Veterinary Epidemiology: Principles and Methods

Part 2: Studying Disease in Animal Populations
Chapter 8: Theoretical Epidemiology: Systems Analysis and Modeling

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CHAPTER 8

Theoretical Epidemiology: Systems Analysis and Modeling

Animal agriculture is an activity primarily carried out to produce food and fiber by the deliberate and controlled use of plants and animals (Spedding 1979). In this context agriculture can be thought of as being manipulative ecology with its basic operational units being production systems.

Animal production systems are complex. They are composed of and influenced by complex interactions among biologic, climatic, economic, social, and cultural factors. The biologic component includes plants, animals, disease, and the association between disease and animal productivity. Because of the complexity of production systems, decisions based on simple analyses involving only a few factors may not be effective in improving the efficiency of the system. Rather, optimal decisions are likely to be those based on an objective and holistic analysis. How to conduct such an analysis as well as the necessary decision-making strategies are embodied in the systems approach.

8.1 Systems Approach

Biologic systems may be thought of conceptually and practically in a vertical manner beginning with the smallest systems (atoms) and progressing through cells, organs, body systems, individuals, and populations (e.g., farms). Although it is an oversimplification, research at levels below the individual may be deemed reductionistic, whereas research at levels above the individual is holistic. The systems approach is based on the recognition that a broad perspective is necessary when investigating any type of organized system. Since the various parts of the system are linked together in an interactive and interdependent manner, examination of isolated components can lead to erroneous conclusions because critical feedback within the system may be overlooked (Morley 1972).

As mentioned earlier, veterinarians are becoming increasingly concerned with ecologically-complex health-related problems. Disease per se is only part of the production system, but it needs to be investigated with consideration given to both the complex interactions between factors that influence disease levels and to the possible ramifications of control procedures. This has led to a realization that the approach to health care must be based on comprehensive information using continuously upgraded decision-making skills. While philosophically accepted, this holistic approach has been rarely adhered to in practice because no appropriate method of analysis was available for complex systems. Investigators attempting to consider all factors tended to become lost in a mass of details.

Modern computers have provided a partial solution to this impasse, and in recent years there has been a rapid expansion in research that has used the computer to perform the time-consuming work associated with analyzing and simulating the behavior of complex biological systems. The computer allows problems to be approached in new ways and it allows one to deal with whole problems, not just parts of them.

The systems approach using electronic devices is not new. Airline pilots practice for hours on flight simulators before taking on the responsibility of passengers' lives. These professionals use models to test various alternatives prior to implementation and the making of potentially costly errors.

Systems thinking is not new to veterinarians either. Rather than using computers and complex mathematical functions, veterinarians have relied on experience, judgment, and common sense. However, the tasks are becoming more complex as the scale of enterprises increases, as the depth and diversity of technology intensify, and as the array of production alternatives broadens. As this happens, it becomes unrealistic for an individual's mind to master and retain an understanding of all parts of the system and the consequences of interrelationships within the system.

Although systems thinking is not new to veterinary medicine, what is perhaps more recent is the selection of end points other than disease (e.g., health and productivity), and the growing concern with levels of organization above the individual animal.

One of the roles of the epidemiologist is to bring together data from the field and the laboratory. In doing this the epidemiologist creates at least a conceptual model of the system under consideration, including its state of health, and wherever possible attempts to quantify the role of each component in the system. This is not a simple task because very often little is known about the quantitative aspects of agent transmission or the association of disease with productivity. One major benefit of modeling is that in attempting to construct a model one becomes aware of key data that are missing; this in itself is instructive in terms of understanding complex problems. Once constructed, most models can be used to help decide between alternative control procedures under various situations (i.e., they can be used as a tool to aid decision making).

The purpose of this chapter is to present some basic modeling concepts and to illustrate several of the common types of models. Further applications of models will be presented in subsequent chapters.

8.1.1 Definitions

Systems analysts and "modelers" often use words in a specific context that is different from their everyday meaning. Hence a set of definitions is useful (Anderson 1974).

System – a group of interacting components operating together for a common purpose, capable of reacting as a whole to external stimuli; it is unaffected directly by its own outputs and has a specified boundary based on the inclusion of all significant feedback pathways (Spedding 1979).

Model – representation of a real system; it is not an exact representation, merely a simplification of one form or another.

Components – identifiable units within the system.

Relational or flow diagram – one that is used to show the interrelationships of the components in a system.

Driving variables – those variables that affect the system but are not affected by it (e.g., meteorologic factors).

System state variables – components of the system that may change state (e.g., from healthy to diseased) over time.

Experiment – the process of observing the performance of the system or its model under a specified set of conditions.

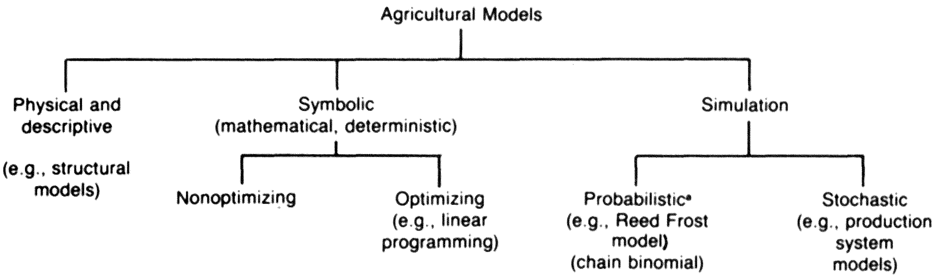
Model characteristics – referred to as "simular," their real-life counterparts referred to as "simuland."

8.2 Types of Models and Their Development

Models are used in an attempt to approximate or mimic real-world systems and as such there are a number of different types. For present purposes, agricultural models will be classified as illustrated in Figure 8.1.

8.2.1 Physical and Descriptive

Physical models have been used for many years and in many different areas of activity. Chemists construct models of molecules in an attempt to gain a better understanding of their structure and properties. Agricultural engineers build models of farm buildings and test the effects of building design and placement on local air movement (including the accumulation of



*Probabilistic models may be either deterministic or stochastic depending on how they are formulated.

