THE ROLE OF MODELLING IN THE MANAGEMENT OF STORED-PRODUCT PESTS

B. C. LONGSTAFF

CSIRO Division of Entomology, GPO Box 1700, Canberra, ACT 2601, Australia

ABSTRACT

The term "modelling" means different things to different people. This paper seeks to provide an overview of the modelling process: the philosophy behind modelling, the types of approach available and the relevance to applied situations, such as the management of the storage ecosystem. It is argued that both of the traditional forms of mathematical modelling, theoretical and simulation, are valuable tools for the development of strategies and tactics for the solution of applied problems, although the benefits are rather different. A relatively new form of modelling, developed in the artificial intelligence arena, is that of "Expert Systems". This approach seeks to combine information derived from the more traditional experimental method with that derived from experience, and deliver a decision or prediction in a verbal form that is interpretable by non-experts. The benefits and drawbacks of these various approaches are discussed.

INTRODUCTION

Contrary to the belief of many non-modellers, systems modelling is not a mathematical technique, nor even a group of mathematical techniques. It is rather a broad research strategy that may use mathematical techniques and concepts to provide order to collections of observations, perhaps suggesting general results that are contained in them but not apparent. Where the output from a model, derived from the entire theoretical structure relating a set of observations, does not conform with the expectations of the scientist, it is the theory, and not the model, that is incomplete. Modelling is thus a powerful tool to assess the completeness of a theory and, sometimes, may suggest new avenues for research.

In this paper I intend to give an overview of the general modelling process and then look at the developments in the stored-product pests arena, particularly in relation to management issues.

THE MODELLING PROCESS

The general modelling process may be illustrated as a series of discrete activities with feed-back between various stages (Fig.1). Frequently, a general analytical model is developed in the early phases of an investigation and evolves over time to incorporate increasing levels of detail, with generality giving way to specificity and precision as the problem becomes better defined.

What constitutes a good model? According to Rosenblueth and Wiener (1945), "...the best material model of a cat is another , or preferably the same, cat". This *reductio ad absurdum* is true in terms of safety, since it avoids the problems associated with the introduction of metaphorical elements, but it is the worst possible model in terms of instructive value. A model is, above all, an abstraction from observed facts, and thus certain features of the situation are considered irrelevant and are ignored. To quote Lewontin (1960), "A model airplane is a valid model of a jet bomber not *because* it is smaller and made of different

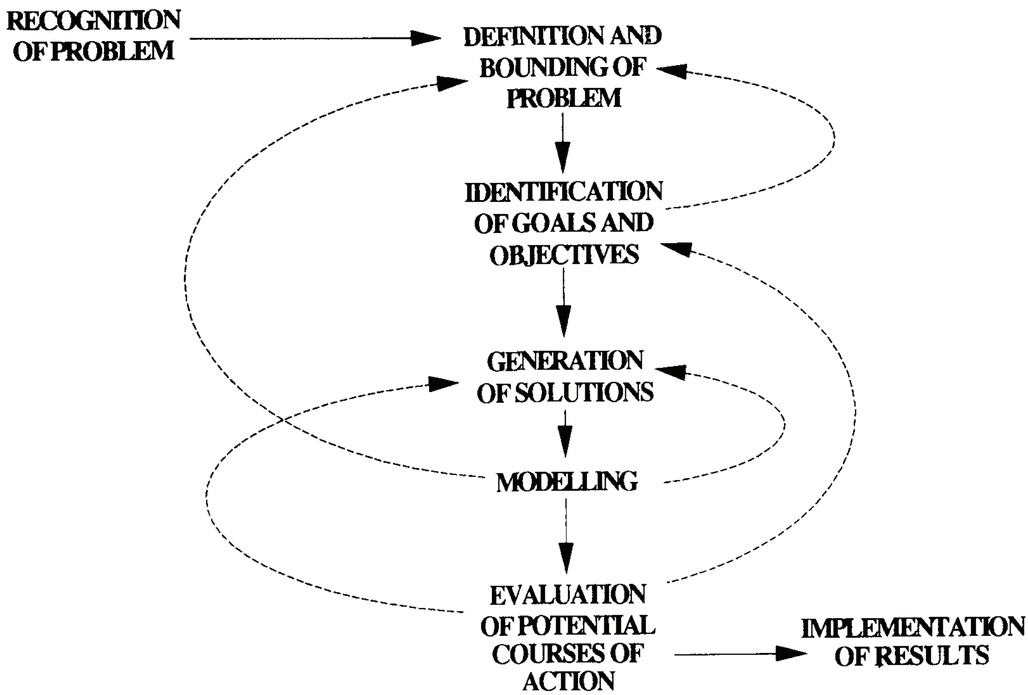

Figure 1. The feedback relationships involved in the modelling process

Figure 1. The feedback relationships involved in the modelling process (from Jeffers, 1978)

materials but *in spite* of these differences. The results of wind-tunnel tests are useful only insofar as the size and material of the model are irrelevant to the answers sought".

