THE APPLICATION OF SIMULATION TECHNIQUES TO THE STUDY OF GRAZING SYSTEMS

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Decision making studies in agriculture are often made difficult by the complex and dynamic nature of bio-economic systems. Simulation is one of the newer systems research techniques which as yet has had limited use in farm management research. This paper discusses some methodological aspects of simulation with specific reference to grazing systems. Problems arising in the development and use of simulation models are discussed and the need for inter-disciplinary co-operation to overcome data problems is indicated. One approach to experimentation is illustrated by reference to a model of a sheep grazing system and the problem of cropping for winter grazing. It is concluded that simulation is a potentially useful technique for management-oriented systems research in agriculture.

Grazing Systems and Systems Research

Grazing systems, like most farming systems, are essentially biological systems which are managed or controlled to achieve economic objectives. The distinguishing feature of grazing systems is that animals consume pasture *in situ* to meet most, if not all, of their feed requirements. The importance of grazing systems to the Australian economy is reflected in the considerable portion of the total agricultural research effort devoted to their study and the fact that the grazing industries contribute about five per cent of gross national income in Australia.

The nature of grazing systems presents a number of major difficulties for management-oriented research. They are extremely complex and our knowledge of the many components and inter-relationships involved in even a simple system is far from complete. The complexity of grazing systems and, indeed, of all farming systems, has resulted in the fragmented development of agricultural research into a number of highly specialized fields. This has led to problems of communication and co-operation between research workers in the various fields—a problem, of course, not restricted to agricultural research. Boulding [1, p. 199] aptly refers to this type of situation as "the spread of specialized deafness". The problem is apparent in both the biological sciences and agricultural economics, where experimental results are often operationally meaningless in relation to the original system. If research is to be efficient, the results of experimentation must eventually be evaluated in relation to the operational goals of the system to which the research is directed. This is most likely to be achieved by an integrated approach to agricultural research [10, 12].

A second research difficulty is that management control over grazing systems is incomplete and, because of the stochastic nature of the climatic and economic environment, the management of a grazing system involves making decisions with imperfect knowledge. This lack of control, particularly in relation to climate, means that experiments must be repeated over a number of years to accumulate sufficient results for a meaningful analysis. Physical experimentation on grazing systems can thus be extremely costly and time-consuming, even when the system is considerably simplified and reduced in scale. A possible means of reducing these problems is to experiment with a model of the system rather than the real system itself. This is the basis of the simulation approach.

Simulation

Over the last decade simulation has become a standard systems research technique in business, industry and defence. To date, however, it has had only limited application to the study of farming systems [6, 9, 18] yet these systems exhibit many of the characteristics of systems for which simulation has been found to be a useful research technique. This situation is probably due to lack of experience with simulation techniques and to problems of data availability.

Simulation is usually considered to be a two-phase technique in which a model of the real system is constructed, and experiments are then performed on the model [13]. The modelling phase alone can be extremely useful in terms of gaining a better understanding of the structure and operation of complex systems. However, the major benefits of simulation are likely to stem from the experimental phase. The appeal of a simulation approach is that the inter-relationships and temporal aspects of complex stochastic systems can be incorporated in a model. Providing that the model is a close description of reality, it will react to changing input patterns and decision variables in a similar fashion to the real system. By experimenting with the model, the behaviour of the real system can be explored quickly and cheaply for a variety of climatic and economic conditions.

Unlike techniques such as linear programming and dynamic programming, simulation does not involve solving a model to find a unique optimum. As a result, simulation is not used to define a precise optimal operational strategy although an optimum can be approached on a 'cut and try' basis. A simulation study would generally be concerned with locating the optimal region of production, and the point within this region at which a system would be operated would then be determined by the personal preferences of the decision maker. For many problems relating to dynamic systems, simulation may give more useful results than can be obtained by using optimizing techniques. These techniques generally restrict the form of the model and do not have the same facility for representing the dynamic behaviour of the system.[1]

Simulation can be used for both the analysis and synthesis phases of systems research.[2] Management-oriented research, which is the primary

[1] Techniques such as linear programming and dynamic programming can also be classified and used as simulation in the sense that they involve models of reality [7]. In common usage, however, the term simulation is generally reserved for studies in which the form of the model is not restricted by the requirements of the mathematical technique.

