THE DESIGN OF BIOLOGICAL MONITORING SYSTEMS FOR PEST MANAGEMENT

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ABSTRACT

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By

Stephen Melwood Welch

With the rising world population and the increased value of food and fiber production, losses due to agricultural pests have become intolerable. This has led to the emergence of sophisticated philosophies of pest control including pest management. Biological monitoring is an important component of management systems which has not received adequate analysis in the literature. This thesis formulates a design procedure for biological monitoring systems which incorporates biological, economic, and stochastic factors and time delays.

Such a system is viewed as having a hierarchical structure. One or more decision makers receive data from a sampling point located within a geographical monitoring unit. A regional system is composed of a set of these units. Monitoring resources are allocated among the units by a regional controller so as to meet system goals. Important time delays exist at the regional level, at the monitoring unit level, and at the decision making level. Information flowing between levels is subject to noise which can degrade overall system performance.

Biological factors include (1) the biological demand for monitoring, (2) distributions of target species, (3) the biological interpretation of monitoring results, and (4) the biological effect of time delays. Biological models are discussed as a method of formalizing this information.

The stochastic discussion combines the effects of spatial and sampling variation with time delays to assess the reliability of monitoring data. Bayesian statistics are employed to show how likelihood distributions are altered by these processes. Examples are drawn from the population dynamics of the European red mite, Panonychus ulmi (Koch).

The economic analysis of biological monitoring proceeds from two points of view, that of the decision maker who must profitably use the data he pays for and that of the monitor who expends resources to acquire the data. Utility theory is used to relate the decision maker's losses to his decisions and perceived likelihoods. The monitor's economics are viewed as an investment for which a return can be calculated via a discounted cash flow analysis.

The logistics of monitoring are studied by decomposing total activity into a series of actions each with its own time delay. Methods for the separate analysis of each action are presented.

The most important portion of the thesis demonstrates mathematical linkages between the four classes of factors just discussed. There are, in actuality, only two degrees of freedom among these four variable types. This makes it possible to construct a chart on which the performance of design alternatives can be determined graphically. Such a chart is constructed for an organism like the European red mite.

The last chapter summarizes the design procedure and presents arguments demonstrating the broad applicability of the method both within agriculture and outside it.

THE DESIGN OF BIOLOGICAL MONITORING SYSTEMS FOR PEST MANAGEMENT

By

Stephen Melwood Welch

A DISSERTATION

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DEDICATION

To the six most important people in my life:
Mary Lou, Jack, Virginia, Chris, Jack, and Grace

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INTRODUCTION

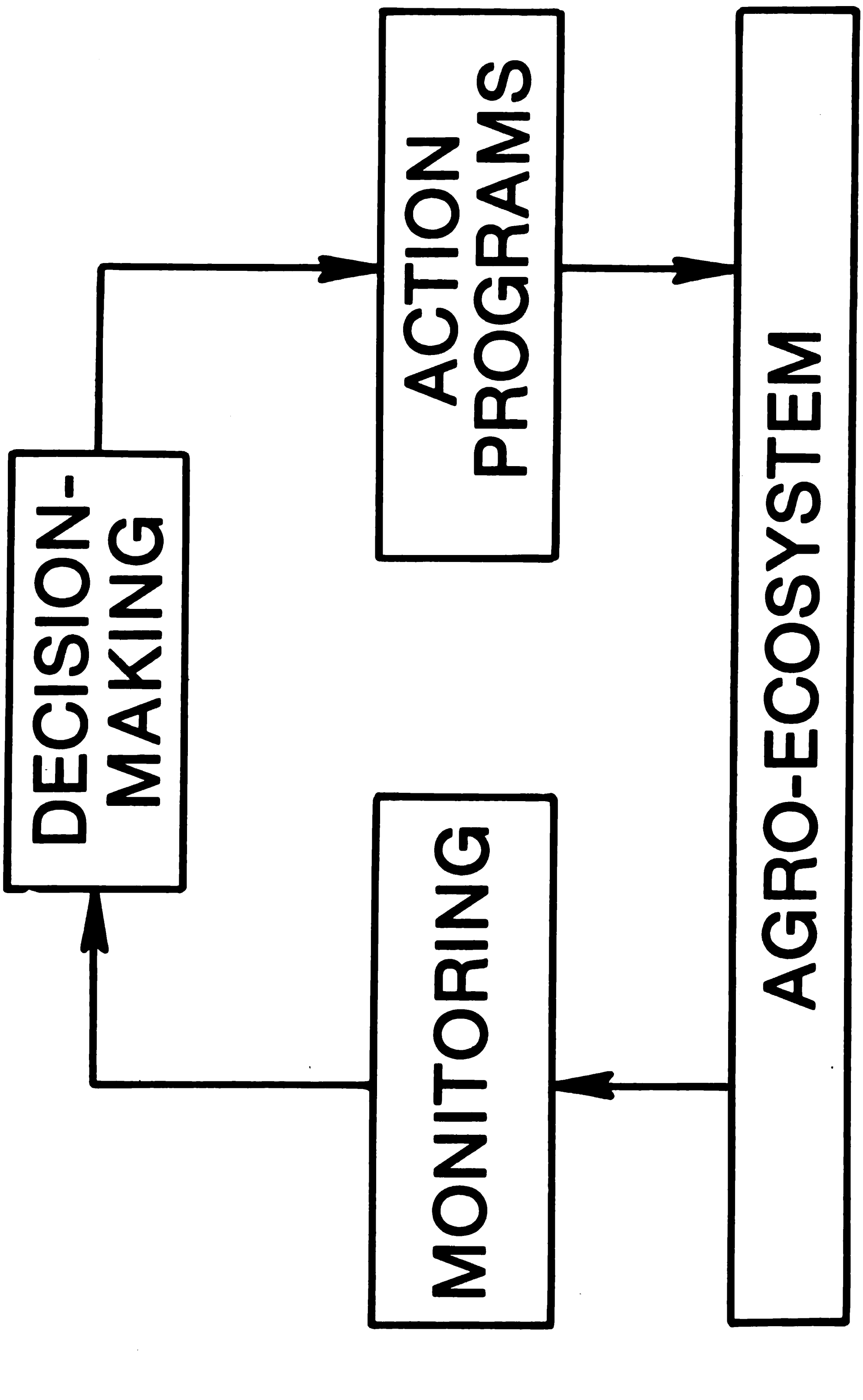
With the rising world population and the increased value of food and fiber production, the losses due to agricultural pests have become intolerable. This situation has been aggravated by the spread of resistance to chemical biocides and the resultant failure of many pest control systems developed over the last 25 years. This has led to the emergence of more sophisticated pest control methodologies and their incorporation into systems of pest management. Luckmann and Metcalf (1975) citing Geier (1966) describe pest management as

> "(1) determining how the life system of a pest needs to be modified to reduce its numbers ... below the economic threshold; (2) applying biological knowledge and current technology to achieve the desired modification ...; and (3) devising procedures for pest control suited to current technology and compatible with economic and environmental quality aspects ..."

There are three basic components of any pest management system: a monitoring component which provides data, a decision making component which determines a control strategy based on the monitoring results, and an action component which implements the control decision. In previous types of control systems these components often have operated in an "open-loop" fashion. That is, relevant states of the crop ecosystem (be they pest status or cumulative damage or just calendar date) were sensed in a rather crude manner, a control decision made, and then implemented with only limited concern for long-range effects. Pest management recognizes that these components cannot be considered outside the context of the crop or agro-ecosystem. This system integrates the effects of control inputs with biological and physical factors in ways which can subsequently be monitored. This results in a "closed-loop" system as shown in Figure 1. The closed-loop topology clearly suggests that control is an ongoing process where today's actions can influence tomorrow's decisions for good or for ill.

This realization has resulted in a significant alteration in the conceptualization of management systems and a clear need for new types of analysis to cope with design and implementation problems (National Academy of Science, 1969; Luckmann and Metcalf, 1975; Tummala _et_ _al_., 1976). Various authors have grappled with pieces of the problem, especially as regards the decision making and implementation components. Headley (1971) and, later, Hall and Norgaard (1973) examined the relation between population biology and control in a deterministic sense. Others, particularly Carlson (1969a, 1969b, 1970, 1971) have dealt with stochastic and Bayesian approaches to decision making. As yet there has been little analysis of modern monitoring systems for pest management with the exception of physical factors in the environment (_e_._g_., Haynes _et_ _al_, 1973).

Figure 1. _A simplified block diagram of a closed-loop management system._


DECISION-
MAKING
ACTION
PROGRAMS
AGRO-ECOSYSTEM
MONITORING

The purpose of this dissertation is to describe an encompassing technique for the design and analysis of systems for monitoring biotic as opposed to physical parameters. Of necessity, monitoring activities must be considered in the context of the entire management system. Information from the monitoring component undergoes a number of transformations as it is processed around the control loop of Figure 1. It is impossible to know how useful the data are without knowing their intended uses.

Examination of Figure 1 suggests four classes of factors which, between them constitute an adequate description of a management system. They are: biological processes within the agro-ecosystem, stochastic features of the system being observed and of the monitoring component, the economics of monitoring and decision making, and the time delays of the entire control loop particularly as affected by the level of technology. The biological input specifies the dynamics of the system being controlled while economics is required to describe the objective function (i.e., goal) of the control process. The quality of the information on which decisions are based can only be assessed if the stochastic elements of the system are understood. Finally, the dynamics of the complete closed-loop system cannot be specified unless the time delays of the management process are known.

The basic ideas behind this thesis emerged in the period between 1973 and 1976 as a result of the author's work with the management of phytophagous mite populations in orchards (Croft _et al_., 1976b), the development of extension data delivery systems (Croft _et al_., 1976a), and the analysis of general modeling problems (Welch _et al_., in prep.). This experience is reflected in the specific examples used herein, but the discussion will make clear how to apply these techniques to a wide variety of systems.

A note on the format of the thesis is also necessary. The normal dissertation proceeds in chronological order from problem statement and literature review through materials, methods, and results, to conclusions and future outlook. This outline is adequate for field studies or reports on specific topics. In this thesis, the contribution being made is a synthesis of a variety of separate but related subjects. The synthesis is original even though the raw ideas may not be new. For this reason, the discussion is organized topically rather than chronologically.

The first topic is a general topology for an operational pest management system. Basically it consists of the four components of Figure 1 but elaborates them in a way that emphasizes biological monitoring activities. The system is outlined in a hierarchical manner which demonstrates that pest management is an activity which is distributed in space and time. In particular the types of activities and functions carried out at three levels (a decision making level, a monitoring unit level, and a regional level) are defined and discussed.

The second chapter focuses on biological aspects of monitoring design. Topics include the biological requirements for sampling, the need for studies of the distributions of target species to aid in statistical design, and the extrapolation of population processes through time. Biological modeling is introduced as a method of integrating data so it can be applied at several points in the design process. The specific data sets that modeling requires as well as useful criteria for "good" models are also identified.

The following chapter deals with the stochastic elements of systems design. By applying the common language of Bayesian probabilities to the design problem, this chapter serves an integrative function. The specific discussion centers on how to combine spatial variation, measurement error, and time delays to determine the probabilities of various ecosystem states as seen by the decision maker. This chapter also begins an extended example concerning the dynamics of the European red mite, Panonychus ulmi (Koch), in predator-free systems. The example is intended to demonstrate monitoring analysis calculations in cases where pests are subject to sudden exponential outbreaks. The methods presented are general enough to be applied to the less common case where significant natural enemies exist, but the author felt that the extra complexity would detract from the example's illustrative value.

Chapter IV begins the discussion of economics. For convenience the treatment is broken into two chapters (IV and VII). Chapter IV deals with the economics of monitoring as perceived by the decision maker. Because pest management decisions are made at risk the costs of monitoring, control, and damage are distributed random variables. Various methods are presented to interrelate these variables with results of the stochastic analysis to arrive at measures of the utility of monitoring.

The fifth chapter demonstrates an important mathematical relationship which exists among the classes of variables discussed in chapters II, III, and IV. Two theorems are proved showing that there are only two degrees of freedom between typical variables describing allowable time delays, monitoring unit variability, system workload, and economic risk. A chart or nomogram is proposed on which, for a given system, knowledge of any two variables will allow the prediction of the other (with one minor exception). Such a chart is constructed for a predator-free European red mite system.

The application of the nomogram is further developed in the next two chapters. Chapter VI discusses system time delays. Total delay is decomposed into discrete processing activities each of which is separately analyzed. The nomogram is used to give a direct readout of the effect on system performance of alterations in these delays. By way of example, it is shown how a 14 percent increase in resolution could, in a hypothetical mite monitoring system, cause a ten-fold increase in economic risk due to increased time delays.

Chapter VII, resuming the economic discussion, presents the viewpoint of the monitoring service. The establishment of a monitoring system is viewed as an investment whose utility must be judged. A screening program which calculates a return on investment via a discounted cash flow analysis (Park, 1973) is presented. This is combined, via the nomogram, with the constraints on system performance developed in the preceding chapters to make the final choices on technology, price structure, etc.

Chapter VIII is a synopsis of the design procedure outlined in the body of the dissertation. Following standard system design methods (Manetsch and Park, 1974) it begins with an analysis of management needs. Next the designer constructs several alternative methods of meeting these needs. These designs are then modeled so that they may be optimized, evaluated, and the best one selected. This stage involves the types of biological, statistical, economic, and timing studies discussed in earlier chapters. At some point during this process, one or more of the alternatives will be subjected to field testing. The chapter describes the types of auxiliary data (travel times, grower acceptance, etc.) which must be taken to complete the analysis. The nomogram of chapter V provides the mechanism for interpreting this data. Once the best design has been chosen the last step is implementation. By this time, because of the extensive field work and contact with all affected parties, the selected alternative should be seen as an effective pest management tool. Even after implementation, however, the system must be periodically reevaluated so it can adapt to changing conditions.

In conclusion, the dissertation emphasizes the broad applicability of this approach to a variety of other agricultural and resource management tasks.

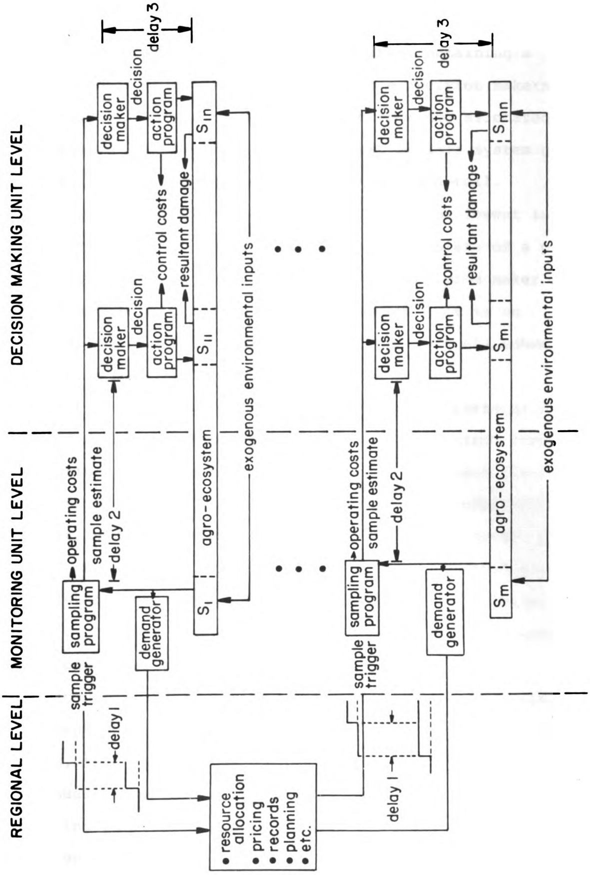
CHAPTER I

GENERAL ORGANIZATION OF A MONITORING-MANAGEMENT SYSTEM

The methods employed for monitoring a biological system never exist in isolation; they are always part of some larger structure which utilizes the data to some purpose. Often the information collected by monitoring will be subjected to processes of interpretation and extrapolation. Each such operation will affect the utility of the data. On the one hand each manipulation will make the data more meaningful or more widely applicable. However, the variances associated with the data are generally increased by these activities making the results less reliable. Only by studying the monitoring component within the context of its overall system will the designer be able to maintain a favorable balance between meaningfullness and reliability. For this reason this chapter is devoted to the construction of a generalized management system. This schema will be so ordered as to reveal the important transformations of biological monitoring data.

A management system can be conceived as having three hierarchically organized levels each with its own activities and characteristics (Figure 2). We shall refer to these as the decision making level, the monitoring unit level, and the regional level. Briefly, the decision maker is the ultimate

Figure 2. A detailed diagram of a pest management system. Each decision maker has control over a portion of the extended agroecosystem. He acts on information from a sampling program which monitors conditions at a point somewhere within a geographical unit containing one or more decision makers. Sampling activities are optimized at a regional level to meet system goals such as profit, efficient service, etc. Important time delays are (1) the time required to respond to a request for sampling, (2) the time necessary to transmit the monitoring results to the decision maker, and (3) the time needed by the decision maker to interpret and act upon the monitoring data.


REGIONAL LEVEL
MONITORING UNIT LEVEL
DECISION MAKING UNIT LEVEL
resource allocation
pricing
records
planning
etc.
sample trigger
delay 1
sampling program
operating costs
sample estimate
delay 2
demand generator
decision maker
decision
action program
control costs
resultant damage
delay 3
agro-ecosystem
exogenous environmental inputs
S_1
S_{11}
S_{1n}
S_m
S_{m1}
S_{mn}

recipient of monitoring outputs who converts the data into action programs and sustains the resultant benefits or losses. The monitoring unit is a geographical area containing a sampling point which services one or more decision makers. At the regional level, monitoring resources are allocated among the monitoring units so as to best achieve system goals. We shall now discuss each of these levels in detail.

The decision making level. This forms the lowest level of the system. Each decision making unit consists of a parcel of land (or other production unit) plus a decision maker who makes the control decisions for that parcel. It is an important defining property of these units that all subsections of the unit behave and are treated identically.

In Figure 2 these units are diagrammed as parts of an extended agro-ecosystem. In addition to the control inputs from action programs, the parcels receive exogenous environmental inputs such as solar radiation, temperature, precipitation, etc. It is the purpose of the monitoring component to provide the decision maker with "acceptably accurate" data on "relevant aspects" of the agro-ecosystem in a "timely manner". Precise meanings of the quoted phrases will emerge in the course of the dissertation.

Because the thrust of this thesis concerns monitoring we will treat the decision making process in an aggregated sense. That is, the "decision maker" is taken to consist of all individuals and organizations who mediate the conversion of monitoring outputs into action programs. Croft et al. (1976a, p21) give a breakdown of these groups for Michigan integrated pest management. Two exceptions to this aggregation must be noted. Organizations such as testing laboratories which process raw sample materials are properly considered as part of the monitoring component. Another special case is when one individual or group makes distinct decisions for two or more production units. In this instance each unit is considered to have a separate decision maker.

The activities of the decision maker, however lumped, form the single most important transformation which the monitoring data undergo. For this reason it is incumbent to discuss the various types of decision rules in use in pest management and identify some common class on which to base the analysis.

The simplest and earliest rule was "there (is) no good bug except a dead bug" (Stern, 1973). Better procedures are based on the relationship between pest density and potential damage. Shotwell (1935) was one of the earliest to describe such a relation. He set up a rating system based on visual counts of grasshoppers and determined that at 15 individuals per square yard, 40 percent of the cropland could suffer some loss. Formally, this type of rule states that control measures should not be instituted below that density at which the marginal cost of control just exceeds the marginal damage. This is called the economic injury level (Stern _et_ _al_., 1959).

Because it takes time to reach a control decision and then act (see delay 3 in Figure 2) a useful modification of this rule has come into vogue. A new term, "economic threshold", has been introduced which is defined as "the density at which control measures should be applied to prevent an increasing population from reaching the economic injury level" (Stern *et al.*, 1959). It has long been recognized that thresholds and injury levels are dependent on meteorology, host maturity and other characteristics, and the cost of control. The economic threshold is additionally dependent on the manner (*i.e.*, time delay) in which the control is applied. The dependence of damage on these factors will be discussed further in the next chapter.

Another refinement in decision rules was achieved with the recognition that there may be several distinct decision periods through the course of a season and that the outcome of one period can affect later decisions. One example of such a breakdown is the traditional spray calendar based on crop phenology. It is possible to specify early season application rules which control impacts on non-target species so as to achieve payoffs later on. Croft (1975) describes such a program for plant feeding mites on apples.

Mathematical techniques such as dynamic programming (Shoemaker, 1973a) can be used to quantify this idea. This method adjusts the losses perceived in a given period to reflect the results of possible decisions made during that period. This adjustment is the sum of control costs plus terminal costs for an optimal strategy beginning in the next period based on current outcomes (Wagner, 1975). A major defect of this technique is that, except in very simple cases, the formulations are so complex that they burden the largest computers (Shoemaker, 1973c).

All of the decision rules discussed to this point have been essentially deterministic in that they either utilize average ecosystem behavior or rely on specific realizations of stochastic variables. In practice, of course, great risk attends all pest management decisions. One method to take risk into account is statistical decision theory (Carlson, 1970). This method explicitly notes three important characteristics of pest management decisions: (1) they are selections among finite sets of alternatives, (2) they have as their goal the maximization of some objective function (see chapter IV), and (3) the decisions have associated probabilities of error.

The decision theoretic approach partitions the possible monitoring results into sets which correspond to distinct control alternatives. The management decision is to implement the strategy corresponding to the set into which the actual monitoring outcome falls. The sets are constructed so as to maximize the probability of optimal results.

It is evident that this procedure contains the other rules as special cases. Rules involving thresholds can be dealt with by partitioning monitoring results into two sets, those above and those below the threshold. Most multi-period decision methods assume finite sets of alternatives and are therefore amenable to the same treatment. By adopting a statistical decision theory approach we shall be able to link biological, spatial, temporal, economic, and stochastic parameters via the common language of probabilities. For this reason, we shall follow this paradigm in what follows.

<u>The monitoring unit level</u>. A monitoring unit consists geographically of one or more decision making units. The defining characteristic of the monitoring unit is that it contains just one sampling point which serves all the decision makers in the unit. These data may be transformed in some standard way for all users or tailored to their individual needs.

The events which take place at this level deal solely with monitoring and occur in a sequence we shall call the <u>sampling cycle</u>. The first event is the determination that the time to sample has arrived. How this happens depends on the system design. One method is to sample at certain pre-specified points in chronological or physiological time. Provided that the sampling interval is short enough, precise population tracking is possible. Biological rate functions determine the sampling rates one should use. According to the sampling theorem (Bekey and Karplus, 1968) accurate reconstruction of a signal is not possible unless that signal is sampled at a rate at least twice as fast as its most rapid fluctuation. Unfortunately, this is often not possible in practice. An acceptable substitute is to sample at a rate several times (at least twice) as fast as the most rapid fluctuation of <u>major amplitude</u>. Oscillations more rapid than this will appear as spurious low frequency components in the data but their small amplitude will make them unimportant.