8.1. Classification of agricultural models.

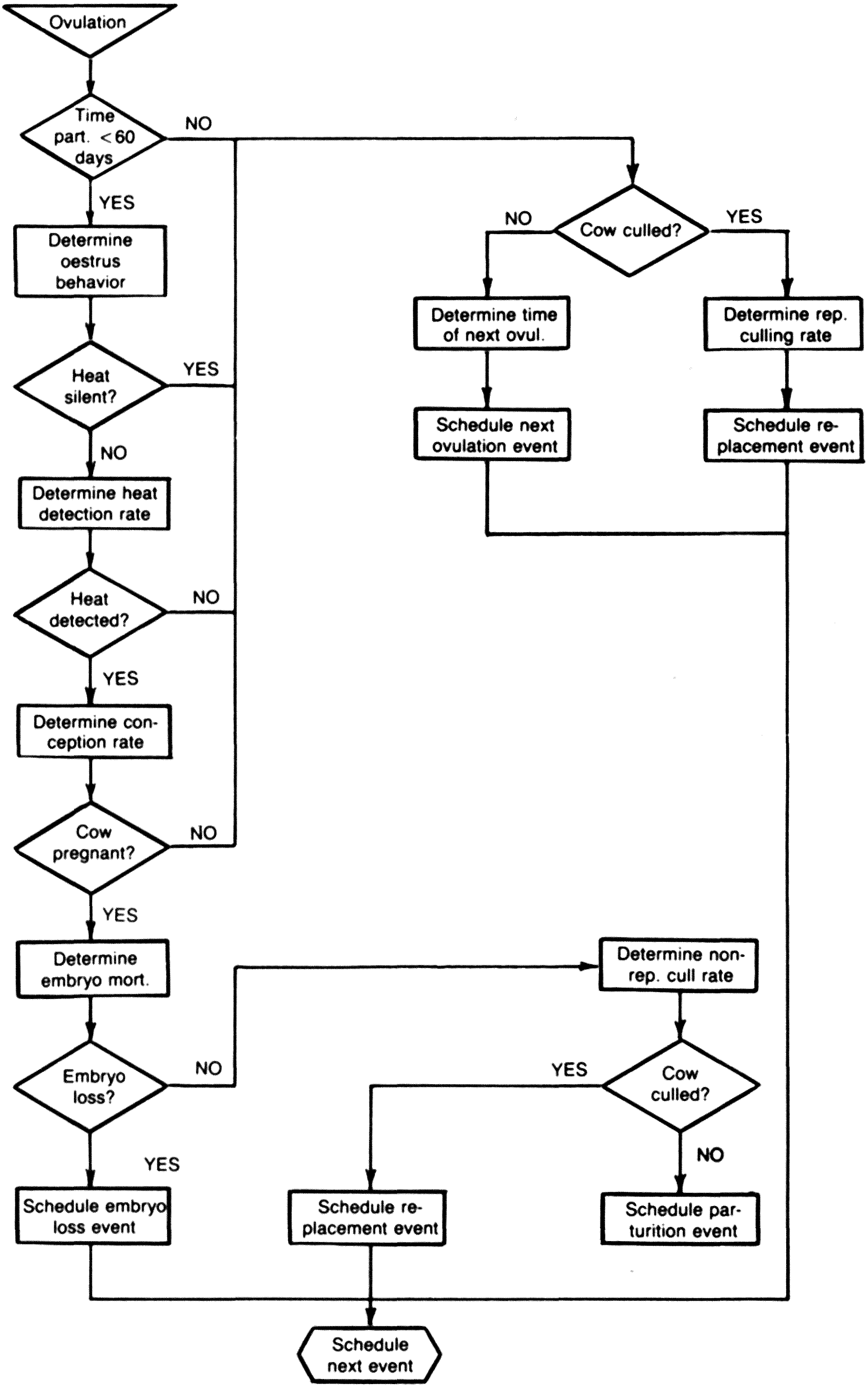
snow) in wind tunnels. The latter models allow for modifications to be made prior to large expenditures being committed to construct full-scale buildings.

Descriptive models include diagrams and charts designed to portray a real-world system or subsystem. These usually include the major inputs, outputs, and internal processes. Such relational diagrams can be used for a number of purposes including assisting with the organization of available information and identifying gaps in knowledge. An example of a relational diagram depicting events associated with reproduction in dairy cattle is presented in Figure 8.2 (Oltenacu et al. 1980). While they can help with the conceptualization of problems, such models do not yield information concerning how the system will perform under various conditions. To achieve this objective it is usually necessary to transform the model into mathematical form. One way of achieving this is through path models as was discussed in Chapter 5; other approaches are described here.

8.2.2 Symbolic

In general, symbolic models use mathematical symbols to describe the status of variables at a given time and to define the manner in which they change and interact (Emshoff and Sisson 1970). These models are usually deterministic in nature (i.e., they are concerned with average results). The output from deterministic models is controlled solely by the values of the parameters; there is no element of randomness, and hence output for a given set of inputs is always the same. Models of this type can be further subdivided into optimizing and nonoptimizing. An example of a symbolic nonoptimizing model would be the well-known law of physics $E = mc^2$. Models of this type will not be discussed further.

An optimization model is one that seeks the best mix of inputs to achieve an objective, and it usually consists of a mathematical function to



8.2. Relational diagram depicting events associated with reproduction in dairy cattle. (Source: Oltenacu et al. 1980, with permission) be maximized or minimized and a series of constraints. Optimization models are frequently used in biometrics and economics, although perhaps the best known application of the technique is the use of linear programming (linear objective function) in least-cost feed formulation. An example of linear programming is presented in 8.3.1.

8.2.3 Simulation

A simulation model implies a dynamic process or representation of a system achieved by building a model and moving it through time.

In general, simulation models are designed to mimic the system under study as closely as possible. Hence, the model builder tries to achieve a substantial degree of epidemiologic realism in the structure of the model, and the parameters used are chosen so they can be readily related to features in the system being modeled. Simulation models are built using combinations of arithmetic and logical processes and, in this sense, have features in common with symbolic models. They are generally used to search for the best alternative, often by a process of trial and error.

For present purposes, simulation models have been subdivided into probabilistic and stochastic (Fig. 8.1). As the name implies, probabilistic models include basic concepts of probability theory and may (depending on how they are formulated) be deterministic or stochastic.

8.2.3.1 CHAIN BINOMIAL. Chain binomial models allow the investigation of patterns of binomial phenomena over time. A well-known deterministic probability model is the Reed-Frost model of a theoretical epidemic (Abbey 1952). The model allows for the calculation of the number of cases and susceptibles in the population in successive periods of time; hence a chain binomial model results. The latter model will be discussed in 8.3.2.

8.2.3.2 MARKOV CHAIN. If a system can be represented by a discrete number of possible states, and at each time interval individuals can move between states according to some given probability, the system may be modeled using a process called a Markov chain. Specifically, if the vector representing the number of individuals in each of n states is known (state vector S_1, $S_2, \ldots, S_n$), the probabilities of moving from one state to another can be represented as a transition probability matrix (P) with the following format:

$$
\begin{matrix}
P_{11}\ P_{12}\ \ldots\ P_{1n} \\
P_{21}\ P_{22}\ \ldots\ P_{2n} \\
\cdot \\
\cdot P_{ij} \\
\cdot \\
P_{n1}\ P_{n2}\ \ldots\ P_{nn}
\end{matrix}
$$

where P_{ij} is the probability of going from state i to state j.

