A dynamic simulation model for planning and controlling grazing systems

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ABSTRACT

This study reports on the development of a stochastic dynamic model to simulate a pastoral sheep enterprise. The event driven model was constructed using the iconic simulation package, Extend^{TM}. Events corresponded to the shifting of animals from one paddock to another. Each paddock was represented as a single entity with inherent attributes such as grazing area, sward characteristics and pasture production potential. The rotation sequence for grazing was determined by always allocating the flock of ewes, flock replacements or lambs to the paddock with the greatest pasture mass. Herbage mass was divided into three fractions: leaf, stem and dead. Pasture growth and senescence rates for individual paddocks were calculated from pasture leaf mass. A Micherlich-type function was used to relate leaf mass to total pasture growth. Senescence was assumed to increase linearly with herbage mass. Deterministic or stochastic pasture growth rate data can be generated by the model. Pasture responses to nitrogen were estimated dynamically and moderated for the farm by entering a user-defined response for a standard 50 kg/ha nitrogen application.

Animal performance was calculated using average attributes for ewes, ewe hoggets and rams, but lambs were simulated individually. Lamb performance is affected by its date of birth and sex, and this information was generated by a sub-model for mixed-age ewe and ewe hogget reproduction. The potential herbage intake of the sheep was defined by their rumen fill and physiological energy demand, and herbage availability which was defined by pre-grazing green herbage mass and green herbage allowance for rotational grazing and leaf mass for continuous grazing. The grazing time spent in each paddock was derived from a linear interpolation of user-defined herbage allowances for each month of the year. The proportion of leaf, stem and dead material in the diet was calculated according to the proportion of these fractions in the sward and herbage availability. If animals were supplemented they consumed all of the material offered. This caused pasture substitution by decreasing the physiological energy demand and utilising rumen space otherwise taken up by grazed pasture. The partitioning of nutrients by animals was estimated from the ratio between energy intake and energy demand in an animal growth sub-model. This was driven by the DNA, protein and fat content of individual lambs and the average for animals in other sheep classes. Lambs were drafted for sale and graded according to user-defined threshold drafting weights. Carcass weight and fatness (GR) were generated from the live weight and sex of individuals lambs. A genetic optimisation algorithm was developed to optimise the systems control variables incorporated in the model. These were pasture allowance, supplement fed, nitrogen applied and lamb drafting weight.

The model was evaluated against three New Zealand "farmlet" grazing experiments. This validation suggested re-parameterisation of the physiological intake limit is needed and that the British equation used to relate intake to leaf mass availability is overly sensible to the pasture conditions found in New Zealand. The model was also used to test the effects of pasture measurement errors on the profitability of a grazing system. Significant differences in profitability occurred when a CV of 40% in measurement of pasture mass was assumed (Gross margin = $NZ 495 /ha vs. $NZ 542 /ha and $NZ 570 /ha for 20 and 0% CV in measurement estimations and normal variability in pasture accumulation rates and Gross margin = $NZ 587 /ha, $NZ 576/ha and $NZ 519/ha, respectively for 40, 20 and 0% CV in measurement estimates and no pasture accumulation rate variability). It was concluded that low gains in system performance can be expected by improving the accuracy of measuring pre-grazing herbage mass beyond the level (13-16% CV) provided by the correct use of current measurement techniques.

Keywords: Model, grazing management, Extend^{TM}, optimisation, variability
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INTRODUCTION

1.1 Overview and objectives

Numerous simulation models of grazing systems have been developed and improved upon in the last three decades (e.g. Smith and Williams, 1973; Arnold et al., 1977; Galbraith et al., 1980; White et al., 1983; McCall, 1984; Loewer et al. 1987; Finlayson, 1989; Larcombe, 1989; Marshall et al., 1991 ; Finlayson et al., 1995; Cacho et al., 1995; Freer et al., 1997). These models have helped researchers to: extrapolate experimental results to different farming conditions (Clark et al., 1994), study the potential of alternative management policies (e.g. McCall, 1984; Finlayson, 1989), undertake experiments which otherwise would be too time consuming or expensive to conduct in reality (Cacho and Bywater, 1994) and provide decision support for on-farm management (e.g. Larcombe, 1989, Marshall et al., 1991; Loewer et al., 1993; Freer et al., 1997). Some of the models have progressed from a research application to commercial use (e.g. UDDER, Larcombe, 1989, STOCKPOL, Marshal et al., 1991 and GRAZPLAN, Freer et al., 1997).

The potential benefits of applying computerised decision support systems to farm management are great (Thornley and France, 1984; Little, 1985; McKinion et al., 1989). However, to date, most simulation models have been designed to provide decision support for strategic planning. Operational and tactical management (Parker, 1993a) continue to be superficially tackled in most models of grazing systems, although a model for planning and monitoring the day to day rotational grazing of sheep and cattle was developed and applied by Parker (1987). Jalvingh (1992) pointed to the need for agricultural simulation models to guide tactical and operational management of farms in order to address questions such as: How long should the animals be left grazing in a paddock?, How much area should be allocated to the animals in a day?, How much nitrogen should be applied? or How much supplement should be fed out to the animals?. Questions of this type are regularly faced by farmers and need to be addressed by decision support models.

While the number of publications concerning models of grazing systems is increasing, it is also important that new developments are not totally independent of earlier research. The structure, assumptions and equations implicit in the available models should be compared against new developments in contributing disciplinary research (e.g. in pasture production or modelling techniques) before embarking on a new model. By this means the strengths and weaknesses of existing models, including on-farm evaluation, can be identified. Only after this work has been done should work commence on developing a new or improved model.

Most models have been developed using traditional compiling languages such as Pascal (e.g. STOCKPOL; Marshall et al., 1991) or spreadsheet packages (e.g. AEM; New Zealand Forest Research Institute, 1995), but iconic simulation packages promise faster development and lower programming requirements, and a level of speed not achievable in simulations based on spreadsheet packages. There is a need to evaluate the capabilities of iconic simulation packages for developing large-scale agricultural models, such as those for whole farm grazing systems.

A considerable amount of research has focused on the influence of stochastic variables in terms of choosing a portfolio of enterprises for an agricultural business (e.g. Dake, 1994), but their effect on the productivity and profitability of grazing production systems has almost totally been disregarded, except in the recent work of Cacho and Bywater (1994) and Pleasants et al. (1997). This area requires a greater emphasis in farm management modelling research because risk has many practical repercussions for farmers in their decision making.

This thesis addressed the three areas identified above as gaps in existing knowledge concerning the simulation of pastoral systems. Specifically the objectives were:

1. To develop a model framework that linked the strategic, tactical and operational management of livestock on pasture.

2. To study the effect of including stochastic variables on the performance and outputs of a grazing system model relative to a deterministic analysis.

3. To test the suitability of an iconic simulation package for developing an agricultural decision support system.

1.2 Organisation of thesis

The thesis is presented in six chapters. A review of the application of decision support systems in farm management and the role, classification, implementation and evaluation of simulation models are presented in Chapter 2. This chapter also contains a brief review of databases and expert systems and the advantages to management of combining these technologies within simulation models.

The iconic simulation package used for model development is introduced in Chapter 3 and aspects of how a model can be structured with the package are discussed. This chapter also includes a review of the equations adopted to describe the components of the sheep production system modelled. The components are separated into sheep reproduction, pasture growth and senescence, herbage intake, grazing dynamics, diet composition and energy value, energy dynamics and mob dynamics and trading (or gross margin). The development of the equations and processes for the model used in this study are reviewed in the context of associated disciplinary knowledge and existing models.

An evaluation of the model outputs is presented in Chapter 4. Chapter 5 describes a series experiments that were conducted with the grazing model, including an optimisation experiment of control variables in a grazing system. The effect of quantifying sensor errors on farm system profitability is also shown in Chapter 5.

In Chapter 6 conclusions to the study are drawn by evaluating the research outcomes relative to the initial objectives proposed for the thesis. A range of practical applications that arose during the model's development and application are also discussed.

LITERATURE REVIEW

2.1 Introduction

Computers are increasingly becoming an integral part of the management of agricultural systems (Nuthall, 1992). The adoption of computer technology by farmers is creating the opportunity to increase the efficiency with which data, information, knowledge and expertise is transferred from universities, research institutions and private companies to farmers and consultants. This is rapidly increasing the amount of data available to farmers which needs to be processed to provide information that is useful for decision making. Software technologies such as databases, spreadsheets, expert systems and simulation models all have a part to play in improving the speed and quality of on-farm decisions.

Agricultural simulation modelling is still a relatively controversial field: approaches and concepts are both steadily changing as the field develops in conjunction with new computer technology (Sinclair and Seligman, 1996). Nevertheless, some concepts are becoming firmly established and experience in applying different types of models to farming problems is increasing. It is therefore important to define how simulation models and other computer-based technologies "fit" into farm management. This role, and concepts associated with, simulation models and other techniques used for decision support in farm management are reviewed in this Chapter. The advantages of, and prospects for, combining various techniques for building decision support systems are also discussed.

2.2 Decision support systems and management

2.2.1 *Decision making and problem solving*

Improving the quality of decision making and problem solving skills is an important concern in any field of management since, as described by Kay (1986), "management is the decision making process in which resources are allocated to a number of production alternatives in order to attain the goals and objectives in mind". Pratt (1986) and Stuth et al. (1991)

suggested decision making can be defined as a process involving perception and evaluation of a problem regarding choices between alternative actions. The decision is made relative to the aims and goals of the business, and is influenced by the precision required and information available.

In contrast, problem solving goes beyond the decision. It also involves the implementation of the decisions taken (Figure 1;Turban, 1988) and from this perspective, management may be better defined as concerning problem solving rather than just decision making. Problem solving depends not only on taking the best decision, but also on the effectiveness of putting it into practice (i.e. implementation). In this context, a good decision includes an assessment of the efficiency with which the system can be manipulated. Implementation is usually not instantaneous nor absolutely precise, and also requires different financial and labour resources. The timeliness, precision and the resources required by the "actuators" to implement decision alternatives available all need to be accounted for when making an "optimum" decision.

According to Simon (1977), followed by Turban (1988) and Huirne (1990), decision making involves three major phases: intelligence, design and choice (Figure 2.1).

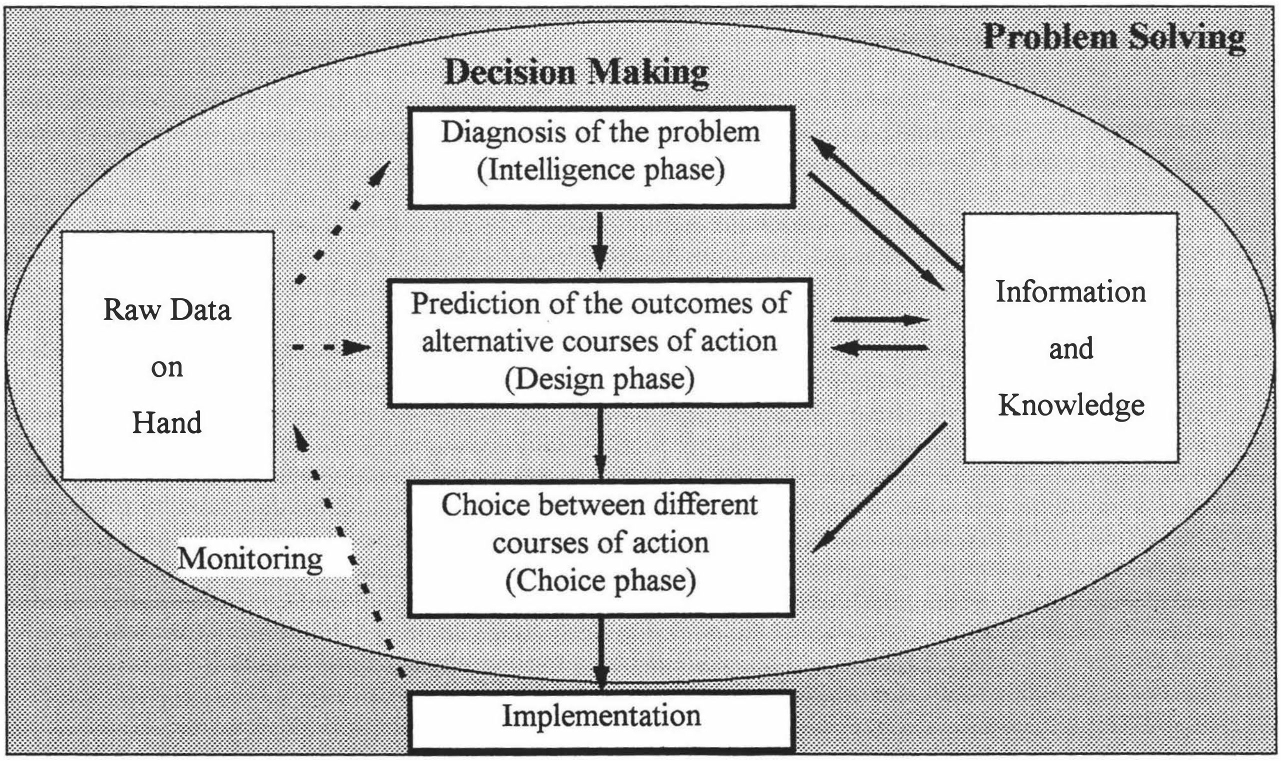


Figure 2.1 Diagrammatic representation of the problem solving and decision making processes. The whole diagram included in the rectangle represents the problem solving process. The boxes and arrows included in the circle represent the decision making process. Full lines represent information flows, dashed arrows represent data flows (Adapted from Turban, 1988).

Intelligence, also called diagnosis (Turban, 1988), involves examining and processing the data and information available in order to identify problems and/or opportunities. Correct diagnosis is fundamental to problem solving. However the extent to which it is necessary to adopt formal approaches for this phase varies with the type of problem. The diagnosis of the problem may concern structured routine problems (also called programmed problems; Turban, 1988) such as the allocation of crops to areas or of animals to paddocks or unstructured problems such as diagnosis of diseases, metabolic disorders, and nutrient deficiencies of animals and plants. In structured problems the diagnosis is usually clear and straightforward and does not require formal methods. In such problems the design is the limiting phase for decision making analysis. However, in unstructured problems diagnosis is usually the key for problem solving and this can be accelerated and improved by the adoption of formal approaches.

Design includes formulation, development and analysis of possible courses of action. This involves understanding the problem or opportunity and testing alternative solutions for their feasibility and optimality. Therefore the outcomes of each alternative path should be estimated, either objectively or subjectively, in order to make a choice amongst the alternatives. Successful design depends, however, on the correct diagnosis of the problem. If the problem is not correctly identified, further development of decision analysis will be in vain.

Evaluation of the outcomes requires previous experience and deduction, and/or information about the characteristics and outcomes of the alternative management options. While previous experience and deduction are extremely useful in on-farm decision making, they also have their limitations. The experience/deduction approach can lead farmers into bias in two ways: first, it is possible that farmers take decisions based on the observation of an insignificant sample of weather, price or other variables outcomes; and second, the deduction may be incorrect (i.e. despite making a correct observation of the system's behaviour, the manager attributes this to the wrong cause). Both deficiencies are likely in the farm business environment where, usually, the implementation of several management modifications is on going and biological, marketing and human factors change dynamically.

Choice, the third phase of the decision making process, involves selecting one alternative for implementation based on the feeling (i.e. the intuitive information based on the data at hand) or the objective information gathered and prepared about the various options to take. This phase includes most of the decision analysis methods developed to date.

2.2.2 *Decision support systems in farm management*

Decision analysis involves processing the data on hand in order to highlight courses of actions that are most likely to have a successful outcome. In this context, decision support systems can help in the diagnosis of a problem, the prediction of the outcomes of alternative paths of action and/or in choosing between alternatives according to the preferences of the decision maker (Figure 2.1). Some decision support tools may even include two or three of these steps.

The role of decision support systems commences by facilitating and reducing the cost of handling and storing large amounts of data. Relational databases implemented on adequate computer software can perform these tasks very well. Also, the fact that the data are available to the computer allows their fast flow to data processing tools (such as simulation models and expert systems).

Turban (1995) classified problems into: structured (also called programmed) processes where there are routine or repetitive problems for which standard solutions exist; semi-structured; and unstructured, in which some or none of the phases have a standard methodology for solution, respectively.

Some decision support systems, particularly those embodying artificial intelligence, address the diagnosis of problems and opportunities, particularly in the areas of crop management (e.g. McKinion et al., 1989; Nevo and Amir, 1991; Nevo et al., 1994), choice of beef breeds (e.g. Hockman et al., 1991; 1995), and allocation of cows to feedlot groups (Grinspan et al., 1994). The maintenance of adequate databases is also a key factor in diagnosing problems. Trends or abnormalities in the data monitored can readily highlight problems or opportunities.

Farmer experience and deduction can be greatly improved by increasing their access to information about the outcomes of alternative policies (Turban, 1988), since the decision making problem arises in the first place because of incomplete information or knowledge about the results of the alternative actions that could be taken (Blackie and Dent, 1979). While complete information is impossible to obtain and therefore any decision involves risk, increasing the information about the alternative actions improves the effectiveness of decision making (Anderson et al., 1977; Turban, 1988; Stuth and Smith, 1993).

Simulation models can be the core of the design phase. Their main strength is flexibility of formulation. While mathematical programming and other techniques are quite limited in terms of describing system behaviour, simulation modelling allows the oddest characteristics of the system to be described mathematically (Rothemberg, 1989; Mayer et al., 1996). Simulation with the mathematical model will estimate system responses and this allows rapid evaluation of alternative policies. Also, the addition of an optimisation algorithm enables superior courses of action, given conditions and constraints, to be highlighted. In the design phase, the manager is responsible for the formulation of the alternatives, but mathematical models can improve the analysis and evaluation of the different actions that can be taken with respect to these alternatives.

Sometimes, it may be necessary to carry out the process of problem decomposition before evaluating the outcomes for the alternatives available in order to match parts of the problem with the tools available for the analysis (Turban, 1988). By combining the results from such tools, information to improve decision making can be generated, although according to system theory, summing the solutions to parts of a problem will not necessarily give the optimum solution for the whole problem (Spedding, 1988).

Choosing between alternative actions should rest with the decision maker rather than the decision support system (Stuth and Smith, 1993), except in the case of on-line operational control systems where the computer automatically monitors and commands the actuators of the system as may happen with automated greenhouses or milking parlours (e.g. Jacobson et al., 1989; Devir et al., 1993). However, off-line decision support systems, despite being unable to act directly the system, may recommend alternative courses of action for analyses. The process of recommendation may be carried out either objectively or subjectively depending on the structure of the problem. In assisting with the choice phase, computers may use one of several methods of objective decision making analysis. Recommendations may be based on information about expected outcomes for the alternatives specified directly by the farmer or from the outputs of a simulation model or an expert system.

Finally, Stuth and Smith (1993) suggest that the programming of decision support systems into computers can improve the efficiency of problem and decision making processes by: performing large numbers of calculations beyond the capability of conventional methods;

storing and updating large data sets quickly and retrieving these for other calculations; incorporating heuristics and uncertainty; and accessing remote sources of information about the problem at hand.

2.2.3 *Data and information processing: The role of DSS*

As emphasised before, one of the main roles of DSS is the processing of data available to the decision maker into information and/or data, and information into knowledge (Blackie and Dent, 1979; Farrell et al., 1992). The owner of the problem or the stakeholder still bears responsibility for decisions: the DSS assists by providing more of the knowledge necessary to take better decisions (Stuth and Smith, 1993). They can integrate very different types of information into a common framework and provide help at each of the steps of the decision making process.

Currently, a unanimous definition for data and information does not exist in the literature. Blackie and Dent (1979) suggested that information is data which are understood by the manager and relevant to the decision to be made. To become information useful for decision-making data requires analysis and interpretation.

The second view is similar but slightly more precise. Debenham (cited by Farrell et al., 1992) defined data as the fundamental, individual objects represented within a system. They can be either qualitative or quantitative. For example the pasture cover of a farm at the beginning of a given month is 1500 kg DM or the dominant grass species is ryegrass. In this view also, one datum cannot *per se* improve decision making, they have to be processed by combining two or more datum in order to generate information. For example, a feed budget model can combine the following data: start of month pasture cover (1500 kg DM/ha), expected pasture growth rate (15 kg DM/ha/day), expected intake (25 kg DM/ha/day) and output the information that the expected pasture cover starting next month will be 1200 kg DM/ha. Similarly for qualitative data, according to the example given by Farrell et al. (1992) in relation to nutrient deficiency diagnosis, the data (nutrient = zinc) and location of the deficiency symptom (= new leaves), can be combined to state that, “The location of zinc deficiency is on new leaves”. The latter statement represents new information. Thus, the general concept given by these authors is that information is generated by the association of data.

Knowledge, in contrast to information, is a general rule that is not made explicit by the combination of data. In the feed budget example, pasture cover for (month $_{i+1}$) = pasture cover (month $_i$) + monthly pasture growth - monthly herd intake) can be regarded as knowledge because it is not explicit in the original data. Also, in simulation models relationships between rainfall, temperature, pasture cover and animal production can be regarded as knowledge. According to Hicks and Lee (1988), knowledge is the organisation of perceptive processes in such a way that significant conclusions can be drawn. Knowledge therefore describes how new information may be derived from the current state of the database including not only information but also experimentation, common sense, perception and intuition.

In this sense DSS's can be viewed as a formalised representation of knowledge that is necessary to process data or information in order to help decisions. For example in expert systems, a knowledge base may be programmed to incorporate the expertise of people in the subject area. At the same time a simulation model can be viewed as a representation of the quantitative knowledge about the behaviour and interactions between components in a system.

2.3 Implementation of decision support systems

2.3.1 *Simulation models*

2.3.1.1 Definitions

Mathematical simulation models are one of the main methodologies for developing decision support systems. The need to simulate arises from the impossibility of finding the set of desired solutions algebraically in systems governed by non-linear and interactive relationships (Hannon and Ruth, 1994).

Simulation models in farm management have, since their very early stage of development, been linked with systems theory so that they are often confounded as being the same thing. The core of systems theory is the concept that the behaviour of the whole system is different from the sum of its parts (Doyle, 1990). The interactions and interrelationships between components of a system over time are a primary determinant of its behaviour (Bywater, 1990). Therefore, an isolated study of system components is inadequate for gaining an understanding of the complete system.

Obtaining a common definition for mathematical computer models is somewhat more difficult, since researchers tend to adopt their own particular meaning for their models. Broad definitions were given by Spedding (1988) who stated: “Models are simplified representations of the reality” and Rothemberg (1989) who wrote: “A model is an abstraction of reality to allow us to deal with the world in a simplified manner, avoiding the complexity, danger and irreversibility of reality”. Thornley and France (1984), usefully restricted the definition to mathematical models, which are “an equation or set of equations (and algorithms) used to represent the behaviour of a system”.

System models typically include a number of equations that are individually either an hypothesis about the behaviour of one process or an interpretation of the relationships among variables (Baker, 1996). Therefore a model is a hypothesis (Dent and Blackie, 1979), or a collection of hypotheses (Sinclair and Seligman, 1996) about the behaviour of the system.

Simulation models are not the only methodology used for systems research. Bywater (1990) classified “systems” approaches as being either formal or informal. Informal approaches are defined as those that attempt to accommodate the dynamic interactions of the system by descriptive or intuitive means rather than by mathematical quantification. Formal system approaches are defined as those that employ techniques that explicitly quantify the effects of dynamic interactions within the system being analysed.

According to Bywater (1990) traditional farm management techniques such as feed or cash budgeting can be regarded as informal approaches. On the other hand, mathematical simulation models are included within the category of formal systems. Informal approaches depend on the assignment, by the user, of expected responses by the system to changes in its inputs (i.e. the tool is not able to work out the interactions and response(s) of the system). With formal approaches, the response of the system is endogenously determined by its previous mathematical formulation. The performance of informal system approaches depend, therefore, on the assumptions and estimates made about the system response by the individual using them and they are, as a consequence, subject to their personal experiences and knowledge.

2.3.1.2 Modelling as an approach to synthesis

Most authors involved with systems research, recognise that modelling is an exercise in synthesis rather than analysis (Wright, 1973; Thornley and Johnson, 1990). On the other hand, the need to gain a better understanding of the components of a system is typically carried out by disciplinary analysis using conventional research methods, particularly experimentation. Systems analysis research or conventional research is usually carried out by conducting controlled "micro" experiments under artificial conditions in which the whole system is not operating (Wright, 1973). The need to study system's components at an increased depth leads to disciplinary and reductionist approaches, while the need to minimise variance in order to compare changing factors leads scientists to conduct studies under controlled conditions. These characteristics of conventional research make it difficult to reassemble the system from the information gathered. This is because most studies of system components are carried out without serious regard to how the system will be reassembled (McCall, 1984). Miller (1982) suggested reductionist approaches to agricultural science have resulted in much effort being devoted to explaining the effect of isolated factors, but relatively few attempts have been made to develop general theories of the processes incorporating all of the known variables. Because of the lack of well-formulated models, recommendations have been based on generalisations and dominated by the search for, and elimination of, the most limiting factors (McCall, 1984). Also, the necessity to work in artificial conditions in order to control system variability sometimes produce data which are not appropriate for direct application to the study of whole systems. One example is the use of equations generated by grazing behaviour experiments conducted with hand-made swards that have uniform vegetative tillers which, despite their invaluable contribution to understanding grazing behaviour, fail to produce realistic relationships for actual pasture conditions where variability between tillers exist and senescent material and mature stems are present.

The analysis work carried out by conventional research usually concerns the study of the components at an increasingly lower level of aggregation (Figure 2.1). The shortcoming of using this approach alone is that problems perceived at a higher level of aggregation within a system may be not solved directly from isolated information derived at a lower level of aggregation because of the interactions between components. It is therefore necessary for synthesis work to follow component experimentation in order to solve real word problem(s).

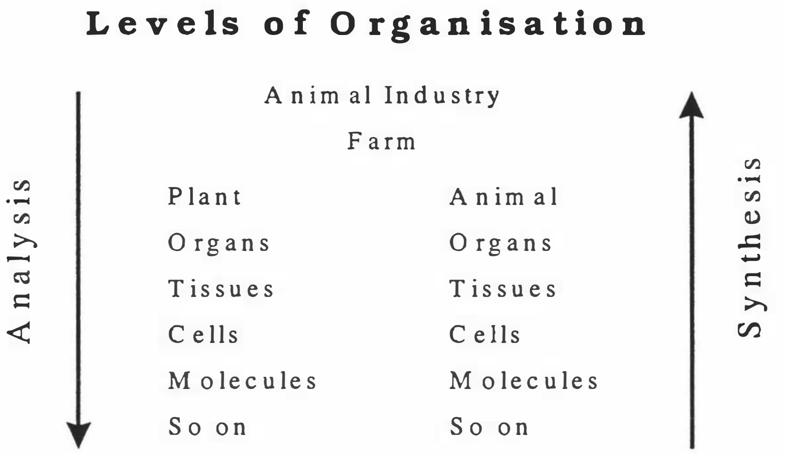


Figure 2.1. Levels of aggregation in the analysis and synthesis approaches to agricultural research.

The limitations of component studies are readily seen, particularly where the interfaces between components are complex. A good example, can be seen from animal production systems where the grazing interface involves a number of complex interrelated factors and the diet of a grazing animal is determined partly by interrelated features of the forage on offer and animal behaviour (Miller, 1982; Parsons et al., 1994; Newman et al., 1994). According to Boote et al. (1996) and Simpson et al. (1996) simulation models are particularly valuable for integrating findings from reductionist research.

2.3.1.3 *The role of simulation models in research and extension*

Defining farms as systems is the first step in recognising that simulation models are useful for decision support in practice, as well as in agricultural education and research. Farms are multi-component units of production. The components (such as soil, plants, labour, machines and animals) interact continuously to generate the final products. Rainfall, sunshine, fertilisers and other production factors may be identified as inputs beyond the farm boundary. As the components of the farm system interact amongst them, changes in any one component may affect other components and the farm as a whole. Farms can therefore fit the definition of system presented by Spedding (1988): "A system is 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".

The state and outcomes of farm systems therefore reflect the sum of the dynamic interactions between its components. At the highest level of aggregation, soil, herbage, animals and management are at the core of pastoral systems (Kristensen and Sorensen, 1989). In order to mechanistically model the farm for simulation purposes, it is necessary to analyse each component to determine, at a lower level of aggregation, how the system's inputs and the interaction between system's components govern the outputs. Simulation models are therefore related to the predictive capacity of the knowledge accumulated through component disciplinary research. Fick et al. (1994) stated: "One of the characteristic attributes of a mature science is the capacity to predict..." and "...predictive capability is demonstrated by the construction and application of quantitative models". In this context, the inability to model a system, or parts of it, usually reflects the absence of appropriate quantitative knowledge.

Modelling and component research are, therefore, complementary and interactive (Wright, 1973). Wright (1973), Little (1985), Stuth et al. (1991) and Boote et al. (1996) all expressed the usefulness of the development of mathematical simulation models in highlighting information deficiencies or "gaps" in the current knowledge of systems phenomena. Also, Little (1985) and Boote et al. (1996) stressed the importance of modelling in "putting together the pieces" from disciplinary research knowledge, and in bringing scientists from several disciplines to work together on a common project. According to Thornley and France (1984), the engagement of researchers in model development forces them to be more objective and quantitative in preparing the design of experiments and to focus experiments on areas where knowledge is most lacking. For example, Boote et al. (1996) described how crop models have been successfully used as a focal point to organise experimental data. Modelling encourages, and is encouraged by, the formal storage of data and use of the results from a series of experiments, as in the Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project and the American National Database Program (Dill et al., 1990).

The use of models in research or in decision support has the potential to accelerate the evaluation and adoption of new technologies (Dougherty et al., 1985) and the development of mechanistic management models, which often evolve from research models, can be used to test scientific findings in the "real world" (Thornley and France, 1984). Thus models are capable of promoting the integration of extension and research. Linking systems' analysis, decision analysis and field research through decision support systems enables future disciplinary or interdisciplinary research that could improve system performance and its management, to be identified (Stuth et al., 1991). Mechanistic modelling may also accelerate the practical application of basic research to farm systems (Seligman, 1993; Boote et al., 1996; Simpson et al., 1996; Freer et al., 1997).

2.3.1.4 Classification of mathematical models

Mathematical models can be classified in numerous ways. In fact there are so many classifications that Dillon and Anderson (1990) stated: "There seem to be almost as many schemes for classifying models as there are modellers themselves". Dent and Anderson (1971) provided the following basic classification:

- *Iconic models* - Are similar to the real system in that the relevant properties are represented except at a different scale. They are also called physical models.

- *Analogue models* - Are based on the use of one property to represent another. An example is a graph, where lines represent the variation of some quantities when other quantities are changed. The mechanical mowing of pasture as a substitute for animal grazing is another example. Flow diagrams used in some steps of model construction and maps are also analogue models.

- *Symbolic models* - Are models where properties are represented by symbols. These are usually mathematical and logical. In general, symbolic models are the most abstract and the easiest to manipulate. Mathematical computer simulation and artificial intelligence models are examples.

Symbolic models, the focus of interest here, are the most abstract of the models (Shannon, 1975). Mathematical models, which explicitly quantify dynamic interactions between system components, require the assistance of a numeric processor, hence they are almost always computer-based models (Bywater, 1990).

Shanon (1975) and Thornley and Johnson (1990) proposed a simple classification to divide mathematical symbolic models into: empirical, mechanistic or teleonomic; static or dynamic;

and deterministic or stochastic. Empirical models are related to tasks like curve fitting, regression and the direct application of mathematical formulae to observed data. They are usually not constrained by scientific principles or any knowledge of mechanism(s) and are usually focused at just one level of organisation or hierarchy. Mechanistic models are integrative and concerned with the mechanism by which the components of the system interact. Mechanistic models, according to Thornley and Johnson (1990), are "hard" science, and they follow the thinking of traditional reductionist methods used in most of the biological sciences. They are constructed by breaking down the system into components and lower level sub-components into lower level components and by determining their proprieties and interactions. The lower level components explain the behaviour of the higher level components.

Thonley and Johnson (1990) believe that the responses in mechanistic models are determined by much more complex relationships and generally explain an observed data set less well than a empirical model because of the limitations implicit in the assumptions used. However, mechanistic models can be used in a wider range of circumstances than empirical models (Bywater, 1990; Thornley and Johnson, 1990). Also mechanistic models are much "richer" than empirical models because they take into account the scientific basis of the system's behaviour, and thus offer more possibilities for the system to be manipulated and improved (Thornley and Johnson, 1990).

The formulation of mechanistic models includes two steps: establishing the structure (variables, functional relationship among the variables and equation formulation) and estimating the parameters (Bywater, 1990). The structure depends on the theoretical background of the modeller and his/her inventiveness, while parameter estimation should ultimately be derived from empirical data, although modellers sometimes make use of parameters estimated for earlier models or from analysis of earlier experiments.

Teleonomic models (also called teleological or goal seeking models) are less common than mechanistic and empirical models in agriculture. Except for ecology they currently only play a minor role in plant and crop modelling. Teleonomic models look upward at higher hierarchical levels. They are goal seeking in the sense that the goals of the i^{th} level can be viewed as a requirement imposed by the level i+1. In contrast to the mechanistic approach, where the responses for a given level of aggregation are explained by the behaviour of lower level components, in teleonomic models they are determined by higher level components. These models assume that, during evolution, higher level components were forced to assume certain behaviour which determined the characteristics of lower level components. Consequently, the behaviour of the lower level components appears to be goal driven as in the cost-benefit model of grazing ruminants by Thornley et al. (1994).

Models also differ in the way time is treated. Time is disregarded in static models. Examples of such models include ordinary linear programming models, goal programming, risk programming, regression and other mathematical equations that are not time dependent (Murthy et al., 1990). Models of this kind have been published in the agricultural field to, for example, predict animal maintenance, intake and performance (Sauvant, 1988; AFRC, 1993). The suitability of static models depends on the level of responsiveness of the outputs of the system to time and how the dynamic interactions between the variables affect system behaviour (e.g. in continuous grazing, increasing the stocking rate in the month n will lead to lower pasture cover in month n + 1 which may result in lower pasture growth and feeding levels in the month n +1).

Dynamic models can be divided into continuous and discrete models (Dent and Blackie, 1979; Brockington, 1979; Pidd, 1988). In continuous simulation models, the variables in the model are recalculated at a fixed small time step so that the model can represent the smooth changes in system components. Pidd (1988) highlighted that changes cannot be occurring continuously within a "continuous" simulation computer model because digital computers operate only with discrete quantities. However, in computers, continuity is achieved by the recalculation of the variables for a large number of fixed points in simulated time.

In continuous simulation models, the choice of a time step requires a compromise between speed of execution and accuracy (Finlayson, 1989). The shorter the time step, the higher the execution time (which may be a concern for large and complex models) but the greater the smoothness and accuracy.

Once the time scale has been chosen for a model the system variables can be classified according to their rate of change in relation to the time scale of the model. The variables can be slower, contiguous or faster than the time scale of the problem (Pleasants et al., 1997). Slower variables are those whose rate of change can be regarded as zero with respect to the period of time simulated (i.e. they can be modelled as constants for the time period). Contiguous variables are those whose rate of change is significant during the simulation; they need to be included explicitly in the model and recalculated during the simulation. Fast variables change more quickly than can be perceived within the time scale of the model and are therefore ignored. Such variables, through their interactions, may act to change the model's state variables so that they cause deviations from the predictions for a given time scale.

The classification of the variables may, however, change depending on the time spell of the model or the process being simulated. For instance the weight of the animals in a mob can be regarded as a slower variable and therefore constant over the simulation of the grazing time in one paddock, but it would be contiguous in a year round simulation. Also, during the simulation of grazing time in one paddock, some variables such as biting rate or bite size may be regarded as being fast variables. For the purposes of most whole farm grazing simulation models they are therefore ignored due to their rates being too rapid to recalculate over one time step

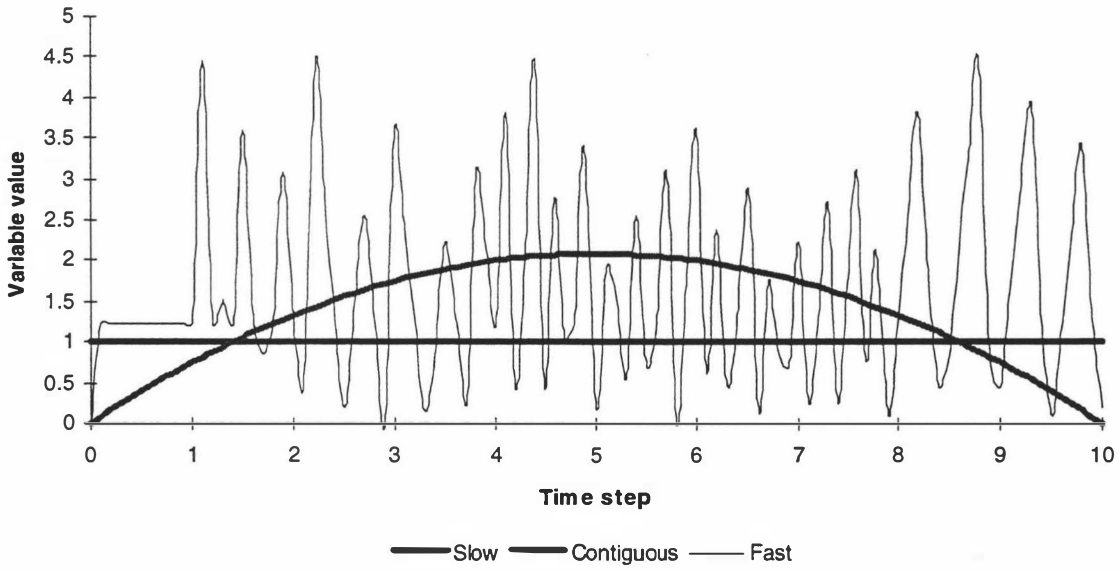


Figure 2.2: Illustration of the time behaviour of fast, slow and contiguous variables

In terms of decision support models, however, it is important to bare in mind what level of accuracy is likely to affect the decision to be taken. Also, it makes no sense to try to improve accuracy or "smoothness" in a model by decreasing the time step if it is known that it's equations are crude estimations of reality anyway.

In event driven models, the time step is not predetermined by the modeller or the user, but is calculated by the model itself. These models are designed to predict the time interval for the occurrence of a new event and to recalculate all the system variables at this time (Brockington, 1979). In order to calculate the time interval in discrete event models, all of the routines which produce events place the time of its next event in a slot of an array of events, or a "future events chain" (Pidd, 1988). This array is then searched for the closest time point and the simulation clock is set for the exact time of next event (for a more detailed description of this process see Section 2.3). In these models the emphasis is usually on discontinuous, abrupt changes of state rather than a smooth progression through time in regular steps.

Stochasticity refers to random or probabilistic events. According to Pidd (1988), models that incorporate distributions of probabilities to explain the variance inherent within the events it is simulating can be termed stochastic. Models which do not incorporate probabilities in their results are deterministic. Dent and Blackie (1979) suggested that the deterministic treatment of a system assume that its behaviour is entirely predictable or that the average of the values can adequately explain its behaviour.

Anderson (1976) claimed that only by incorporating stochasticity into simulation models could the present degree of understanding of a system be totally reflected. Furthermore, Dent and Blackie (1979) stated that planners could not afford only to work with single value estimates of intrinsically risky phenomena. Anderson (cited by Dent and Blackie, 1979) pointed out that modellers should provide guidance and data which recognise the full extent of risk inherent in any policy to decision makers.

In spite of the agreement of these authors about the importance of including stochasticity in models to fully represent the farm system, some practical problems in doing so have been identified in the literature. Dent and Blackie (1979), for example, pointed out that suitable data sets to estimate the variability of events are rarely available. Another problem is that the computer time necessary to generate a stochastic solution is many times greater than that of deterministic models, because conclusions from stochastic simulations can be only drawn after a number of runs, each with a different output. The results of several simulations may be used to generate statistics which describe the studied variable such as the mean, coefficient of variation and distribution functions (Jalvingh, 1992). The number of runs necessary to generate these output attributes is dependent on the variability of the output studied and the level of statistical confidence required.

It is important that stochastic features should be incorporated at an acceptable level and in understandable form for model-users (Dent and Blackie, 1979). In some models the addition of stochasticity may create confusion and reduce the acceptability of the model to the user. Dent and Blackie (1979) therefore recommended introducing stochastic elements only when deterministic models appear inadequate and stated that it is better to have a simple deterministic model which meets the stated objectives and which will be used, than to have a complex stochastic model which is too expensive, too clumsy or too obscure to be satisfactory to the user.

Usually stochasticity is added only to one or few inputs or parameters within a stochastic model in order to avoid excessive complexity (Jalvingh, 1992). For pastoral livestock production systems, variability in pasture production and prices are the basic determinants of the variability in the economic performance of the system and are the factors most likely to affect decision making.

The addition of stochasticity to a model can affect decision making in two ways. The first is related to risk aversion theory which says that sensible decisions are those which involve the choice of less risky alternatives at a given level of return and that risk and returns may be interchangeable in a decision-maker's utility function. If the mean and the variability of the returns from alternative policies and the utility function of the decision maker are known, then it is possible to highlight efficient solutions. The second effect of adding stochastic parameters in simulation models, when the system includes asymmetric response functions is that, the mean of several stochastic events may be quite different to that predicted by the mean (Antle, 1983; Pleasants et al., 1997). If the response to the stochastic input x is asymmetric, the deterministic solution of the model (using the mean of the stochastic variable) will be different from the mean of the stochastic simulations. Pleasants et al. (1997) gives the example of a simple exponential equation e^x. If one makes x vary uniformly between 1 and -1, the expected value of the stochastic model will be greater than that generated by the deterministic model, i.e. $e^0 = 1$ (Figure 2.3). Therefore even for risk neutral dynamic production models, risk affects both expected productivity and optimal resource allocation.

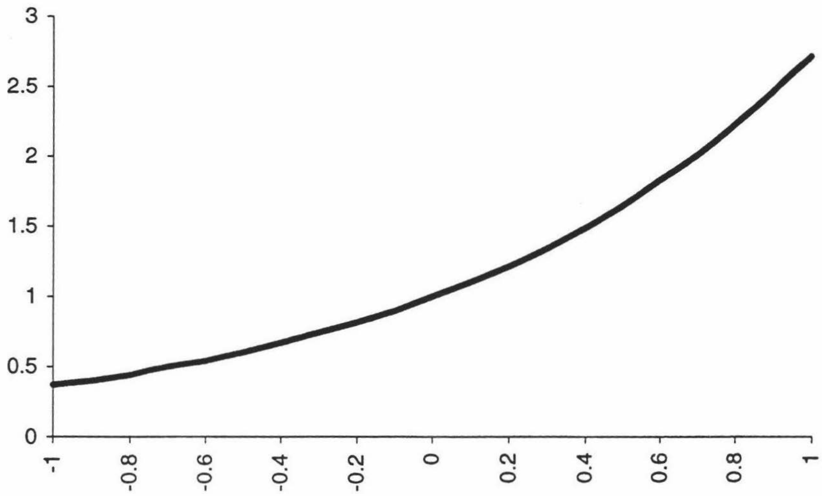


Figure 2.3. Illustration of the effect of asymmetry on the expected value of the function $y = e^x$ over the interval -1; +1. The mean estimation of y by the deterministic model is $e^0=1$ while that for the stochastic estimation is 1.175 (After Pleasants et al., 1997).

An example of a risk neutral effect of stochasticity in production models was given by Cacho and Bywater (1994) who compared 7 different stocking rates, varying from 9 to 21 sheep stock units per ha (ssu/ha) using either a deterministic or a stochastic version of model described by Finlayson (1989) and Finlayson et al. (1995). The stocking rate for the maximum gross margin was 17 ssu/ha using the stochastic version while in the deterministic version, gross margins continued to increase up to the maximum stocking rate tested (21 ssu/ha) (Figure 2.4).

