The design of biological monitoring systems for pest management

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1 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.

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 were sensed, a control decision made, and then implemented with only limited concern for long-range effects. Pest management recognizes that these components interact within the context of a complete agro-ecosystem. This results in a 'closed-loop' system as shown in Fig. 1. The closed-loop topology clearly suggests that control is an ongoing process where today's actions can influence tomorrow's conditions for good or for ill.

This realization has resulted in a clear need for new types of analysis to cope with management system design (National Academy of Sciences, 1969; Luckmann & Metcalf, 1975; Tummala, 1976). Various authors have grappled with pieces of the problem. Headley (1971) and, later, Hall & 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).

The purpose of this monograph is to present an encompassing technique for the design and analysis of biological monitoring

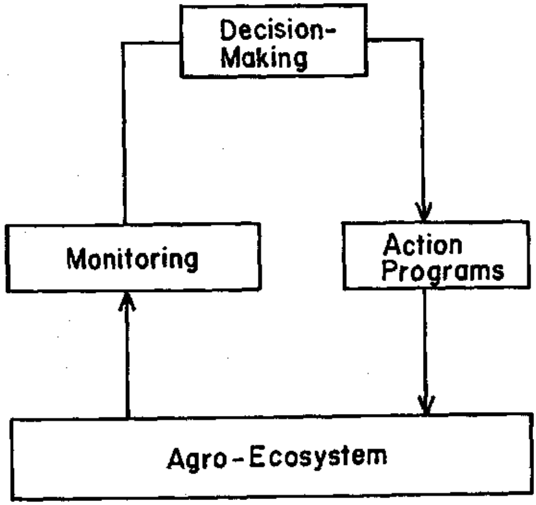


Fig. 1. A simplified block diagram of a closed-loop management system.

systems. Of necessity, monitoring activities must be considered in the context of the entire management system since it is impossible to know how useful data are without knowing their intended uses.

Fig. 1 suggests four classes of factors which, among them, describe 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. 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 monograph emerged in the period between 1973 and 1976 as a result of work on phytophagous mite management 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., 1978). 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.

The first topic discussed (Chapter 2) is a conceptual model of an operational pest management system. Basically it consists of the four components of Fig. 1 but elaborated so as to emphasize biological monitoring activities. The types of activities and functions carried out at three hierarchical levels (a decision-making level, a monitoring-unit level, and a regional level) are defined and discussed.

This chapter also introduces the main practical example of the monograph. Three alternative systems for monitoring mite populations under orchard conditions are presented. Two of these involve the use of mobile van-based laboratories while the third is a traditional scouting program. These systems are quantitatively analyzed in the chapters that follow.

Chapter 3 focuses on biological aspects of monitoring design. Topics include the biological requirements for sampling, the need for studies of the distribution 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 to system design. A model of the interaction of the European red mite with the predator *Amblyseius fallacis* (Garman) is presented as an illustration. This model is used in a variety of ways throughout the monograph.

The following chapter (4) 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, By way of example, the dynamics of the European red mite under predator-free conditions are studied. The example demonstrates monitoring analysis calculations in cases where pests are subject to sudden exponential outbreaks.

Chapter 5 presents economic considerations. The treatment is broken into two sections: the economics of the decision maker and the economics of the monitoring service. 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 as perceived by the decision maker. Alternatively, the establishment of a monitoring system may be viewed as an investment whose value must be judged. A screening program, which calculates a return on investment via a discounted cash flow analysis (Park, 1973), is presented. This return represents the total profitability of the system to its operator.

Chapter 6 discusses system time delays. Total delay is decomposed into a sequence of separately analyzed processing steps so that potential bottlenecks can be detected. As an illustration the effect on average service time of requiring progressively more accurate mite counts is calculated.

The seventh chapter demonstrates important mathematical relationships existing between the classes of variables discussed in Chapters 3–6. 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 two (with one minor exception). Such a chart is constructed for the predator-free European red mite system. In two examples the nomogram is used to examine tradeoffs (1) between grower risks and monitor profits and (2) between sampling accuracy and the probability of loss.

Chapter 8 is a synopsis of the design procedure. Following standard system design methods (Manetsch & Park, 1974), it begins with an analysis of management needs. Next the designer constructs and models several alternative methods of meeting these needs. Modeling involves the 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 7 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 alternatives 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 broad applicability of this approach to a variety of other agricultural and resource management tasks is emphasized.

2 General organization of a monitoring-management system

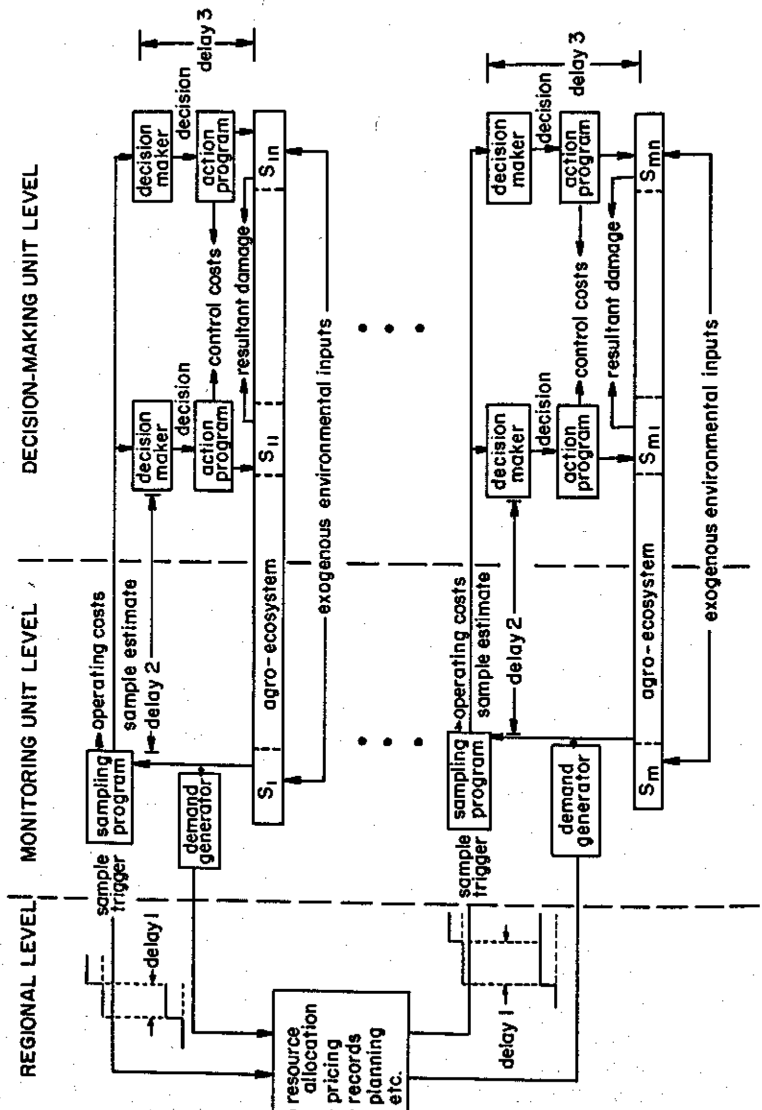
Biological monitoring activities are always part of some larger system which uses the data for some purpose. Usually monitoring data require interpretation and extrapolation. While such manipulations make the data more useful, sample variances are generally increased by these activities making the results less reliable. Only by studying the monitoring component in the context of its overall system can the designer maintain a favorable balance between utility and reliability. This chapter is therefore devoted to the construction of a conceptual model of the flows and processing of biological data within a pest management system.

Such a system can be conceived as having three hierarchically organized levels (Fig. 2): the decision-making level, the monitoring-unit level, and the regional level. The decision maker uses the monitoring data to select appropriate action programs and sustains the resultant benefits or losses. The monitoring unit is a geographical area within which sampling serves one or more decision makers. At the regional level, monitoring resources are allocated among the monitoring units so as to best achieve system goals.

2.1 The decision-making level

This forms the lowest level of the system. Each decision-making unit consists of a production unit (e.g., parcel of land, herd, grain bin,) plus a decision maker who chooses control practices for that unit. It is assumed that all subsections of a unit are treated identically. The units are, of course, parts of an extended agro-ecosystem and receive environmental inputs such as solar radiation, temperature and precipitation.

To maintain a focus on monitoring, the decision-making process will be treated in an aggregated sense. That is, the 'decision maker' will be defined as all individuals and/or organizations involved in selecting action programs based on monitoring results. Croft et al. (1976a, p. 21) gave a breakdown of these groups for Michigan's


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

integrated pest management. Two exceptions to this aggregation are (1) organizations like testing laboratories which process raw sample materials and are properly considered as part of the monitoring component; and (2) individuals or groups who make distinct decisions for two or more production units. In this latter instance, each unit is considered to have a separate decision maker.

The processing of monitoring data into action recommendations (i.e., 'decision making') is the single most important transformation which the monitoring data undergo. For this reason it is important 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 that no pests could be tolerated. Better procedures are based on the relationship between pest density and potential damage. Stern et al. (1959) stated that control measures should not be instituted below that density (called the economic injury level) at which the marginal cost of control just exceeds the marginal damage. Because, however, it takes time to reach a control decision and then act (Delay 3 in Fig. 2) the 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). The economic threshold is therefore dependent on the manner in which the control is applied. Additional factors affecting both thresholds and injury levels are meteorology, host maturity and other characteristics, and the cost of control.

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. Croft (1975), for example, described a program for plant feeding mites on apples in which early season application rules control impacts on non-target species so as to achieve payoffs later on. Mathematical techniques such as dynamic

Fig. 2. A conceptual model of a pest management system. Each decision maker has control over a portion of the extended agro-ecosystem. He acts on information from a sampling program which monitors conditions 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.

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 (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 deterministic; 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. Statistical decision theory (Carlson, 1970) permits this risk to be accounted for. This method explicitly notes three important characteristics of pest management decisions: (1) they are selections among finite sets of alternatives (e.g., no, low, or high spray rates), (2) they have as their goal the maximization of some objective function (e.g., profit), 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 that set into which the actual monitoring outcome falls. The sets are constructed so as to maximize the probability of optimal results. This procedure contains the other rules as special cases. For example, setting a threshold is the same as 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. Because statistical decision theory is based on probability distributions, as are many other areas of biology and economics, it seems to provide a basic framework within which all of these phenomena may be interrelated. For this reason, we shall follow this paradigm in what follows.

2.2 The monitoring unit level

A monitoring unit consists geographically of one or more decision making units. Sampling is carried on within the monitoring unit to provide the decision makers with timely, relevant data on local conditions. These data may be transformed in some standard way for all users or tailored to their individual needs. The agroecosystem is *assumed* to be homogenous within the monitoring unit boundaries. Thus, these units define the spatial resolution of the monitoring system.