When the state vector is multiplied by the transition probability matrix, the number of individuals in each state at the end of the time period (t) under consideration is:

$$(S_1, S_2, \ldots, S_n)_t \times P = (S_1, S_2, \ldots, S_n)_{t+1}$$

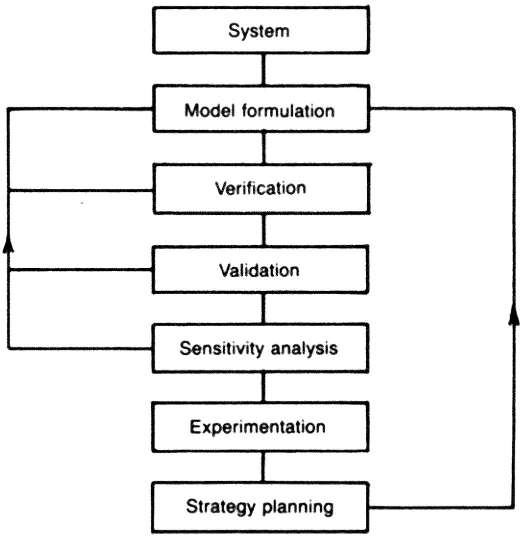
8.2.3.3 STOCHASTIC. Models of this type include an element of randomness. Hence, the outcome of the model for a given set of inputs can vary depending on the element of chance. It is generally believed the inclusion of chance variation (randomness) makes the model more biologically realistic than could be achieved by the corresponding deterministic model. Monte Carlo sampling is basic to the concept of simulation models containing stochastic elements.

Monte Carlo sampling is a method of allowing for the effects of chance. In the application of this technique, random numbers are produced by computer programs and are then used to either sample continuous distributions or to decide whether a change of state of a binomial variable occurs. In the former case, a number between 0 and 1 is randomly produced and then used to select a sample from the cumulative distribution function of the biological variable under consideration. For example, if the biological variable is approximately normally distributed, this process will result in values at and about the mean of the distribution being sampled more frequently than those at the extremes. In the latter case a random number is produced between 0 and 1, and its value is compared to the long term expected probability of the event occurring. If the generated number is less than or equal to the defined probability, the event is considered to occur. In this way individual events occur stochastically, while the long-term frequency of occurrence is determined by the specified parameter value. If the model included the event milk fever occurrence, and it had previously been determined that the probability (rate of occurrence) of the condition in the age and breed of cattle under consideration was 0.15, the generated values would be compared to 0.15 to decide whether the individual animal would or would not develop the disease at that point in the modeling process.

8.2.4 Stages in Model Development

The general sequence of steps followed in model development within an overall systems analysis is outlined in Figure 8.3.

8.2.4.1 MODEL FORMULATION. There must be a clear statement of objectives. Models developed as ends in themselves will probably not turn out to be useful. In general, one should start simply and only build a complex model if necessary. This process necessitates a thorough systems analysis, which



8.3. Stages in model development.

consists of studying the system under consideration with a view to determining its principal components and their interrelationships. This usually culminates in a flow diagram. Boundaries for the system must be established, and the various driving and state variables and processes involved must be clearly outlined as well. Finally, the major features and relationships of the system are synthesized into a logical structure that may be implemented on a computer.

8.2.4.2 VERIFICATION. After implementation the model must be verified. This is the process of ensuring that the model behaves in the manner that the modeler intended and assesses the adequacy of the equations and functions.

8.2.4.3 VALIDATION. This is the process of assessing the accuracy of model output and of ensuring the usefulness and relevance of the model. Specifically, validation is an attempt to ensure that the model adequately mimics the simuland to justify proceeding. Ideally, subsections of the model should be validated as separate exercises prior to validation of the model as a whole, because errors in one section may be completely or partially compensated for by errors in another section. However, the most rigorous form of validation involves the detailed comparison of model output and historical or experimental measurements on the simuland when the driving forces for the model (e.g., meteorological data) are the same as those measured in the simuland.

8.2.4.4 SENSITIVITY ANALYSIS. This involves varying parameter values of the model in a systematic fashion and observing the resultant changes in model output (Anderson 1974). Sensitivity analysis may be conducted to demonstrate the degree to which conclusions based on initial parameter values remain valid if the values used are not accurate estimates of the true population value. Alternatively, it permits the simulator to evaluate the likely consequences of deliberately varying the parameter from the initial value as might be done in the assessment of alternative disease control strategies.

8.2.4.5 MODEL EXPERIMENTATION. If the model is epidemiologically realistic, and if the conclusions drawn from the validation testing and sensitivity analysis are correct, the model may be applied to the evaluation and comparison of alternative control strategies for the disease under study. All the considerations and criteria used in conventional experiments are more or less applicable to experiments with models.

8.2.4.6 STRATEGY PLANNING AND IMPLEMENTATION. The purpose of the above experiments is to guide the decision maker in establishing strategies (policy) as well as implementing them. This necessitates that the results of the model (perhaps a ranking of possible disease control options) be combined with other knowledge by the decision maker.

8.3 Example Applications

8.3.1 Linear Programming

As mentioned earlier, linear programming models are generally of the symbolic optimizing type (Fig. 8.1). As an example (Osburn and Schneeberger 1978), suppose a farmer wishes to grow hay or grain. He has 160 acres of cropland, \$20,000 in operating capital, and 300 hours of labor available in each of the spring and summer periods. The requirements per acre for these resources are as follows:

	Grain	Hay
Spring labor (hr)	3.0	1.5
Summer labor (hr)	0.5	2.0
Operating capital	\$100.0	\$60.0

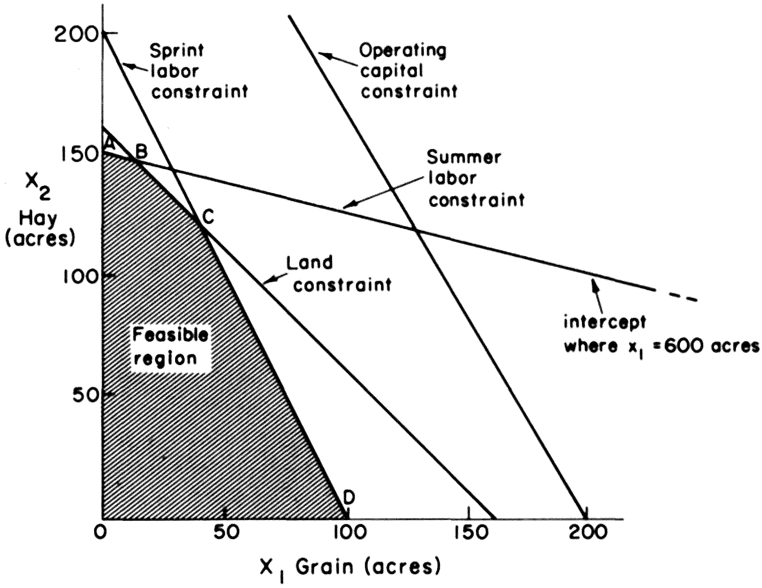
If hay returns \$55 net per acre and grain returns \$90 net per acre, what combination of hay and grain will maximize returns?