Some models concerned with dairy production and management simulate occurrences such as heat detection, conception, foetal death, sex and viability of the calf, involuntary culling and death as stochastic events (Jalvingh, 1992; Sorensen et al., 1992). The stochastic treatment of these variables make these models ideal for studying of the effect of different management policies as illustrated by Sorensen et al. (1993) who investigated the effects of different lengths of dry period on the production and economy of a dairy herd.

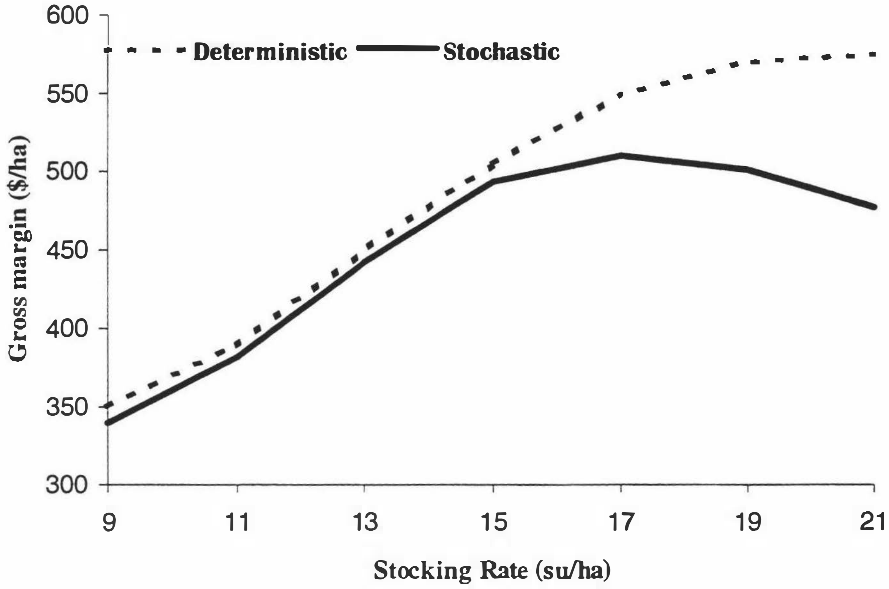


Figure 2.4 Comparison of deterministic (solid lines) and stochastic results (small squares) from Finlayson's model of a sheep farm (from Cacho and Bywater, 1994).

2.3.1.5 *Implementation of computer simulation models*

Several approaches have been described in the literature for developing and implementing computer simulation models. For example, Miller (1982) suggested that the development of models naturally follows an evolutionary sequence:

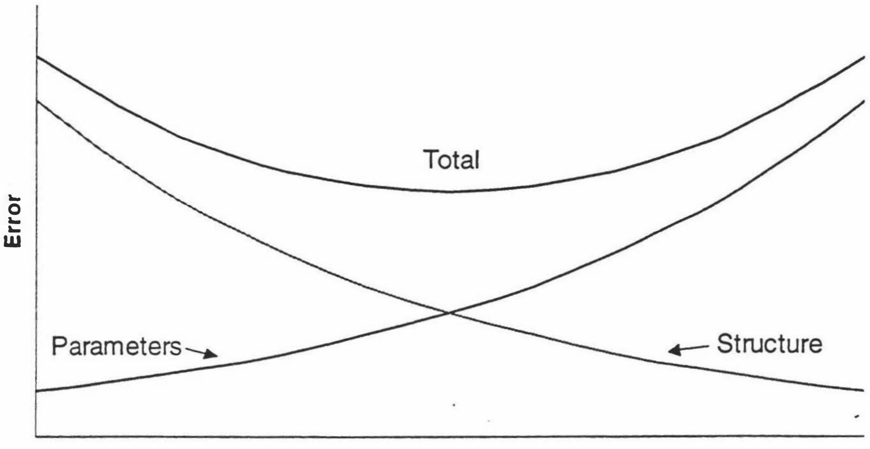
Mental ⇒ Verbal ⇒ Diagrammatic ⇒ Mathematical

After the mathematical formulation of the relationships, the implementation of a computer simulation model requires the transfer of knowledge (so far present in the form of concepts and rules) and information to the computer in the form of formulas, algorithms and data structures.

The definition of the system and objectives of the simulation model to be constructed should be stated before model construction starts (McCall, 1984). Different systems and aims require different modelling approaches. At the broadest level, the definition of the system boundaries and the time scale that the model will operate under will determine which variables and processes should be taken into account in the simulation (Pleasants et al., 1997). The organisational level of the problem (e.g. farm, enterprise, crop, canopy, plant, animal) should also determine model structure. Usually simulation models should have just two, and at most three, levels of organisation (de Wit 1970; Sinclair and Seligman, 1996).

The objectives of the final user or of the study will determine the level of complexity that should be adopted. According to Boote et al. (1996) there is a strong case for both comprehensive and simple models. Several points arise here and need to be considered. When a model is constructed with a narrow well-defined purpose it is easier to keep the level of complexity low. However, increased generality usually requires the addition of more inputs, variables and equations. The demand for increased complexity may also came from the variables which are to be studied. Here, for instance, the objective of the research was to study impact of variability and management control on the biological and economic performance of a farm enterprise. Control variables therefore needed to be modelled realistically, as well as pasture and animal performances and their economic consequences: combined this generated a reasonably complex model.

Two main sources of error affect the accuracy of mathematical simulation models. The first arises from parameter estimation and the second from systematic bias from oversimplification (Passioura, 1996). With increased complexity the errors in parameter estimation may accumulate and be multiplied in the relationships implicit in the model, while the error in the structure of the model may decrease because of the increased realism (Figure 2.5). It is necessary to bare in mind that a model of an agricultural production system will necessarily be highly simplified, even when defined in great detail, because of their inherent complexity. In contrast to what was thought during the early years of modelling research in agriculture, increased complexity does not always improve prediction power (Sinclair and Seligman, 1996; Passioura, 1996). Sinclair and Seligman (1996) show several examples of cases where the use of more complex model did not lead to greater prediction accuracy.



Increasing:

Number of inputs
Execution time
Cost of information
Knowledge

Figure 2.5. The components of model prediction error versus level of model complexity (Source: Passioura, 1996).

Examples of simple to complex models can be found in both management and research models, however, they seem to have divergent objectives. For example, Thornley and France (1984) and Bywater (1990) agree that management and research models are completely different in both their aims and structure. While research models attempt to include as many of the known variables as possible in order to explore the behaviour of the system and the effect of each of the variables on it, management models should restrict the components and interactions represented to those which significantly impact on decision making. By increasing the number of variables represented in a model it may be possible to improve output accuracy and knowledge about the system, but longer execution times and greater computer memory will be required. A larger volume of data are also required and all of these factors obviously lead to increased costs and possibly lower precision in obtaining farm data as more detail is required by the model. It is also important to determine what organisational levels should be included in the model.

Model complexity should not be taken to a level which precludes mathematical analysis and experimentation. While mathematical analysis is only feasible for relatively small models, simulation may allow experimentation with larger models. Computing requirements for stochastic runs and the use of optimisation algorithms are likely to constrain a model's complexity.

Bywater (1984) suggested that management models should evolve from research models by aggregating afresh the components that are most important for representing the system's behaviour. A high level of aggregation is important in a management model in order to maintain positive marginal returns from the data collected and acceptable execution time and computer requirements. Because only the most important predictors are theoretically used in the re-aggregation process, Bywater (1984) suggested that re-aggregated models would have lower prediction error compared with models developed from scratch at the same level of aggregation.

However the re-aggregation of research models rarely happens directly, even in the same project or with the same researchers. This is because agricultural systems and management modellers are usually not the same people as the biological modellers and there is a great deal of difference between the interests of the two. However, most management modellers use, in one way or another, the developments of biological research models either by the use some of their equations and structure or through the adoption of some of their concepts.

Research models are usually constructed on the basis of scientific concepts and quantitative experimental data. In some large projects of model development, the experimental data may be generated specifically for model development, while in other smaller projects available data-sets and equations may be used exclusively. Management models, in contrast, have much more commonly been developed by using equations already used and tested in research models, and seldom involve further experimental work.

For the development of large models it is frequently necessary to divide the system into a number of smaller sub-systems to, first simplify model development and evaluation and, second, where a group of researchers are involved, as a means to integrate the expertise of individuals (Goodall, 1976).

In spite of their conceptual differences, all models, according to Thornley and France (1984), whether constructed for research or management purposes, are founded on a mix of observational data and currently accepted knowledge and conjecture. It is suggested, however, that while research models may incorporate a high proportion of conjecture, in order to evaluate different hypotheses, a management model must incorporate more consistent and accepted knowledge in order to provide a high level of confidence in its predictions. Van Dyne and Abramsky (1975) described two basic strategies that may be followed when constructing mechanistic models. The first, named the "top-down" approach, refers to the construction of the model based on a series of initially determined objectives. The "coarse" features of the system are modelled first and more detail is added depending on its importance to the central objective. The second strategy, the "bottom-up" approach, is characterised by initially building independent and detailed models of individual sub-systems that are later joined together. However, difficulties in uniting independently developed sub-models and the lack of central purpose are weaknesses of this approach (Innis et al., 1980). Also, the development of independent sub-models may result in difficulties in joining the pieces together later on, except where the work of groups (or individuals) is very well co-ordinated.

For the development of mechanistic models the first step, after defining their purposes, general features (i.e. stochastic or deterministic, dynamic or static, event-driven or continuous time) and computer package(s) to be used, should concern the study of the system to be simulated. It is important that major sub-systems, components and relationships within each sub-system, links between sub-systems, environmental variables and control points are identified during this stage (Dent and Anderson, 1971). Several authors have recommended a diagrammatic representation of the system for this purpose (e.g. Forrester, 1968; Dent and Blackie, 1979; Spedding, 1988). The dynamics of the system to be simulated are often drawn using the diagrammatic representation suggested by Forrester (1968) as illustrated in Figure 2.6a. In order to identify and extract sub-systems, Spedding (1988) proposed circular diagrams (Figure 2.6b). Dent and Blackie (1979) proposed a generalised representation of the system by block diagrams (boxes indicating the major components and linking arrows indicating flows of material or information). While following a consistent diagrammatic representation is recommended, there is room for creativity in order to handle the needs of different types of models (never forgetting that clear definition of the symbols is essential).

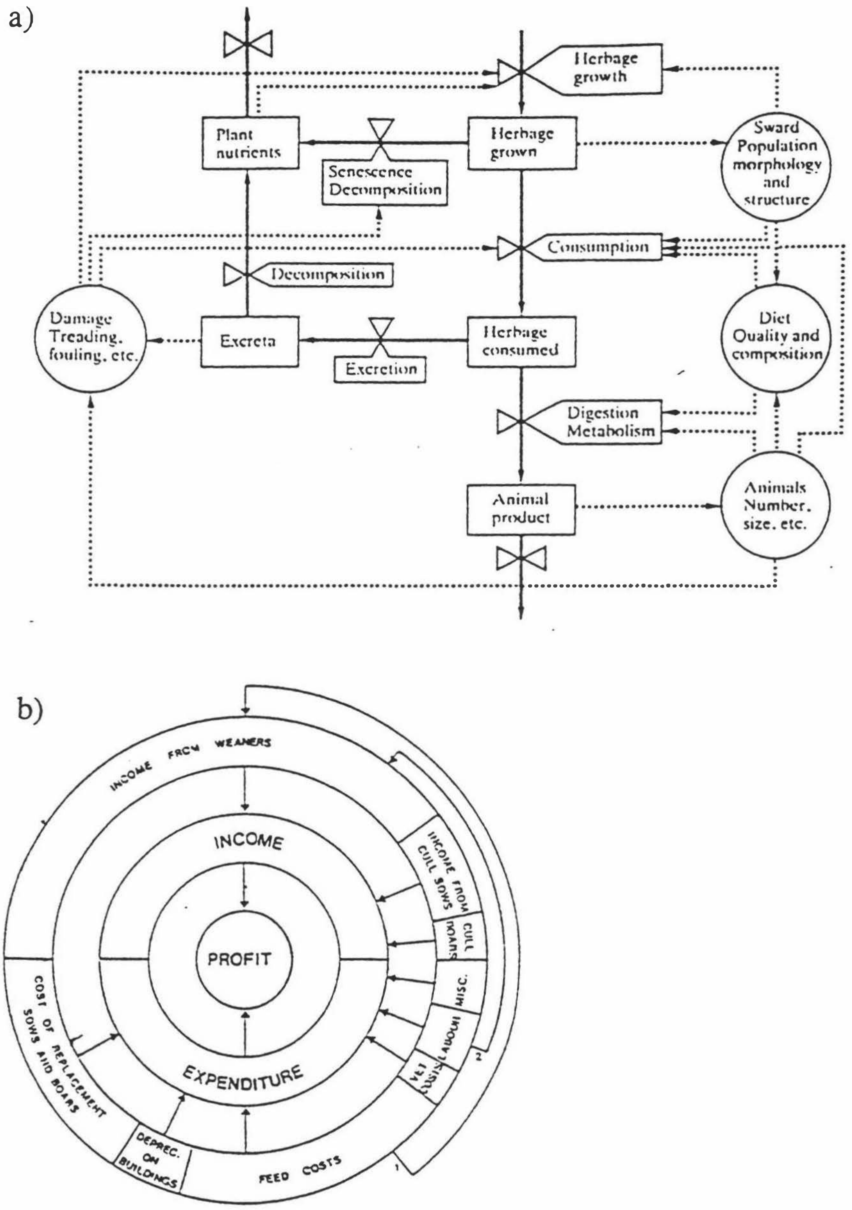


Figure 2.6 (a) Flow diagram of system dynamics (after Hodgson, 1990). (b) Sub-model identification using a circular diagram (From Spedding, 1988).

According to Dent and Anderson (1971), the diagrammatic model provides a basis for identifying the sort and form of data required. The availability of data will probably lead to considerable changes in the model. It is not necessary to model all of the details of the system being represented. In the development of decision support systems, only the parameters that are likely to affect decisions should be modelled (Gillard and Monypenny, 1988). Similarly in research models only the factors likely to significantly impact on the behaviour of the variables of interest should be included.

The third stage of model development involves searching the data for and/or defining quantitative relationships (i.e. equations) (Dent and Blackie, 1979). At this stage, limitations or "gaps" in the information available will almost always be found. Alternative ways of representing system components and estimation of values for some variables may be necessary.

Once the data have been assembled and equations formulated, the model can be implemented as computer code. This phase involves coding and debugging, parameterisation, calibration and documentation (Carlson et al., 1993). Algorithms, data structures, user-interface and other software development concerns also become important during this phase, but the relative importance of these factors depend on the objectives set for the model. Once these problems are solved, the computer program represents the definitive form of the model that is able to simulate the behaviour of the system (Brockington, 1979).

Models have been written using several types of computer packages or programming tools. The most common option is to use a third generation programming language such as Pascal, Fortran, C, C++, Basic, Delphi, Visual C or Visual Basic. These languages are very versatile and can be used for almost any software development project. They allow a customised user-interface and provide database capabilities. Despite the huge advances in computer technology over the past decade, speed, memory and system requirements are still an important issue in the development of complex mechanistic models. Because most computer languages produce compiled programs, models run faster and with less memory and fewer system requirements in this format. Models such as STOCKPOL® (Marshall et al. ,1991), UDDER (Larcombe, 1989) and GRAZE (Loewer et al., 1987) were built using general purpose languages.

The time span taken for development is also a concern for modellers because it influences the cost and commitment necessary to carry out the project. Despite the current improvements brought by the visual and object oriented languages, the time required for development is high for third generation languages and this has caused several developers to move towards faster development tools, particularly where small projects are concerned.

Simulation languages have been deliberately tailored to make it relatively simple to represent the common features of dynamic systems. This include languages such as CSMP, Dynamo, GPSS, Simscript, Gasp and Simula (Kreutzer, 1986). Probably because of their high cost and the necessity to learn a new computer language, few (if any) of the current computer simulation models in agriculture have been developed using such tools.

Another set of non-specific fast development tools which have had a much greater impact on the development of simulation models are the spreadsheets packages (Farrel et al., 1992). Packages such as Microsoft Excel ®, Borland Quattro ® and Lotus 1-2-3 ® have been used successfully to translate models to the computer. These tools allow the development of a user-friendly front-end, have some database capability and have enough flexibility to handle complex mathematical formulae (including built-in sets of algorithms for the calculation of mathematical functions), provide graphic capabilities, include a random number generator, have built-in optimisation algorithms and allow access to programming in an object-oriented language. These features have enabled the successful development of models such as AEM (New Zealand Forest Research Institute, 1995). However, the increasing complexity of models, particularly for the simulation of mechanistic and dynamic systems, means that these tools soon become limited, particularly in terms of speed and computer requirements.

Since the late 1980's, interest in using iconic simulation packages, also labelled by their authors as "Dynamic Decision Support Tools", has increased. According to Murphy (1995), those packages address a demand for the use of computer models in decision support by business managers rather than scientists. A number of packages have already being successfully marketed. Those include: Extend (Imagine that !; San Jose CA, USA), Power Sim (Model Data AS; Bergen, Norway), I Think (High Performance Systems; Hanover, Germany), Stella (High Performance Systems; Hanover, Germany), Process Charter (Scitor Corporation; Menlo Park, CA, USA) and Sim View (InterDynamics Ltd.; Inglewood, Australia).

Iconic simulation packages are particularly suitable for the development of dynamic models. They, in contrast to spreadsheets where the units for model building are cells, have icons that represent the processes to be modelled. The icons can have their characteristics customised and mathematical formulae can be included within them. Usually the blocks work with compiled code, which makes the models run much faster than those developed on spreadsheets, and this allows the development of quite complex models. The pre-programmed blocks save a significant part of the programming work. Also graphs, random number generators and the capability to model discrete event systems (the latter is quite difficult to do in a spreadsheet) are included in most of the iconic simulation packages.

Parameter estimation may follow coding and debugging. Models can be very sensitive to certain parameters and poor parameterisation can, therefore, endanger the model's performance. Parameterisation is a very important phase and requires considerable time and information (Calson et al., 1993). Depending on the access the intended user requires to information parameters may be internally estimated or user-defined. There is also the possibility of having an option for the user to modify parameters in the model (e.g. UDDER, Larcombe, 1989), but this should be provided with caution, particularly in cases where inputs are not physically based, since this may make it difficult for the user to rationally chose and adjust, non-fixed parameters.

Calibration is carried out between the parameterisation and validation stages. Calibration is performed by altering the values of parameters in a logical way in order to obtain the best fit between the simulated output and measurements made on the real system (Carlson et al., 1993). It is a test of the paramerisation procedure and is similar to validation, except it does not aim to test the model's hypothesis but adjusts its behaviour to the system being simulated (see Section 2.3.1.6).

As simulation models concern the processing of data into information (Section 2.2.3.1), the format of data inputs and information outputs needs to be considered during model formulation. The inputs required by a model should be restricted both by the extension of the databases available to the user and by the cost of gathering extra data to feed into the model. Increasing the complexity and realism of a model leads to a higher data input requirement, and therefore the costs of measuring or searching for the data required must be weighed against the marginal value of additional output information for decision making.

According to Boehlje and Eidman (1984), the marginal returns on time, effort and money required for gathering data should be higher or equal to the revenue that could be generated from other alternatives for the use of these resources. Also, only data which can be measured or retrieved adequately by the user should be asked for. The term "adequate data" means that farmers can, in an everyday farm routine, gather the data in a timely manner and with pertinent reliability, for the information to be outputted in relation to the decisions supported by the model.

On the other hand, according to Anderson (1974), output specification involves a compromise between the "mountain" of output (that can be produced by a model) and the information that is really important to the user. Substantial improvements to the computer-user interface have been made in the last few years (Baars, 1995) and these allow the user to exercise a greater degree of control over the output generated. A concern of the model builder should be to facilitate data input and provide graphic and animation options which aid visualisation and understanding of the model and the behaviour of the system under study. Help files and some explanation of model assumptions should be included in the interface of DSS models.

As stated by Carlson et al. (1993), it is important to highlight that model development is, or should be, an interactive process that includes design, re-implementation and re-evaluation, and consequently an ultimate version of the model is likely to be never reached as long as added insight into biophysical processes continues to be gained.

2.3.1.6 *Evaluation of Computer Simulation Models*

The parameterisation, calibration and initial implementation of the model into computer code is not the end of a model's development. After this stage it is critical to evaluate the model to ensure that it meets the purposes for which it was built. Carlson et al. (1993) suggested that model validation is a critical process in the interactive development of a model, because it is only through the evaluation process that the modeller begins to truly understand the model's performance and the system's function. The evaluation process can be divided into verification and validation.

Verification is a continuous and interactive process during model development. It refers to the inspection of the computer program for logical consistency and behaviour, and to its agreement with current knowledge about the system. Verification therefore comprises the subjective assessment of the model's "correctness" by its developers, or by experts on the system modelled, and the testing and debugging of the computer program (McCall, 1984).

The second stage of evaluation, called validation, refers to the fact that since a model is a hypothesis of the behaviour of one system, it should be tested against the system modelled to see whether the hypothesis can be accepted or not. Validation is defined as "the process of testing if the model behaviour is in agreement with the real system it represents with respect to the specific purposes for which the model has been designed" (Levis and Levis, 1978). Thus, validation is a procedure that compares the output of the model against recorded data of the system been imitated or the subjective judgement of an expert. The aim is to develop an acceptable level of confidence that inferences drawn from the performance of the model are correct and applicable to the real world system.

The last option can be used in the early phases of model validation where no data are available. According to Grant (1986), the validation should:

1. Examine the capability of the model to address the problem as defined in the conceptual model;
2. Examine the resonableness of the model structure and individual mechanisms;
3. Examine the qualitative correspondence between the model and the real system; and
4. Provide a sensitivity analysis.

Data for model validation can be gathered from three main sources (Anderson, cited by Dent and Blackie, 1979): historical or published experimental data not used in model building (1); historical or published experimental data collected since the model was completed (2); and experimental data specifically generated or collected for validation (3). A problem to be guarded against when using historical data is circular reasoning; it is necessary to ensure complete independence of the validation data from that used to construct the model (McCall, 1984). Therefore, the data used for parameterisation of the model's equations are not acceptable for validation, though it can be essential for verification.

Published experimental data, case studies and the historical databases of farms can provide good material for model validation. Sometimes, when there is no prospect of generating information for model validation, some of the data available for parameterisation of the model can be set apart in order to test the model. The disadvantage of this approach is that leaving out some of the data available for parameterisation will probably reduce the accuracy of parameter estimation, particularly where data are scarce. On the other hand, establishing model validity by using data generated after its completion, has production and publication risks. Also, it may be desirable to undertake model validation straight after its development in order to give the user and the developer some idea of its reliability.

Experimental data generated specially for model validation are the best, both in terms of the appropriateness of the measurements and their timeliness relative to model testing. The limiting factor for validation is usually the lack of complete data sets for comparison with simulation inputs and results (DeCoursey, cited by Carlson, 1993).

Several types of tests for model validation are described in the literature. Examples include: graphing system performance and model output in a time series, regression analysis of model outputs and real system measures, tests of means, analysis of variance and covariance, goodness of fit, regression analysis and the sensor noise test (Shannon, 1975; Murthy et al., 1990)

One of the simplest and widely accepted validation methods for dynamic models is to plot the model output and the system's performance in a time series. The exogenous variable data will be the same, but error terms within the model will generate a different sample of output (Dent and Blackie, 1979).

Simple regression analysis is perhaps the simplest statistical test of validation and one of most widely used until recently. It is performed between means of model-outputs and real system measures as paired observations. A perfect model would provide a line passing through the origin with slope equal 1 ($Y = \alpha + \beta X$, where $\alpha = 0$ and $\beta = 1$). An F statistical test may be performed to verify if the hypothesis ($\alpha = 0$, $\beta = 1$) is accepted or not.

However, Harrison (1990), in reviewing the regression of a model on real system output, concluded that it does not met the statistical assumptions for the method for either stochastic or deterministic models. In fact this test may reverse the statistical decision from valid to invalid following progressive refinement. Also, by simulating data, Harrison demonstrated that a valid model can produce a slope of 0.04 or less, and therefore is likely to be rejected by the F test. Harrison, further stated that the assumptions for the most frequently used statistical tests are seldom met when testing dynamic stochastic models, and therefore suggested that procedures such as graphical comparison of results and evaluation by specialists should be encouraged. It is argued that confidence in using the model should be build-up during its development.

Murthy et al. (1990) pointed out that a crucial decision is to choose the test for validation. If it is too stringent, the modelling process will require a large number of interactions to complete the test and accordingly the final model which passes the test is likely to be too complex for its intended purpose. On the other hand, if the test is not stringent enough, models with an inadequate level of precision will pass the test. Greig (1979) suggested that the choice of significance levels should be based on the costs and probabilities of making a Type I (rejecting a valid model) or Type II (accepting an invalid model) statistical error.

According to Shannon (1975) the concept of validation should be considered as being a matter of degree rather than an "either-or" notion (not a binary decision variable where the model is valid or invalid). In this respect the validity of a model can be considered on a scale from 0 to 1, where 0 represents absolute invalidity and 1 represents absolute validity. As the validity of the model increases, its value to the decision-maker will increase (at a decreasing rate), but the cost of the model will increase too (Figure 7).

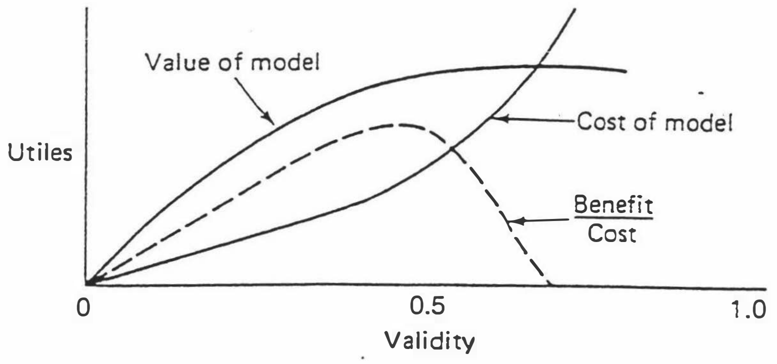


Figure 2.7 Conceptual illustration of variation in cost and value of a model by increasing its level of reliability or validity (From Shannon, 1975).

2.3.2 *Expert systems*

Conventional programs are based on algorithms which clearly define, step by step, procedures to solve a problem. On the other hand, artificial intelligence (AI) applications, such as expert systems, basically use search and pattern matching to find the recommended action in relation to a problem or opportunity. This means that once given some initial information the software searches its knowledge-base looking for specific rules or facts which match or fit the information (Hicks and Lee, 1988; Turban, 1992).

Because AI programs use symbolic representation and manipulation, they are also called symbolic processing programs (Rauch-Hindin, 1988). In AI a "symbol" is a letter, word, or a number that is used to represent objects, processes and relationships. By using symbols, it is possible to create and manipulate a knowledge-base (Turban, 1992). The knowledge-base is that part of the expert system in which expert knowledge is placed in the form of rules, frames, facts, concepts and events. This knowledge is kept separate from the procedural programming, called the inference engine, which searches the knowledge-base to find a solution to the problem concerned (Beerel, 1987). Another characteristic of expert systems is the use of heuristic methods. Heuristics, derived from the Greek word for discovery, are rules about how the problem should be solved. Heuristics are used to reduce the search in a problem activity. This is simply because a blind search for the best alternative would lead to a combinatorial explosion[1] on any, except very simple, problems (Biondo, 1990; Turban, 1992). The main components of an expert system are therefore: knowledge-base, inference engine and user interface (Figure 2.8).

The inference engine contains the algorithm that drives the search and pattern matching of the expert system (Hicks and Lee, 1988). It represents the control or procedural logic that updates the global database, determines how to use the rules in the knowledge-base and establishes the sequence in which they are manipulated to solve the problem (Schutzer, 1987). According to Nevo et al. (1994), the inference engine controls an expert system consultation in order that: the same question is asked only once; only relevant rules are searched (avoiding blind searches); related questions are grouped; questions are logically ordered; sensitive menu choices are stated; appropriate responses to user input are given; and checks for input errors are made. Keeping the algorithms (placed in the inference engine) and the knowledge-base separate makes it easier to modify the knowledge embedded in the program and also enables the search and pattern matching procedures to be implemented in a straightforward manner (Biondo, 1990).

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[1] Combinatorial explosion: Problem in which adding variables, or even values to variables, increases the size of the problem exponentially, resulting in an astronomical number of potential solutions to the problem (Turban, 1992)

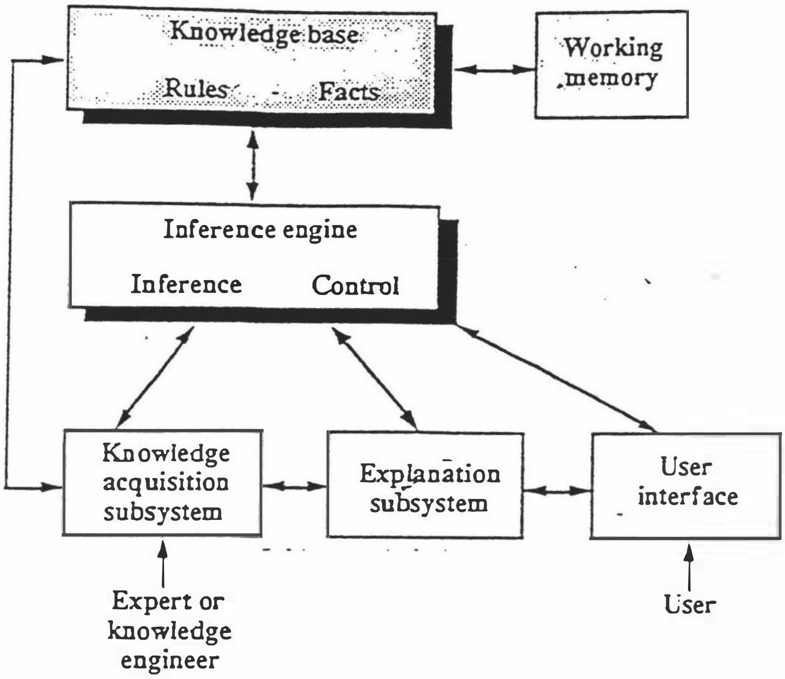


Figure 2.8 Diagrammatic representation of the components of an expert system (Kemp and Apperley, 1992).

According to Stuth and Smith (1993), the heart of many DSS will always be good simulation models. However, it was soon recognised that there is not enough knowledge available about the biology of farm systems in order to base all DSS on experimentally tested mathematical equations. Many aspects of grazing systems remain relatively understudied, and in some cases elements of these systems are based on practical experiences and/or qualitative studies. These "fuzzy" aspects of the system can be modelled into an expert system. Expert systems should have an advantage over mathematical models because they can be developed when information to precisely determine mathematically superior courses of action is not available. As knowledge about the system evolves it is possible that mathematical models can provide more sophisticated rules for an expert system, while they in turn, fill gaps in knowledge for simulation models (Widman and Loparo, 1989; Stuth and Smith, 1993).

Models use mathematical knowledge which is usually based on scientific laws and experimentally established relationships (that are not always understood) amongst the system components, while expert system are based on heuristic knowledge (rules of thumb and other formulations) used by experts to solve problems (Harrison, 1991; Wagner, 1993). As stated before, the requirement of a large amount of sometimes costly quantitative data is a problem with mathematical models. The ability of expert systems to make good use of qualitative data can improve the capability of a DSS by aiding decision making through more effective use of the information available.

The capabilities of expert systems and simulation models are in many ways complementary and several successful attempts to integrate them have been made. Some examples are Jones et al. (1987), McKinion et al. (1989) and Nevo et al. (1994).

2.3.3 *Databases*

According to Stuth and Smith (1993) information and the relationships between pieces of information, form the basis of effective decision making. Improved decisions therefore require objective, consistent and timely information about the issues involved. Therefore, DSS not only concern data processing but also the storage of relevant data to be processed.

Starfield and Bellach (1986) identified two main constraints to the progress of modelling. The first constraint relates to the level of understanding about the system. Without an understanding of the intrinsic relationships within the system and within the data collected concerning the system's variables, data processing is halted. On the other hand, some processes may be well understood and data processing procedures known, but suitable data are not available (Figure 2.9).

Success in the construction of a DSS therefore requires the existence of both good databases and a good understanding of the processes either relative to decision making or to system relationships. In modelling it is possible to apply the principle of the most limiting factor (i.e. the output is proportional to the most limiting factor). As such models may be limited by an imperfect understanding or by the lack of suitable databases and difficulties in data collection. As discussed before, the suitability of data for collection depends on the cost-benefit analysis between the cost of data gathering and the incremental value of the data after it has been processed into information. However, it is not always easy to apply this concept of positive marginal returns, since data collected often do not have an immediate value for decision making but they may be very usefully carried forward to assist future decisions. In other cases, data may have both an immediate and a future value. The recognition of this "carried over" value, provides the endorsement to store historic data within databases.

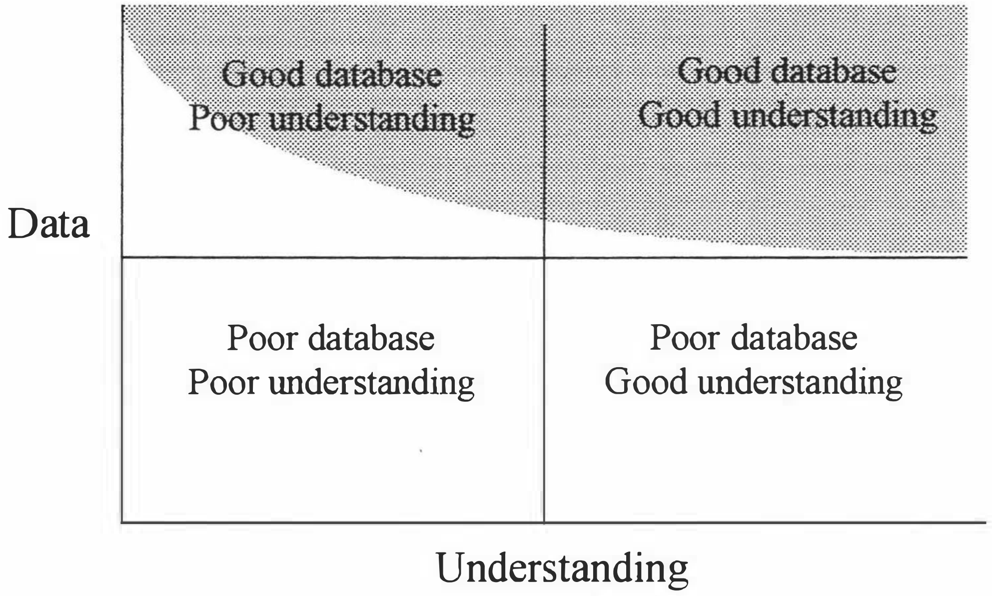


Figure 2.9 Conceptual classification of constraints to the progress of modelling. The shaded are indicates the possibility of successful modelling (Adapted from Carlson et al., 1993).

Databases required for on-farm decision support may be classified into on-farm databases and remote databases. In pastoral livestock production systems, on-farm databases are valuable for both planning and controlling the system. For example, cow files that include production and reproduction performance data may help decisions with respect to selling or culling individual animals and/or breeding (Tomaszewski, 1992). Also, data about on-farm pasture production such as, soil tests and economic performance are very useful in helping decision-making.

Remote databases, which are also called external databases, have the potential to become more important for DSS and farm management. Remote databases may store large amounts of data that are relevant not only for one farm but for a large number of farms. Information such as historic climatic and economic data, average levels of production, parameters describing plant and animal species and cultivars/breeds, average market prices, soils and feedstuff characteristics, climatic forecasts and digital photography are examples of data that can be stored in a central database and retrieved by individual farmers (Stuth and Smith, 1993).

Currently the distribution of much of this information is made periodically via printed periodic publications, as for instance through the Lincoln Budget Manual (Burtt, 1997).

There is a growing opportunity for the creation of on-line databases at regional, national and international levels. Central databases may be distributed on disk, CD-ROM, or accessed via the Internet (Bloom et al., 1991). Access to the Internet brings the advantage of allowing much more regular updating than periodic printed publications, and allows the retrieval of data in a computer format, which can be designed to be read by DSS, saving the time required to type data into the system. The volume of data available to users can be much greater and the costs of information access reduced by Internet technology relative to the cost of printing and distributing books.

2.4 Conclusions

Decision support systems have the potential to significantly improve the management of pastoral farms. They can help in all three phases of decision making (i.e. diagnosis, design and choice) via the application of several methodologies (e.g. databases, simulation models and rule-based systems). The main role of DSS seems to be in speeding-up and facilitating the processing of data into information which can be used by the manager for decision making. They can also be used as tools to disseminate knowledge and expertise from research centres to farmers, particularly because of their ability to bridge the gap between experimental studies of system components and the practical application of the associated research findings at the farm-level.

Simulation models are especially suited to the design phase of structured problems. However, they rely heavily on quantitative knowledge about the behaviour of the system and on the data available to describe specific conditions of the system in question. Linking simulation models to expert systems can allow aspects of the system which cannot be defined with mathematical rigor to be introduced into the DSS. Increasing the availability of on-farm and remote databases may encourage greater use of simulation models by farmers to improve the effectiveness and efficiency of their decision making.

MODEL DESCRIPTION

3.1 Introduction

The structure, equations and assumptions of the model are described in this Chapter. The model was designed to simulate the effect of control variables such as herbage allowance, nitrogen, supplements and stocking or de-stocking on system performance. While the model can be run in a deterministic mode, variability in pasture production and pasture mass measurement error can also be introduced by the user. Because the time frame for the research did not allow field experimentation, most of the animal sub-model was based on models which have been tested earlier, including those by McCall (1984), Finlayson (1989), Finlayson et al. (1995), Cacho et al. (1995) and Freer et al. (1997). The structure of the model, particularly with respect to the dynamics of paddock use is significantly different from any of these models. An event-driven approach was chosen and implemented using an iconic simulation package, Extend^{TM} , instead of a traditional compiled language or a spreadsheet package (see Section 1.5.1.5). Also a genetic algorithm was implemented to optimise the model's control variables.

The level of complexity of the model is comparable to other sheep production models such as those developed by McCall (1984), Finlayson (1989), Finlayson et al. (1995) and Cacho et al. (1995) and Freer et al. (1997). The simulations typically ran in 1 - 4 minutes on a Pentium 75 MHZ , 24Mb RAM PC. Speed and computer requirements, and the need to run a high number of iterations limited the number of experiments that could be performed with numerical optimisation in this study. Re-aggregation of some of the sub-models in the future would mitigate this problem, as well as improve the model's use as a DSS for farm management.

3.2 The simulation package

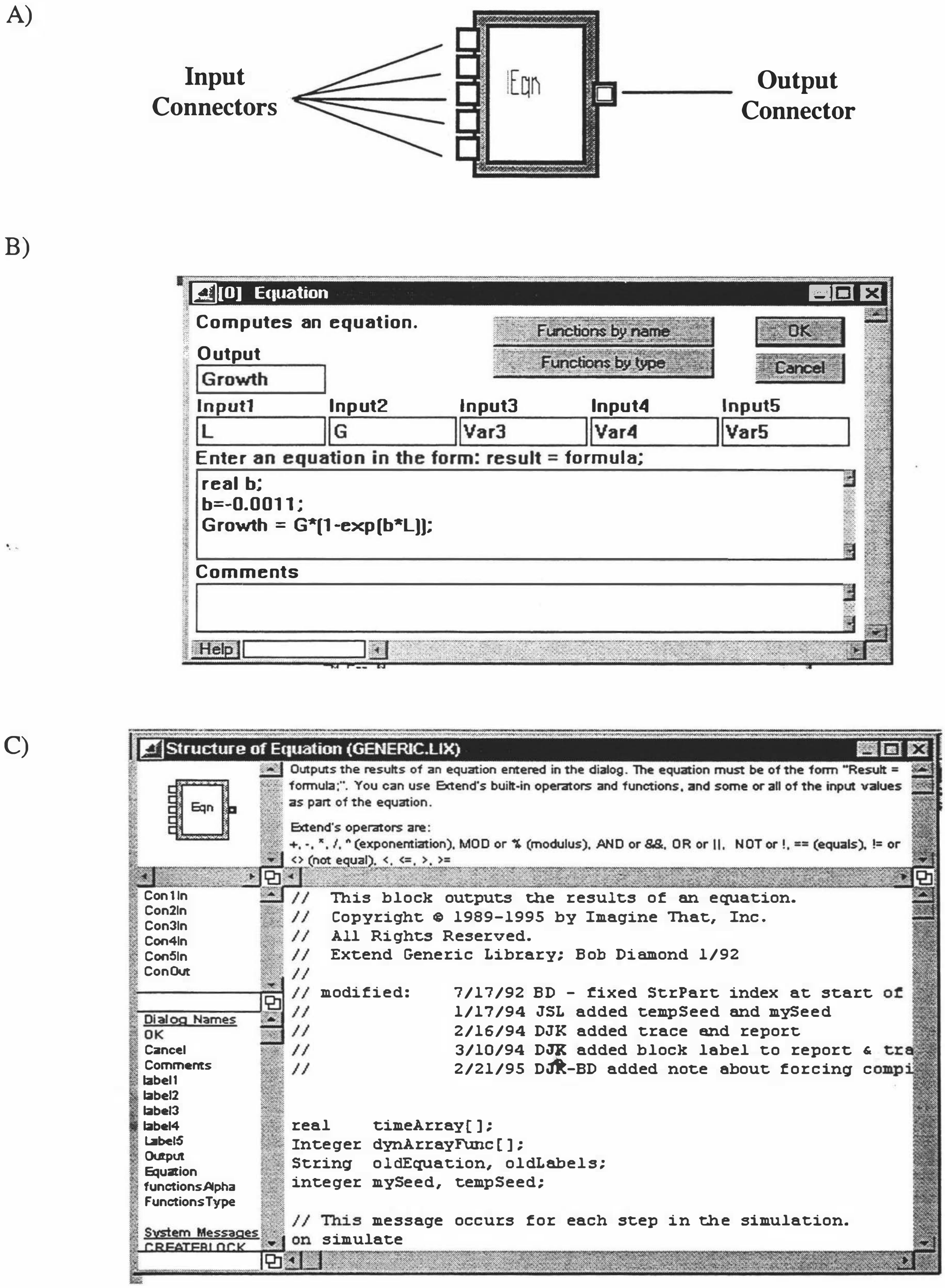
The mathematical model was constructed using the iconic simulation package Extend^{TM}. This package allowed the model to be built by using a mix of pre-programmed blocks from Extend's standard libraries and customised programmed blocks using the Extend^{TM} C-Like language: ModL.

Each of Extend's blocks is a modular piece of code which represent a process as an icon. This allows the processes, and their connections, in the model to be grasped visually as illustrated in Figure 3.2. The blocks can be responsible for one or more processes and contain their own variables, procedures and functions. A sample of Extend's programming language is found in Appendix 1 which contains the code of the genetic algorithm block, programmed in the model development. Each block includes a dialogue box which enables the user to define parameters and preferences for the processes to be simulated when the model is run.

During a simulation, the blocks that comprise the model perform calculations according to the inputs received by their connectors. When calculations are completed, the blocks set the output connectors to the value of the results so that they be accessed by other blocks. This process is similar to that carried out through traditional procedural and functional programming methods (Kreutzer, 1986). While procedures and functions may calculate values and return them to variables, an Extend block returns them to a connector. In fact, Extend connectors are real variables (Extend, 1995). The use of blocks makes the program modular and this facilitates modifications and debugging, and allows the code used for a block to be applied to a range of models.

The use of blocks facilitates the addition of new features to a model. The model can be expanded by simply connecting new blocks and plotters, and then adding the desired new features. Thus, a model can be built by using either bottom-up or top-down modelling approaches (Section 1.5.1.5).