Biological monitoring activities occur in a sequence we shall call the *sampling cycle*. 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. Biological rate functions determine the sampling rates one should use. According to the sampling theorem (Bekey & Karplus, 1968), accurate reconstruction of a signal requires sampling at a rate at least twice as fast as the most rapid fluctuation. Unfortunately, this is often not possible in practice. An acceptable substitute is to sample at a rate several times as fast as the most rapid fluctuation of *major amplitude*. In this way, the most prominent biological features will be observed.

The disadvantage of fixed period sampling is that much effort may be expended while nothing of significance is occurring. Other methods attempt to restrict sampling to those periods of particular interest. Usually this involves keying the observation to some meaningful biological or physical event (or 'trigger'). Triggers should have three properties: (1) they should be observable, (2) they should bear a reasonably direct relationship to the ultimate agro-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, monitoring can be linked to the phenology of the host crop or other indicator plants. Many countries (Hopp et al., 1972; Journet & Touzeau, 1979; Benedek, 1979) maintain networks of standard phenological gardens within which frequent observations are made. Tying these data to pest biology would permit observations of plant conditions to serve as sampling triggers. Jones (1976) described an apple scab monitoring program triggered directly by the environment. Two conditions are required for scab infection: the presence of a spore inoculum 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 & LaPlante, 1951).

Two other important types of trigger are the predictive trigger and the post-control trigger. When the biology of a species is well understood, it is often possible via biological models to predict when the population will require monitoring. In post-control monitoring, sampling is scheduled to occur at some specified interval after a control measure has been applied. What both of these methods have in common is that time Delay 1 (Fig. 2) is eliminated because the 'trigger' occurs before sampling is actually required. This forewarning makes it easier for the monitoring resource allocator to function efficiently.

Typically, however, some delay will occur, its length depending 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 6 and 7).

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 & 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 4). According to the Bayesian philosophy of Savage (1954, 1962), this distribution encodes the total result of a measurement procedure; a detailed knowledge of sample design (sequential versus fixed size, relative versus absolute measures, etc.) can add nothing beyond this. This approach establishes a direct and generalized link with the statistical decision procedures of the last section.

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 direct, face-to-face conversation to the use of various electronic media (Haynes et al., 1973; Croft et al., 1976a). Each method has important associated time delays and costs which must be explicitly accounted for in the system design.

2.3 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 operating resources, (2) the distribution of these resources to meet demand, (3) the determination of the prices charged end users, (4) all necessary accounting and record keeping, and (5) advanced planning.

In Chapter 5 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) that 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 5, 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. 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).

The conceptual model in Fig. 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.

2.4 An example

We shall now introduce an example which will receive recurrent attention throughout the remainder of this monograph: advanced systems for monitoring mite populations in Michigan apple orchards. These systems will illustrate the application of the concep-

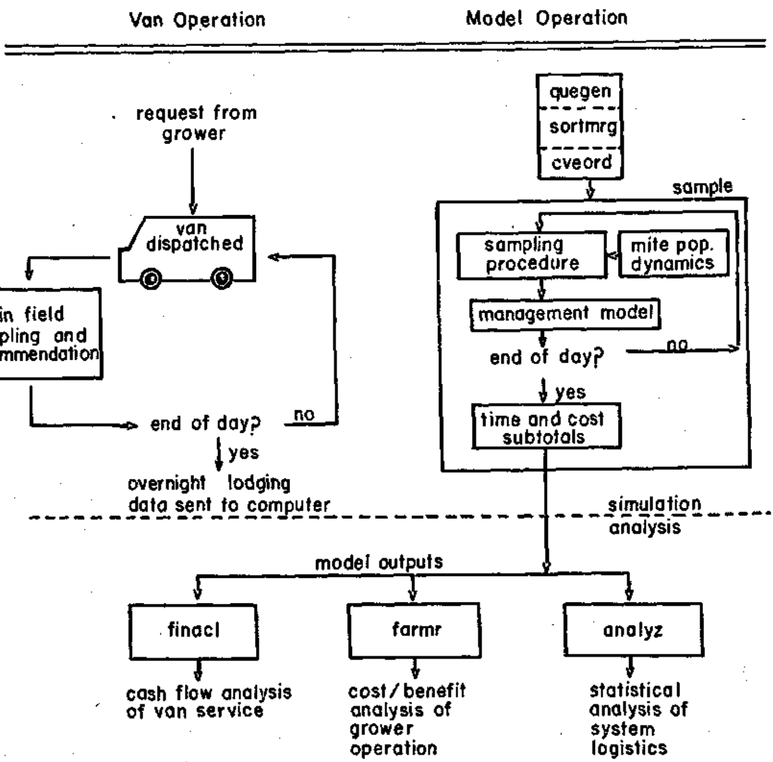


Fig. 3. Mite monitoring simulation software. Computer analysis of the three alternative mite monitoring systems involved seven programs. The first four formed a quantitative simulation of the conceptual model. The last three analyzed the simulation outputs in various ways (after Croft et al., 1979).

the van drives to an overnight lodging site where the appropriate data communication and computer activities take place (for the FS and RS I alternatives). In Reduced System II the overnight location is one of the three central laboratories. For this alternative, mite counting is simulated as occurring at the laboratory the next day while the van collects more samples.

The outcomes of SAMPLE are computer analyzed in three separate ways. Program ANALYZ tabulates distributions of logistical data such as travel times, waiting times, manhours spent sampling, etc. Program FINACL provides an economic summary of the monitoring system from the point of view of the system operator. Program FARMR does the same thing from the grower's perspective. Results of these analyses will appear throughout the remainder of the monograph.

3 Biological aspects of design

As a primary pest 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 (i.e., biological models).

3.1 The biological demand for monitoring

Through time, target populations will develop and, perhaps, disperse within the monitoring region. At various times local populations will reach stages requiring monitoring. The spatial and temporal distribution of the corresponding trigger events constitute the biological demand for monitoring. Clearly, it is undesirable to expend resources where they are not needed. Biological demand therefore forms the baseline from which actual demand (conditioned by economics, logistics, and the distribution of decision making units) can be calculated.

Biological demand may be projected from historical records or calculated from target species phenology. For example, to estimate the demand for phytophagous mite monitoring, data on mite densities from 146 Michigan apple growers (Croft, unpub. data) were examined. The resulting frequency of triggering (i.e., first occurrences of densities between 3 and 10 mites per leaf) was determined by date for each of the seven management areas in the state.

When species' developmental rates, perhaps as affected by environmental parameters, are known weather charts or other data sources may be used to construct maps showing the distribution of triggering (Fulton & Haynes, 1975). Developmental data may be based on either laboratory or field experiments although the latter are preferable. One problem with this phenological approach is that it fails to take the geographic distribution of the species into account. That is, the conditions for triggering might be correct at some point without the species actually being present. Thus the method is more useful for species which are either ubiquitous or whose range is at least partially known.

Biological demand should be expressed as a probability of triggering per unit time per unit area or per decision-making unit. Demand is thus stated in the same probabilistic vocabulary as other variables in the management system model. This also permits the calculation of demand for various hypothetical or actual distributions of decision makers. Thus, the approximate magnitude of demand can be established early in the design so that unrealistic goals may be avoided.

3.2 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.

This was done for *P. ulmi* and its predator *Amblyseius fallacis* by Croft et al. (1976b). Visual counts of approximately 66 000 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 & 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. In the study cited above, Croft et al. (1976b) determined the variance of within tree means as a function of overall mean density. These results were

$$V(\bar{x}) = 0.93\bar{x}^{1.82} \quad \text{for} \quad P.\ ulmi$$

and

$$V(\bar{x}) = 0.72\bar{x}^{1.48} \quad \text{for} \quad \textit{A. fallacis.}$$

This information is relevant to the design of optimal sampling plans which divide sampling efforts rationally into within tree and between tree components. It is also important in validating population models at the orchard level. Dover et al. (1979) show that between tree variation can dramatically affect the observed duration of prey-predator interactions. This has implications for the calculation of permissible time delays (Chapter 6).

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 (including both biotic and abiotic factors). Dispersal attenuates spatial variation because the presence of a dispersing individual at one location implies a likelihood of others nearby. For example, dispersal in the red mite is primarily limited to the leaf surfaces within a single tree resulting in the between tree variation first documented. Certain spray practices like alternate row middle application can cause significant variation even within a single tree (Hull et al., 1976).

The six-spotted leafhopper, *Macrosteles fascifrons* (Stal), 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 & 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.

Variability in environmental parameters (mediated by species physiology and behavior) also results in biological variation. 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 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 probabilistically. There are numerous examples of microvariation and its effect on monitoring in the literature. Fye et al. (1969) showed that internal emergence cage temperatures can vary significantly from external temperatures. Observations by Richardson (pers. commun.) 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 & Tummala (1976) present data from Gage & 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 may well be 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.

3.3 The extrapolation of population processes through time

Often the variable actually monitored is only indirectly related to the variable of interest. 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; the state of a population at the time monitoring is triggered may differ from the 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. To estimate, therefore, the ultimate system efficacy, it is necessary to extrapolate population processes through time.

This is only possible if the designer has access to some form of biological model. The 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.

3.4 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). According to Welch et al. (1978), well designed models provide three useful features: (1) a systematic method of recording data and, therefore, (2) a specific impetus to certain avenues of research, and (3) a body of mathematical methods for manipulating the data in useful ways.

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 & 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 should be compiled of the types and, if known, the efficiency of the monitoring methods. For controllable stages, of types and costs of control should be tabulated and the efficiency of each method (e.g., percent mortality) noted. It is quite possible for a particular measure to affect a number of stages, perhaps differently; all effects must be listed. It is also 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 important. It should not be ignored that damage is inherently integrative; the damage a species does *per unit time* is related to pest activity.

This suggests that damage potential should be expressed in units such as pest-days. For example, Hoyt & Burts (1974) expressed the effect of phytophagous mites on apples in terms of the reduction in yield per mite-day. In another case involving the Colorado potato beetle (*Leptinotarsa decemlineata*), it was found useful to consider a potato plant canopy to consist of 3 000 beetle-consumption days (Sarrette, pers. commun.).

Of course the most important data about a stage concerns its contribution to the species' population dynamics. The classes of data needed are developmental, reproductive, and demographic. Developmental data primarily include the stage durations. These may be in units of days, degree-days, developmental units (Shelford, 1927), or other measures. Reproductive data may be expressed as depending on the maturity of the reproducing stage and/or on environmental parameters. 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.

Finally, it is necessary to relate the species to the pest management community. Data needed include a list of regions where the species is found and which personnel in those regions are responsible for its management. Note should be 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 boundaries of the model.

3.5 A *P. ulmi-A. fallacis* model

Dover et al. (1979) developed a simulation of the European red mite-*Amblyseius fallacis* prey-predator system. Welch (in press) compared this model to similar work by other investigators. This model was instrumental in evaluating the alternative mite monitoring systems so we shall summarize it here.

