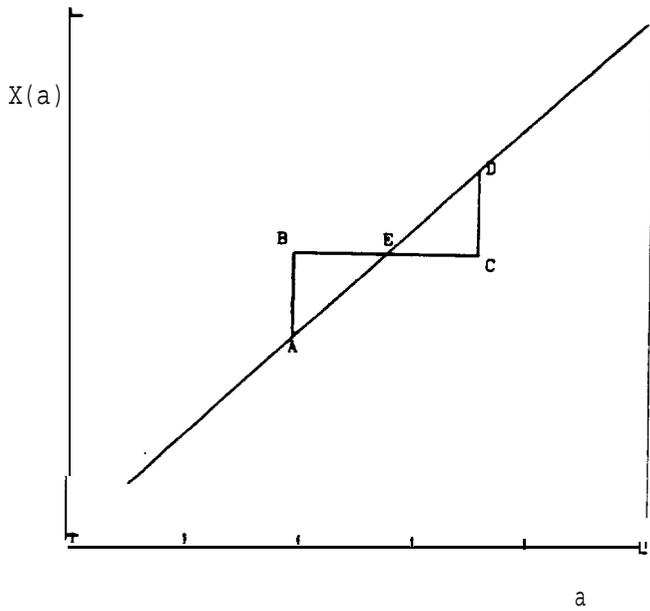
Figure 3

Illustration of the propagation of error along the measurement chain. In each graph, the uncertainty in X_i is "passed along" to X_{i+1} in the manner shown.

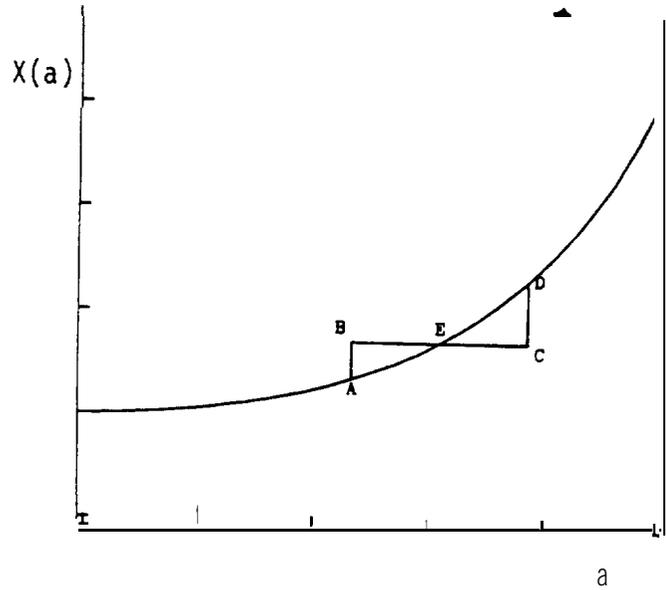
General Results: The 'Fallacy of the Mean" and 'Error Biomagnification"

Quantities such as fish productivity or water clarity, indeed any parameter to which a numerical range can be ascribed, can be characterized by a mean value and a range of uncertainty about that mean. Because it **is** much simpler to focus on a mean value, which is a single number, rather than on the range of uncertainty, which is at the very least a range **of** numbers (often with a complicated interpretation attached explaining what that range really refers to) **it** is not uncommon for analysts to be asked questions **such as** 'if I take the mean value of the pollutant concentration and substitute that into the formula relating concentration to plankton survivability, then what mean value will I **obtain** for plankton survivability?" This question reflects a fundamental confusion: a function evaluated at the mean value of its independent variable is generally not equal to the mean value of the function. Indeed, as shown below, considerable error can result if mean values are estimated by **committing** this 'fallacy of the mean".

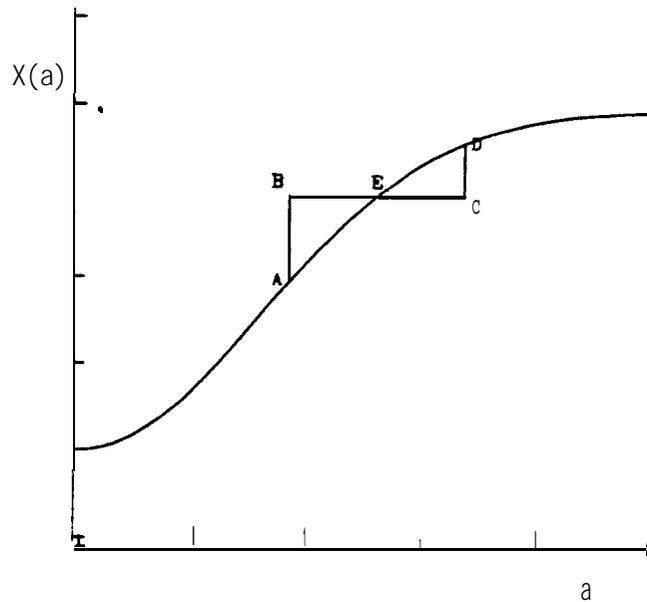
How **will** the general shape of the graph (as is Figure 1) of the relation between two successive stages in impact assessment influence the error committed by assuming that **a** function of the mean equals the mean of the function? Figure 4 illustrates the answer to this question. In this figure, the parameter, **a**, **has** equal **probability of** lying anywhere in the range from B to C and its mean is midway between at E. **At** the upper end of this range, $x(a)$ takes on the value **D** while at the lower end **it** takes on the value A. As the figure shows, if the relation between an independent variable, **a**, and a dependent variable, **x**, **is** linear, then despite uncertainty in our knowledge of **a**, the mean value of **x**, denoted by **X**, is equal to **x(a)** evaluated at **a**, the mean value of **a**. In equation form, $x = x(a)$. For the case of a threshold-type relation, this figure shows why $X > x(a)$, while for a saturation process, $x < x(a)$.