[2] For a more detailed discussion of the distinction between analysis and synthesis see Cohen and Cyert [2], and McMillan and Gonzalez [11, pp. 17-20].

concern of this paper, will generally use simulation for systems synthesis, that is to aid the design of new systems and improved methods of control. When simulation is used for systems analysis a different approach is used. Systems analysis is concerned with explaining the structure and operation of a system and the model will generally include as much detail as possible in order to focus attention on the unknown part of the system. In addition, the problem of model verification is rather different.

Model Verification

An important part of a simulation study is that of verifying whether the model is in fact an adequate representation of reality. The approach to verification will partly depend on the purposes of the simulation exercise. If the objective is to investigate the structure of the actual system, then fairly rigorous verification of both the components and the model as a whole will be required to prove or disprove hypotheses with any degree of confidence. This situation is most typical when simulation is used as a tool of systems analysis. The alternative situation arises when simulation is used for systems synthesis. That is, to solve a management problem in terms of specifying a set of operating or decision rules to achieve some objective. The objective of the study should be kept in mind when deciding on the severity of verification procedures. There is little point in insisting that the model should predict to a given degree of accuracy, if this accuracy cannot be incorporated into the management decision.

Ideally, the model as a whole should be verified by testing how well the simulated results match the performance of the real system. This presupposes that the real system exists, and that there are suitable records of system inputs and outputs. However, as Conway, Johnson and Maxwell [4] have noted, even if such a test can be performed it is by no means conclusive. The fact that the model behaves like reality for one set of inputs and operating rules is encouraging, but does not prove anything about the validity of the model for a different set of conditions. It may be that a number of selective input combinations may 'test' the model sufficiently well, but there is no body of theory available to determine the validity of such a test.

These problems mean that for many simulation models, verification has to be a largely subjective procedure. This is not so much a limitation of the simulation technique as a characteristic of the sort of problems for which simulation has been found to be useful. While the primary interest is in verifying the behaviour of the model as a whole, some attempt should also be made to verify, either statistically or subjectively, the individual relationships used in the model.[3] This should at least give some idea of the limitations of the model in terms of its adaptability for studying a variety of problems.

Experimentation

The main difference between physical and simulation experiments lies in the treatment of stochastic variability. In physical experimentation,

[3] If it is only possible to verify output as a function of input, then the model can only be regarded in the sense of a 'black box' [8]. The processes of transformation within the box may bear little resemblance to reality, even though the results of the transformation are acceptable over the range of inputs relevant to the problem.

experimental procedures and the analysis of results are largely based on the assumption that there will be an element of variability beyond the control of the researcher. In a simulation experiment, however, stochastic variability is deliberately included in the model,[4] so that it is possible to compare alternative treatments under exactly identical conditions, (i.e. the alternatives can be run with identical sequences of stochastic influences). This serves to highlight the difference between alternatives although the analysis of variance cannot be used as the assumption of independent results no longer holds. As Conway [3] has noted, this is not necessarily a disadvantage, as the analysis of variance may not be appropriate for problems involving the comparison of alternatives. It should be noted, however, that comparison of treatments under identical conditions yields results that are applicable only to that set of conditions. Typically, these conditions will merely be one sample from a stochastic process, and further sampling will be necessary to give results which are of general application. Since samples are drawn from probability distributions of the stochastic elements according to a pseudo-random sequence, it is a simple matter to create new conditions by changing the start number of the pseudo-random sequence.

Most decision problems that are likely to be tackled with simulation models of grazing systems will fall into one or other of the following categories:

(i) to compare alternative courses of action;
(ii) to estimate the response of the system to changes in the level of a single input;
(iii) to explore the response surface generated for different combinations of levels of inputs;
or
(iv) to estimate the input combination required for an optimal or near optimal level of output.