The formulation of this model followed the steps outlined above. Fig. 4 shows the decomposition into life cycle stages. While most stages are morphological in character, the preoviposition stage exists

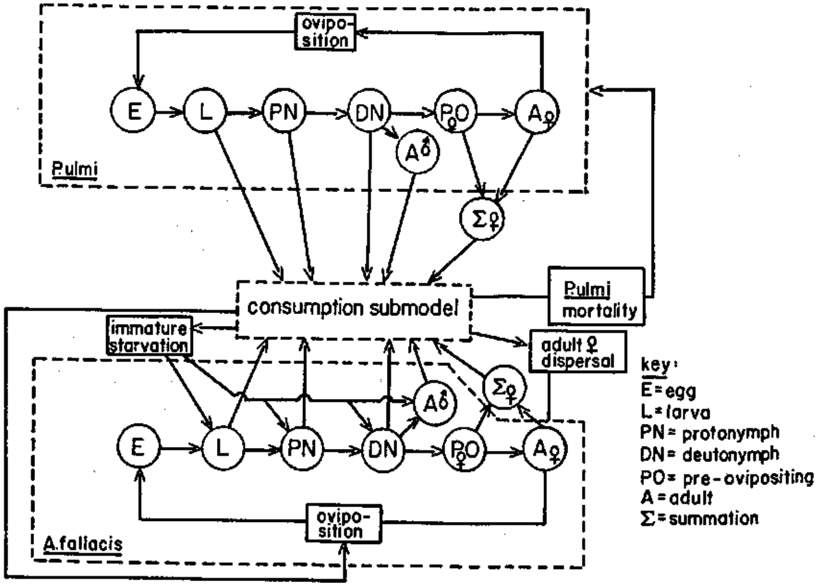


Fig. 4. Block diagram of a *P. ulmi-A. fallacis* simulation model. A detailed description of this model is given in Dover et al. (1979).

for convenience only. All active stages of the pest are viewed as capable of being monitored and controlled (by the predator). They also, of course cause leaf feeding damage (Hoyt & Tanigoshi, 1978). The *P. ulmi* egg stage is neutral. It is neither damaging nor preyed upon by this predator. Furthermore, it is ignored in the three alternative monitoring schemes because of the large numbers usually present.

As might be expected, predation, as a form of control, differs significantly from stage to stage. The model incorporates a variety of factors into the consumption submodel. These include (1) the stage distribution of both prey and predator populations, (2) stage-specific consumption rates, (3) competition among predators, (4) mean prey density, and (5) the spatial distribution of prey and predators throughout the tree.

The model also incorporates developmental, reproductive, and demographic data. Developmental data consists of stage-specific developmental rates expressed as functions of temperature. Repro-

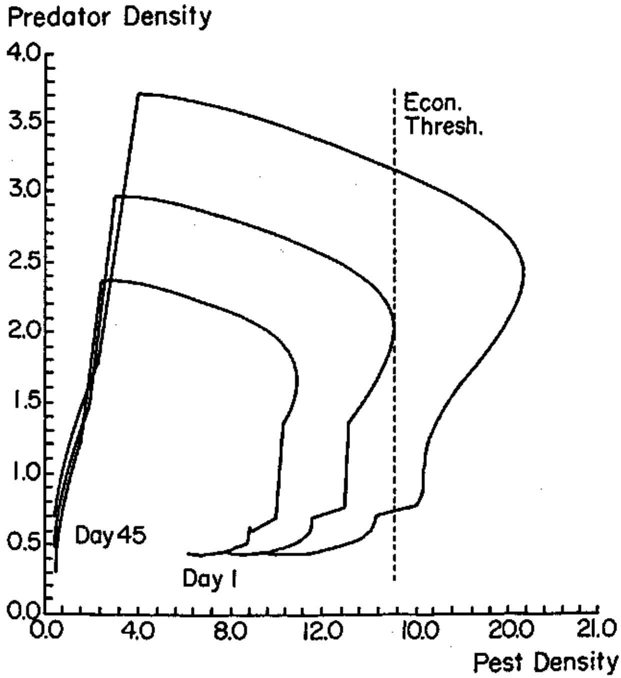


Fig. 5. A phase plane plot showing simulations of three interactions of the European red mite (horizontal axis) with *A. fallacis*. The three curves are characterized by progressively poorer initial prey-predator ratios resulting, ultimately, in a failure of biological control.

ductive rates depend on adult female maturity and temperature. In addition, the predator oviposition rate is related to prey consumption. The predator population is also affected by demographic factors. Under conditions of low prey density, adult predators will exhibit an unique dispersal behavior (Johnson & Croft 1975) and leave the tree. This reduction in effective population size is included in the model.

The following features were noted in relating the model to the pest management community: (1) the division of the state into management areas, (2) the activities of the scouts, (3) the presence of a network of weather stations which provide daily maximum and minimum temperatures, and (4) the abilities of growers to respond to model outputs.

Once the model equations were complete, they were coded using the FORTRAN language. The program also included routines to produce graphic outputs to aid validation (Fig. 5). File manipulation routines were added to facilitate access to the data sources described in the previous paragraph. These latter routines permit the model to operate in conjunction with Michigan's computerized extension information delivery system (Croft et al., 1976a; Brunner et al., in press). Validation procedures, results, and the quantitative details of this model are described in Dover et al. (1979) to which the reader is referred.

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 judgement to determine whether a system is well enough understood to allow design to proceed.

4 Stochastic aspects of design

Elements of randomness and uncertainty assert themselves at several points in the monitoring-management control loop. First of all there is sampling error which prevents us from being certain of the true state of the agro-ecosystem. Secondly, this state is continuously changing; delays in decision making or action programs may result in the application of inappropriate controls. Lastly, spatial variation may limit to small areas the applicability of monitoring results and decisions.

This chapter is devoted to a detailed mathematical examination of stochastic factors in monitoring. The chapter makes use of the theory of continuous probability distributions; readers unfamiliar with this topic may wish to consult an elementary text such as Wadsworth & Bryan (1960). The whole point of the chapter is to show how the various sources of error combine to affect the ultimate decision making risks. In the next chapter, we shall discuss some of the economic aspects of these risks.

We begin by considering two points A and S in the monitoring unit. At some point in time $t = t_0$, the sampling point (S) achieves state λ_{s,t_0} 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 $p(\lambda_{s,t_1} \mid \lambda_{s,t_0})$[1] where $t_1 = t_0 + \tau_1$. 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

$$p(\lambda_{s,t_1} \mid x_s) = \frac{p(x_s \mid \lambda_{s,t_1}) p(\lambda_{s,t_1})}{\int p(x_s \mid \lambda) p(\lambda)\, d\lambda}. \tag{4.1}$$

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

Frequent use of this theorem is made in what has come to be called Bayesian statistics (Savage, 1954, 1962; Binder, 1964). One of the major tenets of this theory which we shall utilize is that the posterior distribution, $p(\lambda_{s,t_1} \mid x_s)$, expresses the total result of the measurement.

Similarly, the bivariate distribution $p(x_s \mid \lambda_{s,t_1})$ 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, suppose 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 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. Straightforward calculation and the application of the Central Limit Theorem (Feller 1968, Vol. 2) yields

$$p(x_s \mid \lambda_{s,t_1}) = N(x_s; \lambda_{s,t_1}, (\sigma_1^2 + \sigma_2^2)/nm) \tag{4.2}$$

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 side of Eqn 4.1, we have yet to discuss $p(\lambda_{s,t_1})$ which is called the prior distribution. If λ_{s,t_0} and τ_1 are exactly known, then

$$p(\lambda_{s,t_1}) = p(\lambda_{s,t_1} \mid \lambda_{s,t_0}). \tag{4.3}$$

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

$$p(\lambda_{s,t_1}) = \int_0^\infty \int_\lambda p(\lambda_{s,t_0+\tau} \mid \lambda_{s,t_0}) p(\lambda_{s,t_0}) p_1(\tau)\, d\lambda_{s,t_0}\, d\tau \tag{4.4}$$

where $p(\lambda_{s,t_0})$ is the probability of a certain state triggering monitoring and $t_1 = t_0 + \tau$.

In the mite monitoring analysis, examination of historical records yielded $p(\lambda_{s,t_0})$ as shown in Fig. 6. Fig. 7 shows the $p_1(\tau)$ distribution as determined by program ANALYZ for an assumed market of 315 growers. Restricting ourselves to predator-free systems, we can

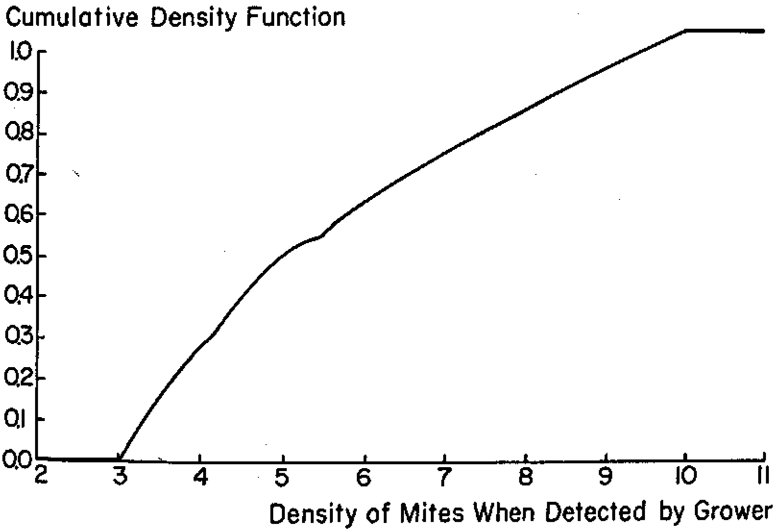


Fig. 6. The cumulative distribution of red mite densities at the assumed time of first detection. This corresponds to $p(\lambda_{s,t_0})$ in the text.