The disadvantage of fixed period sampling is that much effort may be expended while nothing of significance is occurring. Other methods attempt to allocate resources to those periods ("windows") of particular interest. Usually this involves keying the observation to some biological or physical event (or "trigger") to which a knowledge of the target species attaches a special meaning. Triggers should have three properties: (1) they should be observable, (2) they should bear a reasonably direct relationship to the ultimate ecosystem variable of interest, and (3) they should occur early enough to permit the monitoring-management system to respond to the conditions the triggers herald.

There are many possible types of triggers. For example, in an experimental mite monitoring program (Welch, 1976) anecdotal observations on the presence of mites made by growers in the course of their normal activities served as the monitoring stimulus. Sampling can also be linked to observable phenological stages of the host crop or of some other indicator plant. To aid in this a network of phenological stations has been set up in the northeastern United States based on the Persian lilac (*Syringa persica*). Hopp *et al*. (1972) reports that by 1971 498 "standard phenological gardens" had been established in 28 states plus Quebec. Careful observations were being made relating lilac development to environmental parameters. Tying these parameters to pest biology would permit observations of the lilac to serve as a sampling input. Jones (1976) describes an apple scab monitoring program triggered directly by the environment. Two conditions are required for scab infection: the presence of a spore innoculum and wet foliage. In this program, leaf wetness meters trigger rotary spore traps automatically. The traps are then examined by technicians who are also "triggered" by rainfall. The level of spore discharge is converted to a control recommendation by use of a Mills chart (Mills, 1944; Mills and LaPlante, 1951).

Two other important types of trigger are the predictive trigger and the post-control trigger. In situations where the biology of a system is well understood it is sometimes possible to predict when the population will require monitoring. In the next chapter we shall discuss how this can be achieved with biological models. In post-control monitoring, sampling is scheduled to occur at some specified interval after a control measure has been applied. This can be used either as a check on the success of control or as input to the next stage of some multiperiod decision process. What both of these methods have in common is that time delay 1 (Figure 2) is eliminated. This is because the "trigger" in both systems occurs before the sampling is actually required. This forewarning can make it much easier for the monitoring resource allocator to function efficiently.

Typically, however, some delay will occur, the length of which depends on system design and available resources. A general result from queuing theory (Baily, 1964) states that delay increases exponentially as the average triggering rate approaches the rate of service. One of the major design goals is to determine the level of resources needed to satisfy demand (see the next chapter) without excessive delay (chapters V and VI).

The next step is to collect and process the sample. It is very difficult to discuss specifics in this area because of the wide variety of sampling schemes available (Cochran and Cox, 1957; Pielou, 1974; Kirk, 1968) and the hundreds of economic species to which they can be adapted. Instead, we shall treat this component as a "black box" by focusing on the important characteristics of sampling inputs and outputs. That is, we shall view the sampling program as consuming resources and generating a distribution describing the likelihood of various ecosystem states (see chapter III). In this we shall follow the "Bayesian" philosophy of Savage (1954, 1962) who argues that this distribution encodes the total result of a measurement procedure and that a detailed knowledge of sample design can add nothing beyond this. This approach enables us to deal with factors like quality and utility of results without requiring assumptions on such points as sequential versus fixed size designs, absolute versus relative measures, and so on. These topics are adequately treated elsewhere.

The last step of the sampling cycle is to transmit the results of the operation to the decision makers contained within the monitoring unit. This can be done in any expedient fashion from simply handing the decision maker the results of a procedure conducted at the site of production to the use of various electronic media (Haynes et al., 1973; Croft et al., 1976a). As will be discussed in chapters VI and VII, there are important time delays and costs associated with any possible method. It is crucial that these be explicitly accounted for in the system design.

The regional level. The highest or "regional" level of a management system consists of the geographical union of all monitoring units. Organizationally it is the level at which the whole system is operated. There are five major types of activities which take place at this level: (1) the acquisition of the resources needed for monitoring and data transmission, (2) the distribution of these resources to meet demand, (3) the determination of the prices charged end users for these resources, (4) all necessary accounting and record keeping, and (5) advanced planning.

In chapter VII we shall study design budgets of resource needs. These resources include materials and labor and their costs can be divided into capital and operating costs. How these resources are allocated determines sampling delay. The designer must choose a distribution algorithm which minimizes this delay. There are numerous appropriate operations research methods (Wagner, 1975) which can be applied.

Pricing decisions require a detailed understanding of market conditions, financial position, and organizational character. The designer, however, is only responsible for a general evaluation of system potential. This often involves a rough screening of alternative price structures. In chapter VII we shall adopt the point of view that a monitoring system is an investment whose desirability must be determined.

The record keeping and planning functions are quantitatively important to the designer only as they contribute to system overhead costs. Speaking qualitatively, however, they are essential to smooth system operation. Good records are necessary to track the finances and efficiency of an organization. Records of monitoring results are of use not only to the decision makers for whom they are intended but also as biological input to the planning function. This planning capability is required because improvements in technology are always occurring as are shifts in demand, resource costs, and other market parameters. The organization must continually strive to anticipate these costs and adapt to meet them (Scanlan, 1974).

A conceptual structure such as Figure 2 can be applied to a wide variety of actual programs. It is not necessary that all of the functions described here be carried out by visibly distinct groups or individuals. For example, a grower might do his own monitoring when he felt it was necessary. In such a system, functions at the regional, monitoring unit, and decision making levels would all be accomplished by the same person. Nevertheless, by separating these components as we have done, we are in a better position to analyze the outcomes and value of such a procedure. The rest of this dissertation is devoted to the particulars of this analysis.

CHAPTER II

BIOLOGICAL ASPECTS OF DESIGN

One of the major characteristics of modern pest management is a reliance on sound ecological principles (Luckmann and Metcalf, 1975). As a primary management component, biological monitoring requires a thorough knowledge of target species biology. There are three major design areas where biological data are needed: (1) assaying the biological demand for sampling, (2) distribution and dispersal studies for statistical design, and (3) the extrapolation of population processes through time. We shall discuss each of these in turn.

The biological demand for monitoring. As time passes, a target population will develop and, perhaps, disperse throughout the monitoring region. Local populations will reach stages requiring monitoring at various points in time and space. This is the "triggering" referred to in the last chapter. The spatial and temporal distributions of these trigger events constitute the biological demand for monitoring. This demand is an important determinant of the overall pattern of monitoring resource allocation; clearly, it is undesirable to expend resources where they are not needed. Biological demand forms the baseline from which actual demand (conditioned by economics, logistics, and the distribution of decision making units) can be calculated.

Two simple methods of determining biological demand are projection from historical records or calculation from target species phenology. For example, in a study by the author to project the demand for phytophagous mite monitoring, historical data on mite densities from 146 Michigan apple growers (Croft, unpub. data) were examined. The monitoring trigger was a population density of 3 to 10 mites per leaf (well below the nominal economic threshold of 15 per leaf). It was assumed that growers could detect such populations in the normal course of their activities. The relative frequency of triggering was determined by date for each of the seven areas of the state for which records were available.

Another method can be used when something is known of the developmental rates of the species, perhaps as affected by environmental parameters. In this case reference to weather charts or other data sources permits the construction of maps which show the distribution of triggering (Fulton and Haynes, 1975). The developmental data can be based on either laboratory or field experiments although the latter are preferable. The problem with this phenological approach is that it fails to take the spatial distribution of the species into account. That is, the conditions for triggering might be correct at some point but the species might not actually be present. For this reason the method is most useful for species which are either ubiquitous or whose spatial distribution is at least partially known.

Once biological demand has been calculated it should be expressed as a time-varying rate or as a probability of triggering per unit area or per decision making unit. This permits the calculation of demand for various hypothetical or actual distributions of decision makers. Thus, the approximate scale of the project can be established early in the design so that unrealistic goals may be avoided.

Distribution studies. The selection of proper statistical techniques demand an understanding of the properties of the target species distribution. In this section we shall examine two common types of studies and certain biological mechanisms which cause variation in space.

The first type of study attempts to develop a reasonable hypothesis about the (possibly time-varying) distribution of individuals among sampling units. This may range from a simple test for non-normality or heteroskedasticity to fits of any of a number of discrete distributions (e.g., Poisson, negative binomial, etc.). The purpose of such studies is to facilitate the selection of estimators or transformations, if necessary, or tests.

An example of this type of study is work done by the author with B. A. Croft and M. J. Dover (Croft et al., 1976b) on the distribution of Panonychus ulmi (Koch) and Amblyseius fallacis (Garman) on apple tree leaves. Visual counts of approximately 66000 leaves taken 10 per tree under a wide range of commercial orchard conditions were analyzed. The goodness-of-fit of the negative and positive binomial, Neyman A, Poisson, logarithmic, and several other distributions were determined (Gates, 1972; Bliss and Owen, 1958; Elliot, 1971). It was found that, in the density ranges over which most management-oriented monitoring would take place, the negative binomial provided an acceptable fit. This information was then used to derive sample size equations applicable in orchard blocks up to 10 acres in size.

In the second type of study, one desires to know how the sample variance is partitioned between samples and subsamples. For example, in the design of a sampling procedure for red spider mites (*Oligonychus coffeae*) on tea in India (Sen, 1971) bushes were selected from certain rows of particular sections of various tea estates. Pilot studies estimated the division of total variance between estates, between sections within estates, between rows within sections, and between bushes within rows. A cost function based on the total time required for monitoring was devised and then optimized to achieve the best tradeoff between bushes, rows, sections, and estates.

Both of these types of studies examine variation in space. Two primary determinants of this variation are dispersal behavior and response to variation in the environment. This includes both abiotic factors such as weather and biotic inputs like the resource base and natural enemies. The effect of dispersal is to attenuate spatial variation. This is because the presence of a highly dispersable stage at one location is likely to imply its presence nearby thus indicating a high spatial correlation. Examination of two species with widely different dispersal capabilities, the

European red mite and the six-spotted leafhopper, _Macrosteles fascifrons_ (Stal), demonstrates this. Dispersal in the red mite is limited to walking about on the leaf surfaces within a single tree. This can result in great density variations from one tree to the next. Certain spray practices like alternate row middle application can cause significant variation even within a single tree (Hull _et al._, 1976). This makes red mite sampling in large blocks difficult at low densities (Croft _et al._, 1976b).

The six-spotted leafhopper, an aster yellows disease vector, presents a completely different picture. Although this species overwinters locally in the egg stage throughout its range, it is the influx of migratory adults each spring which must be monitored. The migratory phase begins when the grain crop host plant becomes fully headed (Drake and Chapman, 1965). Because crops in the south develop more quickly than their northern counterparts, migratory adults can arrive in Wisconsin before local nymphs can mature. Because the migration proceeds on a broad front as determined by weather (Huff, 1963) monitoring for this pest could be done with a comparatively wide mesh grid (see Figure 3).

A major cause of biological variation is variation in underlying environmental parameters as mediated by species physiology and behavior. Environmental variation has several scales ranging from macro-effects such as north-to-south climate gradients to meso-level phenomena like lake shore effects and the rural effects of cities. The most important form of variation and the one most difficult to

Figure 3. The migration of *M. fascifrons* (Stal) into Wisconsin. The squares are placed to indicate how a fairly wide mesh grid of sampling points might be sufficient to track the advancing population front. The contour lines, taken from Drake and Chapman (1965), show the migration after successive time periods.

deal with is, however, microhabitat variation. These effects occur on a scale measuring from a few centimeters to several hundred meters. While larger scales of variation can be dealt with deterministically, microvariation must, as a matter of practicality, be handled statistically. There are numerous examples of microvariation and its effect on monitoring in the literature. Fye *et al*. (1969) showed that temperatures inside common forms of emergence cages can vary significantly from temperatures outside. Observations by Richardson (pers. comm.) have demonstrated that the temperatures experienced by codling moth larvae, *Laspeyresia pomonella*, inside apples can vary as much as 9°F from the north to the south side of the same tree.

The response of a species to environmental variation can either augment or reduce its effect. For example, Haynes and Tummala (1976) present data from Gage and Haynes (1975) which show that *Tetrastichus julis* (Walker), a cereal leaf beetle parasite, can emerge up to 100 degree-days (base 48°F) earlier in oat stubble than in straw as measured by an external reference. This is presumably due to microhabitat variation between the various grasses. On the other hand, by seeking the sun in early morning and the undersides of leaves later in the day, the tobacco hornworm, *Manduca sexta*, on Jimson weed is able to keep its body temperature very close to that of the air (Casey, 1976). This would tend to moderate the physiological effects of microhabitat temperature variation.

The important point of these examples is that the variation perceived by the monitoring component results from a complex set of biological interactions. On balance we can identify two major classes of species. For a large class of organisms factors such as dispersal dominate, thus permitting monitoring units to be physically larger. For others developmental factors are more important necessitating much more intensive monitoring.

This is certain to affect the organization of the monitoring system. Dispersive species might well be best handled by regional networks where the average decision maker would have little contact with the sampling technicians. Instead, they would receive pest advisories similar to the present weather advisories. The other class of species would require monitoring in the production unit itself thus promoting more direct contact. Obviously, intermediate systems would also have their place.

The extrapolation of population processes through time. Often the relation between the quantity of interest and the quantity actually monitored is an indirect one. For example, when attempting to forecast locust migrations, one measures the egg densities of preceding generations. Even when the quantity of interest is directly measured, time delays can confound the issue. This is because the state of a population at the time monitoring is triggered may well be significantly different from the population state actually sampled. Different still might be the state of the population when subjected to the ultimate control measure. Beyond this is the relationship between current pest activity and terminal damage. The elucidation of all these effects requires the extrapolation through time of population processes significant to man. This is necessary to evaluate the terminal effects of various possible magnitudes of monitoring system error.

To answer questions like these, the designer must have access to some form of biological model. This model may be a quantitative mathematical model, a mental conception of the species, or some experimental preparation which can be used as a surrogate for the real population (e.g., a growth chamber simulation). If it is a quantitative model it may or may not be distinct from the decision rules we have discussed previously. In any case, it must be based on a careful biological study of the target organism's population dynamics. In the following chapters, several design applications of models will be discussed.

Biological models. In a sense all science consists of the construction of models. In any branch of inquiry these models will appear, evolve, and disappear as new techniques and perceptions become available (Kuhn, 1970). The introduction of life tables from the field of human demography caused such an alteration in the field of entomology. Life tables provided three crucial features which any model must have: (1) a systematic method of recording data and, therefore, (2) a specific impetus to certain avenues of research, and (3) a body of methods (in this case, mathematical) for manipulating the data in certain ways deemed useful.

As time passed and the techniques of systems science were applied to ecology and entomology (Tummala, 1976), it became evident that there are better ways to conceptualize life histories than the life table although these still retain their descriptive value (Harcourt, 1970). Such a synthesis has been developed by the author in work on a generalized phenological model (Welch _et al._, in prep.). This structure incorporates data similar to life tables plus other information relevant to pest management with a more advanced formulation of population dynamics.

Biological data about a species can be classified by stage of the life cycle. For some species these stages may be distinct developmental steps while for others like host crops they may be arbitrary but easily recognizable morphological units (Chapman and Catlin, 1976). Stages may be defined as capable of being monitored, controllable, damaging, a combination of these, or neutral. A neutral stage is of no particular relevance to pest management except as a developmental delay between more interesting stages.

If a stage can be monitored, a list is compiled of the types and, if known, the efficiency of the monitoring methods. For phenological modeling one would monitor the occurrence of important events such as first or peak adult emergence or the onset of larval damage as detected by examination of the host crop.

For controllable stages, the types and costs of control are tabulated. The efficiency of each method (_e.g._, percent mortality) is noted. It is quite possible for a particular measure to affect a number of stages, perhaps differently.

In this case it is necessary that all effects be listed. Since one of the purposes of phenological modeling is to schedule control, it is necessary to note how far ahead field personnel must be alerted in order to implement the control measure.

For damaging stages the types and effects of damage are noted. An important point which is often ignored is that damage is inherently integrative. This is because, over some range at least, the damage a species does per unit time is proportional to pest activity. We can therefore write

$$\frac{d}{dt} D = f(D,P) \tag{2-1}$$

where damage (D) and pest activity (P) are functions of time. If activity depends on environmental parameters as well, then t might denote physiological time. If significant host self-repair capabilities exist then a term of $-g(D)$ may be appended.

This suggests that damage potential should be expressed in units such as pest-days. For example, one study attempted to express the effect of phytophagous mites on apples in terms of the reduction in yield per mite-day (Hoyt and Burts, 1974). In another case involving the Colorado potato beetle (*Leptinotarsa decemlineata*), it was found useful to consider a potato plant canopy to consist of 3000 beetle-consumption days (Sarrette, pers. comm.).

Of course the most important data about a stage concerns its contribution to the species' population dynamics. For any given species these will be known to a greater or lesser precision. Great disparities in the quality of data on a species serves notice where research is needed. The classes of data are developmental, reproductive, and demographic. Developmental data primarily include the stage durations. These may be in units of days, degree-days, or other measures such as "days-with-average-temperature-above-a-threshold". For well studied populations, data on developmental variances may also be included. It is a common phenomenon for the maturity distribution (or some analogue such as size) to undergo a progressive spreading as development proceeds. Data on this rate of spread can also be tabulated. Reproductive data may be expressed as depending on the maturity of the reproducing stage or on environmental parameters. Depending on the state of knowledge, reproduction can be specified as a time-varying rate, as some propagule complement, or just as an arbitrary relative number. Reproduction is an important component even for purely phenological models because of the dramatic effect it can have on events like peak hatch, etc. Demographic data include information on non-reproductive factors affecting the population size. Examples are immigration, emigration, and mortality. In addition, there may be factors which alter the effective size of a population without changing its numbers. An example is diapause which removes individuals from the active population without killing them. These processes can be phenologically significant in that they can, for example, alter emergence curves by changing the shape of the maturity distribution. This has, in fact, been observed in the codling moth, Laspeyresia pomonella (L.), (Riedl et al., 1977).

The final type of information is used to relate the species to the pest management community. These data include regions where the species is found and which personnel in those regions are responsible for it. Note is taken of the forms of warning these individuals require to institute effective management and what inputs to the model they supply. Also important is the general time frame during which the pest is dangerous. For example, an asparagus pest may feed on the plant all season but cease to be of economic significance after the crop has been harvested. Data in this class set the spatial, temporal, and institutional limits on the applicability of the model.

Quantitative models can be developed quite easily once the data are in this form. It is necessary only to select a suitable mathematical formalism. The author found the following useful in selecting among the various structures available for the phenological modeling project mentioned previously:

(1) the model should permit description of the population as a maturity distribution which changes with time, say $x(z,t)$;

(2) whenever possible (see below), the model should be formally linear in $x(z,t)$;

(3) preferably, the formalism would allow the convenient compartmentalization of developmental, reproductive, and demographic factors;

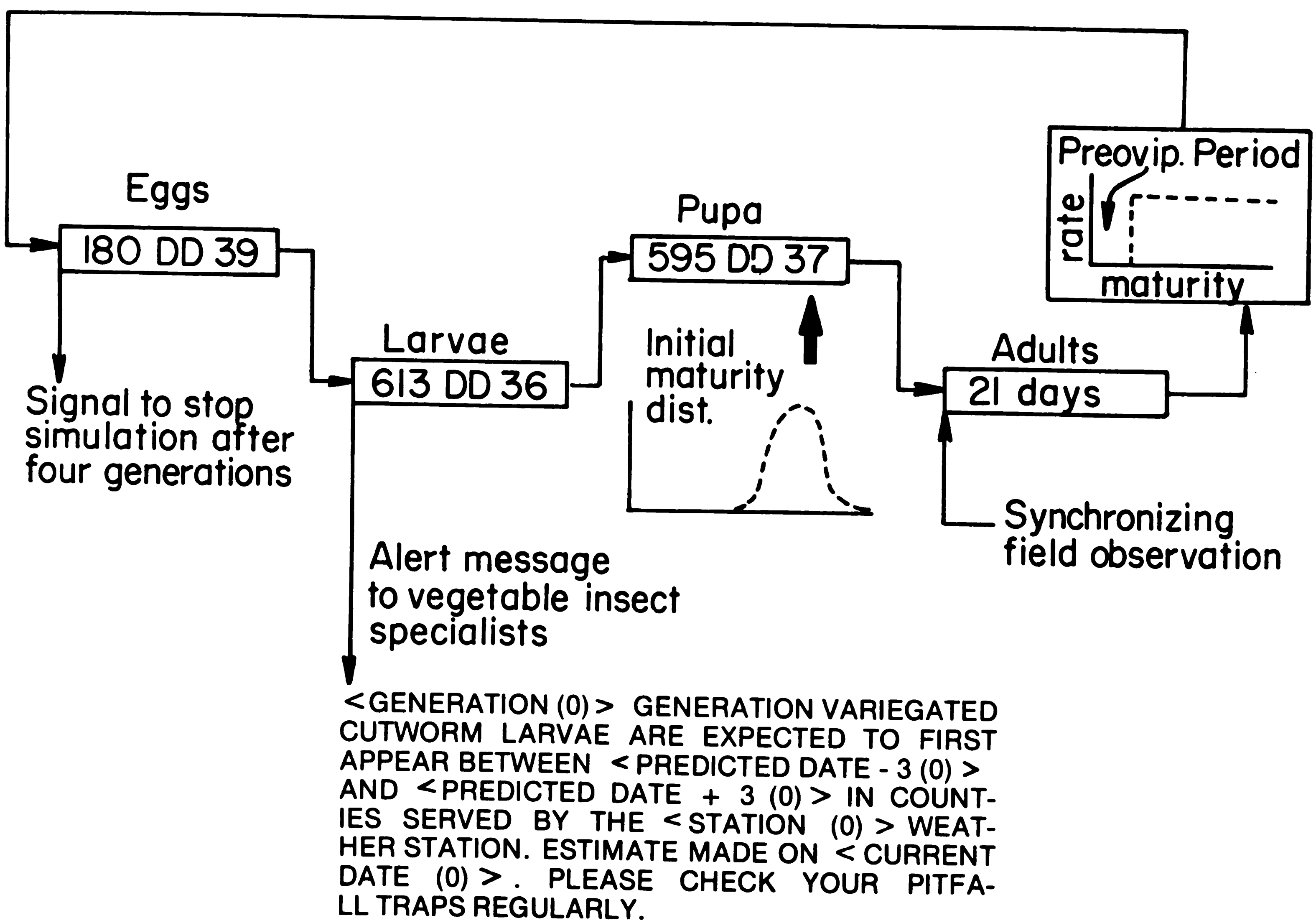
(4) well developed methods should exist for numerically solving the model equations.

Criterion 1 permits factors to be incorporated which are functions of maturity within a stage such as insect oviposition or distributed mortality. Models satisfying criterion 2 have an advantage in that they may employ either absolute or relative densities or activities as determined by the current state of biological knowledge. Linear models are by no means a necessity but may be used (1) when convincing data indicate true linearity or (2) when data are too sparse to justify the assumption of specific forms of nonlinearity. Thus, linear models are particularly useful when little is known about the organism. The advantages in terms of clarity and ease of modification granted by criterion 3 are obvious. A model which violated criterion 4 would have little practicality due to the cost of the many computer runs needed to analyze a monitoring system. Although it was not needed in the phenology project, a fifth requirement would be ease of coupling species together. This would be important in the analysis of prey-predator or host-parasite systems.