Stated mathematically, the problem is to:

$$
\begin{aligned}
\text{maximize net returns, } Z &= 90x_1 + 55x_2 \\
\text{where } x_1 &= \text{acres of grain} \\
x_2 &= \text{acres of hay} \\
\text{subject to } x_1 + x_2 &< 160 \text{ acres of land} \\
3x_1 + 1.5x_2 &< 300 \text{ hours of spring labor} \\
0.5x_1 + 2x_2 &< 300 \text{ hours of summer labor} \\
100x_1 + 60x_2 &< 20{,}000 \text{ dollars}
\end{aligned}
$$

This problem can be solved in several ways. For this simple problem one can draw a graph and use it to find the desired solution (Fig. 8.4). In order to graph the inequalities, draw a straight line between the plotted positions reflecting the equality signs. For example, with regard to the land constraint, if x_1 is set to 0, x_2 becomes 160 and vice versa.

With regard to Figure 8.4, points on the feasible region surface ABCD may be viewed as the frontier of production possibilities, and some point on the line will satisfy the objective of maximum possible income. In this example, net returns are maximized with 40 acres of grain and 120 acres of hay [(40 × \$90) + (120 × \$55) = \$10,200] given the linear constraints of the problem.



8.4. Plot of resource restrictions and region of feasible solutions for hypothetical 160-acre farm. (Adapted from Osburn and Schneeberger 1978)

For further reading, Carpenter and Howitt (1980) have applied this technique to determine the most economically optimal approach to the control or eradication of brucellosis in beef cattle in California.

8.3.2 Reed-Frost Model

Herd immunity can function to prevent the successful entry of an organism into a group or population of animals, and/or it can minimize the extent and rapidity of the spread of that organism once it becomes established. A simple model that describes major factors involved in herd immunity is known as the Reed-Frost model. As discussed earlier, the Reed-Frost model is of the chain binomial type. Although a number of the events and factors have been simplified somewhat to make the model workable, the model has proven useful in demonstrating those factors of paramount importance in herd immunity. The major assumptions in the model are: (1) infection is spread directly from infected individuals to others by "adequate contact" and in no other way; (2) once contacted, the individual (if susceptible) will develop the disease and be infectious in the next time period, following which it will be immune; (3) there is a fixed probability of adequate contact between any two individuals.

The number of immune and susceptible individuals and the number of cases (case as used here describes either a clinically diseased individual or an infected individual) are recorded at each time period after the introduction of the first infected individual. The single factor that carries the epidemic from one time period to the next is the probability of adequate contact. The latter is defined to be the likelihood in any time period that an infected individual will have contact with another individual sufficient to transmit the infection if the latter individual is susceptible.

The mathematical formulation of the Reed-Frost model is $C_{t+1} = S_t(1 - Q^{C_t})$, where C is the number of cases, S is the number of susceptibles, and Q is the probability of no adequate contact. (The probability of no adequate contact is found by subtracting the probability of adequate contact [P] from 1.) The subscript t serves as a time counter, and the length of the time period usually is set equal to the incubation or latent period of the disease. The time at which the first case enters the population is time 0 and each unit of time thereafter is numbered sequentially.

Specifically, the model equates the number of cases at any time to the number of susceptibles in the immediately preceding time period and the probability of contact of each individual with a case. Examples of output from the model under various conditions are presented in Table 8.1 and Figure 8.5.

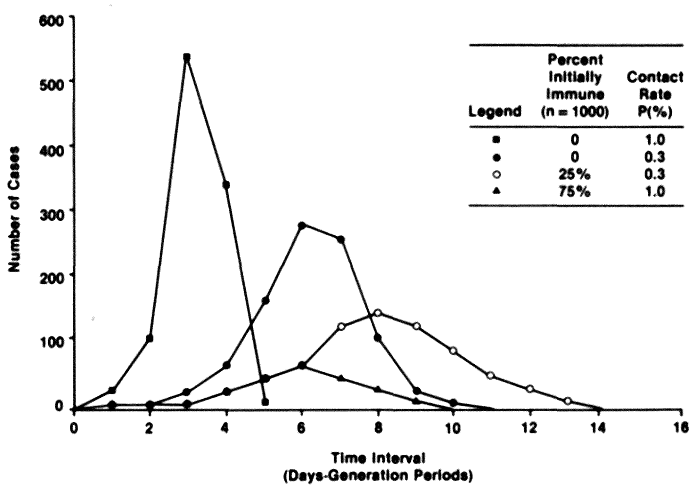
This and other models together with studies of actual epidemics demonstrate that epidemics die out because of a combination of a low rate of adequate contact and a reduced number of susceptible individuals. Specifi-

**Table 8.1. An epidemic curve predicted by the Reed-Frost model*[a]*

Time interval (t)	Number of susceptibles (S_t)	Number of cases (C_t)	Number of immunes (I_t)
0	100	1	...
1	96	4	1
2	82	14	5
3	46	36	19
4	11	35	55
5	3	8	90
6	2	1	98
7	2	0	99

[a]The formula for the model is: $C_{t+1} = S_t(1 - Q^{C_t})$ given $P = 0.04$, $Q = 0.96$.
$C_1 = 100(1 - 0.96^1) = 4$; $S_1 = 100 - 4 = 96$.
$C_2 = 96(1 - 0.96^4) = 14$; $S_2 = 96 - 14 = 82$.

cally, if $P \times S$ is greater than 1, the epidemic can occur; whereas if $P \times S$ is less than 1, the epidemic will die out or not occur in the first instance. These constraints are much more instructive about the phenomenon of herd immunity than the simple statement that a specified percentage of the population must be immune to give the population protection. In fact, even if the percentage is high, if there are sufficient susceptibles that have contact with each other, and if the infection enters the population it will likely spread, since $P \times S$ is greater than 1. It must be remembered that the variable "the probability of adequate contact" is a complex variable and contains factors



8.5. Epidemic curves generated by Reed-Frost model.

specific to certain disease agents as well as to the social structure of the animal population. The actual probability of adequate contact can be estimated from observed epidemic curves by successively applying the following formula: $P = (C_{t+\text{incubation period}})/(S_tC_t)$.