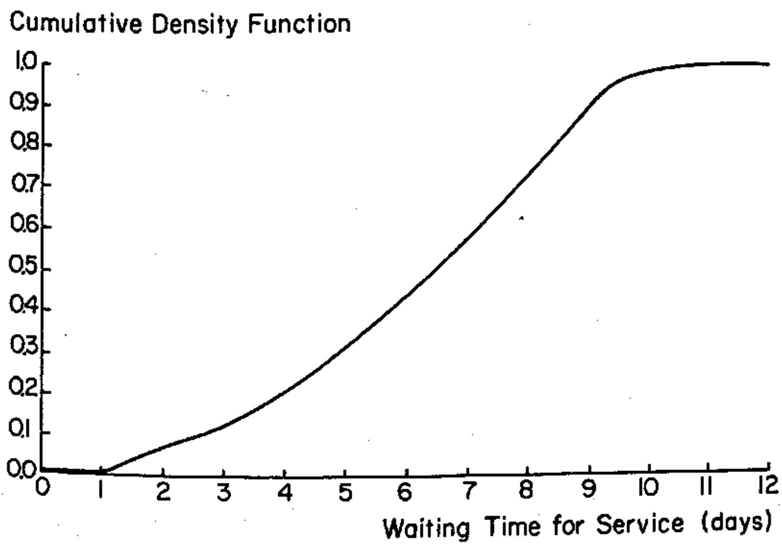


Fig. 7. The cumulative waiting time distribution from a simulation study of a mobile van-based mite counting service. This is delay 1 in Fig. 2 and corresponds to $p_1(\tau)$ in the text.

describe the species dynamics by a simple exponential growth model

$$p(\lambda_{s,t_0+\tau} \mid \lambda_{s,t_0}) = \delta(\lambda_{s,t_0+\tau} - \lambda_{s,t_0} e^{r\tau}) \tag{4.5}$$

where r was taken as 0.135 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 (2) by internal effects like intra-specific 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 Eqn 4.4 for various values of λ_{s,t_1} yields Fig. 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

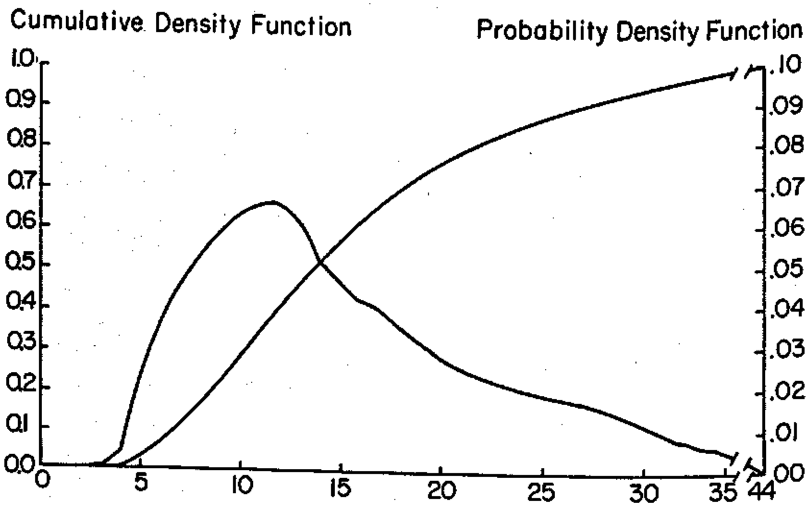


Fig. 8. The prior density function from Eqn. 4.4. The calculation assumes that the distributions of Figs 6 and 7 are employed and that a simple exponential outbreak model is appropriate for the developing population. This curve estimates the likelihood a mite counter would attach to various mite densities before the field had been seen.

values of λ and if the sampling design yields a strongly peaked $p(x_s \mid \lambda_{s,t_1})$, 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 distribution 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 distribution of Fig. 8 and from a uniform prior distribution covering the same range of mite densities. The distribution $p(x_s \mid \lambda_{s,t_1})$ was based on Eqn 4.2 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. Fig. 9 illustrates that

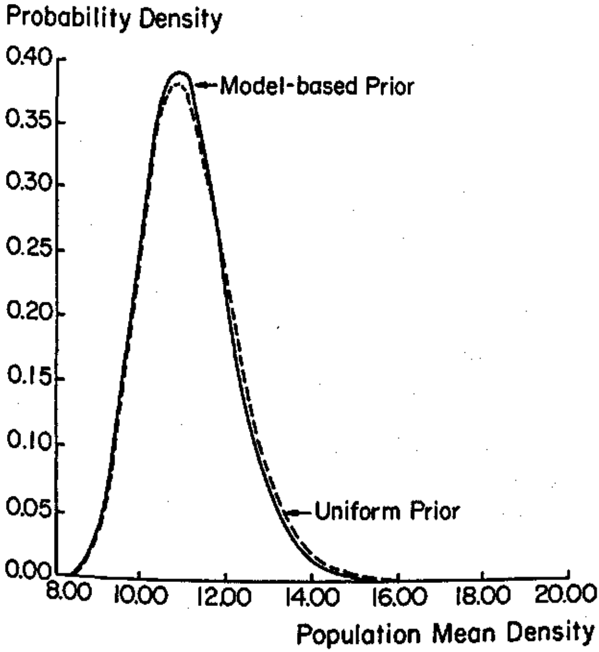


Fig. 9. A comparison of the posterior effect of a uniform versus a more complex, model-based prior distribution. The similarity of these two curves indicates that the principle of stable estimation seems to hold for European red mite monitoring. That is, it makes very little difference whether a designer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

the non-uniform prior distribution based on grower characteristics and time delays had little statistical effect in this instance. While this 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

$$\lambda_a = \alpha_{AS}(\lambda_s) + \beta_{AS}(\lambda_s)\varepsilon_{AS}. \tag{4.6}$$

In this equation ε_{AS} is assumed to be a random variable with zero mean and unit variance. The distribution $p(\varepsilon_{AS})$ 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 $p(\varepsilon_{AS})$ to be skewed left; 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 $E(\lambda \mid \lambda_s)$ and $Var(\lambda \mid \lambda_s)$, respectively. We begin by noting

$$E(\lambda_a \mid \lambda_s) = \alpha_{AS}(\lambda_s) \tag{4.7a}$$

$$Var(\lambda_a \mid \lambda_s) = \beta_{AS}(\lambda_s)^2 \tag{4.7b}$$

$$p(\lambda \mid \lambda_s) = \int_R p(\lambda_a = \lambda \mid \lambda_s)p(A)\, dR. \tag{4.7c}$$

In Eqn 4.7c, 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

$$E(\lambda \mid \lambda_s) = \int \lambda (p(\lambda \mid \lambda_s)\, d\lambda \tag{4.8}$$

$$= A_R^{-1} \int \lambda \int_R p(\lambda_a = \lambda \mid \lambda_s)\, dR\, d\lambda.$$

By switching the order of integration and using Eqn 4.7a we have

$$E(\lambda \mid \lambda_s) = A_R^{-1} \int_R \alpha_{AS}(\lambda_s)\, dR \doteq \bar{\lambda}. \tag{4.9}$$

From an elementary identity we have

$$\mathrm{Var}(\lambda \mid \lambda_s) = \int \lambda^2 p(\lambda \mid \lambda_s)\, d\lambda - (\bar{\lambda})^2. \tag{4.10}$$

Substitution and simplification yields

$$\mathrm{Var}(\lambda \mid \lambda_s) = A_R^{-1} \int_R (\alpha_{AS}(\lambda_s)^2 + \beta_{AS}(\lambda_s)^2)\, dR - (\bar{\lambda})^2. \tag{4.11}$$

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 $p(\lambda \mid \lambda_s)$ 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 & Calvert, 1974) this assumption will lead to designs which err on the side of conservation.

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

$$p(\lambda_a \mid \lambda_s) = N(\lambda_a;\, \alpha_{AS}(\lambda_s),\, \beta_{AS}(\lambda_s)^2). \tag{4.12}$$

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 & Fye, 1970; Fulton & Haynes, 1977).

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

$$\lim_{d_{AS}\to 0} \alpha_{AS}(\lambda_s) = \lambda_s \tag{4.13a}$$

$$\lim_{d_{AS}\to \infty} \alpha_{AS}(\lambda_s) = E(\lambda_a) \tag{4.13b}$$

$$\lim_{d_{AS}\to 0} \beta_{AS}(\lambda_s) = 0 \tag{4.13c}$$

$$\lim_{d_{AS}\to \infty} \beta_{AS}(\lambda_s) = \mathrm{Var}(\lambda_a)^{1/2}. \tag{4.13d}$$

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).

The formulas 4.6 to 4.13 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

$$p(\lambda_{t_1} \mid x_s) = \int p(\lambda_{t_1} \mid \lambda_{s,t_1}) p(\lambda_{s,t_1} \mid x_s)\, d\lambda_{s,t_1} \tag{4.14}$$

where $p(\lambda_{t_1} \mid \lambda_{s,t_1})$ is the normal distribution whose parameters were constructed in Eqn 4.9 and Eqn 4.11 and where $p(\lambda_{s,t_1} \mid x_s)$ is from Eqn 4.1.

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_0. 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 determined by

$$\beta_{AS}(T_s) = \sigma(1 - e^{\beta x}) \tag{4.15}$$

where x is their separation. These assumptions are consistent with the limits in Eqn 4.13. Equations 4.9 and 4.11 yield

$$E(T \mid T_s) = T_s \tag{4.16a}$$

$$V(d) \doteq \mathrm{Var}(T \mid T_s) \qquad (4.16b^1)$$
$$= \sigma^2\{1 + (\beta d)^{-1}(e^{\beta d} - 4)e^{\beta d}$$
$$+ (\beta d)^{-2}(4(e^{\beta d} - 1) - (e^{2\beta d} - 1)/2)\}.$$

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

$$r = k(T - T_h). \qquad (4.17)$$

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

$$\lambda_s = P_0 \exp\left(\int_0^t k(T_s - T_h)\,dt\right) = P_0 \exp(\bar{r}_s t) \qquad (4.18)$$

where

$$\bar{r}_s = \frac{1}{t}\int_0^t k(T_s - T_h)\,dt. \qquad (4.19)$$

Similar relations hold for λ. Algebra yields

$$\ln\lambda - \ln\lambda_s = (\bar{r} - \bar{r}_s)t. \qquad (4.20)$$

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 Eqn 4.20 gives

$$E(\ln\lambda - \ln\lambda_s) = E(\ln\lambda) - \ln\lambda_s \qquad (4.21)$$
$$= tE(\bar{r} - \bar{r}_s)$$
$$= k\int_0^t E(T - T_s)\,dt = 0.$$

1. The appropriate application of L'Hopital's Rule will show that $\lim_{d\to 0} V(d) = 0$.

Therefore,

$$E(\ln \lambda) = \ln \lambda_s. \tag{4.22}$$

Taking variances on both sides of Eqn 4.20 gives

$$\begin{aligned} \mathrm{Var}(\ln \lambda - \ln \lambda_s) &= \mathrm{Var}(\ln \lambda) \qquad (4.23) \\ &= t^2\, \mathrm{Var}(\bar{r} - \bar{r}_s) \\ &= k^2 \int_0^t \mathrm{Var}(T - T_s)\, dt = k^2 t \mathrm{V}(d). \end{aligned}$$

Substituting for t from Eqn 4.18 yields

$$\mathrm{V} \doteq \mathrm{Var}(\ln \lambda) = k\left[\frac{\ln \lambda_s - \ln P_0}{\bar{T}_s - T_h}\right]\mathrm{V}(d) \tag{4.24}$$