The model selected by the author for the generalized phenology project (called PETE for Predictive Extension Timing Estimator) is based on the forward Kolmogorov equations (Barr *et al.*). A computer software package was designed and implemented which enabled the computer to determine all necessary model parameters from a species description such as that in Figure 4. This allows biologists working with descriptive data to generate computer models without the need for computer programming.

These models can be used for system operation as well as system design. For example, PETE has the capability of

Figure 4. PETE description of a variegated cutworm phenology model. The model begins with the initial maturity distribution shown. Simulation starts with a field observation of first adult. Eggs are laid after a preoviposition period. A nominal oviposition rate is used because little is known about cutworm reproduction. The model cycles through the developmental stages, each of which introduces the indicated delay. Warning messages are transmitted one week before each occurrence of larvae. The computer substitutes the data indicated by brackets, < >, into the message text. After four generations the simulation stops.


Eggs
180 DD 39
Signal to stop simulation after four generations
Larvae
613 DD 36
Alert message to vegetable insect specialists
<GENERATION (0)> GENERATION VARIEGATED CUTWORM LARVAE ARE EXPECTED TO FIRST APPEAR BETWEEN <PREDICTED DATE - 3 (0)> AND <PREDICTED DATE + 3 (0)> IN COUNTIES SERVED BY THE <STATION (0)> WEATHER STATION. ESTIMATE MADE ON <CURRENT DATE (0)>. PLEASE CHECK YOUR PITFALL TRAPS REGULARLY.
Pupa
595 DD 37
Initial maturity dist.
Adults
21 days
Synchronizing field observation
Preovip. Period
rate
maturity

integrating the population description with real-time weather data from up to 37 field stations in Michigan's lower peninsula to produce predictive monitoring triggers. Such a trigger, for variegated cutworm, Peridroma saucia (Hubner), is shown in Figure 5. These triggers can be transmitted directly to the field staff via modern data communications techniques. From Michigan State University this is possible through the Pest Management Executive (PMEX) system (Croft et al., 1976a) which was designed and implemented by the author and John Howes.

This chapter has stated the needs of the monitoring system designer for biological data. These needs touch on virtually every aspect of population biology, so the use of biological models is advocated to help organize these data. Because of the elaborate nature of some models it is natural to ask how detailed and complete these models must be. The answer is that system design can only be based on the best information currently available. One of the major purposes of the model is to assess the effects of monitoring errors. By repeated runs of the model it is also possible to determine the sensitivity of the model to errors in its own parameters. By extension, the effects of these on system performance can also be tested. As always, however, in the final analysis it requires an act of human judgment to determine whether a system is well enough known to allow design to proceed.

Figure 5. An automatically generated pest warning from the PETE system. This type of alert is used to direct the attention of extension specialists and agents to particular problem areas in a predictive, management-by-exception mode.

PMEX PETE AUTOMATIC PEST WARNING -- SENT AT .17.14.22. ON 09/03/76
4TH GENERATION VARIEGATED CUTWORM
LARVAE ARE EXPECTED TO FIRST APPEAR BETWEEN
SEPTEMBER 7TH, 1976 AND SEPTEMBER 13TH, 1976
IN COUNTIES SERVED BY THE SALINE
WEATHER STATION. ESTIMATE MADE ON
SEPTEMBER 3RD, 1976. PLEASE CHECK YOUR
PITFALL TRAPS REGULARLY.

CHAPTER III

STOCHASTIC ANALYSIS OF MONITORING SYSTEM DESIGN

In this chapter we shall present a detailed examination of the stochastic aspects of monitoring and show how the various sources of random error combine with time delays to create total error.

We begin by considering two points A and S in the monitoring unit. At some point in time $t=t_o$ the sampling point (S) achieves state λ_{s,t_o} which triggers monitoring. Before monitoring can occur, however, time delay τ_1 elapses during which the system evolves. We can represent this process by constructing a probability density function $p(\lambda_{s,t_1}|\lambda_{s,t_o})$[1] where $t_1=t_o+\tau_1$. Such a distribution can be determined via simulation studies using a biological model as outlined in the last chapter.

Monitoring produces an observation x_s. It is desirable to express our new knowledge of λ_{s,t_1} in terms of what we know about the sampling design and the system being monitored. From Bayes' theorem we have

$$(3\text{-}1) \qquad p(\lambda_{s,t_1}|x_s) = \frac{p(x_s|\lambda_{s,t_1})p(\lambda_{s,t_1})}{\int p(x_s|\lambda)p(\lambda)d\lambda} .$$

This theorem, along with the controversial concept of "personal probabilities" (Savage, 1954, 1962), forms the

---

1. The notation $p(A|B)$ reads "the probability of event or condition A given that event or condition B has occurred."

basis of Bayesian statistics. A good, non-partisan review of the subject is given by Binder (1964). One of the major tenets of this theory which we shall utilize is that the posterior distribution, $p(\lambda_{s,t_1}|x_s)$, expresses the total result of the measurement.

Similarly, the bivariate distribution $p(x_s|\lambda_{s,t_1})$ encodes all available information on the sampling protocol and the underlying distribution among the sampling units for a given λ_{s,t_1}. For example, consider an organism for which a two stage sampling design has been constructed which involves n subsamples for each of m samples. Suppose that λ_{s,t_1} is to be estimated by $\bar{x}_s$, the grand mean over all subsamples. Further, assume that a one-way analysis of variance has revealed the variance of sample means around the grand mean to be σ_1^2 and the within-sample variance to be σ_2^2. Straight foreward calculation and the application of the Central Limit Theorem (Feller, 1968, vol. 2) yields

(3-2) $$p(x_s|\lambda_{s,t_1}) = N(x_s\ ;\ \lambda_{s,t_1},\ (\sigma_1^2 + \sigma_2^2)/nm)$$

where $N(x,\mu,\sigma^2)$ denotes a Gaussian distribution with mean μ and variance σ^2. In this example the underlying distribution among the sampling units is denoted by λ_{s,t_1} and $(\sigma_1^2+\sigma_2^2)$ while the sampling protocol is encoded by $1/nm$.

Among the factors on the right hand side (RHS) of (3-1), we have yet to discuss $p(\lambda_{s,t_1})$ which is called the prior distribution. If λ_{s,t_o} and τ_1 are exactly known, then

(3-3) $$p(\lambda_{s,t_1}) = p(\lambda_{s,t_1}|\lambda_{s,t_o}) .$$

In general, however, triggering may not occur at a precise value of λ. Even if it does, we may expect the waiting time for monitoring (τ_1) to be a distributed random variable. If we call this distribution $p_1(\tau)$, then a more realistic prior is

$$(3\text{-}4) \quad p(\lambda_{s,t_o}) = \int_0^\infty \int_\lambda p(\lambda_{s,t+\tau}|\lambda_{s,t_o})p(\lambda_{s,t_o})p_1(\tau)d\lambda_{s,t_o}d\tau$$

where $p(\lambda_{s,t_o})$ is the probability of a certain state triggering monitoring and $t_1=t_o+\tau$.

Work done by the author on the design of a mobile van for monitoring within orchard densities of the European red mite (Welch, 1976) provides an example. The trigger for sampling was an observation by a grower that mites were present. On the assumption that growers can first detect mites at densities between 3 and 10 per leaf, examination of historical records yielded $p(\lambda_{s,t_o})$ as shown in Figure 6. To determine $p_1(\tau)$ simulations of system logistics (discussed in chapter VI) were undertaken. For a market assumed to contain 315 growers the curve in Figure 7 was obtained. Restricting ourselves to predator-free systems, we can describe the species dynamics by a simple exponential growth model

$$(3\text{-}5) \quad p(\lambda_{s,t_o+\tau}|\lambda_{s,t_o}) = \delta(\lambda_{s,t_o+\tau}-\lambda_{s,t_o}e^{r\tau})$$

where r was taken as .135 per day. This model (with different r values) can be used for a variety of pests during those outbreak phases preceding economic injury. In real systems, population growth rates may be reduced by (1) the effects of exogenous factors such as weather or predators or

Figure 6. The cumulative distribution of red mite densities at the assumed time of first detection. This corresponds to $p(\lambda_{s,t_o})$ in the text.

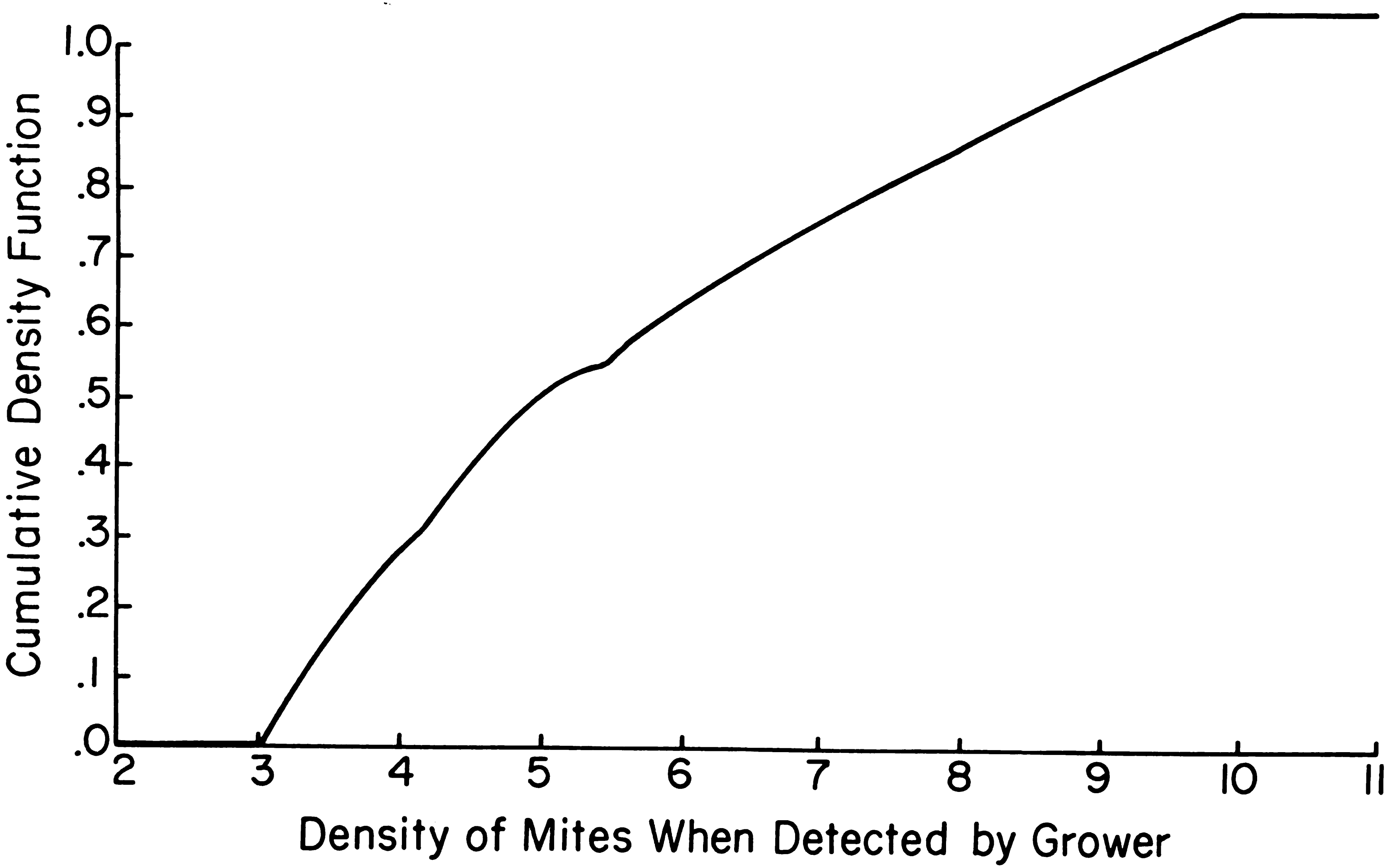
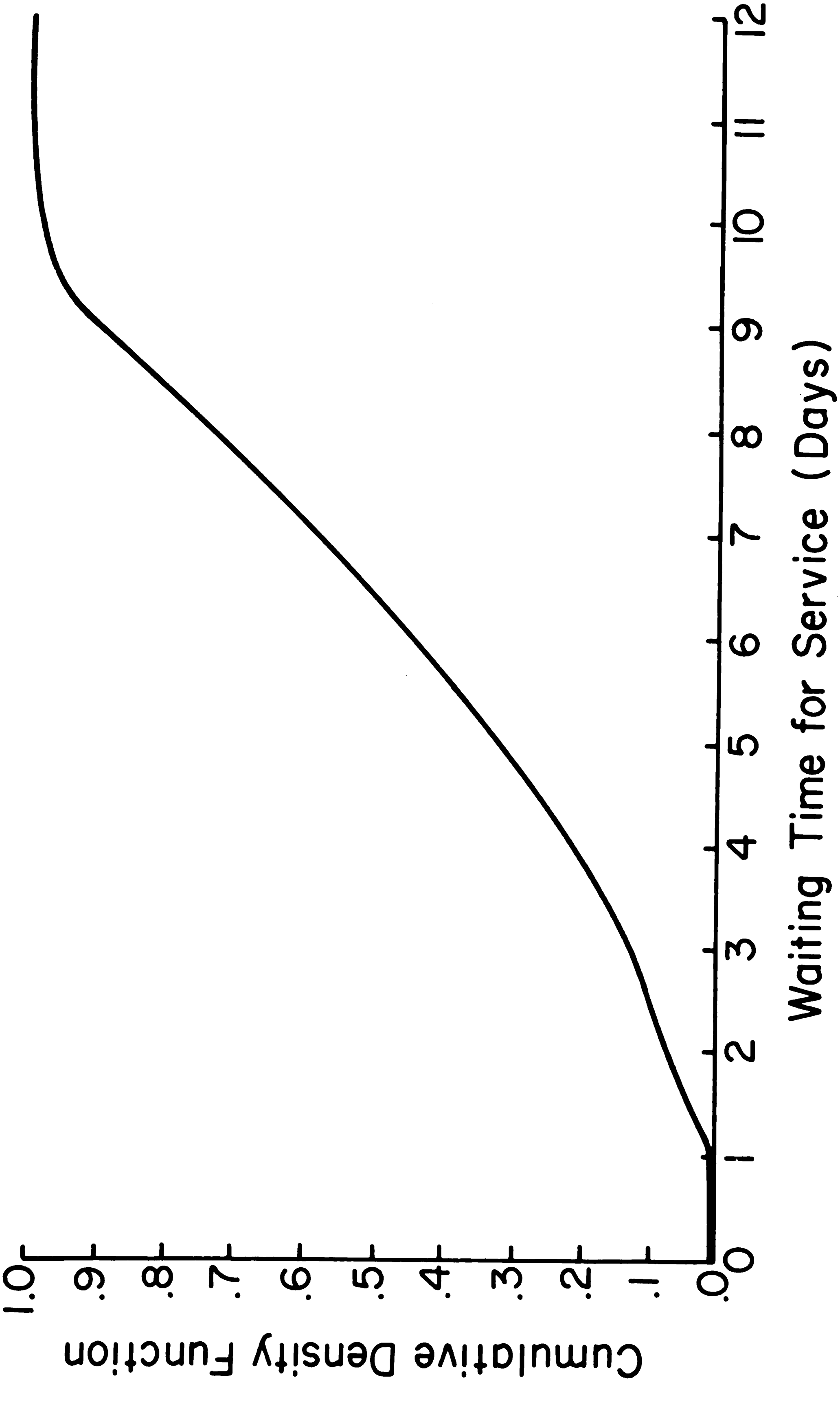

Cumulative Density Function
1.0
.9
.8
.7
.6
.5
.4
.3
.2
.1
.0
2
3
4
5
6
7
8
9
10
11
Density of Mites When Detected by Grower

Figure 7. The cumulative waiting time distribution from a simulation study of a mobile van-based mite counting service. This is delay 1 in Figure 2 and corresponds to $p_1(\tau)$ in the text.

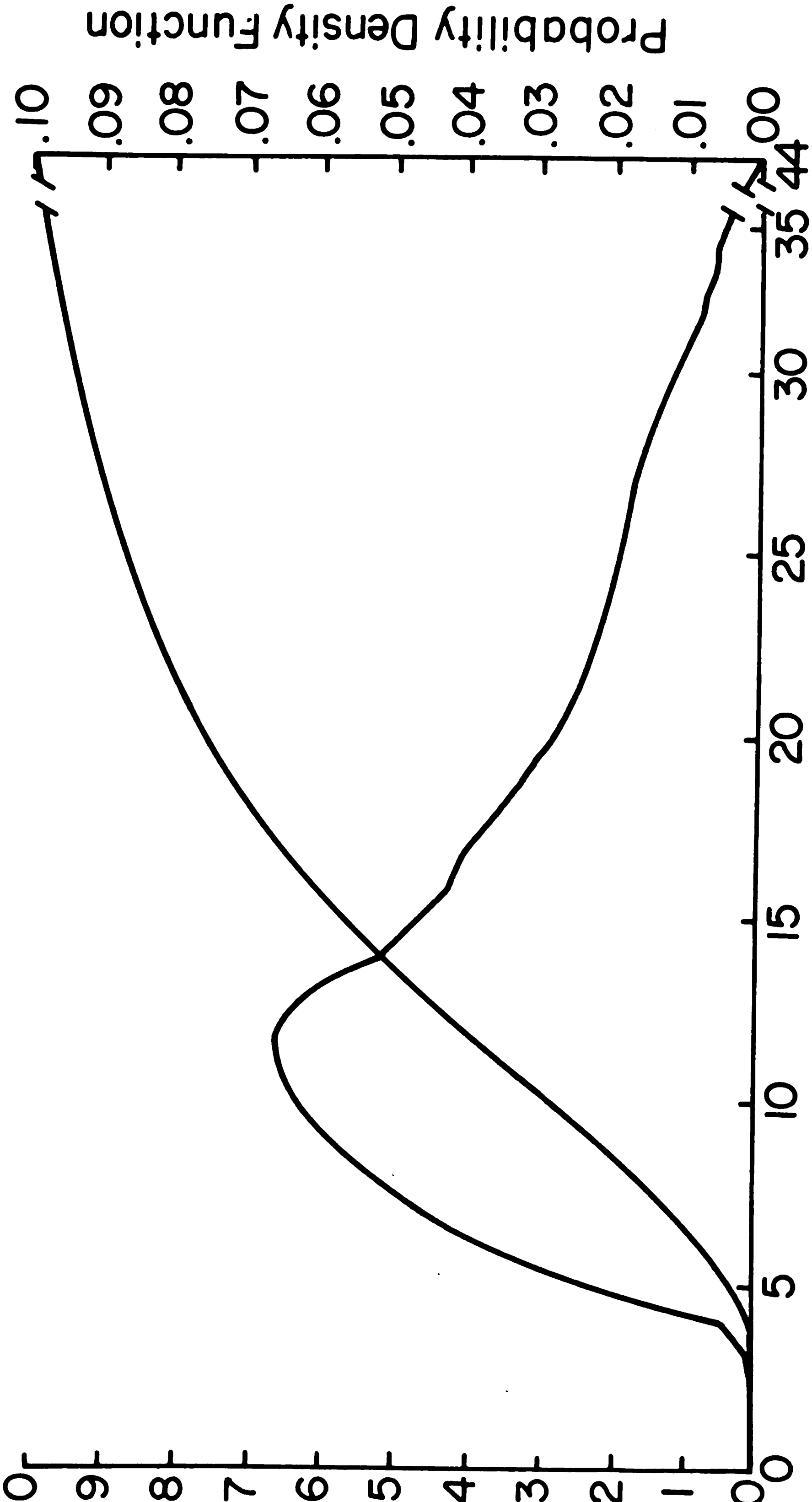

Cumulative Density Function
Waiting Time for Service (Days)
0.0
.1
.2
.3
.4
.5
.6
.7
.8
.9
1.0
0
1
2
3
4
5
6
7
8
9
10
11
12

(2) by internal effects like intraspecific competition. Exponential growth provides a conservative baseline for estimating the behavior of systems subject to the former effects; generally the latter processes occur too late to be significant to management. Solving (3-4) for various values of λ_{s,t_1} yields Figure 8.

One of the common criticisms of Bayesian statistics is the requirement of knowing this distribution. The counter-argument relies on the "principle of stable estimation" (Ward et al., 1963). This principle states that if we have no strong preferences for particular values of λ and if the sampling design yields a strongly peaked $p(x_s|\lambda_{s,t_1})$ then the form of the prior distribution has little effect on the posterior density function.

