SYSTEMS SIMULATION IN AGRICULTURE

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Preface

A fast-growing interest in the concepts and application of systems research has spawned a wide and general literature over the past decade. Most disciplinary areas have been touched, but commerce, engineering and military studies have, perhaps, been best served with outstanding texts. No provision has so far been made for a general book at introductory level of direct relevance to agricultural science, technology and management. General reviews are, of course, valuable to the agricultural-systems researcher but agricultural systems, with important biological components interacting with equally vital social and economic elements, embody particular characteristics which influence the approach to their study. This book is written in the belief that the concepts as well as the technology of the systems approach have a basic rôle in the rational advancement of the agricultural discipline and in the improvement of efficiency in agricultural research and practice. A basic and introductory text is an essential pre-requisite to this role being realised.

A reiteration of basic concepts is expressed in the introductory chapter while in the final chapter particular attention is given to the general problems of integrating systems concepts in research, extension and practice. The dialogue of these chapters is necessarily brief and in some respects speculative but it is supported by appropriate bibliography.

The main body of the text is concerned with the methodology of systems research; the conception, construction, implementation, validation and exploitation of computer-based simulation models of agricultural systems. The book has been structured for ease of reference for the agricultural researcher who has had little opportunity to become involved in systems studies and who would like to become familiar and operational in this area. It is also hoped that the experienced modeller will find something of value in the book; perhaps a refreshment of ideas, perhaps inspiration to correct entrenched faults, perhaps some additional view of familiar procedures or perhaps, through disagreement with our view, he may gain further insight into general methodology or application.

Obviously, we anticipate that readers will have a general appreciation of agriculture as well as a firm understanding of their own speciality and will have a basic grounding in statistical method. However, no previous experience in model-building is assumed though those with some association with computers and a computer language will find progress through the book simpler and quicker than those without this experience. In general, it would be an advantage to have completed an introductory course in computer methods before detailed study of this book. In the belief that learning is more effective by involvement and practice, the text is reinforced by reference to two detailed examples and it is hoped that those without previous association with computers will find these particularly valuable. The two different examples are described and defined in appendices to early chapters and are gradually woven into the text to assist in the explanation of various procedures.

The text has been extended from an original draft by the authors' association with Dr Steve Harrison whose recent work at the University of Queensland on experimental methods with computer models has been built into Chapter 6. We are most grateful for his involvement with this chapter as well as for many helpful comments on early drafts of the book. Data for one of the detailed examples used throughout the text were kindly provided by Dr P. S. Teng and Dr Ron Close of Lincoln College. Dr Tony Bywater, University of California, Dr Peter Chudleigh, Lincoln College, Dr Gary Fick, Cornell University, Dr Steve Filan, University of New South Wales and Dr P. S. Teng all made valuable contributions to earlier drafts. Many other colleagues and associates helped in a variety of ways to formulate and clarify the ideas expressed in this book; residual inadequacies and omissions remain our responsibility.

We would like to thank Ruth Frampton for transforming our incredibly rough pencil sketches into appropriate illustrations and Marion Mischler for patience and customary skill in typing the drafts.

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Principles of Model-Building

For most people, discussion concerning a model provokes thoughts of some kind of physical representation of a real object—usually in miniature form. Such models will look like and often function in a similar (though often markedly simplified) way to the real object. Such physical models (classified as 'iconic' by Churchman, 1971) embrace children's toys, tailor's dummies and mock-ups of buildings and structures to be later constructed in real form. Representation of town planning developments or of the prospective layout of controls in a nuclear submarine are examples of useful iconic models and illustrate the point that models can be constructed of objects or situations not yet in existence in real form. It is not only miniature or life-size iconic models which prove useful; chemists, for example, find it expedient to construct greatly magnified physical representations of the structure of complex molecules. There is, however, an extremely useful class of model which bears little or no physical resemblance to the system it is intended to represent and it is this type of model which will be our major concern in this book. Churchman (1971) classifies such models as 'symbolic'. Symbolic models are abstract in form and are perhaps more difficult to comprehend than iconic models. The abstraction of the model frees it from the limits of physical form, thus rendering this type of model considerable flexibility in both the mode of its construction and the manner of its use.