Calculations are performed by the blocks within the model in response to system messages or messages from other blocks. Five main system messages (Table 3.1) are sent to all blocks. Extend™ also supports user defined messages which can be sent from one block to another; these allow the implementation of blocks with global functions. Global variables, can be assigned in the block's code and thereby become available to all connected or unconnected blocks.



[0] Equation

Computes an equation.

Output: Growth

Input1	Input2	Input3	Input4	Input5
L	G	Var3	Var4	Var5

Enter an equation in the form: result = formula;

```
real b;
b=-0.0011;
Growth = G*(1-exp(b*L));
```

Comments

Structure of Equation (GENERIC.LIX)

Outputs the results of an equation entered in the dialog. The equation must be of the form "Result = formula;". You can use Extend's built-in operators and functions, and some or all of the input values as part of the equation.

Extend's operators are:
+, -, *, /, ^ (exponentiation), MOD or % (modulus), AND or &&, OR or ||, NOT or !, == (equals), != or <> (not equal), <, <=, >, >=

```
//  This block outputs the results of an equation.
//  Copyright © 1989-1995 by Imagine That, Inc.
//  All Rights Reserved.
//  Extend Generic Library; Bob Diamond 1/92
//
// modified:     7/17/92 BD - fixed StrPart index at start of
//               1/17/94 JSL added tempSeed and mySeed
//               2/16/94 DJK added trace and report
//               3/10/94 DJK added block label to report & tra
//               2/21/95 DJK-BD added note about forcing compi


real    timeArray[];
Integer dynArrayFunc[];
String  oldEquation, oldLabels;
integer mySeed, tempSeed;

// This message occurs for each step in the simulation.
on simulate
```

Figure 3.1 Components of an Extend block. a) Icon: each "block" is represented by an icon in the computer screen which can be connected to other blocks by input and output connectors. b) Each block has one dialogue box which allow preferences, parameters and equations to be defined for a simulation. c) Structure of an Extend^{TM} block. The structure of a block includes icon (top left window), help text (top right window) and code (bottom right window). Connectors, dialogue names, system messages and variables are displayed in the bottom left window.

Table 3.1 Description of Extend^{TM} system messages sent to all blocks.

Message	Description
CheckData	It is sent before the simulation starts and is suitable for running the code that checks if the parameters inputted are coherent to the simulation and if the block is connected properly.
StepSize	It is sent after all check data messages. It is suitable for setting the maximum tolerable step size.
InitSim	It is sent just before the simulation starts. It is usually used to run code that set static variables, dialog items or connector values.
Simulate	This message is sent over and over, at every step of the simulation. Most of the code, particularly that containing the dynamic function that represent the system is run in response to this message.
EndSim	This message is sent at the end of the simulation. This code usually cleans up memory used by dynamic arrays and can be also used to reset values for the next simulations.

Blocks which do not have inputs, but run their code in response to system messages to generate inputs to the simulation, are run first. Next, blocks which have their inputs connected to the initiating blocks are simulated. Thus, the simulation proceeds with the blocks following the input-output connection order. Unconnected blocks are executed in a left to right order.

In the case of event driven models, some blocks can pass items rather than values through some connectors. Items can have different priority (concerning processing), value (i.e. the number of item clones which are simulated as one multiple item during a moment in the simulation) and attributes (i.e. the value of several variables inherent to the item). Items priorities, values and attributes are kept in global arrays and are processed through the Executive block which is necessary for any event driven simulation in Extend^{TM}. Examples of how a simulation is performed in Extend^{TM} are shown in Appendix 2.

When model complexity increases beyond the level which can be represented by one or two dozen of blocks (icons) on the screen, the layout of the model starts to become messy. Extend^{TM} allows blocks to be grouped into hierarchies in order to isolate sub-systems and/or to improve the layout and documentation of complex models. A hierarchical block contains blocks connected in the same manner as in other parts in the model. When a hierarchical block is opened the blocks nested within it are shown. This enables a model to be initially shown as a few simple steps and assumptions (at the highest hierarchical level) before revealing its complexity at lower levels of hierarchy.

Extend™ allows extremely fast development of models of low to medium complexity because most processes can be represented by pre-programmed blocks. The possibility of modifying the pre-programmed blocks code is also a good way of speeding-up model development and improve model programming skills. However, complex processes which demand data transfer and calculations with arrays, for example, require programming skills and time similar to that spent in modern third generation language compilers.

Design of the user interface for the model is also limited in Extend™. The package eases model development and its interface is adequate to the model developer, facilitating model design and visualisation. However, it is limited for the design of an interface that is suitable for consultants and farmers, particularly for whole farm models where large amount of inputs, charts and tabled outputs must be organised. The impossibility of having multiple dialogues in one block and the inability to customise pull-down menus and windows are examples of these limitations.

3.3 Model structure

An event driven approach was adopted to simulate rotational grazing in a pastoral livestock production system. The model therefore does not have a fixed time step; instead a recalculation is made every time the herd/flock is shifted from one paddock to another. The control of the event driven simulation is performed by a run-time control system (RTCS), scheduler or simulation executive (Kreutzer, 1986). In Extend™ it is implemented through the Executive block whose main function is to determine the next step of the simulation.

The Executive block performs the task of calculating the next simulation time by creating an array named TimeArray (Extend™, 1995) , also known in simulation jargon as a "future event chain" and an "event queue" (Pidd, 1988) or "sequencing set" (SQS), "event list", "noticeboard" or "scheduling list" (Kreutzer, 1986). This array is global and can be accessed by any block in the simulation. Each of the blocks which are able to generate events, calculate their next event and places this in a slot of the Time Array. The program then checks the array for the closest time value to the current simulation time and sets the new time to this value.

The grazing model consists of 79 blocks grouped into 8 hierarchical blocks. These are labelled as the: *Executive block*, *Paddocks block*, *Decide Graze block*, *Graze block*, *Grow block*, *Reproduction block*, *Joint block* and *Control Panel block*. The Executive block, as outlined earlier, controls the simulation of discrete events. The Paddocks block initialises the paddocks for the simulation and sets the initial attributes for each paddock: area, herbage mass, leaf, stem and dead fractions, mass and production potential. Decide Graze block, sorts the paddocks by herbage mass and assigns the paddock with the greatest mass to be grazed and the remaining paddocks to the Grow block. The Graze block calculates the effects of defoliation on pasture quantity and composition during grazing and estimates animal intake and performance during grazing. Also, reproduction is simulated and gross margins and cash flow calculations are completed within this block. The Grow block simulates the growth and senescence of the pasture within paddocks during their rest (non-grazing) period. The Reproduction block is responsible for simulating reproduction in the flock, at the start of mating season and generates an array defining the parturition distribution, number of lambs and lamb sex. The Joint Block combines paddocks from the Grow and Graze blocks, measures pasture cover, harvests pasture and applies nitrogen when these events are assigned by the Control Panel block. The Control Panel block obtains inputs and save outputs to text files, stores information of multiple simulations and allows change to most decision variables used in the simulation. The optimisation algorithm is also placed in the Control Panel block.

Unlike the actual farm system, where the mob or herd is allocated to paddocks, the grazing system was modelled by allocating paddocks to a mob. This allow the number of paddocks, and paddock variables, to be redefined prior to and during simulation. Paddocks are represented by items which are submitted for processing (grazing, growth or harvesting). The items (Paddocks) are “created” by the Paddocks block at simulation time = 0, with initial attributes for ID number, pasture cover and annual production potential. Subsequently, the paddocks are released by the Paddocks block and reach the Decide paddock block.

The Decide Graze block includes a queue which sorts paddocks by herbage mass and a set of “gates” and “prioritisers” which then directs paddocks to the desired process (i.e. grazing or growth). The paddock with the greatest herbage mass is assigned for grazing while the remaining paddocks are assigned to the Grow block (Figure 3.2). The decision to graze the paddock with greatest herbage mass was based on the modelling simulations of Woodward et al. (1993) which indicated that this strategy is almost always best.

Following the approach adopted by McCall (1984), Doyle et al. (1989) and Cacho et al. (1995), pasture mass was divided into three pools: leaf lamina, pseudostem and dead material. There are two advantages with this approach: first, it accounts for the loss of pasture mass because of senescence, which, in combination with animal intake enables the effect of transferring feed through time to be simulated; second, because leaf content is treated as an independent variable, it is possible to differentiate growth and intake responses of pasture with the same pasture mass but submitted to different previous management. For instance, a paddock may achieve a pasture mass by growing up to it, being grazed down to it from a different initial herbage mass, being maintained as it is through continuous grazing or being harvested to it. Pasture growth and intake responses are obviously different for each of these scenarios.

In the Grazing block, the time spent grazing each paddock is determined from a pre-defined herbage allowance, leaf content of the pasture, the percentage of leaf in the diet consumed by the animal and the intake rate of the animal during the period concerned (Section 3.4.4). The same data are used to calculate the post-grazing leaf, stem and dead material content and these are then set as attributes of the grazed paddock (see Section 3.4.4). Also, based on the composition of the diet (leaf %, stem % and dead %) and time of the year, the digestibility of the diet is calculated. Intake and digestibility are then used to estimate the metabolisable energy available to the animals and to calculate animal performance (Section 3.4.7).

Supplementation is also handled by the Grazing block. When supplements are used, a substitution effect is estimated from rumen-fill and feed-drive effects (Section 3.4.3). Ewe performance is simulated for an average animal, while lamb performance is calculated and recorded individually.

The Grow block can receive and process as many paddocks at one time as necessary. Pasture production is based on seasonal parameters for maximum growth and senescence rate and on the leaf content of each paddock. Growth is partitioned between leaf and stem, and the senescent material accumulated in the "dead" pool. Also, the "dead" pool experiences decay (i.e. a portion of the dead material is subtracted from it due decomposition).

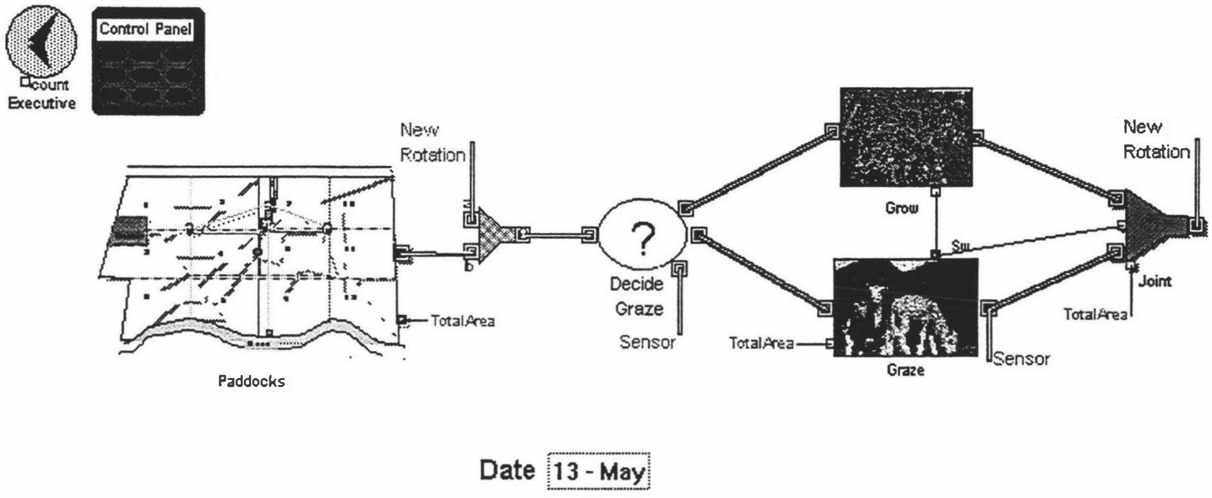


Figure 3.2 A diagrammatic representation of the grazing model. The items (paddocks) are created by the Paddocks block which specifies attributes that can be processed by the Grow or Graze blocks. Items and values are defined to be passed from one block to another by linking their connectors by lines or named connectors. Items and values are passed by distinct connections (Appendix 2). The Executive block (at the top left corner) is required by Extend ™ to control the arrays containing items attributes, values and priorities and to define the next time step of the simulation.

Paddocks leaving the Grazing and Grow blocks are combined in the Joint block. This block is responsible for calculating the average pasture cover of the farm according to the herbage mass and effective area of individual paddocks. Also, harvesting of pasture and nitrogen application take place in this block. Grass harvested is accumulated in one of the of Joint blocks and the information is recorded to calculate the costs and quantity of supplements made and therefore available on the farm for feeding to animals.

When under continuous grazing all the paddocks are assigned to the graze block. Growth and intake are then calculated solely in this block. In this circumstance, the model assumes a fixed time step of 1 day.

Global arrays were used when the information contained was relevant to several blocks, particularly when those were grouped in different hierarchical blocks. This was accomplished in order to avoid excessive number of connection which would make the model structure awkward. Five main arrays were created to store and transfer information among blocks. They are the Control array, Pcover array, Sheep array and Parturition array and ProdAndEconomics array.

The control array transfers all the control variables from the Control Panel hierarchical block into the model. The Genetic Algorithm block, which belongs to the Control Panel hierarchical block define all the control variables in the model and therefore can change them during the optimisation process. When the optimisation module is disabled, user defined parameters for the control variables (also inputted via the Genetic Algorithm block dialogue box) are executed.

Parturition array is a large array, created by the Reproduction block, which stores information about lambing and lamb growth. This array stores the lambing date, sex, twin or single, lamb live weight, body fat, protein and DNA content, if the lamb is or not to be kept as replacement, milk production and the lactation adjustment factor for the dam. In this array twins are maintained together. Twins therefore have same value for all parameters in the array, including sex. Despite this seems at first glance to be a limitation in the model, as usually large number of lambs are simulated, the effect of this incorrect assumption is insignificant. The Sheep array stores information about the number of individuals, empty body weight, maximum empty body weight, body fat, protein and DNA content of each sheep category.

ProdAndEconomics array have the function of storing and transferring information about production and economic variables among the model blocks. The variables stored by this array include: accumulated wool production, wool price, accumulated kg of lamb carcass sold, price for each category of lambs, cull ewes sold, cull ewes price, average price of ewes kept on the mob, accumulated nitrogen applied, nitrogen price, accumulated supplement fed, supplement price, total mob value, total revenue and total expenses.

Finally, ArrayPCover transfers information about pre- and post- grazing herbage mass of the grazed paddocks and the average pasture cover of all paddocks in the simulation.

3.4 Processes and equations

3.4.1 *Reproduction:*

The distribution of lambing is an important component of the seasonal pattern of feed demand of a sheep flock because it affects the proportion of ewes that are pregnant and lactating, and the requirements of lambs for maintenance and growth over time. Similarly, it affects the pattern of lamb drafting, which is specified in the model. Several models have been developed to predict the parturition pattern for cattle (Bailie, 1982; Morant, 1985; Larcombe, 1989) and sheep (Shadbolt, 1982; McCall, 1984; Cacho et al., 1995; Freer et al., 1997). The structure of the reproduction sub-model is similar to that adopted by Larcombe (1989), however while Larcombe (1989) divided conception into probabilities of mating and conception, here conception is predicted by one single equation (Eqn. 3-3).

Reproduction is simulated by a single block (i.e. it is not a hierarchical block). The lambing pattern calculated at the end of the mating season and the lambing date, number (single/twins) and sex of the lambs are stored in the Parturition array which is passed to other blocks. The pregnancy requirement during mating season is ignored. The user inputs the start and end dates for the breeding season. The simulation process is illustrated in Figure 3.3. At the start of the reproduction simulation, all MA ewes and two-tooths in the mob are allocated for breeding. The reproduction simulation has a time step fixed at one day, ewes that conceive are removed from the simulation at the next cycle. Because of notable differences in their reproductive traits, MA ewes and ewe hoggets are simulated separately and the arrays containing the lambing pattern, sex and number of lambs for each age group are subsequently combined and sorted. The cycle length is assumed to be 17 days for MA ewes and 14 days for ewe hoggets.

The reproductive performance of ewes follows a seasonal cycle (Bruère and West, 1993). They start cycling around the beginning of February and this extends until the end of August. Peak reproductive activity is in April-May and therefore the probability of estrous is time dependent. McCall (1984) and Cacho et al. (1995) predicted the lambing distribution by multiplying the percentage of cycling ewes by the rate of conception in a given cycle, while Freer et al. (1997) predicted the parturition pattern directly from the number of animals, body condition and day of the year.

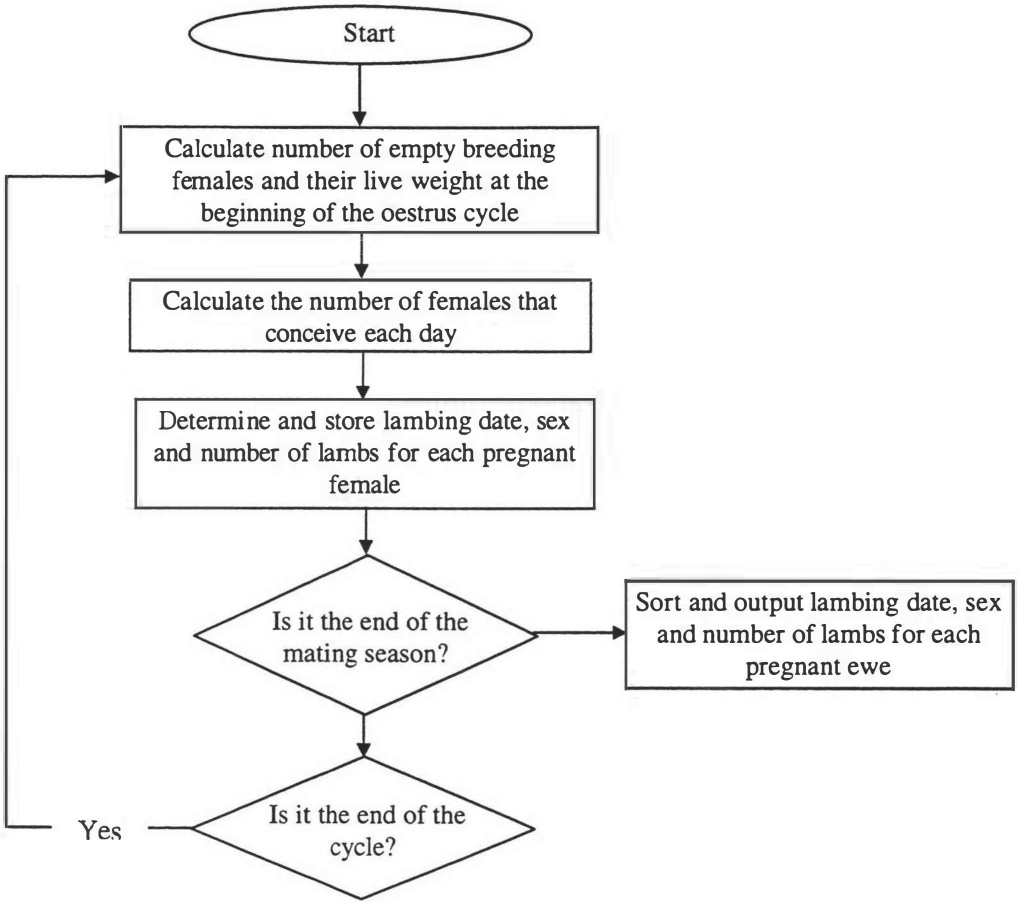


Figure 3.3 Flowchart of the reproduction simulation to determine a flock's lambing performance.

McCall (1984), based on data published by Hight and Jury (1973), used a truncated quadratic equation to relate body weight and the percentage of ewes cycling as follows:

$$Cic = \begin{cases} 0 & \text{if W} < 18.5 \\ a + bW + cW^2 & \text{if } 18.5 < \text{W} \leq 50 \\ 1 & \text{if W} > 50 \end{cases}$$

Where W is the average live weight of the flock (kg), a = 1.5216, b = 0.102 and c = 0.00104. However, the effect of live weight on the percentage of mature ewes cycling seems to be more closely related to their body condition than their absolute live weight (Freer et al., 1997). The sigmoid equation of Freer et al. (1997) was rewritten (Eqn. 3-1) and calibrated to fit data published by Hight and Jury (1973):

$$f_w = \frac{\left(PW_a \big/ \alpha_h\right)^{\alpha_1}}{1+\left(PW_a \big/ \alpha_h\right)^{\alpha_1}}$$ **Eqn. 3-1**

where:

$$PW_a = \frac{EBW}{EBW_{max}}$$ **Eqn. 3-2**

where f_w is the conception rate multiplier related to the body condition of the ewes, PW_a is the proportion of the maximum empty body weight of the ewes, α_h is the proportion of normal live weight which inhibit oestrus for 50% of the mature ewes, EBW is the empty body weight of the animals and EBW_{Max} is the standard maximum body weight related to the flock's breed and potential for mature weight.

The seasonal variation in reproductive performance and conception rates were accommodated using a sine function, adapted from Freer et al. (1997):

$$CR = CR_{max} - \alpha_2\left(1 - sin\left(\frac{2\pi(t-\alpha_3)}{365}\right)\right)f_w$$ **Eqn. 3-3**

Where CR is the predicted conception rate, CR_{Max} is the maximum conception rate at its seasonal peak and t is day of the year (day 1 = 1 January). CR_{Max} was assumed to equal 1 by Freer et al. (1997) and this value was used as a default of the model. The parameters varied for ewes and two-tooth as shown in Table 3.1. Lambing date (Ld) is calculated for each ewe according to:

$$Ld = Md + PL$$ **Eqn. 3-4**

where Md is the mating date (day of the year) and PL is the pregnancy length, assumed as normally distributed with mean of 147 days and a standard deviation of 3 days.

In practice, the probability of bearing twins depends on a series of factors including body weight and ewe nutrition at mating, time of the breeding season, ewe age, genetic potential and ewe health (Bruère and West, 1993). The effect of nutrition and time of the breeding season on ovulation rate was modelled according to Cacho et al. (1995), where the probability of bearing twins (P_{Twins}) was estimated according to the static (MO_S) and dynamic (MO_D) effects of live weight on multiple ovulation (Equations 3-5, 3-6 and 3-7). The probability of multiple ovulations is therefore described as:

$$P_{Twins} = (MO_S + MO_D)ES \qquad \textbf{Eqn. 3-5}$$

where the static effect of live weight on multiple ovulation rate is:

$$MO_S = \alpha_4 - \alpha_5\left(\left(\frac{EBW_i}{EBW_{Max}}\right)^2 - \frac{2EBW_i}{EBW_{Max}} + 1\right) \qquad \textbf{Eqn. 3-6}$$

EBW_i is the empty body weight of the ewe at the beginning of the mating season, and EBW_{Max} is the standard maximum body weight related to the flock's breed and potential for mature weight. The dynamic effect, related to the body weight gain is given by:

$$MO_D = (1 - \alpha_5)(1 - exp(-\alpha_6 M_{Gain})) \qquad \textbf{Eqn. 3-7}$$

where M_{Gain} is the live weight gain of the ewes during flushing. The model disregards triplets. Also, following the assumptions of Cacho et al. (1995), no multiple ovulations occur when EBW is less than 0.6 EBW_{Max} and the rates of embryonic survival are assumed to be constant and independent of a nutritional effect. The rate of embryonic survival (ES) is 0.8 by default, but can be modified by the user. The sex of the lambs was determined randomly for each lamb. A probability of 0.5 for males was assumed.

In order to allow a consistent input for the lambing pattern for multiple runs, which may be particularly necessary for deterministic analysis of alternative policies, a table was generated for a deterministic lambing schedule. The schedule can be defined by simulating the lambing pattern and outputting results to the table for use in all desired simulations. Alternatively, the expected lambing schedule can be placed directly into the table. The proportion of males and females, and the lambing percentage can be fixed by the user. Fixing the lambing pattern can prevent the "noise" generated by simulating different lamb distributions and proportions of males/females. On the other hand, the generation of a stochastic lambing pattern is likely to be of interest to users concerned with production risk.

Table 3.2 Parameter estimates for the reproduction sub-model.

Parameter	Eqn.	Parameter values		Source
α_1	3-1	6		Calibrated with data of Hight and Jury (1973)
α_h	3-1	0.45		Calibrated with data of Hight and Jury (1973)
α_2	3-3	0.34		Freer et al. (1997)
α_3	3-3	10		Freer et al. (1997)
α_4	3-6	MA ewes	0.79	Cacho et al. (1995)
		Ewe hoggets	0.20	Assumed by the author for ewe hoggets
α_5	3-6, 3-7	MA ewes	2.30	Cacho et al. (1995)
		Ewe hoggets	1.00	Assumed by the author for ewe hoggets
α_6	3-7	MA ewes	2.37	Cacho et al. (1995)
		Ewe hoggets	1.00	Assumed by the author for ewe hoggets

3.4.2 *Pasture growth and senescence*

Pasture (or herbage) growth is defined as the increase in size and/or weight of new leaf and stem tissue (Hodgson, 1979). On the other hand, pasture production (also called net herbage production or herbage accumulation rate) is defined as the balance between pasture growth and senescence (Korte et al., 1987). The practical importance of separating the concepts of growth and accumulation is that rate of herbage growth sets the potential production for a sward, but the efficiency of utilisation of forage by grazing animals is determined by the partitioning between consumption and senescence (Hodgson, 1990).

In broad terms pasture growth is affected by temperature, soil water content, nutrients, light, specie and the physiologic state of the plant (Cooper, 1970; Eagles and Wilson, 1982; Korte et al., 1987). Increasing air temperature accelerates chemical reactions in the plant up to the point of enzymatic denaturation (Ting, 1982), and the processes of photosynthesis and respiration increases with temperature up to a certain level. As a result, net photosynthesis (i.e. the difference between gross photosynthesis and respiration) increases up to an optimal level and then declines because the marginal increase in photosynthesis is lower than that of respiration. Growth also depends on sinks for carbohydrates. In the absence of strong sinks, plant growth and further photosynthesis is inhibited (Robson, 1981). Therefore, low temperatures can stop plant growth and result in the accumulation of carbohydrates which can further inhibit photosynthesis. Thus, high levels of soluble carbohydrates are present in plant tissues during New Zealand's winter (Korte et al., 1987). Responses to photosynthesis to metabolite demand also may be seen during periods such as flowering and stem growth. Korte et al. (1987) estimated that reproductive growth in ryegrass during spring was 85% greater than vegetative tillers growing at the same temperature and solar radiation. This occurred because of the strong sink of carbohydrates created by elongation of the stem and seedhead production during flowering. According to Korte et al. (1987), ryegrasses have optimum growth rates at around 18 °C, while for clovers it occurs at around 20-23 °C.

Seasonal water deficits are one of the most important climatic factors determining pasture production. Lack of water leads to a diminution of growth far before it affects photosynthesis *per se* (Boyer, 1970). Variation in spring-summer rainfall accounts for at least 60% of annual pasture production (Radcliffe and Baars, 1987). In agreement with this statement, Stocker (1979) showed a decrease in year-to-year variation of pasture production from 48% to 12% by using irrigation. However, in sites where pasture production is depressed by high temperatures in the summer, the effect of irrigation may be not so dramatic. For example, Baars and Coulter (1974), working in the Waikato region, found a correlation coefficient of only 0.46% between summer pasture growth and soil moisture availability.

A rainfall shortage causes the upper surface layers of soil, which have the highest nutrient concentration, to rapidly dry and this affects the absorption of nutrients (Norton, 1982). A water balance and nutrient deficiency can also affect leaf senescence. If the water deficit is small and simply inhibits the demand for metabolite, senescence may be delayed, but if the deficit is greater, senescence is accelerated (Hill, 1980; Wilson, 1982).

Senescence seems to be related more to a decrease in synthesis than to an increase in destruction of proteins (Hill, 1980). The maintenance of protein synthesis and cell division in plants depends on cytokinin, which is produced by the roots. Increased shading of the leaves, decreases protein synthesis because of stomatal closure and a lower level of transpiration reduces the transport of cytokinin to the older leaves. During senescence both photosynthesis and respiration decrease. Metabolic processes fall rapidly, reserves are transferred to other regions of the plant and the tissues die (Ting, 1982). Increasing levels of herbage mass or leaf area, lead to increasing losses of plant material through senescence (Bircham and Hodgson, 1983; Johnson and Parsons, 1985).

Besides the effect of weather described above, and included in most models of pasture growth, large variations in pasture growth rates are associated with soil fertility, type, drainage and slope (Ledgard et al., 1982; Lambert et al., 1983; Scott et al., 1985). These factors certainly limit the ability of simulation models, without large inputs of local soil and weather data, to predict the attainable pasture growth rate. For example, GRAZPLAN (Donnelly et al., 1997) relies on a database collected from 16000 weather stations and 1.1 Gb is required for the files which drive the prediction of pasture growth rates and other related variables. Also GRAZE (Loewer et al., 1989) relies on weather files and a detailed description of site location for its pasture growth rate prediction.

In practice, however, pasture growth rates can be only slightly manipulated by pasture management (Hodgson, 1990) and major gains in productivity and profitability are likely to be associated with the ability to regulate intake of the animals and feed transference from periods of surplus to periods of deficit in order to combine high levels of feed utilisation and animal performance throughout the year. For most purposes, historical or used-defined potential pasture accumulation rates (the latter relying on farmer's experience or on-farm records of pasture accumulation rates) are suitable and used in successfully marketed decision support models (e.g. STOCKPOL, Marshall et al., 1991).

Management planning or control both require estimates of future pasture accumulation rates, while past accumulation rates can be measurable through changes in pasture cover. In this sense, predictions based on pasture accumulation records or on historical weather patterns have the same effect on decision making in most situations. However, prediction of pasture growth from weather files or simulated weather (as used by Rodriguez et al., 1990) enables to predict some plant responses, which otherwise would be difficult to be estimated (e.g. increased senescence with drought, responses of production to water availability and responses to nitrogen application and temperature and soil moisture).

The ability of a grazing model to accurately simulate the losses during the transfer of pasture (caused by senescence) is therefore important in ranking alternative livestock policies. In standard feed budgets (Parker, 1993a) and some other models (e.g. Larcombe, 1989; Woodward et al., 1995, Barioni et al., 1996) senescence is disregarded and net growth rate is used to calculate pasture movements with time. In other models, pasture growth and senescence are modelled as two distinct variables (McCall, 1984; Doyle et al., 1989; Cacho et al., 1995) and as discussed in Section 3.3, this is an advantage when simulating the transfer of feed from one month to another.

For the purposes and constraints of the model described here (including difficulty in creating weather files), user-defined average pasture accumulation rates were adequate. Adjustments were made for the effects of pasture leaf mass on growth and senescence.

Growth was modelled as a function of leaf mass, in a Micherlich-type function (Thornley and Johnson, 1990):

$$G = \overline{Ac} f_{Adj} (1 - exp(\beta_1 L) \qquad \textbf{Eqn. 3-8}$$

where G is the daily pasture growth rate (kg DM ha $^{-1}$ day $^{-1}$), $\overline{Ac}$ is the standard accumulation rate (kg DM ha $^{-1}$ day $^{-1}$), calculated by interpolation of user-defined average accumulation rates for the 15th day of each month of the year. When the accumulation is assigned to be stochastic, inputted estimation of the standard deviation of accumulation rates (kg DM ha^{-1} day^{-1}) for each month are used to calculate $\overline{Ac}$. f_{Adj} converts average accumulation rate into pasture growth rate and L is leaf mass (kg DM ha^{-1}). The factor f_{Adj} was determined by a regression analysis of pasture growth over pasture accumulation rates. It was accomplished by integrating numerically the growth and senescence equations within the usual range of leaf mass encountered under grazing (400-1500 kg DM of leaf) for several values of a ceiling herbage mass. A regression analysis was carried out and a exponential function fitted, determining Eqn. 3-9.

$$f_{Adj} = \beta_2 exp({}^{\beta_3}\!/_{L_{Ceil}}) \qquad \textbf{Eqn. 3-9}$$

The relationship between senescence and leaf mass is a controversial matter in the literature. Bircham and Hodgson (1983) fitted linear regressions to describe the relationship between herbage mass and senescence in continuously grazed swards between 500 and 1700 kg of organic matter per ha. Cacho et al. (1995) assumed linear increases of senescence rate with herbage mass by assuming a constant proportion of green herbage mass that suffered senescence each day. They accommodated the seasonal variation of senescence rates by interpolating senescence rates between a maximum of 2% of the green dry matter (GDM) day^{-1} on 31 January and a minimum of 1% GDM day^{-1} on 1 August. Fick (1980) also assumed a linear rate over 500 kg DM but the rate could fluctuate because of drought. Under normal conditions, they assumed senescence of 5% GDM day^{-1} for swards over 500 kg GDM. McCall analysing data of Hunt (1970) showed non-grazed swards also fitted a linear increase in senescence rate (0.8% GDM day^{-1}). In contrast, Simpson et al. (1996) proposed an exponential increase in senescence with pasture mass, however the mathematical formulation and parameterisation for this was not presented. Using a mechanistic simulation model of grass growth, Johnson and Parsons (1985) also found linear increases in senescence in relation to leaf area index in continuously grazed swards, while an exponential increase was observed for swards during ungrazed periods.

The large differences between models in the parameter values used for senescence and the divergence about its shape reflect the scarcity of experiments which have provided objective measurements of senescence under grazing conditions. This is understandable, considering the difficulties of measuring senescence under grazing, but it is important to realise that research in this area is essential in order to calibrate and validate models of pasture growth or complete grazing systems models. Here, senescence was assumed to increase linearly in relation to leaf mass according to Eqn. 3-10, as illustrated in Figure 3.4:

$$S = \beta_4 L \qquad \textbf{Eqn. 3-10}$$

where S is the rate of senescence (kg ha $^{-1}$ day $^{-1}$) and L is the leaf mass of the sward (kg DM ha^{-1}). The rate of accumulation of green leaf mass is therefore:

$$Ac_{Green} = G - S \qquad \textbf{Eqn. 3-11}$$

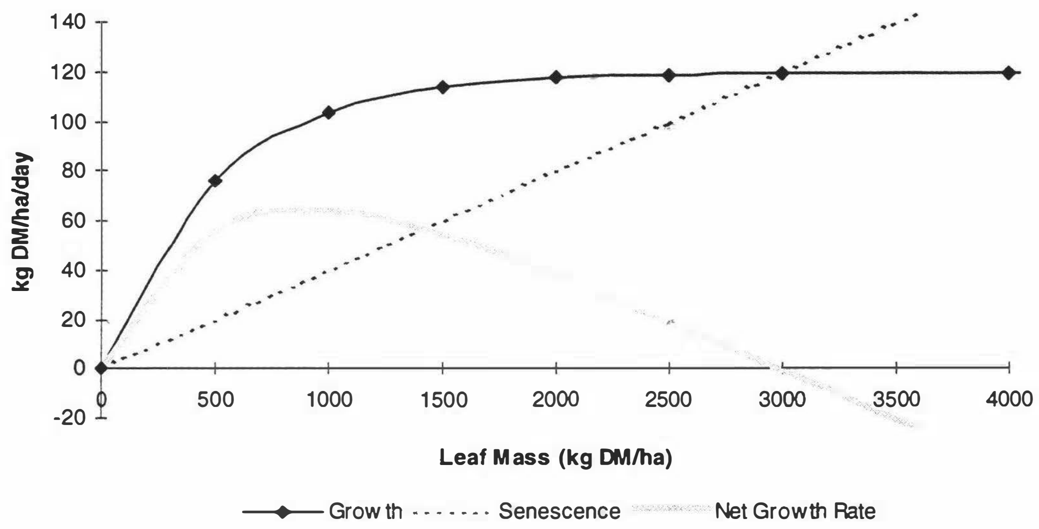


Figure 3.4 Model predictions total pasture growth, senescence and net growth rate as function of leaf mass or LAI for a ceiling leaf mass of 3000 kg DM ha^{-1} (approx. LAI 8).

The ceiling leaf mass (L_{Ceil}) for a given time of the year (kg DM ha^{-1}) is defined by:

$$L_{Ceil} = \overline{L_{Ceil}} + (L_{CeilMax} - L_{CeilMin})\cos\left(2\pi\frac{t-\beta_5}{365}\right) \qquad \textbf{Eqn. 3-12}$$

where:

$$\overline{L_{Ceil}} = \frac{L_{CeilMax} + L_{CeilMin}}{2} \qquad \textbf{Eqn. 3-13}$$

and $L_{CeilMax}$ and $L_{CeilMin}$ are user defined limits for the seasonal variation of ceiling leaf mass. By default these limits are assigned to 1500 and 6500 kg DM respectively, as suggested by Cacho et al. (1995).

At the ceiling leaf area senescence equals growth and it is therefore possible to show that:

$$\overline{Ac}f_{Adj}\beta_1(1-exp(\beta_1 L_{Ceil})) = \beta_4 L_{Ceil}$$

The parameter β_4 can be then estimated as:

$$\beta_4 = \frac{\overline{\mathrm{Ac}f}_{Adj}\,(1\ -\ \exp\,(\beta_1\,L_{Ceil}))}{L_{Ceil}} \qquad \textbf{Eqn. 3-14}$$

The effects of nitrogen and different grazing management on the partitioning of pasture growth were ignored. Although models of decay have been described in the literature (e.g. Hunt, 1977), including the effects of temperature, water and nitrogen on the rate of decomposition of the dead material in the pasture, it was impossible to show this level of detail in the current model without simulating weather. Besides, given the purposes of the model, this level of detail was unnecessary. Decay is then calculated as a proportion of the dead material and varied seasonally (Eqn. 3-15).

$$Dk = \beta_6 D \qquad \textbf{Eqn. 3-15}$$

where Dk is the decay rate (kg DM ha $^{-1}$ day $^{-1}$) and D is the dead material mass in the sward (kg DM ha $^{-1}$).

In the *Grow* Block, dynamics of leaf lamina, stem plus pseudostem and dead material are calculated for each paddock as:

$$L_{(t_{Pre}+GT)} = L_{(t_{Pre})} + P_{Leaf}G - S\left(\frac{L_{(t_{Pre})}}{L_{(t_{Pre})} + St_{(t_{Pre})}}\right) \qquad \textbf{Eqn. 3-16}$$

$$St_{(t_{Pre}+GT)} = St_{(t_{Pre})} + (1 - P_{Leaf})G - S\left(\frac{St_{(t_{Pre})}}{L_{(t_{Pre})} + St_{(t\,Pre)}}\right) \qquad \textbf{Eqn. 3-17}$$

$$D_{(t_{Pre}+GT)} = S - D_{(t_{Pre})}\,\beta_6 \qquad \textbf{Eqn. 3-18}$$

where GT is grazing time defined by Eqn. 3-32, P_{leaf} is the proportion of total growth partitioned to leaf, $L_{(t)}$, $St_{(t)}$ and $D_{(t)}$ are the total dry matter of leaf, stem and dead material (kg DM ha^{-1}), respectively, in the sward at the beginning of the period. Following Cacho et al. (1995), the proportion of leaf lamina growth in relation to total pasture growth has assumed to be 70% for a sward during the vegetative period and 65% during the reproductive period (P_{leaf} = 0.7 and 0.65, respectively). Senescence rates of pseudostem/stem and leaf lamina were assumed to be the same for both vegetative and reproductive swards.

3.4.2.1 *Effect of nitrogen*

Responses to nitrogen fertiliser are normally observed in the grass component of the sward, because the internal nitrogen requirements of clover can usually be satisfied by symbiotic nitrogen fixation. Usually grasses respond to nitrogen by increasing tiller growth and tillering (Ball and Field, 1982).

After nitrogen application, a phase of rapid N uptake by the plant occurs which increases the concentration of N in its tissues. However, responses in terms of dry matter accumulation occurs gradually during the subsequent 3 to 10 weeks (O'Connor, 1982). The period of response is inversely related to the scale of the initial boost in pasture growth rate (O'Connor, 1982). The response depends on the weather conditions at the time of application and during the subsequent growth period.

Here, because the model did not simulate weather, the nitrogen response was user-defined. It was assumed that the response is mostly related to farm location and the month of application, but the user may accommodate the effects of slope, species and so on by choosing a suitable response factor. It is known that the efficiency of nitrogen application (kg DM kg N^{-1}) is inversely related to the quantity applied and that the total response follows a curve of decreasing increments. Inverse polynomial equations (e.g. $N_{Resp} = \frac{(a + b\,dose)}{(1 + c\,dose + d\,dose^2)}$) have been used to predict N response (Morrison et al., 1980). On the other hand, O'Connor (1982) assumed that plant responses to N increase at the square root of the dose applied ($NR = f_{L,P}\sqrt{N}$, where NR is total nitrogen response and N is nitrogen dose). In order to account for differences in response due to location and period of application, O'Connor (1982) introduced a multiplier ($f_{L,P}$) and estimated it for several locations and periods of application. In order to give a physical meaning for the user defined parameter, it was transformed into a standard nitrogen response for a 50 kg N ha^{-1} application (Eqn. 3-19). The implicit efficiency of nitrogen application for the factor chosen is immediately calculated by the model and displayed for the user to assess. The model stores standard values for several New Zealand locations. These were calculated from the data published by O'Connor (1982).

The function adopted for N fertiliser response, following O'Connor (1982), was:

$$\begin{cases} NR = NE_{50}N & \textbf{if } N \leq 50 \\ NR = NE_{50}\dfrac{\sqrt{N}}{\sqrt{50}} & \textbf{if } N > 50 \end{cases} \qquad \textbf{Eqn. 3-19}$$

where NR is the total nitrogen response (kg DM ha^{-1}), N is the quantity of N applied. (kg N ha^{-1}) and NE$_{50}$ is the efficiency of nitrogen response to a 50 kg N ha^{-1} application (kg DM kg N^{-1}).

The equation adopted has two limitations. First, it does not have a point of maximum response beyond which yield is expect to respond negatively to further N application as in an inverse polynomial. This problem, however has no practical importance for users of the model because the maximum response to N far exceeds the usual applications rates for pastoral systems. The second limitation is that the equation tends to overestimate responses for low nitrogen doses, as noted by O'Connor (1982). In order to minimise this problem, the efficiency of N was assumed to be constant to applications under 50 kg N ha^{-1} (Eqn. 3-19). This produces a linear response up to that nitrogen level, which is consistent with experimental results (e.g. Morrison et al., 1980; Ball and Field, 1982).

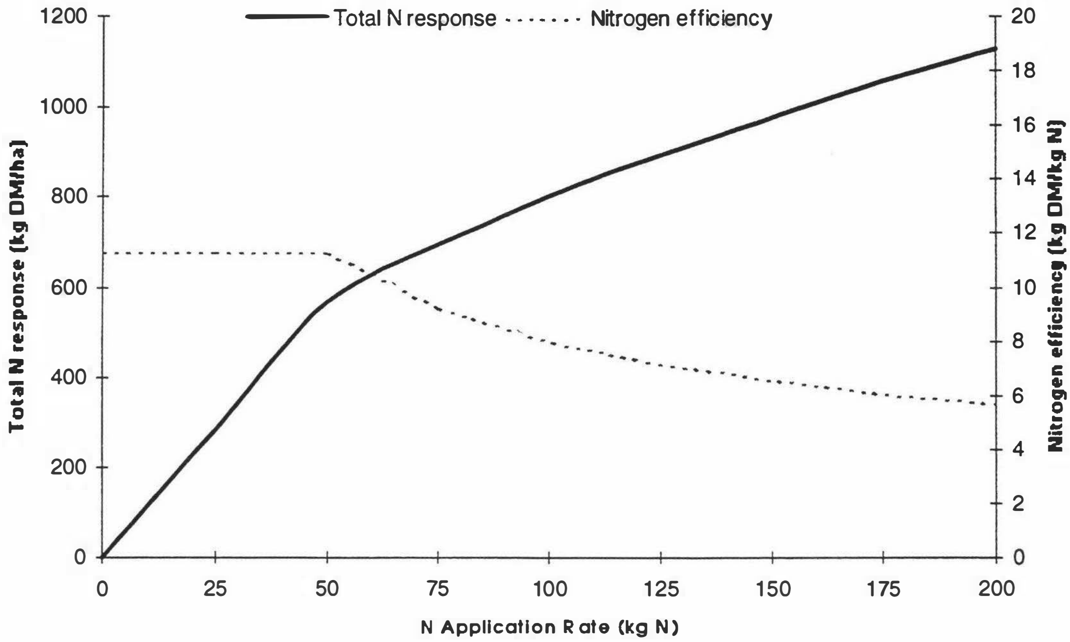


Figure 3.5 Variation in the total pasture response to nitrogen application and efficiency of conversion of nitrogen into pasture dry matter predicted by Eqn. 3-19.