a. IF $BE=EC$, THEN $AB=CD$



b. IF $BE=EC$, THEN $DC > BA$



c. IF $BE=EC$, THEN $AB > CD$

Figure 4

The relation between the mean **value** of X and the **value** of X evaluated at the mean value of the parameter, a , upon which it depends, is shown for the three cases of a linear (a), upward curving (b), and downward curving (c) relation between X and a .

This can be very important **in** practice; for relations characterized by very steeply curved functions the use of the mean value of the independent variable for evaluating the mean **value** of the dependent one can lead to a gross **under-** or over-estimation, depending on the type of curvature in the functional relation. To illustrate this, we present the following example.

The attenuation of light with depth in a relatively transparent lake obeys a simple formula: $I(d) = I_0 \exp(-vd)$, where $I(d)$ is the intensity at depth d , I_0 is the intensity of light at the surface, and v is a constant characterizing the transparency of the water. The more opaque the water, the larger the value of v . Primary productivity of aquatic plants at any particular depth will be roughly proportional to the value of **I** at that depth, although it also depends, of course, on concentrations of essential nutrients such as nitrate and phosphate. Suppose siltation results in a large value of v . We will assume that the mean value of v is 0.3/meter and that the range of uncertainty is ± 0.02 /meter. We will interpret this range to mean (for the sake of simplicity) that the actual value of v is equally **likely** to lie anywhere **in** the range from 0.28 to 0.32/meter. Suppose erosion control is expected to reduce the value of v to 0.17 ± 0.09 , with the range of uncertainty increased because it is not known how effective the control program will be. At a depth of, say, 20 meters, the mean value of I prior to the erosion control that would be calculated (incorrectly) by substituting the mean value of v into the formula for $I(d)$ is $I_0 \exp(-6.0)$ or $0.0025 I_0$. After the control is implemented, the similarly incorrect value is $I' = I_0 \exp(-3.4) = 0.0331 I_0$ an **increase** of I by a factor of about **12**. However, if the actual mean value of I is calculated properly, not by substituting into $\exp(-vd)$ the mean value of v but rather averaging over the range of uncertainty in v , then we find that erosion control results, on the average, **in** twice as great an increase in mean light intensity at 20 meters. Leaving

aside subtleties such as whether plants respond to the average light intensity they receive or to some more complicated value that depends on the fluctuations, there is clearly a large potential for error in naively estimating mean values by being oblivious to the uncertainties.

We emphasize that the propagation of error by this means can result either from a situation where one knows what the uncertainties are but uses the incorrect formula relating mean values, or from a situation where one simply **under-** or overestimates the magnitudes of the uncertainties but uses a correct averaging procedure for estimating mean values.

In the modular approach to error propagation discussed in the previous section, there is an opportunity for errors of this type to either be reinforced or to cancel. If a sequence of relations between the variables describing the successive stages **in** the impact chain are all of, say, the threshold type, or more generally, of any similar curvature, then the error propagation that results from ignorance of the true range of uncertainty **will** be reinforcing, leading to greater and greater errors as one moves along the chain. In contrast, if curves of types **1.b** and **1.c** from Figure 1 are equally represented in the chain, then the tendency will be for the errors of that type to cancel.

Next, we turn to the topic of 'error **biomagnification**'. Error, like many a toxic substance, will frequently increase as one probes higher up the food chain (not to be confused with the impact assessment chain in Fig. 1), although the mechanism that accounts for error **biomagnification** is quite different from that for toxic substance **biomagnification**. To see how error **biomagnification** arises, consider the following relatively simple model for a food chain. Figure 5 illustrates the model, showing the inflows and outflows of biomass from each link in the chain. The links can be thought of as