Chemists will often represent molecular structure in symbolic form as part of the statement of a chemical reaction such as, for instance, the example below.

$$2H_2O + 2Cl_2 = 4HCl + O_2$$

Here we have an example of a model whose symbolic manifestation bears no physical resemblance to the real form; it is nevertheless a direct representation of the real chemical reaction and hence should be considered as a model of the reaction.

A fundamental principle of model-building, therefore, is that the type of model to be constructed depends on the use to be made of it: the model should represent those facets of the real system relevant to the model-uses. So iconic models of molecular structure, while valuable to the physical chemist, are translated into symbolic form by the industrial chemist in the study of chemical reactions.

Model-building is not an exact science: indeed, Mihram (1972) defines it as the 'art of mimicry'. Given that the function of a model is to mimic the behaviour of a real object or situation then the determination of what format the model should take and what degree of detail should be represented remains a matter of judgement on the part of the model-builder. In this text, we will be considering the issues faced by the model-builder in all aspects of his work. Guidelines to assist the modeller in making the necessary value judgements will be presented together with examples drawn from actual modelling experience.

Symbolic models are diverse in form, and classification has been attempted by a number of authorities (see, for example, Anderson, 1974; Mihram, 1972; Shannon, 1975; and Throsby, 1973 in the reference section at the end of this chapter). This text, however, is confined to a single form of symbolic model which we will call a computer-based simulation model. This model-type has particular strength in mimicking complex situations characterised by uncertainty and change over time. (Model-builders refer to such situations as being complex, stochastic and dynamic.) In the last decade, computer-based simulation models have gained acceptance in most branches of learning and have found application in fields as separate as defence-system development, corporate management and ecology. Many of the concepts and approaches set out in this text have been developed in other disciplines and have been adapted for application in an agricultural context. Of course, many other disciplines are beset with the same basic need to consider change in uncertain circumstances; to this extent the procedures developed in this book may, in principle, find application in diverse areas outside agriculture. Reference will be made to studies seemingly unconnected to agriculture but which have value in illustrating particular aspects of simulation practice. For the most part, however, examples will be drawn from two models—a detailed biological model of barley-leaf-rust disease and a more pragmatic management-orientated model of a pig-production unit. Between them, these two models include many features of interest to biological and agricultural model-builders. These two models are presented in detail in the appendices at the end of this and subsequent chapters. The reader may find it useful to refer to these appendices from time to time in reading through this text.

Why the Computer?

Simulation models may be divided into two classes, predictive simulation models and mechanistic simulation models: the first is concerned with providing forecasts (predictions) relating to alternative options, the second involved with assisting understanding of the situation under study, perhaps with a long-term view of controlling it more effectively. Both predictive and mechanistic simulation models can take a number of forms, one of which is computer-based. The computer then is not essential in simulation modelling. Indeed in agriculture at present, it would be the exception rather than the rule.

Consider the barley-leaf-rust model described at the end of this chapter. Once the farmer has planted a crop of barley, that crop is susceptible to leaf rust during certain parts of the growing season. This disease can severely depress yields depending on the stage of crop growth and weather conditions when it attacks. Present New Zealand farming practice is to spray the crop with fungicide at regular calendar intervals during that part of the season when disease outbreaks are most likely to occur. This practice is based on a very simple 'mental' simulation model which assumes

1. disease will always occur in the crop;
2. yield reduction and hence financial losses from the disease will be heavy in the absence of fungicide application.

Where fungicide and application costs are low, this simple mental model may be quite adequate. However, as the margin between cost of spraying and the potential economic yield loss caused by disease narrows, so it becomes important to construct a more sophisticated model to direct decisions about fungicide application. Such a model would include a disease-loss relationship which is dependent upon past and future weather patterns and crop growth stage. It would then be possible to use this relationship to examine the dynamics of the disease epidemic on a specific crop. The complexities involved in such a model render it capable of expression only by implementation on a computer.