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

$$p(\lambda \mid \lambda_s) = (2\pi \mathrm{V})^{-1/2} \exp((\ln(\lambda_s/\lambda))^2/(2\mathrm{V}))/\lambda. \tag{4.25}$$

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 -0.12 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 been made actually 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* (Dover et al., 1979) were averaged to give a T_h of 50°F. By using the previous value of r, Eqn 4.17 was solved for k. P_0 was set to a nominal 0.5 mites per leaf. Assuming the same sampling design used previously and the principle of stable estimation, we obtain the density function shown in Fig. 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

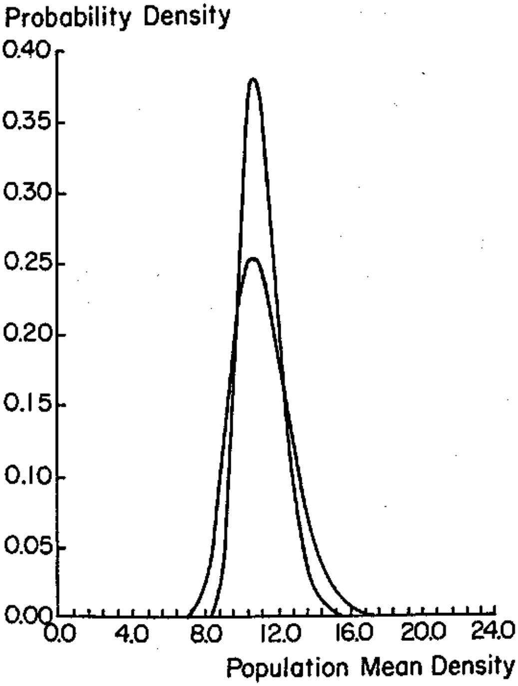


Fig. 10. The change in a likelihood function resulting from the extrapolation of data taken at a point over an extended spatial area. The figure demonstrates that the variance associated with an estimate increases when one tries to extrapolate from a single point (the peaked curve) to all of a monitoring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

relevant ecosystem states. It was demonstrated how the principle of stable estimation can be used to eliminate the troublesome need for a prior distribution. 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.

5 Economic aspects of design

The ultimate evaluation of any system must be economic. Many authors have related biological phenomena, economic decisions, and risk (Headley, 1972, 1975; Hall & Norgaard, 1973; Carlson, 1970). There are two distinct viewpoints which must be recognized: the monitoring system must make economic sense both to its operators and to its users.

5.1 Decision-maker economics

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

$$L(D, x_s) = \int_\lambda l(D, x_s, \lambda_{t_3}) p(\lambda_{t_3} \mid x_s)\, d\lambda_{t_3}. \tag{5.1}$$

The distribution $p(\lambda_{t_3} \mid x_s)$ describes the probability of various possible ecosystem states at time $t_3 = t_0 + \tau_1 + \tau_2 + \tau_3$ when control is actually implemented (see Fig. 2). By analogy with Eqn 4.4, we calculate

$$p(\lambda_{t_3} \mid x_s) = \int_0^\infty \int_\lambda p(\lambda_{t_1+\tau} \mid \lambda_{t_1}) p(\lambda_{t_1} \mid x_s) p(\tau)\, d\lambda_{t_1}\, d\tau \tag{5.2}$$

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. Each of these costs may be a

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	$\$_3(D, \lambda)$

random variable. For example, the cost of monitoring could depend on sampling labor and, thus, 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. Different decision-makers may pay different prices for the same decision if some realize economies of scale in the bulk purchase of control materials. Finally, the cost of damage depends on the (stochastic) state of the agro-ecosystem and the decision taken.

Because of this randomness it is best to base the loss function on the corresponding probability 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 be measured in dollars because they are not market commodities. Typical examples are aesthetic values, the desire to avoid risk and personal security. Utility theory (Scott, 1973; Nicholson, 1972) provides mechanisms for taking these factors into account. While utilities, in general, are not directly measurable, an exception is when one can make probability statements about the various possible outcomes (as is the case here).

There are two methods in common use for constructing utilities from dollar distributions. The first is simply to take the expected or mean value of the distribution. Under this method we have

$$l_1(D, x_s, \lambda) = \mathrm{E}(\$_1(x_s)) + \mathrm{E}(\$_2(D)) + \mathrm{E}(\$_3(D, \lambda)). \tag{5.3}$$

For the alternative mite counting systems expected costs equalled the sum of a fixed monitoring charge plus the expected costs of control and damage. The latter was found by multiplying the cost of significant damage by the probability of non-control (PNC) given the monitoring results. Because the quantitative relation between mite feeding and damage is obscure, the following assumptions were made:

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 for 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

$$\text{cost of damage} = 131.24 + \sum_{n=0}^{4} \binom{4}{n} r^n (1-r)^{(4-n)} (131.24\text{n}). \tag{5.4}$$

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

$$\text{cost of damage} = 131.24(1+4r). \tag{5.5}$$

This formula shows that, by reducing the risk of cumulative damage, we can lessen the impact of damage when it does occur.

Historical records (Croft, unpub. data) reveal that growers using the RS II system exceeded 15 mites per leaf on an average of $r = 0.11$ of the cases in any one year. Substituting this value in Eqn 5.5 yields a cost of damage of \$189 per acre.

The prey-predator simulation model was used to evaluate the probability of exceeding 15 mites per leaf given a particular monitoring outcome. 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 $\mathrm{I}_{15}(\lambda) = 1$; if not, $\mathrm{I}_{15}(\lambda) = 0$. The probability of non-control was then ascertained for particular values of x_s by

$$\mathrm{PNC}(x_s) = \int \mathrm{p}(\lambda_{t_3} \mid x_s) \mathrm{I}_{15}(\lambda_{t_3})\, d\lambda_{t_3}. \tag{5.6}$$

In many cases decision makers, understandably, wish to avoid situations where significant probabilities of great loss exist even

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

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,

$$l_2(D, x_s, \lambda) = l_1(D, x_s, \lambda) - A \cdot \mathrm{Var}(\$_1 + \$_2 + \$_3). \tag{5.7}$$

In most cases this method of determining losses yields optimal policies which are suboptimal according to Eqn 5.3. 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 this approach with linear programming methods which designers may desire to use. An alternative method without this defect has been proposed by Boussard & 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 & 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 & Cooper (1959) and Charnes et al. (1965). We shall employ constraints of this form in an example in the next chapter.

5.2 Monitoring-service economics

Many monitoring-management systems are initially funded on grant capital from public or private sources. At some point, however, a system which is to continue operations must switch to some more permanent source. The economics of the system must be well understood to justify the conversion. By estimating the economic performance of a system ahead of time, one can choose design alternatives likely to survive 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 section 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 the following six inputs.

1. Average annual sales or revenues. This is the number of samples

taken times the cost to the grower of each sample plus any "revenues" derived from other sources (i.e., public subsidy payments, sales of unused monitoring resources, etc.).

2. Direct production costs. These are the per sample costs of monitoring such as materials, labor paid on a piecework basis, etc.
3. Indirect, fixed, or overhead costs. This includes costs which are related to time rather than to number of samples (salaries and wages, capital charges, facility rental, etc.).
4. 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 entry (4). On the other hand, if the overall viability of the enterprise is being examined, this quantity should not reflect subsidies.

5. Economic project life. This is the period, in years, over which it is estimated that the system will operate as designed.

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. 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 (Park 1973)."

6. 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.

Table 2 illustrates the DCF algorithm. Lines 7 to 12 determine the net cash flow which is revenues minus production costs, overhead, and taxes. This can be thought of as the money in the bank at the end of the year. It is numerically equal to and is calculated as net profit after taxes plus depreciation.

One next calculates (as in Line 13) the percentage of the initial capital investment recouped each year. This is called the capital recovery rate (CRR). The CRR is a useful index of how fast the system will pay off but the ROI is a better indicator of total profitability.

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 the loan rate then, after paying off the

Table 2. 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×line 9
11	Net profit after taxes	line 9−line 10
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).

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

$$0=\sum_{i=0}^{n}\frac{NCF_i}{(1+ROI)^i} \tag{5.8}$$

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

$$CRR=\frac{ROI(1+ROI)^n}{(1+ROI)^n-1} \tag{5.9}$$

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.

A DCF analysis was conducted (program FINACL, Fig. 3) for the FS, RS I and RS II mite monitoring systems. The assumption was made that the systems are operated as Cooperative Extension Service projects employing student labor. The results are given in Tables 3, 4, and 5. As is evident, RS II with its low capital cost, is by

Table 3. Discounted cash flow analysis of the full system (FS)

Line	Description	Entry	Total
1	Revenue (315 samples @ \$30)		\$9 450.00
2	Direct production costs		
	Supplies (315 samples @ 25¢)	78.75	
	Postcards (29 samples @ 10¢)	2.90	
	Gas and van maint. (9 657.1 miles @ 10¢/mile)	965.71	
	Telephone charges (57 days @ \$3/day)	171.00	
			1 218.36
3	Indirect, fixed, and overhead costs		
	Salaried employee (4 months)	1 500.00	
	Non-salaried employee (353 h @ \$2.50/h)	882.50	
	Motel rooms (57 days @ \$20/day)	1 140.00	
	Food allowance (114 man-days @ \$10/day)	1 140.00	
			4 662.50
4	Net investment		
	Van	4 500.00	
	Computer terminal	2 500.00	
	Calculator	2 500.00	
	Miscellaneous electronics	700.00	
	Laboratory equipment	500.00	
	Power	525.00	
			11 225.00
5	Economic life of system		5 years
6	Income tax rate		zero
7	Average annual depreciation		2 245.00
8	Total deductions		8 125.86
9–11	Net profits		1 324.14
12	Net cash flow		3 569.14
13	Capital recovery rate		0.3179
14	Return on investment (ROI)		17.7%

Table 4. Discounted cash flow analysis of the reduced system one (RS I)

Line	Description	Entry	Total
1	Revenues (315 samples @ $30)		$9 450.00
2	Direct production costs		
	Supplies (315 samples @ 25¢)	78.75	
	Postcards (315 samples @ 10¢)	31.50	
	Gas and van maint. (9 657.1 miles @ 10¢/mile)	965.71	
	Telephone charges (57 days @ $3/day)	171.00	
			1 246.96
3	Indirect, fixed, and overhead costs		
	Data entry technician (57 days × 3 h/day @ $2.50/h)	427.50	
	Salaried employee (4 months)	1 500.00	
	Non-salaried employee (353 h @ $2.50/h)	882.50	
	Terminal (4 month rental @ $ 60/mo)	240.00	
	Motel rooms (57 days @ $20/day)	1 140.00	
	Food allowance (114 man-days @ $10/day)	1 140.00	
			5 330.00
4	Net investment		
	Van	4 500.00	
	Calculator	2 500.00	
	Laboratory equipment	500.00	
	Power	525.00	
			8 025.00
5	Economic life of system		5 years
6	Income tax rate		zero
7	Average annual depreciation		1 605.00
8	Total deductions		8 181.96
9–11	Net profits		1 268.04
12	Net cash flow		2 873.04
13	Capital recovery rate		0.3580
14	Return on investment (ROI)		23.1%

far the most profitable (ROI = 55.1%) although all systems appear viable.