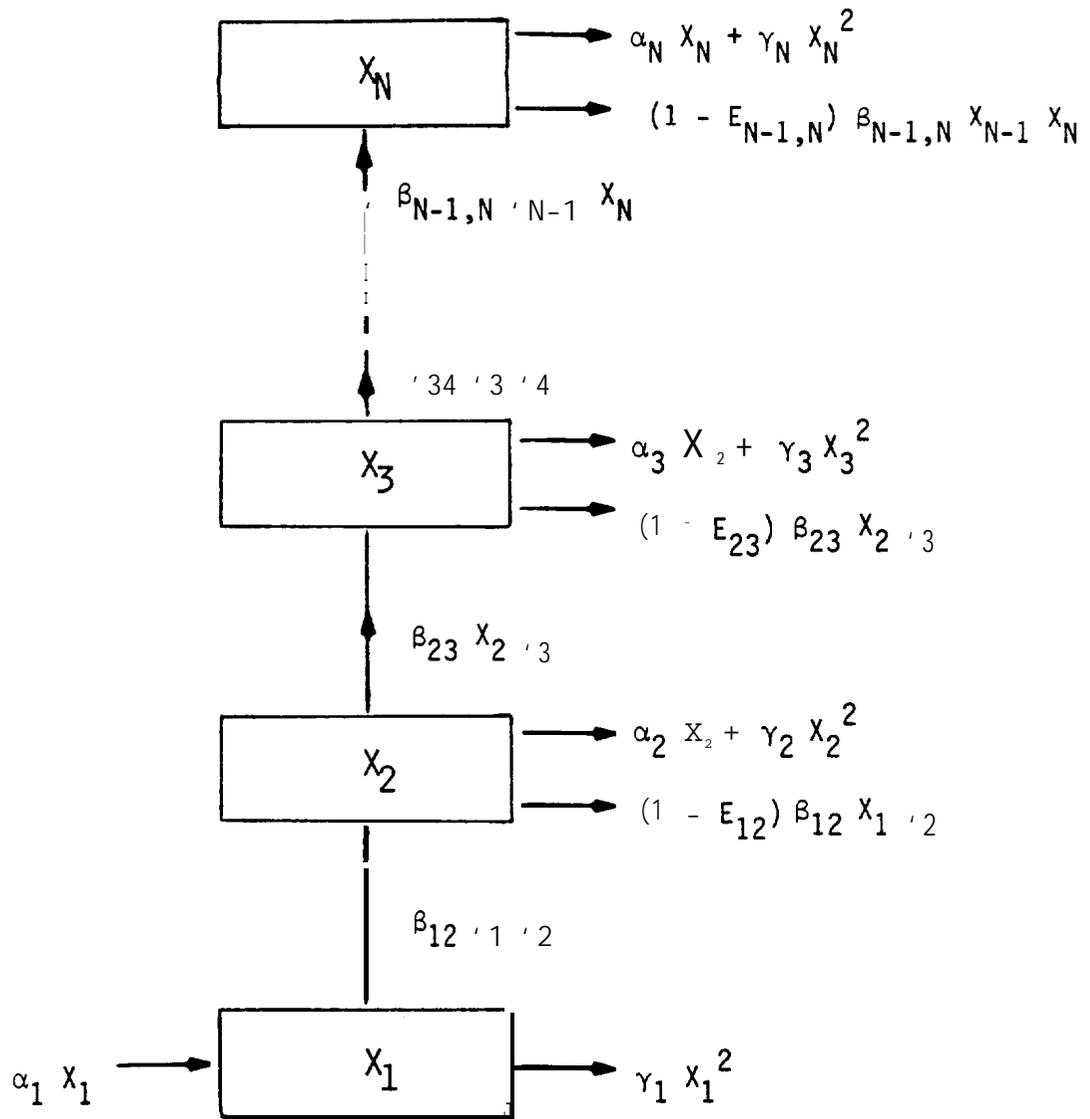


Figure 5

A **trophic** chain and the rates of biomass input and output from each **link** in the chain as described by a simple **Lotka-Volterra** model.

species (for example, grass, which is eaten by rabbits, which are eaten by lynx, etc.) or as functional groupings of species (for example, primary producers, herbivores, first carnivores, . . . and on up to top carnivores).

In equation form, the model reads as follows:

$$\begin{aligned} \frac{dX_1}{dt} &= \alpha_1 X_1 - \gamma_1 X_1^2 - \beta_{12} X_1 X_2 \\ \frac{dX_2}{dt} &= E_{12} \beta_{12} X_1 X_2 - \alpha_2 X_2 - \gamma_2 X_2^2 - \beta_{23} X_2 X_3 \\ \frac{dX_3}{dt} &= E_{23} \beta_{23} X_2 X_3 - \alpha_3 X_3 - \gamma_3 X_3^2 - \beta_{34} X_3 X_4 \\ &\vdots \\ \frac{dX_N}{dt} &= E_{N-1,N} \beta_{N-1,N} X_{N-1} X_N - \alpha_N X_N - \gamma_N X_N^2. \end{aligned}$$

In these equations, the X_i are the **biomasses** of the components; the coefficients β_{ij} are rate constants describing the predation of species j upon species i ; the coefficients E_{ij} describe the efficiency of incorporation of prey biomass by the predator; and the coefficients α_i and γ_i are **growth** and death rates for the individual species. The presence of the γ_i terms represents a negative feedback mechanism induced by the finite carrying capacity of any realistic environment. They result in steady-state solutions that are stable against perturbations such as the removal of some percentage of the biomass of the system. Indeed, the only solution to these equations **is one in which all** the x_i approach time-independent **values**. Although real populations are not found in steady-state (that is, the numbers of individuals **in** real populations generally **exhibit** both cyclic and random time dependence), models with steady-state solutions are often used to study the

time-averaged behavior of such populations. Although simple models of this sort are generally unreliable for making detailed predictions of the values of the variables, $X_i(t)$, they are useful for exploring the qualitative features of ecosystems.