If the number of susceptible animals in the population is decreased by increasing the proportion that is immune, the peak of the epidemic can be delayed and/or the magnitude and duration can be greatly reduced. Such an increase in immunity could come about because of a formal immunization process, or the resistance of the animals could be increased by more indirect means such as changes in husbandry and/or management practices. The latter may also be used to lower the probability of adequate contact.

8.3.3 Markov Chain Models

Carpenter and Riemann (1980) used a Markov chain model to conduct a benefit-cost analysis of a *Mycoplasma meleagridis* eradication program in turkeys in the United States.

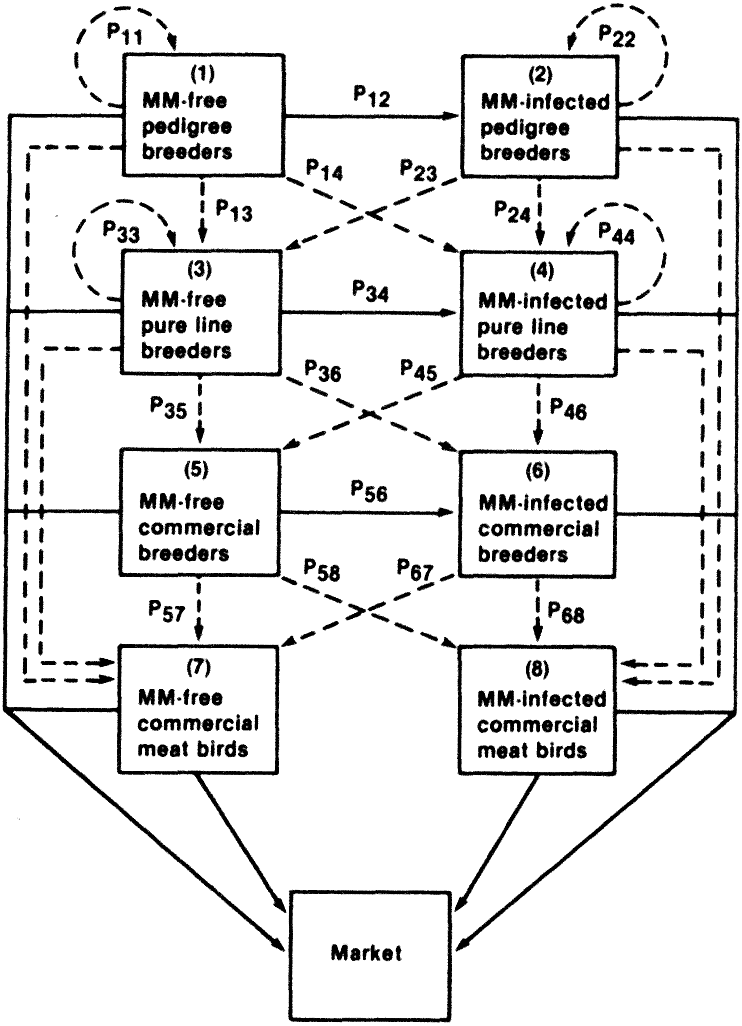
Figure 8.6 presents a flow diagram depicting the various states of nature for both breeder and commercial meat birds. The transition between the various states represented by solid lines signifies a change in infection status or a bird being sent to market. Transitions represented by broken lines signify progeny or poult production. The probability values for each of these transitions are represented by their respective P_{ij} values and these are presented in Tables 8.2 (disease and marketing transition) and 8.3 (poult production). For example, the probability of moving from *M. meleagridis* free pedigree breeder status to a *M. meleagridis* infected pedigree breeder is signified as $P_{1,2}$ (Fig. 8.6) and the value for this is 0.05 (Table 8.2, row 1 column 2).

Once the structure of the model is defined and probabilities have been quantified, it is a reasonably simple matter to perform the actual simulation. However, since matrix algebra is used, the simulation is greatly facilitated if the model is implemented on a computer.

Table 8.2. Disease transition matrix for *Mycoplasma meleagridis*

	MM-free pedigree breeders	MM-infected pedigree breeders	MM-free pure-line breeders	MM-infected pure-line breeders	MM-free commercial breeders	MM-infected commercial breeders
MM-free pedigree breeders	0.95	0.05				
MM-infected pedigree breeders	0.00	1.00				
MM-free pure-line breeders			0.70	0.30		
MM-infected pure-line breeders			0.00	1.00		
MM-free commercial breeders					0.10	0.90
MM-infected commercial breeders					0.00	1.00

Source: Carpenter and Riemann 1980.



8.6. Flow chart between the generation levels and infection status (solid line) and poult production (broken lines). (Source: Carpenter and Riemann 1980)

Table 8.3. Turkey poult production transition matrix for *Mycoplasma meleagridis* (MM)

	MM-free pedigree poults	MM-infected pedigree poults	MM-free pure-line poults	MM-infected pure-line poults	MM-free commercial breeder poults	MM-infected commercial breeder poults	MM-free commercial meat poults	MM-infected commercial meat poults
MM-free pedigree breeders	.024	.000	.207	.011			.606	.152
MM-infected pedigree breeders	.023	.001	.196	.022			.076	.682
MM-free pure-line breeders			.018	.001	.226	.056	.559	.140
MM-infected pure-line breeders			.017	.002	.028	.254	.070	.629
MM-free commercial breeders							.800	.200
MM-infected commercial breeders							.100	.900

Source: Carpenter and Riemann 1980.

8.3.4 Stochastic Simulation Model of Ovine Fascioliasis

A simulation model of ovine fascioliasis (Meek and Morris 1981) will be described both to present the general process of building a model and to illustrate a stochastic simulation model. The overall objectives of this model were to investigate the factors influencing the epidemiology of ovine fascioliasis and to compare the economic value of various alternative control strategies for the disease.