The computer is ideally structured both to hold and recall vast amounts of information and to follow faithfully the changing state of many interacting variables over time. A simulation model that exploits these characteristics of the computer can have operational advantages over the mental simulation model. Provided the data base is adequate and the computer-based simulation model is appropriately constructed and programmed, the assessment of alternative decisions will be more comprehensive. The operational value of such a model will depend on factors such as the cost of its construction, the ease with which the decision maker can have access to it and the added value from more comprehensive assessment of options. The computer is an extension of human mental capacity (not a replacement for it) and the computer-based simulation model permits a more formal consideration of the information pertaining to a decision. This imposes on the modeller a responsibility to ensure that his data base is compatible with the complexity of the system under study, that his use of the data is valid, that his construction of the model is not biased and is related to current knowledge and that his computer programming is accurate. Many of these demands remain in the realm of subjective judgement by the modeller. The form of this book may now be seen in rather more detail since it presents

1. concepts to assist these judgements;
2. methods to ensure model-construction proceeds logically and efficiently;
3. procedures for handling data for modelling;
4. approaches for testing the validity of models in relation to their required function; and
5. a philosophy for the application of computer-based simulation models to agriculture.

A Definition of System

The word system is commonly used in a general sense and usually the meaning inferred is of a complex set of related components within an autonomous framework. We have all used terms such as the 'telecommunications system' or the 'transport system'; in agriculture, we are familiar with the meaning of 'harvesting system' or 'metabolic system'. The term defines, in a general way, the limits of autonomy and it implies that within these limits there is an unprescribed complex organisation. Usually it is assumed that the organisation is established or exists in order to carry out or maintain some function(s) (even if this is simply to maintain an existing equilibrium between the components of the system).

The striking implication is that the complex interrelationships between components precludes legitimate study of sectors of the system in isolation. Because the interrelationships are so important, the whole system is more complex, more comprehensive, than the sum of the individual components. Protagonists of the system approach agree that this is a fundamental fact applying to all systems and is the unifying theme in systems theory. Any defined system will have its own specific characteristics but all systems will conform to the following general features:

1. A system is fully defined both by a set of identifiable entities (or components) and interconnections between them and by the limits to their organisational autonomy.
2. A system is a hierarchical structure comprising a number of subsystems each capable of autonomous definition; in turn subsystems similarly embody the next layer of detail in autonomous sub-subsystems. The point of entry into the hierarchy in any systems study is related to the objectives for which the system is being studied. The number of layers of the hierarchy included in any study will depend on the judgement of the researcher but certain rules of thumb have been established. These will emerge in later discussion. (See also de Wit, 1970).
3. The most important characteristics of systems emerge over time so that the understanding of systems requires explicit consideration of time and rates of change.
4. Systems are sensitive to the environment in which they exist. This environment is usually unpredictable and certainly variable.

Systems research is therefore the study of systems: it involves, first, an analysis of the components and relationships of a system and, secondly, a synthesis phase. This latter phase might involve either the development of new systems or the more efficient use of the original system. Analysis and synthesis are usually not distinct in time; rather a cycling between the two develops (Wright, 1971). Systems research generally involves the construction of a computer-based simulation model. Obviously, such a stage will follow considerable analysis of the system, but after a certain point the model itself can begin to guide analysis so that experimental resources are more effectively used. To be effective the model not only must be technically sound but also must faithfully present the four general characteristics outlined above. The model is an integral part of systems research, acting as

1. a medium by which experimental studies can be guided;
2. a method whereby the results of such work are accumulated (and assessed);
3. a platform to guide the development of new systems or to control (assist decision making) in existing systems.