Suppose that the growth rate of the primary producers is affected by a pollutant, but that there is some uncertainty about the magnitude of the effect. In other words, suppose that the value of α_1 is known only to be in the range between $\bar{\alpha}_1 + \sigma$ and $\bar{\alpha}_1 - \sigma$ where $\bar{\alpha}_1$ is the mean value and σ is a measure of the uncertainty in the mean. How will the uncertainty in affect the uncertainty in the steady-state values of the Individual variables, X_i ? A simple two-level model illustrates the general idea:

$$\frac{dX_1}{dt} = \alpha_1 X_1 - \gamma_1 X_1^2 - \beta_{12} X_1 X_2$$

$$\frac{dX_2}{dt} = E_{12} \beta_{12} X_1 X_2 - \alpha_2 X_2 - \gamma_2 X_2^2.$$

For this case the steady-state solutions for the X_i are:

$$X_1 = \frac{\alpha_2 \beta_{12} + \alpha_1 \gamma_2}{E_{12} \beta_{12}^2 + \gamma_1 \gamma_2} \quad \text{and}$$

$$X_2 = \frac{\alpha_1 E_{12} \beta_{12} - \alpha_2 \gamma_1}{\beta_{12}^2 + \gamma_1 \gamma_2}.$$

A measure of the relative uncertainty in the x_i caused by the uncertainty in α_1 is $(\sigma/X_1)(\partial X_1/\partial \alpha_1)$. Thus the ratio of the relative uncertainty in X_1 to that in X_2 , which we denote by R_{12} , is

$$R_{12} = \frac{(\sigma/X_1)(\partial X_1/\partial \alpha_1)}{(\sigma/X_2)(\partial X_2/\partial \alpha_1)}.$$

This can be shown to equal $(\gamma_2 X_2)/(\alpha_2 + \gamma_2 X_2)$, which is less than unity. In

other words, the **relative error in X_2** induced by the uncertainty in α_1 is necessarily greater than that for X_1 . For this two-level model, if the uncertainty lies in our knowledge of a_2 , the parameter characterizing the death rate of the predator rather than the growth rate of the prey, then the result is ambiguous; the **value of R_{12} will depend on the** relative magnitude of α_1 and $\gamma_1 X_1$. In particular, if the latter term is not small compared to the former, then **again R_{12} will be less** than unity. Thus **in** this two-level model, if the uncertainty lies **in** our characterization of the base of the food chain, then uncertainty **"biomagnifies"** up the chain, whereas if it lies at the top of the chain, then it may or may not magnify down the chain.

Results from three-level and four-level models are shown **in Figure 6**, both for the case in which the original uncertainty lies at the base of the food chain and the error propagates up to higher **trophic** levels and for the case in which the original uncertainty lies at the top of the food chain and the error **'bounces off'** the base and propagates back up. Note how a relatively small initial error in either the **phytoplankton** growth rate or the fish death rate results in progressively larger uncertainty as one progresses up the food chain.

It would be of considerable interest to characterize the system properties that determine the degree to which error **"biomagnification"** occurs. It is likely that properties of the food chain such as the ratios of **biomasses** or population densities at successive levels and the ratio of predation rates to other death rates will be important factors **in** more complex situations than **in** the grossly over-simplified models treated here.

The implications of this for ecological impact assessment can be of great importance. The interest of the public is usually **in** the higher levels of the food chain--be it fish for recreation and **food** or exotic wildlife for