Table 3.3 Examples of the efficiency of nitrogen response by region and month of the year (calculated from O'Connor, 1982).

Month	Masterton	Dannevirke	A. Canterbury	Southland
Jan	---	---	---	---
Feb	---	---	---	14.4
Mar	---	14.3	8.60	8.90
Apr	11.9	13.6	7.30	5.90
May	7.90	13.9	3.30	---
Jun	---	---	---	---
Jul	---	17.7	---	---
Aug	16.5	14.4	13.6	11.2
Sep	15.8	8.90	14.7	14.6
Oct	9.80	14.4	23.8	14.4
Nov	---	---	---	---
Dec	---	---	---	---

The dynamics of the nitrogen response was modelled using two parameters: the initial nitrogen response (Kg DM ha^{-1} day^{-1}) and the spell before grazing (days). It was assumed, for simplicity, that the potential response to nitrogen decreases linearly with time after application. It is important to note that this does not mean that the actual response decreases with time, because the response is also determined by the leaf area of the sward. Based on the data of

O'Connor (1982), the initial nitrogen response and the response associated with "spell length" were modelled as:

$$Spell = \beta_7 - (\beta_8 Ac_{Green})$$ **Eqn. 3-20**

where $Spell$ is the total duration of nitrogen response (days), and Ac_{Green} is the green pasture accumulation rate as defined by Eqn. 3-11.

The rate of response to the nitrogen immediately after the application is given by Eqn. 3-21 as follows:

$$INR = \frac{2N_{Resp}}{Spell}$$ **Eqn. 3-21**

where INR is the initial nitrogen response and N_{Resp} is the total nitrogen response (kg DM ha^{-1}). Response to a nitrogen application over a grazing period is then defined by:

$$N_{Boost} = \frac{Ac_{Green}}{\overline{Ac}} 2GT\left(INR - \frac{INR}{Spell}\left(t + \frac{GT}{2} - NAD \right)\right)$$ **Eqn. 3-22**

where N_{Boost} is the response to nitrogen in a grazing period (kg DM ha^{-1}) and NAD is the nitrogen application date (day of the year).

The effect of leaf mass on the nitrogen response was assumed to be proportional to its effect on net growth rate by including the factor $\frac{Ac_{Green}}{\overline{Ac}}$. Lower efficiency is expected from urea compared to other N fertilisers when it is applied in warm and dry conditions. However, such conditions are usually not the case with tactical applications in New Zealand (Ball and Field, 1982) and therefore no difference in response between different types of nitrogen fertiliser was included in the model.

Table 3.4 Parameters for the pasture growth sub-model.

Parameter	Eqn.	Value	Source
β_1	3-8, 3-14	Vegetative = 0.0014 Reproductive = 0.0023	Estimated from Leaf et al. (1974)
β_2	3-9	1.202	Estimated numerically (see text for details)
β_3	3-9	953	Estimated numerically (see text for details)
β_4	3-10, 3-14	Calculated by Eqn. 3-10	Inputted monthly ceiling herbage mass
β_5	3-12	355	Cacho et al. (1995)
β_6	3-15, 3-18	0.02 - 0.05	Cacho et al. (1995)
β_7	3-20	80	Estimated from O'Connor (1982)
β_8	3-20	0.6	Estimated from O'Connor (1982)

3.4.3 *Herbage intake*

Prediction of herbage intake is one of the greatest challenges in modelling grazing livestock production systems. Forbes (1994), Van Soest (1994) and Mertens (1994) in reviewing the mechanism of intake control in ruminants, concluded that feed intake results from the interaction of several factors that are integrated by the central nervous system to produce an overall response. The factors include physical, physiological and psychogenic modulation (Mertens, 1994). It has been hypothesised that several signs, such as the blood concentration of volatile fatty acids, rumen fill, temperature, light, and others, are sent by various sensors to the central nervous system which in turn, controls the initiation and cessation of eating, sensation of rumen fill, rumen motility and grazing time. These mechanisms are not fully understood, but some hormonal and neuronal responses have been demonstrated (e.g. Baile and Della-Fera, 1988). Van Soest (1994) proposed the integration and control of feed intake as shown in Figure 3.6.

Poppi et al. (1987) segregated the herbage intake limit of grazing animals into nutritional (rumen fill and physiological regulation) and non-nutritional (concerning the limitations imposed by the ability and behaviour of the animal in harvesting pasture) factors. Herbage intake is limited predominantly by grazing behaviour when herbage availability is low, while nutritional mechanisms regulate the upper limit of herbage intake by grazing animals (Figure 3.7).

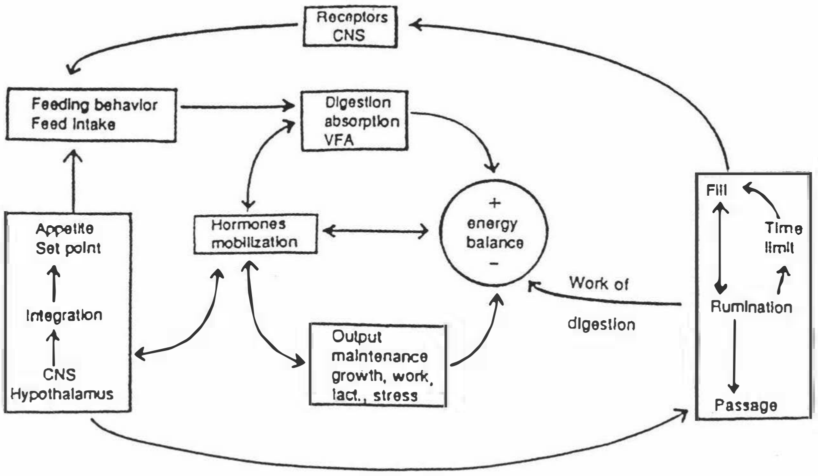


Figure 3.6 Integration of the various mechanisms of intake regulation (after Van Soest, 1994).

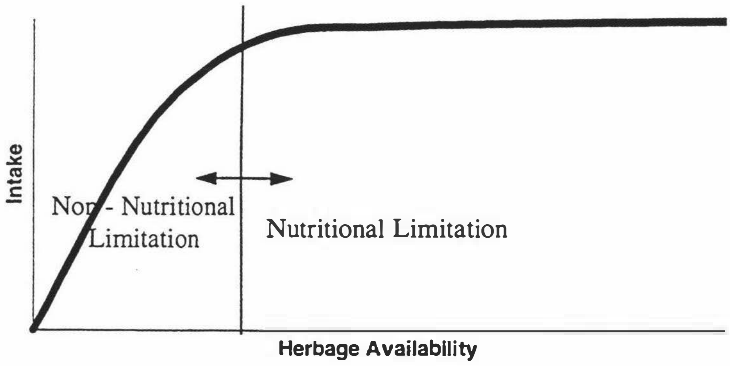


Figure 3.7 Primary limit to intake in relation to herbage availability (Poppi et al., 1987).

3.4.3.1 *Physiological limits to intake*

The nutritional limits to intake are related to rumen fill and physiological control. The physiological potential is related to the maximum capacity of the animal to metabolise nutrients. When the amount of nutrients eaten exceeds the capacity of the animal to convert it into tissue or products such as milk and wool, metabolites accumulate in the bloodstream and trigger the cessation of eating and cause a sensation of satiety between meals. This mechanism can operate in either short-term or long-term control of intake. The long-term physiological control is set by the genetic potential of the animal (Van Soest, 1994). The physiological potential for intake varies with a range of factors, including species, sex, physiological state (i.e. maintenance, growth, pregnancy and lactation), size, body shape and health. When animals are fed high energy diets which have low rumen fill and are palatable and readily digested, intake is regulated to meet the energy demand of the animal (Conrad, 1966; NRC, 1989; Mertens, 1994). Increasing the energy concentration of the diet when energy demand is satisfied leads to a decrease in dry matter intake while energy intake remains constant (Figure 3.8).

In practice, determining the physiological limit for intake (i.e. the capacity of the animal to metabolise nutrients) is difficult. The ability of the animal to store and recover energy in glycogen and fat reserves provides a buffer to short-term and long-term variation in intake. Also, intake is inversely correlated to the animal's fat reserves (NRC, 1989) and this factor has been explicitly included in some sheep and cattle models (e.g. Larcombe, 1989; Freer et al., 1997). It also adds complexity to the study of intake control, mainly with regard to categories such as ewes and cows, because during certain time periods energy output may be greater than energy input at the expense of body reserves. The partitioning of mobilised and consumed nutrients is controlled hormonally and is a function of the genetic merit age and physiological state of the animal (lactating, pregnant, growing or maintenance).

Increasing energetic expenditure by animals is known to increase the physiological limit to intake. For instance, lactating and growing animals have higher feed intake than non-lactating animals (NRC, 1989). Animals with higher generic merit and milk production eat more and graze longer than lower producing animals (Cowan, 1975), although in this case it is difficult to know what is the cause and the effect. Also ewes raising twins (Parker and McCutcheon, 1992) have a higher intake compared with those suckling singles. Increased energy expenditure due to cold stress also increases intake (Weston, 1982; Young, cited by Ketelaars and Tolkamp, 1992). An exception seems to be pregnancy because no conclusive evidence exists that the higher energetic demand caused by the foetus(es) and related structures increases intake (McCall, 1984; Ketelaars and Tolkamp, 1992). In fact, some evidence shows that intake decreases in the last trimester of pregnancy (Weston, 1982; Forbes, 1986).

In spite of the evidence confirming the effect of genetic merit on energy demand, intake and performance, most models assume a standard and uniform genetic merit for animals and estimate their potential intake based on live weight and physiological state. Larcombe (1989), for instance, set potential intake (PRI, kgDM d^{-1}) using the equation: **PRI = 4.84 + 0.039**

LWT (0.749 - 0.000155 SOL + **0.0839 LN** (SOL)), where: LWT is average cow live weight; SOL is average stage of lactation; and LN (SOL) is the natural logarithm of the stage of lactation. Also the intake equations of Doyle et al. (1989) assumed a standard genetic pattern for beef cattle. Finlayson et al. (1995) varied the physiological limit for intake according to the normal empty body weight for different breeds. Similarly, Freer et al. (1997) scaled the potential intake of animals to a standard reference weight. Doyle et al. (1989) estimated the physiological intake limit for bull beef by summing the energy demand of the animals (maintenance, muscular work, normal growth and compensatory growth) and dividing this value by the energy content of the feed consumed. This simpler approach is possible for growing cattle because there is no need to account for differences in energy partitioning among processes other than body energy deposition.

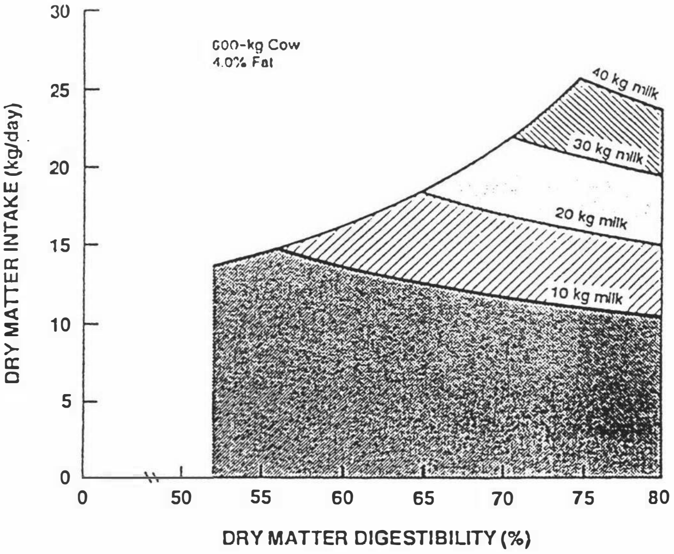


Figure 3.8 Bi-phasic model of dry matter intake regulation, showing that with low energy concentration-high fill diets, intake is limited by the physical capacity of the rumen. With increasing energy concentration and a decreasing "fill effect" of the diet, the metabolic demand of the animal may be reached and from that point energy intake is maintained constant while dry matter intake falls with further increases in energy intake (after NRC, 1989).

Obesity depresses intake, particularly in mature animals. McCall (1984) used a multiplier to adjust the intake for ewes over 50 kg (Figure 3.9). On the other hand, the equations for the physiological feed demand of Finlayson et al. (1995) and Freer et al. (1997) inherently accommodate the depression of intake in obese animals (Figure 3.9). Finlayson et al. (1995) used a function developed by Oltjen et al. (1986) in which the physiological limit for intake was assumed to be a function of the current live weight of the animal and the empty body weight of a normally fat mature animal. This parameter is different for rams, castrates and females. The same function is used for growing and mature animals (Figure 3.9).

Several models include explicit physiological limits for intake (e.g. Finlayson, 1989; Doyle et al., 1989 and Finlayson et al., 1995); others however provide no clear cut separation of effects of physiological and rumen fill limits for ewes or their progeny (McCall, 1984; Freer et al., 1997). In the latter models the physiological feeding drive was accommodated by predicting intake using different functions of pasture quality and availability for young and mature animals (animals were considered to be young up to 30 kg of live weight) and by applying a multiplier for stage of lactation and mature live weight.

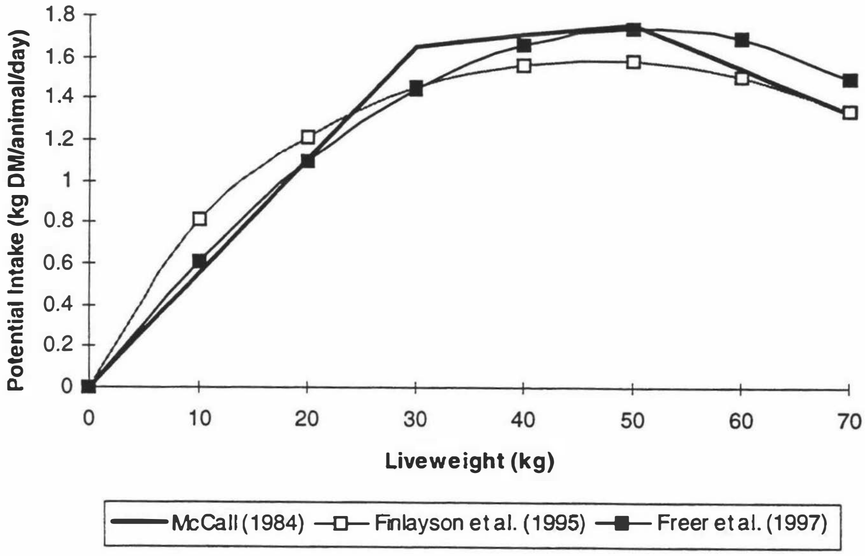


Figure 3.9 Comparison of the relationship between intake and live weight assumed in the equations used by McCall (1984), Finlayson et al. (1995) and Freer et al.(1997). For the comparison it was assumed the equations applied to a mixed breed female with a standard reference weight of 60 kg (EBW = 65.4) and consuming forage with 11 MJ ME kg DM^{-1}.

The model described here follows Finlayson et al. (1995) who defined physiological intake limit as:

$$I_P = \left(\lambda_1 - \frac{\lambda_2 EBW}{EBW_{Max}} \right) EBW^{\lambda_3} f_L$$

where I_P is the physiological limit of feed intake on animal in maintenance, *EBW* is the animal empty body weight, EBW_{Max} is the standard mature body weight for a mature animal and f_L is the effect of lactation on the physiological intake limit (Eqn. 3-24). Adapting the equation for feeding supplements, it becomes:

$$I_P = \left(\lambda_1 - \frac{\lambda_2 EBW}{EBW_{Max}} \right) EBW^{\lambda_3} f_L - Suppl\ E_{Suppl}$$ **Eqn. 3-23**

where Suppl is the amount of supplement fed and E_{Suppl} is the energy content (MJ ME $kgDM^{-1}$) of the supplement.

Following (McCall, 1984) and Freer et al. (1997), pregnancy was assumed to have no effect on intake. Lactation was assumed to have a multiplicative effect on the animal's physiological intake potential (Eqn. 3-23). The function used here was derived from McCall (1984) and is shown in Eqn. 3-24. It is in contrast to Finlayson's model where the effect of pregnancy and lactation was handled as an additive rather than a multiplicative effect. The increase in potential intake is a function of the metabolic energy demand with a time delay calculated by a function adapted from Purser and Moir (1966). The function is: $IPI = \sum_{i=1}^{t} (R_{tc-i+1} - R_{tc-i})(1 - D^i)$, where *IPI* is the increment on the physiological intake limit caused by the reproductive stage of the animal; *R* is the metabolisable energy required for reproduction (i.e. pregnancy + lactation); D is a delay factor; and *tc* is the number of days after conception. In spite of the advantage of directly linking the increase in energetic expenditure with intake potential, this equation predicts increased intake for pregnant animals which, as discussed previously, has not been observed empirically.

$$f_L = \lambda_4 t^{\lambda_5} exp(\lambda_6 t_L)$$ **Eqn. 3-24**

where f_L is the effect of lactation on the animal feed intake and t_L is the number of days of lactation.

Compensatory live weight gain has been handled in different ways in pastoral simulation models. While McCall (1984) disregarded compensatory growth, Doyle et al. (1989) included an explicit factor to account for it when potential growth rates are underachieved. Freer et al. (1997) allowed for compensatory gain by having different predictors for herbage intake and maintenance requirements. Maintenance requirements depended on the base weight, while potential intake depended on the weight of the animal relative to the standard reference weight. A more mechanistic approach was adopted by Finlayson at al. (1995) and in the model described here. Compensatory gain is driven by the faster deposition of DNA than protein during periods of undernutrition which causes a higher partitioning to body protein in relation to fat in the recovery period and therefore a higher live weight gain (see Equations 3-47 to 3-60). Neither Finlayson's or the current model, include a feedback mechanism to describe the increased feed intake of animals achieving compensatory growth.

3.4.3.2 *Physical limits to feed intake*

There is considerable evidence that distension of the digestive tract limits intake. Depression of feed intake can be demonstrated by feeding a bulky diet or introducing inert materials such as balloons, sponges or plastic ribbon into the rumen (Van Soest, 1994). Even for highly concentrated diets with long-term control due to chemostatic mechanisms, control by one specific meal through rumen fill can be demonstrated (Campling, 1970).

The rumen fill effect is related to the bulkiness, degradation and passage rate of the food in the rumen. Several characteristics of feeds have been used to correlate their bulk effect in the rumen. Digestibility was used by Kahn and Spedding (1984). The soluble fraction of the dry matter (Carro et al., cited by Forbes, 1994) has also been shown to be highly correlated to the rumen fill effect of feeds. The current trend is to use the cell wall content (approximated equal to the neutral detergent fibre (NDF) content of the plant (Van Soest, 1994)) to predict the bulkiness of a feed (Mertens, 1994).

Mertens (1985 cited by Mertens, 1994), using data from dairy cows, proposed a constant maximum quantity of NDF that can be handled daily per unit of rumen size. Assuming rumen size is proportional to the live weight of the animal, Mertens (1985) fitted empirical data, to show that the intake of dairy cows is limited by rumen fill at approximately 12.5g NDF kg body weight^{-1} day. Earlier Van Soest and Mertens (1977) had demonstrated a higher correlation between intake and cell wall material (NDF) than with digestibility. NDF has been preferentially used for evaluation of forages and intake prediction since then (Van Soest et al., 1978; Van Soest, 1994; Mertens, 1994). Despite this evidence, digestibility is used much more widely than NDF, particularly for pastures, and several models describe the rumen fill effect of a diet in terms of digestibility. For example, Doyle et al. (1989), Finlayson (1989) and Finlayson et al. (1995) use the concept of indigestible bulk, as originally suggested by Lehmann (cited by Van Soest, 1994) to explain the rumen fill effect on feed intake. The original equation was:

$$I_f = \frac{d_{Max} W}{(1 - Dig_{Diet})}$$

where I_f is the rumen fill limit to dry matter intake, d_{Max} is the limit for intake of indigestible matter, Dig_{Diet} is the diet digestibility and W is animal live weight. This model was refined by Finlayson et al. (1995) and adopted here.

$$I_f = \frac{\lambda_7 RC}{(1 - Dig_{Diet})}$$ **Eqn. 3-25**

where,

$$RC = \lambda_8 W (1 + f_L) - \frac{Suppl(1 - Dig_{Suppl})}{\lambda_7}$$ **Eqn. 3-26**

RC stands for rumen capacity (kg DM), *Suppl* is the amount of supplement fed and Dig_{Suppl} is the digestibility of the supplement offered.

The term $(1 + f_L)$ added by Finlayson et al. (1995) and used here tries to accommodate the increased capacity of the rumen of lactating animals in digesting feed, however it is unlikely that the rumen volume increases by the same extent as energetic demand. In such cases it should be interpreted as a mathematical "trick" rather than a mechanistic explanation.

Despite the fact that they apply different concepts, the models of Mertens (1994) and Conrad (1966) followed Kahn and Spedding (1984) and here, produce similar intake behaviour in relation to forage quality (Figure 3.10). Because of the scarcity of NDF estimates for New Zealand pastures, digestibility was used in the current study as a predictor of the rumen fill limit.

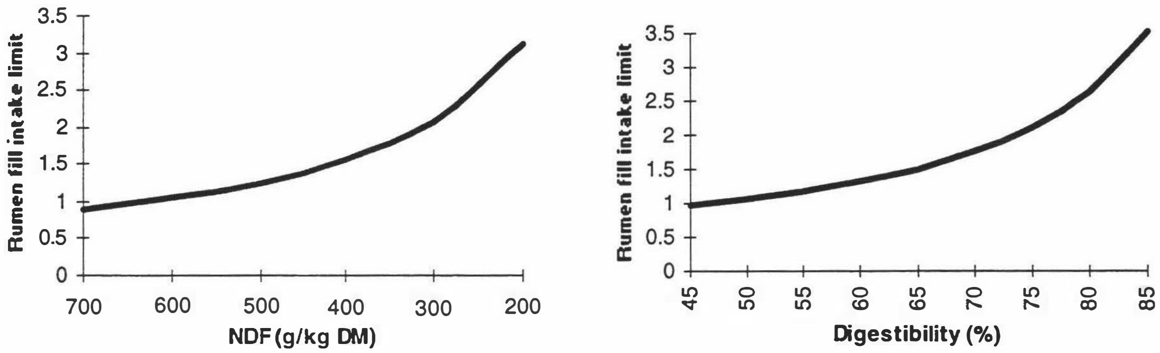


Figure 3.10 Responses of rumen fill limits to feed intake in relation to forage quality predicted by the (a) the constant NDF model of Mertens (1985) and (b) the constant undigestible bulk of (Conrad, 1966; Kahn and Spedding, 1984).

One of the problems of using rumen fill is that the rumen volume does not remain at a constant maximum (Gill et al., 1988); animals can support different degrees of rumen fill depending on their physiological state and energy demand (Ketelaars and Tolkemp, 1992). Also gastrointestinal motility and passage rates can be regulated, to a certain extent, by the central nervous system and hormonal action (Ketelaars and Tolkemp, 1992; Van Soest, 1994). Dynamic models of ruminal digestion, such as that developed by Mertens and Ely (1979), account for rates of passage, degradation and so on, but increasing the complexity of the rumen fill sub-model to this level would have cost too much in terms of computer and development requirements, while probably providing little increase in the model's predictive power for the conditions it was being designed for.

3.4.3.3 *Ingestive behaviour limits to herbage intake*

It has been known for a long time that herbage intake is limited by sward availability (Johnstone-Wallace and Kennedy, 1944), however, it was not until in the 1970's that conclusive evidence and quantification of the relationship between forage availability and herbage intake was published (Allden and Whittaker, 1970; Stobbs, 1973a, b; Chacon and Stobbs, 1976).

The decrease in intake with declining of herbage availability has been explained in terms of the mechanisms of the food gathering process (Stobbs,1973a, b; Chacon and Stobbs, 1976; Hodgson et al., 1994; Parsons et al., 1994b; Thornley et al., 1994). In order to identify the effect of the grazing process on herbage intake, the harvesting processes were divided into three main components: bite size, biting rate and grazing time (Allden and Whittaker, 1970). Experiments have subsequently shown that of these variables, bite size is the most responsive to changes in sward conditions (Hodgson et al., 1994).

Bite size is a product of the density of forage in the grazed canopy and bite volume. Bite volume is the product of bite depth and bite area. In temperate swards, bite depth responds mostly to sward height (Mitchell et al, 1991; Hodgson et al., 1994) or more precisely to the depth of the leafy canopy (Hodgson, 1990).

Biting rate is accepted to be function of bite size (Laca et al., 1992); bigger bites being associated with a lower biting rate. However, intake rate (g DM min^{-1}) increases with bite size. The grazing animal responds to the lower intake rate on short swards by increasing grazing time. Laca et al. (1992) found that the number of jaw movements per bite increased in a linear way (number of jaw movements per bite = 0.17 + 0.76 bite weight (g)) for cattle. This is analogous to the relationship assumed by Parsons et al. (1994b) for sheep (handling time (seconds) = 0.375 + 7500 bite mass (kg DM)). However, increased grazing time is not enough to maintain constant daily intake in swards grazed below a critical level.

The mechanism by which these responses are controlled are still not understood, but most of the reasoning has been based on optimal foraging theory (Thornley et al., 1994; Newman et al., 1995). According to this theory, increasing grazing time represents a cost to the animal both in energy (Thornley et al., 1994) and predation time (Newman et al., 1995). The animal would then weigh the marginal cost of grazing longer against the marginal benefit of increased dry matter intake in order to optimise its fitness. However, this theory is not universally accepted (e.g. Provenza and Balph, 1990).

For continuous grazing, most models use herbage mass (e.g. Woodward et al., 1993, 1995), or leaf area index (e.g. Johnson and Parsons, 1985) as intake predictors, while pre-grazing mass and herbage allowance (sometimes defined as area allowed per animal at a given pre-grazing mass, Larcombe, 1989), and green allowance and green pre-grazing herbage mass are used for rotational grazing simulations (McCall, 1984; Finlayson, 1995). Improvements in the accuracy of prediction for herbage mass, pasture allowance or sward height have been found by including the proportion of leaf in the sward. Hodgson (1990) argued that the depth of the leafy canopy is likely to be the major factor affecting intake rate. This statement agrees with Daugherty et al. (1992), who found that the bite of animals is limited by pseudostem height. Holmes (1987) suggested that dry matter intake would be better predicted from green herbage allowance than dry matter herbage allowance. Similarly, Butler et al. (1987) claimed it would be better to base intake predictions on estimates of green leaf mass than on total herbage mass.

Based on the evidence described above, prediction of herbage intake in the model was based on leaf mass. An equation developed by Johnson and Parsons (1985) was adopted for this purpose (Eqn. 3.27). As there is a high correlation between leaf mass and leaf area ($r^2 = 0.91$ according to King et al., 1979), and this ratio is almost constant throughout plant growth, the original parameters (for leaf area index) were converted to leaf mass using the relationship 1 LAI = 290 kg DM leaf ha^{-1} (Doyle et al., 1989). The shape of equation 3-24 is shown by Figure 3.11.

$$f_a = \frac{\left(\frac{L}{\lambda_9}\right)^{\lambda_{10}}}{1+\left(\frac{L}{\lambda_9}\right)^{\lambda_{10}}}$$ **Eqn. 3-27**

According to Hodgson (1977), the rate of herbage intake during rotational grazing is likely, at any point in time, to be influenced by the conditions of the grazing horizon. Herbage allowance therefore affects the rate animals graze toward limiting conditions. Following this reasoning, Woodward et al. (1993) proposed that intake be calculated on the basis of herbage mass by integrating intake and growth over time, an approach also adopted by Barioni et al. (1996). Testing the model of Barioni et al. (1996) revealed that this approach however tends to generate a much steeper response to allowance and herbage intake (compare Figure 3.12 and Figure 3.14).

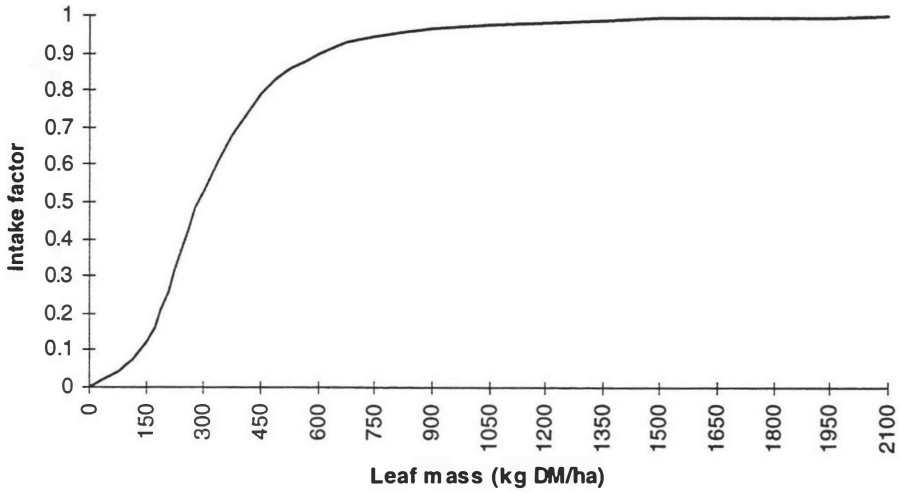


Figure 3.11 Intake multiplier related to herbage availability as predicted by Eqn. 3-27.

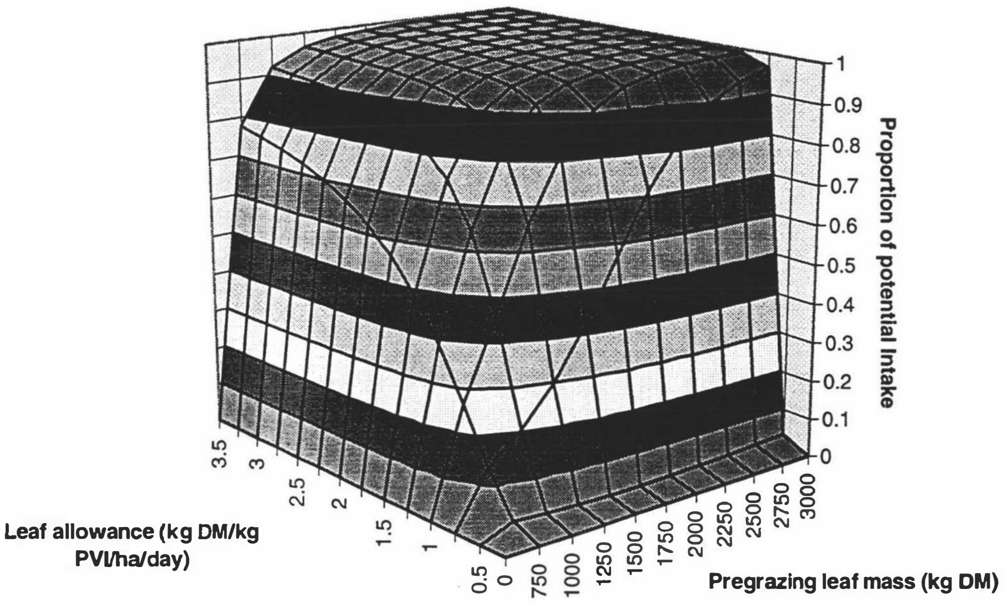


Figure 3.12 Response surface from the numerical integration of the intake function given by Eqn. 3-27.

This is probably because it assumes that the variability and selection opportunities under both continuous and rotational grazing are similar. However, the opportunity for selection *ceteris paribus*, is higher for animals continuously grazing. Grazing animals select for patches that provide for a higher intake rate (Black and Kenney, 1984; Griffiths et al., 1996) and they may therefore take advantage of the higher variability and selection opportunity when submitted to continuous grazing. Therefore, deriving functions of intake response to herbage availability in rotational grazing by integrating functions developed from continuous grazing experiments does not seem to be an adequate technique for explaining differences in intake. This topic deserves further research.

Several authors agree that animal intake under rotational grazing is affected by both pre-grazing (leaf) mass and (green) herbage allowance. This seems to be true for both sheep and cattle. For example, Larcombe (1989) fitted a function to explain the herbage intake of animals in relation to pre-grazing herbage mass, area grazed per cow each day and the digestibility of the sward before grazing. Unfortunately, herbage mass and not leaf mass was used in the equations. However, according to Larcombe (1989) the inclusion of pre-grazing digestibility was introduced primarily to account for the effect of leafiness on the herbage intake of the animals. The function is:

$$\mathbf{C_t = APC / {-0.00067} \, ({-0.00089}(0.538+13.2APC). \ln \, (Z + (1 - Z) \exp \, ({-0.00067} \, ({-0.00089}(0.538+13.2APC).PRI \; t/APC)}$$

where:

$$\mathbf{Z = \exp \, ({-0.00067} \, ({-0.00089}(0.538+13.2APC) \, (HMi - 31 - 35.1 \, (80 - Pdig \,)))}$$

and C_t is the total feed consumed by a cow (kg DM) at time t (days), APC is the area allocated per cow (ha), PRI is the potential rate of intake under ideal conditions at a specified stage of lactation (kg DM cow^{-1} day), HMi is the initial herbage mass at time t = 0 (Pre-grazing herbage mass) and P_{dig} is the pre-grazing digestibility (%DMD). Assuming a dry matter digestibility of 72% and potential intake of 18 kg DM, the effect of pre-grazing and herbage allowance on intake by dairy cows can be plotted as illustrated in Figure 3.13.

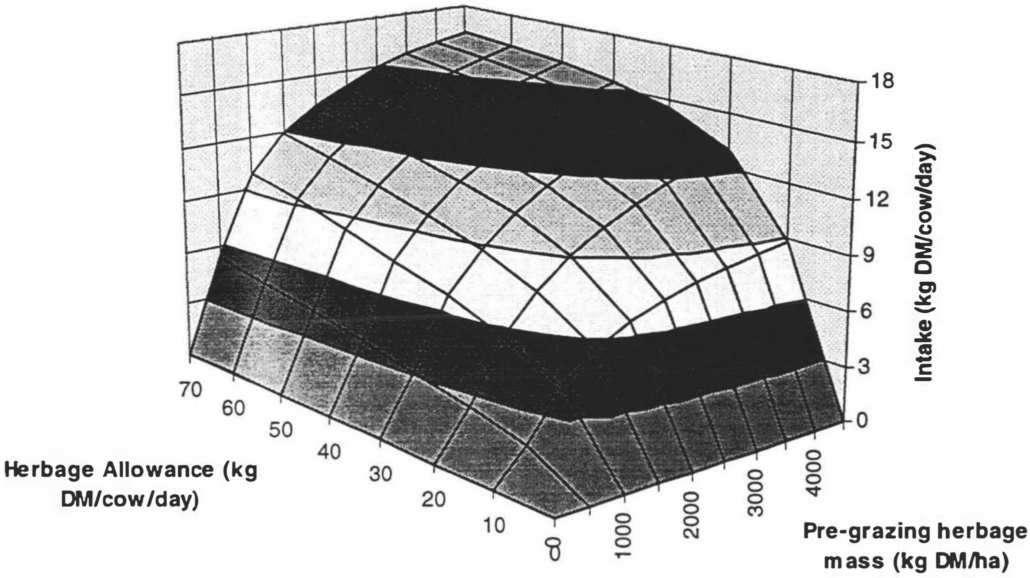


Figure 3.13 Three dimensional response surface for the dry matter intake by dairy cows to pre-grazing herbage mass and herbage allowance as predicted by the equations formulated by Larcombe (1989) assuming a dry matter digestibility = 72 % and potential intake = 18 kg DM.

Unfortunately no suitable equation relating leaf mass to intake was found for rotational grazing. However, McCall (1984) derived a similar equation for sheep by correlating pre-grazing green herbage mass and green herbage allowance to intake restriction (described as a multiplier to the potential voluntary intake). The equation derived by McCall (1984) is described mathematically as:

$$f_a = 1 - \lambda_{11} exp(-\lambda_{12} GDM) exp(-\lambda_{13} exp(-\lambda_{14} Allow)) \qquad \textbf{Eqn. 3-28}$$

where

$$GDM = L_{(t_{Pre})} + St_{(t_{Pre})} \qquad \textbf{Eqn. 3-29}$$

and f_a is the intake restriction factor related to herbage availability, GDM is the pre-grazing herbage mass (kg DM ha^{-1} day^{-1}). “Allow” is the interpolation of the monthly user defined green herbage allowance as multiple of voluntary intake (kg GDM kg PVI^{-1} day^{-1}) and includes an adjustment for pasture grown in the period under consideration. As the time spent by animals in one paddock is variable (see Section 3.4.4), pasture growth accounted for in order to minimise the problem with prediction that is inherent when applying the herbage allowance concept to longer periods of grazing. This was done by adding the net pasture growth expected for that period to herbage allowance and then calculating intake. Allow is therefore:

$$Allow = Allow_{Def} + GT\,Ac_{Green} \qquad \textbf{Eqn. 3-30}$$

where Allow is the total green herbage allowance, $Allow_{Def}$ is the user defined herbage allowance at the starting of the grazing period, Ac_{Green} is the green pasture accumulation rate, calculated by Equation 3-11 and the other variables and parameters are as defined previously.

By plotting the intake restriction factor against pre-grazing green herbage mass and green herbage allowance, and comparing Figure 3.13 and Figure 3.14, it is possible to show the shape of the sheep and cattle functions are similar, even though they were originally fitted for different species.

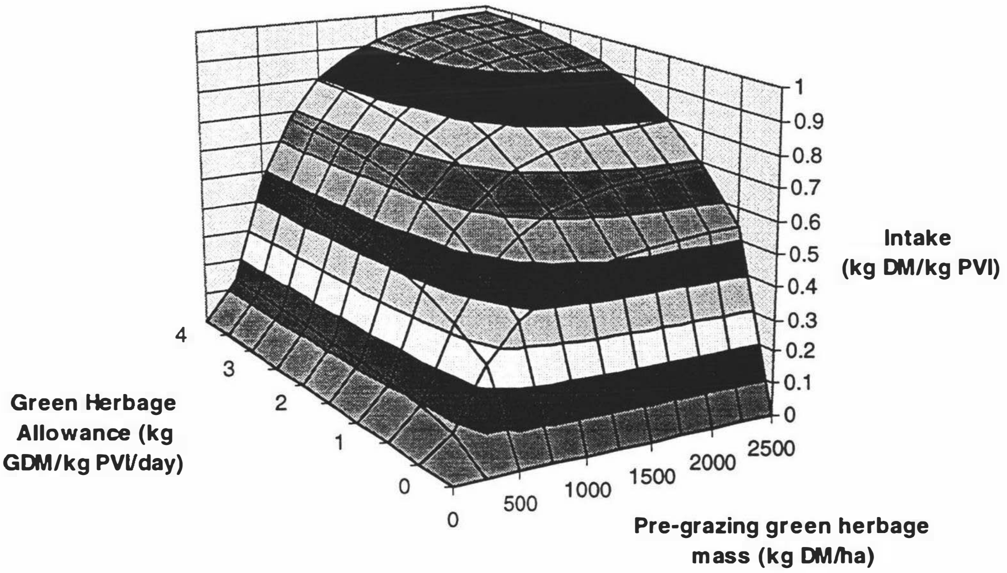


Figure 3.14 Response surface of dry matter intake by sheep to pre-grazing green herbage mass and green herbage allowance predicted by Eqn. 3-28.

3.4.3.4 *Integration of the intake control mechanisms*

Forbes (1986) hypothesised that intake is an additive intake response to several causal impulses. However, his hypothesis lacked formal mathematical formulation and validation. According to Van Soest (1994) integration of intake factors is an area that requires more research.

In practice, grazing models have usually adopted two main approaches to describe the control of intake. The first, adopted by Doyle et al. (1989), assumes that the three factors described above are independent and intake is determined by the most limiting factor of the intake factors, i.e.: $\boldsymbol{I = Min\ (I_P,\ I_f,\ I_a)}$, where I is the dry matter intake, I_p is the physiological limit to intake; I_f is the physical limit to intake; and I_a is the limitation to intake imposed by herbage availability. However, most evidence to date demonstrates that the limit to intake related to herbage availability depends on the energy demand of the animal. It is known that higher genetic merit cows are able to achieve a higher intake than low genetic merit cows under the same sward conditions (Bao et al., 1992). Positive relationships between milk production and grazing time have also been found (Cowan, 1975) and animals which have had their rumen contents removed, graze for longer than those who have not (Chacon and Stobbs, 1976). Parsons et al. (1994a) observed that lactating ewes have larger bites (over 80% bigger) than dry ewes probably by grazing deeper into the canopy. Larger bites of pasture were measured by Newman et al. (1994) in fasted compared to non-fasted ewes.

This evidence reinforces the second approach used by McCall (1984), Larcombe (1989), Finlayson (1989) and Finlayson et al. (1995). With this approach, the effect of pasture availability on intake is modelled as a multiplier to the nutritionally determined potential intake. The model discussed here followed this approach and daily intake is therefore defined as:

$$I = \frac{min(I_p, I_f)\, f_a}{Dig_{Diet}\, \lambda_{15}} \qquad \textbf{Eqn. 3-31}$$

where f_a is the intake multiplier related to herbage availability and the other parameters as previously defined.

Table 3.5 Parameters for the dry matter intake sub-model.

Parameter	Eqn.	Value	Source
λ_1	3-23	1.833	Finlayson et al. (1995)
λ_2	3-23	1.095	Finlayson et al. (1995)
λ_3	3-23	0.73	Finlayson et al. (1995)
λ_4	3-24	0.017	McCall (1984)
λ_5	3-24	1.4	McCall (1984)
λ_6	3-24	Singles = - 0.05 Twins = - 0.075	McCall (1984)
λ_7	3-25; 3-26	0.063	Finlayson et al. (1995)
λ_8	3-26	0.17	Finlayson et al. (1995)
λ_9	3-27	370	Johnson and Parsons (1985)
λ_{10}	3-27	3	Johnson and Parsons (1985)
λ_{11}	3-28	1.42	McCall (1984)
λ_{12}	3-28	0.00198	McCall (1984)
λ_{13}	3-28	1.016	McCall (1984)
λ_{14}	3-28	1.0308	McCall (1984)
λ_{15}	3-31	0.157	AFRC (1993)

3.4.4 *Grazing dynamics and harvesting*

Under continuous grazing the model recalculations are made daily (i.e. GT = 1). In contrast, when the model is assigned to simulate rotational grazing, the time spent in each paddock is calculated according to user defined monthly herbage allowances. The allowance is interpolated to the time the mob starts grazing the paddock (t_{Pre}). In order to achieve consistent herbage allowances in a mob with several categories represented and each of which has dynamic live weight per animal and physiological states, it was decided to calculate grazing time based on herbage allowance per unit of potential herbage intake as defined in Eqn. 3-31. However, instead of using green herbage allowance, which may be difficult to determine on a farm, total pasture allowance was used.

$$GT = \frac{HM_{Pre}\, I_{Max}}{Allow_{Interp}} \qquad \textbf{Eqn. 3-32}$$

where:

$$HM_{Pre} = L_{(t_{Pre})} + St_{(t_{Pre})} + D_{(t_{Pre})} \qquad \textbf{Eqn. 3-33}$$

$$I_{Max} = \sum_{i=1}^{3} Min(I_{P_i}, I_{f_i})N_i + \sum_{j=1}^{n} Min(I_{P_j}, I_{f_j}) \qquad \textbf{Eqn. 3-34}$$

$Allow_{Interp}$ is the linear interpolation of monthly user defined herbage allowances. The variable I_{Max} represents the nutritional intake limit of the whole mob and is determined by summing nutritional intake limits of all categories in the flock. The first component of the equation, $\sum_{i=1}^{3} Min(I_{P_i}, I_{f_i})N_i$ stands for the sum of the nutritional intake limit of each category except lambs (i = ewes, ewe hoggets, rams). N_i is the number of individuals in each category. The second component of the equation, $\left(\sum_{j=1}^{n} Min(I_{P_j}, I_{f_j})\right)$, represents the sum of the nutritional intake limit of the lambs and j = 1, 2...n, represents each of n lambs in the flock.