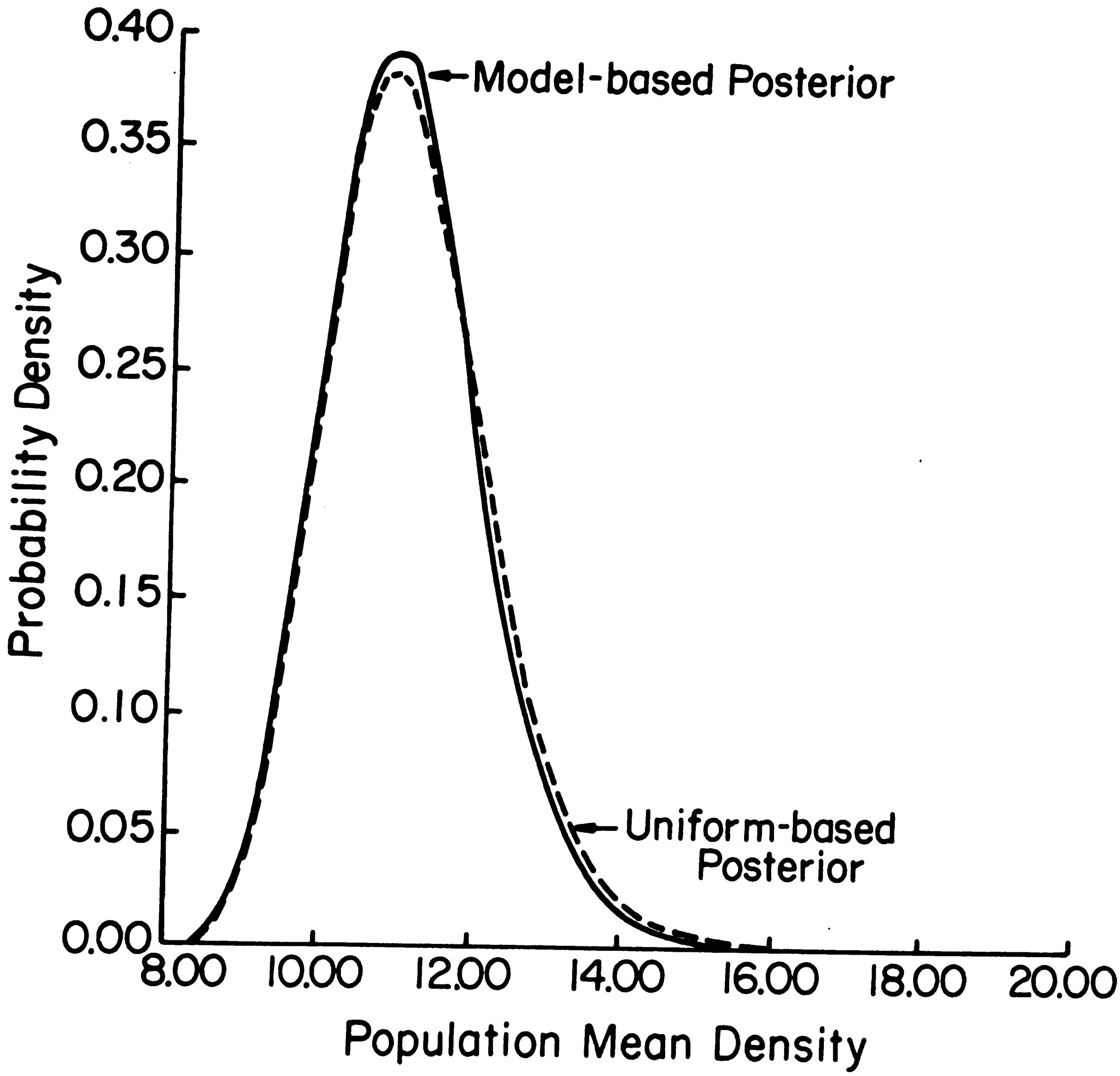
It would seem likely that this principle might apply to many biological monitoring situations because of the large variances typical in the field. Indeed, in our previous example the prior was quite uniform; the peaked appearance is due to the 200-fold vertical magnification. To examine the effect in this instance, posterior densities were calculated from the prior of Figure 8 and from a uniform prior covering the same range of mite densities. The distribution $p(x_s|\lambda_{s,t_1})$ was based on equation (3-2) with x_s=11. The variances σ_1^2 and σ_2^2 were calculated from Croft et al. (1976b) and the assumption was made that m=200 leaves were collected n=1 per tree. Figure 9 illustrates that the non-uniform prior based on grower characteristics and time delays had little statistical effect in this instance. While this

Figure 8. The prior density function from equation (3-4). The calculation assumes that the distributions of Figures 6 and 7 are employed and that a simple exponential outbreak model is appropriate for the developing population. This curve estimates the likelihood a mite counter would attach to various mite densities before the field had been seen.



Probability Density Function
.10
.09
.08
.07
.06
.05
.04
.03
.02
.01
.00
Cumulative Density Function
1.0
.9
.8
.7
.6
.5
.4
.3
.2
.1
0.0
0
5
10
15
20
25
30
35
44
Number of Mites per Leaf

Figure 9. A comparison of the posterior effect of a uniform versus a more complex, model-based prior distribution. The similarity of these two curves indicates that the principle of stable estimation seems to hold for European red mite monitoring. That is, it makes very little difference whether a designer uses the distribution of Figure 8 or replaces it with a constant.


0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Probability Density
Model-based Posterior
Uniform-based
Posterior
8.00
10.00
12.00
14.00
16.00
18.00
20.00
Population Mean Density

greatly simplifies the statistical design, it does not mean that these factors can be dropped completely from the analysis; these delays can still be of great biological significance as we shall see.

Once the statistics of monitoring at point S have been worked out the problem of extrapolating these results to point A, elsewhere in the monitoring unit, arises. This situation can be modeled by decomposing the relationship between λ_a and λ_s into deterministic and stochastic parts as follows

$$\text{(3-6)} \qquad \lambda_a = \alpha_{AS}(\lambda_s) + \beta_{AS}(\lambda_s)\varepsilon_{AS}.$$

In this equation ε_{AS} is assumed to be a random variable with zero mean and unit variance. The distribution of ε_{AS} depends on the particular pair of points being considered. For example, suppose λ_a and λ_s denote some measure like mean instar number. If location A was significantly warmer than S, we might expect ε to be predominantly positive whereas the reverse would be true if S were the warmer spot.

In spite of this problem, it is possible to calculate the expectation and variance of the biotic state at some point selected randomly from within monitoring unit R. We shall denote these quantities as $E(\lambda|\lambda_s)$ and $Var(\lambda|\lambda_s)$ respectively. We begin by noting

$$\text{(a)} \qquad E(\lambda_a|\lambda_s) = \alpha_{AS}(\lambda_s)$$

$$\text{(3-7)} \qquad \text{(b)} \qquad Var(\lambda_a|\lambda_s) = \beta_{AS}(\lambda_s)^2$$

$$\text{(c)} \qquad p(\lambda|\lambda_s) = \int_R p(\lambda_a=\lambda|\lambda_s)p(A)dR.$$

In (3-7c) A denotes some small element dR of R and p(A) is the probability of choosing that point. In the last chapter it was noted that the distribution of decision makers has important effects on sampling. The distribution p(A) is the mechanism by which this effect can be calculated. For this discussion, however, we shall assume that decision makers are distributed homogeneously within R so $p(A)=A_R^{-1}$ where A_R is the area of R. This yields

$$(3\text{-}8)\qquad E(\lambda|\lambda_s) = \int \lambda p(\lambda|\lambda_s)d\lambda = A_R^{-1}\int \lambda \int_R p(\lambda_a=\lambda|\lambda_s)dRd\lambda.$$

By switching the order of integration and using (3-7a) we have

$$(3\text{-}9)\qquad E(\lambda|\lambda_s) = A_R^{-1}\int_R \alpha_{AS}(\lambda_s)dR \doteq \bar{\lambda}.$$

From an elementary identity we have

$$(3\text{-}10)\qquad \mathrm{Var}(\lambda|\lambda_s) = \int \lambda^2 p(\lambda|\lambda_s)d\lambda - (\bar{\lambda})^2.$$

Substitution and simplification yields

$$(3\text{-}11)\qquad \mathrm{Var}(\lambda|\lambda_s) = A_R^{-1}\int_R (\alpha_{AS}(\lambda_s)^2 + \beta_{AS}(\lambda_s)^2)\ dR-(\bar{\lambda})^2.$$

If we were fortunate enough to have complete knowledge of α_{AS}, β_{AS}, and ε_{AS} for all A in R, we could determine the exact form of the λ distribution but, in general, this will not be the case. A result from information theory, however, suggests that it would be proper to assume $p(\lambda|\lambda_s)$ to be normally distributed. This is because, among all distributions with a given mean and variance, the Gaussian distribution maximizes entropy (Mardia, 1972). Since entropy can be interpreted as average uncertainty (Young and Calvert, 1974) this assumption will lead to designs which err on the side of conservatism.

As an aside, the application of this same principle to the conditional distribution of a particular λ_a yields

$$(3\text{-}12) \qquad p(\lambda_a | \lambda_s) = N(\lambda_a \; ; \; \alpha_{AS}(\lambda_s),\; \beta_{AS}(\lambda_s)^2 \;).$$

This lends a certain amount of support to the idea of using regression techniques in the experimental determination of α and β as some authors have done (Bohnam and Fye, 1970; Fulton and Haynes, in press).

In the previous chapter comments were made concerning several biological mechanisms which affect the α's and β's. These included dispersal and developmental rates particularly as modified by environmental variation. A further factor which might be mentioned is "distance". This might be the actual number of miles between A and S or some other index of size such as area or similarity. If d_{AS} denotes this distance measure for A and S we can make some plausible statements about the asymptotic behavior of the α's and β's, namely

$$(3\text{-}13) \qquad \begin{array}{llll} \text{(a)} & \lim\limits_{d_{AS}\to 0} \alpha_{AS}(\lambda_s)=\lambda_s & \text{(b)} & \lim\limits_{d_{AS}\to\infty} \alpha_{AS}(\lambda_s)=E(\lambda_a) \\ \text{(c)} & \lim\limits_{d_{AS}\to 0} \beta_{AS}(\lambda_s)=0 & \text{(d)} & \lim\limits_{d_{AS}\to\infty} \beta_{AS}(\lambda_s)=\mathrm{Var}(\lambda_a)^{1/2}. \end{array}$$

These relations simply say that α and β yield the sample values at the sampling point while at infinity λ_a and λ_s are independent (i.e., the best prediction of λ_a is the mean of λ_a). We shall have cause to refer to these limits below.

The formulas (3-6) through (3-13) imply knowledge of the actual state λ_s. To calculate the probabilities of various λ_a's based on an observation x_s we use the equation

$$(3\text{-}14)\quad p(\lambda_{t_1}|x_s) = \int p(\lambda_{t_1}|\lambda_{s,t_1})p(\lambda_{s,t_1}|x_s)d\lambda_{s,t_1}$$

where $p(\lambda_{t_1}|\lambda_{s,t_1})$ is the normal distribution whose parameters were constructed in (3-9) and (3-11) and where $p(\lambda_{s,t_1}|x_s)$ is from (3-1).

Let us now continue our red mite example. We shall assume that as winter ends the density of mites in the monitoring unit can be characterized by some low value P_o. Because of the limited abilities of red mites to disperse, we shall assume that differences in mite densities found later in the season are due to different temperature histories. Let us suppose that the monitoring unit is small enough so that the average temperatures at two points in a monitoring unit of size d are the same. However, let the variance between points be

$$(3\text{-}15)\qquad \beta_{AS}(T_s) = \sigma(1-e^{\beta x})$$

where x is their separation. These assumptions are consistant with the limits in (3-13). Equations (3-9) and (3-11) yield

$$\text{(3-16)}\quad \text{(a)}\quad E(T|T_s) = T_s$$

(b)[1] $$V(d) \doteq Var(T|T_s) = \sigma^2 \{1+(\beta d)^{-1}(e^{\beta d}-4)e^{\beta d} + (\beta d)^{-2}(4(e^{\beta d}-1)-(e^{2\beta d}-1)/2)\}.$$

For simple exponential growth (such as might characterize an outbreak phase of many pests) we have the well known relation $r = G^{-1}\ln R$ where R is the rate of replacement and G is the generation time. If we assume that R is a fixed propagule complement unaffected by longevity and that the rate of development G^{-1} is proportional to temperature (T) above a threshold (T_h) then we have

$$\text{(3-17)}\qquad r = k(T-T_h).$$

If λ_s and λ are the densities of mites a sampling point S and at a random point in the monitoring unit we have

$$\text{(3-18)}\qquad \lambda_s = P_o \exp\left(\int_0^t k(T_s-T_h)dt \right) = P_o \exp(\bar{r}_s t)$$

where

$$\text{(3-19)}\qquad \bar{r}_s = \frac{1}{t}\int_0^t k(T_s-T_h)\, dt.$$

Similar relations hold for λ. Algebra yields

$$\text{(3-20)}\qquad \ln\lambda - \ln\lambda_s = (\bar{r} - \bar{r}_s)t.$$

---

1. The appropriate application of L'Hospital's Rule will show that

$$\lim_{d\to 0} V(d) = 0$$

In the derivations which follow, it is important to note that λ_s is a population parameter and, therefore, a constant. On the other hand, λ is a random variable since it results from the random selection of a point from within a monitoring unit. Taking expectations on both sides of (3-20) gives

$$(3\text{-}21)\qquad \begin{aligned} E(\ln \lambda - \ln \lambda_s) &= E(\ln \lambda) - \ln \lambda_s \\ &= tE(\bar{r} - \bar{r}_s) \\ &= k \int_0^t E(T - T_s)\, dt = 0. \end{aligned}$$

Therefore,

$$(3\text{-}22)\qquad E(\ln \lambda) = \ln \lambda_s.$$

Taking variances on both sides of (3-20) gives

$$(3\text{-}23)\qquad \begin{aligned} \mathrm{Var}(\ln \lambda - \ln \lambda_s) &= \mathrm{Var}(\ln \lambda) \\ &= t^2 \mathrm{Var}(\bar{r} - \bar{r}_s) \\ &= k^2 \int_0^t \mathrm{Var}(T - T_s)\, dt = k^2 t V(d). \end{aligned}$$

Substituting for t from (3-18) yields

$$(3\text{-}24)\qquad V \doteq \mathrm{Var}(\ln \lambda) = k \left[\frac{\ln\lambda_s - \ln P_o}{\bar{T}_s - T_h} \right] V(d)$$

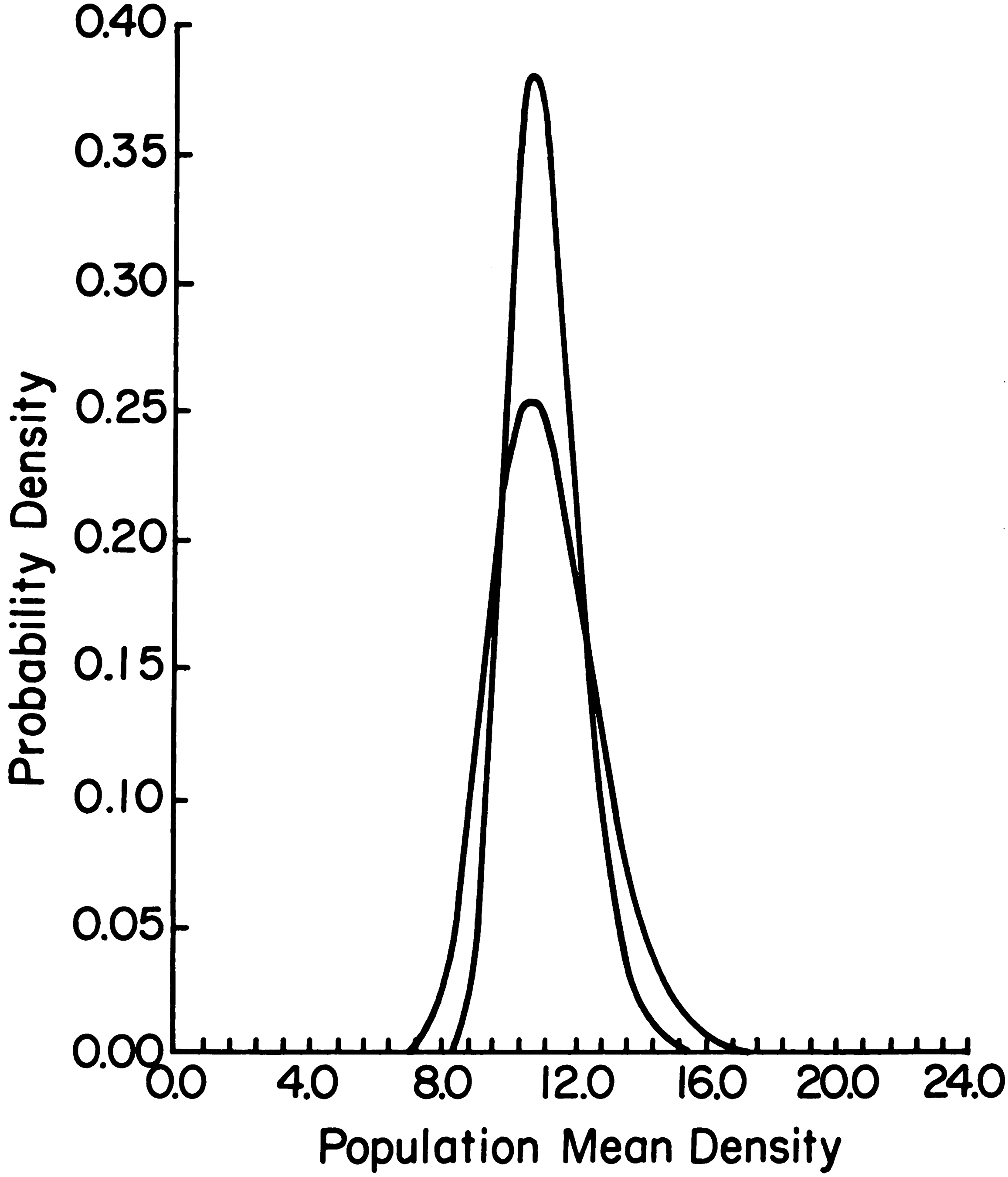
where $\bar{T}_s$ denotes an average value. Assuming normality for $\ln \lambda$ means that λ has a lognormal distribution with density function

$$(3\text{-}25)\quad p(\lambda|\lambda_s) = (2\pi V)^{-1/2} \exp((\ln(\lambda_s/\lambda))^2/(2V))/\lambda.$$

To calculate a numerical example a plausible value for σ of 11 was selected based on 77 years of July temperatures for Grand Rapids, Michigan (point S). A value of $\bar{T}_s$ of 72.3°F was determined from the same source. The parameter β was set to -.12 on the ad hoc assumption that temperatures from two places five miles apart would be within five degrees (°F) of one another 68 percent of the time. Because measurements of this have not, in actuality, been made in the field on this small a scale the results of this example may not be realistic. It must be remembered that the point of this example is how the different types of variation are coupled to achieve an estimate of system performance. To continue, developmental thresholds for the life stages of P. ulmi (Welch, unpub.) were averaged to give a T_h of 50°F. By using the previous value of r, equation (3-17) was solved for k. P_o was set to a nominal .5 mites per leaf. Assuming the same sampling design used previously and the principle of stable estimation, we obtain the density function shown in Figure 10 for x_s=11. The increase in the size of potential confidence limits caused by extrapolation over an entire monitoring unit is evident.

In this chapter we have studied how time delays in measurement and extrapolation through space can degrade the value of a measurement. The first step involved the use of Bayes' theorem to link measurement outcomes with the likelihood functions of various relevant ecosystem states. It was demonstrated how the principle of stable estimation can be used to eliminate the troublesome need for a prior distribution.

Figure 10. <u>The change in a likelihood function resulting from the extrapolation of data taken at a point over an extended spatial area.</u> The figure demonstrates that the variance associated with an estimate increases when one tries to extrapolate from a single point (the peaked curve) to all of a monitoring unit with finite spatial extent (the broad curve).



0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Probability Density
0.0
4.0
8.0
12.0
16.0
20.0
24.0
Population Mean Density

During this discussion methods of extrapolating distributions through time via conditional probabilities were presented. The problem of spatial extrapolation was handled by partitioning estimators into deterministic and stochastic portions. Means and variances were calculated in terms of this partition. In the next chapter we shall show how these parameters are affected by delays between monitoring and decision making and how they are incorporated into the decision maker's economic objective function.

CHAPTER IV

THE ECONOMICS OF THE DECISION MAKER

In the final analysis, the evaluation of any system must rest on a firm economic base. As might be expected much work has been expended on relating biological phenomena, economic decisions, and risk (Headley, 1972, 1975; Hall and Norgaard, 1973; Carlson, 1970). There are two distinct viewpoints which must be recognized. On the one hand is the decision maker who has to balance the cost of monitoring against the value received. This view is of importance to the designer who has to sell his product in a skeptical market. On the other hand, the financial prospects of the monitoring service are important because an impractical venture is sure to fail. This chapter will deal with the economics of decision making while chapter VII will examine the monitoring service.

The decision maker receives data x_s from the monitoring component and makes decision $D = D(x_s)$. He then implements this decision and is subject to loss

$$L(D,x_s)=\int_{\lambda} l(D,x_s, \lambda_{t_3})p(\lambda_{t_3}|x_s)\, d\, \lambda_{t_3}. \tag{4-1}$$

The distribution $p(\lambda_{t_3}|x_s)$ describes the probability of various possible ecosystem states at time $t_3 = t_o+\tau_1+\tau_2+\tau_3$ when control is actually implemented (see Figure 2). By analogy with equation (3-4) we calculate

$$(4\text{-}2) \quad p(\lambda_{t_3}|x_s) = \int_0^{\infty}\int_{\lambda} p(\lambda_{t_1+\tau}|\lambda_{t_1})p(\lambda_{t_1}|x_s)p(\tau)\, d\lambda_{t_1}d\tau$$

where $t_3 = t_1+\tau$. Multiple runs of biological models can be used to assess these probabilities.

The loss function $l(D,x_s,\lambda)$ is more complicated. A useful breakdown of costs is shown in Table 1. It is important to note that each of these costs may be a random variable. For example, while the cost of monitoring could be a fixed (non-random) charge, it could also be dependent on the time required for sampling and thus, roughly, on x_s. In cases where monitoring units contain many decision makers, each may pay some fraction of the cost or all may benefit from some public subsidy. Public policy might adjust this subsidy according to user characteristics to encourage utilization by particular parties. The cost of control, $\$_2(D)$, depends on the type of control implemented. It is even possible that different decision makers may pay different prices for the same decision. This can happen, for instance, if certain decision makers can realize economies of scale in the bulk purchase of control materials. Finally, the cost of damage depends on the state of the agro-ecosystem and the decision taken. This has obvious stochastic elements.

Because these variables are distributed it is difficult to construct a convenient loss function in terms of the variables directly. A better approach is to base the loss function on their distributions. To do this we introduce the idea of utility as developed by the neoclassical economists. Many factors which enter into human decision making cannot

Table 1

Schedule of decision maker's costs

I.	Cost of management	
	A. Cost of monitoring	$\$_1(x_s)$
	B. Cost of control	$\$_2(D)$
II.	Cost of resultant damage	$\$_3(D,\lambda)$

be measured in dollars because they are not market commodities. Typical examples are the desire to avoid risk or the value which goods have in use as opposed to exchange. Utility theory (Scott, 1973; Nicholson, 1972) provides mechanisms for taking these factors into account. One of the major defects of utility theory is that utilities, in general, are not directly measurable. Fortunately for this application, one of the exceptions is when it is possible to make probability statements about the various possible outcomes.

There are two methods in common use for constructing utilities from dollar distributions. The first is simply to take the expected value of the distribution. This is (roughly) equivalent to saying that over some range of values an individual is indifferent to a choice between receiving one dollar with certainty versus receiving x dollars with probability 1/x. Under this method we have

$$(4\text{-}3) \qquad l_1(D,x_s,\lambda) = E(\$_1(x_s)) + E(\$_2(D)) + E(\$_3(D,\lambda)).$$

This method can be applied to the analysis of the mobile mite counting van mentioned previously. In the initial study, expected costs equalled the sum of a fixed monitoring charge plus the expected costs of control and damage. This latter was found by multiplying the cost of significant damage times the probability of non-control (PNC) given the monitoring results. Unfortunately, subsequently to this analysis, an error was detected in the calculation of damage cost. This error, however, has been corrected in the account which follows.

Because the quantitative relation between mite damage and yield is biologically obscure, an indirect method must be used to assign a dollar value to the phrase "significant damage". Such a value may be calculated from the following assumptions:

(1) mite damage is cumulative so the cost of damage must include a measure of the contribution to future damage potential;

(2) five consecutive years with populations peaking above 15 red mites per leaf so damages a tree that the grower is forced out of the fresh fruit market into the process market;

(3) one year of vigorous, mite-free growth is sufficient to allow the tree to repair previous mite damage;

(4) each future year can be considered statistically as an independent Bernoulli trial (Feller, 1968, vol. 1) where the probability of damage is given by r, the economic risk of the monitoring-management system (PNC is the probability of damage this year).