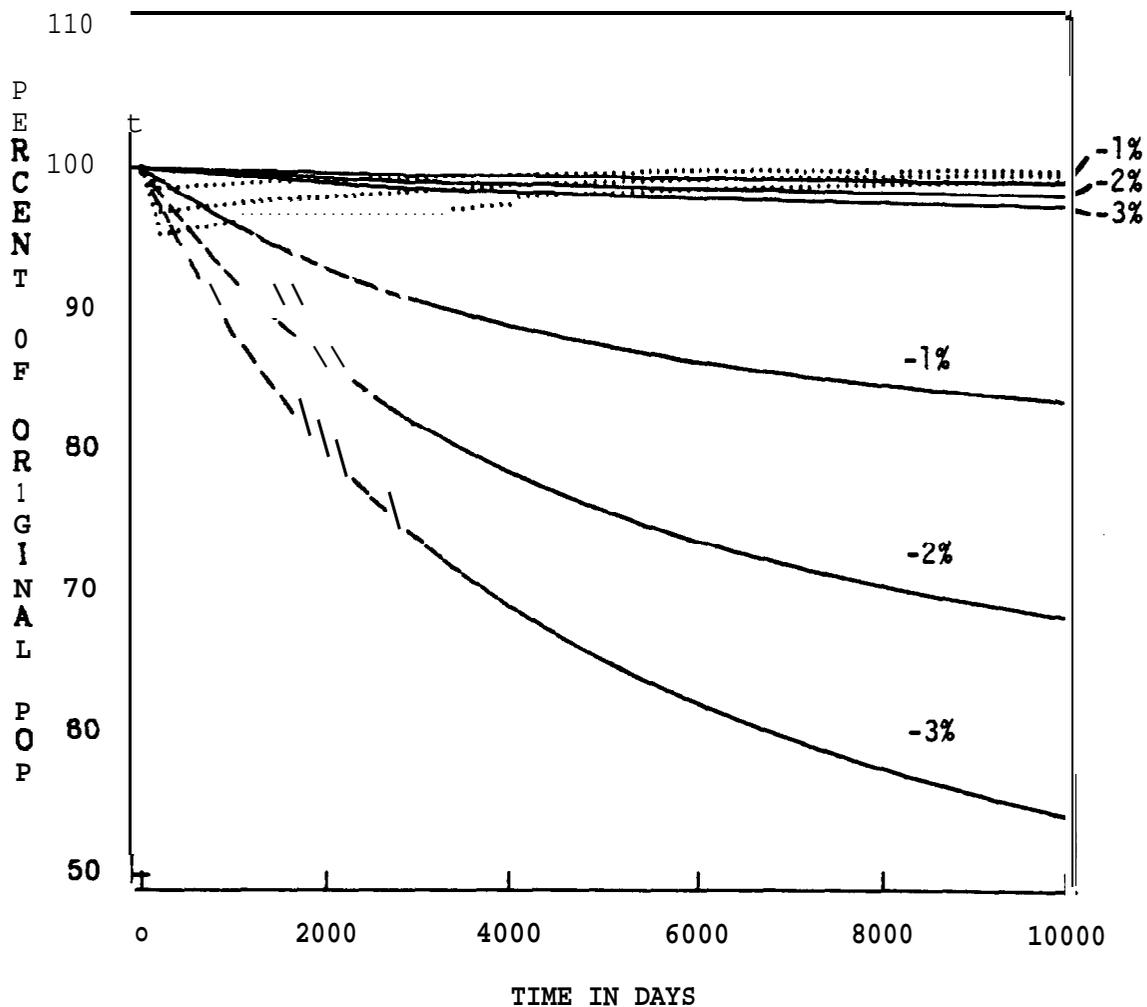


Figure 6a

The response of the populations in a three-tiered aquatic ecosystem (measured in biomass per unit area, initial biomass ratios: 50 phytoplankton: 10 zooplankton : 1 small fish) to -1%, -2%, and -3% changes in the phytoplankton growth rate. Solid, dotted, and (partially) dashed lines give the paths for phytoplankton, zooplankton, and small fish, respectively. This figure corresponds to a situation in which the degree of perturbation in the growth rate, caused, for example by pollution, is uncertain, but is known to lie within some range. The effect of this uncertainty on the relative magnitudes of population changes in the three trophic levels is shown.