Paddocks exceeding a threshold herbage mass are harvested. Also, the user defines a post harvesting pasture mass which the paddocks are harvested to. Modelling harvesting in pastoral livestock systems has been a disregarded area of research. This is probably due to the extreme variations in leaf, stem and dead distribution within the canopy on harvesting. The assumption made here was that the post-harvesting leaf, stem and dead material mass varied according to their pre-grazing values and post-grazing herbage mass as follows:

$$L_{AH} = L_{BH}\left(1 - \frac{HM_{Pre}}{HM_{Post}}\right) \qquad \textbf{Eqn. 3-35}$$

$$St_{AH} = St_{BH}\left(1 - \frac{HM_{Pre}}{HM_{Post}}\right) \qquad \textbf{Eqn. 3-36}$$

$$D_{AH} = D_{BH}\left(1 - \frac{HM_{Pre}}{HM_{Post}}\right) \qquad \textbf{Eqn. 3-37}$$

where L_{AH}, St_{AH} and D_{AH} are leaf, stem and dead material mass after harvesting (kg DM/ ha), respectively; L_{BH}, St_{BH} and D_{BH} are the leaf, stem and dead material mass before grazing (kg DM/ ha), respectively; HM_{pre} is the total herbage mass pre-harvesting and HM_{Post} is the post-harvesting herbage mass.

3.4.5 *Diet composition*

The ability of the animal to select leaf rather than dead material and stem in the model is expressed as a function of the proportion of leaf, stem and dead material in the sward, the total herbage mass available, and herbage allowance for rotational grazing. The approach used to predict diet composition is a modification of that used by Finlayson et al. (1995). It was assumed that selection ability increases with stocking rate and that the components of the diet are selected according to the sequence described below:

$$Leaf > Stem + Pseudostem > Dead$$

The proportion of leaf, stem and dead material is assumed to be maximum under continuous grazing and under this condition, the diet composition is assumed to be:

$$Sel_L = \frac{L^{k_1}}{L^{k_1} + St^{k_2} + D^{k_3}} \qquad \textbf{Eqn. 3-38}$$

$$Sel_{St} = \frac{St^{k_2}}{L^{k_1} + St^{k_2} + D^{k_3}} \qquad \textbf{Eqn. 3-39}$$

$$Sel_D = \frac{D^{k_3}}{L^{k_1} + St^{k_2} + D^{k_3}} \qquad \textbf{Eqn. 3-40}$$

where Sel_L, Sel_{St} and Sel_D are the proportion of leaf, steam and dead material selected under continuous grazing. L is pasture leaf mass (kg DM ha^{-1}), St is pasture stem mass (kg DM ha^{-1}) and D is pasture dead mass (kg DM ha^{-1}).

The degree of selectivity is given by the ratio of k_1, k_2 and k_3.The proportion of leaf, stem and dead in the diet of the animals is calculated from herbage allowance as:

$$Diet_L = L\% + (Sel_L - L\%)\left(1 - exp\left(k_4\left(\tfrac{1}{Allow}\right)^{k_1}\right)\right) \quad \textbf{Eqn. 3-41}$$

$$Diet_{St} = Sel_{St} + (St\% - Sel_{St})\left(\left(\tfrac{1}{Allow}\right)^{k_2}\right) \quad \textbf{Eqn. 3-42}$$

$$Diet_D = 1 - (Diet_{St} + Diet_D) \quad \textbf{Eqn. 3-43}$$

where $Diet_D$ is the proportion of dead material in the animal diet, $Diet_{St}$ is the proportion of stems in the animal diet, $L\%$ is the proportion of leaf in the pasture offered, $St\%$ is the proportion of stem in the pasture offered and Allow is green herbage allowance as a multiple of voluntary intake (kg GDM kg PVI^{-1}).

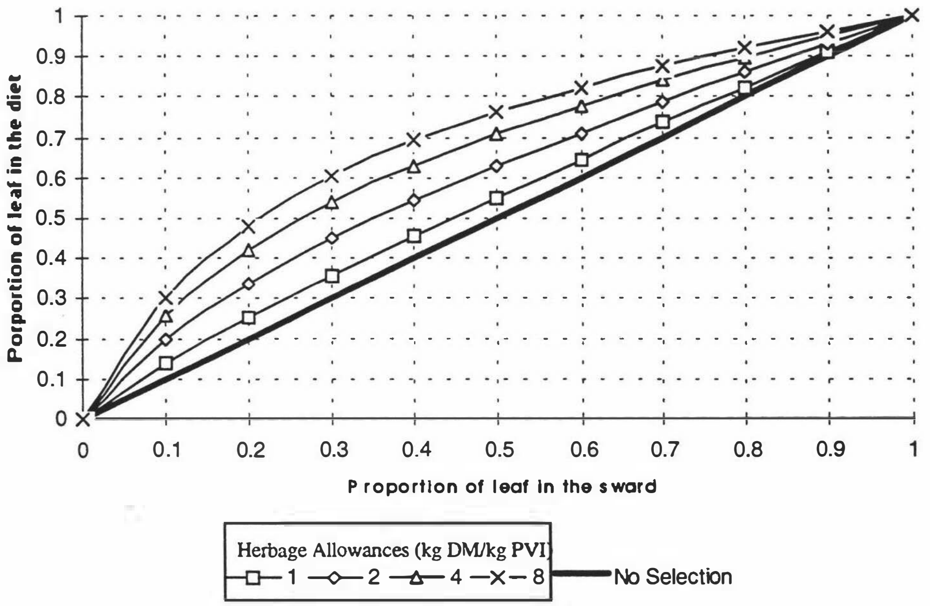


Figure 3.15 Prediction of the proportion of leaf in the diet in relation to the proportion of leaf in the sward and herbage allowances using equations 3-28 to 3-33 in the model.

The post-grazing leaf, stem and dead material mass can be therefore calculated as follows:

$$L_{(t_{Pre}+GT)} = L_{(t_{Pre})} - I_{Max} Diet_{Leaf} \qquad \textbf{Eqn. 3-44}$$

$$St_{(t_{Pre}+GT)} = St_{(t_{Pre})} - I_{Max} Diet_{Stem} \qquad \textbf{Eqn. 3-45}$$

$$D_{(t_{Pre}+GT)} = D_{(t_{Pre})} - I_{Max} Diet_{Dead} \qquad \textbf{Eqn. 3-46}$$

In contrast to the approach used here, Loewer et al. (1989, 1993) and Freer et al. (1997) divided available herbage into several pools based on their digestibility. The animals were assumed to select exclusively based on digestibility. The highest digestibility pool is eaten first and the animals then start eating lower and lower "digestibility pools" until a threshold of satiety is achieved. However in this model it was decided to maintain the link between pasture model state variables and physical plant components, because it was believed this would simplify parameterisation, evaluation and adaptation of the model to other species and environments.

3.4.6 *Energy value of the diet*

The energy value of the diet was based on diet composition and season using Finlayson et al.'s (1995) model, but incorporating a multiplier added to adjust for seasonal changes in pasture quality. It was felt necessary to include such an adjustment because of changes in species composition, with clover increasing in summer and decreasing in winter (Waghorn and Barry, 1987). Further, temperature and light both affect the digestibility of each of the morphological fractions (leaf, stem and dead) of the species in the sward. Wilson et al. (1991) found that the NDF content of ryegrass leaf blades and stems increased, while digestibility decreased with increasing temperature. These findings agree with those of Rattray (1978) and Clark et al. (1982) who showed that the digestibility of ryegrass-dominant swards follow a seasonal trend, even in a leafy sward maintained by close grazing. The diet digestibility was therefore assumed to be:

$$Dig_{Diet} = (\,Diet_L Dig_L + Diet_{St} Dig_{St} \;+ Diet_D Dig_D\,) f_{season} \qquad \textbf{Eqn. 3-47}$$

where Dig_{Diet} is the digestibility of the diet, Dig_L is the annual average of leaf digestibility; Dig_{St+} is the annual average of stem digestibility; Dig_D is the annual average of dead material digestibility and f_{Season} is the effect of season on diet digestibility as defined by Eqn. 3-48.

$$f_{Season} = 1 + k_5 \cos\left(\frac{2\pi(\,t-240\,)}{365}\right) \qquad \textbf{Eqn. 3-48}$$

The metabolisable energy of the diet (ME; MJ $kgDM^{-1}$) is then estimated using Eqn. 3-49 (from AFRC, 1993).

$$ME = \lambda_{15} Dig_{Diet} \qquad \textbf{Eqn. 3-49}$$

Table 3.6 Parameters used in the diet composition and quality sub-model.

Parameter	Eqn.	Value	Source
k_1	3-38; 3-39; 3-40; 3-41	1	Assumed by the author
k_2	3-38; 3-39; 3-40; 3-42	0.9	Assumed by the author
k_3	3-38; 3-39; 3-40	0.8	Assumed by the author
k_4	3-41	1.9	Assumed by the author
k_5	3-48	0.03	Calibrated to Clark et al. (1982)
Dig_L	3-47	0.8	Finlayson et al. (1995)
Dig_{St}	3-47	0.65	Finlayson et al. (1995)
Dig_D	3-47	0.5	Finlayson et al. (1995)

3.4.7 *Animal performance*

In temperate pastures, energy is the most limiting factor to animal production. In the present model, following the example of other models of livestock production from pasture (Doyle et al., 1989; Larcombe, 1989; Finlayson et al., 1995) animal performance is assumed to be limited uniquely by energy intake. Protein and minerals are assumed to be not limiting.

Calculating animal performance from a known energy intake and requirements for the various pathways of energy expenditure is an exercise in the partitioning of nutrients. Energy necessary for maintenance is always assumed to be spent unconditionally. If the energy intake of the animal is lower than its maintenance requirements, it is assumed that the animal will mobilise some of its organic reserves in order to attend to the demand of physiological processes related to maintenance.

On the other hand, if energy intake is greater than maintenance, surplus energy is partitioned to growth, deposition of reserves, pregnancy (foetal growth), wool growth and lactation, according to the physiological condition of the animal, the size of the energetic surplus and the energetic demand of each of these metabolic sinks.

For the purpose of the current model adequate simple calculations were found for maintenance, growth and lactation requirements. Maintenance was based on empty body weight (Eqn. 3-50) following Finlayson et al. (1995):

$$En_{Maint} = z_1 EBW^{z_2} \qquad \textbf{Eqn. 3-50}$$

where En_{MainL} is the daily energy requirements for maintenance (MJ ME day^{-1}) and *EBW* is the empty body weight (Eqn. 3-71).

Pregnancy requirements are based on the live weight of offspring. The offspring live weight is predicted using Eqn. 3-51 adapted from Donald and Russel (1970).

$$W_0 = e^{(z_3 LN(W) - z_4)} \qquad \textbf{Eqn. 3-51}$$

where W_0 is the lamb birth weight.

Pregnancy energy requirements were then calculated according to AFRC (1993) by the following formulas:

$$Et = 10^{(z_5 - z_6 \exp(z_7 t_p))} \qquad \textbf{Eqn. 3-52}$$

$$En_{Preg} = \frac{W_0(z_8 Et \exp(z_7 t_p))}{z_9} \qquad \textbf{Eqn. 3-53}$$

where Et is the total energy content of the gravid foetus, En_{Preg} is the daily energy requirements for pregnancy (MJ ME day^{-1}) and t_p is the numbers of days after conception.

The energy required for milk and wool production are calculated by Eqn. 3-54 and Eqn. 3-55 as follow:

$$En_{Lact} = \frac{z_{E_{Milk}} MP_{Act}}{z_{K_{Milk}}} \qquad \textbf{Eqn. 3-54}$$

$$En_{Wool} = \frac{z_{E_{wool}} Wool}{z_{k_{wool}}} \qquad \textbf{Eqn. 3-55}$$

where En_{Lact} and En_{Wool} are the daily energy requirements for lactation and wool production (MJ ME day^{-1}), respectively; $z_{k_{Milk}}$ and $z_{k_{wool}}$ are the efficiency of energy metabolisation for milk and wool production and $z_{E_{Milk}}$ and $z_{E_{wool}}$ are the net energy content of milk and wool, respectively. MP_{Act} and Wool are calculated by Equations 3-80 and 3-81, respectively.

In growing animals, the energy surplus (after maintenance) is partitioned between DNA, protein and fat accretion. In mature animals energy is partitioned amongst pregnancy, lactation and fat deposition. Partition depends on the amount of energy available in relation to the metabolic potential for energy usage. When energy intake equals the genetic potential, all of the productive processes are carried out at their maximum rate. As energy eaten decreases in relation to the metabolic potential of the animal, partitioning of energy changes according to the relative biological priority of each process (Figure 3.16). Here the partitioning of nutrients is generally predicted to follow the approach used by Finlayson et al. (1995), where the energy partitioned into protein, wool and milk production is a function of the physiological potential and body condition of the animal, and a multiplier is used to adjust the proportion of energy ingested in relation to the animal's physiological potential. The ratio between actual and potential energy available is given by:

$$P_N = \frac{I\lambda_{15}Dig_{Diet} + z_{10}z_{E_{Fat}}Fat}{I_p + z_{10}z_{E_{Fat}}Fat_{Max}} \qquad \textbf{Eqn. 3-56}$$

where P_N is the proportion of actual and maximum energy available for physiological processes and Fat_{Max} is the maximum body fat, calculated by Eqn. 3-57 as:

$$Fat_{Max} = z_{11}EBW^{z_{12}} \qquad \textbf{Eqn. 3-57}$$

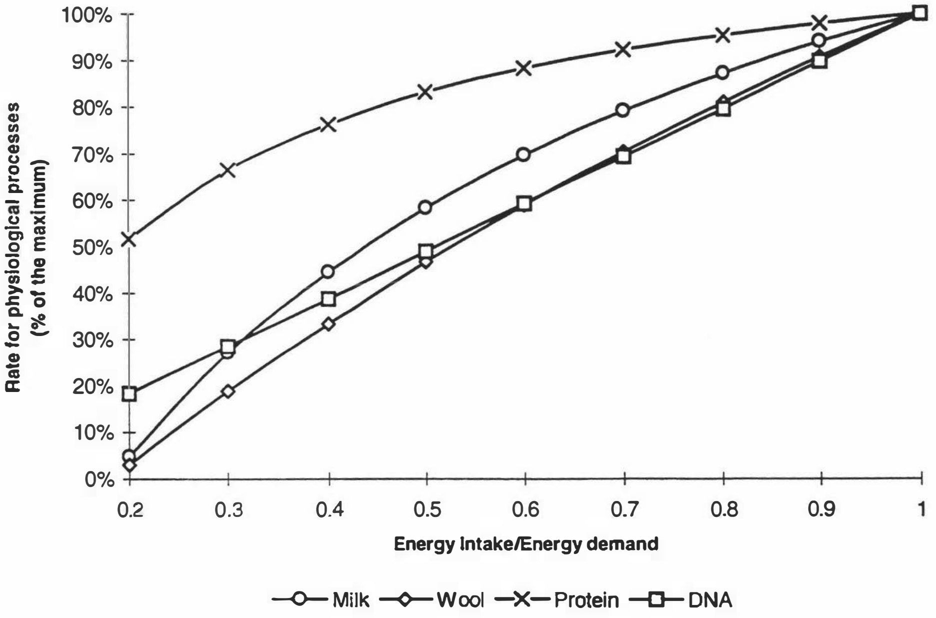


Figure 3.16 Rate of the physiological processes for milk, wool, protein and DNA synthesis as influenced by the ratio between energy intake and energy demand of the animals. Note that the actual protein accretion is affected much more by energy intake than protein synthesis, once energy degradation is assumed to remain relatively constant according to Eqn. 3-63.

The effect of changes in the partitioning of the metabolic sink is defined by:

$$Nut_J = 1 - \frac{z_{13,j}}{z_{14,j} + 1} + \frac{z_{13,j} P_N}{z_{14,j} + P_N}; \quad \text{j = protein, wool, milk}$$ **Eqn. 3-58**

$$Nut_{DNA} = 1 + (P_N - 1) z_{13,DNA}$$ **Eqn. 3-59**

where Nut_{DNA} is the effect of nutrition on the rate of accretion of body *DNA*.

3.4.7.1 *Animal growth*

Baldwin and Black (1979) developed a model of tissue and organ growth where DNA was used to predict the potential rate of protein accretion. Oltjen et al. (1985, 1986 a, b), Doyle et al. (1989) and Finlayson et al. (1995) successfully used the same concept in the prediction of rat, cattle and sheep growth, respectively. The advantage of this approach is that it allows the prediction of live weight change, as well as body composition. This approach was followed by applying equations formulated by Finlayson et al. (1995).

The rate of change in body protein content is derived by the difference between protein synthesis and degradation:

$$\Delta_{Prot} = Prot_{syn} - Prot_{deg}$$ **Eqn. 3-60**

where Δ_{Prot} is the rate of variation of body protein content (kg day^{-1}), $Prot_{syn}$ is the rate of protein synthesis (kg day^{-1}) and $Prot_{deg}$ is the rate of protein degradation (kg day^{-1}).

Protein synthesis is defined as:

$$Prot_{syn} = \theta_{Prot} \frac{z_{K_{Prot}}}{z_{E_{Prot}}} Nut_{Prot}$$ **Eqn. 3-61**

where:

$$\theta_{prot} = z_{15} DNA^{z_{16}} z_{17}$$ **Eqn. 3-62**

θ_{prot} is the energy potentially required for protein synthesis, K_{prot} is the efficiency of metabolisation of protein and E_{prot} is the energy content of protein (MJ ME kg^{-1}). Protein degradation is function of the current level of body protein so that:

$$Prot_{Deg} = z_{18}\, Prot^{z_{19}}$$ **Eqn. 3-63**

The energetic balance resulting from protein turnover is then given by:

$$\boldsymbol{En_{Prot} = \Delta Prot \frac{z_{E_{Prot}}}{z_{K_{Prot}}}}\text{, if } \Delta_{Prot} > 0$$ **Eqn. 3-64**

$$\boldsymbol{En_{Prot} = \Delta Prot\, z_{E_{Prot}}}\text{, if } \Delta_{Prot} \leq 0$$ **Eqn. 3-65**

where En_{Prot} is the energy resulting of protein metabolism and $\Delta Prot$ is the rate of variation in body protein content (kg day^{-1}).

DNA accretion is calculated from the current level of DNA, DNA content at maturity, empty body weight at maturity and the energy balance:

$$\Delta DNA = z_{20} \left(\frac{EBW_{Max}}{z_{21}} \right)^{z_{22}} \left(DNA_{Max} - DNA \right) Nut_{DNA}$$ **Eqn. 3-66**

where DNA_{Max} is the DNA body content at maturity, defined by Eqn. 3-67 as:

$$DNA_{Max} = z_{23} W_{Max}^{z_{24}}$$ **Eqn. 3-67**

W_{Max} is the standard mature live weight calculated by transforming EBW_{Max} into live weight using Eqn. 3-71.

The energy balance is then calculated as the difference between energy intake and the energy spent in maintenance and on productive processes according to the formula:

$$E_{Bal} = I\,ME - (En_{Maint} + En_{Preg} + En_{Prot} + En_{Wool} + En_{Lact}) \quad \textbf{Eqn. 3-68}$$

where E_{Bal} is the energy balance (MJ ME day^{-1}). A negative energy balance leads to mobilisation of fat while fat reserves are increased during periods of a positive energy balance. The variations in body fat content (ΔFat; kg day^{-1}) is calculated by Eqn. 3-69.

The E_{Bal} balance is related to fat reserves (either accretion or mobilisation) according to the equation:

$$\Delta FAT = \begin{cases} \dfrac{E_{Bal} z_{k_{Fat}}}{z_{E_{Fat}}} & \textbf{if EBal > 0} \\ \dfrac{E_{Bal}}{z_{E_{Fat}}} & \textbf{if EBal} \leq \textbf{0} \end{cases} \quad \textbf{Eqn. 3-69}$$

where ΔFAT is the rate of variation of body protein content (kg day^{-1}), E_{Bal} is the energy balance (MJ ME day^{-1}) and E_{Fat} is the energy concentration of fat. Empty body weight is calculated from the amount of body fat and protein of the animals as:

$$EBW = \frac{PROT}{z_{25}} + FAT \quad \textbf{Eqn. 3-70}$$

Actual live weight of the animals (W) is calculated from their empty body weight using Eqn. 3-71 (modified from ARC (1980)):

$$W = \begin{cases} 1.06EBW + W_{wool} & \textbf{if } t_L < 40 \\ 1.09EBW + z_{26} + W_{Wool} + W_{Preg} & \textbf{if } t_L \geq 40 \end{cases} \quad \textbf{Eqn. 3-71}$$

where W_{Wool} is the accumulated wool production between shearings (shearing dates are user-defined) and the extra live weight due to pregnancy (W_{Preg}) is the sum of the extra live weight for n pregnant ewes in the mob calculated by Eqn. 3-72. In Eqn. 3-71 it is assumed that the lambs are pre-ruminants up to the day 40 of life.

$$W_{Preg} = \sum_{i=1}^{n} \frac{z_{27} EtW_0 n_{foetus}}{z_{28}} \qquad \textbf{Eqn. 3-72}$$

where n_{foetus} is the number of foetus carried by the i^{th} ewe and the other variables and parameters are as previously defined.

3.4.7.2 Milk production

Usually milk production is predicted in pastoral livestock production models from a standard lactation curve that is modified according to the energy available for milk production. Also some models predict the "placement" of the curve according to animal parameters such as live weight, body condition score and number of lambs (e.g. Freer et al., 1997). The effect of breed and genetic merit, however, was not taken into account in the models reviewed. The function used here was adapted from McCall (1984) and Freer et al. (1997). The shape of the lactation curve is shown in Figure 3.17 and the function is described mathematically as:

$$MP_{Std} = f_{Lamb}\left(\frac{z_{29}+t_L}{7}\right)^{z_{30}} exp\left(-z_{31}\left(\frac{z_{29}+t_L}{7}\right)\right) f_w \qquad \textbf{Eqn. 3-73}$$

where:

$$f_{Lamb} = \begin{cases} 0.35W_0 & \text{if single} \\ 0.5(W_0+1) & \text{if twins} \end{cases} \qquad \textbf{Eqn. 3-74}$$

$$f_w = \begin{cases} 1 & \text{if } EBW_{Max} z_{32} > 1 \\ \dfrac{EBW}{EBW_{Max} z_{32}} & \text{if } EBW_{Max} z_{32} \le 1 \end{cases} \qquad \textbf{Eqn. 3-75}$$

where MP_{Std} is the standard lactation curve of a well fed ewe (kg day^{-1}), f_{Lamb} is the curve shape factor related to the number of lambs, LW_p is the current live weight (kg) and EBW_{Max} is the standard ewe's maximum live weight (kg).

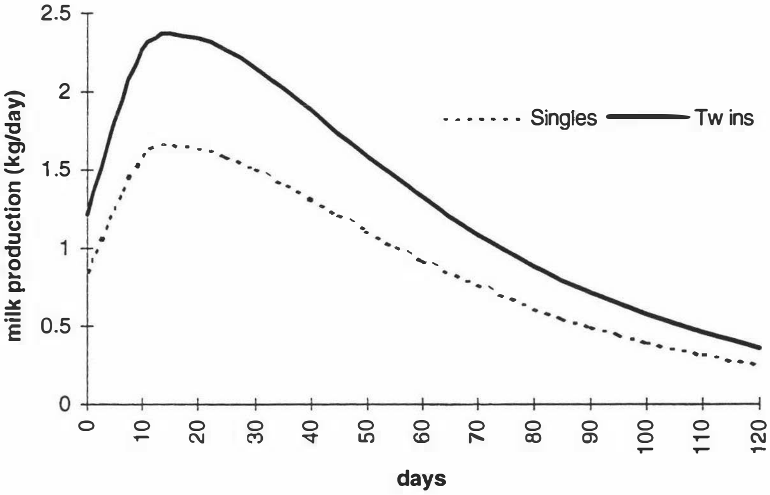


Figure 3.17 Standard lactation curve of a ewe weighing 55 kg at parturition and lamb birth weight of 4.8 kg for singles and 3.8 for twins (from Eqn. 3-73).

The standard milk curve is modified by two multipliers. The Nut_{Milk} multiplier described by equation Eqn. 3-58 represents the immediate effect of the level of nutrition on milk production. Milk production responds also to a carryover effect related to the nutritional deficit in earlier stages of lactation as in the models of Eldesten and Newton (1975), McCall (1984) and Freer et al. (1997). In McCall's (1984) model, the carryover effect of a nutritionally induced depression in milk production was accounted for by just impeding increases in milk production during the decreasing phase of lactation. In contrast, Eldesten and Newton (1975) and Freer et al. (1997) adopted a multiplier to adjust both the potential production and a carryover effect. The multiplier adopted by Eldesten and Newton (1975) is quite simple and consists of a factor activated from day 60 after lambing which is reduced by 3.5% every time the ewe looses weight so that the adjustment to lactation has a permanent effect. In the model of Freer et al. (1997), the multiplier is more elaborate and the adjustment, also incorporated in the model described here, follows the function[1]:

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[1] The operator $\longleftarrow$ is used here to indicate that the value of the variable is updated and its value on the previous day forms part of the right hand side of the equation.

$$\Delta CO_{Milk} = \begin{cases} 0 & \text{if } t_L < 15 \\ -z_{33}(LR - DR) & \text{if } t_L \geq 15 \end{cases} \qquad \textbf{Eqn. 3-76}$$

where:

$$LR \leftarrow z_{34}DR + (1 - z_{34})LR \qquad \textbf{Eqn. 3-77}$$

$$MP_{Act} = MP_{std}Nut_{Milk}CO_{Milk} \qquad \textbf{Eqn. 3-78}$$

$$DR = \frac{MP_{Actual}}{MP_{Std}} \qquad \textbf{Eqn. 3-79}$$

$\Delta\ CO_{Milk}$ is the variation of the lactation multiplier related to the carryover effect of nutrition and MP_{Actual} is the actual current level of milk production.

3.4.7.3 Wool growth

Wool growth in temperate sheep breeds is known to vary seasonally. McCall (1984) modelled wool production using linear regressions of wool growth and energy intake and interpolating the regression parameters over the year. Finlayson et al. (1995) improved the smoothness of the wool growth function by using a sine function (see the comparison of the functions in Figure 3.18). Freer et al. (1997) used a more general function based on weather files and the effect of day length on wool grow. However, this approach was impossible to apply to the model described here because weather files at present are not included and climatic parameters such as day length are not simulated. Greasy wool growth (Wool) is predicted using the equations developed by Finlayson et al. (1995):

$$Wool = \frac{\left(W_{Base} + z_{35}W_{Base}SIN\left(\frac{2\pi}{365}(t + z_{36})\right)\right)Nut_{Wool}}{z_{E_{Wool}}} \qquad \textbf{Eqn. 3-80}$$

where W_{Base} is the average energy requirement for wool growth throughout the year (MJ ME day^{-1}), NUT_{Wool} is the effect of nutritional status upon wool growth as predicted by Eqn. 3-58 and $z_{E_{Wool}}$ is the net energy content of wool (MJ kg^{-1}).

Wool yield (i.e. clean : greasy ratio) was assumed to equal 0.7 following McCall (1984) and Freer et al. (1997).

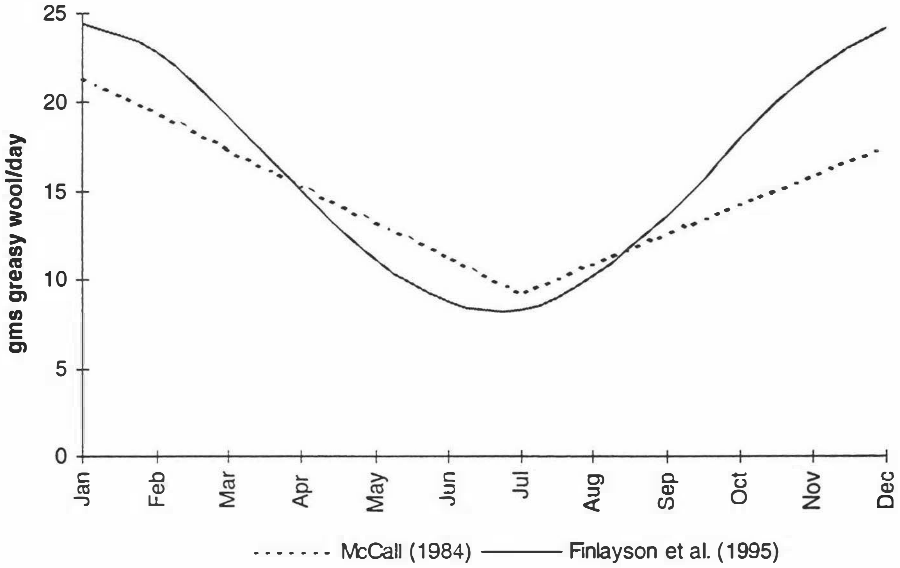


Figure 3.18 Comparison of wool growth functions used in animal simulation models for a empty 55 kg ewe consuming 15 MJ ME/day.

Table 3.7 Parameter estimates used in the animal performance sub-model.

Parameter	Eqn.	Value	Source
z_1	3-50	0.5	Finlayson et al. (1995)
z_2	3-50	0.75	Finlayson et al. (1995)
z_3	3-51	singles = 0.721 twins = 0.741	AFRC (1993)
z_4	3-51	singles = -1.453 twins = -1.049	AFRC (1993)
z_5	3-52	3.322	AFRC (1993)
z_6	3-52	4.979	AFRC (1993)
z_7	3-52; 3-53	-0.00643	AFRC (1993)
z_8	3-53	0.07372	AFRC (1993)
z_9	3-53	0.133	AFRC (1993)
z_{10}	3-56	0.02	Finlayson et al. (1995)
z_{11}	3-57	0.0159	ARC (1980)
z_{12}	3-57	1.868	ARC (1980)
$z_{13,j}$	3-58; 3-59	$z_{13,\text{milk}} = 2.5$ $z_{13,\text{prot}} = 1.518$ $z_{13,\text{DNA}} = 1.201$ $z_{13,\text{wool}} = 4.0$	Finlayson et al. (1995)

Table 3.8 Parameter estimates used in the animal performance sub-model (cont.).

Parameter	Eqn.	Value	Source
$z_{14,j}$	3-58	$z_{14,prot} = 0.176$ $z_{14,milk} = 0.5$ $z_{14,wool} = 2.0$	Finlayson et al. (1995)
z_{15}	3-62	0.9794	Finlayson et al. (1995)
z_{16}	3-62	0.73	Finlayson et al. (1995)
z_{17}	3-62	male = 1.095 female = 0.966	Finlayson et al. (1995)
z_{18}	3-63	0.0437	Finlayson et al. (1995)
z_{19}	3-63	0.73	Finlayson et al. (1995)
z_{20}	3-66	0.00256	Finlayson et al. (1995)
z_{21}	3-66	80	Finlayson et al. (1995)
z_{22}	3-66	-0.27	Finlayson et al. (1995)
z_{23}	3-67	0.9445	Finlayson et al. (1995)
z_{24}	3-67	0.917	Finlayson et al. (1995)
z_{25}	3-70	0.2035	Finlayson et al. (1995)
z_{26}	3-71	2.9	ARC (1980)
z_{27}	3-72	1.6	Assumed by the author
z_{28}	3-72	24.39	Calculated from AFRC (1993)
z_{29}	3-73	3	Freer et al. (1997)
z_{30}	3-73	0.5	McCall (1984)
z_{31}	3-73	0.19	McCall (1984)
z_{32}	3-75	0.9	Assumed by the author
z_{33}	3-76	0.01	Freer et al. (1997)
z_{34}	3-77	0.1	Freer et al. (1997)
z_{35}	3-80	0.5	Finlayson et al. (1995)
z_{36}	3-80	102	Finlayson et al. (1995)
z_{Emilk}	3-52	4.81	Finlayson et al. (1995)
z_{Ewool}	3-53, 3-79	17.0	ARC(1980)
z_{Efat}	3-55	39.3	ARC(1980)
z_{Eprot}	3-60	23.6	ARC(1980)
z_{Kmilk}	3-52	0.59	Finlayson et al. (1995)
z_{Kwool}	3-53	0.30	Finlayson et al. (1995)
z_{Kfat}	3-55	0.72	Finlayson et al. (1995)
z_{Kprot}	3-60	0.30	Finlayson et al. (1995)

3.4.8 *Mob dynamics and trading*

3.4.8.1 Transfer of animals between classes

The model includes five sheep classes: rams, MA ewes, ewe hoggets, two tooths and lambs. After the lambing pattern has been generated by the reproduction sub-model, lambs are grown individually from birth and are sold automatically when they exceed a month by month user defined live weight threshold. The lamb weight is checked every time the mob is shifted from one paddock to another. The user can also define the number of females to keep for flock replacements. When this option is selected, the defined number of replacements are marked at random from the lamb array and not sold when the live weight threshold is exceeded.

Female lambs are transferred into ewe hoggets at the beginning of the new calendar year. The ewe hoggets' live weight, body protein, body fat and DNA are calculated from the mean of the replacements selected. Ewe hoggets are grown separately as a mob until the start of the mating season when they are then transferred into the ewe or two tooths mob (user-defined).

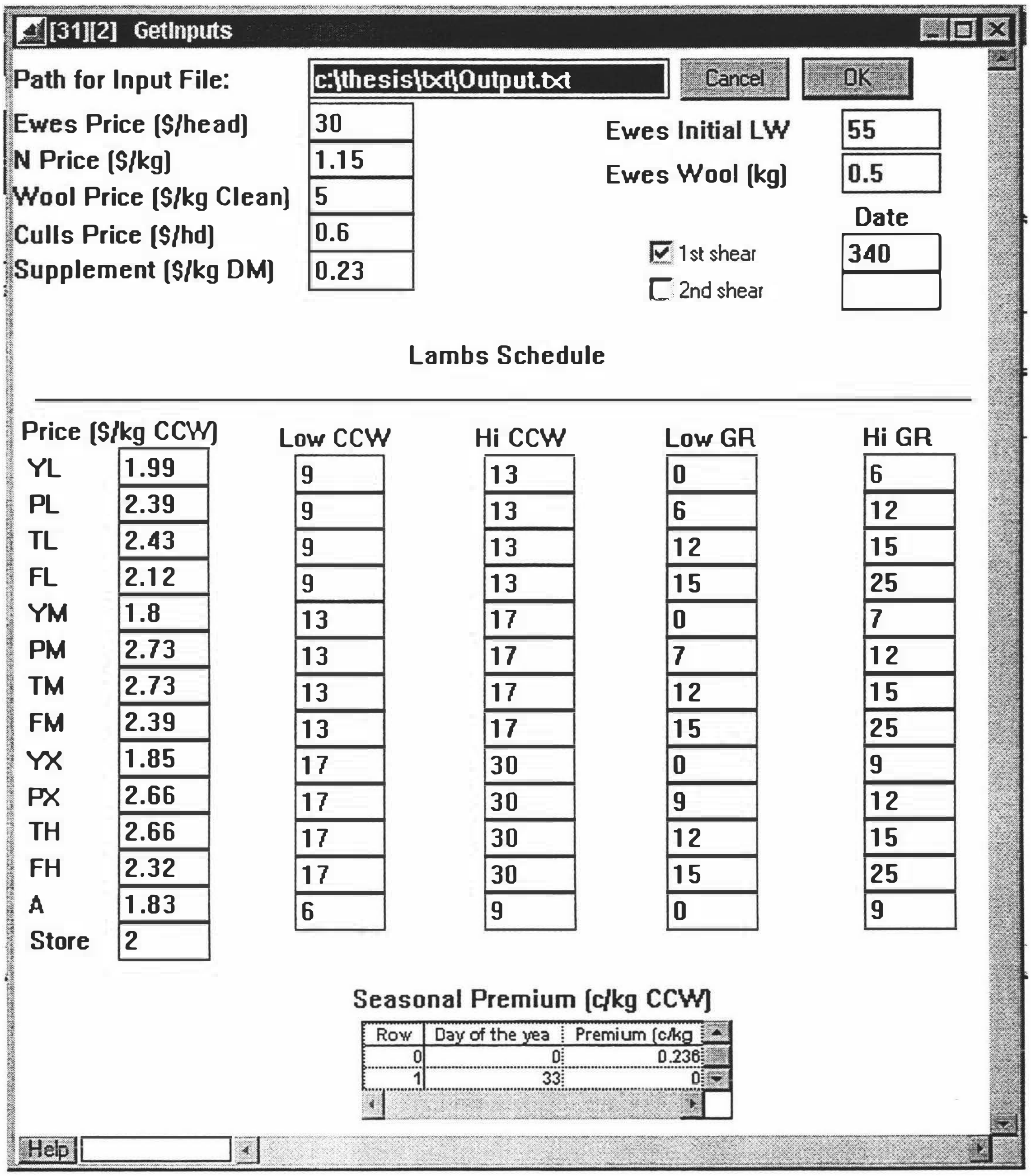
3.4.8.2 Trading and Economics

All price inputs and categories for carcass weight and fatness are user defined according to the dialogue box shown in Figure 3.19.

The farm cash flow is calculated monthly. The calculations are performed by the model when the first paddock is swapped over in the following month. Because the model forecasts the cash flow, inflation was included in the farm expenses according to the expected annual inflation rate, as recommended by Parker (1993b). When the total value of the flock and/or wool on the "back" of the ewes change during the simulation, the gross margin is adjusted by this difference to allow a status quo comparison between alternative enterprise strategies per year.

The user can define one or two shearings per year. The wool accumulated between shearings is sold and computed in the cash flow. Expenses associated with nitrogen and supplements are also accumulated for computation in the gross margin and are assigned to the cash flow in the month of application.

The model defines five categories of ewes. They are ewe hoggets, young and old ewes for reproduction, empty ewes after weaning and cull ewes. All of these categories can be sold at user defined dates. Up to two annual sale dates can be defined for each category except for ewe hoggets and empty ewes after weaning.



Path for Input File: c:\thesis\txt\Output.txt

Ewes Price ($/head) 30
N Price ($/kg) 1.15
Wool Price ($/kg Clean) 5
Culls Price ($/hd) 0.6
Supplement ($/kg DM) 0.23

Ewes Initial LW 55
Ewes Wool (kg) 0.5

Date
☑ 1st shear 340
☐ 2nd shear

Lambs Schedule

Price ($/kg CCW)		Low CCW	Hi CCW	Low GR	Hi GR
YL	1.99	9	13	0	6
PL	2.39	9	13	6	12
TL	2.43	9	13	12	15
FL	2.12	9	13	15	25
YM	1.8	13	17	0	7
PM	2.73	13	17	7	12
TM	2.73	13	17	12	15
FM	2.39	13	17	15	25
YX	1.85	17	30	0	9
PX	2.66	17	30	9	12
TH	2.66	17	30	12	15
FH	2.32	17	30	15	25
A	1.83	6	9	0	9
Store	2				

Seasonal Premium (c/kg CCW)

Row	Day of the yea	Premium (c/kg
0	0	0.236
1	33	0

Figure 3.19 Dialogue box to input prices and carcass weight (CCW) category thresholds.

Prices for each category are independent and user defined. Cull ewe prices are defined in $NZ/kg CCW. The weight of cull ewes is assumed to be the same as the average live weight of the ewe mob and is converted to carcass weight according to Garrick et al. (1986). When lambs exceed the live weight threshold and are then sold, their live weight is converted into carcass weight and fatness (measured as GR[2]) using Equations 3-81 and 3-82 as defined by Garrick et al. (1986):

$$\mathbf{CCW = C_1\,W - C_2} \qquad \textbf{Eqn. 3-81}$$

where CCW is the carcass weight and W is live weight of the animal.

$$\mathbf{GR = C_3\,CCW - C_4} \qquad \textbf{Eqn. 3-82}$$

Table 3.9 Parameters for the DM intake sub-model.

Parameter	Eqn.	Value	Source
C_1	3-80	Ram = -2.04 Wether = -1.92 Ewe = -1.80	Garrick et al. (1986)
C_2	3-80	0.473	Garrick et al. (1986)
C_3	3-81	Ram = -10.8 Wether = -13.0 Ewe = -15.2	Garrick et al. (1986)
C_4	3-81	Ram = 1.2 Wether = 1.5 Ewe = -1.8	Garrick et al. (1986)

3.5 Optimisation module

3.5.1 *Background*

The performance of grazing systems is affected by several factors including state variables (e.g. pasture cover, leaf proportion of the pasture and animal live weight) and control variables (e.g. herbage allowance, harvesting surplus pasture, supplementation and adjusted stocking rate). It is the combination of these factors which maximises system performance in either economic or biological terms. The multi-dimensional nature of the grazing decision problem makes it almost

---

[2] GR is the total tissue thickness between the surface of a lamb carcass and the rib at a point 11 cm from the midline in the region of the 12th rib. This measurement was first suggested by the Meat Producers Board Chief Supervising Grader, Mr. E. Greville, hence GR (Kirton, 1989).

impossible to determine an optimum state - control variable sequence based exclusively on a series of sensitivity analysis. This is particularly true because a single control mechanism is generally not applied independently of others; rather a combination of control alternatives provides the best option for management. Decisions on the use of such control alternatives also have a temporal dimension because different decisions apply to different seasons of the year. This creates a combinatorial problem too big for a blind search to complete (Turban, 1992). For instance, if it is relevant to consider the control variable, expressed as a herbage allowance of 1 to 4 kg DM head^{-1} day^{-1} in a given month (at intervals of 0.2 kg DM head^{-1} day^{-1}), which is relevant to the decision at hand, 16 alternative herbage allowances need to be simulated to solve the problem. If the optimum allowance for 12 months was to be determined, 16^{12} simulations would be required. Obviously it is infeasible to solve a problem of this size via a random search. The possible combinations with other control variables increases considerably with the number of alternative strategies that needed to be evaluated.

Several optimisation methods have been developed and applied to agricultural systems. Mathematical programming is already popular in agriculture (e.g. Boisvert and McCarl, 1990). It has the advantage of relatively simple computation, but is quite restrictive in its formulation (Rothemberg, 1989). On the other hand, the use of simulation models within an optimisation framework, because of their flexibility, is more likely to be useful for solving practical problems. However, optimisation of multi-dimensional problems in non-linear simulation models is not an easy task. Simulation models, according to Mayer et al. (1995), typically present three problems to optimisation methods: first, no derivative functions are available and where these are required, they have to be approximated numerically; second, most models include practical constraints that have to be accommodated by the use of penalty functions or a constrained optimisation method; third, the multi-dimensional response surfaces are rarely smooth or convex and can vary from “bumpy” to “almost chaotic” in relation to the inputs (Mayer et al., 1995). Another problem arises because multiple optima are common (Mayer et al., 1995), indicating that alternate management policies, whether they are biological or economically driven, can result in similar consequences.

Goldberg (1989) and Mayer et al. (1995) pointed to the problem that gradient-type methods, often used for optimisation, track uphill to the closest local maximum and cannot usually escape from local optima which are unlikely to be the global optima in multi-dimensional problems (Figure 3.20). The identified local optima are therefore contingent upon the starting values used for the simulation.