Assumption 2 implies that, at 1975 prices, the grower would sustain a loss of \$656.20 per acre (Hines, 1976) after five years of damage or \$131.24 per consecutive year. Taking the other assumptions together, we have, by the binomial theorem

(4-4) cost of damage =

$$131.24 + \sum_{n=0}^{4} \binom{4}{n} r^n (1-r)^{(4-n)} (131.24n).$$

That is, the cost of damage equals the damage this year plus the expected cost of damage over the next four future years. A more economically complete argument would discount these future costs but, for the sake of simplicity, we shall not consider this point. Rearranging terms and using the rule for the expectation of a binomially distributed random variable yields

$$\text{cost of damage} = 131.24(1 + 4r). \tag{4-5}$$

This formula shows that, by reducing the risk of cumulative damage, we can lessen the impact of damage when it does occur. As an example, examination of historical records (Croft, unpub. data) reveals that growers using a particular monitoring-based, integrated control scheme (the RS II system of chapter VII) exceeded 15 mites per leaf on an average of $r = .11$ of the cases in any one year. Substituting this value in (4-5) yields a cost of damage of $189 per acre.

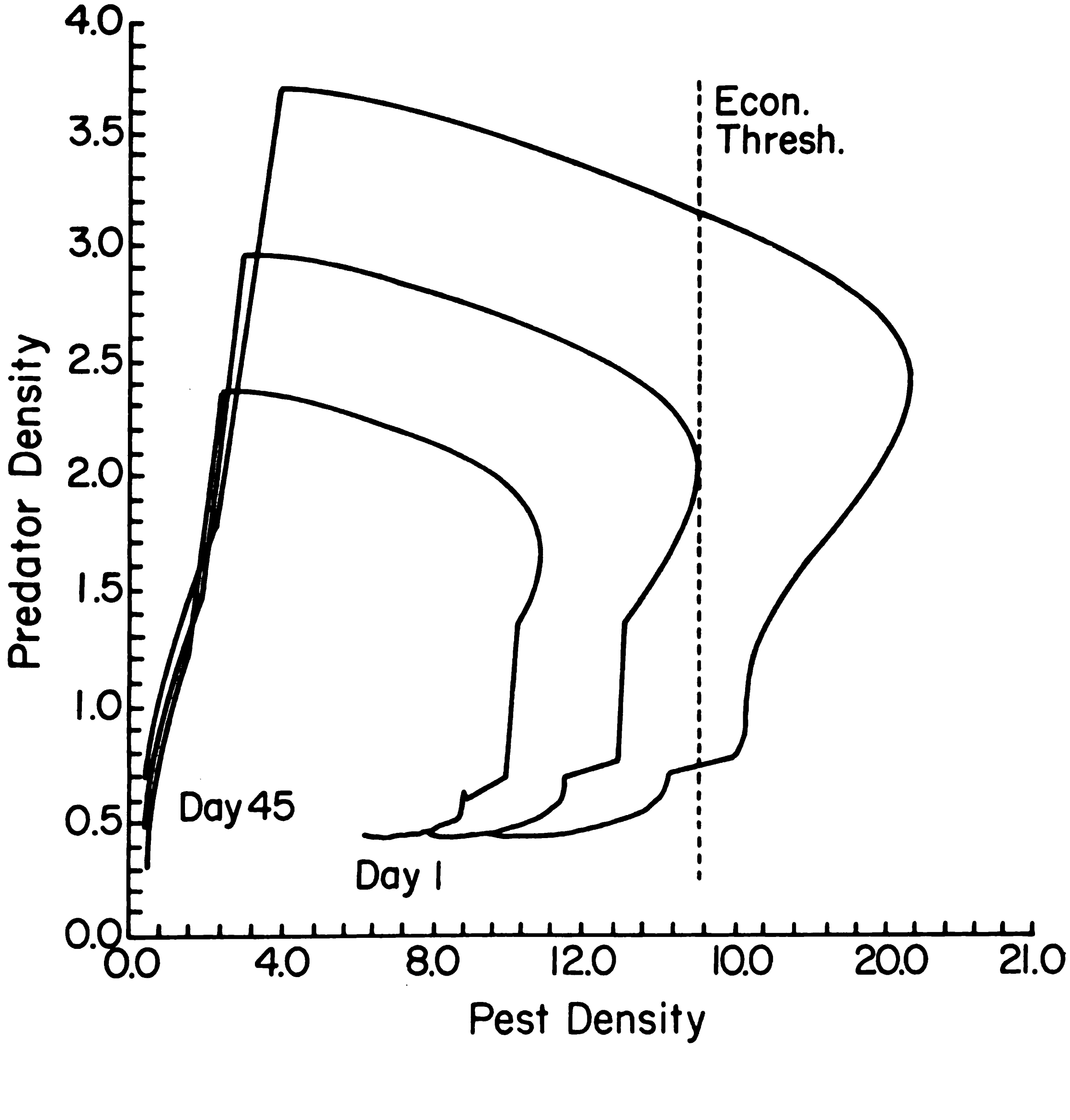
To evaluate the probability of exceeding 15 mites per leaf given a particular monitoring outcome a biological model was used. Each sample was taken to represent a point in the prey-predator phase plane. The area of the plane where most samples fall was divided into a grid of 300 points. The model was run using each of these points as initial conditions and it was determined for each run whether or not red mites peaked above 15 per leaf. If so, the point was assigned[1] a value of $I_{15}(\lambda) = 1$; if not, $I_{15}(\lambda) = 0$. Figure 11 illustrates this for three initial points. The probability of non-control was then ascertained for particular values of x_s by

$$PNC(x_s) = \int p(\lambda_{t_3} | x_s) I_{15}(\lambda_{t_3}) d\lambda_{t_3}. \tag{4-6}$$

---

1. Statisticians would term I_{15} an "indicator function".

Figure 11. A phase plane plot showing simulations of three interactions of the European red mite (horizontal axis) with *Amblyseius fallacis* (vertical axis). The three curves are characterized by progressively poorer initial prey-predator ratios resulting, ultimately, in a failure of biological control.


4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Predator Density
Econ.
Thresh.
Day 45
Day 1
0.0
4.0
8.0
12.0
10.0
20.0
21.0
Pest Density

In many cases decision makers, understandably, wish to avoid situations where significant probabilities of great loss exist even when these are offset by the chance of great gain. This is termed risk aversion. A common method of quantifying this (Markowitz, 1952) is to attach a penalty to the loss function proportional to the variance of the dollar distribution. Thus,

$$(4\text{-}7) \qquad l_2(D,x_s,\lambda) = l_1(D,x_s,\lambda) - A\cdot\mathrm{Var}(\$_1+\$_2+\$_3).$$

In most cases this method of determining losses yields optimal policies which are suboptimal according to (4-3). The difference may be thought of as the amount the decision maker is willing to pay to avoid risk.

One difficulty with the utility approach is that it is sometimes difficult to interrelate it with linear programming methods which designers may desire to use. An alternative method without this defect has been proposed by Boussard and Petit (1967). In this method the probability of some "surprisingly great" loss is kept below some level. This loss is called the "focus of loss", a term introduced by Shackle (1949, 1961). Boussard and Petit have taken the focus of loss to be an amount which would result in insufficient income to cover unavoidable expenses. The general technique is called "chance constrained programming" and has been reviewed by Charnes and Cooper (1959) and Charnes et al. (1965). We shall employ constraints of this form in an example in the next chapter.

CHAPTER V

MATHEMATICAL RELATIONS BETWEEN DESIGN FACTORS

In this chapter we shall mathematically combine several of the classes of factors discussed previously. These include variability within monitoring units, economic risk, management system time delays, and intensity of operations. There are quite a few specific parameters which might be used as indices of any one of these classes (see Table 2). Indeed, a designer may desire to examine several from each class to gain a more complete picutre. Let us suppose, however, that some particular combination (v,i,t,r) of variables has been chosen, one per class, where the variable names are as in Table 2.

The discussion below focuses on cases when the following relations may be assumed true.

(5-1) $$t = h(r,v)$$

(5-2) $$i = g(v,t)$$

(5-3)

(a) $\frac{\partial t}{\partial v} < 0$ (b) $\frac{\partial t}{\partial r} > 0$

(c) $\frac{\partial i}{\partial v} < 0$ (d) $\frac{\partial i}{\partial t} < 0$

We shall take g and h to be defined, continuous, and differentiable over the region of interest.

The parameter v relates to all factors which might broaden the confidence limits assigned to particular estimates within a monitoring unit. Many projections made in pest

TABLE 2

Some representative variables from each of the four important design parameter classes

Variability within monitoring units (v)
Variance of monitored variables
Geographic size of monitoring unit
Dissimilarity index of sites within unit
Etc.
Intensity of monitoring (i)
Man-hours spent monitoring
Number of samples taken per unit time
Total monitoring expenditures per season
Etc.
Management system time delays (t)
Average time from monitoring to action
Maximum time from monitoring to action
Etc.
Economic risk (r)
Expected total loss
Probability of exceeding economic injury level
Probability of sustaining focus of loss
Etc.

management depend on determinations of biological rates (chapter II). Uncertainty in the value of a rate at a given sampling point or systematic variation in a rate from point to point in space (chapter III), when integrated over time (*cf*. equation 3-23), progressively degrades the value (*i.e.*, increases the variance) associated with monitoring estimates.

The function g (equation 5-2) relates the variability of the monitoring unit (or scale if this is correlated) and time (specifically, the delays of Figure 2) to a measure of the intensity of the operation. Intensity is meant to refer generally to the *inputs* to sampling, that is, to sampling *effort*. It might therefore include components of frequency, sampling point density, or redundancy. However, it would not directly measure, say, accuracy which is a characteristic of sampling output; it *would* measure any extra effort needed to achieve that accuracy. The measure may be a parameter with actual physical or economic meaning or just a relative index as we shall use later in this chapter.

The designer can and should minimize the effect of monitoring unit variation by selecting units as internally homogeneous as possible. Beyond this, however, reductions in v can be achieved only by increasing the number of sampling points and, thus, the overall sampling effort. This is embodied in inequality (5-3c). The other way to improve the reliability of monitoring estimates is to decrease the delay time over which variation is allowed to integrate. By requiring the system to work faster, we are, again, increasing the required effort. Inequality (5-3d) states this relationship.

The function h (equation 5-1) yields the maximum allowable delay in terms of monitoring unit variability and permissible risk level. It is determined primarily by the biology of the organism being managed. As delays progress and the variances of our posterior likelihood functions increase, the more conceivable is the possibility (risk) that the system has entered an injurious state (assuming that the sampling trigger takes place before damage begins). Inequality (5-3b) says that the higher the level of allowable risk, the longer we may delay the monitoring-management process. Inequality (5-3a) maintains that the greater the within-unit variability (i.e., the confidence limit "spreading rate"), the quicker we must act to avoid undue risk to portions of the monitoring unit.

In view of the preceding paragraphs, it seems likely that the relations in (5-3) will hold in many practical cases although they must be verified in each specific instance. Later in this chapter an example of such verification will be shown. First, however, we shall demonstrate two important results about variables satisfying (5-1) through (5-3d).

Theorem 1: There exists a one-to-one transformation between the ordered pairs (r,v) and the ordered pairs (t,i).

Proof: Consider the transformation defined by the equations

$$t' = t'(r,v) = h(r,v)$$

$$i' = i'(r,v) = g(k(r,v),h(r,v))$$

where $k(r,v) = v$. We shall prove that this transformation is one-to-one by proving that its Jacobian

$$J = \begin{vmatrix} \frac{\partial t'}{\partial r} & \frac{\partial t'}{\partial v} \\ \\ \frac{\partial i'}{\partial r} & \frac{\partial i'}{\partial v} \end{vmatrix}$$

cannot vanish. Using the chain rule for differentiation and the definition of determinants we have, after simplification

$$J = \frac{\partial t}{\partial r}\left[\frac{\partial i}{\partial v} + \frac{\partial i}{\partial t}\,\frac{\partial t}{\partial v}\right] - \left[\frac{\partial i}{\partial t}\,\frac{\partial t}{\partial r}\right]\,\frac{\partial t}{\partial v}\,.$$

Suppose that $J = 0$. Rearranging terms and canceling $\partial t/\partial r$ which is not zero by equation (6-3b) yields

$$\frac{\partial i}{\partial v} + \frac{\partial i}{\partial t}\,\frac{\partial t}{\partial v} = \frac{\partial i}{\partial t}\,\frac{\partial t}{\partial v}\,.$$

But this implies that $\partial i/\partial v$ is zero which contradicts equation (5-3c). Therefore the transformation is one-to-one.

This result says that all four variables can be graphed in a single plane without any point having more than one four-tuple assigned to it. An even stronger result is

<u>Theorem 2</u>: Specifying values for any two of the variables v, i, r, t determines values for the other two uniquely with one exception; given i and r it <u>may</u> not be possible to solve for v and t.

<u>Proof</u>: Define the following four univariate functions

$$h_{r_x}(v) \doteq h(r_x,v) \qquad h_{v_x}(r) \doteq h(r,v_x)$$

$$g_{v_x}(t) \doteq g(v_x,t) \qquad g_{t_x}(v) \doteq g(v,t_x)$$

where the subscript x is an "o" for given values and an "s" for solved values. Equations (5-3a,b,c,d) show that these functions are strictly monotone in the region of interest and, therefore, their inverses exist and are one-to-one. Not counting (i,r) there are five possible pairs of given variables and we shall treat them one by one.

Given	Solution for the other pair
r_o, v_o	$t_s = h(r_o, v_o)$, $i_s = g(v_o, t_s)$
t_o, v_o	$i_s = g(v_o, t_o)$, $r_s = h^{-1}_{v_o}(t_o)$
i_o, v_o	$t_s = g^{-1}_{v_o}(i_o)$, $r_s = h^{-1}_{v_o}(t_s)$
t_o, r_o	$v_s = h^{-1}_{r_o}(t_o)$, $i_s = g(v_s, t_o)$
i_o, t_o	$v_s = g^{-1}_{t_o}(i_o)$, $r_s = h^{-1}_{v_s}(t_o)$

If we are given i_o and r_o we proceed by substituting (5-1) into (5-2) giving the system of equations

$$t = h(r_o, v)$$

$$i_o = i'(r_o, v)$$

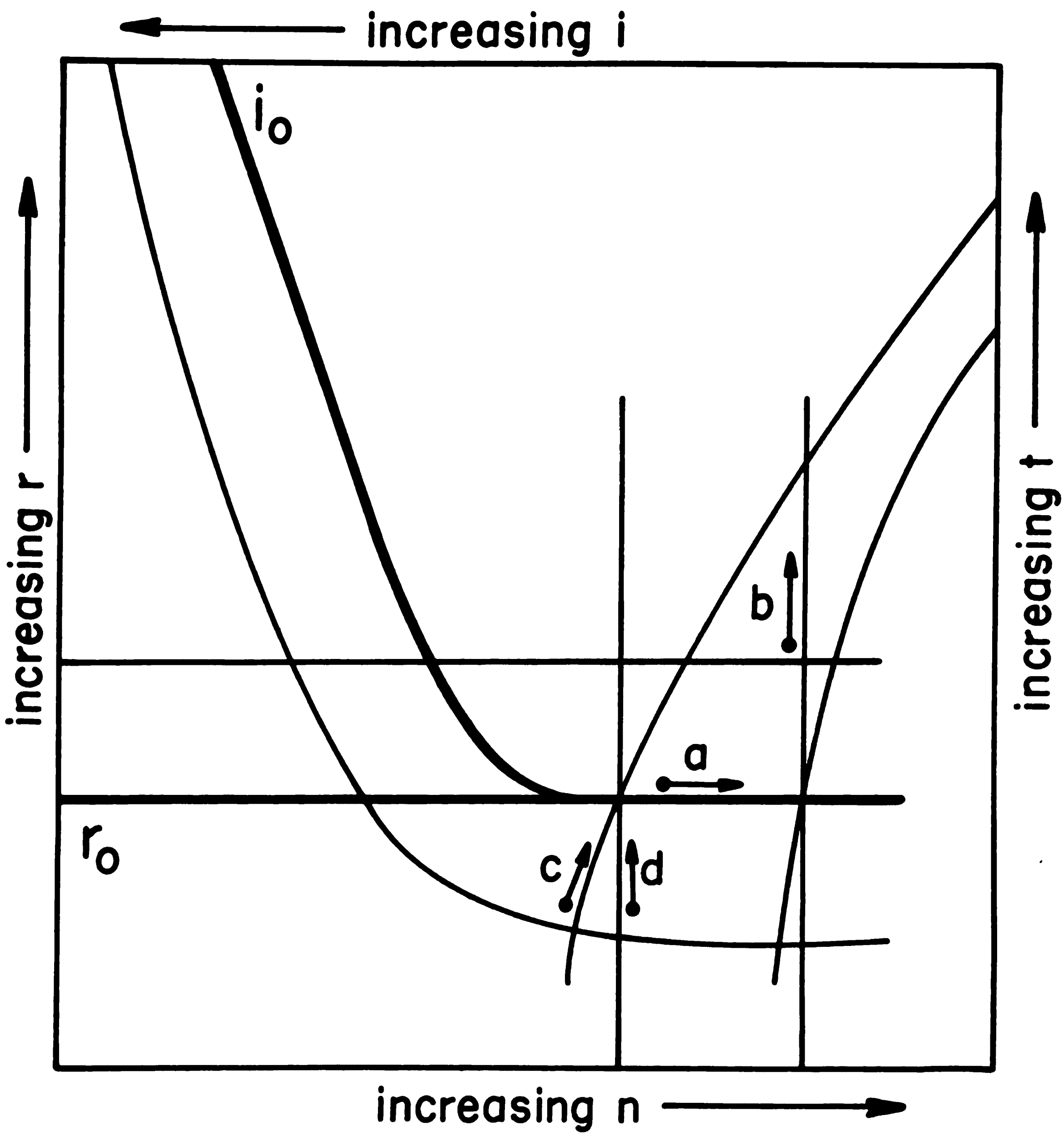
where i' is defined as in Theorem 1. This system can be solved if and only if

$$i'^{-1}_{r_o}(i_o)$$

is unique. An example of when this fails to occur is shown in Figure 12. Examination of this figure shows all of the relations (5-3a,b,c,d) to be satisfied.

The importance of these theorems is that they permit us to construct a nomogram of particular use to monitoring system design. This is done by plotting contour lines of any two of the four classes of variables on a grid made up of the other two. Theorem 2 provides the only constraints on the choice of pairs. As the following chapters will show, such a chart enables the designer to assess quickly the effects of various

Figure 12. *A counterexample for Theorem 2.* In this instance, i_o and r_o are given. Motion along the trajectories indicated by the arrows (a, b, c, d) demonstrates that the corresponding inequalities in equations (5-3a,b,c,d) hold. In spite of this, it is evident that there is no unique solution for v and t.


increasing i
i_o
increasing r
increasing t
b
a
r_o
c
d
increasing n

time delays, technologies, pricing structures, etc.

This chapter will conclude with an example of the construction of a chart such as we have discussed. The steps involved are (1) the selection of a suitable set of parameters v, i, t, r, (2) the derivation of the functions g and h, (3) the proof that these functions satisfy the conditions of the two theorems, and (4) the preparation of the chart.

For this example we shall continue our discussion of an organism similar to the European red mite. So as not to obscure the illustrative value of the example we shall select measures for v, i, r, and t which are somewhat simpler than might be justified in practice. For instance, let us define v to be the radius of the monitoring unit and r to be the probability of exceeding a nominal injury level (P_D) of 15 mites per leaf. In this example we shall use these variables as axes and plot contour lines for i and t. Let us suppose that we have a method of requesting sampling which, as a worst case, triggers at the tolerance level (P_O) of 7 mites per leaf. We define t to be the maximum delay allowed between triggering and the application of control. For the intensity of monitoring we use the following <u>ad hoc</u> index

$$(5\text{-}4) \qquad i \doteq g(v,t) = Ct^{-1}v^{-2}$$

where C is an arbitrary normalizing constant. This function has the reasonable properties that (1) it is proportional to the minimum rate of sampling and (2) it is proportional to the density of sampling points in the region.

To derive h(r,v) we first note that we have, from equations (3-22) and (3-18),

(5-5) $$E(\ln\lambda) = \ln\lambda_s = \bar{r}_s t + \ln P_o \quad ,$$

and, from equation (3-23),

(5-6) $$\mathrm{Var}(\ln\lambda) = k^2 V(v) t.$$

Since we have assumed normality for $p(\ln\lambda \mid \ln\lambda_s)$ we have

(5-7) $$r = 1 - \mathrm{erf}\left(\frac{\ln P_D - \ln P_o - \bar{r}_s t}{kV(v)^{1/2} t^{1/2}} \right)$$

where erf is the cumulative distribution function of a standardized normal variate. We note that some algebra suffices to rewrite (5-7) as

(5-8) $$c = (a + t)/(bt^{1/2})$$

where

(5-9)
$$\text{(a)} \quad a = -\frac{1}{\bar{r}_s} \ln(P_D/P_o) < 0$$
$$\text{(b)} \quad b = -\frac{1}{\bar{r}_s} kV(v)^{1/2} < 0$$
$$\text{(c)} \quad c = \mathrm{erf}^{-1}(1-r) > 0 \ .$$

The inequalities (5-9a,b) are obvious by inspection; (5-9c) declares that we are not interested in economic risks greater than 50 percent. Solving (5-8) yields

(5-10) $$t^{1/2} = \tfrac{1}{2}(cb \pm (c^2 b^2 - 4a)^{1/2})$$

which, from (5-9), has exactly one positive and one negative root. Discarding the negative root as not meaningful gives

$$(5\text{-}11) \qquad t = h(r,v) = \tfrac{1}{4}(cb + (c^2b^2 - 4a)^{1/2})^2$$

The next step is to show that g and h satisfy the conditions of the two theorems. It is clear that

$$(5\text{-}12) \qquad \begin{aligned} &(a) \quad \frac{\partial i}{\partial v} = -2Ct^{-1}v^{-3} < 0 \\ &(b) \quad \frac{\partial i}{\partial t} = -Ct^{-2}v^{-2} < 0 \end{aligned}$$

so (5-3c,d) hold. Differentiating h yields

$$(5\text{-}13) \qquad \begin{aligned} &(a) \quad \frac{\partial t}{\partial v} = \tfrac{1}{2}f_1 f_2 b_v \\ &(b) \quad \frac{\partial t}{\partial r} = \tfrac{1}{2}f_1 f_3 \end{aligned}$$

where

$$(5\text{-}14) \qquad \begin{aligned} &(a) \quad f_1 = (cb + (c^2b^2 - 4a)^{1/2}) > 0 \\ &(b) \quad f_2 = c + c^2b(c^2b^2 - 4a)^{-1/2} \\ &(c) \quad f_3 = (c_r b + b_r c + \tfrac{1}{2}(c^2b^2 - 4a)^{-1/2} \\ &\qquad\qquad \cdot (2cc_r b^2 + 2c^2bb_r - 4a_r)) \end{aligned}$$

and the subscript "r" and "v" refer to partial differentiation. Since $a_r = b_r = 0$ we can rewrite f_3 as

$$(5\text{-}14c') \qquad f_3 = c_r b + cc_r b^2/(c^2b^2 - 4a)^{1/2}$$

From the inequalities (5-9) we have

$$(5\text{-}15) \qquad \begin{aligned} &(a) \quad bc^2/(c^2b^2 - 4a)^{1/2} > bc^2/\ |cb| = -c \\ &(b) \quad cc_r b^2/(c^2b^2 - 4a)^{1/2} > cc_r b^2/\ |cb| = -c_r b \end{aligned}$$

or, upon rearranging terms across the inequalities

$$(5\text{-}16) \qquad f_2 \, , \, f_3 > 0$$

This yields (5-3b) directly. To complete the proof of (5-3a) we note that

$$(5\text{-}17) \qquad b_v = - \frac{k}{2\bar{r}_s} \; V(v)^{-1/2} \; \frac{\partial V}{\partial v}$$

Since, when the parameter values from chapter III are used, both V(v) and its derivative are positive over a reasonable interval (see Figure 13), we have b_v and, therefore, $\partial t/\partial v$ negative.