It should be noted that there are a variety of other types of project analyses in common use. These include breakeven analysis (what price results in zero profits), payout time analysis, and

Table 5. Discounted cash flow analysis of the reduced system two (RS II)

Line	Description	Entry	Total
1	Revenues (315 samples @ $30)		$9 450.00
2	Direct production costs		
	Supplies (315 samples @ 25¢)	78.75	
	Postcards (315 samples @ 10¢)	31.50	
	Gas and van maint. (11 480.1 miles @ 10¢/mile)	1 148.01	
	Telephone charges (55 days @ $1/day)	55.00	
	Refrigeration (315 samples @ 10¢)	31.50	
			1 344.76
3	Indirect, fixed, and overhead costs		
	Salaried employee (4 months)	1 500.00	
	Technicians (3 @ 55 days × 5 h/day × $2.50/h)	2 062.50	
	Terminals (3 @ $60/mo rental for 4 months)	720.00	
	Food allowance (55 man-days @ $10/day)	550.00	
			4 832.50
4	Net investment		
	Van	4 500.00	
	Laboratory equipment	500.00	
	Power	275.00	
			5 275.00
5	Economic life of system		5 years
6	Income tax rate		zero
7	Average annual depreciation		1 055.00
8	Total deductions		7 232.26
9–11	Net profit		2 217.74
12	Net cash flow		3 272.74
13	Capital recovery rate		0.6204
14	Return on investment (ROI)		55.1%

cost/benefit analysis. The combination of methods described in this chapter includes these types of analyses and others as special cases. Breakeven charges may be calculated by comparing Line 1 with Line 8. Payout time is just (1/CRR). Cost/benefit ratios may be determined by interrelating the results of the decision maker and monitoring service analyses over the management region and comparing the results to those of the current system. In this way the full economic impact of the proposed system may be ascertained.

6 The analysis of system time delays

For any monitoring mission there are a variety of suitable technological alternatives each possessing associated costs and time delays. In this chapter we shall analyze the total monitoring time delay by decomposing the sampling cycle into a series of discrete actions as in Table 6.

Table 6. 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 Fig. 2 for an explanation of delays 1, 2, and 3.

6.1 Transmission of the trigger event

The length of this delay, although usually short, depends on the nature of the trigger. For example, this delay might be effectively zero for those designs that involve sampling at preset times or at a fixed interval following an easily observable event. In the FS and RS I systèms, grower use of the telephone to make requests yields a very short delay (perhaps one day). Systems which rely on environmental parameters (heat units, rainfall, etc.) to schedule sampling are, as a minimum, subject to any delays in acquiring these data. This is also the case for sampling protocols triggered by biological observations of some other species.

6.2 Transportation to the sampling site

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). 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 & Ellington, 1973) most biological parameters still require manual sampling. If there are many sites or if sites are widely scattered sample collections can involve significant amounts of travel time.

To determine the distribution of travel time delay in the mite counting system, each of the seven management regions was divided into two approximately equal subareas. The average trip length within a subarea was calculated as

$$\text{distance} = \tfrac{1}{2}A^2 \qquad (6.1)$$

where A is area. Optimal routes were selected for trips between subareas. Matrices of inter-subarea distances and travel times were created 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. In determining travel times 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; Croft et al., 1979). Fig. 11 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 40.

6.3 Collection of the sample (or data) and processing

Categories 3 and 5 of Table 6 include all activities in the sampling protocol (capturing specimens, drying or dissecting them, counting them, etc.). This type of delay may be analyzed by decomposing the protocol into a series of steps and determining how the duration of each step varies with workload, desired accuracy, etc. The basic timing data for this analysis can be taken by adding to data notebooks a notation for each sample as to how long the various

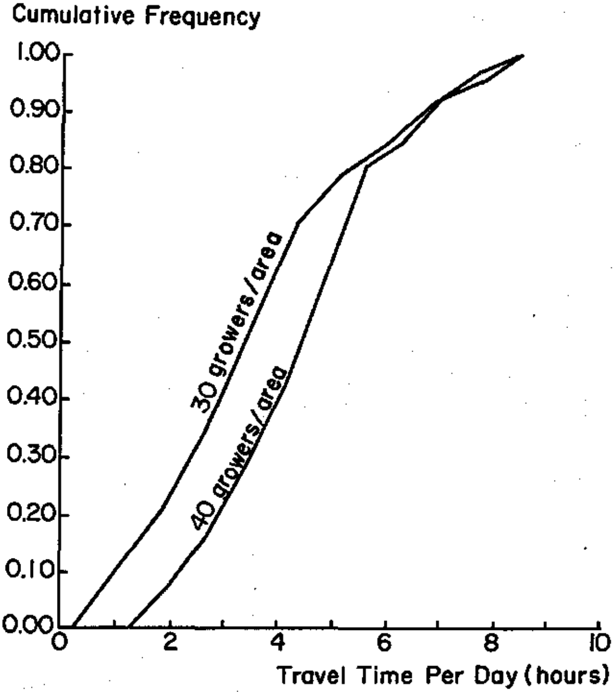


Fig. 11. The cumulative density functions of travel time per day for two different levels of demand. The distributions were generated by a simulation of the logistics of the FS mite counting service.

processing steps took. This data may be collected prior to the design process because the protocol will often consist of techniques in current use. Even for new techniques there is almost always a period where new and old methods are operated side by side and timing comparisons are made.

For mite counting the protocol was partitioned as shown in Table 7. The column on the right 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

$$\text{collection delay} = 0.25 + 0.00833(\text{NTR}) + 0.00167(\text{NTR})(\text{NLV}) \qquad (6.2a)$$

Table 7. Partition of a mite sampling protocol into discrete actions and the required times

Time to pick the leaves	
1. Fixed factors	0.250×10^{0} h
2. Factors proportional to #trees	0.833×10^{-2} h/tree
3. Factors proportional to #leaves	0.167×10^{-2} h/leaf
Time to count leaves	
1. Fixed factors	0.449×10^{-2} h
2. Factors proportional to #leaves	0.670×10^{-3} h/leaf
3. Factors proportional to pest density	0.500×10^{-4} h/mite
4. Factors proportional to predator density	0.340×10^{-3} h/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.

$$\text{processing delay} = 0.00449 + (\text{NTR} \cdot \text{NLV})(0.00067 + (\text{A})(\text{M})) \tag{6.2b}$$

where

$$\text{M} = 0.00005(\text{NES}) \cdot (\text{ER}) + 0.00034(\text{NAS})(\text{AF}). \tag{6.2c}$$

The variable definitions are given in Table 8. In actual use NAS and NES can be determined from sample size curves based on the densities of mites in the sample (Croft et al., 1976b). For a sample of 200 leaves taken 5 per tree, Fig. 12 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 Fig. 12 are due to the integer nature of the number of plate sectors counted.

Table 8. Definition of variables in the timing equation (6.2)

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

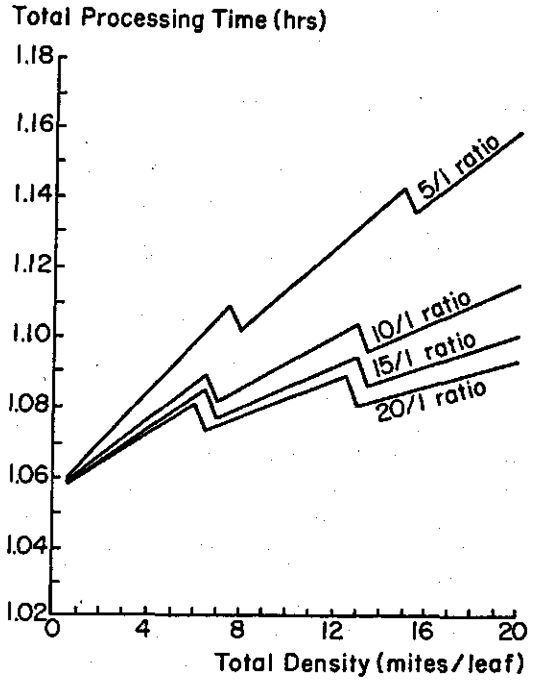


Fig. 12. The total processing time for mite samples as a function of total mite density and prey-predator ratio.

6.4 Transportation to the processing site

In most cases samples are not processed at the collection site but are transported to a specialized laboratory for examination. Alternatively, samples may be examined in the field but the resultant data require further manipulation (statistical, mathematical, comparison with previous data, etc.). In either case, transportation must be included as a component of total delay.

An example is provided by the BLITECAST system (Krause et al., 1975) which integrates rainfall, relative humidity, and temperature to produce a spray recommendation for potato late blight (*Phytophthora infestans*). Data are taken in the field and processed by a central computer. As is frequently the case when plant pathogens are involved, any time delay is critical. In one case on record, a two-day delay in data transmission resulted in a grower loss of approximately 50 000 dollars (Bird, pers. commun.). This testifies to the importance of characterizing *all* sources of delay.

6.5 Transmission of results to the decision maker

Some types of materials, such as raw biological samples, must be transported in physical form. Other data, however, can be either transported or sent electronically by such devices as Code-a-phones® (telephone playback equipment), data terminal networks, or the mass media (e.g., mailed circulars). 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 (Croft et al., 1976a; Brunner et al., in press). 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 and, when appropriate, the transmission of alert messages. Using this system, 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.

6.6 Accomplishment of the control action

This is the delay between the decision maker's reception of the monitoring results and the implementation of a control action. 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.

6.7 An example

After all seven of the delays in Table 6 have been analyzed, the next step is to determine how they are altered by changes in design

1. Published cooperatively by the Coop. Ext. Serv. and the Departments of Entomology, and Botany and Plant Pathology, Michigan State University, East Lansing, MI 48824.

parameters and how this affects system performance. One of the goals of the mite monitoring analysis was to determine the effect of requiring more accurate estimates of mite density. On the one hand, more accurate data should result in better decisions. Better data, however, require more labor, and this could have adverse effects on time delays and costs.