The problem of comparing alternatives is basically one of deciding what significance to place on the difference in system output. For example, a grazing system model might be used to compare two policies for selling store lambs. When there is a single measure of system performance, say profit per acre, the most useful approach may be to specify the minimum difference of interest.[5] Unless the actual difference is greater than the specified minimum, the alternatives would be regarded as 'not significantly different'. In part, the relative magnitude of this minimum difference will reflect the experimenter's confidence in the realism of the model.

The second situation, that of estimating system output for a single variable input, is a form of sensitivity analysis. Because the model is only an approximation of reality, the trend in system output is likely to be more meaningful than the absolute values for any particular level of input. An example of this type of problem is discussed later.

The exploration of response surfaces will generally call for the use of experimental designs in order to make the most efficient use of computing

[4] It may, of course, be omitted entirely in which case the model becomes deterministic.

[5] Because stochastic influences are involved, the variance of model output may also need to be considered in making a comparison between alternative policies.

facilities. For most problems there is probably little point in trying to define the optimal point on the surface, even if the model is sufficiently realistic to allow this to be done with any degree of confidence. A general specification of the optimal region of the surface is likely to be of more value than a single estimate of the optimal point [15]. This is particularly true when the results are intended for general application since the 'optimal' point for system operation will vary for individual decision makers. The use of simulation to explore response surfaces for grazing systems could be of considerable use as a complement to physical experimentation. Because simulated experimentation is relatively cheap and fast, it could be used to give some indication of the general form of the surface, in order to sharpen the focus of physical experiments.

The final situation, that of finding the input combination for optimal output, involves the use of search strategies to determine the optimum or near-optimum with a minimum number of experimental duns.[6] However, the stochastic and dynamic nature of bio-economic systems means that it is difficult, if not impossible, to define precise optima for system operation. Again, a general specification of the optimal region, including some estimation of the sensitivity to structural relationships within the model, is likely to provide more useful information on which to base management decisions.

Problems of Data Availability

One of the major problems of developing simulation models of grazing systems is tne lack of directly suitable biological data. The system will have to be simplified to reduce it to manageable proportions, and the relationships required to describe the simplified system do not always correspond to those being investigated by biologists. Typically, the model builder will have to modify experimental results to fit the particular model, and may even have to 'synthesize' relationships from little or no data. This situation is not entirely unexpected given the analytic orientation of most biological research. There is, however, an undoubted 'waste' of potentially useful data in biological research [14]. Results which fail to meet the significance tests of the analyst may be useful to the synthesist faced with the problem of having to make an assumption about a particular relationship.

When there is a major data problem a co-operative effort between model builder and biologist will be required to develop the necessary relationships. This approach was used in the construction of a specific model of a sheep grazing system. The grazing model was not developed to study any particular management problem, but rather to explore the problems involved in developing and using models based on biological relationships for decision-making studies. For this reason the model is not presented in detail although a simplified schematic representation is shown in Figure 1.

In order to estimate pasture production in terms of weekly dry matter output, the simplifying assumption was made that weekly pasture growth

[6] A comprehensive treatment of this approach is contained in Wilde and Beightler [17], and Zusman and Amiad [18] give an empirical example in an agricultural context.