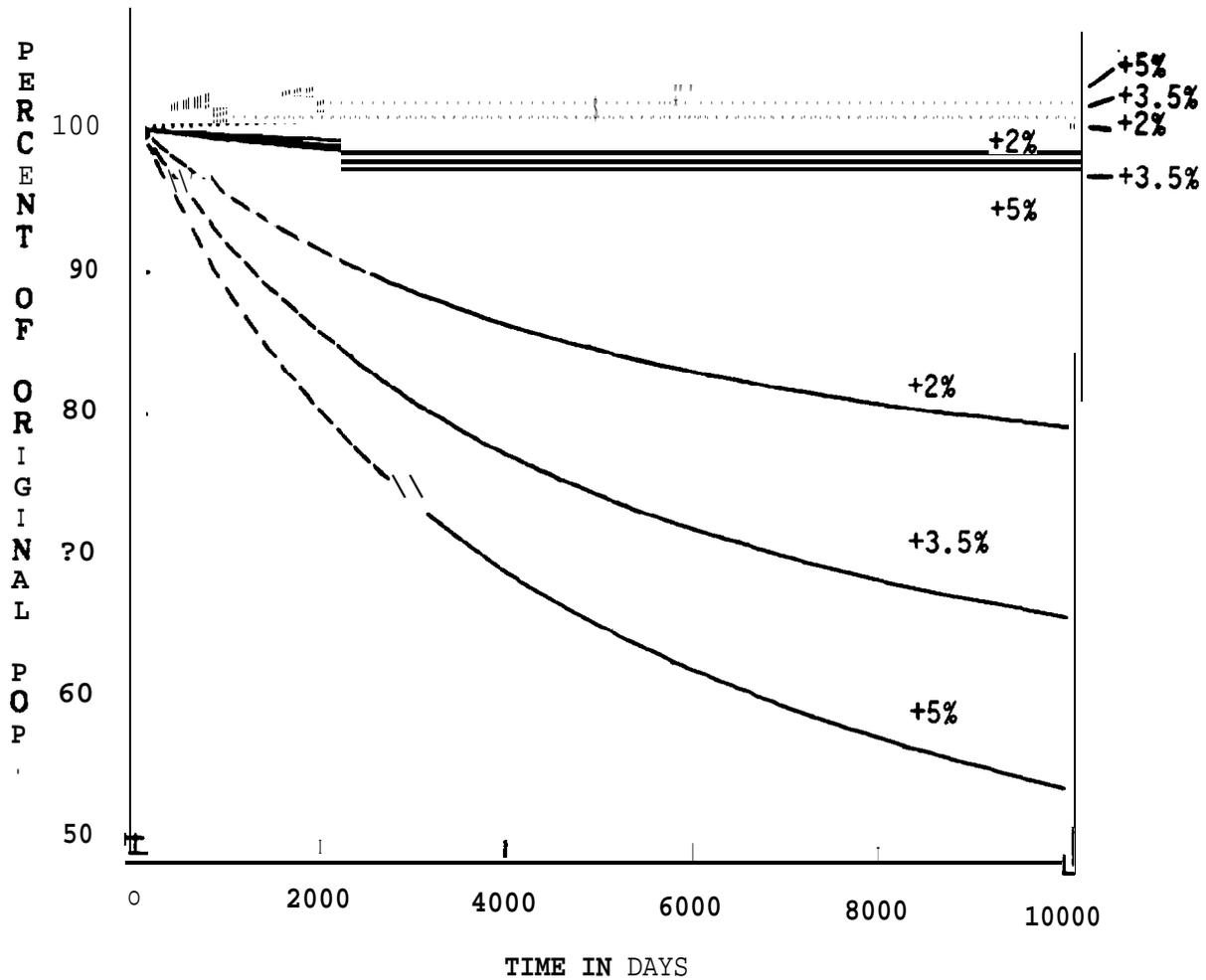


Figure 6b

The response of the populations in a three-tiered aquatic ecosystem (measured in biomass per unit area, initial biomass ratios: 50 phytoplankton: 10 zooplankton : 1 small fish) to +2%, +3.5%, and +5% changes in the rate at which fish die off. Solid, dotted, and (partially) dashed lines give the paths for phytoplankton, zooplankton, and small fish, respectively. This figure corresponds to a situation in which the degree of perturbation in the die-off rate is uncertain, but is known to lie within some range. The effect of this uncertainty on the relative magnitudes of population changes in the three trophic levels is shown.