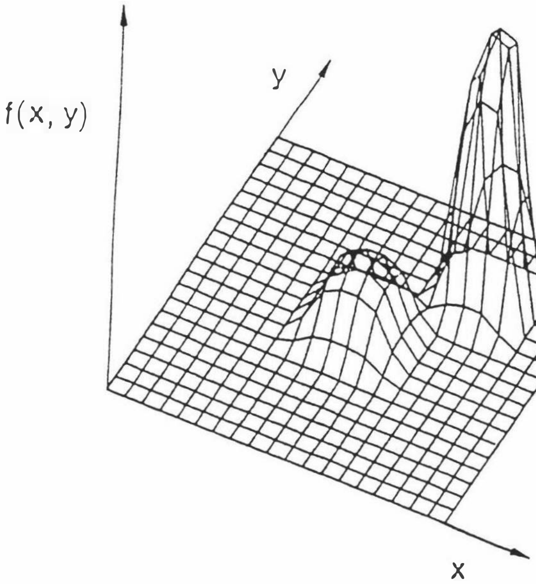


Figure 3.20 In functions with multiple peaks, gradient type methods may climb the wrong hill and miss the global optima as illustrated here (After Goldberg, 1989).

More recent methods of optimisation, such as genetic algorithms and simulated annealing, are much more robust than gradient type methods and are not dependent on the parameter values assumed for the first iteration. While the majority of optimisation algorithms search the decision space by moving from point to point according to some transition rule, genetic algorithms maintain multiple solutions concurrently, climbing many peaks in parallel and are therefore less susceptible to the problems of local maxima and "noise" (Goldberg, 1989; Buckles and Petry, 1992). This agrees with the results obtained by Mayer et al. (1996), who tested four methods of optimisation for a dairy model including 16 management variables (with 10^{13} possible combinations of management options). They concluded that simulated annealing and genetic algorithms were superior to the other methods tested for finding the optima.

Genetic algorithms are based on the mechanisms of natural selection and genetics. Candidate solutions (organisms) are grouped into sets called populations. All candidates in a population solution are tested and compared using a figure of merit for each organism. The best candidate solutions then have a higher chance of passing their parameters (genes) to the next population. Because of selection pressure, the individuals within a population are expected to improve in been evaluated or a designated termination criteria is reached (Grefenstette, 1992). Abstractly, the skeleton of a genetic algorithm code can be described as:

```
generate initial population, G(0);
evaluate G(0);
t := 0;
repeat
        t:= t+1
        generate G(t) using G(t-1);
        evaluate G(t);
until the termination condition is reached.
```

In most applications, an organism consists of a single chromosome. A chromosome of length n is a vector of the form:

$$<x_1, x_2, \ldots, x_n>$$

where x_i is the i^{th} gene or variable assigned to optimisation (e.g. pasture allowance, dose of nitrogen, stocking rate). The domain of values from which x_j is chosen is called the problem "alphabet". Frequently, the alphabet consists of the binary digits {0,1} and each gene or allele is a combination of binary numbers, although other alphabets are possible (Goldberg, 1989). The number of binary digits allocated to each parameter depend on the level of definition that is required. The number of possible values to be tested for one parameter (NP) increases exponentially with the number of digits (n) allocated to that parameter ($NP = 2^n$). Each individual will be then represented by a string of binary numbers as shown in Figure 3.21.

$$\underbrace{\mathbf{1101}}_{x_1}\underbrace{\mathbf{101}}_{x_2}\underbrace{\mathbf{0010}}_{x_3}\mathbf{01011010111001100111101010110}\underbrace{\mathbf{0111}}_{x_n}$$

Figure 3.21 A chromosome or string of binary digits (1,0) which represent the genes ($x_1..x_n$) of an individual in a genetic algorithm. More sophisticated applications may represent individuals with more than one chromosome.

The initial population is usually generated randomly, by assigning a probability of 0.5 for 1 and 0 in each bit of the string (Goldberg, 1989). Each individual is then evaluated according to a fitness function. In general, the fitness function is the composition of two functions:

$$u(x) = g(f(x))$$

where *f* is the objective function (Grefenstette and Backer, 1992) or phenotype (Goldberg, 1989) and g transforms the value of the objective function into fitness (Grefenstette and Backer, 1992). The transformation of the objective function has two main objectives: first, the transformation should ensure that the fitness of any individual does not assume negative values as this would cause problems in the selection routine(s); second, to scale the value of “fitness” so that selection pressure is maintained at a suitable level throughout the generations.

In the early generations it is important to avoid excessive differences in “fitness” because this would cause extraordinary individuals to take over a significant proportion of the finite population and decrease the number of schemata (hyperplanes) represented in the population. This would lead to a premature convergence. After some generations have passed, the exact opposite problem may occur. As the “fitness” of the average members of the population approaches the population best fitness, the selection pressure towards better structures decreases and the search stagnates (Goldberg, 1989; Grefenstette, 1992). Several methods of scaling can be used. Linear scaling is probably the most common and requires a linear relationship between scaled “fitness” (f’) and raw “fitness” (f) as follows:

$$f' = af + b$$

Goldberg (1989) suggested that the expected number of copies for the best population member can be determined by applying the rule:

$$f'_{max} = C_{mult} f_{avg}$$

where C_{mult} will be the number of expected copies desired for the best population member. Goldberg (1989) suggest C_{mult} should vary from 1.2 to 2 for a normal sized population.

3.5.2 *Crossing over and mutation*

As emphasised before, one of the greatest sources of robustness in genetic algorithms is their ability to search for several possible solutions in parallel in order to avoid convergence to a local optimum. It is therefore necessary to maintain a certain level of variability in the population so that the sample of hyperplanes in the population do not became too small, and hence hide the global optima.

Genetic algorithms use two instruments, derived from concepts of natural genetics, in order to maintain population variability. They are crossing over and mutation. Crossing over is the exchange of parts of chromosomes of two selected individuals (usually individuals are selected two by two by genetic algorithms), thereby generating different individuals in the next generation. In the simplest applications single point crossing over only is allowed. The point for crossing over is selected randomly within the chromosomes of a pair of individuals chosen as illustrated in Figure 3.22.

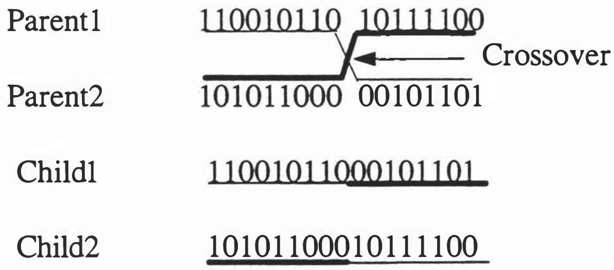


Figure 3.22 Illustration of the modification in the parameters of the individuals of the next generation caused by crossing over. The child individual has inherit parameters derived from both parents.

Mutation is a secondary search operator whose primary aim is to prevent any bit position remaining converged to a single value in the entire population (Figure 3.23; Grefenstette, 1992). A low probability of mutation is assigned to each binary number in the chromosome. When mutation occurs, the bit position changes from a value of 1 to 0 or vice-versa. It is possible for one or more mutations to happen simultaneously in a single chromosome in a given generation (Figure 3.23(b)).

a)

Individual Number	String
1	10**0**101
2	11**0**100
3	01**0**010
4	01**0**110
5	10**0**011
6	00**0**101

b)

Individual 1 (before mutation) 10**0**101

Individual 1 (after mutation) 10**1**101

Figure 3.23 Illustration of the importance of mutation. a) All individuals in the population have the third bit position (in bold) converged to 0. Absence of mutation would prevent possible solutions including the presence of 1 in that bit position. b) Mutation in the third bit position introduces the missed schemata again.

3.5.3 *Genetic algorithm operational parameters*

The performance of genetic algorithms depends on the parameters defined to manage the search. The best combination of parameters depends on the type of problem at hand and the amount of computation required to solve the problem. Nevertheless, certain general rules can be followed in order to develop an effective search for alternative solutions. The main operational parameters (also called control parameters) are: population size, crossover rate, mutation probability, generation gap and selection strategy (Grefenstette, 1992; Mayer, 1995).

Genetic algorithms generally perform poorly with very small populations because of insufficient sample size and the possibility of premature convergence (Grefenstette, 1992). On the other hand, large populations require more evaluations per generation, and this may result in an unacceptably slow rate of convergence. The optimum population size usually varies from 30 to 80 individuals (Table 3.10).

The higher the crossover rate, the quicker new structures will be introduced into the population. If the crossover rate is too high there is a risk that high performance structures will be discarded too fast and this would prevent further improvements being made to following populations. Effective crossover rates usually range from 0.45 to 0.95 (Table 3.10). The highest value can be applied for quick searches with small populations, otherwise it tends to the smallest value. The optimum mutation rate usually varies from 0.001 to 0.01(Table 3.10), as a high level of mutation leads to an almost random search. The generation gap is the proportion of the population to be replaced during each generation. A generation gap of 1 means that every individual is replaced. Some authors suggest a generation gap of around 0.9 would have a positive effect on the performance of comprehensive searches (Grefenstette, 1992), but most authors (e.g. South et al., 1993; Mayer et al., 1995) have found that replacing all of the individuals in a population (i.e. a generation gap of 1) usually provides the best strategy.

The selection strategy concerns the use (or not) of elitism. An elitist strategy occurs when an individual with the best performance is passed intact onto the next generation. This strategy was found to be superior to pure selection in most, but not all cases, particularly in comprehensive searches (Table 3.10; Grefenstette, 1992).

Table 3.10 Operational parameters recommended for efficient optimisation with genetic algorithms (Adapted from Mayer, 1995).

Source	Population Size	Crossover Rate	Mutation Probability	Generation Gap	Elitism
Davis (1991)	50	0.65	0.008		
South et al. (1993)					
Standard	50	0.60	0.001	1	yes
Quick	30	0.95	0.01	1	yes
Comprehensive	80	0.45	0.01	1	yes
Mayer et al. (1995)	40	0.60	0.001	1	yes
Grefenstette (1992)					
on-line	30	0.95	0.01	1	yes
off-line	80	0.45	0.01	0.9	no

3.5.4 *Implementation*

The genetic algorithm was implemented as a block in Extend^{TM}. This block is run at the beginning of the simulation and when assigned to optimisation, gets the model parameters that are to be optimised. The control variables assigned for optimisation were: herbage allowance in each month of the year, application of nitrogen (May and August), lamb drafting weight (Mar-Nov, Dec, Jan and Feb) and winter supplementation (May-Aug). Stocking rate and initial pasture cover can be optimised by user choice.

In order to use a consistent parameter for herbage allowance for the mob of sheep comprising different categories and live weight, it was defined in relation to the potential intake of the animals (kg DM / kg PVI^{-1}). The genetic algorithm coding was designed to search for allowances of 0.5 to 2.75 (at intervals of 0.15) kg DM offered/kg DM potential intake from January to June and 1 to 4.75 (at intervals of 0.25) kg DM / kg PVI^{-1} from August to December. Different ranges were used because the trend is toward higher allowances while ewes are lactating (Geenty and Rattray, 1987). For the optimisation exercises undertaken, only two annual nitrogen applications were allowed; one in autumn and one in spring, in the month of maximum N response, respectively. For Palmerston North, April and August were chosen (O'Connor, 1982). Rates of nitrogen application varied from 0 to 87.5 kg N/ha at intervals of 12.5 kg N/ha for each application. Supplementation was considered only from May to July. Supplementation of 0 to 0.7 kg DM ewe^{-1} day was considered at intervals of 0.1 kg DM ewe^{-1} day^{-1}. Initial pasture cover from 1200 to 2700 kg DM ha^{-1} was considered at intervals of 100 kg DM ha^{-1}. Initial pasture cover was optimised only when assigned by the user. Optimisation of stocking rate is user defined. When all of the parameters described above were assigned, a 17 dimensional optimisation problem was created. The total length of the strings was 65 bits, and the number of possible solutions was therefore 2^{65} (3.69×10^{19}). The coding assigned for each gene (parameter) is shown in Table 3.11.

The algorithm was assigned to maximise the system's gross margin. Variations in mob value were also taken into account in the optimisation. The parameters are transferred to the model at the beginning of the simulation via a global array named *ControlArray*. The gross margins are assigned to each individual at the end of the simulation via a global variable which stores the gross margin value.

The initial basis for the implementation of the genetic algorithm in Extend^{TM} was the "Simple Genetic Algorithm" originally coded in Pascal by Goldberg (1989). The original code was modified by adding a linear scaling mechanism to the code (see Section3.5.1). Also a stochastic remainder procedure was implemented to substitute for the roulette wheel selection and an elitist selection strategy was adopted.

Table 3.11 Correspondence between binary code, herbage allowance, initial pasture cover, N applied and supplement fed in the designed genetic algorithm.

Allele	Herbage Allowance (Jan - Jul)	Herbage Allowance (Aug - Dec)	Initial Pasture Cover (kg DM/ha)
0000	0.50	1.00	1200
1000	0.65	1.25	1300
0100	0.80	1.50	1400
1100	0.95	1.75	1500
0010	1.10	2.00	1600
1010	1.25	2.25	1700
0110	1.40	2.50	1800
1110	1.55	2.75	1900
0001	1.70	3.00	2000
1001	1.85	3.25	2100
0101	2.00	3.50	2200
1101	2.15	3.75	2300
0011	2.30	4.00	2400
1011	2.45	4.25	2500
0111	2.60	4.50	2600
1111	2.75	4.75	2700

Allele	N Applied (kg N/ha)	Supplement (kg Ewe/day)
000	0	0
100	12.5	0.1
010	25.0	0.2
110	37.5	0.3
001	50.0	0.4
101	62.5	0.5
011	75.0	0.6
111	87.5	0.7

In the stochastic remainder procedure, the number of times an individual is selected is not completely randomised as occurs in the roulette wheel selection method. Instead the number of copies is given by rounding the expected number of copies down to the nearest integer, in a deterministic way. The residual fraction of all individuals is then submitted to the stochastic selection. This procedure was found to perform better than the roulette wheel selection (Goldberg, 1989).

The number of generations and number of individuals per generation is user defined (default values are 25 generations and 40 individuals per generation). The number of runs of Extend is then calculated (Number of generations x Number of individuals per generation) and assigned to the program. By default, the crossover rate and mutation probability were assigned values of 0.6 and 0.01, respectively.

The algorithm implemented is specific to each problem and modifications may be necessary for different types of problems. Before being used to optimise the model described earlier, the algorithm was tested on a problem with a similar number of dimensions and known optimum, and was found to have reasonable performance within 20 - 30 generations and 40 individuals per generation. The large number of iterations required (25 generations x 40 individuals/ generation = 1000 iterations) and the long execution time of the model (about 60 sec/simulated year for a 8-12 paddock farm using a Pentium 75 computer with 24 Mb RAM), forced off-line computation of the optimum control sequencing. It took about 17 hours to find the optimum. Obviously, this restricts the possibilities for extensive experimentation with the current model. The code implemented is shown in Appendix 1.

3.6 Summary

The structure processes and equations adopted for the model development were presented in this Chapter. The initial section of the chapter described the simulation package, Extend^{TM}, used in model development. In that section, the package's versatility and ability to speeding-up model development was highlighted. The limitations of Extend^{TM} in designing a suitable user-interface for a on-farm decision support system was also discussed. The event driven structure of the model, which enabled a multi-paddock grazing system to be represented was described in the second section of the Chapter.

The later sections of the Chapter covered a review of the relevant literature, including the current knowledge about the components and processes to be modelled. Where pertinent, the assumptions adopted in other were models were compared and their advantages and disadvantages discussed. Sub-models for reproduction, pasture growth and senescence, herbage intake, diet composition and animal performance were described. A significant part of the model was dedicated to predicting animal intake and performance. The nutritional limit for intake was predicted from calculations of rumen fill and physiological demand. This potential intake was then modified according to herbage availability. In the pasture accumulation sub-model, pasture accumulation was not predicted from weather but modified from a standard monthly pasture accumulation rate for the farm. This approach was adequate for the purposes of the model, despite some advantages of including weather files and more complex prediction of accumulation rates being missed. The assumptions made for selling animals and transferring them between age categories was also described.

A genetic algorithm was implemented in order to optimise the control variables of the model. This will allow targets to be established for tactical and operational levels of management that can be pursued by farmers. The advantages of genetic algorithms in relation to conventional methods of optimisation and the concepts and design of the algorithm implemented were also discussed.

The addition of stochasticity to some of the model's variables was made assuming normal functions, but future developments should include further study of the shape of these distributions.

Model evaluation and experimentation are themes for chapters 4 and 5.

MODEL EVALUATION

4.1 Introduction

As discussed in Section 2.5.1.6, it is almost impossible to evaluate a computer simulation model for all possible situations in which it will be applied; complete validation is therefore impracticable. However it is important, if the model is to be used with confidence as a decision support system, to compare its predictions with data sets derived from experiments with “real” systems. This process allows the model’s performance to be evaluated and imperfections to be diagnosed for later improvement.

While complete data sets, including year round measurements were not available to validate the model, results of three experiments, independent of its development, were suitable. The first data set was derived from a farmlet exercise with rotational grazing of pregnant ewes that was a compulsory part of the Massey University paper 71.495-Introduction to New Zealand Pastoral Systems. The other two were published experiments with sufficient information to set up the simulation model and compare several of its outputs with the field measurements. The experiments chosen for evaluation of the model were Parker and McCutcheon (1992) and Morris et al. (1993). Both papers contain consistent information about pasture and animal conditions at the start and during the experiment, and involved continuous grazing of ewes on ryegrass dominant swards. The three data sets are complementary and enabled the testing of several model outputs as described in the ensuing sections.

4.2 Data sets and model set-up

4.2.1 *Farmlet exercise*

A 0.8 ha farmlet at the Keeble sheep farm unit at Massey University, Palmerston North was monitored in detail from 20 May to 13 September 1996. The farmlet was divided into paddocks of 0.1 ha each. The flock comprised 16 Romney ewes (the proportion of two tooth and mixed age ewes was not recorded) and their offspring, born from 23 August to 8 September. The lambing pattern was estimated according to the first weighing of the lambs after birth (usually carried out every two or three days during the lambing period). The paddocks were rotationally grazed until 13 August when the ewes were set stocked for lambing. Unfortunately, lambs were weighed on only two occasions (near birth and on 6 September) and the growth period was therefore too short for model validation. Pre-grazing and post-grazing mass were measured weekly. Ewes were weighted on four occasions during the period (20 May, 15 June, 18 July, 13 August). Pasture accumulation rates and sheep intake were estimated by the difference between pre- and post-grazing measurements of pasture mass. Pasture allowance was estimated from the pre-grazing mass and grazing time spent in each paddock.

The model was set up to simulate the farmlet. The average ewe live weight (52.5 kg) at the start of the period and monthly average pasture growth rates (Table 4.1), calculated from field measurements, were inputted into the model. The ewes were assumed to have a maximum empty body weight of 63.7 kg, as suggested by Finlayson et al. (1995). Pasture allowance was also averaged by month (Table 4.1). The model could not allow changes from rotational to continuous grazing within a month (as happened to the farmlet on 13 August): continuous or rotational grazing had to be assigned for a whole month. Therefore continuous grazing was assigned from 1 September in the model simulation. The initial proportions of leaf, stem and dead material were assumed to be 0.6, 0.2 and 0.2, respectively and was then determined by the model for each time step of the simulation.

Table 4.1 Monthly average pasture growth rates, allowances, pre- and post-grazing herbage mass recorded in the farmlet exercise.

Month	Pasture growth rate (kg DM/ha/day)	Average herbage allowance (kg DM/ewe /day)	Average herbage allowance (kg DM/kg PI/day)	Pre-grazing herbage mass (kg DM/ha)	Post-grazing herbage mass (kg DM/ha)
May	33.0	1.35	0.90	2289	609
Jun	14.3	1.62	1.08	2507	1009
Jul	10.0	1.67	1.11	2803	1033
Aug	14.1	3.30	2.20	1880	1064
Sep	47.3	----	----	----	----

4.2.2 *Morris et al. (1993)*

Morris et al. (1993) measured the herbage intake and performance of Leicester x Romney ewes, lambed in June and August and continuously grazed on swards with different "fixed" heights. In the experiment, the swards were maintained at approximately constant surface heights of 2.0, 4.0, 6.0 and 8.0 cm by the addition of non-trial buffer stock until lambing. Average pasture mass was measured for each treatment as shown in Table 4.2. After lambing, all the ewes and their lambs were grazed on a 4.0 cm sward.

Eight runs were carried out with the model, each simulating one of the experiment's treatments. It was assumed that the treatments, kept at a constant sward height, had a constant leaf mass during the experimental period (i.e. grazing did not affect the leaf, stem and dead content of the sward). The model's code was modified in order to allow a constant leaf mass to be simulated during pregnancy and to change from the pre-lambing treatment leaf mass to the post-lambing 4.0 cm sward. It was assumed that the sward grazed by the lactating ewes (4.0 cm height according to the authors), had a herbage mass of 1000 kg DM/ha for both winter and spring lambing ewes. The proportion of leaf, stem and dead material was assumed to be 0.6, 0.2 and 0.2, respectively for all treatments. The model was run assuming all the lambs were born on the mean lambing dates (i.e. 3 June and 17 August for the winter and spring lambing ewes, respectively). The mean initial ewe body weight and lambing weight were inputted for each treatment as described in the publication. The ewes were also assumed to have a standard empty body weight of 63.7 kg, as suggested by Finlayson et al. (1995) for sheep of a similar type. Birth weight was entered as the average birth weight for each sward height treatment, but were considered to be the same for the winter and spring lambing ewes.

Ewe live weight was measured at the beginning of the simulation on pregnancy day 115, 128 and 140 and lactation day 54 and 77 (P115, P128, P140, L54 and L77, respectively). Lamb live weight was also recorded at L54 and L77 and compared to model outputs.

Table 4.2 Average sward height and pasture mass of each sward height treatment as inputted to the model (Source: Modified from Morris et al., 1993).

Treatment	Measured sward surface height (cm)	Inputted pasture mass (kg DM/ ha)
2.0 (winter lambing)[1]	2.8	740
4.0 (winter lambing)	4.0	1152
6.0 (winter lambing)	7.1	1795
8.0 (winter lambing)	8.5	2438
2.0 (spring lambing)	2.7	548
4.0 (spring lambing)	4.0	792
6.0 (spring lambing)	5.9	977
8.0 (spring lambing)	7.8	1885
After lambing [2]	-	1000

[1] The figures displayed out of the brackets are the nominal sward height of the treatment.

[2] After lambing all ewes were transferred to paddocks with swards with a nominal surface height of 4.0 cm and pasture mass of 1000 kg DM/ha.

4.2.3 *Parker and McCutcheon (1992)*

Parker and McCutcheon (1992) also studied the effect of sward height on herbage intake and production performance of Border Leicester x Romney ewes under continuous grazing during lactation.

The model was set up to simulate the five treatments of the experiment which evaluated sheep performance on nominal sward surface heights of 3.5, 5.0, 6.0, 7.0 and 8.5 cm. Average pasture mass was measured for each treatment and this was inputted to the model as shown in Table 4.3. The proportion of leaf, stem and dead were assumed to be 0.6, 0.2 and 0.2, respectively for all treatments.

The simulation started one day before lambing and all lambs were assigned to be born at the mid-point of lambing for the experiment, 20 August (in the experiment all lambs were born within 9 days). All other model inputs were set up for the simulation as described for the experiment of Morris et al. (1993) in Section 4.2.2.

Table 4.3 Average sward height and pasture mass of each treatments as inputted to the model. (Source: Modified from Parker and McCutcheon, 1992).

Treatment	Measured sward surface height (cm)	Inputted pasture mass (kg DM/ ha)
3.5 [1]	3.4	574
5.0	4.9	1161
6.0	6.1	1423
7.0	7.2	1556
8.5	8.4	1996

[1] Nominal sward height of the treatment.

4.3 Results

4.3.1 *Ewe live weight*

The model tended to underestimate ewe live weight particularly in late pregnancy and at weaning, while it approached measured live weights soon after lambing (Figure 4.1 and Figure 4.2). This pattern was consistent for both data sets containing pregnant animals (i.e. the farmlet exercise and Morris et al., 1993). During lactation, the predictions also tended to underestimate ewe live weight at weaning, despite good agreement between predicted and measured live weight on L54 (Morris et al., 1993; Figure 4.2). Likewise, the simulations consistently underestimated ewe live weight at weaning compared with the result reported by Parker and McCutcheon (1992; Figure 4.4). Altogether, the model tended to underestimate ewe live weight from 2 to 6 kg as shown in Figures 4.2, 4.3 and 4.4. Pasture and diet quality were not measured in the farmlet exercise but it is unlikely that the dry matter digestibility (DMD) was much greater than that predicted by the model (between 75 and 79 % during the period studied) in order to obtain proportionately higher levels of sheep performance. The level of DMD predicted by the model (Table 4.4) was similar to that recorded in the experiments of Parker and McCutcheon (1992) and Morris et al. (1993). Overestimation of milk production could be a cause of excessive weight loss during lactation, but, despite milk production not being measured, there was no evidence that this was the case in terms of the simulated and measured lamb live weights (Section 4.3.3; Figure 4.8).

The herbage intake predicted by the model and measured in the experiments, were most different for the short pastures (Table 4.5). This could also have caused the underestimation of live weight. This aspect of the model deserves further analysis, as described in the following section. It is also possible that the model underestimates the weight the placenta, uterus growth and other structures related to pregnancy, which are represented by the factor W_{Preg} in Eqn 3-61. Mammary development and milk weight, which were disregarded in the model, may also account for some of the deviations encountered. The latter aspects were not further investigated since feed intake seemed to be the major factor contributing to the live weight deviations.

Table 4.4 Comparison of measured and simulated dry matter digestibility (DMD %).

Experiment (Treatment)	**Measured**	**Simulated**
Farmlet (May)	---	73.0
Farmlet (Jun)	---	71.5
Farmlet (Jul)	---	74.5
Farmlet (Aug)	---	77.8
Farmlet (Sep)	---	78.3
Morris et al., 1993 (2 cm Jun)	71.5[1]	77.5
Morris et al., 1993 (4 cm Jun)	73.3[1]	77.5
Morris et al., 1993 (6 cm Jun)	74.3[1]	77.5
Morris et al., 1993 (8 cm Jun)	74.3[1]	77.5
Morris et al., 1993 (2 cm Aug)	74.3[1]	78.1
Morris et al., 1993 (4 cm Aug)	76.3[1]	78.1
Morris et al., 1993 (6 cm Aug)	76.3[1]	78.1
Morris et al., 1993 (8 cm Aug)	76.3	78.1
Parker and McCutcheon, 1992 (3.5 cm)	75.7	78.0
Parker and McCutcheon, 1992 (5 cm)	78.8	78.0
Parker and McCutcheon, 1992 (6 cm)	77.9	78.0
Parker and McCutcheon, 1992 (7 cm)	78.5	78.0
Parker and McCutcheon, 1992 (8.5 cm)	77.2	78.0

[1] Estimated from DMOD using the relationship DMD = (DOMD + 4.8)/0.98 (Geenty and Rattray, 1987).

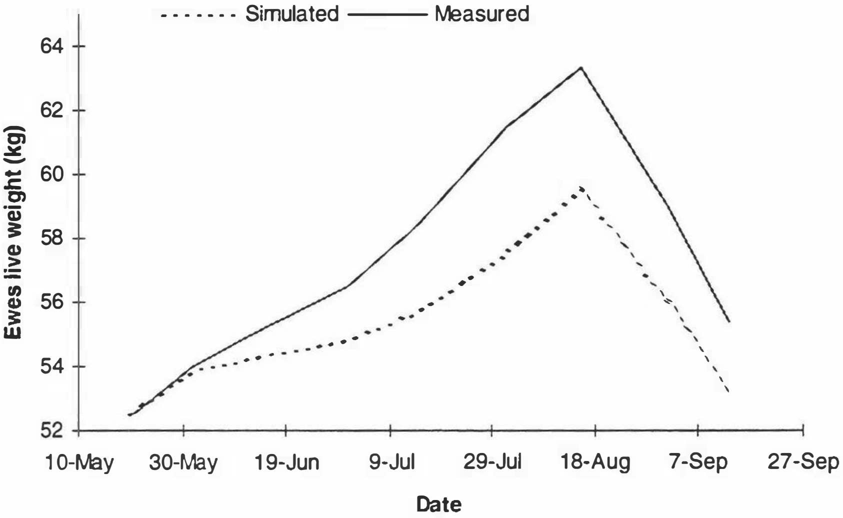


Figure 4.1 Measured and simulated ewe live weights for the farmlet exercise (see Section 4.2 for details).

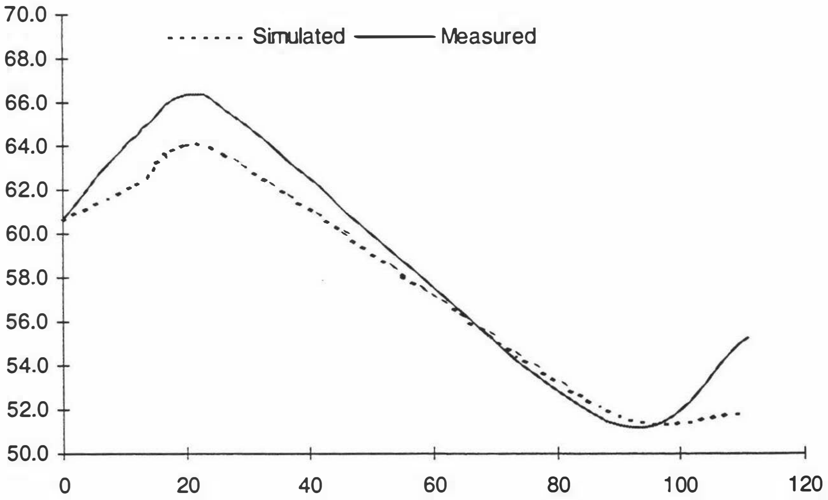


Figure 4.2 Measured and simulated ewe live weight (average of all treatments for Morris et al., 1993).

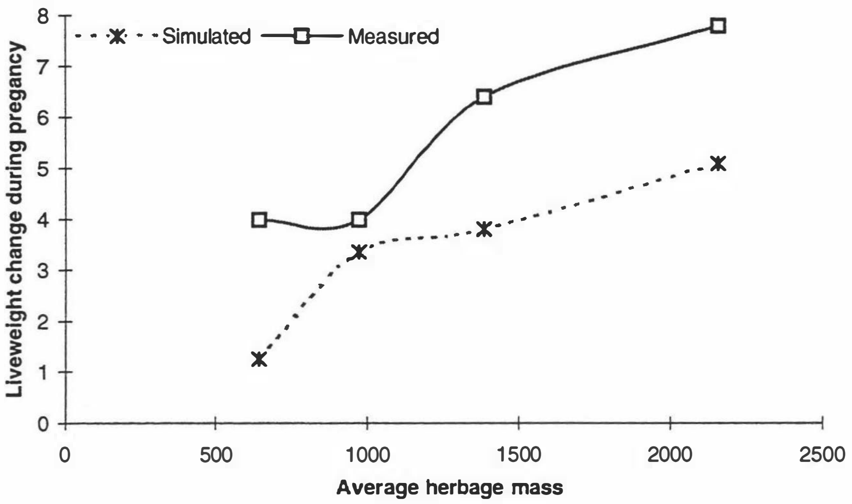


Figure 4.3 Measured (Parker and McCutcheon, 1992) and simulated live weight change during pregnancy across several levels of sward herbage mass.

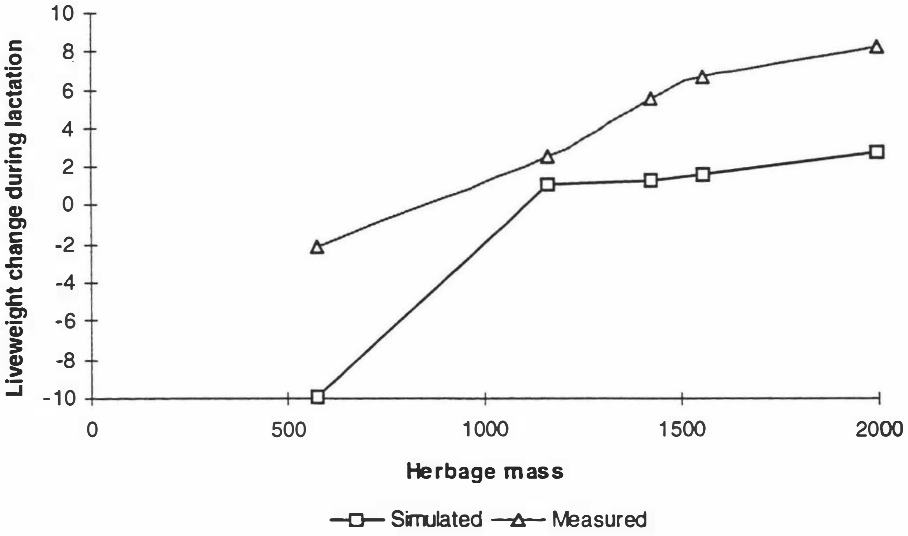


Figure 4.4 Comparison of measured (Morris et al., 1993) and simulated live weight change during lactation across several levels of sward herbage mass.

4.3.2 *Herbage intake*

Ewe herbage intake was generally underestimated both in pregnancy and lactation (Table 4.5), and this suggests a review of the herbage intake equations is required. The nutritional limit to intake may be underestimated. It was noted that, the rumen fill limit imposed by Eqn 3-23, rarely limits herbage intake of mature animals within the level of diet digestibility usually predicted by the model (i.e. 70 - 80 %). The physiological and rumen fill limits predicted by the model are shown in Figure 4.5.

As described earlier, the prediction of the physiological limit to intake is made using two separate equations to predict the basal level of intake (at maintenance) which is modified by a multiplier during lactation. These two equations were gathered from different models and it is likely that they need to be re-calibrated against one another. The basal intake equation developed by Finlayson et al. (1995) and adopted here (Eqn. 3-20), predicted the lowest herbage intake for mature animals of the equations reviewed during model development (see Section 3.5 and Figure 3.9). However, in Finlayson's model, intake is increased during pregnancy and greater increases are predicted during lactation than those derived from the equation of McCall (1984) and adopted here (Figure 4.6).

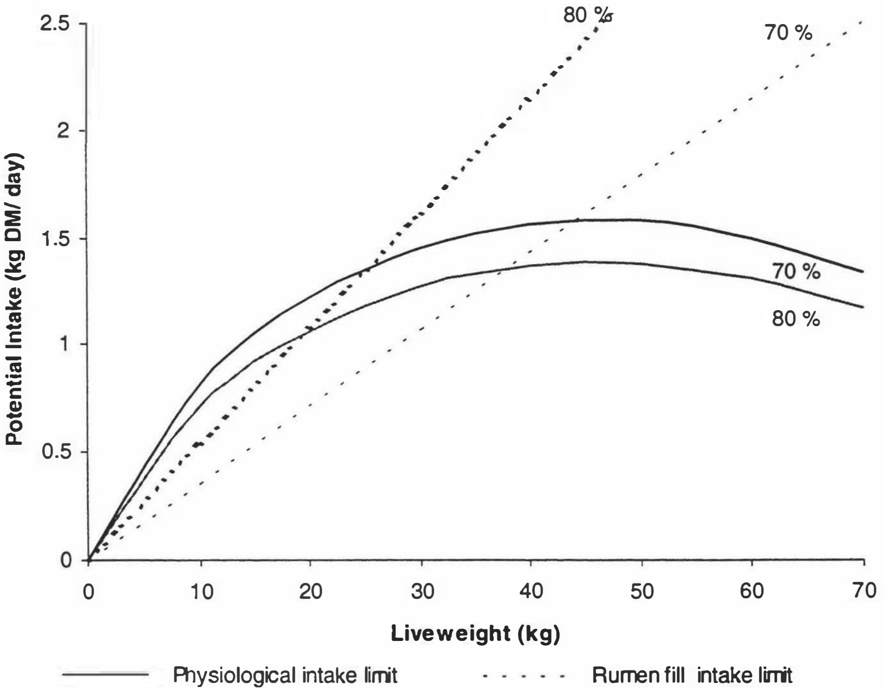


Figure 4.5 Physical and physiological intake limits for common levels of live weight and digestibility. Note that the model predicts that intake is usually physiologically restricted for mature animals at the usual levels of diet digestibility encountered in temperate pastures.

Table 4.5 Comparison of simulated and measured intake for three field experiments during the winter spring.

Experiment (Treatment)	Measured	Simulated
Farmlet (May)	1.58	1.50
Farmlet (Jun)	1.16	1.29
Farmlet (Jul)	1.06	1.41
Farmlet (Aug)	1.54	1.73
Farmlet (Sep)	-	-
Morris et al., 1993 (2 cm Jun)	1.60	0.89
Morris et al., 1993 (4 cm Jun)	1.60	1.22
Morris et al., 1993 (6 cm Jun)	1.60	1.32
Morris et al., 1993 (8 cm Jun)	2.00	1.32
Morris et al., 1993 (2 cm Aug)	1.60	0.57
Morris et al., 1993 (4 cm Aug)	1.60	0.96
Morris et al., 1993 (6 cm Aug)	1.60	1.21
Morris et al., 1993 (8 cm Aug)	2.00	1.33
Parker and McCutcheon, 1992 (3.5 cm)	2.20	0.73
Parker and McCutcheon, 1992 (5 cm)	2.26	1.47
Parker and McCutcheon, 1992 (6 cm)	2.30	1.51
Parker and McCutcheon, 1992 (7 cm)	2.21	1.53
Parker and McCutcheon, 1992 (8.5 cm)	2.28	1.59

Following the derivation of the model estimates of herbage intake (Table 4.5), the equations used to determine intake were reviewed. A comparison of the output for the lactation intake multiplier with that of Finlayson (1989) and Finlayson et al. (1995) showed that under some pasture conditions, the factor used here would underestimate intake by 20.9 % during the first 70 days of lactation and 13.2 % for the whole year for a 50 kg ewe (Figure 4.6). In relation to the model of McCall (1984), the model underestimate intake by around 10.1% through the year. The parameters of both the base intake and the lactation multiplier functions therefore need to be re-evaluated in order to improve the predictions for live weight change in mature sheep. This modification would calibrate the predictions of the model with other models developed for New Zealand conditions and measurements recorded experimentally *in situ*.

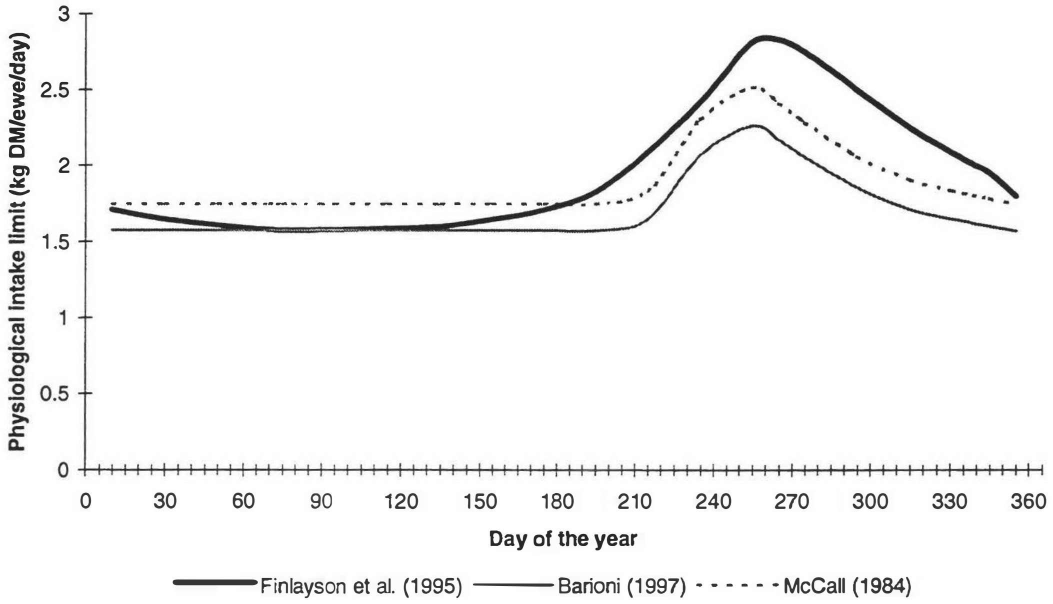


Figure 4.6 Comparison of physiological intake limit predicted by the models of McCall (1984), Finlayson et al. (1995) and Barioni (1997).

The simulated results for intake for both the Morris et al. (1993) and Parker and McCutcheon (1992) experiments make "more sense" at the low leaf mass than the experimental data. The greatest deviations from the real system tended to occur under the conditions of lowest pasture mass for both ewes (particularly for the data set of Parker and McCutcheon, 1992) and lambs (see Section 4.3.3). This can be partially attributed to overestimation of pasture dry matter intake in the experiments because of soil consumption. The soil consumption would be particularly high when sheep are grazing on very short pastures (Parker, 1990) and it would therefore contribute to the differences encountered. However, in cross-checking intake and animal performance it was noted that the effect of leaf mass on intake was much milder than that predicted by the model. This suggests that the parameters adopted for the equation of Johnson and Parsons (1985) lead to too steep a response in intake to leaf mass (Figure 3.11). This may be because the intake equation was originally calibrated in Britain where swards tend to be denser than in New Zealand (Hodgson, 1990). Thus, the same leaf mass would correspond to a lower height, restricting bite mass more severely than under New Zealand sward conditions. Calibration of the intake equation to New Zealand conditions therefore seams to be necessary.

4.3.3 *Predictions of lamb live weight*

Lamb live weight gain during the first 70 - 80 days after birth was relatively well predicted by the model. Growth was slightly overestimated when compared to Morris et al. (1993), so that the final live weight was overestimated by 1.1 kg at L77, although a larger difference occurred at L54 (16.6 vs. 14.0 kg) for simulated and measured values, respectively (Figure 4.7). In contrast, lamb live weight was underestimated when compared to those measured by Parker and McCutcheon (1992). The differences were small (0.9 to 1.4 kg) for lambs grazed with ewes on swards of more than 1400 kg DM (Figure 4.8), but increased for the shorter swards because of the underestimation of intake as discussed in the previous section. However, as for ewe live weight, the model was very sensitive to low leaf mass content and therefore significantly underestimated lamb live weight (21.5 vs. 14.2 kg for measured and simulated values at 574 kg DM/ha, respectively), re-enforcing the necessity to re-calibrate the pasture availability multiplier.

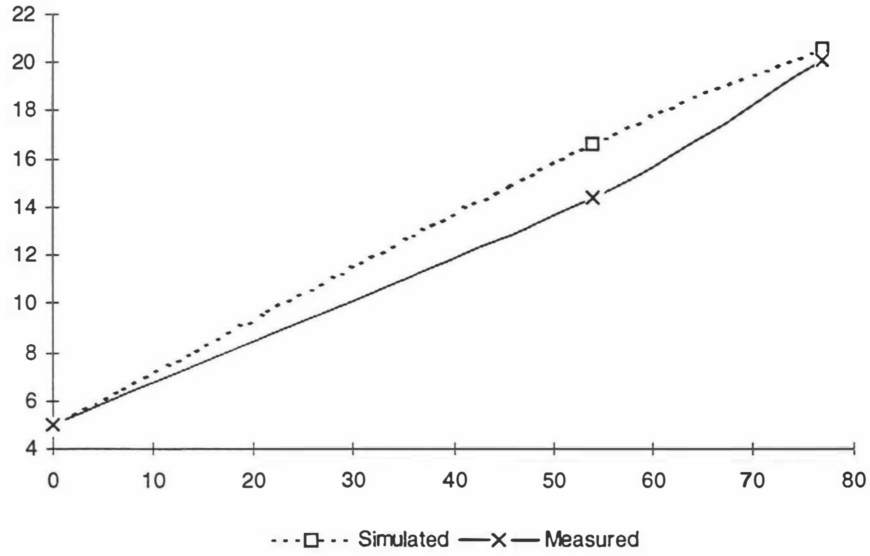


Figure 4.7 Comparison of lamb growth measured by Morris et al. (1993) and simulated by the model. The lines represent the average for all treatments.