The final step is to plot the contour lines of g and h. Figure 14 shows the resultant computer generated plot when all parameters are as before. As a simple example of the use of this chart let us consider chance constrained programming. In Figure 14 r is defined as the probability of exceeding an economic injury level but it could easily have been the chance of suffering the focus of loss (Table 2). Under these circumstances a chance constraint could be represented by a horizontal line as in Figure 14. Only those designs which resulted in operation below this line (such as point A) would be acceptable. Other alternatives, even those with the same workload (point B) or total time delay (point C), would not be effective. As the following chapters will show, this type of chart can also be used to evaluate a variety of design parameters.

In summary, this chapter has demonstrated that it is

Figure 13. *The function V(v) graphed by assigning the parameter values of chapter III.* This describes the variance of a series of temperature readings from points selected randomly within monitoring units of different sizes. Clearly, both V and its derivative are positive over the range of values shown.

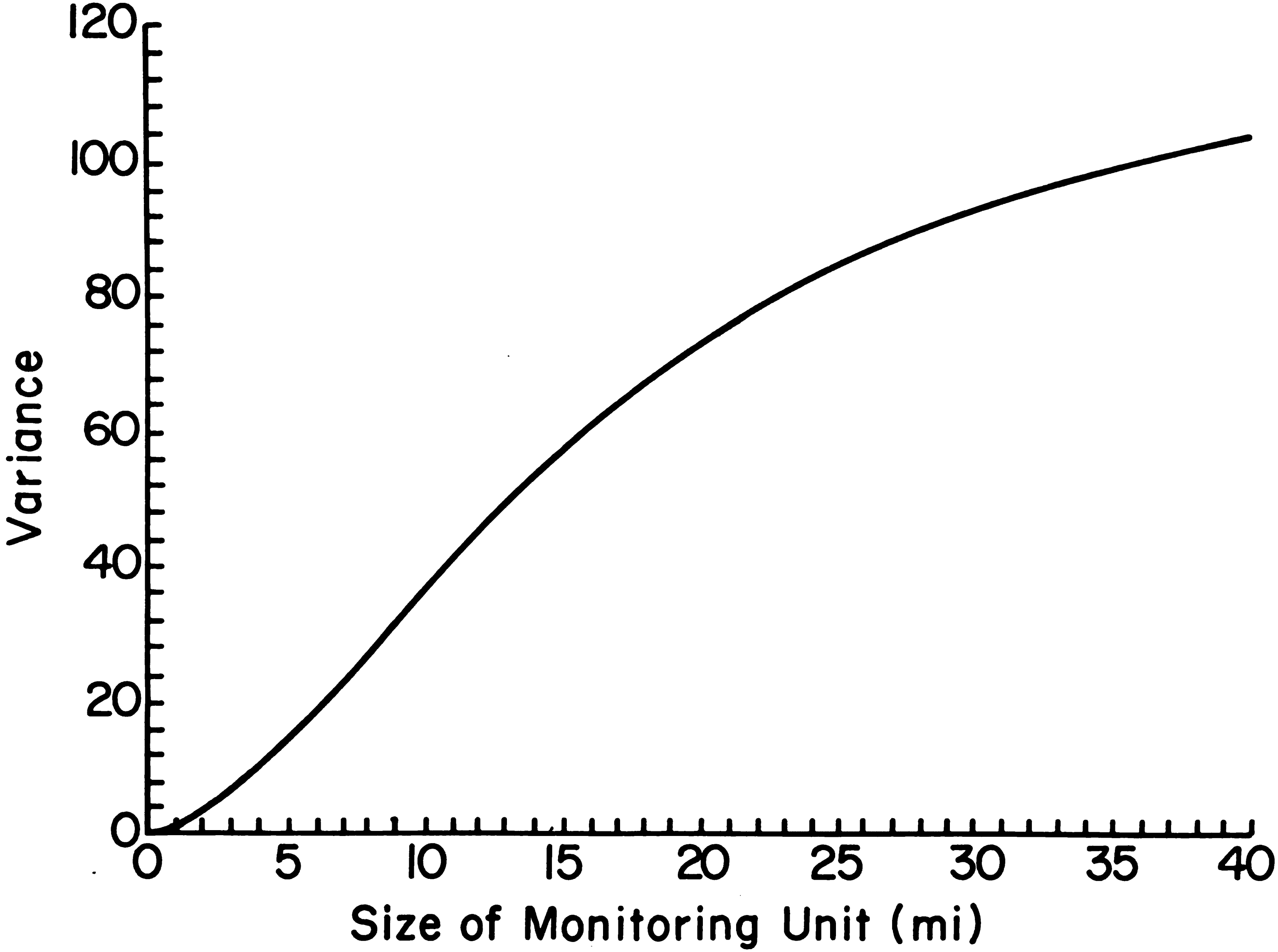
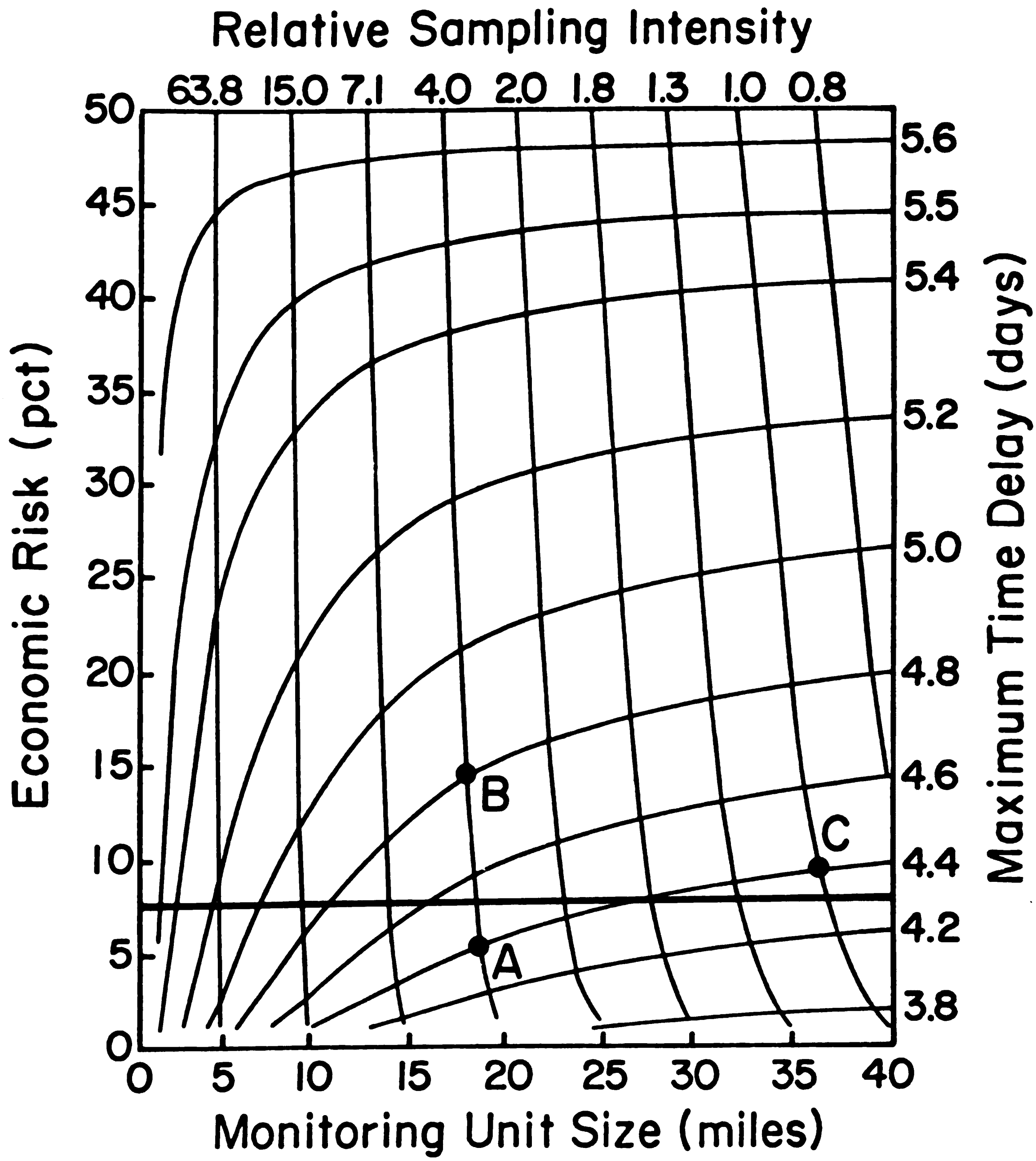

120
100
80
60
40
20
0
Variance
0
5
10
15
20
25
30
35
40
Size of Monitoring Unit (mi)

Figure 14. <u>Contour lines of sampling intensity and maximum allowable time delay as a function of risk and monitoring unit size.</u> The points A, B, and C and the 7.5 percent chance constraint are explained in the text.


Relative Sampling Intensity
63.8 15.0 7.1 4.0 2.0 1.8 1.3 1.0 0.8
Economic Risk (pct)
0 5 10 15 20 25 30 35 40 45 50
Maximum Time Delay (days)
3.8 4.2 4.4 4.6 4.8 5.0 5.2 5.4 5.5 5.6
A
B
C
0 5 10 15 20 25 30 35 40
Monitoring Unit Size (miles)

possible to greatly simplify relations between certain classes of variables provided they behave in certain plausible ways. Charts based on these relations can simplify the analysis of system performance. In the example given, the system is simple enough to permit analytic solution; this may not always be the case. In these instances simulation models can be used to construct the charts by approximation. In the next chapter we shall see how this may be done with system time delays.

CHAPTER VI

THE ANALYSIS OF SYSTEM TIME DELAYS

For any monitoring mission there are a variety of suitable technological alternatives. Perhaps the most important parameters associated with a technology are its direct cost (including any social or environmental costs to which the designer is responsive) and its time delays (which may indirectly affect cost through damage as previously discussed). In this chapter we shall decompose and analyze the total monitoring time delay. Table 3 shows how the sampling cycle can be partitioned into a series of discrete actions. We shall consider each of these entries in turn.

Transmission of the trigger event. The length of this delay depends entirely on the nature of the trigger although it is usually short. For example, this delay might be effectively zero for those designs which involve sampling at preset times or after a preset interval following an easily observable event. In the case of the mobile mite counting van mentioned previously, the growers were given a telephone number to call after they first detected mites. This, too, yields a very short delay (perhaps one day). On the other hand, systems which rely on environmental parameters such as heat units or rainfall to schedule sampling would, as a minimum, be subject to any delays in acquiring these data.

Table 3

The decomposition of total monitoring delay

Time delay 1[1]

(1) Transmission of the trigger event
(2) Transportation to the sampling site

Time delay 2

(3) Collection of the sample (or data)
(4) Transportation to the processing site
(5) Processing the sample (or data)
(6) Transmission of results to the decision maker

Time delay 3

(7) Accomplishment of control action

---

1. See Figure 2 for an explanation of delays 1, 2, and 3.

This would also be the case for sampling protocols triggered by biological observations of some other species.

<u>Transportation to the sampling site</u>. The vast majority of biological monitoring involves the collection of materials from the sampling site (although "materials" may mean only some form of recording media). If there are many sites or if sites are widely scattered sample collection can involve significant amounts of travel time.

The simulation analysis of the mobile sampling van provides an example of how these delays can be calculated. It was desired in that study to determine the distribution of travel time delay as a function of demand. There are seven regions in Michigan where the Michigan State University Integrated Apple Pest Management Project is active (Thompson *et al.*, 1973). Each of these regions was divided into two approximately equal subareas and the average trip within a subarea calculated as

$$\text{(6-1)} \qquad \text{distance} = \tfrac{1}{2}A^2$$

where A is area. Optimal routes were selected for trips between subareas. A matrix of inter-subarea distances was created by hand using county and state road maps. Probable routes were chosen according to criteria which combined short distances with best available roads. Interstate and state highways were given preference to other routes while unpaved roads were selected infrequently. A similar matrix for inter-subarea time factors (time divided by distance) was constructed. In determining these time factors the

Michigan Department of State Highways' road classification was used. Each road type was assigned a speed based on previous Highway Department studies (Marino, 1972; Welch and Marino, unpub.). The road classification, distance matrix, and time factor matrix are reproduced here as Tables 4, 5, and 6 respectively. These tables were combined with data on biological demand (chapter II) and processed by an algorithm which selected sites to be visited so as to minimize travel time to the next site. Figure 15 shows the cumulative frequency functions for two situations, one in which there are 30 growers being served in each management region and one in which there are 45.

The only type of system lacking transportation delays is one which (1) has transducers located permanently at the sampling site and which (2) transmits its data automatically to the site of processing. However, while many automatic systems exist for measuring biologically relevant physical parameters (Haynes _et al._, 1973; Klein _et al._, 1968; Atmar and Ellington, 1973) most biological parameters still require manual sampling.

Collection of the sample (or data) and processing. Included in these categories (3 and 5 in Table 3) are all the manipulations required by the sampling protocol. Examples might be capturing specimens, drying or disecting them, counting them, etc. To analyze this type of delay, it is necessary to decompose the protocol into a series of steps and determine how the length of each step varies with work-load, desired accuracy, and so on. In many cases the

Table 4

Road classification system

	Category	Definition	Assigned Speed
1.	Freeway	Divided highway limited access	55 mph
2.	Multilane, divided	Multilane, divided, free access	55 mph
3.	Paved, 2 lane	Two lane roads upgraded to state highway standards	45 mph
4.	Bituminous surfaced roads	Two lane roads not upgraded to state highway standards	45 mph
5.	Gravel roads	Roads with gravel surface	25 mph
6.	Improved dirt roads	Roads with dirt surface	------
7.	Unimproved dirt roads	Two tire tracks	------

Table 5

Inter-subarea distance matrix (miles)[1]

Subarea	1	2	3	4	5	6	7
1	2.8						
2	7.5	2.8					
3	120.0	109.0	3.8				
4	122.0	111.0	12.0	4.0			
5	125.0	114.0	14.0	14.0	4.6		
6	138.0	126.0	26.0	28.0	15.0	4.9	
7	121.0	110.0	17.0	8.0	27.0	29.0	4.2
8	128.0	117.0	24.0	13.0	35.0	41.0	12.0
9	148.0	137.0	87.0	79.0	99.0	112.0	89.0
10	163.0	152.0	101.0	94.0	114.0	127.0	93.0
11	209.0	198.0	136.0	123.0	149.0	162.0	125.0
12	224.0	213.0	140.0	127.0	153.0	166.0	129.0
13	42.0	31.0	97.0	98.0	109.0	122.0	102.0
14	43.0	32.0	98.0	99.0	110.0	123.0	103.0

	8	9	10	11	12	13	14
1							
2							
3							
4							
5							
6							
7							
8	4.1						
9	68.0	4.8					
10	81.0	14.0	4.9				
11	113.0	56.0	48.0	3.8			
12	117.0	72.0	65.0	16.0	3.7		
13	111.0	127.0	140.0	188.0	205.0	3.1	
14	111.0	121.0	134.0	183.0	193.0	5.9	3.0

1. Matrix is symmetric. Distances within a subarea are assumed to be one half the square root of the area of the subarea.

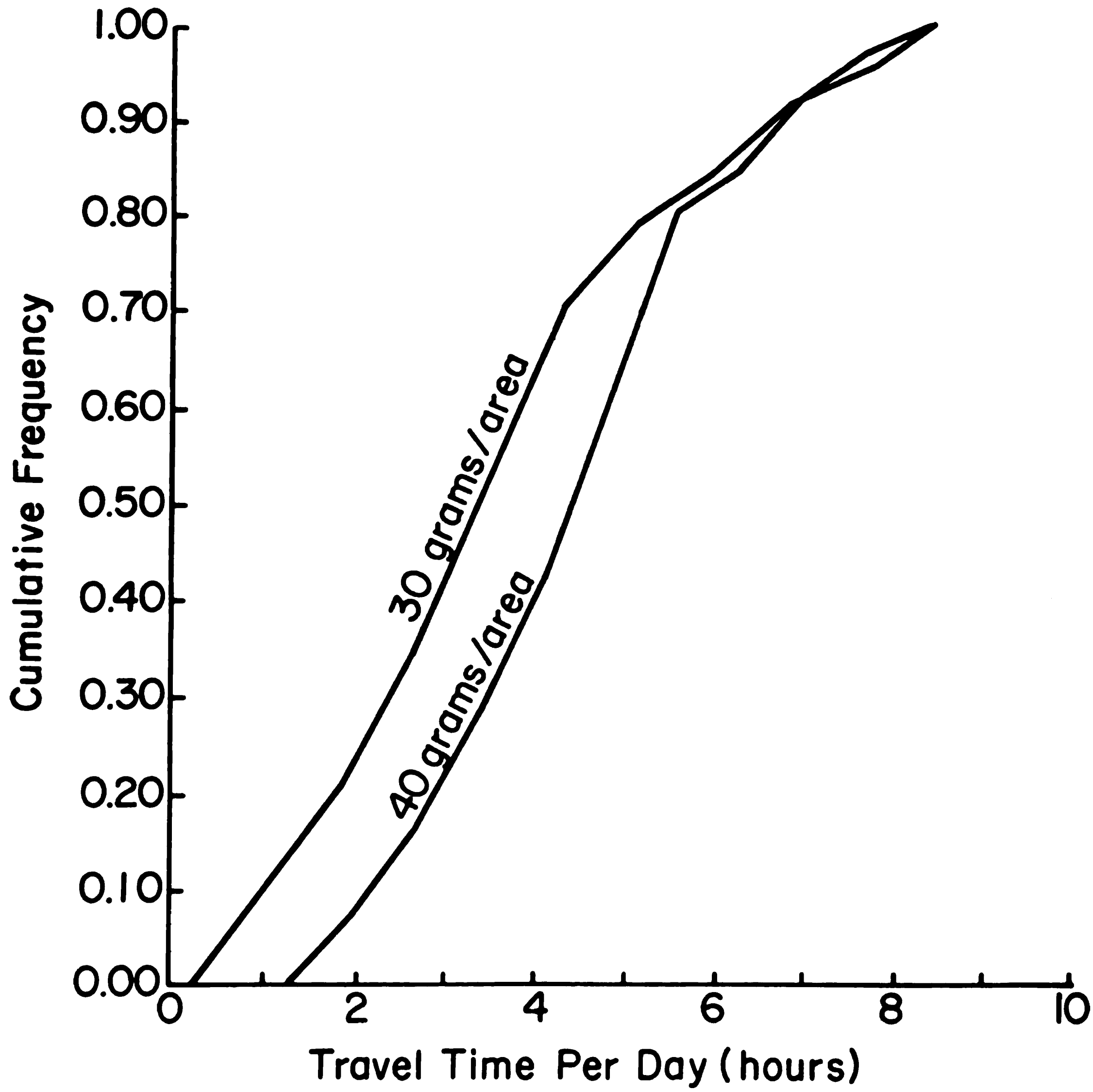
Table 6

Inter-subarea time factor matrix
(hours per mile)

Subarea	1	2	3	4	5	6	7
1	.0278						
2	.0278	.0278					
3	.0185	.0186	.0222				
4	.0188	.0188	.0222	.0222			
5	.0188	.0188	.0232	.0235	.0236		
6	.0192	.0191	.0231	.0236	.0236	.0236	
7	.0187	.0188	.0230	.0292	.0229	.0255	.0245
8	.0187	.0190	.0222	.0222	.0334	.0232	.0245
9	.0187	.0188	.0192	.0192	.0195	.0196	.0222
10	.0191	.0191	.0197	.0197	.0199	.0196	.0235
11	.0193	.0199	.0222	.0222	.0233	.0242	.0233
12	.0187	.0201	.0222	.0222	.0267	.0267	.0242
13	.0185	.0187	.0183	.0183	.0185	.0187	.0187
14	.0186	.0188	.0184	.0194	.0186	.0187	.0187

Subarea	8	9	10	11	12	13	14
1							
2							
3							
4							
5							
6							
7							
8	.0245						
9	.0222	.0222					
10	.0222	.0222	.0222				
11	.0233	.0222	.0222	.0222			
12	.0245	.0267	.0222	.0222	.0222		
13	.0183	.0184	.0184	.0184	.0184	.0222	
14	.0184	.0187	.0187	.0187	.0187	.0222	.0222

Figure 15. <u>The cumulative density functions of travel time per day for two different levels of demand</u>. The distributions were generated by a simulation of the logistics of a mobile, van-based mite counting service.


Cumulative Frequency
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
0
2
4
6
8
10
Travel Time Per Day (hours)
30 grams/area
40 grams/area

protocol will consist of well established techniques. Even if the techniques are new with the system being designed, there is almost always a period where the new and the old methods are operated side by side. It is during these periods that the basic timing data can be taken. This can be done by simply adding to the data notebook a notation for each sample as to how long the various processing steps took. The designer will then be in a position to determine the contribution of the protocol to total delay.

An analysis of mite sampling will serve as an example. The current method of choice for mite counting is to take a leaf sample, mechanically brush the mites on to a sticky glass plate, and count sectors of the plate under a low power binocular microscope (Morgan _et_ _al_., 1955). The time involved in these activities was partitioned as shown in Table 7. The right-hand column shows the times for each action. These were determined from multiple linear regression fits of data taken during time-motion studies of mite counting (Croft, unpub. data). With these values we can construct the following predictive equations for collection and processing delays

$$
\begin{aligned}
&\text{(a)}\quad \text{collection delay} = \\
&\qquad .25 + .00833(\text{NTR}) + .00167(\text{NTR})(\text{NLV}) \\
\text{(6-2)}\quad &\text{(b)}\quad \text{processing delay} = \\
&\qquad .00449 + (\text{NTR}\cdot\text{NLV})(.00067 + (\text{A})(\text{M})) \\
&\qquad\qquad\qquad\qquad\qquad \text{where} \\
&\text{(c)}\quad \text{M} = .00005(\text{NES})(\text{ER}) + .00034(\text{NAS})(\text{AF}).
\end{aligned}
$$

The variable definitions are given in Table 8. In actual use NAS and NES can be determined from sample size curves

Table 7

Partition of a mite sampling protocol into discrete actions and the required times

Time to pick the leaves			
(1)	Fixed factors	$.250 \times 10^{0}$	hrs.
(2)	Factors proportional to #trees	$.833 \times 10^{-2}$	hrs./tree
(3)	Factors proportional to #leaves	$.167 \times 10^{-2}$	hrs./leaf
Time to count leaves			
(1)	Fixed factors	$.449 \times 10^{-2}$	hrs.
(2)	Factors proportional to #leaves	$.670 \times 10^{-3}$	hrs./leaf
(3)	Factors proportional to pest density	$.500 \times 10^{-4}$	hrs./mite
(4)	Factors proportional to predator density	$.340 \times 10^{-3}$	hrs./mite[1]

1. The difference in counting times for the two types of mite is probably due to the great difference in their densities resulting in longer search times.