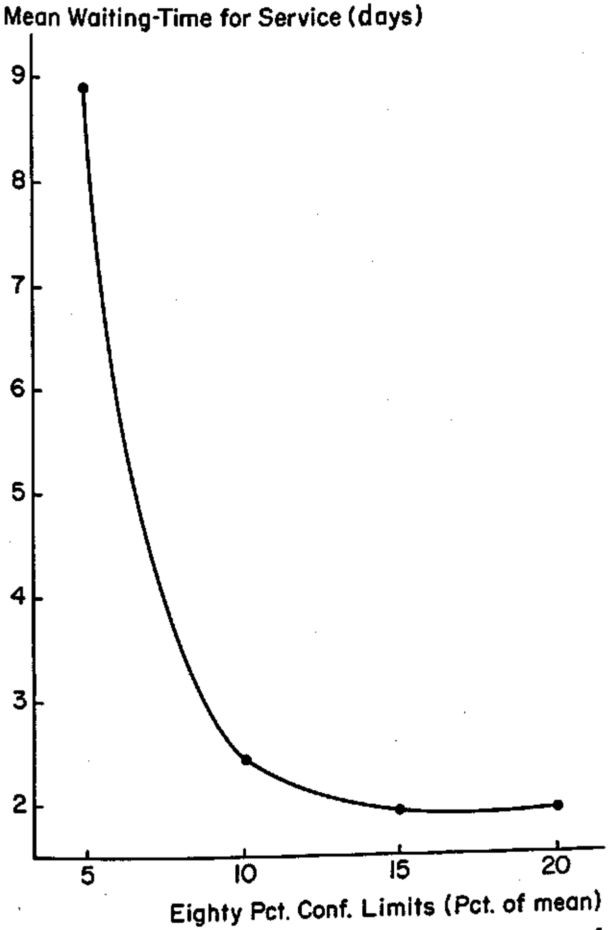


Fig. 13. The mean waiting time for service as a function of desired accuracy. As greater accuracies are demanded, processing times increase generating a system bottleneck. This leads to the exponential rise in service wait times.

The first step was to find mean waiting time for service as a function of desired accuracy. Accuracy was defined as one half the width of the 80 percent confidence limits expressed as a percentage of the estimated mean mite density. Sample size equations, when combined with the workload equations 6.2 a, b, and c yielded per sample time costs. Simulation runs incorporating these figures and the other delays just discussed resulted in Fig. 13 for the Full System.

As is evident, requiring greater accuracies increases processing times to the point where a severe bottleneck is created. This leads to an exponential rise in service wait times. In the next chapter we shall see the effect this can have on, among other things, risk to the grower.

7 Mathematical relations between design factors

This chapter probes certain mathematical relationships between previously discussed design factors including variability within monitoring units, economic risk, management system time delays, and intensity of operations. We shall refer to these factors as v, r, t, and i, respectively. There are many variables which can be used as indices for each of these factors (Table 9) and a designer may desire to examine several to gain a more complete picture.

Table 9. 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.

7.1 Mathematical relations

Given a particular combination of indices we assume that the following relations hold for two continuous and differentiable functions, $t=\mathrm{h}(r, v)$ and $i=\mathrm{g}(v, t)$ defined over the region of interest:

$$\frac{\partial i}{\partial v}<0 \tag{7.1a}$$

$$\frac{\partial i}{\partial t}<0 \tag{7.1b}$$

$$\frac{\partial t}{\partial r}>0 \tag{7.1c}$$

$$\frac{\partial t}{\partial v}<0 \tag{7.1d}$$

The function g relates the variability of the monitoring unit and system time delays to monitoring intensity (frequency, number of sampling points, redundancy, etc.). Variability and delays affect the risk associated with ultimate use of the data; increases in either one may degrade the utility of the results. Other than by selecting homogenous monitoring units, v can be reduced only by increasing i. This is stated by inequality 7.1a. Improving reliability by decreasing time delays also requires increased effort (7.1b).

The function h yields maximum allowable delay in terms of monitoring unit variability and permissible risk level. The form of h depends heavily on biological factors. The longer the sampling cycle takes, the more conceivable the possibility (i.e., risk) that significant damage has occurred. Inequality 7.1c merely states that the higher the permissible risk, the longer the permissible delay. Inequality 7.1d states that we must act quickly in order to avoid risk in uncertain (i.e., highly variable) circumstances.

Although they must be verified in each specific instance, it seems likely that the relations in Eqn 7.1 will hold in many practical cases. Two important results follow from these conditions.

Theorem 1: There exists a one-to-one transformation between the ordered pair (r, v) and the ordered pair (t, i).
Proof: Consider the transformation defined by the equations

$$t'=t'(r, v)=\mathrm{h}(r, v)$$

$$i'=i'(r, v)=\mathrm{g}(k(r, v), \mathrm{h}(r, v))$$

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

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

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 cancelling $\partial t/\partial r$ which is not zero by Eqn 7.1c 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 Eqn 7.1a. 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

Theorem 2: 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 *may* not be possible to solve for v and t.
Proof: Define the following four univariate functions

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

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

where the subscript x is a '0' for given values and a 's' for solved values. Equations (7.1a, 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_0, v_0	$t_s = \mathrm{h}(r_0, v_0)$,	$i_s = \mathrm{g}(v_0, t_s)$
t_0, v_0	$i_s = \mathrm{g}(v_0, t_0)$,	$r_s = \mathrm{h}_{v_0}^{-1}(t_0)$
i_0, v_0	$t_s = \mathrm{g}_{v_0}^{-1}(i_0)$,	$r_s = \mathrm{h}_{v_0}^{-1}(t_s)$
t_0, r_0	$v_s = \mathrm{h}_{r_0}^{-1}(t_0)$,	$i_s = \mathrm{g}(v_s, t_0)$
i_0, t_0	$v_s = \mathrm{g}_{t_0}^{-1}(i_0)$,	$r_s = \mathrm{h}_{v_s}^{-1}(t_0)$

If we are given i_0 and r_0 we proceed by substituting h into g giving the system of equations

$$t = \mathrm{h}(r_0, v)$$

$$i_0 = i'(r_0, v)$$

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

$$i'^{-1}_{r_0}(i_0)$$

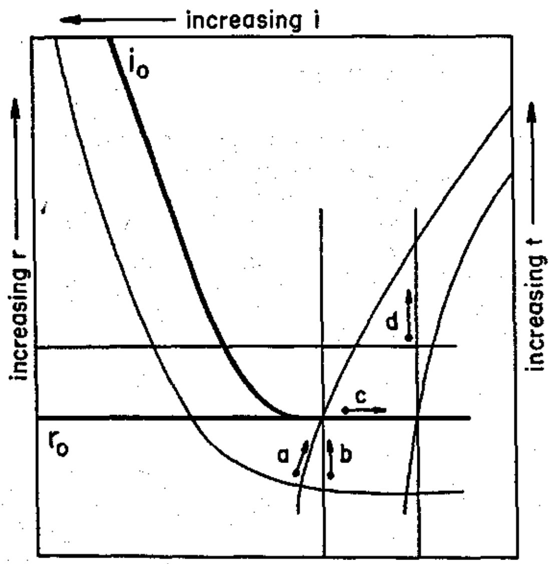


Fig. 14. A counterexample for Theorem 2. In this instance, i_0 and r_0 are given. Motion along the trajectories indicated by the arrows (a, b, c, d) demonstrates that the corresponding inequalities in Eqns 7.1 a, b, c, d hold. In spite of this, it is evident that there is no unique solution for v and t.

is unique. An example of when this fails to occur is shown in Fig. 14. Examination of this figure shows all of the relations (7.1 a, b, c, d) to be satisfied.

The importance of these theorems is that they permit us to construct a nomogram which displays graphically the relation between time delays, technologies, pricing structures, etc. 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. The contours can be calculated using whichever scheme in the proof of Theorem 2 is most convenient.

7.2 Mite counting systems: function derivation

In applying the results of the previous section one must (1) select a suitable set of parameters v, i, t, r, (2) derive the functions g and h, (3) prove that these functions satisfy the conditions of the two theorems, and (4) prepare the chart.

So as not to obscure the illustrative value of this example we shall select measures for v, i, r, and t which are somewhat simpler than might be justified in practice. Let v be the radius of the monitoring unit and r be the probability of exceeding a nominal injury level (P_D) of 15 mites per leaf. 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_0) of 7 mites per leaf. Let t be the maximum delay allowed between triggering and the application of control, and i be the following *ad hoc* index

$$i = g(v, t) = Ct^{-1}v^{-2} \tag{7.2}$$

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

To derive $h(r, v)$ we first note that we have, from Eqns 4.22 and 4.18,

$$E(\ln \lambda) = \ln \lambda_s = \bar{r}_s t + \ln P_0, \tag{7.3}$$

and, from Eqn 4.23,

$$\mathrm{Var}(\ln \lambda) = k^2 V(v) t \tag{7.4}$$

where we have renamed d as v. Since we have assumed normality for $p(\ln \lambda \mid \ln \lambda_s)$ we have

$$r = 1 - \operatorname{erf}\left(\frac{\ln P_D - \ln P_0 - \bar{r}_s t}{k V(v)^{1/2} t^{1/2}}\right) \tag{7.5}$$

where erf is the cumulative distribution function of a standardized normal variate. We note that some algebra suffices to rewrite Eqn 7.5 as

$$c = (a + t)/(bt^{1/2}) \tag{7.6}$$

where

$$a = -\frac{1}{\bar{r}_s} \ln(P_D/P_0) < 0 \tag{7.7a}$$

$$b = -\frac{1}{\bar{r}_s} k V(v)^{1/2} < 0 \tag{7.7b}$$

$$c = \operatorname{erf}^{-1}(1 - r) > 0. \tag{7.7c}$$

The inequalities (7.7 a, b) are obvious by inspection; Eqn 7.7c declares that we are not interested in economic risks greater than 50 percent. Solving Eqn 7.6 yields

$$t^{1/2} = \tfrac{1}{2}(cb \pm (c^2 b^2 - 4a)^{1/2} \tag{7.8}$$

which, from Eqn 7.7, has exactly one positive and one negative root. Discarding the negative root as not meaningful gives

$$t = h(r, v) = \tfrac{1}{4}(cb + (c^2 b^2 - 4a)^{1/2})^2 \tag{7.9}$$

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

$$\frac{\partial i}{\partial v} = -2Ct^{-1}v^{-3} < 0 \tag{7.10a}$$

$$\frac{\partial i}{\partial t} = -Ct^{-2}v^{-2} < 0 \tag{7.10b}$$

so Eqns 7.1 a, b hold. Differentiating h yields

$$\frac{\partial t}{\partial v} = \frac{1}{2} f_1 f_2 b_v \tag{7.11a}$$

$$\frac{\partial t}{\partial r} = \frac{1}{2} f_1 f_3 \tag{7.11b}$$

where

$$f_1 = (cb + (c^2b^2 - 4a)^{1/2}) > 0 \tag{7.12a}$$

$$f_2 = c + c^2b(c^2b^2 - 4a)^{-1/2} \tag{7.12b}$$

$$f_3 = (c_r b + b_r c + \tfrac{1}{2}(c^2b^2 - 4a)^{-1/2}(2cc_r b^2 + 2c^2 bb_r - 4a_r)) \tag{7.12c}$$