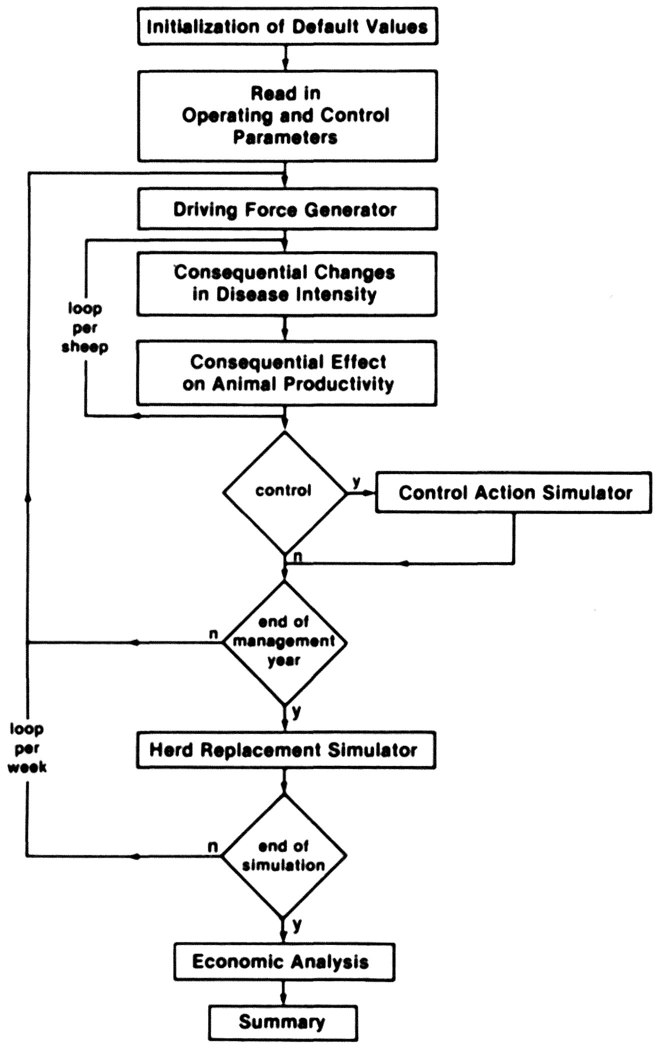
8.3.4.1 MODEL FORMULATION. Ovine fascioliasis (*Fasciola hepatica*) is a disease that can cause serious economic loss. The disease is biologically complex with interactions among a number of factors, including meteorologic factors, pasture growth, the disease agent (*F. hepatica*), the intermediate snail host (*Lymnaea tomentosa*), and the mammalian host(s). Hence, the process of choosing the best control strategy for particular circumstances can be difficult since it is not easy to take all relevant factors into account.

The general form of the model is illustrated in Figure 8.7. The model uses a combination of algebraic functions and Monte Carlo sampling from defined probability distributions to generate observations and changes of state. The model was designed to simulate the life cycle of *F. hepatica* and the dynamics of the usual intermediate snail host in Australia, *L. tomentosa*. It also simulates soil moisture, pasture production, sheep feed intake, and the resultant generation of marketable products. The life cycle of *F. hepatica* is greatly influenced by temperature and soil moisture. Temperature determines the rate of advancement through the life cycle and hence influences the timing of infection. Soil moisture acts as a limiting factor on the life cycle and hence influences both the timing of infection and its intensity.

The simular flock was composed of a maximum of 60 nonreproductive sheep. Animals are simulated individually with respect to such factors as intake (of both herbage and metacercariae), growth, and parasite burden, but are simulated as a flock with respect to grazing pattern and routine management practices.

In the model, sheep are shorn and culled at the end of each management year. The maximum percentage of sheep culled each year is assumed to be 20% of the initial flock size. The actual number culled decreases from this maximum if there has been a reduction in the number of sheep over the course of the management year (i.e., if simular deaths have occurred). All sheep that die or are culled are replaced at the end of the management year with shorn yearling wethers.

The simular pasture is defined to be 2 hectares in area and can be specified to be either irrigated or nonirrigated. The area is considered to be closed to external contamination by any stage of the *F. hepatica* life cycle. For purposes of simulation the area is subdivided into ten equal subareas.



8.7. General form of liver fluke simulation model. (Source: Meek and Morris 1981, with permission)

Simular herbage can be regarded as a perennial species for which an annual cycle of sexual reproduction is not essential. Herbage growth rate is defined to be a function of day length, temperature, available soil moisture, and the quantity of herbage already present on the subarea.

The snail habitat is contained within the tenth subarea of the paddock. The maximum proportion of the subarea to be occupied by the habitat may be stipulated by the person conducting the simulation. The actual size of the habitat (within the defined limit) at any point in simular time is a function of temperature and moisture.

A schematic representation of the epidemiology of the disease (as modeled) is presented in Figure 8.8. The driving variables for the model are meteorologic factors, including maximum and minimum daily temperature and moisture (as either rainfall or irrigation).

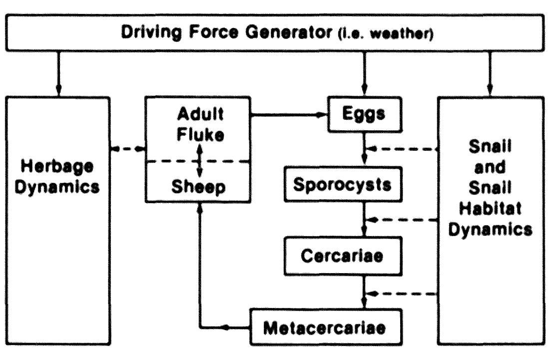
The model simulates for the main part on a weekly basis. However, within the main cyclic pattern there are some daily cycles (such as the intake of metacercariae by sheep and the sheep/liver fluke interaction).

Egg contamination of the snail habitat is a function of the adult fluke burden of individual animals, the grazing pattern of sheep with respect to the snail habitat, and the size of the habitat. The rate at which the life cycle proceeds is a function of ambient temperature and the biologic state of the intermediate host snail.

Simulated sheep come in contact with encysted metacercariae if they graze contaminated herbage in subarea 10. The number of metacercariae consumed is a function of the animal's dry matter intake and grazing behavior and the concentration of metacercariae on the herbage.

A proportion of the consumed metacercariae develop to adult liver flukes. Parasitized sheep contaminate the paddock with eggs as long as the sheep survives or until the fluke burden is eliminated by a simular treatment.

Facility has been provided in the model for specifying the use of simular anthelmintics, molluscicides and management practices such as rotational grazing. These control methods can be simulated either singly or in combination.



8.8. Schematic representation of interaction of major components involved in epidemiology of ovine fascioliasis, as represented in model. (Source: Meek and Morris 1981, with permission)

All financial items are calculated on the basis of a standard flock of 100 sheep. At the end of each management year an expected margin over variable costs is calculated. (The term variable strategy costs is used to include all expenses directly attributable to the control strategy being simulated.)