Table 8

Definition of variables in the timing equation (7-2)

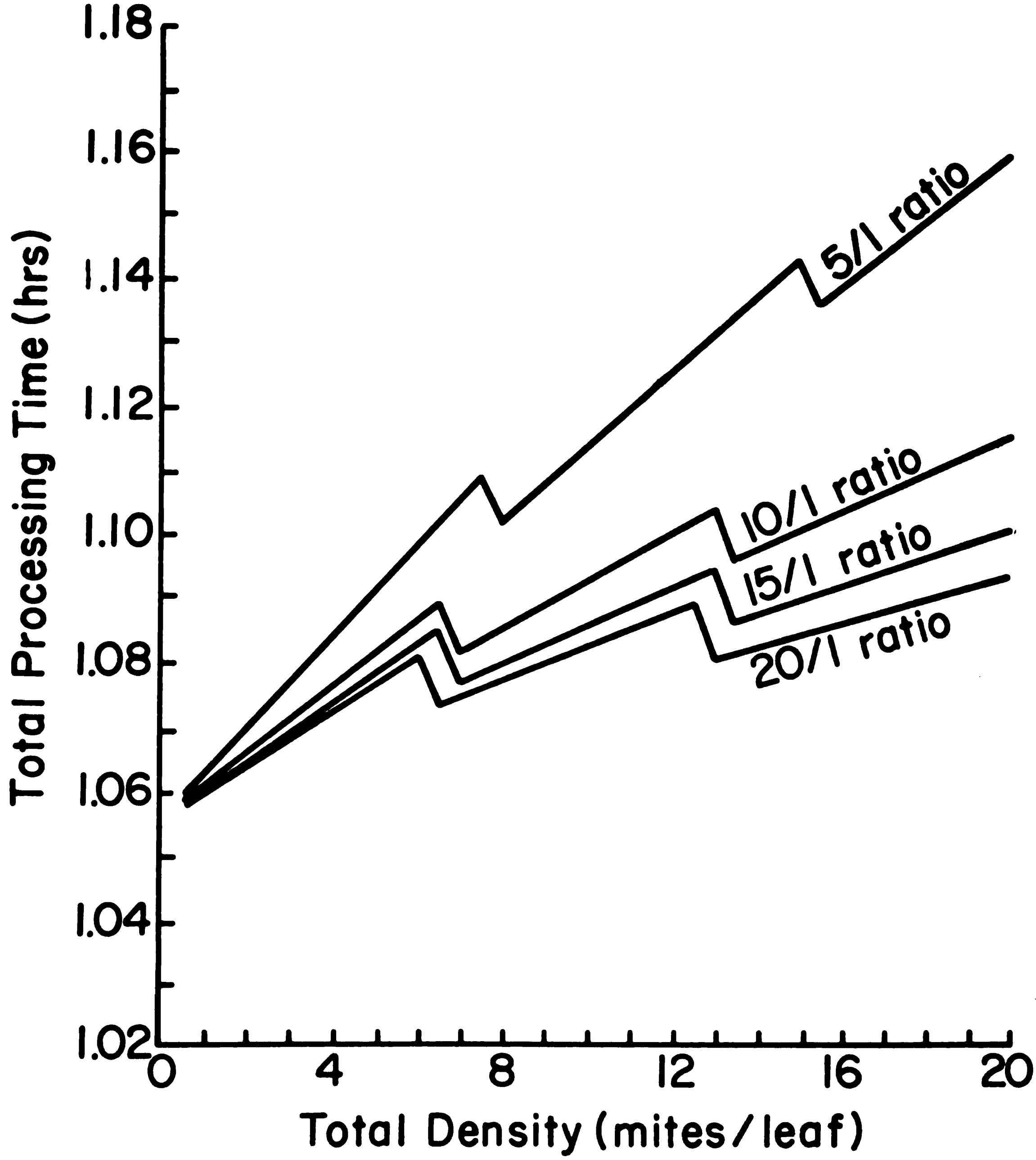
A	- The relative area of one plate sector
AF	- The per leaf density of predatory mites
ER	- The per leaf density of phytophagous mites
NAS	- The number of plate sectors counted for predators
NES	- The number of plate sectors counted for pest mites
NLV	- The number of leaves taken per tree
NTR	- The number of trees sampled

based on the densities of mites in the sample (Croft *et al*., 1976b). For a sample of 200 leaves taken 5 per tree, Figure 16 shows the processing delay for various total densities and prey-predator ratios. In this case most of the delay is consumed in collecting and preparing the sample. The breaks in the curves in Figure 16 are due to the integer nature of the number of plate sectors counted.

Transportation to the processing site. In most cases samples are not processed at the same place they are collected. Instead, they are transported to some specialized facility or laboratory for examination. In other designs, the sample may be examined in the field but the resultant data require further manipulation. This may occur because some statistical computation is necessary or the results must be compared with previous data or run through a biological model. In any such case transportation must be included as a component of total delay.

An example is provided by the BLITECAST computer program developed by Krause *et al*. (1975). This program integrates rainfall, relative humidity, and temperature to produce a spray recommendation for potato late blight (*Phytophthora infestans*). Although the data are taken in the field, computer processing at a central site is necessary. As is frequently the case when plant pathogens are involved, any time delay is critical. For example, in one case on record a two day delay in transmitting data to the BLITECAST program resulted in a grower loss of approximately 50,000 dollars (Bird, pers. comm.). This testifies to the

Figure 16. The total processing time for mite samples as a function of total mite density and prey-predator ratio. Counting time is most likely sensitive to the latter factor due to the extra search time required for the counter to find the relatively rare predators.


Total Processing Time (hrs)
1.18
1.16
1.14
1.12
1.10
1.08
1.06
1.04
1.02
0
4
8
12
16
20
Total Density (mites/leaf)
5/1 ratio
10/1 ratio
15/1 ratio
20/1 ratio

importance of characterizing all sources of delay.

Transmission of results to the decision maker. An interesting dichotomy exists between information which must be transported in physical form and that which can be transmitted via the electronic media. Some forms of information, such as raw biological samples, are inherently frozen in physical form. Other data, however, can be freely interconverted. For example, written material can either be mailed or sent electronically by such devices as Code-a-phones® (telephone playback equipment), data terminal networks, or the mass media. Although the latter methods may have high capital costs, they often result in significantly reduced delay times and lower operating costs.

An example of this is the transmission of pest alert information via the Michigan State University Pest Management Executive (PMEX) system of which the author was one of the two principal designers. This system consists of a statewide network of data terminals linked via the direct dial telephone service to a central computer at Michigan State University. Software on this computer permits the rapid accessing and updating of biological monitoring data bases by pest management personnel. In addition, if monitoring reveals results of wide interest, alert messages can be sent directly to all affected individuals. During the 1976 growing season over 300,000 words of information passed through the system to more than 70 extension personnel with concerns in fruit, vegetables, and field crops. Because of the selective nature of the Executive system, _only_ those individuals interested in particular types of data received them. The most important result of this system from our point of view is that data which previously took a week to ten days to reach users (principally through the mails as the "Insect, Disease, and Nematode Alerts"[1]) now reach them in a few minutes. Further details of the PMEX system are discussed by Croft _et al_. (1976a).

Accomplishment of the control action. This delay covers the time it takes the decision maker to arrive at and implement a control decision once he receives the monitoring results. Typically the designer has no control over the length of this delay because it depends solely on how the decision maker schedules his activities. Nevertheless, the designer must take this interval into account because biological interactions are unceasing.

After all seven of the delays in Table 3 have been analyzed, the next step is to determine how they are altered by changes in design parameters and how this affects system performance. At this point it is appropriate to describe an extension of the graphical technique we introduced in the last chapter. Consider a system whose design is complete. The operation of the system can be represented by a point in the (v,i,t,r) plane whose exact location is a function of

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the design parameters. Changes in these parameters will cause the point to trace out some curve in the plane. Changes in single variables or in sets of variables with only one degree of freedom will produce a line. Changes in sets with more than one degree of freedom will have more complex results which can be analyzed by additional contour lines. The use of these graphical methods can greatly facilitate the design process.

In the analysis of the mobile mite counting van, it was desired to determine the effect of requiring more accurate estimates of mite density on system performance. Accuracy was represented as one half the width of the 80 percent confidence limits expressed as a percentage of the estimated mean density. It was possible to relate these to delay times as shown in Figure 17 by using the methods discussed in earlier examples in this chapter. We can plot these data on the nomogram by equating the average distance traveled to reach a monitoring site with monitoring unit size. Figure 18 shows the results. Each point on the curve was plotted by reading monitoring unit size off the bottom axis and delay off the righthand axis. Because of the properties of the nomogram, however, the curve can be used to read risks and sampling intensities for each "technology" on the continuum. The results show that, for these technologies at least, improving the accuracy of sample estimates far from pays off when confidence limits are already tight. If this example is combined with the chance constrained programming example of the last chapter one concludes that confidence

Figure 17. The mean waiting time for service as a function of desired accuracy. The data for this figure come from the previously mentioned logistic simulation of the mobile mite counting service. As greater accuracies are demanded, processing times increase generating a system bottleneck. This leads to the exponential rise in service wait times.

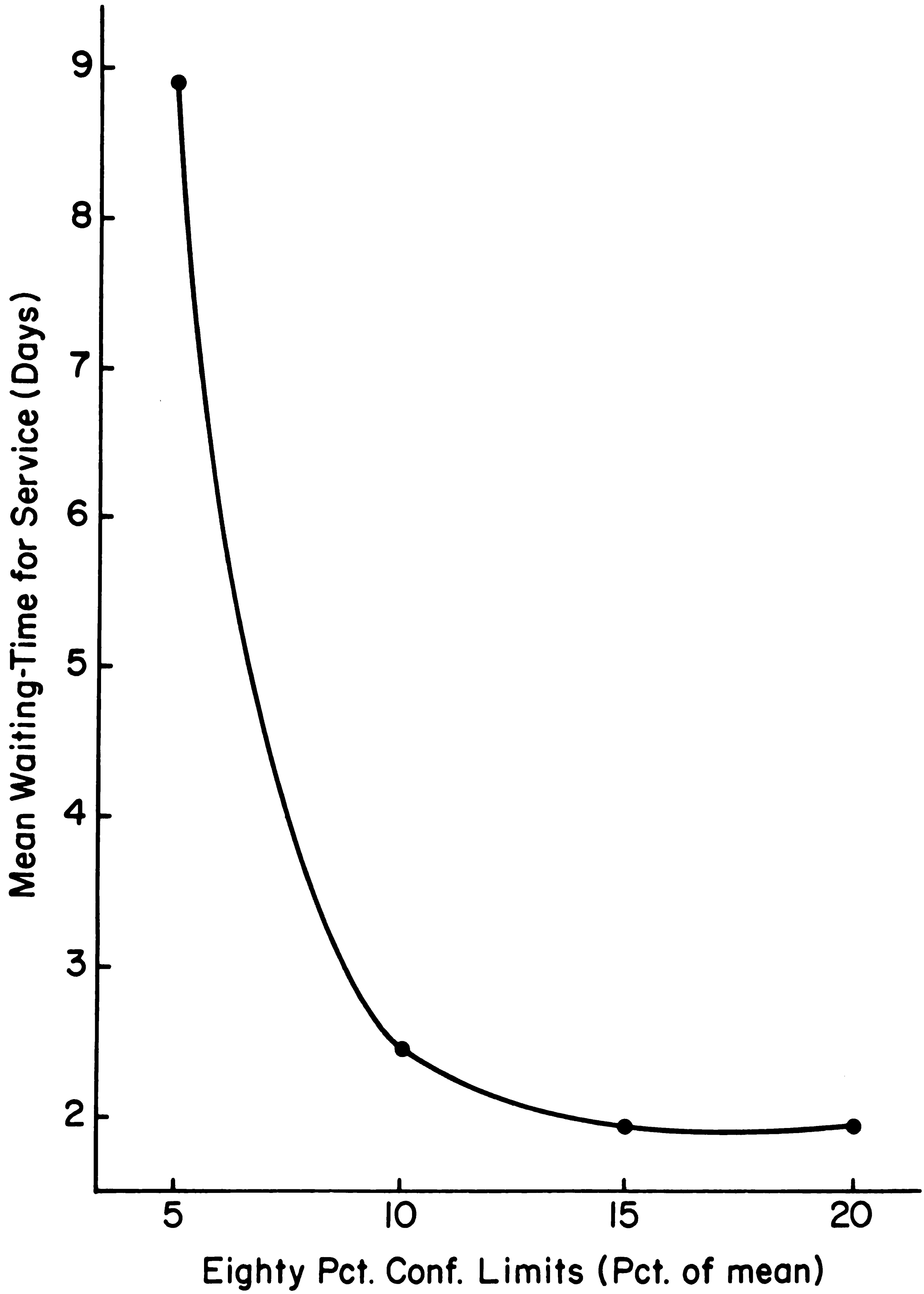
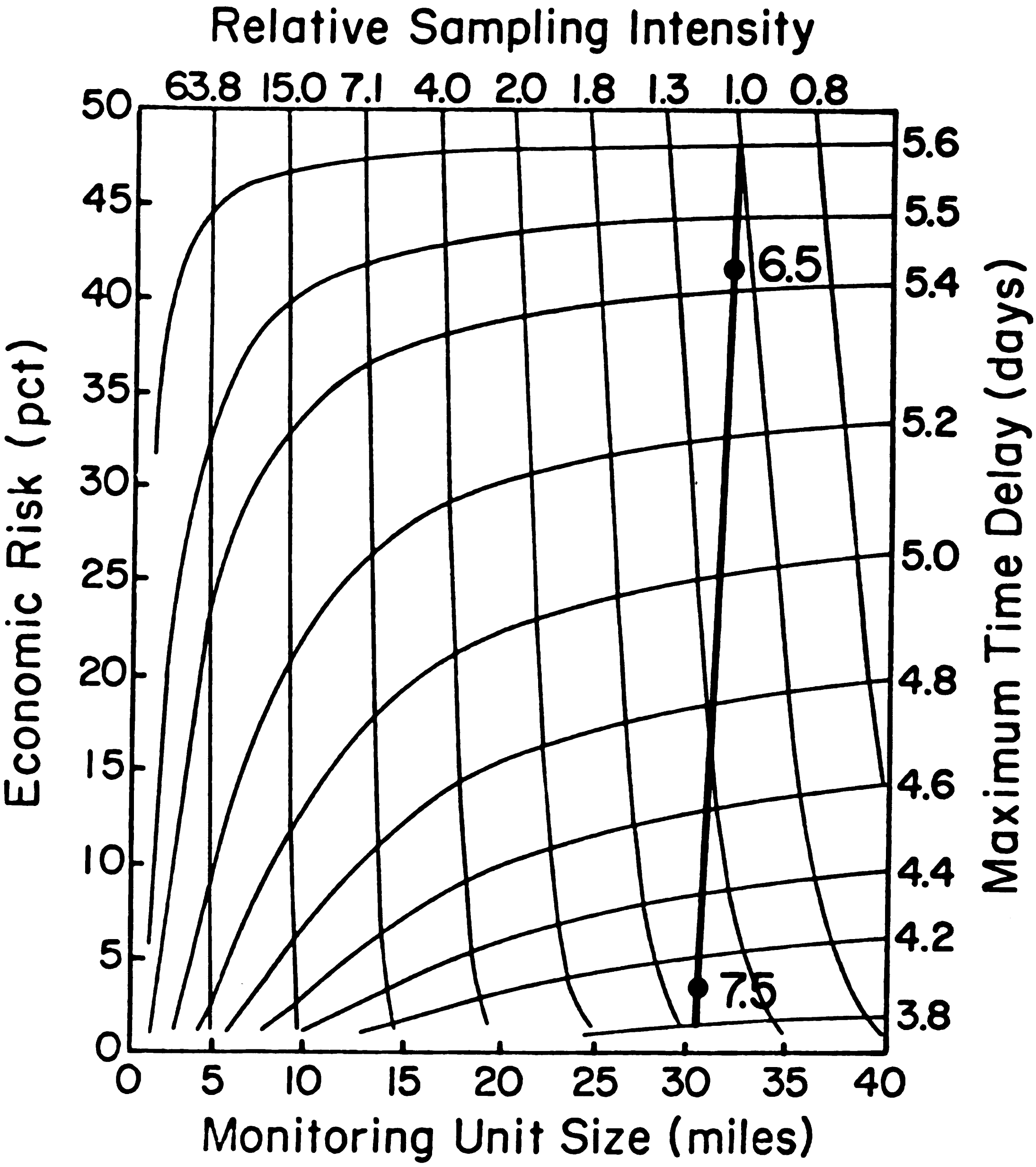

Mean Waiting-Time for Service (Days)
9
8
7
6
5
4
3
2
5
10
15
20
Eighty Pct. Conf. Limits (Pct. of mean)

Figure 18. <u>A continuum of technologies indexed by desired sampling accuracy</u>. Each point on the graph was plotted by taking the time delay from Figure 17 and the monitoring unit size from the original simulations (see text). The figure illustrates that when confidence limits are already tight (7.5 percent) even modest further improvements can dramatically alter grower risk.



Relative Sampling Intensity
63.8 15.0 7.1 4.0 2.0 1.8 1.3 1.0 0.8
Economic Risk (pct)
50
45
40
35
30
25
20
15
10
5
0
Maximum Time Delay (days)
5.6
5.5
5.4
5.2
5.0
4.8
4.6
4.4
4.2
3.8
6.5
7.5
0 5 10 15 20 25 30 35 40
Monitoring Unit Size (miles)

limits narrower than 7.2 percent should not be demanded of this system. By way of comparison, field experience shows that accuracies in the range of 20 to 50 percent are adequate for management (Croft *et al.*, 1976b).

In this chapter we have diagnosed the typical causes of delay in monitoring systems and shown methods of relating them to system parameters such as sample size and the spatial distribution of demand. By use of the nomogram the impact of these delays can be assessed for various possible design alternatives. In this manner parameter values may be chosen so as to insure that the resultant systems operate within their performance constraints.

CHAPTER VII

THE ECONOMICS OF THE MONITORING SERVICE

In chapter IV we discussed the economics of monitoring as seen by the decision maker. In this chapter we take up the subject from the point of view of the monitoring service. In designing monitoring systems and choosing between alternative configurations, it is necessary to budget the activities of those systems. Many such systems are initially funded on capital granted the developer by various public or private sources. At some point, however, a system which is to continue operations must switch from developmental monies to some more permanent source. The economics of the system must be understood very well if the conversion is to be seen as justifiable. By estimating the economic performance of a system ahead of time one can choose design alternatives which will facilitate this transition. Conversely, failure to consider these aspects of the problem can result in initial funding and credibility being wasted on impractical systems.

In this chapter we shall view initial capital as money to be invested and alternative system designs as an array of possible investment choices. To help make the investment decision we shall adopt a slight modification of an investment screening program described by Park (1973). This method combines various economic components to calculate a return on investment (ROI) via the discounted cash flow (DCF) technique. The method requires inputs which we shall describe using Park's terminology. Although this nomenclature has an industrial slant, the application to agriculture is clear.

Average annual sales or revenues. This is simply the number of samples taken times the cost to the grower of each sample plus any "revenues" derived from other sources. These might include public subsidy payments, sales of unused monitoring resources, etc.

Direct production costs. These are the per sample costs of monitoring. They cover materials, any labor paid on a piecework basis, etc.

Indirect, fixed, or overhead costs. This category includes costs which are related to time rather than to the number of samples. Salaries and wages, capital charges, facility rental, and so on would come under this heading.

Net investment. This is the total capital cost of putting the system in operation. If the goal of the analysis is to see how attractive the system would be to the private sector, then any public subsidies should be deducted from this entry. On the other hand, if the overall viability of the enterprise is being examined, this quantity should not reflect subsidies.

Economic project life. This is the period, in years, over which it is estimated that the system will operate as designed. It can also be defined as the period over which the capital costs will be recovered. To simplify the calculations we shall assume (1) that sales, costs, and tax rates (as applicable) will remain constant over this period and (2) that capital costs are amortized on a uniform straight line basis. Park (1973) states that most projects will have a life of five to ten years since "less than five years is unrealistic and conditions beyond ten years can seldom be anticipated". This last is particularly true in an evolving discipline such as pest management.

Income tax rate. This refers to the total of all income based taxes minus any applicable credits. This may be zero for systems operated in the public sector.

Once these quantities are known they can be entered in the program of calculations illustrated in Table 9. The goal of the first part of the analysis (lines 7 to 12) is to determine net cash flow which is revenues minus production costs, overhead, and taxes. It is also numerically equal to net profit after taxes plus depreciation which is the algorithm used in the table. It can be thought of as the money in the bank at the end of the year.

From the net cash flow one can calculate the percentage of the initial capital investment recouped each year. This is the capital recovery rate and is determined as in line 13. While this rate is a useful index of how fast the system will pay off, it gives little indication of the total profitability.

The ROI is helpful in this regard. According to the DCF method, the ROI is defined as the discount rate which makes the sum of the discounted cash flows identically zero. To interpret the ROI, suppose that the initial capital for the project was borrowed from a bank. If the ROI exceeded

Table 9

Simplified investment screening algorithm[1]

Line	Description	Calculation
	- - - - - Inputs - - - - -	
1	Average annual sales or revenues	
2	Direct production costs	
3	Indirect production costs	
4	Net investment	
5	Economic life of system	
6	Income tax rate	
	- - - Net cash flow - - -	
7	Average annual depreciation	line 4/line 5
8	Total deductions	line 2+line 3+line 7
9	Net profit before taxes	line 1-line 8
10	Income taxes	line 6 x line 9
11	Net profit after taxes	line 9-line 1
12	Net cash flow	line 7+line 11
	- -Return on investment- -	
13	Capital recovery rate	line 12/line 4
14	Return on investment (ROI)	see text

1. After Park (1973, p. 63)

the loan rate then, after paying off the bank, there would be cash left over at the end of the system life. If the loan rate was greater than the ROI then the project would end up in debt.