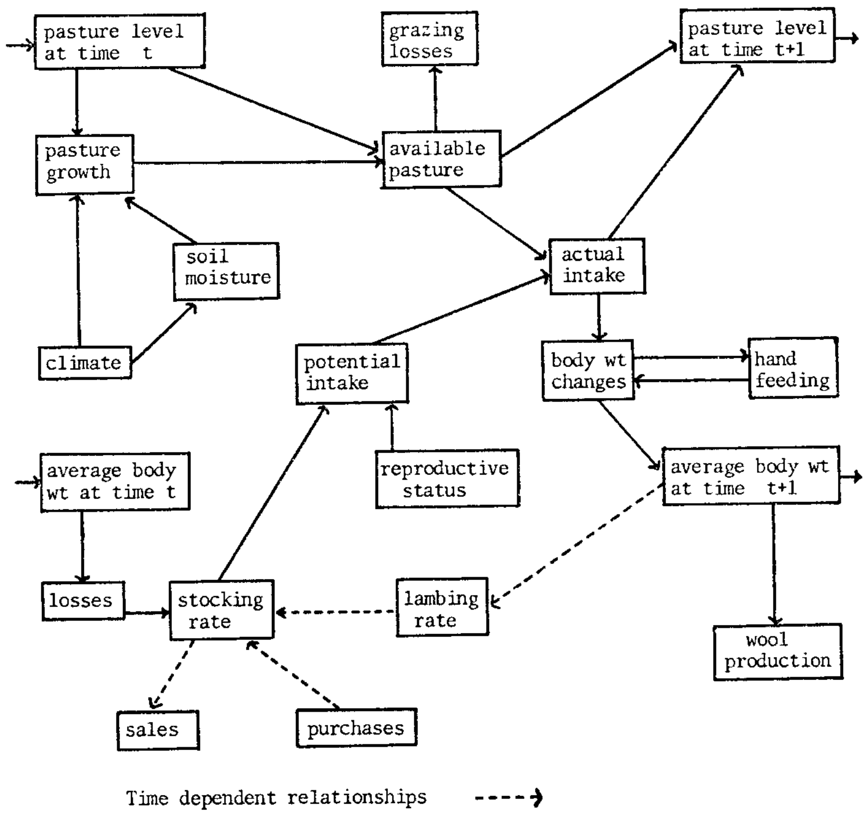

FIG. 1—Diagrammatic Representation of Simplified Grazing System. (operative period—1 week)

was a function of the state of the pasture,[7] available soil moisture and the time of the year. There were no directly suitable experimental data available for the specific semi-improved phalaris/white clover pasture so resort had to be made to work based on mono-cultures of these two species.[8] Potential weekly growth was first estimated as a function of the state of the pasture at the beginning of the week under the assumption of unlimited soil moisture. This potential figure was then modified by a growth factor determined by available soil moisture and atmospheric demand for water.[9] The necessary relationships for determining pasture growth were estimated from the mono-culture data by an agronomist. The important point is that the agronomist was in the best position to make the necessary assumptions about the pasture production process. The model provided a useful medium for illustrating the need for, and the implications of these assumptions. On a subjective basis, the model gave quite realistic results in terms of total pasture production, and the seasonal pattern of production. Figure 2 illustrates the pasture produc-

[7] Pasture state refers to the total amount of pasture in terms of lb. DM per acre.

[8] G. G. Johns, University of New England—unpublished data.

[9] This procedure was similar to the one described by Flinn and Musgrave [5] except that the time unit involved was a week rather than a day.