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

$$f_3 = c_r b + cc_r b^2/(c^2b^2 - 4a)^{1/2} \tag{7.12c'}$$

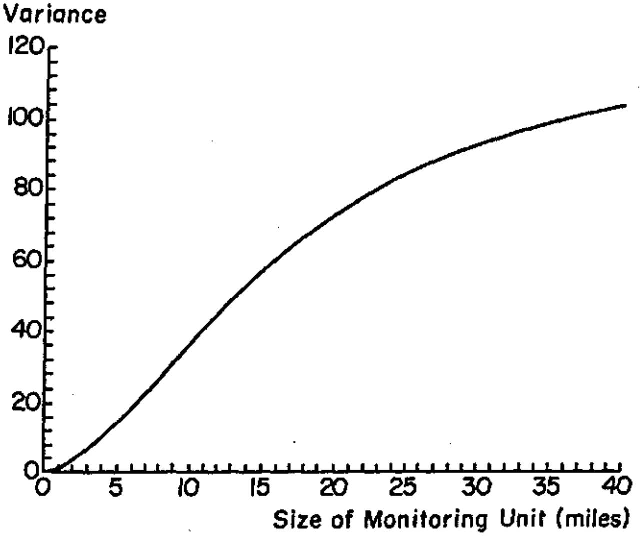


Fig. 15. The function V(v) graphed by assigning the parameter values of Chapter 4. This describes the variance of a series of temperature readings from points selected randomly within monitoring units of different sizes. Clearly, both V and its derivative are positive over the range of values shown.

From the inequalities 7.7 a, b, and c we have

$$bc^2/(c^2b^2-4a)^{1/2} > bc^2/|cb| = -c \tag{7.13a}$$

$$cc_rb^2/(c^2b^2-4a)^{1/2} > cc_rb^2/|cb| = -c_rb \tag{7.13b}$$

or, upon rearranging terms across the inequalities

$$f_2, f_3 > 0 \tag{7.14}$$

This yields Eqn 7.1c directly. To complete the proof of Eqn 7.1d we note that

$$b_v = -\frac{k}{2\bar{r}_s} V(v)^{-1/2} \frac{\partial V}{\partial v} \tag{7.15}$$

Since, when the parameter values from Chapter 4 are used, both $V(v)$ and its derivative are positive over a reasonable interval (see Fig. 15), we have b_v and, therefore, $\partial t/\partial v$ negative. Fig. 16 shows the resulting contour plot.

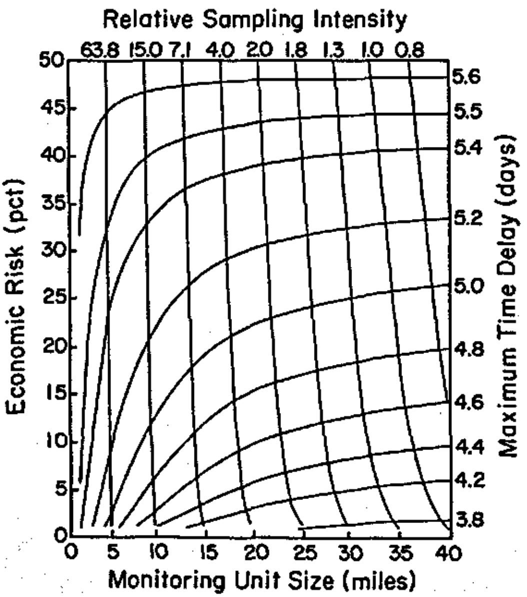


Fig. 16. Contour lines of sampling intensity and maximum allowable time delay as a function of risk and monitoring-unit size.

7.3 Mite counting systems: nomogram applications

Two uses of the nomogram are presented in this section: (1) further interpretation of the cash flow (DCF) analysis and (2) grower impacts of highly accurate sampling plans.

In the DCF example, the ROI values for the FS, RS I and RS II systems are plotted (Fig. 17) on the nomogram. Their positions are determined from (1) the time delay submodel and (2) the average distance traveled between sampling points (for monitoring unit size). Once plotted, sampling effort and risk to the grower may be read from the chart. There is no significant difference in the performance of FS and RS I. The results for RS II are interesting because the predicted risk (12 percent) is almost identical to the level actually realized (11 percent as mentioned in Chapter 5).

Suppose, as an example of chance constrained programming, we were interested only in those systems in which risk to the grower was less than, say, 7.5 percent. This constraint could be realized by rejecting all systems whose performance lay in the region above the horizontal line in Fig. 17. In this instance, 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 the previous chapter the effects of increased sample accuracy on mean waiting time for service were discussed. We now take this a step further and assess grower impacts. To do so we shall extend slightly the plotting technique used in the last example. The location of the points in that example were functions of the design parame-

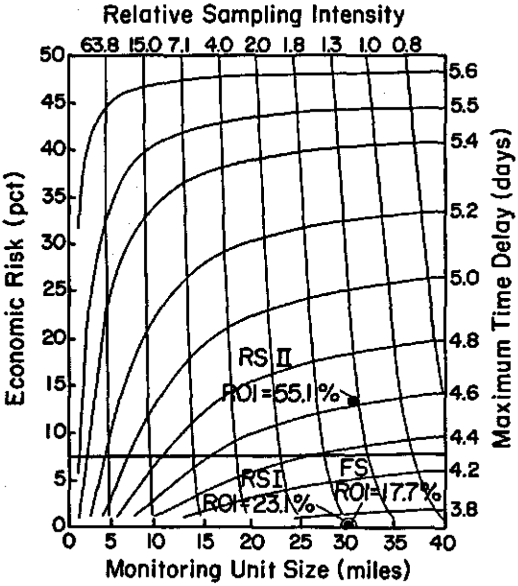


Fig. 17. The return on investment for three mite monitoring systems plotted on a nomogram showing system performance. The horizontal line represents a constraint on system risk. This illustrates that the most profitable system (RS II) is also the most risky to the grower.

ters. Changes in those parameters would cause the points to trace out curves in the plane. Changes in single variables or in sets of variables with only one degree of freedom would produce a line. Changes in sets with more than one degree of freedom would have more complex results which can be analyzed by additional contour lines.

Fig. 18 shows the results of transposing data of Fig. 13 onto the nomogram. The delays were read using the nomogram axis on the right and the sampling accuracies of two points were labelled on the resulting line. Because of the properties of the nomogram, 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 previous chance constraint, one concludes that confidence limits narrower than about 7.2 percent should not be

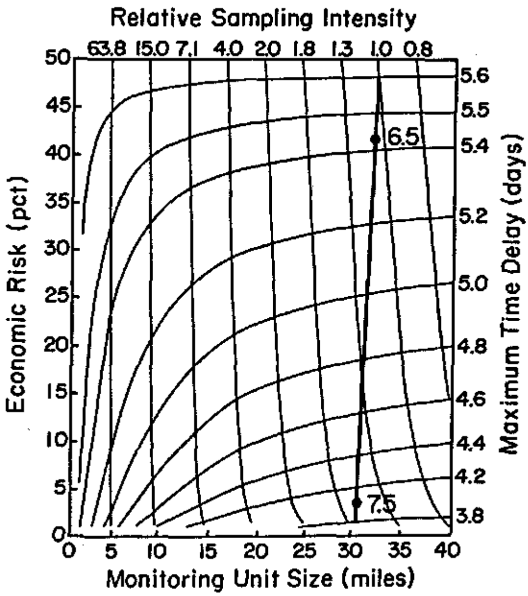


Fig. 18. A continuum of technologies indexed by desired sampling accuracy. Each point on the graph was plotted by taking the time delay from Fig. 17 and the monitoring unit size from the original simulations (see text). The figure illustrates that when confidence limits are already tight (7.5 percent)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

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 summary, this chapter has demonstrated mathematical and graphical procedures which can be used to relate the design factors in a simplified manner. When these data are plotted together with the relevant constraints, the final choice of a feasible configuration can be made.

8 Synopsis of design procedure

The previous chapters discussed the factors and data necessary to design the monitoring component of a management system. In this chapter we present a unified and integrated plan for the design process 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 is biological investigation of the pest ecosystem (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 3. 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.

This general information is combined into a detailed statement of management needs which specifies 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 the ultimate system must be acceptable to these personnel.

The designer next determines if it is feasible to meet these needs with current technology. This involves the rough screening of 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, construction proceeds on the monitoring component and the decision algorithms it drives. This involves detailed studies of the population dynamics and the formulation of a model of the pest ecosystem (Chapter 3). 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 are the influences of environmental factors on these processes. 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, 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 constant rate of five percent per day.

These studies will require monitoring of field populations (as may the preceding needs analysis). Monitoring methods may be taken from the literature, from experience with similar species, or be created *de novo* for the new system. Several distinct monitoring approaches should be compared. 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 should 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 fieldwork is to evaluate the use of these latter methods and provide the statistical, timing, and cost data necessary to implement an optimized monitoring component.

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 6. 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.

When several sampling methods are being used, they may not all measure exactly the same thing or they 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.

If there are very few methods available (perhaps only one) or if initial screening yields one of clear superiority, then protocol variations should be employed. That is, one alters such parameters as sample size, number of subsamples, etc. 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 6) 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.

Another category of auxiliary data which should be recorded concerns travel times to remote sites and the costs of vehicle operation. While the map-based methods of Chapter 6 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.

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 Chapter 5. 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 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 7). 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 5, 6, and 7). 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 Fig. 2) in conjunction with the planning function described in Chapter 2. 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.

It is useful to comment here on the relationship between the approach outlined in this monograph and actual pest management programs which have been developed in the United States in recent years. In many of these programs dichotomies exist in the early developmental stages between the activities of research and extension. Research has tended to emphasize the synthesis of mathematical models of agro-ecosystem processes, the construction of new or improved decision-making rules, and the development, where necessary, of field sampling techniques (Gutierrez et al., 1977; Shoemaker, 1973c). The implementation of field delivery systems has been (quite properly, many would argue) extension's contribution. These efforts have encompassed the creation of extension pest management programs, grower-owned pest management cooperatives, and, in some instances, private advisory services (Hepp, 1976).

We argue that, since experience indicates that program success is directly related to the degree of cooperation and early feedback between research and extension, a design approach which unites the constraints and objectives of both groups should be extremely useful. The design process outlined here is typical of the systems approach to problem solving (Manetsch & 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 monograph will play a determining role.

Chapter 3 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 dominated by a few large, diversified, oligopolistic producers. In contrast to the example in Chapter 3, 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 pest control 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. Fig. 2 might well serve as a management schematic for any number of these. In any such instance, the analysis set forth in this monograph 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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