Mathematically the ROI is determined from the equation

$$(7\text{-}1) \qquad 0 = \sum_{i=0}^{n} \frac{NCF_i}{(1+ROI)^i}$$

where NCF_i is the net cash flow for year i and n is the system life. Under the simplifying assumptions adopted above, the ROI can be calculated from the capital recovery rate CRR from the equation

$$(7\text{-}2) \qquad CRR = \frac{ROI(1+ROI)^n}{(1+ROI)^n - 1}$$

Under the most common patterns of investment, problems of multiple or imaginary roots for the ROI generally do not arise. In his more complete treatment of cash flow analysis Park (1973) gives more complete algorithms for the ROI including methods for incorporating risk in order to obtain a probability distribution for the ROI.

To illustrate the use of the ROI we shall compare three possibilities for monitoring mite populations with the mobile sampling unit we have discussed previously. We shall refer to these alternatives as the full system (FS), reduced system one (RS I), and reduced system two (RS II). In the full system the van is equipped with both a calculator and a data terminal. The staff consists of two individuals who collect and process the leaves and use the calculator to store the data and make a control recommendation. Data are transmitted to a centralized computer directly from the van at the end of each day via the data terminal. If the computer detects unusual field conditions which invalidate the calculator's recommendation then a postcard with the correction is mailed the next day. Reduced system one differs in that the data are sent in vocally by telephone rather than by terminal. This necessitates an extra employee at a central site who spends a few hours each day entering data into the computer. In reduced system two only one person operates the van. Rather than counting mites in the orchard, the samples are refrigerated and taken to one of three field stations at the end of the day. They are counted there the next day by technicians who mail the recommendations to the growers on post cards.

By use of a model incorporating biological, logistical, and statistical factors as discussed in the previous chapters we can predict the number of samples taken, resources used, time delays encountered, etc. By assigning costs to these items and conducting a DCF analysis of the results we obtain Tables 10, 11, and 12 for FS, RS I, and RS II respectively. These figures are based on the assumption that the systems are operated as Cooperative Extension Service projects employing student labor. By noting system time dealys we can plot these three alternatives on the nomogram (Figure 19). There is no significant difference in the performances of FS and RS I. The results for RS II are interesting because (1) this method has been, in fact, employed for several years prior to and in parallel with the mite counting van and (2) the predicted level of risk to the grower (12 percent) is

Table 10

Discounted cash flow analysis of the full system (FS)

Line	Description	Entry	Total
1	Revenues (315 samples @ $30 ea.)		9450.00
2	Direct production costs		
	Supplies (315 samples @ 25¢ ea.)	78.75	
	Postcards (29 samples @ 10¢ ea.)	2.90	
	Gas and van maint. (9657.1 miles @ 10¢/mi.)	965.71	
	Telephone charges (57 days @ $3/day)	171.00	
			1218.36
3	Indirect, fixed, and overhead costs		
	Salaried employee (4 months)	1500.00	
	Non-salaried employee (353 hrs @ $2.50/hr)	882.50	
	Motel rooms (57 days @ $20/day)	1140.00	
	Food allowance (114 man-days @ $10/day)	1140.00	
			4662.50
4	Net investment		
	Van	4500.00	
	Computer terminal	2500.00	
	Calculator	2500.00	
	Miscellaneous electronics	700.00	
	Laboratory equipment	500.00	
	Power	525.00	
			11225.00
5	Economic life of system		5 years
6	Income tax rate		zero
7	Average annual depreciation		2245.00
8	Total deductions		8125.86
9-11	Net profits		1324.14
12	Net cash flow		3569.14
13	Capital recovery rate		.3179
14	Return on investment (ROI)		17.7%

Table 11

Discounted cash flow analysis of the
reduced system one (RS I)

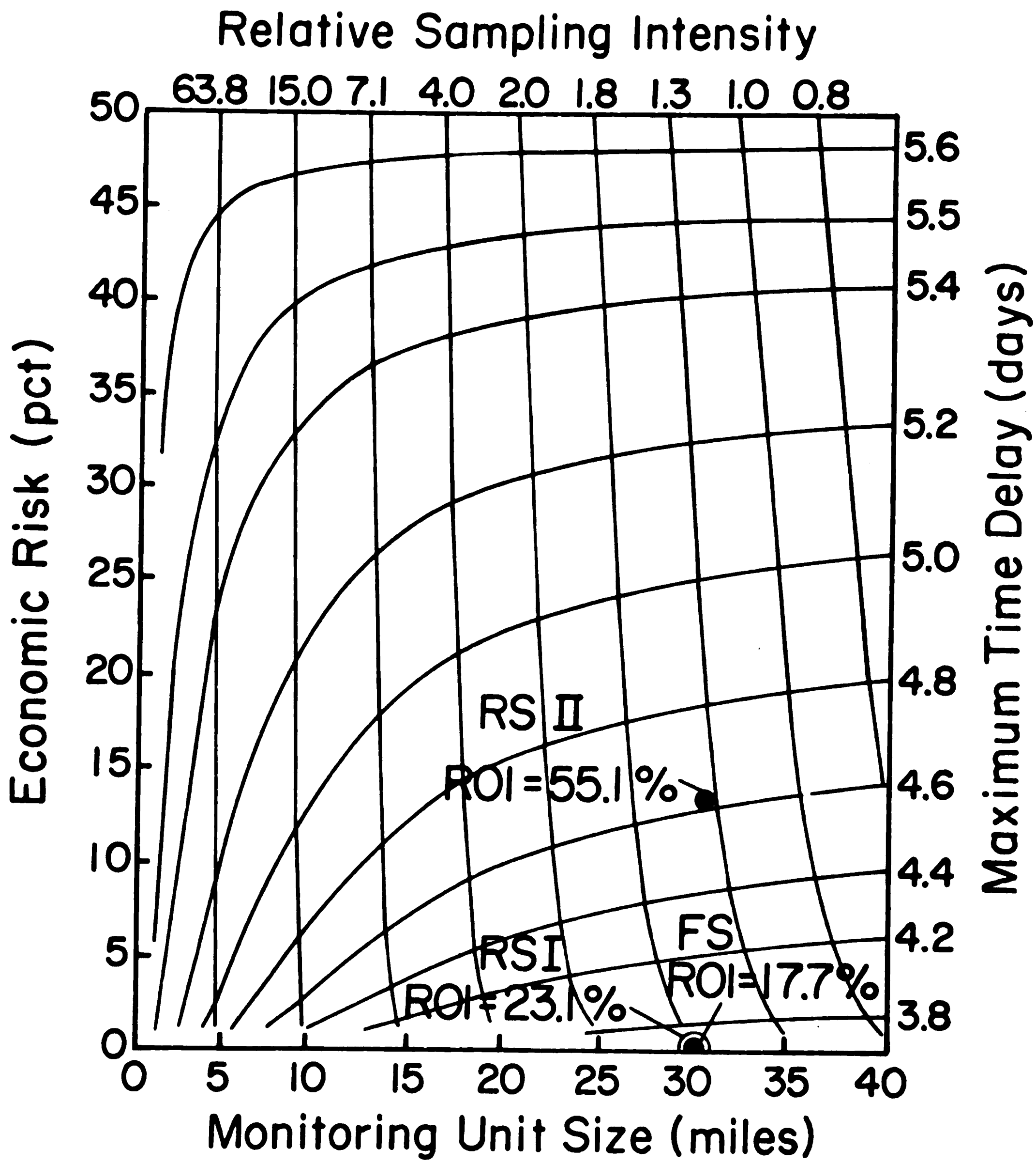
Line	Description	Entry	Total
1	Revenues (315 samples @ $30 ea.)		9450.00
2	Direct production costs		
	Supplies (315 samples @ 25¢ ea.)	78.75	
	Postcards (315 samples @ 10¢ ea.)	31.50	
	Gas and van maint. (9657.1 mi @ 10¢/mi.)	965.71	
	Telephone charges (57 days @ $3/day)	171.00	
3	Indirect, fixed, and overhead costs		1246.96
	Data entry technician (57 days x 3 hrs/day @ $2.50/hr)	427.50	
	Salaried employee (4 months)	1500.00	
	Non-salaried employee (353 hrs @ $2.50/hr)	882.50	
	Terminal (4 month rental @ $60/mo)	240.00	
	Motel rooms (57 days @ $20/day)	1140.00	
	Food allowance (114 man-days @ $10/day)	1140.00	
4	Net investment		5330.00
	Van	4500.00	
	Calculator	2500.00	
	Laboratory equipment	500.00	
	Power	525.00	
5	Economic life of system		8025.00
			5 years
6	Income tax rate		zero
7	Average annual depreciation		1605.00
8	Total deductions		8181.96
9-11	Net profits		1268.04
12	Net cash flow		2873.04
13	Capital recovery rate		.3580
14	Return on investment (ROI)		23.1%

Table 12

Discounted cash flow analysis of the reduced system two (RS II)

Line	Description	Entry	Total
1	Revenues (315 samples @ $30 ea.)		9450.00
2	Direct production costs		
	Supplies (315 samples @ 25¢ ea.)	78.75	
	Postcards (315 samples @ 10¢ ea.)	31.50	
	Gas and van maint. (11480.1 miles @ 10¢/mi.)	1148.01	
	Telephone charges (55 days @ $1/day)	55.00	
	Refridgeration (315 samples @ 10¢ ea.)	31.50	
			1344.76
3	Indirect, fixed, and overhead costs		
	Salaried employee (4 months)	1500.00	
	Technicians (3 @ 55 days x 5 hrs/day x $2.50/hr ea.)	2062.50	
	Terminals (3 @ $60/mo rental for 4 months ea.)	720.00	
	Food allowance (55 man-days @ $10/day)	550.00	
			4832.50
4	Net investment		
	Van	4500.00	
	Laboratory equipment	500.00	
	Power	275.00	
			5275.00
5	Economic life of system		5 years
6	Income tax rate		zero
7	Average annual depreciation		1055.00
8	Total deductions		7232.26
9-11	Net profit		2217.74
12	Net cash flow		3272.74
13	Capital recovery rate		.6204
14	Return on investment (ROI)		55.1%

Figure 19. The return on investment for three mite monitoring systems plotted on a nomogram showing system performance. The key point here is that the most profitable system (RS II) is also the most risky to the grower.


Relative Sampling Intensity
63.8 15.0 7.1 4.0 2.0 1.8 1.3 1.0 0.8
Economic Risk (pct)
50
45
40
35
30
25
20
15
10
5
0
Maximum Time Delay (days)
5.6
5.5
5.4
5.2
5.0
4.8
4.6
4.4
4.2
3.8
RS II
ROI=55.1%
RS I
ROI=23.1%
FS
ROI=17.7%
0 5 10 15 20 25 30 35 40
Monitoring Unit Size (miles)

almost identical to the level actually realized (11 percent). If we were to impose the 7.5 percent chance constraint used in previous examples (eliminating RS II) we would be led to RS I because of its greater return at no increase in grower risk.

This example raises an interesting point: the system which is best for the decision maker may not be the best for the monitoring service. In the long run, risk levels would, presumably, be subject to bargaining or some other adjustment process between the decision maker and the monitor. However, because of the complexities involved, decision makers may be unaware of the risks attending different levels of service from competing monitors. This lack of perfect knowledge would complicate the approach of the parties to a mutually acceptable equilibrium position. Additional factors which would affect these negotiations might include the partition of total monitoring between the public and private sectors, general market conditions, the degree of organization among decision makers, etc. The main point is, however, that some "avoidable" damage will almost certainly occur during this adjustment period, especially if it is prolonged. The extent, nature, and sources of the certification procedures and insurance mechanisms which might or might not be necessary to ameliorate this effect have not yet been explored.

In this chapter we have examined a method for studying the economics of the monitoring service. Because of its simplicity this investment screening approach can easily be applied to a large number of design alternatives. The nomogram can be used to relate this analysis to the factors considered in earlier chapters. When all these data are plotted together along with the relevant constraints, the final choice of a feasible configuration can be made.

CHAPTER VIII

SYNOPSIS OF DESIGN PROCEDURE

In the previous chapters we have discussed the factors and types of information necessary to design the monitoring component of a management system. As yet, however, we have not presented a unified and integrated plan for the design process. Such a plan is obviously needed to prevent unnecessary waste of the designer's time and money. In this chapter we shall discuss the sequence of activities and methods of recording data to facilitate this process.

Work on methods of monitoring and controlling a pest always begin with a perceived need. Often these needs are rather vaguely defined. An outbreak of a new pest is either observed or anticipated. In many cases it may not be known how serious the pest is or what its potential for spread may be. Even when a pest is known to be dangerous in a neighboring geographic region, its behavior in a new physical and economic environment may be difficult to predict.

The first step, as always, is biological investigation of the pest ecosystem. The goals of this inquiry are four-fold: (1) to provide input to a detailed analysis of management needs, (2) to elucidate the bionomics of the pest under local conditions, (3) to provide for the statistical, logistical, and economic analysis of potential monitoring protocols, and (4) to facilitate the construction of decision making rules.

The types of biological data needed were discussed in chapter II. These include, broadly, where the pest is found, when it is found there, and the types of damage it does. This last should incorporate both biological indices of damage (e.g., 40 percent damage to the photosynthetic surface) and, insofar as is possible, economic measures (e.g., 15 percent reduction in salable yield). Economic measures are, admittedly, difficult to document, particularly for indirect pests. Measures such as the percentage of yield in various quality classes or subjective measures of crop vigor may be more appropriate. In any case, data in some form should be taken to relate biological and economic processes.

All of this fairly general information can be combined into a detailed statement of management needs. This should specify the location, volume, and nature of the affected crops, the types, timing, and severity of damage, and a quantitative description of the ecosystem states which must be maintained to alleviate the problem. It should also include the methods available to achieve these ends but not necessarily how they are to be applied. Any constraints on the operation of the system must be carefully described. Also important is a description of the groups and individuals involved in the management process since one of the design constraints is that the system be acceptable to these personnel.

At this point the designer must determine if it is possible (feasible) to meet these needs with current technology. This involves a very rough look at a number of solution types. This usually means the construction of some promising approaches to the problem; generally, at this point, too little is known about the situation to formulate any specific designs.

If it should develop that no alternatives with more than a marginal value are readily apparent, then it may be necessary to reformulate the needs. This might involve, for instance, a willingness to accept a higher level of damage or a method of control previously classed as unsuitable (e.g., because of secondary effects).

Once the needs have been defined and it appears that feasible solutions may exist, steps can be taken which aid the construction both of the ultimate monitoring component and of the decision algorithms it drives. These steps involve detailed studies of the population dynamics and the formulation of a model of the pest ecosystem (chapter II). These studies may be a continuation of the needs analysis investigations but generally they will contain new elements. The types of data needed are developmental rates and reproductive information, if applicable, of the pest. Dispersal data are also essential for certain organisms. Particularly useful, if obtainable, is the influence of environmental factors on these processes. The importance of having at least some data on these rates cannot be overemphasized. It is from this information that the basic time constants of the management system must be calculated. Fortunately, it is not necessary that these rates be known with great precision. For example, in the construction of a successful model of the interaction of the European red mite and the predaceous beetle *Stethorus punctum*, Mowery *et al*. (1975) assumed merely that the beetle population increased at the flat rate of five percent per day.

The investigation of population dynamics typically requires the biological monitoring of field populations (as may the preceding needs analysis). Monitoring methods may be taken from the literature or from experience with similar species or be created *de novo* for this system. There may, and hopefully will, be several distinct monitoring approaches. Of necessity this monitoring must be accomplished without the monitoring design it is meant to facilitate (except for generic features which may carry over from previously designed systems). The earliest steps must therefore be exploratory and may be devoted to improving sampling sufficiently to get reliable data to design the ultimate monitoring-management system. The riddle of the chicken and the egg has a certain relevance here.

Two major classes of monitoring can be distinguished at this stage. The first contains those specialized measurements which, while necessary for a particular experiment, would probably not be made in a management context. The remaining protocols might well be used in a management scheme even if the preliminary experiments are only indirectly related to decision making. A major goal of the preliminary field work is to evaluate the use of these latter methods and provide the statistical, timing, and cost data necessary to implement an optimized monitoring component.

There are two steps which should be taken to facilitate this process. First of all, auxiliary records should be kept of the timing and cost of sampling. Protocols should be decomposed into their constituent activities and timed. This permits studies such as those described in chapter VI. Strict accounts should be maintained of the consumption and prices of labor and sampling materials. This record keeping may add to the time required to process the samples. To a certain extent this can be alleviated by only recording rigorously a fraction of the samples and keeping less complete or no records on the remainder. Beyond this it can only be emphasized that it is easier in the long run to maintain good records as one goes along than to have to go back and make specialized studies later on.

Another related category of auxiliary data concerns travel times to remote sites and the costs of vehicle operation. While the map-based methods of chapter VI can be used, better results will be achieved from data obtained by actually traversing the management region. In cases where the region consists of a relatively homogeneous mixture of rural country roads and two-lane highways, records of total distance and total time may be sufficient. In cases where interstate or limited access freeways are involved, somewhat more complex records may be needed.

A second major point is that a variety of sampling methods, if available, should be used. Often, different methods may not measure exactly the same thing or may measure it with different efficiencies. For this reason certain portions of the samples should be measured by more than one technique. This will provide a direct comparison of the methods on the same materials. Other portions of the samples can be analyzed by single methods so that complete duplication of effort does not result. When there are very few methods available (perhaps only one) or when initial screening yields one of clear superiority, then protocol variations should be employed. That is, such parameters as sample size, number of subsamples, etc. are altered in several combinations. The total duration of a sample procedure will depend on several independent factors. The use of multiple protocols will give each factor a chance to express itself. Ideally, to permit multiple regression studies of time requirements (see chapter VI) there should be one more variation than the number of activities into which the protocol has been decomposed. Each protocol variation must, of course, be consistent with the requirement for sound biological data.

It is important to remember that while this work is going on, a parallel effort is designing and testing decision algorithms. These two programs, ideally, will act to reinforce one another. The testing of decision rules in the field generates data useful to model building and monitoring evaluation; the evolving model can be used to test nascent decision rules in ways not possible in the field.

The development and testing of decision rules can begin as soon as the management needs have been completely specified, although it is possible that a period of biological investigation might necessarily intervene. Once actual field testing of one or more sets of decision rules begin, there are several types of data which should be recorded. First of all there is, obviously, the data on which the decision is based, what decisions are made, what control was actually implemented, and what the result was. Also, however, economic data should be taken. What was the cost of monitoring; what was the cost of the control recommended; what was the cost of the control actually applied; and what was the cost of the outcome. These data are necessary to quantify the economic aspects of the system as discussed in chapters IV and VII. It must be remembered that pest management is an economic as well as a biological problem. The designer of decision making strategies should always be sufficiently aware of conditions in the pest control market to know the costs of his recommendations. By recording these right along with the biological data the embarrassing alternative of having to make later "guesstimates" can be avoided.

At several points in the previous paragraph a distinction was made between the recommended control and the control actually implemented. This difference becomes particularly important when field testing is being done with cooperators who may be unwilling or, for various reasons, unable to follow completely the given recommendation. By recording this information, a much better understanding of potential performance can be formulated.

When cooperators are involved in pilot studies, the opportunity also exists to determine what institutional mechanisms and price structures will be most acceptable in the ultimate system. In this way the market potential for various levels of service can be estimated. Equally important, satisfied pilot project cooperators are an invaluable aid in getting a new system accepted once it is fully operational. Indeed, these pilot programs should be as closely tailored to actual operating conditions as possible so they can serve as stepping stones to an in-place system.

As data from both the biological and control strategy programs become available in the forms of models and decision rules, the development of nomograms can proceed. As mentioned earlier, it may be possible to make a beginning based on the needs analysis alone. In this case, the initial crude efforts may prove very useful in making gross feasibility decisions. In any event, as soon as possible, one or more relevant sets of (v, i, t, r) parameters should be selected (chapter V). Charts constructed on the basis of these variables can be improved as research proceeds. By showing which alternatives appear most likely to succeed at each stage, the charts serve to guide the design effort. Also, of course, their use in optimization has already been mentioned (chapters V, VI, and VII). Finally, using models, charts, and pilot studies as winnowing agents, only one design will remain.

The last step is implementation. By this time, through field demonstrations, publications, analysis, and contact with the affected parties, the system should be perceived as an effective pest management tool. All that should remain is the formal act of instituting full operation. Even after this happens it is necessary to check system operation periodically. This may best be done by the regional-level system control (see Figure 2) in conjunction with the planning function described in chapter I. This is necessary because the system must be able to adapt to meet any changes in its operating environment. These changes may range from simple incremental improvements in technology up to and including a complete replacing of the system or the phasing out of operations.

The design process outlined here is typical of the systems approach to problem solving (Manetsch and Park, 1974). The procedure begins with the recognition of needs which are then analyzed in detail. Next, a set of potentially feasible approaches are proposed and studied. For monitoring (and the corresponding decision making components) this entails the integration of biological, statistical, logistic, and economic factors. By the use of graphical models it is possible to design, optimize, and, perhaps after several iterations, to choose a suitable system.

The robustness of this design approach is its most important characteristic. Agriculture possesses great diversity. Hosts may be animal or vegetable; they may be short lived or live for many years. Pests can vary in severity, number of generations per year, damage mechanisms, etc. Agricultural components may operate in the public or the private sector. Finally, marketing arrangements range from virtually free market conditions, through oligopoly and government regulation. Nevertheless, no matter what the unique properties of a given situation might be, the four types of factors discussed in this thesis will play a determining role.

Chapter II contained an example which showed that, while different levels of pest spatial variation could affect the scale of management, the design process remained the same. Consider now two alternative marketing structures, each of which is confronted by a pest whose dispersal behavior makes large scale, regional monitoring preferable. Suppose that the first structure consists of many small, undiversified operators acting independently. Let the second market be at the other end of the spectrum; that is, let it be dominated by a few large, diversified, oligopolistic producers. In contrast to the chapter II example, the main comparison here is economic rather than biological. In spite of the differences between the two structures, the designer must still ask questions about risks, decision maker costs, and monitoring service economics. Only the answers are different. Diversification would allow the large producers to tolerate higher levels of risk than could the small independents. Because of the size of their operating budget, however, the large operators may not always choose to do so. For instance, they may realize sufficient economies of scale in the bulk purchase of control materials to lower their perceived economic injury levels. While small agriculturists may have to turn to cooperatives or public agencies to administer the regional management system, the large producers are more likely to internalize these costs. They may even do so by forming wholly owned subsidiaries which might well be permitted to operate at a loss (which would not show on a consolidated statement). Except, possibly, for a public agency, this would not be a feasible design alternative for the small producer case. The freedom to operate at a loss would be an important element in the determination of level of service. The appropriate form of monitoring-management system is developed by utilizing the differing answers to the common questions posed by the unified design procedure.

This design approach can also be applied to a variety of situations not limited to pest management or even to agriculture. There are a great number of problems in today's world ranging from energy production to waste disposal where strong interactions exist between humanity's economics and biological reality. Figure 2 might well serve as a management schematic for any number of these. In any such instance, the analysis set forth in this dissertation would be applicable. As time passes and management systems become more complex, more automated, and more capital intensive, and as the managed commodities become more valuable, the importance of this and related forms of analysis can only increase.

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