Because a control program for ovine fascioliasis can take up to 5 years to generate its full effects and because costs may vary over time, future costs and returns are discounted (see 9.5.2). To produce a more readily interpretable figure, the net present value for the chosen strategy is converted to an annual annuity. The evaluation and comparison of all control strategies are done on the basis of this annual annuity. For simplicity the annual annuity realized over a 5-year simulation is referred to as the financial return.

8.3.4.2 VERIFICATION AND VALIDATION. Once the model had been formulated and implemented, a series of verification and validation checks was performed, and modifications were made until the modelers were satisfied with the logical structure and operation of the model.

Whole model validation was conducted in two parts. First, the predictions of the model were compared with the result of a field investigation that utilized a resident flock and a series of groups of tracer sheep conducted on both irrigated and nonirrigated pastures near Melbourne, Australia (Meek and Morris 1979). Second, the predictions of the model were compared with the results of a field investigation conducted by an independent group of investigators in another part of Australia.

Validation was conducted using meteorologic data that had been recorded at the site of the field investigation. To do this, simular tracer sheep were allowed to grow throughout the year, but the model was adjusted so that the accumulating fluke burden did not affect the red blood cell volume of each sheep, nor did it decrease the animal's dry matter intake (i.e., equivalent to a series of tracer animals).

Simulations were conducted for each of an irrigated and nonirrigated simular area. The simular patterns of fluke acquisition by the tracer sheep for the 2 simular years that corresponded to the 2 field experimental years and for each of the irrigated and nonirrigated areas are presented along with the field results in Table 8.4. The simular and actual field-cumulative fluke burdens for both experimental years are in good agreement.

8.3.4.3 SENSITIVITY ANALYSIS. It was anticipated that model output would be sensitive to pasture egg contamination and the maximum proportion of the paddock that was defined to be snail habitat. Thus, simulations were conducted using various combinations of those two factors. Weekly pasture egg contamination remained constant at the stipulated level throughout each simulation. The proportion of the stipulated maximum snail habitat

Table 8.4. Comparison of the field[a] and simular fluke burdens

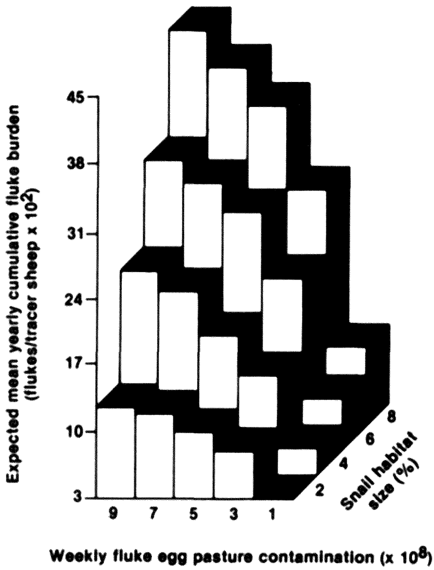
Experimental year	Date[b]	Irrigated Field	Irrigated Simular	Nonirrigated Field	Nonirrigated Simular
1974–1975	16 December 1974	6.4	3.7	0.2	0.0
	17 January 1975	61.6	62.2	0.0	0.0
	13 February 1975	85.2	41.4	0.0	0.0
	13 March 1975	80.8	98.8	0.0	0.0
	10 April 1975	75.0	230.2	0.0	0.0
	8 May 1975	36.5	19.4	0.0	0.0
	5 June 1975	77.2	20.2	0.0	0.0
	3 July 1975	17.2	13.8	0.0	0.0
	31 July 1975	28.8	10.5	0.2	0.0
	28 August 1975	4.0	7.9	0.0	0.0
	25 September 1975	0.8	4.1	0.0	4.6
	23 October 1975	2.0	0.2	0.0	4.2
	20 November 1975	8.0	9.0	3.2	5.0
	Total	483.5	521.4	3.6	13.8
1975–1976	18 December 1975	1.4	21.8	1.8	0.2
	15 January 1976	0.0	0.0	0.4	0.0
	12 February 1976	2.2	0.0	0.0	0.0
	11 March 1976	28.0	0.0	0.0	0.0
	8 April 1976	22.2	0.0	0.0	0.0
	6 May 1976	156.8	616.2	0.0	0.0
	3 June 1976	343.4	413.4	0.0	0.0
	1 July 1976	362.2	62.4	0.0	0.0
	29 July 1976	104.4	6.2	0.0	0.0
	26 August 1976	159.0	0.0	0.0	0.0
	23 September 1976	36.0	0.0	0.0	0.0
	23 October 1976	6.0	0.0	0.0	0.0
	18 November 1976	13.0	26.1	0.0	0.0
	Total	1234.6	1146.1	2.2	0.2

Source: Meek and Morris 1979, with permission.
[a]Mean for group of tracer sheep.
[b]Date at end of 28-day tracer interval. Field experiment commenced 11 November 1974.

size suitable for snail activity was allowed to vary as a function of the interaction between temperature and moisture, and the same meteorologic data file was used for all simulations. The results of this analysis are illustrated in Figure 8.9. Each horizontal surface is the mean yearly cumulative fluke burden for a 5-year simulation.

Simular fluke acquisition appeared to be approximately linearly related to snail habitat size, but resulted in a "logistic" curve with respect to increasing pasture egg contamination.

Under normal simuland conditions, pasture egg contamination is a function of the fluke burden of individual animals. It was therefore postulated that the acquisition of flukes would be sensitive to stocking rate and that both stocking rate and the proportion of the paddock that was snail habitat should be taken into consideration when assessing the effectiveness of any potential control strategy for the disease.



8.9. Expected mean yearly cumulative fluke burden of simular tracer sheep at various levels of total weekly fluke egg contamination and maximum snail habitat size. (Source: Meek and Morris 1981, with permission)

8.3.4.4 MODEL EXPERIMENTATION. At this stage, the model was applied to the evaluation and comparison of alternative control strategies for ovine fascioliasis. Although a number of experiments were conducted, only one will be described here: the use of simular anthelmintics.

Method. Five anthelmintic treatment strategies, selected as being representative of the range of possible strategies that might be employed in the field, were used for this analysis and are presented in Table 8.5. Strategy 1 involved salvage treatments only. Strategies 2–5 involved simular treatment of all sheep during the weeks of the calendar year specified. All treatment strategies were simulated for a 5-year period.

The model was used to estimate the expected financial return from each of the five strategies at each of a number of combinations of stocking rate and snail habitat size. For purposes of this analysis a range of stocking rates (varying from 20 to 30 sheep per hectare of irrigated pasture) and maximum snail habitat sizes (varying from 1 to 10% of the paddock) were used. The range of values used for the latter two factors was considered to be representative of most Australian field situations.