The fact that lamb live weight was underestimated in one experiment while overestimated in another may reflect that some variables were not included in the model (such as variation in intake due to pasture conditions and weather) or even variations in leaf mass not detected because of measurement errors in the experiment. Differences in genetic potential and age of the animals could also account for some of the variation between the experiments but it is unlikely they were the main cause of the differences between simulated and recorded values.

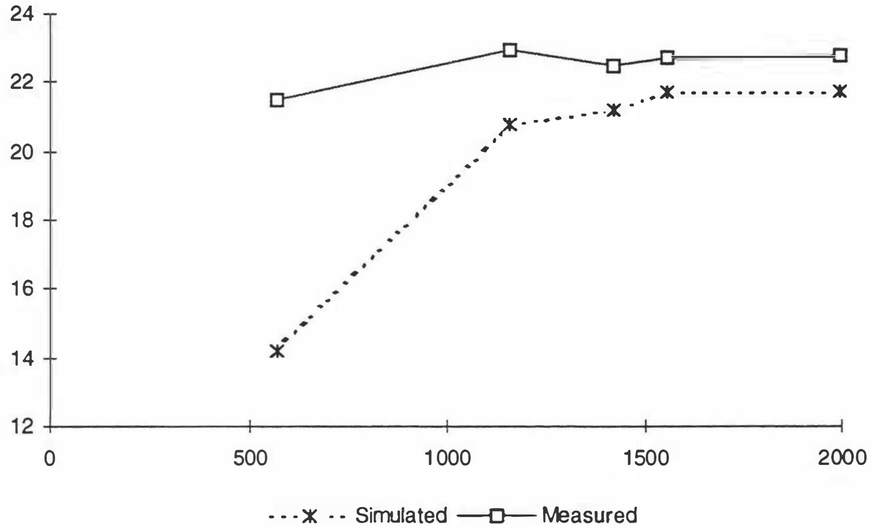


Figure 4.8 Comparison of lamb live weight 76 days after lambing as measured by Parker and McCutcheon (1992) and simulated by the model across several levels of herbage mass.

4.4 Conclusions

Some problems with parameterisation were identified in the model validation reported here. The comparisons of predicted vs. measured results mainly suggest that the model was overly sensitive to low leaf mass and as a consequence ewe intake was underestimated for these grazing conditions. The divergence in the intake response of grazing animals to leaf mass is probably associated with differences in sward structure between England, where the equation was defined, and New Zealand. The intake measurements suggest that New Zealand sheep can maintain intake at lower levels of pasture leaf mass. Also differences in plant growth habits between times of the year seem to affect the intake response, and it may therefore be necessary for the parameters of the intake function to vary through the year. This area requires more research.

The model evaluation also revealed an underestimation of ewe dry matter intake. This may be attributed to the adoption, from different models, of a lactation intake multiplier and an estimate maximum physiological intake at maintenance. A comparison with equations used in other models confirmed the underestimation of intake by the model and suggested that both equations should be re-calibrated in order to adjust to the higher intake achieved by ewes under field conditions in New Zealand.

SIMULATING MEASUREMENT ERRORS[1]

5.1 Introduction

Decision models incorporate uncertainty based on the twin assumptions that decision maker maximise their utility, usually represented as function of the expected income and variance (Anderson et al., 1977), and that they are risk averse (Anderson et al., 1977; Boisvert and McCarl, 1990). However, the several sources of variability that impinge on a production system affect not only the level of variability within the system, but also on its mean productivity and profitability (Antle, 1983). This is caused by the asymmetry in the response of some of the model equations to stochastic variables, as demonstrated by Pleasants et al. (1997; Figure 2.3). This phenomena can be reproduced with dynamic production models by adding the desired stochastic variables as demonstrated by Cacho and Bywater (1994; Figure 2.4).

Grazing systems are subject to several sources of variation and a large amount of variability is intrinsic to each of these. Variation in pasture growth rates (i.e. uncontrollable variables), errors in pasture measurement (i.e. sensor errors) and imprecision in implementing plans can all lead to key production variables, such as pasture cover and animal live weight, being different to that which was predicted (Athans, 1972). These sources of uncertainty and variability may affect system performance by either leading to control errors (i.e. taking sub-optimal decisions based on a wrong measurement or prediction) or affecting the dynamics of the system so that a sub-optimal state is created (as may be caused by uncontrollable variables such as weather). As the intake and productivity response of grazing animals to herbage allowance, sward height, herbage mass or leaf area are typically non-linear and asymmetrical, this raises the question, "To what extent do errors in herbage mass prediction affect the efficiency of a grazing system?".

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[1] This chapter is based on the paper published by Barioni et al. (1997) and addresses the effect of measurement errors on the performance of livestock grazing systems

5.2 Experimental design

An experiment was conducted using a two stage method to determine the effect of measurement errors on the efficiency of a grazing system. First, the genetic algorithm described in Section 3.5 was used to search for the optimum deterministic control sequence for the system and second, variability was introduced to the measurement of pre-grazing herbage mass. Both parts of the experiment were performed using a theoretical 8 ha farmlet with 8 paddocks of equal size and pasture production potential. The optimisation was run for 12 months from 1 March. A mob of 140 ewes (17.5 ewes/ha), at an initial live weight of 55 kg, were grazed on a starting pasture cover of 1500 kg DM/ha. The maximum empty body weight of ewes was assumed to 63.7 kg. Inputted pasture growth rates were typical of those recorded at the Massey University N$^{\underline{o}}$ 4 Dairy Unit (Table 5.1). A lambing pattern was generated for 105 ewes and 35 two tooths using the reproduction sub-model (Appendix 3). This produced a 130% lambing. The lambing pattern was stored and used as required during the optimisation. Barren ewes were sold at the beginning of lambing.

The optimum control sequence for herbage allowance, nitrogen application (restricted to May and August applications), supplementation during winter and lamb drafting weight was identified using the genetic algorithm. Direct costs ($226.61/ha), wool ($5/kg/clean), nitrogen ($1.30/kg N applied) and hay ($0.23/kgDM consumed) were inputted for the gross margin calculation. Lamb schedules were those published on 27 April by the New Zealand Farmer (1997). The seasonal premiums assumed were based on the base lamb schedule prices shown in Figure 5.1. Carcasses were classified according to the carcass weight/GR grid specified by Kirton (1989).

Table 5.1 Daily net pasture growth rates (kg/ha/day) used in the simulations (Source: Dairy N$^{\underline{o}}$4 dairy unit, Matthew et al., 1996).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean[1]	24	23	21	23	29	22	17	27	40	50	47	36
CV%[1]	50.4	47	42.8	35.3	38.0	45.7	42.1	28.6	36.5	24.1	31.7	32.8

[1] For each step of the simulation, pasture growth rate was interpolated linearly assuming the above growth rates on the 15th of each month.

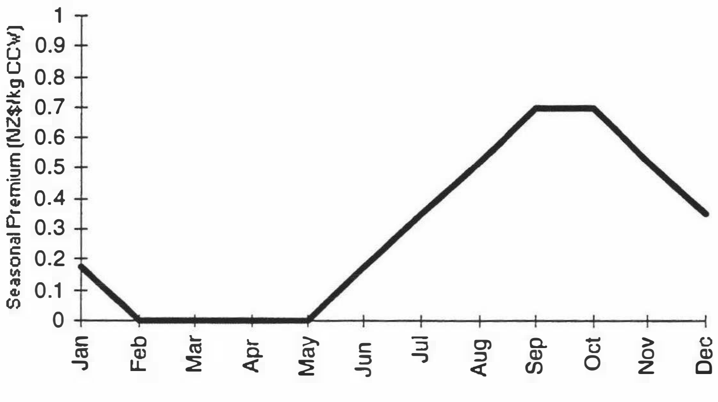

Figure 5.1. Seasonal premiums assumed to be paid on lamb carcasses (c/kg) for the optimisation exercise.

A small set of experiments were carried out on the "virtual" 8 ha farmlet. The effect of measurement errors was tested by running four simulations each over 10 years for the system with and without the inclusion of a sensor error for measuring herbage mass and using the optimal sequence for deterministic control. The sensor error was introduced by calculating the grazing time for a randomly "measured" pre-grazing pasture mass. This was generated from a normal distribution with the mean equal to the actual mean and a coefficient of variation of either 20% or 40%. Coefficients of variation from 13 to 16 % were suggested by L'Hullier and Thomson (1988) for the rising plate meter, pasture probe and visual assessment techniques for measuring pasture mass.

5.3 Results and discussion

The pasture allowances suggested by the optimisation for sheep (Table 5.2) are reasonably consistent with the recommendations of Rattray et al. (1987), except for the relatively high herbage allowances and residual covers in the winter. The higher allowances may reflect the stocking rate used in the experiment as well as the positive responses of pasture growth to leaf area index and of ewe milk production to body condition, in the model. These relationships require further study because in practice most farmers graze ewes much more tightly during the winter-early spring than the model suggests in order to control the level of pasture intake. The model suggests that the farmers' strategy is not without cost in terms of the system's performance. Also, nitrogen was included quite generously in the optimisation relative to

Table 5.2 The optimum solution for the 8 ha farmlet simulation at stocking rate of 17.5 ewes/ha, 130% lambing rate and mating from11 March to 21 May (Gross Margin $NZ 587.47/ ha).

Month	Allowance per potential intake[1]	Nitrogen applied (kg N/ha)	Supplement used (kg DM)	Lambs drafting weight[2] (kg)	Allowance[3] (kg DM/ ssu /day)	Post-grazing (kg DM /ha)	Pasture cover (kg DM/ha)
Mar	2.15	0	0	-	2.67	1042	1461
Apr	2.00	12.5	0	-	2.17	994	1433
May	1.10	0	0	-	1.56	1130	1579
Jun	2.75	0	0	-	3.11	1155	1470
Jul	2.30	0	0	-	2.27	887	1204
Aug	1.25	50	0	-	1.60	914	1291
Sep	2.00	0	0	-	2.78	1303	1753
Oct	2.00	0	0	35	3.53	1712	2127
Nov	3.50	0	0	35	5.00	1881	2259
Dec	3.00	0	0	37	3.46	1664	2167
Jan	1.55	0	0	33	2.28	1488	1986
Feb	2.75	0	0	-	3.41	1334	1708

[1] Calculated as the ratio between the total herbage mass offered daily and the potential intake calculated by the model (this is the control variable used in the optimisation). The units are kg DM/ kg potential intake/day.

[2] Threshold live weight for lamb drafting.

[3] Sheep stock units were calculated relative to a standard live weight of 55 kg.

normal practice (Parker et al., 1994). This reflects the high (1997) lamb prices compared to the cost of N-boosted pasture. One limitation of the model, however, is that lambs and ewes are grazed together throughout the year and distinct pasture management for these sheep classes was not able to be simulated.

One of the main concerns about the methodology used here was that a large part of the sensor error effect on the system's profitability was related to the deviations in pasture cover, which in a real situation are likely to trigger a feedback control response by the farmer. Consequently, the suggested levels of profitability when simulating sensor errors are likely to be lower than those for a 'real' farm situation. Fortunately, the simulations run using deterministic estimates of pasture growth were very stable and deviations that could lead to a control response by the farmer did not occur from the third year of data collection (Figure 5.1). Despite this, it was possible to diagnose a significant effect of sensor error on the profitability of the system (Figure 5.4). When a stochastic mode of pasture growth was simulated, the variability in pasture cover from year to year was similar whether or not sensor errors were included (see Appendix 4). Figure 5.1 shows the pasture cover, as well as the pre- and post- grazing herbage mass, outputted by the model simulation assuming a 20% CV in the measurement of paddock pasture cover.

With deterministic pasture cover, the introduction of measurement error at a CV of 40% caused significant changes ($P<0.05$) in the monthly pasture cover for compared with the situation with no measurement errors (Figure 5.3). On the other hand a 20% CV in the accuracy of pasture measurement did not affect the simulated estimates of future pasture cover for most of the year. Thus, grazing systems seem to have a propensity to return to a dynamic equilibrium between intake and pasture growth in a manner similar to that demonstrated by Noy-Meir (1975) for the static case. Also, subsequent errors from paddock to paddock can have a compensatory effect on herbage intake by the animals (i.e. upside errors can follow downside errors and so on) producing a smaller net effect of incorrect assessment of pasture mass.

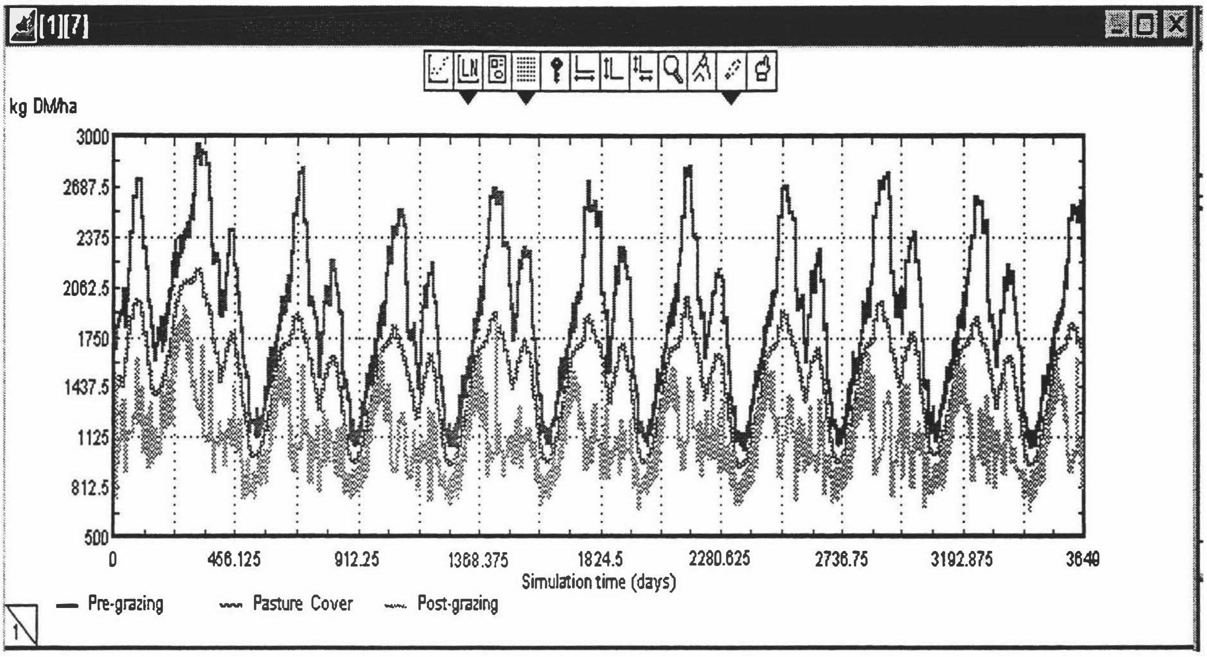

Figure 5.2 Pasture cover, pre- and post-grazing herbage mass outputted by the model when simulating deterministic pasture growth and a 20% CV in measurement estimation for herbage mass.

The introduction of variability to pasture accumulation rates also had a significant effect on the average gross margin of the system. However in contrast to the small changes to pasture cover caused by sensor errors, large deviations were often observed (Appendix 4). This indicates that an accurate analysis of this effect should include a feedback controller within the model so that a farmer's response to undesirable states of the system can be simulated.

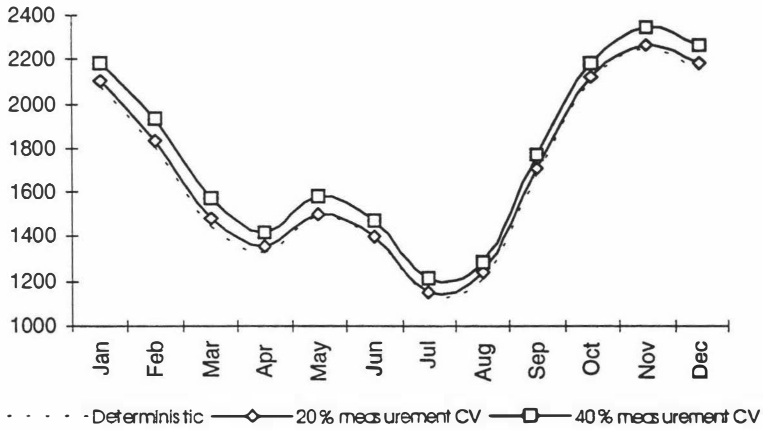

Figure 5.3 Average monthly pasture cover for three levels of sensor error without variability in pasture growth rates.

Gross margins for the system were significantly ($P<0.05$) affected by measurement errors at the level of 40% CV, whether or not pasture growth variability was included (Figure 5.3). A measurement error of 20% CV decreased the gross margins slightly with or without pasture growth variability. The effect was statistically significant ($P<0.05$) when pasture growth variability was excluded but was not significant ($P = 0.086$) otherwise. The simulation results indicate that providing farmers exercise care with their pasture measurement, and in doing so achieve or exceed the levels of accuracy and repeatability that L'Hullier and Thomson (1988) suggest, the control of grazing at the operational level should be close to the optimum. Of course this assumes that other aspects of the farmer's grazing management are of high standard. If this is not the case, and errors such as those simulated for a 40% CV occur, the farmer will pay a significant price for being careless with pasture measurement (e.g. $NZ 74.31/ha for variable pasture growth in the simulation reported here).

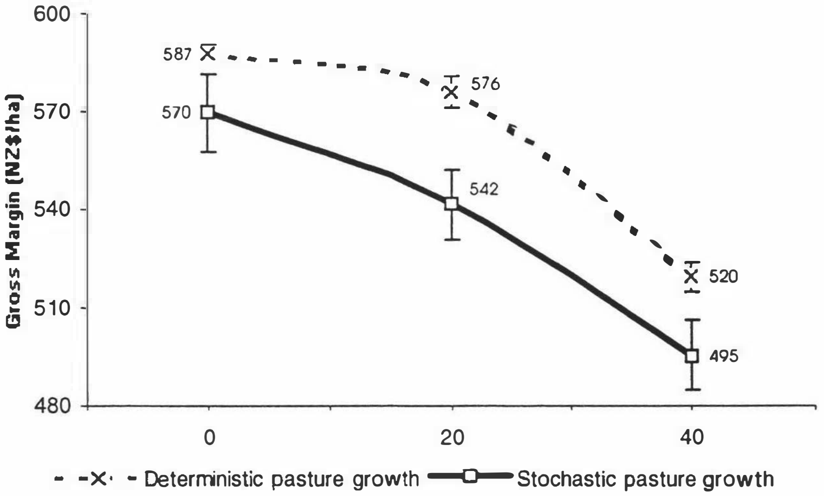

Figure 5.4 Effect of measurement error on the gross margin of the simulated sheep system including or excluding variability in pasture growth. Vertical bars indicate the standard error of the mean.

5.4 Conclusions

The model outputs showed that measurement errors associated with pre-grazing pasture mass can lead farmers to sub-optimal decisions. The performance of the simulated pastoral systems seemed to be tolerant of some errors in pre-grazing pasture mass estimation, providing there is no bias in the sensor used (i.e. the mean of the sensor's estimations are equal to the actual mean), but profitability could decreased significantly if measurement errors increased beyond 20% CV. The analysis reported here suggests very small gains in system performance can be achieved by improving the accuracy of measuring pre-grazing herbage mass beyond the level provided by the measurement techniques currently applied on-farm. This conclusion assumes that bias in measurement is minimised by using the correct regression equation for pasture meters or probes and by calibrating visual assessments of pasture mass with pasture quadrat cuts. Equally, the results show that the failure of farmers to measure pasture accurately in order to control the performance of pastoral systems may have a significant financial cost.

CONCLUSIONS

The prototype model of sheep grazing systems developed here has addressed the areas of deficiency identified in Chapter 1 in existing pastoral modelling research. These areas included the need to: develop a model framework to link strategic, tactical and operational management of livestock on pasture; study the effect of adding stochastic variables on the performance of grazing systems relative to a deterministic analysis; and test the suitability of an iconic simulation package for developing an agricultural decision support system.

The model developed in this study was, as demonstrated through experiments of grazing situations, able to guide major strategic and tactical management decisions, concerning the allocation of feed to a sheep flock. The use of an event driven model design and an optimisation algorithm were important factors in achieving this outcome. The event driven approach allowed the simulation of individual paddocks on a farm, as well as the grazing period for each paddock. It allowed different levels of herbage allowance to be tested and measured in terms of its effects on pre- and post- grazing herbage mass, rotation length, diet quality, animal performance and the enterprise gross margin. Optimisation provided feed management targets at both the operational and tactical levels which farmers should pursue. The speed of the computer hardware and the large size of the simulation forced the optimisation analysis to be made off-line. This capacity limitation needs to be addressed if the model is to be used commercially. It also limited the amount of testing of the optimisation algorithm during the course of this study and for this reason the control parameters for the genetic algorithm for optimising grazing problems and measuring its efficacy and efficiency require further research.

Further improvements in farm system models to guide tactical and operational decisions should pay regard to control measures. Feedback controllers (Athans, 1972) or expert systems could be used to extend the capabilities of the model to guide control.

The Extend^{TM} software had sufficient capacity to accommodate all of the processes necessary to model a grazing system plus incorporate the optimisation algorithm. However complex processes require customised blocks to be created and a reasonable amount of programming time and skills are required to achieve this. Also the package was not suitable for developing an adequate front-end for a decision support model that could be used by farmers or consultants. Software limitations include the impossibility of including multiple dialogues in one block and the inability to customise pull-down menus and windows. New versions of the package should address these limitations if the aim of the software is to provide a comprehensive development environment for decision support models. Another possibility for model developers is to create a user-friendly front-end with a spreadsheet or database package that would allow the transfer of information between model components via text files or some other connecting mechanism.

The development of the model also showed knowledge gaps still exist concerning major components of grazing systems. These gaps need to be addressed in order to refine the predictability of models of the behaviour and performance of grazing systems. For example, the modelling of senescence within pastures is still a controversial area. There is still no consistent agreement about the shape of the relationship between senescence and leaf area or herbage mass. Even in the models that assume a linear relationships between herbage mass and senescence, the parameter values vary widely. In addition, the influence of other factors such as light, temperature, and particularly soil moisture stress on pasture production and senescence need to be studied more objectively, if pasture growth, and its transfer and quality, are to be predicted with greater accuracy.

As shown by the model validation exercises (Chapter 4) predicting feed intake is also a major area requiring further research if animal performance from grazing is to be simulated with greater accuracy. The relationship between metabolic energy demand and rumen fill in determining feed intake by grazing animals is still not clear. When diets exclusively comprise roughage, the responses in intake to digestibility are linear throughout the range found for temperate pasture species (e.g. Hodgson, 1977). Furthermore, metabolic demand is rarely attained in such diets (Van Soest, 1994). This contrasts with the model adopted here, where intake is limited by physiological demand under most conditions, particularly for mature animals. Further research is necessary to separate the effect of how pasture composition limits the harvesting ability of the animal from the mechanisms by which nutritional factors limit herbage intake. It is not clear, for example, if the effect of reducing pasture quality on intake is due directly to having a smaller amount of dry matter than is able to be processed by the rumen or by decreasing bite size because of the accumulation of stem/pseudostem or by the lower density of leaves within the canopy of poorer quality herbage. Perhaps, given the current stage of knowledge, modelling the effect of digestibility using empirical relationships, as in Freer et al. (1997), is still the best way to overcome these gaps in understanding of grazing animals. Nevertheless, it is desirable to understand and model these relationships mechanistically in order to identify opportunities for improving animal production through alternative management practices.

The validation experiments identified some problems with the parameterisation of equations in the model. The model underestimated the dry matter intake and performance of ewes relative to three farmlet experiments conducted in New Zealand. The performance of lambs were, however, relatively well-estimated. The poorer performance of the model with respect to ewe intake may be attributed to mixing the "maximum physiological intake at maintenance" and "lactation intake factor" from different models to determine the physiological potential intake of the ewes. As the mechanistic functions of intake are still not well understood, the equations used in the model were not able to be calibrated against each other. A comparison of the equations used in other models with those used in the present model confirmed the underestimation of intake and suggested that both equations used to estimate physiological intake should be re-calibrated to reflect the higher intake achieved by ewes under field conditions. The model's prediction of herbage intake was also found to be overly sensitive to low leaf mass under conditions of continuous grazing. Intake was therefore crudely estimated for short pastures suggesting the equations adopted from British grasslands should be recalibrated for New Zealand conditions. More extensive evaluation of the model and calibration of its intake equations are areas requiring further research.

The experiments with sensor error (pre-grazing measurement of herbage mass) showed that these can lead to sub-optimal management decisions at the operational level, i.e. miscalculations of grazing time (Chapter 5). The results re-enforced the need to introduce stochastic analysis in agricultural production models, even if the decision maker's preferences in relation to risk are disregarded. However, the performance of pastoral systems seems to be tolerant of some errors in pre-grazing pasture mass estimation and the analysis suggested low gains in system performance can be expected from improving the accuracy of measuring pre-grazing herbage mass beyond the level provided by the measurement techniques currently employed on New Zealand sheep farms.

The model framework could be adapted relatively easily to include beef cattle and dairy enterprises. As most biological processes are similar for all ruminants on improved pasture it would be possible to build a more generic grazing model (as for example Freer et al., 1997) from the base model reported here. Changes in the equation parameters would allow different species and breeds to be simulated.

In this study three research needs in relation to the modelling of livestock production systems based on grazed pasture were addressed. Some insights were obtained into how to incorporate decision support for the tactical and operational management of sheep on pasture. Likewise, the effects of variability on the performance of pastoral systems by simulating pasture measurement errors was investigated and shown to be of value to farm management decision making and deserving of further investigation. Finally, the capabilities and limitation of a new iconic simulation package were shown in the context of a complex pastoral livestock system. Despite these advances in knowledge and understanding of how to simulate grazing systems over the past 25 years, more research is still needed to determine effective ways to link strategic, tactical and operational management for on-farm use. The need for this type of model will grow as computers become more widely used on farms to guide both physical and financial decision making.

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APPENDIX 1 - Code of the genetic algorithm block

```
integer allele, done, done2, count;
integer lchrom, gen, maxgen, LastGen, IndCounter;
integer nmutation, ncross;
integer aborted;
integer parent1[], parent2[], xsite;
integer nselected;
integer lastyear, xpoint;
integer jpick, chosen, nremain, k;
integer choices[];
realPhenotype[];
realFraction[];
realselected, randomI, Penalty, DraftW;
realpcross, pmutation, sumfitness;
realoldpop[][78], newpop[][78];
realx, fitness;
real      avg, max, min, minGM;
realcontrolarray[][8], ArrayPCover[], StartArray[];
realSupplArray[], ProdAndEconomics[], SensitivityArray[];
realxdata[], ydata[];

// This procedure scales the objective function

Procedure Scale(real umin,real umax,real uavg)
{
real delta;

if (umin > (fmult*uavg - umax)/(fmult - 1))
    {
    delta    = umax - uavg;
    a        = (fmult - 1) * uavg / delta;
    b        = uavg * (umax - fmult*uavg)/delta;
    }
else
    {
    delta    = uavg - umin;
    a        = uavg / delta;
    b        = -umin*uavg/delta;
    }
}

// This procedure calculates the individual fitness

Procedure Calcfitness (real a, real b)
{
integer i;

for (i=0; i<Popsize; i++)
    OldPop[i][1] = a*OldPop[i][0] + b;
}
```

```
//   This Procedure outputs the values of the ControlTable (a dialog box table) to
//   the ControlArray which is a global array of inputs to the simulations

Procedure OutputControl()
{
integer r, c;

For (r=0; r<12; r++)
        For (c=0; c<8; c++)
            ControlArray[r][c] = ControlTable[r][c];

If (GetPassedArray(SensitivityIn, SensitivityArray))
    For (r=0; r<12; r++)
        ControlArray[r][1] = SensitivityArray[r];
}


//   This is the procedure outputs the selected individuals by the
//   procedure preselect using the stochastic remainder method.

integer selecttwo()
{
Problem = "Selecttwo";
jpick = random(nremain);
chosen = choices[jpick];
ChoicesValue = Chosen;
If (nremain > 1)
    nremain--;
choices[jpick]   = choices[nremain];
Problem = "After selecttwo";
return (chosen);
}


// Select individuals based on the roulette wheel method.

integer select()
{
realrand, partsum, sumfit;
integer j, i;

partsum = 0;
j         = 0;
sumfit  = 0;

For (i=0; i<popsize-1; i++)
    sumfit += OldPop[i][1];

rand = randomreal()*sumfit;

while (partsum < rand  && j < Popsize-1)
    {
    j++;
    partsum += OldPop[j][1];        **Fitness
    }
```

```
return (j);
}

//    Mutate a bit position

Integer Mutation (integer Parent, integer allele, real pmutation, integer alleleval)
{
integer mutate;

if (randomreal() < pmutation)
      mutate = 1;
else
      mutate = 0;

if (mutate)
      {
      nmutation++;

      if (OldPop[Parent][Allele] == 0)
            return (1);
      else
            return (0);
      }
else
      return (alleleval);
}

// Select individuals deterministically based on the expected number of
// times they should appear in the next population given their fitness level
// The individuals selected are stored in the array "choices"

Procedure preselect()
{
integer j, jassign, winner, i;
real expected, partsum, sumfraction, rand;

Problem = "Preselect";
j=0;
k=0;

nremain = popsize;

makearray(choices, Popsize+1);
makearray(fraction, Popsize+1);

avg = 0;
For (i=0; i<Popsize; i++)
      avg += OldPop[i][1]/Popsize;

While (j < Popsize)
      {
      expected = OldPop[j][1]/avg;       ** j is the number of the individual in the population
      jassign = floor(expected);         ** Expected is the number of times the individual is
      fraction[j] = expected - jassign;  ** expected to be selected and residual fractions are
```

```
    while (jassign > 0)                ** stored.
        {
        choices[k] = j;                **This loop transfer selected individuals
        choicesC[k][0] = j;            **to choice array. ChoicesC is an output to
        k++;                           **a dialog box table.
        jassign--;
        }
    j++;
    }

While (k<popsize)
    {
    partsum = 0;
    j           = 0;
    sumfraction     = 0;

    For (i=0; i<popsize ; i++)
        sumfraction += Fraction[i];

    rand = randomreal()*Sumfraction;

    partsum = Fraction[0];                      ** The fractions stored are used
                                                ** to assign probabilities for the
    while (partsum < rand  && j < Popsize-1)    ** individuals to fill up the required
        {                                       ** number of choices.
        j++;
        partsum += Fraction[j];
        }
    choices[k-1] = j;
    choicesC[k-1][0] = j;
    k++;
    }
}

//  This procedure initialise the first population randomly.

Procedure FirstGeneration()
{
integer r, c;

makearray (OldPop, Popsize+1);

For (c=2; c<76; c++)
    {
//  PopTable[individue][c]      = Random(2);
    OldPop[individue][c]    = Random(2);
    }
}


// This procedure assign the fitness of the individuals based on their
// gross margins. Final pasture cover lower than the initial is penalised.

Procedure Evaluate()
{
```

```
integer c;

If (ArrayPCover[2]<ArrayPCover[3])
    Penalty = (ArrayPCover[3] - ArrayPCover[2])^1.1;

If (aborted == 0)
    {
    If (GetPassedArray(Global16, ProdAndEconomics));
        OldPop[individue][0]   = ProdAndEconomics[13] + ProdAndEconomics[10]
         - ProdAndEconomics[11] - Penalty;
    If (OldPop[individue][0] < 0)
        OldPop[individue][0] = 0;

    Calcfitness(a,b);
    PopTable[individue][1]          = OldPop[individue][1];
    PopTable[individue][0]          = OldPop[individue][0];
    }
else
    {
    OldPop[individue][0] = 0;
    OldPop[individue][1] = 0;
//  PopTable[individue][0]      = 0;
//  PopTable[individue][0]      = 0;
    }

individue++;
}

//  This procedure calculate max, min, average values of gross margins and fitness and
//  outputs the fitness, gross margins and parameters of the best individual of the
//  generation into a dialog table.

Procedure Statistics()
{
integer r, c, i, j, best, gene, done;
real avg;

sumfitness  = OldPop[0][1];
min         = OldPop[0][1];
max             = OldPop[0][1];

sumfitness = 0;
r  = 0;
While (r<Popsize - 1)
    {
    sumfitness += OldPop[r][1];
    if (OldPop[r][1] > max)
        {
        max = OldPop[r][1];
        best = r;
        }
    if (OldPop[r][1] < min)
        {
        min = OldPop[r][1];
        minGM = OldPop[r][0];
```

```
        }
    r++;
    }

MaxOut = Max;

For (i=0; i<14; i++)
    For (j=0; j<23; j++)
        bestindividuals[14-i][j] = bestindividuals[13-i][j];

BestIndividuals[0][0] = OldPop[best][1];

BestIndividuals[0][1] = OldPop[best][0];

For (gene=0; gene<7; gene++)
    {
    BestIndividuals[0][gene+2] = 0.5 + 0.15 * Oldpop[best][(gene*4)+2] +
        0.3 * Oldpop[best][(gene*4)+3] + 0.6 * Oldpop[best][(gene*4)+4] +
        1.2 * Oldpop[best][(gene*4)+5];
    }

For (gene=7; gene<12; gene++)
    {
    BestIndividuals[0][gene+2] = 1 + 0.25 * Oldpop[best][(gene*4)+2] +
        0.5 * Oldpop[best][(gene*4)+3] + 1 * Oldpop[best][(gene*4)+4] +
        2 * Oldpop[best][(gene*4)+5];
    }

BestIndividuals[0][14] = 1000 + 50 * Oldpop[best][64] + 100 * Oldpop[best][65] +
    200 * Oldpop[best][66] + 400 * Oldpop[best][67];

If (OptimiseSR)
    {
    BestIndividuals[0][15] = 120 + 5 * Oldpop[best][64] + 10 * Oldpop[best][65] +
    20 * Oldpop[best][66] + 40 * Oldpop[best][67];
    }
else
    BestIndividuals[0][15] = NEwes;

BestIndividuals[0][16] = 12.5 * Oldpop[best][58] + 25 * Oldpop[best][59] +
    50 * Oldpop[best][60];

BestIndividuals[0][17] = 12.5 * Oldpop[best][61] + 25 * Oldpop[best][62] +
    50 * Oldpop[best][63];

BestIndividuals[0][18] = 5 * Oldpop[best][64] + 10 * Oldpop[best][65] +
    20 * Oldpop[best][66] + 40 * Oldpop[best][67];

For (gene=0; gene<4; gene++)
    {
    BestIndividuals[0][gene+19] = 26 + 1 * Oldpop[best][(gene*4)+50]
     + 2 * Oldpop[best][(gene*4)+51] + 4 * Oldpop[best][(gene*4)+52]
     + 8 * Oldpop[best][(gene*4)+53];
    }
```

```
For(c=2;c<76;c++)
    NewPop[best][c] = OldPop[best][c];

avg = sumfitness/popsize;
averageout = avg;
individualOut = selected;
}

//  This procedure exchage parts of the chromosomes of the parents and calls
//  the function mutation.

Procedure Crossover(integer Parent1, integer Parent2, integer Child1, integer Child2)
{
integer j, jcross;
integer lchrom;

lchrom = 74;

pmutation = 0.01;

if (randomreal()<0.6)
    {
    jcross = random (lchrom) + 2;
    ncross++;
    }
else
    jcross = lchrom + 2;

for (j=2; j<jcross; j++)
    {
    NewPop[Child1][j] = mutation(Parent1, j, pmutation, OldPop[Parent1][j]);
    NewPop[Child2][j] = mutation(Parent2, j, pmutation, OldPop[Parent2][j]);
    }

if (jcross < lchrom + 2)
    {
    For (j = jcross; j<lchrom; j++)
        {
        NewPop[Child1][j] = mutation(Parent2, j, pmutation, OldPop[Parent2][j]);
        NewPop[Child2][j] = mutation(Parent1, j, pmutation, OldPop[Parent1][j]);
        }
    }
}


//  Build up a new generation based on the fitness of the individuals of the
//  old generation.

Procedure Generation(integer indcounter)
{
integer Mate1, Mate2, jcross, j, i, c, r;

If (gen>1)
    {
    Mate1 = Selecttwo();
```

```
     Mate2 = Selecttwo();
     }
else
     {
     Mate1 = Select();
     Mate2 = Select();
     }

j = indcounter;

CrossOver(Mate1, Mate2, j, j+1);
}

// After all the individuals of a generation being evaluated, check statistics
// and make transfer the newpopulation (created by proc generation) to the oldpopulation

Procedure CheckStat()
{
integer r,c,i;

statistics();

For (c=2; c<78; c++)
     For (r=0; r<Popsize-1; r++)
     {
     OldPop[r][c] = Blank;
//   PopTable[r][c] = Blank;
     OldPop[r][c] = NewPop[r][c];
//   PopTable[r][c] = NewPop[r][c];
     }
}


// Initialise variables and clean tables in the first simulation,
// call the procedures of the GA and outputs the values for the simulation.

on initsim
{
integer i,SelectedIndiv, r, c, gene;

GlobalInt2 = 0;
done2      = 0;
count      = 2;
Lastyear   = -1;
xpoint     = -1;

aborted = 0;

GlobalStr0 = "HA";

If (SupplLowStorage)
     GlobalStr1 = "FeedStorage";
else
     GlobalStr1 = "FeedFree";
```

```
MakeArray (ControlArray, 12);

if (currentsim == 0)
    {
    for (r=0;r<15;r++)
        For (c=0; c<23; c++)
            bestindividuals[r][c]=blank;

    mingm = 1;
    sumfitness = 0;
    nselected = 0;
    selected = 0;
    randomi = 0;
    gen = 0;
    individue = 0;

    For (r=0;r<12;r++)
        For (c=0; c<7; c++)
            {
            If (ControlTable[r][c] == 0)
                ControlTable[r][c] = Blank;
            }
    }

If (individue<popsize && Gen ==0)
    {
    FirstGeneration();
    }
else
    {
    If (Individue >= Popsize)
        {
        Individue = 0;
        Gen++;
        }

    makearray (newpop, Popsize+1);

    If (Gen <= NGen)
        {
        If (Individue >= Popsize-1)
            {
            IndCounter = 0;

            If (gen>1)
                Preselect();

            While(IndCounter < Popsize-1)
                {
                generation(indCounter);
                IndCounter = IndCounter + 2;
                }
            checkstat();
            Scale(umin, umax, uavg);
            }
```

```
        }
    else
        AbortAllSims();
    }

If (Optimise)
    {
    For (Gene = 0; Gene < 7; Gene++)
        {
        ControlArray[Gene][1] = 0.5 + 0.15 * OldPop[individue][(Gene*4)+2]
         + 0.3 *OldPop[individue][(Gene*4)+3]     + 0.6 * OldPop[individue][(Gene*4)+4]
         + 1.2 * OldPop[individue][(Gene*4)+5];
        }
    For (Gene = 7; Gene < 12; Gene++)
        {
        ControlArray[Gene][1] = 1 + 0.25 * OldPop[individue][(Gene*4)+2]
         + 0.5 *OldPop[individue][(Gene*4)+3]     + 1 * OldPop[individue][(Gene*4)+4]
         + 2 * OldPop[individue][(Gene*4)+5];
        }

    For (i=2; i<11; i++)
        {
        ControlArray[i][7] = 26 + 1*  OldPop[individue][50] + 2 * OldPop[individue][51]
                        + 4 * OldPop[individue][52] + 8 * OldPop[individue][53];
        }
    ControlArray[11][7] = 26 + 1*  OldPop[individue][54] + 2 * OldPop[individue][55]
                        + 4 * OldPop[individue][56] + 8 * OldPop[individue][57];
    ControlArray[0][7] = 28 + 1 * OldPop[individue][68] + 2 * OldPop[individue][69]
                        + 4 * OldPop[individue][70] + 8 * OldPop[individue][71];
    ControlArray[1][7] = 28 + 1 * OldPop[individue][72] + 2 * OldPop[individue][73]
                        + 4 * OldPop[individue][74] + 8 * OldPop[individue][75];

    IPC                   = 1000 + 50 * OldPop[individue][64] + 100 * OldPop[individue][65]
                        + 200 * OldPop[individue][66] + 400 * OldPop[individue][67];

    ControlArray[3][3]= 0 + 12.5 * OldPop[individue][58] + 25 * OldPop[individue][59]
                        + 50 * OldPop[individue][60];
    ControlArray[3][2]= ControlArray[4][3]*8;
    ControlArray[7][3]= 0 + 12.5 * OldPop[individue][61] + 25 * OldPop[individue][62]
                        + 50 * OldPop[individue][63];
    ControlArray[7][2]= ControlArray[7][3]*8;

    If (OptimiseSR)
        {
        NEwes             = 120 + 5 * OldPop[individue][64] + 10 * OldPop[individue][65]
                          + 20 * OldPop[individue][66] + 40 * OldPop[individue][67];
        }

    For (r=0; r<12; r++)
        ControlArray[r][0] = ControlTable[r][0];
    }
else
    {
    OutputControl();
    }
```

```
Global3 = PassArray(ControlArray);

MakeArray (SupplArray, 6);
SupplArray[2] = ISupplBal;
SupplArray[3] = SupplDig;
SupplArray[4] = 0;
Global6 = PassArray(SupplArray);

MakeArray(StartArray,5);
StartArray[0] = IPC;
StartArray[1] = Interval;
StartArray[2] = NEwes;
StartArray[3] = DraftW;
Global8 = PassArray(StartArray);

LastGen = Gen;
}

// Call the procedure to evaluate the individuals at the end of the simulation


on endsim
{
real bestfitness;
integer r;

jpickc = jpick;
remainc = nremain;
kc = k;

evaluate();
}

// When create block put months numbers on the control table in the dialog.

on createblock
{
integer i;

For (i=0; i<12; i++)
    ControlTable[i][0] = i+1;
}


//   If the pasture cover goes below 700 kg DM/ha, abort simulation. It cannot be optimal!

on simulate
{
integer r, year;

If (GetPassedArray(Global2, ArrayPCover))
    If (Abortiflow)
        If (ArrayPCover[2] < MinPCover && Currenttime > 10)
            {
```

```
            Aborted = 1;
            Abort;
            }

Year = GlobalInt9;

If (Multiyear && !Optimise)
    {
    If (Count == Year)
        {
        Done2 = 0;
        Count++;
        }

    If (Done2 == 0)
        {
        OutputControl();
        Done2++;
        }
    }

GlobalStr0 = "HA";

if (DigHarvest)
    {
    For (r=0; r<12; r++)
        {
        If (ControlArray[r][5] > 0)
            {
            ControlArray[r][5] = SupplArray[5];
            ControlArray[r][6] = SupplArray[5] * 0.157;
            }
        }
    }
else
    {
    For (r=0; r<12; r++)
        {
        If (ControlArray[r][5] > 0)
            {
            ControlArray[r][5] = ControlTable[r][5];
            ControlArray[r][6] = ControlTable[r][6] * 0.157;
            }
        }
    }
}

// Check if data in the dialog is compatible with the optimisation.

on checkdata
{
integer i;

For (i=0; i<12; i++)
    {
```

```
    If (ControlTable[i][1] > 20)
        {
        Usererror ("Allowance is too high");
        Abort;
        }

    If (NGen<4)
        {
        Usererror ("The number of generations is too low");
        Abort;
        }

    If (Popsize < 10)
        {
        Usererror ("The population is too small");
        Abort;
        }

    If (Popsize > 120)
        {
        Usererror ("The population is too big");
        abort;
        }
    }
}

//  Plot the evolution of gross margins in the best individuals of each generation
//  During the optimisation.

on choosetoplot
{
    integer k, numPlot;

    numPlot = 14;

    makearray(xdata,numPlot);
    makearray(ydata,numPlot);

    for (k=0;k<numPlot;k++)
    {
        xdata[k] = k;
        If (!NoValue(BestIndividuals[13-k][1]))
            ydata[k] = BestIndividuals[13-k][1];
        else
            ydata[k] = 0;
    }

    ** install the axes
    installAxis(0, "Input Data",
         "Generations", FALSE, 0,20,
            "Genotype", FALSE, 0,20, "", 0, 0, 0,
            blackpattern, blackcolor, 100);
    installArray(0, 0, "Generations", xdata, 0, 20,
                    0, 0, blackPattern, cyanColor);
    installArray(0, 1, "Genotype", ydata, 0, 20,
```

```
                        0, 0, dkgrayPattern, redColor);

  makeScatter(0, 0);
  ** plot the data

    for (k=0;k<numPlot;k++)
        plotNewScatter(0,0,k,xdata[k],ydata[k]);

  autoscalex(0);
  autoscaley(0);
  showPlot(0, "Input Data");
}
```

APPENDIX 2 - Continuous and discrete event models in ExtendTM.