One basic component of the structure of any system is its boundary. A system's boundary is a contrived component designed to assist the understanding of the system's function; in reality, of course, no such boundary exists on any system. However, without a precisely defined boundary, the performance in terms of output from the system in relation to inputs cannot be determined by way of a model. The placing of the boundary is of considerable importance in modelling the system since it determines exactly which subsystems must be explicitly represented within the model-structure. Across the boundary there is assumed to be no interaction. Hence, in the model it is assumed that input to the system across the boundary provides the total environment in which the system (in model-form) must operate. The data requirements to provide for this environment are quite different from those required to construct the detailed subsystems. The model-environment will be composed of a number of elements which will be termed *exogenous* variables or '*driving*' variables. So far as the model is concerned these exogenous variables represent the only 'contact' with the circumstances outside the defined system. Placing of the boundary in modelling work will depend primarily on the function the model has to fulfil but will be affected by data availability; where, for example, paucity of data means that a subsystem cannot be represented adequately within the boundary, it may be convenient to contract the boundary so that this element of the model is removed from the interacting complex of the system and reduced to the form of an exogenous variable.

Consider again the barley-leaf-rust model. A plant-disease epidemic is a complex parasite–host system where growth of parasite and host, and their interaction, are affected by a large number of factors. The system in this example may be defined as the growing crop and is represented pictorially in Fig. 1.1. The conceptual boundary is drawn around the crop and the system consists of two major subsystems:

1. the fungus *Puccinia hordei* Otth;
2. the crop *Hordeum vulgare* L. (barley).

Since the disease is foliar, the crop subsystem in the model is represented by plant leaf area and progress of the disease is calculated from the percentage of leaf area infected by disease. In the fungus subsystem, the organism assumes different forms during its life-cycle, creating a multicomponent system in which the condition of each component is measured by the number of fungus bodies in each life-cycle form. Exogenous variables are inputs of weather, fungicide and external inoculum and these generate outputs of spores and crop yield across the boundary.

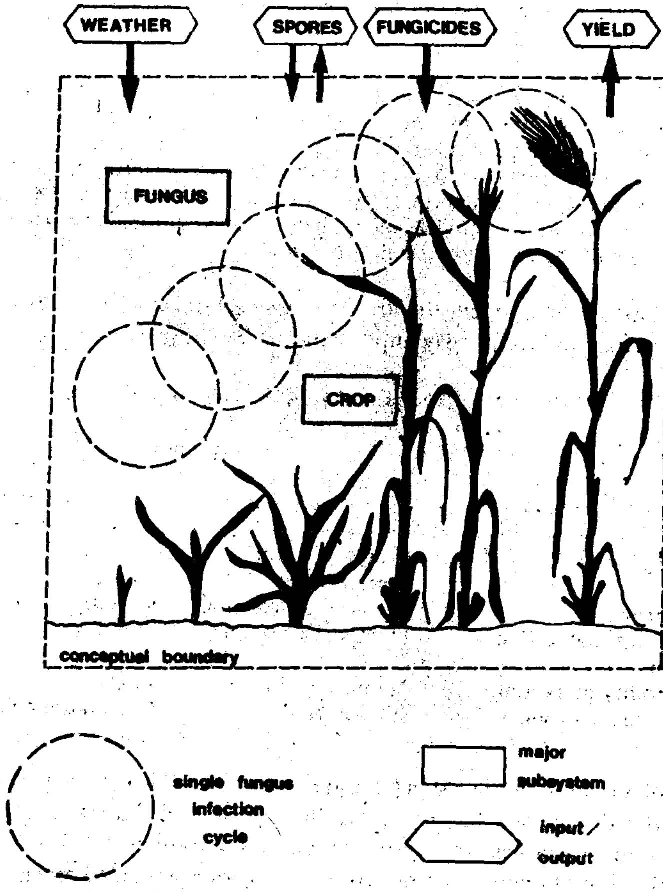

Fig. 1.1. *The leaf rust–barley crop agroecosystem.* (*After Teng, Blackie & Close,* 1978.)

Exogenous variables may usefully be classified as either those which are controllable or those which are uncontrollable by management. The importance of this classification is that it leads directly on to the way in which a particular exogenous variable is represented. Inputs to the system through the boundary that are fully under the control of management are related to policy decisions. Such controllable exogenous variables represent policies the outcome of which the model may be used to assess. Other controllable exogenous factors which are policies that the model will not be used to study explicitly can be considered fixed and simply represented in the model by constants.