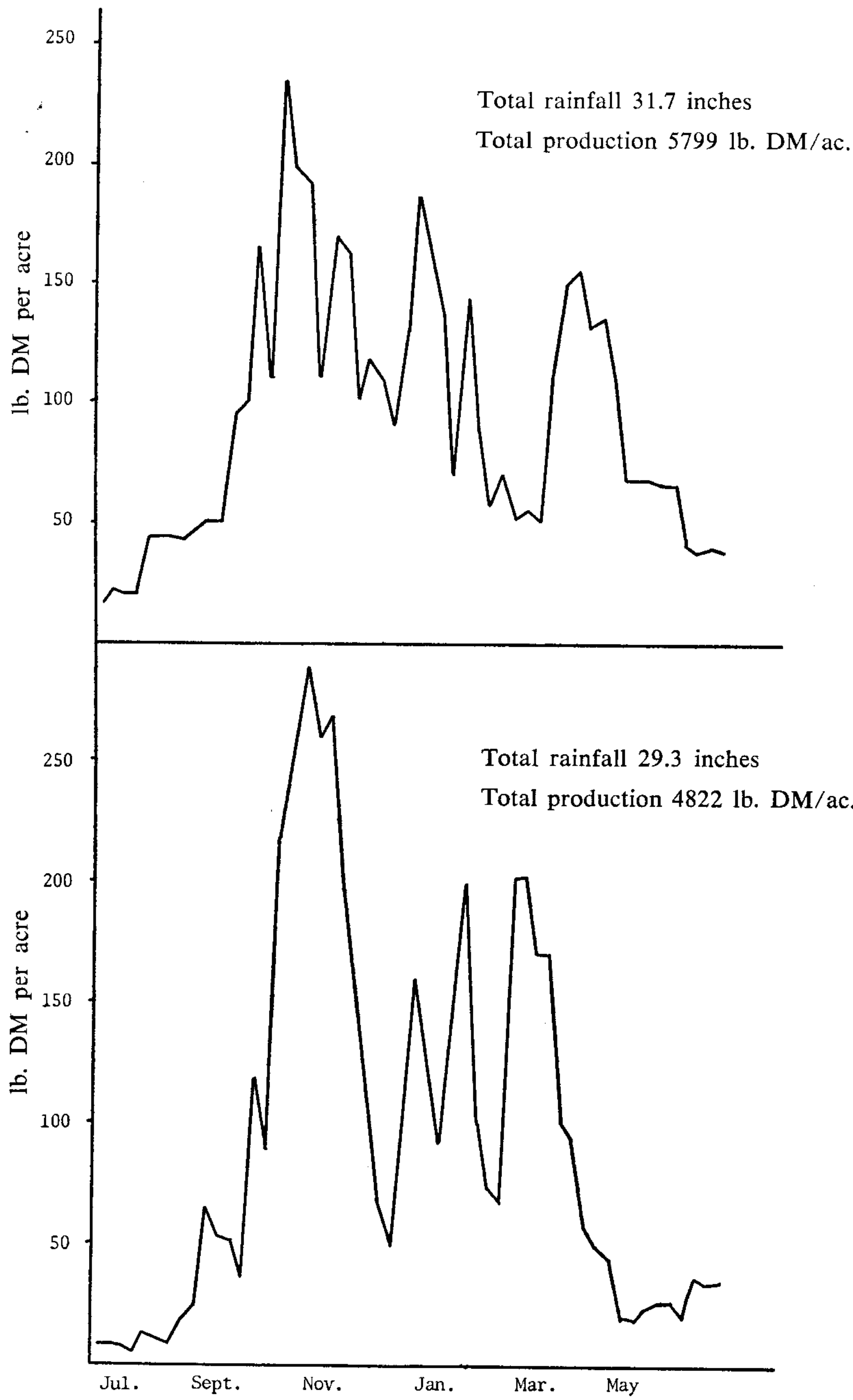

FIG. 2—Illustration of simulated weekly pasture production.

tion figures under a stocking rate of three ewes per acre for two years with a similar total but different patterns of production. This type of data is rarely available from experiments yet is essential for an adequate treatment of many decision problems relating to the dynamic behaviour of grazing systems.

A Simulated Winter Cropping Experiment

A feature of simulation studies noted by Hutton [9] is that a basic model can often be adapted to study a variety of problems. For example, the grazing model could be modified to study problems relating to pasture conservation, pasture irrigation, winter cropping and lamb selling policies. In order to illustrate the experimental phase of simulation, the basic model was adapted to look at the practice of growing oats for winter grazing. This is an example of estimating the response of the system model to a single variable input.

When a portion of a farm is withdrawn from grazing to grow a crop, the average stocking rate on the remainder of the farm is increased. Wheeler [16] has noted that the penalties in terms of decreased animal productivity over this period may be so great as to nullify any benefits when the crop is grazed. Wheeler also concluded that research on a whole farm basis was needed to study the problem adequately. In a sense, the use of a simulation model can be regarded as a whole-farm research approach.