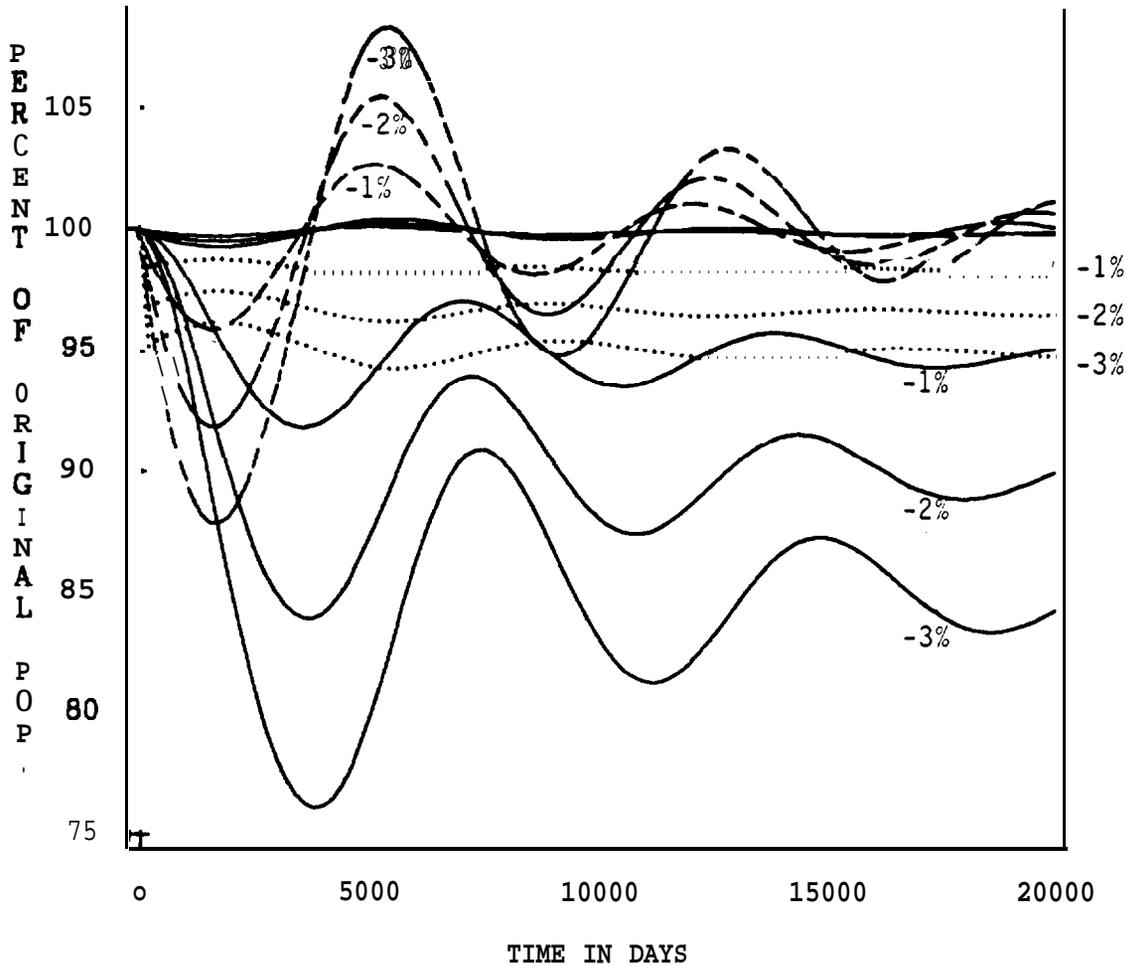


Figure 6c

The response of the populations in a four-tiered aquatic ecosystem (measured in biomass per unit area, initial biomass ratios: 500 **phytoplankton**: 100 zooplankton : 10 small fish: 1 larger fish) to **-1%**, **-2%**, and **-3%** changes in the phytoplankton growth rate. The paths for the responses of the **phytoplankton**, zooplankton, small fish, and larger fish populations are given by the upper solid curve, the dotted curve, and partially dashed curve, and the lower **solid** curve, respectively. This figure corresponds to a situation in which the degree of perturbation in the growth rate, caused, for example by pollution, is uncertain, but is known to lie within some range. The effect of this uncertainty on the relative magnitudes of population changes in the four trophic levels is shown .

nature study (or the public itself, which occupies the top carnivore spot in the global **ecosystem!**). The increase in error as it propagates up the chain will tend to render difficult the prediction of the magnitude of precisely those effects that the public is most concerned about. While an enormous effort is sometimes expended trying to determine precisely the environmental concentration of a pollutant, the effort may be misplaced if error propagation **leads** to large uncertainties higher up in the food chain where the public welfare is more directly and obviously involved.

Like toxic substance **biomagnification**, this magnification of error is unavoidable. It is a consequence of the fundamental ecological dynamics of a food chain and can not be circumvented. Like toxic substance **biomagnification**, whose effects at the higher **trophic** levels can be minimized by keeping the level of the **toxicant** in the environment to a minimum, the effect of error propagation up a food chain can be minimized by keeping to a minimum the initial error in our knowledge of the effect of the toxicant on the growth of the primary producers.

We have not discussed here the question raised in the Introduction concerning the probability distribution of the quantity of interest within its range of uncertainty. As mentioned previously, when a parameter such as a fish population is uncertain, but a probability distribution for it is calculable, then economic valuation is easier than when such a probability distribution **is** unknown. Consider an uncertainty in the **effect of a toxicant** on the growth rate of **a** species of **phytoplankton**, as in our simple food chain model, that **has** the characteristic that the error **in** our knowledge of it is **gaussian-distributed**. What will the distribution of **biomagnified** error be in the fish population? Unfortunately, no general statement that is **model-Independent** can be made about this at present. The particular, unabashedly unrealistic, model used to motivate the existence of the phenomenon of error

biomagnification provides a precise answer to this question, but other models **will** generally provide other answers. Because we lack confidence **in** any particular model or class of models for the analysis of complex ecosystems, further work is clearly needed **here**.

Since our ability to characterize ecological uncertainty with probability distributions **is** presently limited, **it** might seem like a sensible strategy for ecologists to place more emphasis on reducing **the** range of uncertainty. As we show in the following Section, **that approach, too, has its** limits and, **indeed, they are even more stubborn than are the** problems discussed heretofore.