Figure 1(a) is an example of how a continuous simulation is performed in Extend. In this example, the block labelled "Factory 1", responds to the "Simulate" message (Section 3.2) by outputting a variable output according to a user-defined function. This random output represents the discharge of pollutants of "Factory 1" into a lake. The block labelled "Factory 2" represents a factory which has a constant rate of discharge and its output is deterministic. The output of the two first blocks is summed by block 3 and the pollution level is calculated by block 4 (Labelled "Pollution Level").

In block 4, the output connector labelled "C" in the top right corner of the block outputs the current level of pollution in the lake. The outflow of pollutants is calculated from the current level of pollution in the lake multiplied by a constant outflow rate. The pollutants discharged from the lake are then taken out of the accumulated pool, calculated in the block labelled "Pollution Level" by its "want" input connector. The sum of the discharges and the current level of pollution are plotted over time by the "plotter" block in the far lower right of the iconic model (a chart window can either be open when running the models or be opened by double clicking the icon). Note that the blocks need not exclusively be connected by lines but also can be named by connections as in the case of the "Sum of pollutants" in Figure 1(a). Some blocks in the model also can pass whole arrays of data, rather than single values, through a connection. This means pass values or arrays for global variables can be accessed by any block in the model without needing to be connected.

In the case of event driven models, some blocks can pass items rather than values through some connectors. In the model represented by Figure 1(b) for instance, the customers that arrive at a bank are represented by items, generated by the "customers" block. The customers stay in a queue (waiting line) until they are attended by one of the three tellers which are assigned a defined time delay. The length of the waiting line and the number of customers leaving the bank are then plotted by the plotter block.

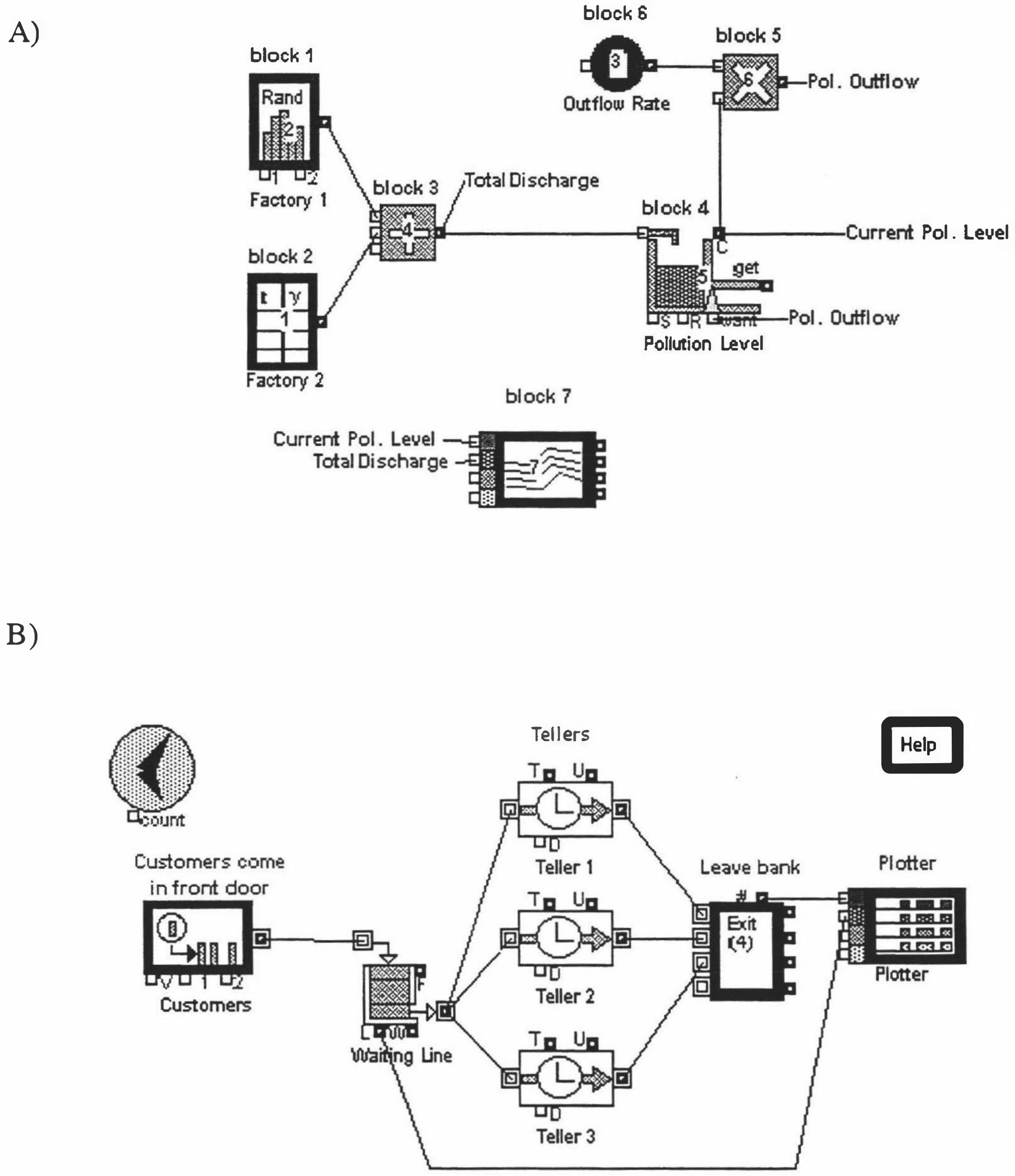

Figure 1 Examples of Extend Models: (a.) The lake pollution model, an example of a fixed step model (b.) The bank line model, an example of an event driven model (See text for details).

APPENDIX 3 - Lambing distribution used in the experimentation.

DOY[1]	(1) Single / (2) Twins	(1) Male / (2) Female
149	2	1
150	2	1
151	2	1
154	2	1
156	1	1
158	1	1
159	2	1
160	2	2
160	2	1
161	1	1
161	2	1
161	1	1
162	1	2
162	1	2
163	2	1
163	1	1
163	2	1
163	1	1
163	2	1
163	1	1
164	1	1
164	2	2
164	2	2
165	2	1
165	1	2
165	1	2
165	1	1
165	1	2
165	1	2
165	1	2
165	2	1
166	1	1
166	1	2
166	1	1
167	1	2
167	1	2
167	2	1
167	2	2
167	1	1
168	1	1
168	2	1
168	1	2
168	1	2
168	1	1
169	1	1
169	1	1
169	2	2
169	1	1
170	1	1
170	1	2
170	2	1
170	1	1
170	1	1
171	2	2
171	1	1
171	2	1
171	2	2
171	2	2
171	1	1
172	2	2
172	1	1
173	2	1
173	1	2
173	2	1
174	2	2
174	1	2
174	2	2
174	1	2
176	1	1
176	2	1
176	2	1
176	1	2
176	2	2
176	2	1
176	2	1
177	1	2
177	1	2
179	1	2
179	1	1
179	2	1
180	1	1
180	1	2
180	2	1
181	2	2
182	1	2
182	2	2
183	1	1
183	2	1
183	1	2
185	2	2
186	2	2
186	2	2
186	1	1
186	1	1
187	2	2
187	2	2
187	1	2
189	2	2
189	1	2
190	2	2
190	1	2
190	2	2
190	1	2
192	1	1
192	2	2
192	1	2
193	2	1
194	1	1
194	2	2
196	1	2
197	2	2
198	2	1
200	2	2
201	2	1
201	2	2
203	1	2
203	1	2
204	1	1
204	2	2
206	1	1
207	1	1
207	1	1
210	1	1
212	1	1
215	2	1
216	1	1
218	2	1

---

[1] DOY is the day of the year (1 January =1).

APPENDIX 4 - Results of the measurement error simulation

Table 1 Summary statistics of gross margins recorded in the sensor error experiment.

Interation	No PGR Variability No Sensor error	No PGR Variability 20 % CV sensor[1]	No PGR Variability 40 % CV sensor	Normal PGR Variability No sensor error	Normal PGR Variability 20 % CV sensor	Normal PGR Variability 40 % CV sensor
1	592.95	586.46	506.71	543.72	522.30	472.60
2	572.28	595.64	456.88	408.34	309.48	535.55
3	585.76	600.61	526.30	366.14	541.87	551.65
4	594.30	580.99	525.03	579.10	587.80	536.90
5	590.06	518.69	547.31	510.40	589.99	501.49
6	572.42	590.38	552.29	592.47	583.86	552.86
7	590.81	552.37	542.96	565.45	520.04	504.73
8	576.91	570.79	557.65	613.88	462.03	565.18
9	570.68	583.09	482.29	596.58	550.88	495.80
10	606.53	590.67	516.21	585.39	553.43	478.08
11	572.43	606.96	516.62	599.98	566.36	536.72
12	599.59	561.90	555.36	595.11	534.96	528.24
13	621.51	568.01	523.53	629.46	543.28	532.51
14	568.35	543.90	535.65	591.87	532.61	525.23
15	596.46	533.22	501.24	566.63	493.04	503.05
16	612.61	530.66	510.83	548.01	518.70	395.27
17	578.73	599.14	466.72	462.39	527.02	433.44
18	580.40	572.43	531.87	573.19	580.99	510.10
19	585.65	580.57	495.81	616.36	575.63	577.44
20	601.14	581.93	520.88	628.32	576.96	501.77
21	587.36	587.59	511.33	600.22	594.52	458.98
22	611.31	545.47	519.41	569.86	593.22	521.15
23	590.01	632.39	522.87	598.22	567.81	386.81
24	579.33	581.76	518.26	594.90	565.34	431.99
25	583.59	589.07	523.25	607.80	554.58	444.32
26	570.74	598.01	540.00	612.10	572.83	384.04
27	594.14	579.30	528.44	588.82	478.80	527.17
28	564.28	570.47	515.74	609.40	571.05	480.43

Table 2 Summary statistics of pasture cover recorded in the sensor error experiment.

Treatment		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Deterministic	Mean	2081	1806	1446	1330	1495	1393	1146	1216	1682	2108	2243	2156
	Range	2075 - 2090	1798 - 1823	1440 - 1462	1318 - 1340	1482 - 1504	1381 - 1399	1135 - 1151	1211 - 1220	1675 - 1688	2100 - 2113	2238 - 2245	2148 - 2157
	SD	4.05	5.42	4.28	7.54	8.30	7.05	6.79	2.19	3.18	3.72	1.83	1.49
	SE	0.72	0.96	0.76	1.33	1.47	1.25	1.20	0.39	0.56	0.66	0.32	0.26
Deterministic +Sensor20	Mean	2101	1837	1484	1356	1506	1403	1156	1240	1713	2123	2266	2180
	Range	2043 - 2156	1769 - 1908	1412 - 1558	1293 - 1411	1463 - 1566	1359 - 1448	1129 - 1195	1183 - 1317	1645 - 1820	2047 - 2165	2214 - 2293	2140 - 2210
	SD	32.25	36.19	31.76	23.69	21.84	21.11	14.96	25.41	39.04	27.35	18.22	17.64
	SE	5.70	6.40	5.61	4.19	3.86	3.73	2.65	4.49	6.90	4.83	3.22	3.12
Deterministic +Sensor40	Mean	2189	1929	1571	1426	1583	1475	1216	1289	1775	2186	2345	2264
	Range	2096 - 2330	1808 - 2105	1472 - 1739	1331 - 1551	1432 - 1683	1403 - 1572	1152 - 1287	1216 - 1363	1626 - 1919	2091 - 2272	2273 - 2437	2180 - 2355
	SD	55.95	69.26	61.16	47.84	49.39	43.48	37.68	37.68	69.53	54.08	43.75	41.52
	SE	9.89	12.24	10.81	8.46	8.73	7.69	6.66	6.66	12.29	9.56	7.73	7.34
StochasticPGR	Mean	2211	1964	1611	1441	1563	1454	1216	1272	1770	2225	2379	2315
	Range	863 - 3364	542 - 2998	441 - 2576	490 - 2107	702 - 2159	817 - 2039	586 - 1627	717 - 1718	1156 - 2222	1251 - 3066	1422 - 3309	1187 - 3304
	SD	560.38	530.53	488.80	421.41	404.65	332.57	250.28	241.99	323.45	441.57	486.18	502.99
	SE	99.06	93.79	86.41	74.50	71.53	58.79	44.24	42.78	57.18	78.06	85.95	88.92
StochasticPRG +Sensor20	Mean	2098	1884	1537	1377	1529	1468	1247	1305	1772	2208	2325	2167
	Range	957 - 3491	915 - 2845	768 - 2524	843 - 2286	880 - 2110	821 - 1939	640 - 1735	680 - 1831	1030 - 2633	1316 - 3210	1367 - 3187	1012 - 3285
	SD	572.49	518.32	464.64	365.31	334.32	278.43	240.45	250.95	357.26	455.05	474.12	546.51
	SE	101.20	91.63	82.14	64.58	59.10	49.22	42.51	44.36	63.15	80.44	83.81	96.61
StochasticPGR +Sensor40	Mean	2347	2071	1704	1504	1598	1500	1256	1330	1785	2194	2366	2334
	Range	1333 - 3298	958 - 3101	711 - 2553	873 - 2184	875 - 2266	776 - 2063	531 - 1715	626 - 1937	1064 - 2458	1380 - 3049	1571 - 3203	1425 - 3327
	SD	515.91	450.53	423.26	382.94	386.69	322.77	271.09	297.33	332.96	428.24	441.06	477.73
	SE	91.20	79.64	74.82	67.69	68.36	57.06	47.92	52.56	58.86	75.70	77.97	84.45

Table 3 Pasture cover without pasture accumulation variability and sensor error.

Iteration	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	2074.872	1798.596	1440.796	1332.584	1499.032	1396.555	1149.781	1213.772	1678.851	2105.566	2241.803	2155.685
2	2083.666	1808.869	1448.466	1337.556	1502.485	1399.005	1151.223	1216.086	1682.403	2109.409	2243.939	2156.598
3	2080.402	1804.686	1445.403	1334.874	1499.824	1382.074	1135.311	1212.712	1677.376	2103.759	2241.225	2156.275
4	2087.363	1812.064	1450.31	1339.041	1503.879	1398.623	1150.843	1217.763	1684.541	2111.92	2245.19	2156.738
5	2081.89	1804.386	1443.989	1320.042	1483.557	1395.892	1149.265	1216.706	1683.333	2111.086	2244.692	2156.56
6	2080.221	1803.807	1444.222	1319.983	1483.766	1396.675	1149.753	1217.074	1683.814	2111.407	2244.887	2156.688
7	2077.963	1801.948	1443.38	1333.758	1499.299	1381.265	1134.819	1212.816	1677.543	2104.027	2241.286	2156.174
8	2085.802	1810.845	1449.716	1338.105	1502.561	1399.262	1151.297	1215.251	1680.451	2106.72	2242.316	2155.818
9	2082.265	1804.545	1443.954	1320.416	1483.941	1395.67	1149.212	1217.736	1684.523	2112.152	2245.071	2156.439
10	2076.776	1800.815	1442.612	1333.511	1499.419	1380.918	1134.636	1213.561	1678.47	2104.894	2241.561	2156.224
11	2085.966	1810.377	1449.092	1338.243	1503.334	1398.446	1150.789	1217.488	1684.239	2111.61	2245.059	2156.718
12	2080.85	1803.998	1444.112	1320.028	1483.749	1396.44	1149.622	1217.159	1683.892	2111.501	2244.898	2156.677
13	2080.202	1803.512	1443.891	1319.757	1483.55	1396.503	1149.643	1216.835	1683.528	2111.176	2244.79	2156.705
14	2082.101	1805.127	1444.672	1320.706	1484.089	1395.989	1149.342	1217.368	1684.089	2111.747	2244.935	2156.556
15	2080.688	1804.145	1444.162	1320.569	1484.09	1395.875	1149.329	1217.793	1684.6	2112.205	2245.118	2156.516
16	2077.939	1801.422	1442.707	1333.745	1499.791	1397.204	1150.169	1214.169	1679.298	2105.898	2241.962	2155.887
17	2078.842	1801.903	1442.975	1333.546	1499.27	1380.956	1134.627	1213.062	1677.853	2104.365	2241.385	2156.286
18	2089.891	1813.987	1450.838	1325.474	1487.514	1396.808	1149.76	1220.262	1687.821	2103.623	2244.432	2156.359
19	2078.618	1822.645	1461.59	1318.188	1482.176	1393.321	1147.89	1217.198	1683.843	2111.84	2244.818	2156.293
20	2076.27	1800.672	1442.65	1333.598	1499.523	1380.887	1134.61	1213.696	1678.632	2105.055	2241.615	2156.151
21	2084.768	1809.684	1448.871	1337.943	1502.917	1398.797	1151.054	1216.744	1683.359	2110.586	2244.584	2156.748
22	2080.784	1804.239	1444.643	1335.084	1500.847	1397.701	1150.458	1215.218	1680.55	2106.888	2242.317	2155.574
23	2083.32	1808.514	1447.96	1322.64	1485.677	1397.517	1150.186	1218.328	1685.233	2112.718	2245.359	2154.189
24	2077.262	1801.992	1443.671	1334.033	1499.543	1381.46	1134.958	1213.131	1677.922	2104.329	2241.396	2156.15
25	2078.982	1802.475	1443.393	1334.546	1500.775	1397.001	1150.019	1215.892	1682.435	2109.912	2244.237	2156.64
26	2084.236	1807.509	1446.284	1322.143	1485.179	1396.111	1149.434	1218.62	1686.017	2101.788	2243.689	2156.526
27	2075.126	1798.111	1440.23	1332.246	1498.893	1396.423	1149.737	1213.985	1679.125	2105.795	2241.875	2155.741
28	2081.418	1807.05	1447.659	1336.157	1500.241	1383.22	1136.145	1212.658	1677.018	2102.732	2240.689	2156.414
29	2087.084	1812.424	1450.886	1339.012	1503.366	1399.48	1151.418	1216.242	1682.539	2109.582	2244.047	2156.563
30	2082.633	1806.4	1446.022	1321.075	1484.458	1397.045	1149.895	1217.14	1683.862	2111.492	2244.951	2156.008
31	2075.826	1800.962	1443.311	1333.161	1497.861	1382.189	1135.719	1210.932	1674.702	2100.148	2238.024	2148.29
32	2089.768	1816.346	1453.615	1340.277	1503.783	1384.128	1136.432	1215.61	1680.84	2106.84	2242.505	2156.038

Table 4 Pasture cover without pasture accumulation variability and 20% of coefficient of variation in sensor estimates.

Iteration	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	2112.159	1851.37	1487.644	1351.122	1516.811	1421.163	1166.392	1270.264	1721.608	2160.491	2288.32	2197.452
2	2148.939	1874.896	1512.2	1379.377	1525.729	1429.475	1166.134	1251.186	1679.565	2109.569	2270.558	2191.806
3	2079.647	1817.923	1489.853	1356.367	1528.507	1405.816	1157.953	1238.865	1687.551	2103.507	2265.716	2160.989
4	2104.218	1840.749	1463.66	1336.032	1494.851	1396.832	1138.013	1231.443	1695.495	2066.828	2248.776	2163.231
5	2043.021	1769.397	1433.968	1324.548	1471.084	1413.917	1174.392	1243.955	1751.116	2142.004	2259.661	2168.689
6	2116.667	1860.22	1488.011	1353.264	1497.534	1397.384	1157.974	1221.555	1676.248	2151.532	2261.828	2189.533
7	2140.39	1888.09	1557.582	1381.636	1503.628	1388.365	1138.497	1213.059	1671.895	2085.798	2260.582	2159.485
8	2065.351	1800.061	1462.711	1363.37	1533.525	1443.571	1194.872	1317.247	1819.701	2164.834	2289.174	2204.366
9	2105.448	1855.702	1481.221	1336.377	1497.973	1405.083	1177.244	1235.456	1705.967	2116.282	2259.377	2176.252
10	2150.237	1908.199	1541.834	1396.513	1554.323	1441.763	1179.79	1265.742	1751.733	2113.519	2270.097	2186.567
11	2099.914	1851.619	1495.85	1360.799	1512.948	1401.566	1158.192	1262.204	1738.417	2128.894	2262.012	2179.794
12	2110.597	1841.87	1499.215	1369.667	1516.435	1403.872	1152.79	1240.073	1724.298	2120.383	2243.66	2158.191
13	2058.809	1797.02	1455.403	1345.676	1500.255	1390.891	1151.709	1210.39	1668.404	2129.1	2285.598	2178.255
14	2068.543	1801.826	1468.302	1338.968	1498.265	1387.908	1143.097	1222.055	1693.209	2136.304	2268.704	2191.377
15	2156.003	1900.774	1523.47	1384.728	1524.357	1448.401	1175.86	1262.719	1763.265	2155.076	2289.288	2196.397
16	2114.029	1834.941	1463.505	1357.679	1513.918	1407.804	1164.608	1263.661	1748.997	2131.716	2292.809	2202.858
17	2099.519	1858.252	1518.334	1376.232	1512.959	1407.698	1154.158	1258.747	1750.165	2126.884	2280.655	2185.223
18	2137.511	1886.307	1535.797	1410.837	1565.863	1427.054	1167.631	1241.187	1742.593	2145.255	2288.85	2210.019
19	2153.902	1883.484	1507.495	1360.66	1501.758	1401.845	1150.879	1236.693	1720.975	2143.762	2288.839	2209.684
20	2146.217	1863.63	1488.378	1353.768	1482.608	1385.409	1136.085	1183.465	1661.51	2132.382	2276.319	2183.671
21	2062.508	1798.479	1449.34	1332.559	1501.947	1406.965	1152.967	1225.084	1652.864	2075.642	2225.252	2140.179
22	2077.794	1817.033	1478.086	1353.422	1505.628	1399.868	1150	1247.774	1714.344	2110.104	2263.848	2172.8
23	2086.127	1811.629	1449.675	1312.405	1463.254	1358.859	1131.323	1234.341	1729.223	2117.636	2261.072	2176.857
24	2091.714	1832.23	1483.358	1354.595	1480.181	1366.103	1129.303	1202.549	1678.462	2106.606	2256.739	2177.981
25	2054.424	1785.158	1469.569	1354.962	1516.168	1422.756	1159.785	1237.152	1705.13	2137.086	2271.697	2181.657
26	2109.621	1853.312	1492.893	1354.439	1503.649	1398.594	1159.044	1253.46	1742.733	2161.297	2260.596	2173.084
27	2099.153	1857.558	1513.719	1380.711	1525.702	1415.257	1163.119	1223.024	1663.108	2115.561	2263.345	2170.803
28	2046.27	1773.309	1411.898	1292.58	1476.836	1396.789	1154.852	1221.129	1722.931	2147.27	2260.287	2173.89
29	2103.32	1829.708	1478.956	1368.682	1492.951	1377.377	1139.525	1224.251	1691.008	2104.486	2240.828	2162.728
30	2112.852	1823.623	1475.416	1358.198	1494.393	1387.229	1152.938	1205.931	1645.453	2046.606	2214.347	2146.621
31	2081.88	1819.009	1469.023	1343.725	1500.413	1395.86	1154.32	1265.942	1749.255	2125.393	2274.855	2204.177
32	2090.909	1811.664	1447.671	1335.882	1493.343	1371.969	1139.561	1254.525	1740.372	2117.202	2267.754	2195.236

Table 5 Pasture cover without pasture accumulation variability and 40% of coefficient of variation in sensor estimates.

Iteration	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	2211.91	1953.868	1620.396	1489.195	1545.762	1438.109	1188.648	1306.977	1716.469	2151.632	2307.361	2235.199
2	2173.493	1916.71	1575.377	1432.993	1619.112	1496.534	1205.832	1241.952	1703.315	2170.352	2364.971	2299.966
3	2266.577	1969.375	1554.335	1451.7	1614.084	1486.732	1217.489	1263.834	1788.439	2210.206	2353.625	2273.512
4	2143.803	1862.992	1518.588	1390.524	1533.853	1429.606	1165.665	1264.111	1765.398	2118.58	2333.436	2286.167
5	2263.185	2031.34	1667.438	1502.199	1578.227	1439.479	1181.874	1244.288	1714.558	2131.905	2273.277	2180.448
6	2137.074	1935.177	1560.743	1407.785	1616.219	1494.376	1231.207	1296.549	1775.285	2120.765	2293.209	2228.199
7	2141.989	1851.017	1531.216	1407.313	1542.741	1418.109	1165.217	1313.685	1800.238	2146.056	2334.95	2264.92
8	2236.555	1975.282	1591.734	1420.036	1585.42	1523.542	1274.268	1292.487	1820.2	2173.804	2325.697	2257.661
9	2329.735	2105.469	1738.517	1550.982	1683.245	1515.479	1232.775	1309.852	1792.775	2247.566	2388.76	2335.246
10	2236.808	2047.029	1666.812	1482.271	1658.415	1572.459	1287.299	1336.226	1781.364	2174.286	2332.096	2249.094
11	2184.947	1920.732	1583.989	1446.517	1590.061	1459.764	1193.898	1290.279	1800.085	2175.705	2325.789	2212.615
12	2137.074	1881.745	1556.802	1404.942	1615.917	1504.246	1227.861	1313.126	1863.855	2247.256	2395.307	2264.836
13	2154.101	1911.446	1575.545	1393.157	1534.511	1411.343	1152.252	1216.423	1631.29	2090.506	2288.019	2203.989
14	2101.512	1807.65	1472.594	1358.403	1575.974	1503.737	1257.561	1362.662	1868.979	2245.238	2339.723	2245.229
15	2110.064	1858.767	1511.605	1346.99	1561.835	1528.887	1249.721	1294.892	1766.16	2175.762	2341.041	2230.816
16	2184.256	1934.928	1570.193	1413.505	1583.695	1460.845	1209.18	1233.434	1626.072	2109.212	2283.504	2205.305
17	2095.656	1809.074	1471.513	1330.857	1432.172	1402.849	1166.855	1252.783	1698.157	2117.919	2303.138	2266.796
18	2201.19	1932.631	1557.237	1439.984	1561.119	1437.937	1175.196	1291.332	1909.394	2262.765	2405.625	2319.384
19	2230.581	1968.675	1593.434	1422.52	1593.598	1498.352	1257.038	1320.212	1869.525	2248.038	2400.301	2318.627
20	2262.769	2011.082	1652.028	1501.418	1656.881	1516.091	1227.695	1332.161	1829.175	2272.159	2407.447	2268.206
21	2118.027	1862.463	1499.427	1374.96	1499.368	1430.512	1206.589	1238.426	1718.452	2264.272	2437.158	2331.059
22	2146.99	1860.231	1515.808	1373.392	1557.854	1410.704	1165.294	1244.266	1764.428	2199.143	2338.886	2286.226
23	2184.08	1897.021	1539.435	1405.818	1585.92	1486.203	1232.402	1301.588	1716.792	2162.239	2353.431	2264.828
24	2216.685	1959.213	1630.104	1470.876	1613.353	1505.326	1261.96	1331.588	1809.698	2254.735	2398.953	2305.36
25	2169.415	1905.818	1546.39	1399.734	1568.276	1444.314	1211.296	1267.676	1762.727	2159.253	2289.287	2220.505
26	2207.66	1988.508	1589.006	1428.605	1586.551	1455.43	1209.895	1270.79	1780.946	2189.283	2332.215	2269.449
27	2130.836	1831.692	1475.767	1405.724	1583.882	1449.846	1191.044	1254.788	1715.795	2183.846	2314.975	2244.438
28	2185.862	1916.022	1599.406	1459.878	1644.222	1553.079	1283.992	1326.374	1771.114	2215.297	2366.563	2285.891
29	2260.981	1990.624	1600.523	1432.323	1600.167	1469.476	1196.021	1358.503	1919.394	2213.984	2341.284	2238.361
30	2173.486	1921.982	1553.644	1425.646	1559.985	1467.7	1206.171	1258.835	1734.921	2185.149	2362.373	2283.16
31	2234.232	1994.207	1625.798	1453.742	1638.952	1527.74	1274.028	1311.143	1753.847	2091.787	2292.318	2229.612
32	2209.32	1914.043	1512.627	1394.999	1540.804	1459.362	1202.306	1303.839	1836.056	2250.213	2417.959	2354.663

Table 6 Pasture cover with pasture accumulation variability and 0% of coefficient of variation in sensor estimates.

Iteration	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	2032.151	1701.916	1153.937	983.2187	1035.941	1095.083	1028.519	1085.61	1457.758	2147.798	2503.486	2400.041
2	2347.787	1999.487	1643.709	1493.099	1456.274	1265.471	1127.198	1411.345	1740.038	1662.218	1421.958	1187.035
3	863.1117	541.6742	440.9119	490.2909	701.9042	817.1851	793.764	830.0572	1155.665	1473.959	1663.167	1750.776
4	1591.839	1526.514	1088.355	864.2156	1132.505	1115.822	932.1891	1070.071	2031.384	3018.029	3309.014	3276.928
5	2972.971	2326.425	1791.591	1578.806	1572.25	1319.231	1093.434	1085.54	1363.907	1661.599	1649.633	1522.17
6	1433.778	1080.565	741.4243	758.5389	1055.642	1102.399	1076.43	1431.974	2067.914	2214.63	2095.977	2185.587
7	2376.793	1961.499	1340.694	961.9896	852.0157	855.3773	903.6885	1274.268	1948.857	2579.423	2938.22	2941.151
8	2730.764	2215.066	1647.992	1288.722	1271.205	1340.211	1271.457	1246.748	1657.615	2332.479	2666.554	2485.441
9	2498.63	2261.551	1939.564	1931.653	2108.234	2038.917	1627.138	1465.674	2040.944	2671.851	2671.948	2414.484
10	2381.421	2064.85	1544.665	1344.501	1397.348	1532.868	1383.74	1191.359	1640.389	2114.804	2099.884	2002.489
11	1985.469	1760.858	1239.23	1052.185	1357.745	1439.082	1403.372	1641.134	2096.795	2159.751	2252.708	2311.471
12	2397.501	2444.191	2212.863	1850.299	2147.452	1990.561	1472.652	1197.296	1692.358	2220.877	2636.445	3304.368
13	3363.653	2997.672	2575.716	2106.992	2142.781	1835.957	1412.209	1432.431	2073.15	2663.043	2836.021	2789.07
14	2386.04	2069.215	1767.269	1564.74	1663.211	1660.091	1329.018	1321.302	1716.504	1787.1	1894.423	2104.224
15	2099.274	1884.571	1560.016	1522.521	1762.755	1689.991	1556.239	1593.379	1929.244	2494.499	2797.503	2479.869
16	2256.312	1849.142	1471.204	1419.085	1190.784	1205.43	1285.466	1277.628	1726.192	2045.832	1956.121	1739.321
17	1836.651	1608.268	1542.573	1490.637	1310.99	1040.964	853.1965	988.0534	1789.478	2344.794	2471.375	2467.841
18	2358.36	2247.88	1860.883	1683.437	1829.931	1413.357	1014.451	1012.71	1362.786	1756.059	1904.069	1895.047
19	1979.834	1640.27	1255.645	1087.006	1172.505	893.553	585.5458	716.5419	1234.617	1660.199	1444.834	1420.754
20	1473.599	1133.084	1048.418	1218.651	1514.244	1510.523	1407.948	1604.624	2105.004	2641.519	2910.068	2527.201
21	2029.355	2035.475	1578.914	1250.763	1607.027	1741.138	1402.765	1295.75	1771.321	2196.335	2531.263	2516.515
22	2478.644	2226.981	1648.295	1334.826	1371.854	1324.591	1213.773	1328.196	1718.24	2133.772	2343.242	2728.807
23	3267.994	2863.586	2238.66	2013.046	2158.766	1818.926	1518.693	1646.028	2221.66	2526.121	2356.714	2113.282
24	2285.726	2421.814	2175.673	2040.47	2082.337	1756.518	1387.751	1457.511	2069.447	2729.69	2709.343	2046.421
25	1099.217	1115.822	1044.458	1118.259	1469.45	1362.789	1134.457	1343.258	2077.717	2500.004	2315.206	2000.687
26	1997.326	2087.655	2066.35	1848.123	1825.889	1599.391	1315.557	1183.755	1175.261	1250.677	1879.167	2345.241
27	2166.691	2103.321	1887.33	1668.645	2051.965	1910.467	1484.614	1718.018	2101.258	2219.235	2635.838	2538.179
28	2442.682	2534.408	2294.883	2077.506	2009.213	1753.84	1403.211	1288.46	1597.56	2191.936	2759.596	2788.077
29	2851.469	2550.826	2123.606	1753.347	1627.246	1411.23	1141.881	1315.236	2211.213	2837.001	3047.184	3110.219
30	2928.83	2411.868	2104.054	1967.31	2110.509	1834.174	1313.969	1176.356	1407.467	1825.905	1947.664	1945.227
31	1945.547	1543.206	1100.061	988.4031	1540.287	1425.876	853.5184	851.6463	1348.57	2078.343	2547.044	2276.158
32	1878.167	1648.427	1419.192	1351.883	1488.948	1428.252	1170.534	1228.225	2120.509	3065.803	2944.166	2476.287

Table 7 Pasture cover with pasture accumulation variability and 20% of coefficient of variation in sensor estimates.

Iteration	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	2603.617	2592.955	2030.048	1639.419	1678.337	1547.064	1247.749	1241.751	1591.4	1984.431	2126.593	1799.489
2	1509.869	1279.359	1055.202	843.1323	944.5797	1090.893	1144.237	1166.072	1353.221	1480.207	1366.579	1011.75
3	957.3735	915.0332	767.5899	914.7547	1105.664	1050.008	1015.894	1338.756	1949.78	2206.52	2427.535	2409.174
4	2255.239	2011.034	1686.434	1481.658	1730.109	1506.345	1008.796	991.7441	1528.913	2068.559	2277.168	2316.96
5	2555.669	2529.391	2399.177	2157.802	2017.225	1804.48	1383.609	1301.221	1608.972	1782.107	2242.763	2703.949
6	2903.955	2323.729	1730.054	1430.466	1538.201	1607.073	1303.223	1131.067	1655.987	2434.961	2823.188	3285.018
7	3491.348	2845.187	2278.68	1905.599	1747.064	1248.448	988.7251	1257.655	1805.761	2178.97	2063.928	1799.493
8	1697.446	1409.689	1078.604	984.8688	1165.206	1249.732	1087.273	1262.544	1814.345	2632.066	3187.198	3057.102
9	2261.899	1899.055	1477.122	1441.754	1827.958	1570.433	1164.274	1091.05	1239.867	1521.689	1505.611	1307.111
10	1204.885	1169.327	950.0501	905.7469	1282.85	1392.384	1291.221	1380.946	2231.302	3066.644	3092.073	2952.871
11	2927.632	2322.621	1548.351	1270.923	1382.58	1365.739	1054.31	929.8126	1311.118	2119.999	2522.318	2619.534
12	2757.632	2814.525	2524.169	1841.756	1667.216	1324.933	934.6451	1036.051	1421.137	1850.699	2011.843	1929.788
13	2017.985	1710.633	1396.099	1356.651	1665.147	1712.679	1576.722	1677.915	2150.593	2267.256	2291.156	2219.506
14	2145.456	2003.484	1525.786	1452.597	1831.897	1677.016	1196.758	1026.771	1029.526	1316.203	1807.005	1638.397
15	1393.215	1254.568	1122.568	1370.994	1881.501	1683.299	1486.011	1613.612	2137.938	2600.747	2467.816	2036.403
16	2030.565	2168.275	1957.211	1680.481	1554.69	1576.439	1527.087	1581.161	1873.055	2358.587	2938.071	3051.228
17	2174.235	1684.688	1072.757	876.6385	1050.435	1062.778	920.9165	1092.135	1584.154	1846.912	1947.692	1666.232
18	1422.274	1305.325	1166.47	1036.024	1186.989	1198.941	1130.817	1231.505	1735.316	2254.095	2436.908	2246.048
19	1868.524	1552.552	1184.213	980.2316	879.5301	821.1668	639.5523	679.7536	1136.721	2225.861	2696.931	2314.604
20	2038.597	1685.663	1266.572	1335.606	1868.193	1814.314	1424.569	1490.922	2267.781	2928.189	2763.692	2357.34
21	2164.873	1974.265	1493.043	1080.901	1118.969	1101.177	1031.319	1082.666	1609.35	2135.802	2153.606	1886.28
22	1711.911	1550.778	1246.645	1361.083	1665.109	1561.216	1284.198	1369.363	2058.181	2665.709	2885.609	2746.411
23	2815.349	2477.77	1798.444	1727.007	1982.712	1759.488	1410.94	1356.813	1585.947	1779.343	1933.576	1993.398
24	2074.513	1913.656	1736.401	1413.937	1369.571	1563.047	1403.632	1349.863	1709.376	1854.818	1888.087	1797.057
25	2817.017	2508.17	2279.282	2286.253	2110.274	1859.362	1661.96	1830.801	2168.3	2406.036	2272.953	1644.82
26	1643.174	1566.534	1335.933	1334.716	1631.403	1785.416	1522.23	1316.334	1958.791	2824.149	2755.682	2417.455
27	2448.792	2117.804	1530.689	1010.503	1032.79	1129.502	1152.108	1441.106	1897.431	2267.555	2465.488	2354.318
28	2152.376	2052.308	1732.811	1466.442	1395.444	1379.698	1240.707	1341.636	1845.865	1859.338	1801.256	1723.843
29	1593.793	1122.276	820.5678	1027.843	1584.469	1413.887	1155.781	1470.367	2122.779	2601.424	2562.765	2038.38
30	1911.596	2061.531	1932.592	1590.521	1482.464	1566.765	1395.629	1369.439	1737.426	1751.368	1421.373	1228.357
31	1403.469	1271.511	1122.208	1231.464	1820.54	1939.115	1734.858	1779.883	1957.117	2178.465	2357.62	2202.762
32	2171.677	2198.91	1930.365	1629.801	1713.097	1603.05	1395.846	1539.032	2633.407	3210.045	2907.187	2592.424

Table 8 Pasture cover with pasture accumulation variability and 40% of coefficient of variation in sensor estimates.

Iteration	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	2715.165	2414.26	1874.207	1438.939	1304.016	1148.854	1013.181	1190.383	1761.764	2339.692	2214.641	2312.53
2	2747.393	2492.775	2011.509	1514.454	1417.805	1203.918	968.9642	1066.159	1631.5	2370.429	2614.142	2710.389
3	2720.128	2373.763	1941.055	1757.171	2043.846	1920.979	1611.79	1601.693	2001.667	2470.992	2582.689	2309.534
4	2044.813	1834.313	1640.186	1489.217	1362.197	1351.302	1351.947	1463.101	2011.636	2535.455	2767.971	2531.415
5	2310.128	1974.493	1568.212	1294.419	1310.132	1358.123	1235.396	1218.315	1653.671	1750.336	1863.549	2354.699
6	2299.224	2175.64	2191.721	1954.123	2017.223	1960.796	1493.656	1527.551	2457.826	2826.686	2831.572	2701.612
7	2457.032	2137.382	1790.986	1570.96	1628.224	1732.934	1644.231	1701.56	1708.422	1746.944	2251.616	2547.756
8	2548.581	2419.066	2095.405	1995.641	2265.784	1942.473	1408.799	1413.408	1856.911	2101.733	2163.489	1988.319
9	1868.513	1497.416	1260.803	1307.148	1495.086	1527.143	1084.053	929.8768	1350.485	2071.106	2500.209	2666.522
10	2693.807	2563.823	2341.867	2183.821	2087.086	1761.053	1408.554	1457.703	1611.225	1662.863	1821.181	2108.822
11	2350.301	2341.25	2129.928	1683.474	1588.927	1428.136	1238.745	1344.125	1974.175	2345.522	2864.311	3074.086
12	2937.17	2559.605	2165.658	2146.994	2144.152	1820.931	1521.762	1576.792	1833.774	2050.647	2494.296	2338.827
13	1993.611	1763.958	1348.317	1105.419	1166.941	1202.649	1056.491	1193.507	2164.724	3049.428	2908.94	2532.126
14	2620.257	2343.45	2012.972	1711.786	1673.046	1488.511	1429.407	1756.238	2062.264	2271.679	2482.893	2996.592
15	3297.81	3101.086	2552.671	2007.327	2028.105	1839.7	1682.88	1683.654	2159.103	2648.588	2504.443	2155.767
16	1890.401	1785.668	1654.926	1524.633	1540.664	1187.266	996.1057	1025.171	1158.152	1380.482	1671.78	1797.437
17	3155.929	2562.533	2018.976	1940.443	2198.254	1945.195	1508.405	1688.302	2117	2383.896	2725.28	2552.734
18	2563.525	2063.007	1221.684	918.5947	874.6017	847.4495	670.9839	626.4391	1064.08	1583.272	1571.159	1627.383
19	1688.006	1436.306	1049.449	878.3733	1264.635	1449.098	1250.338	1150.431	1506.141	2023.357	2245.162	2050.28
20	1628.57	1582.858	1380.067	901.4634	1123.101	1404.831	1236.404	1203.597	1761.845	2525.414	2986.795	2981.732
21	2713.538	2287.887	1883.699	1647.046	1707.805	1712.473	1424.362	1438.4	1885.677	2290.268	2585.19	2596.264
22	2429.776	1952.338	1545.66	1469.944	1676.461	1511.519	1254.058	1708.202	2166.588	2503.554	2717.42	2337.174
23	1993.007	1824.622	1610.992	1628.028	2135.395	2063.209	1714.693	1936.749	2216.999	2020.064	2004.175	1973.283
24	1966.251	1917.043	1728.201	1500.284	1709.446	1582.284	1182.973	1151.487	1811.347	2501.06	2549.944	2576.449
25	2671.267	2351.541	1922.964	1715.404	2023.723	1788.73	1200.219	1327.948	1675.304	1762.458	1955.787	2031.324
26	2232.723	2113.558	1449.024	1156.751	1298.213	1345.807	1217.715	1276.192	1543.637	1731.974	1738.251	1454.186
27	1575.494	1554.891	1373.755	1433.846	1580.054	1550.904	1270.135	1214.932	1584.536	2092.332	1894.247	1424.719
28	1333.151	958.0092	711.1543	872.5439	1071.111	776.2013	531.1607	732.4473	1490.865	2159.081	2474.302	2761.412
29	2609.404	1808.483	1408.359	1280.062	1190.768	1296.996	1234.985	1050.611	1170.338	1394.8	1586.363	1429.349
30	1401.883	1433.54	1147.915	1197.398	1434.957	1199.593	877.2278	1164.474	2220.507	3016.451	3202.954	3327.175
31	3291.209	2706.488	2233.684	1964.144	1755.782	1425.878	1211.789	1358.341	1807.907	2577.664	2782.187	2409.542
32	2371.557	1947.532	1264.119	927.2372	1029.905	1212.624	1244.993	1371.292	1708.474	2004.855	2142.878	2025.734