The model was set up to represent a 500 acre farm carrying 1500 mixed-age Merino ewes mated to Border Leicester rams for prime lamb production. Replacement ewes were purchased annually. The intention was to represent a typical, rather than a highly productive grazing system in the New England region. No provision was made for pasture improvement practices. The basic model was modified to allow different proportions of the total area to be sown to oats. The crop was grazed over the eight weeks immediately prior to lambing, and dry matter yields at this time were estimated as a function of total rainfall over the growing season. Each 'treatment' was simulated for a 25 year period using actual weekly rainfall data for the years 1942/43 to 1966/67.[10]

A summary of the results of the simulation experiment is shown in Table 1. The main conclusion is that, for this specific grazing system, the use of oats for winter grazing is not a worthwhile practice, thus confirming the conclusions of Wheeler.[11] The important feature of the results is the overall trend rather than the absolute figures for any particular level of cropping. The same trend was maintained for different stocking rates and different periods of crop grazing.

The volume of information that can be obtained from simulation experiments can create problems of data analysis and result presentation.[12] While most of the information will be relevant to the problem,

[10] The simulation year started on 1st July.

[11] It is emphasized that these results are only applicable to the specific grazing system described by the models. Provided that the necessary relationships could be specified, the model could be adapted to study the same problem for different climatic regions and grazing systems.

[12] The problem of having too much information is by no means a disadvantage, as has been noted by Hutton [9].

TABLE 1

Results of Simulated Winter Cropping Experiment (Averaged over 25 years)

	Percent of total area cropped[a]				
	0	5	10	20	30
Pasture production[b] lb. DM/acre	4257	4244	4235	4201	4036
Wool production lb./acre	25·9	25·8	25·7	25·4	25·2
Total lamb sales	1470	1466	1465	1454	1405
Percent prime lambs	69	69	68	66	57
Returns per acre ($)[c]	20·9 (±8·14)	20·2 (±8·45)	19·9 (±7·90)	18·3 (±7·57)	15·0 (±7·80)

[a] Average crop yield was 2603 lb. DM/acre
[b] Summed weekly production
[c] This figure represents gross sheep income, less flock replacement, cropping, hand feeding and husbandry costs

there is often a need to summarize it into a few parameters of system output to aid interpretation. In most cases, estimates of mean and variance will be sufficient to identify promising alternatives, and these can then be studied in more detail. The sequence of system output for example, may be of considerable importance and this sort of information is not available from the results shown in Table 1. Given the unfavourable response to cropping, however, there was little point in continuing the analysis along these lines. The ability to follow the behaviour of the system through time is one of the important advantages of the simulation approach.

For response surface exploration least squares regression can be used to relate system output to inputs, as a convenient means of summarizing the results. However, when it is necessary to present results to decision makers, considerably more detail will be needed. Measures of mean and variance may be used to identify an optimal or improved combination of inputs but, for this particular combination, detailed results showing the dynamic behaviour of the system are likely to be needed. Once the model has been programmed the marginal cost of obtaining extra information is relatively low and there is probably little to be gained from trying to economize carefully on computer output.

Conclusions

Simulation is a powerful systems research technique but methodological and data problems may restrict its application to decision problems of grazing systems. On the methodological side, the main problem is the lack of an accepted approach towards the validation of simulation models. The interpretation of experimental results also presents problems which have not been completely resolved.

The lack of suitable data is likely to be the main handicap to the development of grazing system models. The study on which this article was based has shown that it is possible to develop models for decision making studies which give due recognition to the biological processes involved. However, some form of inter-disciplinary co-operation is likely to be required to overcome data limitations and this may restrict this type of simulation work to institutions where such co-operation is possible. The problem is not always one of generating new data, but of making better use of existing data, which in many cases is quite extensive. The promotion of inter-disciplinary communication and co-operation may be one of the significant side benefits of such simulation studies.

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