Refractory Error in Ecology

Some types of uncertainty in impact assessment are easily remedied. If a few more observers spend a little more time gathering **data or improving their** models, a noticeable improvement will result and these remediable types of errors will be eliminated or at least greatly reduced in magnitude. A more interesting class of errors can not be pushed to zero, however, or even significantly reduced in magnitude regardless of how much effort is expended **to** do so. These are the refractory or intrinsic uncertainties whose origin we now discuss. **In a general sense, they stem from two sources: uniqueness and sensitivity to initial conditions. We explain these in turn.**

The uniqueness of individual ecosystems and of the planetary environment **in its entirety renders it impossible to achieve the *sine qua non* of the classical scientific experimental approach--replication of the system under investigation. Without the benefit of replicable systems, a statistically meaningful analysis of the effect of a toxin on an ecosystem **is** unattainable. **The reason **is**** that in any dose-response study, be it **at the level of an** individual organism or at the ecosystem level, one's interest **is always in the****

difference between a treatment and a control system. Inherently, this requires at least two initially identical systems. If replication of the treatment and control systems is also desired so that a measure of the statistical significance of the dose-response **relation** can be derived, then even more identical systems are required. Ecosystems, unfortunately, are not so obliging. Two nearby lakes, two forests in the same region, and even two patches of meadow close by one another differ in **myriad** ways; ecologists will never be aware of all of them, let alone be able to quantify them.

To attempt a resolution of this dilemma, interest in ecological **microcosms** has recently accelerated. Microcosms are segments of natural ecosystems of a size convenient for laboratory replication and analysis. Lake microcosms, for example, consist of containers filled with lake water and possibly lake sediments taken from a real lake. If appropriate precautions are taken in the design, initiation, and operation of these systems, they can be replicated adequately for periods of up to several months and used for toxicological testing. Because they can be put together **in** such a way that a large fraction of the natural ecological diversity in the parent system is present in the microcosms, they offer a partial solution to the problem of uniqueness. Valuable as the microcosm approach is for **ecotoxicological** testing, problems of size or scale inherently limit its usefulness. Most importantly, it is not feasible to place large plants and animals in them; to do so would result in wildly unrealistic behavior, both with respect to chemical concentrations and population densities in the microcosms. Therefore, the very types of organisms of greatest interest to the public can not be studied **in** such systems. In addition, long-term microcosm investigations (usually of more than a few months duration) are not possible without jeopardizing the ecological realism (that is, the degree of similarity between the control microcosms and the parent **ecosystem** from which the

microcosms were derived) of the microcosms.

Which brings us to the second refractory **source** of uncertainty-- sensitivity **to** initial conditions. Ecosystems, like the global climate **system**, are complex at many spatial and temporal dimensions. That is, within **such** systems microscopic **behavior and macroscopic behavior are present and are strongly coupled**. **For example**, the population dynamics of microbes can affect the health of fish in a lake, and at a molecular level, the diffusion of nutrients and the turbulence of the water can affect the microbe populations. In the global climate system, atmospheric turbulence influences climate on a **macroscopic scale**. **In systems where** such different dimensions are coupled and chaotic or turbulent behavior is important, the ability to predict the future consequences of the system is **severly** limited. In a profound analysis of the effect of turbulence on climate prediction, Lorenz (1969) **showed** that microscopic turbulence introduces an intrinsic source of error in the prediction process. In particular, it renders the future behavior of the climate incredibly sensitive to initial conditions. The amount of detailed initial conditions one needs to measure in order to predict future climate with any specified degree of accuracy increases faster than exponentially with the period of time into the future one wants to predict the climate. Long term **prediction with the same detail and accuracy as we now can achieve for one or two day predictions thus becomes intrinsically Impossible for a practical reason: we cannot gather sufficiently detailed measurements on today's climate**.

The deep reason for **this phenomenon is the extreme sensitivity of complex** systems possessing many **scales of motion**, such as systems with turbulence, to **small changes in initial conditions**. Platt et al. (1977) investigated marine **ecosystems and found a similar sensitivity to initial conditions**. **It is likely, in fact, that ecosystems, generally, are characterized by such a**

sensitivity, although this has not been investigated yet.

Conclusion

The major advances in environmentally relevant ecological research in the past decade have not been in the direction of developing models that can predict with greater accuracy the future state of a disturbed ecosystem or the distribution of values of some uncertain parameter within its range of uncertainty. Rather the direction of progress has been in characterizing the features of ecosystems that render them either vulnerable or susceptible to change when subjected to stress and in identifying the major sources of uncertainty. Rather than making substantial progress in the development of one "correct" mathematical model for predicting the future behavior of an ecosystem, the effort has been to search for relatively model-independent truths. Valuable as this information is, it does not necessarily provide the type of information economists need if they are to apply valuation procedures to realistic situations. Error propagation and the existence of refractory sources of uncertainty in ecology must be taken into account if realistic goals for benefit-cost analysis in environmental policy are to be set. Perhaps most importantly, uncertainty about uncertainty--that is, uncertainty about the probability distribution of ecological variables within their range of uncertainty-- limits progress toward more rational decision making. Perhaps error distributions can be better characterized and refractory uncertainties can be reduced by more intensive analysis of ensembles of models in conjunction with properly designed laboratory and field studies. In any event, progress toward the goal of more rational decision making will require that economists and ecologists working at the interface of these two disciplines are aware of the internal constraints of each others' field, while at the same time they sharpen their tools within their own.

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