A multiple regression procedure was then used to produce a surface of best fit to the financial data generated by each of the five treatment regimes. By comparing the value of the dependent variable (financial return)

Table 8.5. Simular anthelmintic treatment strategies

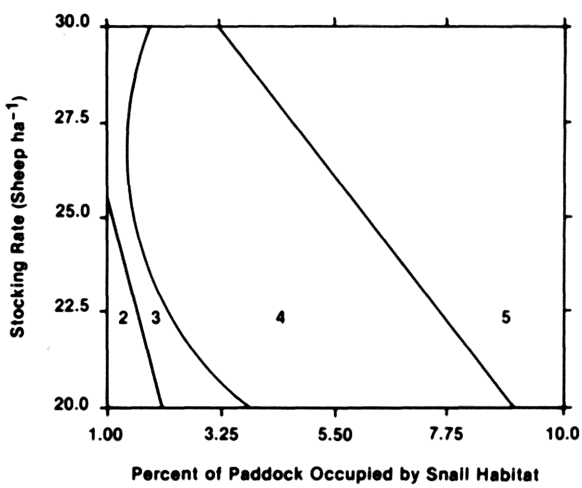
Strategy	Timing of treatments					
1	Salvage only					
2	3[a]	12	21	...	...	...
3	3	12	21	30	...	...
4	3	12	21	30	45	...
5	3	11	19	27	35	45

Source: Meek and Mörris 1981, with permission from Elsevier Applied Science Publishers and the authors.
[a]Week of calendar year.

for the five regression surfaces, the treatment strategies were ranked at each of several thousand combinations of stocking rate and maximum snail habitat sizes. The five selected strategies were not compared with a "no treatment" strategy because of the extreme financial loss that occurred if no control or treatment measures were taken.

The four preplanned strategies were also ranked by percentage return on additional funds invested over and above the investment required for strategy 1 (salvage treatment).

Results. The result of ranking alternatives by highest financial return is presented as a decision chart in Figure 8.10. The contours delineate which of the five control strategies provides the highest net financial return at



8.10. Decision chart for choice of treatment strategy (see Table 8.5) yielding highest margin over fluke control costs, at various stocking rates and maximum snail habitat sizes. (Source: Meek and Morris 1981, with permission) each combination of grazing density and maximum snail habitat size.

A general trend across the surface is that as the stocking rate and/or the size of the snail habitat increases, the number of treatments per annum required for the most profitable strategy also increases. Strategies 4 and 5 are predicted by the model to yield the highest financial return over most of the surface, with the lower cost strategies (numbers 2 and 3) only being optimal at very low stocking rates (number 2) and/or snail habitat sizes (numbers 2 and 3). Note that strategy 1 (salvage treatments only) is not represented because it was not the most profitable strategy under any of the conditions presented.

The results of ranking alternatives by percentage return are presented in Table 8.6. The financial return realized from the use of strategy 4 is only marginally better than that of strategy 5 under the particular circumstances used. However, strategy 3 realized the highest percentage return under all price circumstances.

Table 8.6. Comparison of the financial return from each of the five control strategies

	Strategy[a]				
Item	1	2	3	4	5
Strategy costs ($)	16	21	29	37	44
Margin over variable strategy costs ($)	115	174	396	464	455
Margin over strategy 1 ($)	...	59	281	349	340
Return on funds invested in addition to strategy 1 (%)	...	1180	2162	1662	1214

Source: Meek and Morris 1981, with permission from Elsevier Applied Science Publishers and the authors.

[a]See text and Table 8.5 for details of control strategies and simular circumstances. All monetary values rounded to the nearest dollar.

Discussion. In general, if a farmer has unlimited funds, the strategy with the highest financial return would represent the most profitable option and should be chosen (Fig. 8.10). However, while a farmer would have knowledge of and control over the average stocking rate on a paddock, he may not appreciate the proportion of the paddock that is occupied by snail habitat. Therefore, the strategy chosen would depend to some extent on the farmer's risk aversion. The farmer who was risk averse would perhaps choose strategy 5.

If funds were limited, the decision on which strategy to use should be based on the principle of equimarginal returns, which states that the funds available should be invested progressively in uses that yield the highest marginal return as each successive dollar is invested. Although the percentage return on invested funds gives an imprecise assessment of marginal return, it does have value in facilitating comparison between alternative investments (Anderson et al. 1976). Therefore in situations where funds are very limited, strategy 3 may merit consideration (Table 8.6). The substantial return on funds invested in the use of anthelmintics is the result of the relatively low cost and high efficacy of the currently available products and the substantial gains in productivity that can be realized from their strategic use.

References

Abbey, H. 1952. An examination of the Reed-Frost theory of epidemics. Hum. Biol. 3:201.

Anderson, J. R. 1974. Simulation methodology and application in agricultural economics. Rev. Mark. Agric. Econ. 42:3–25.

Anderson, N., R. S. Morris, and I. K. McTaggart. 1976. An economic analysis of two schemes for the anthelmintic control of helminthiasis in weaned lambs. Aust. Vet. J. 52:174–80.

Carpenter, T. E., and R. Howitt. 1980. A linear programming model used in animal disease control. Proc. 2nd Int. Symp. Vet. Epidemiol. Econ., May 1979, Canberra, Australia.

Carpenter, T. E., and H. Riemann. 1980. Benefit-cost analysis of a disease eradication program in the United States: A case study of *Mycoplasma meleagridis* in turkeys. Proc. 2nd Int. Symp. Vet. Epidemiol. Econ., May 1979, Canberra, Australia.

Emshoff, J. R., and R. L. Sisson. 1970. Design and Use of Computer Simulation Models. London: Macmillan.

Meek, A. H., and R. S. Morris. 1979. An epidemiological investigation of ovine fascioliasis (*Fasciola hepatica*) on both irrigated and nonirrigated pastures in Northern Victoria. Aust. Vet. J. 55:365.

______. 1981. A computer simulation model of ovine fascioliasis. Agric. Syst. 7:49–77.

Morley, F. H. W. 1972. A systems approach to animal production: What is it about? Proc. Aust. Soc. Anim. Prod. 9:1.

Oltenacu, P. A., R. A. Milligan, T. R. Rousaville, and R. H. Foote. 1980. Modelling reproduction in a herd of dairy cattle. Agric. Syst. 5:193.

Osburn, D. D., and K. C. Schneeberger. 1978. Modern Agriculture Management. Reston Va.: Reston.

Spedding, C. R. W. 1979. An Introduction to Agricultural Systems. London: Applied Science.