In the barley-leaf-rust model, a controllable exogenous variable is fungicide application whereas weather and outside inoculum represent uncontrollable exogenous variables. The crop will almost certainly be grown with the application of such other controllable inputs as fertiliser, but for the purpose of the model this type of input is assumed to be constant. Effectively, this means that the model-builder has assumed normal application of fertilisers to the crop subsystem of the model.

Uncontrollable exogenous variables represent inputs to the system which are uncertain and frequently unpredictable. We will be discussing how such

Table 1.1. Examples of various exogenous variables

System definition	*Exogenous variable*	
	Controllable	*Uncontrollable*
Grazing livestock	Number of stock per hectare	Rainfall
Crop growth	Fertiliser application	Sunshine hours
Mechanical harvesting of grain	Number of tractors	Wet days
Commodity marketing	Number of stores	Prices
Rumen metabolism	Feed offered	Dry-matter consumption

variables may be modelled in Chapter 4. For now it is sufficient to note that a greater degree of difficulty is usually experienced than with controllable exogenous variables and that the data requirement for the stochastic specification of uncontrollable exogenous variables can be extensive. Some examples of controllable and uncontrollable exogenous variables are given in Table 1.1.

The outputs from the system are dependent on the stream of exogenous variables imposed upon the system and the structure and organisation of the system itself. In some managed systems the value of the outputs will determine future direction of the controllable inputs. This structure implies an information feedback to the manager in time for him to make adjustments to his management policy. Information systems which have this *cybernetic* (feedback) characteristic are discussed in detail in Chapter 7. Here we should merely note that the value of outputs at one point in time will, in the presence of an information feedback, influence the

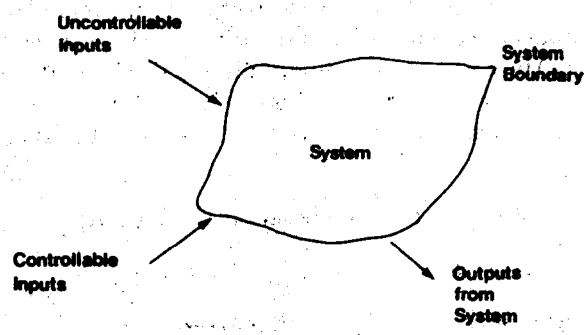

Fig. 1.2. *The concept of a system.*

value of outputs at some later date. The general system may then be represented in schematic fashion as in Fig. 1.2.

To illustrate briefly this concept of feedback, look now at the pig-management model described at the end of this chapter. This model is intended to provide management information on the results of particular strategies adopted by the farmer. The model accepts inputs of feed policies, herd structure, fertility, etc., and generates outputs of production and cash flow from the unit. Consider the case of a manager wishing to examine the economic implications of a different feeding policy for his fattening pigs. The new feed will be cheaper than his present one but will depress the growth rate of the fattening pigs. If his fattening house is already used to capacity, the new feed policy will result in overcrowding in the fattening house. This uncontrolled cybernetic loop will result in increased mortality, injury from stress diseases, such as tail biting, and further depressed growth rate. However, there is a controlled feedback option which is to reduce the input of pigs into the unit to compensate for the reduced outflow of pigs from the unit. The model allows the farmer to examine the economic implications of these and other management options.

The barley-leaf-rust model also provides an example of feedback loops. Assume a crop is infected by an initial dose of inoculum giving rise to a focus of infection. Pustules erupt at this infection site and produce infective spores. Given suitable conditions of weather and crop susceptibility to infection, these spores will germinate in the crop foliage and produce yet more infective pustules. This *positive* feedback gives rise to a disease epidemic. At some stage during the epidemic, a *negative* feedback loop comes into play bringing the epidemic back under control. This negative feedback may be direct management action in fungicide application, or simply occur because so much of the foliage is infected that there are few or no sites left for further infection.

Under the influence of the exogenous variables the state of the system will