What types of models are there? Levins (1966) suggested that no useable model could be general, realistic, and precise, and that one of these characteristics had to be sacrificed to maximize the other two. This assertion leads to the classification of models into three types: "general realistic", "general precise", and "realistic precise". "General realistic" models are models, often graphical in form, whose predictions are usually qualitative rather than quantitative. Such models generally assume that functions are increasing or decreasing or are convex or concave, rather than specifying the mathematical form. A map is a good example of such a model, since the contours and relative distances shown correspond to topographic reality, but the colours and medium of presentation are arbitrary. The second and third types constitute the vast majority of existing models. "General precise" models are usually simple, analytical models, often with very few equations, dealing with general phenomena and they include most of the "classical" ecological models, such as the logistic and Lotka-Volterra equations. "Realistic precise" models, on the other hand, are usually very specific and often incorporate a great deal of detailed information. There has been much heated debate over the relative merits of these two types of approach. I believe that both types have their uses, but that choice between them depends very much on problem and goal definition. I would recommend reading the papers of Hall, Caswell, Onstad and others, presented at a symposium entitled "An Evaluation of the Role of Theoretical Models in Ecology", and published in "Ecological Modelling" in 1988, where a range of differing views on the subject are presented. By and large, management models have tended to be of the "realistic precise" type, especially where specific problems are involved.

MODELLING AND STORED-PRODUCT INSECTS

Stored-product insects have featured prominently in the development of population modelling. The *Tribolium* "model", first developed by Chapman (1928), became the stimulus for an enormous amount of experimental and theoretical investigation. The bulk of the modelling studies were of the "general precise" type (e.g. Bartlett,1957; Leslie, 1958, 1962), and were essentially derivatives of the logistic and Lotka-Volterra equations. Only Stanley (e.g.1932), Landahl (1955), Taylor (e.g 1967), and Niven (e.g.1967) developed models that attempted to include any ecological realism. However, none of these models have been used for management purposes, to date, and so we will not pursue the *Tribolium* "model" any further. Its evolution is discussed in detail by Mertz (1972).

Other stored-product species to have received the attention of modellers include: various bruchids, *Sitophilus oryzae, Ptinus tectus, Rhyzopertha dominica*, and *Cryptolestes ferrugineus*. Most of the work on bruchids has resulted in the development of analytical models that have been used to investigate various life-history strategies (Bellows, 1982a; Smith and Lessells, 1986), although Bellows (1982b) did go on to develop his analytical model into a more detailed simulation model to enable him to describe the daily changes in age-structure and population density. Hagstrum and Throne (1989) developed simulation models for *T. castaneum, R. dominica*, and *C. ferrugineus* that allowed for the effects of temperature upon developmental rate and fecundity. In their current forms, the models for the other species are detailed simulation models that incorporate as much of the available life-history data as possible. The models for *P. tectus* (Nuttall, 1989) and *C. ferrugineus* (Kawamoto *et al.*, 1989) have not, as yet, been used to consider pest management problems, and so now I will go on to discuss the evolution of the *Sitophilus* model.

THE EVOLUTION OF THE *SITOPHILUS* MODEL

This work began with the pioneering studies of L.C. Birch, who carried out a series of detailed life-history studies with *S. oryzae*. These data were summarized, initially, in terms of an intrinsic rate of increase (Birch, 1948) over a range of physical conditions (Birch, 1953a). Further studies led to the fitting of logistic equations to population growth trajectories (Birch, 1953b).

Somewhat later, Hardman (1978) developed a simulation model, based on the logistic model and using additional experimental data, to describe changes in population size and age-structure over time. Using the data of Singh *et al.* (1976), he developed a sub-model to describe aspects of the metabolic activity of the various life-history stages. This enabled the model to estimate the changes in grain moisture content, the proportions of sound grain and frass, and the gaseous composition of the experimental universe. Subsequently, Cuff and Hardman (1980) restructured and extended this model, separating the underlying mathematical model from the computer algorithm. They found this to be a derivative of the classical Leslie matrix model for age-structured populations. This revised model employed a physiological time-scale, based upon a linear day-degree model, and consisted of 41 immature and 132 adult age-classes, each of 10 day-degrees duration. The model was used to look at the effect of the degree of gas-tightness, initial temperature, and initial weevil population size upon the subsequent population growth during storage over winter in an underground granary. It was also used, in tandem with a model describing the heat and mass-transfer processes in aerated grain bulks, by Thorpe *et al.* (1982) to assess the impact of grain cooling upon population growth.

At much the same time, Longstaff (1981a) used an analytical model, again based upon the Leslie-matrix format, to investigate the consequences of combining the application of insecticide with the manipulation of grain temperature. This study estimated population growth rates at various temperatures and then calculated how much insecticide-induced adult mortality would be necessary to give control. The results showed clearly that the combined use of grain cooling with the application of insecticide would require lower application rates than if cooling were not used.

At this point, the Cuff-Hardman model was reviewed and it was felt that many of the functions used to describe aspects of the biology of the rice weevil were probably over-simplifications of reality, but that further development was constrained by lack of appropriate data. Further, Cuff and Hardman (1980) had noted that their linear physiological time-scale could only be applied to temperatures between 16°C and 28°C, which necessarily limited the domain of applicability of their model. Thus, a new phase of laboratory work began, to produce a detailed data set that would provide a broader picture of the relationship between important demographic parameters and environmental conditions (Longstaff, 1981b; Longstaff and Evans, 1983). This, in turn, led to an extensive revision of the Cuff-Hardman model, to enlarge the effective domain of the model and to provide more sophisticated sub-models of age-specific fecundity and survival, based upon continuous functions of time, temperature, and grain moisture-content, instead of tabular information modified by simple linear functions (Longstaff and Cuff, 1984). A new, non-linear, physiological time-scale was introduced, which expanded the temperature domain limits to 15°C and 33°C and included the effect of grain moisture-content. Because the longest observed developmental period was about 30 weeks at 15°C, it was decided that the number of immature age-classes should be 30, thus allowing a transition through a single age-class during a week at this temperature. Subsequent simulations showed it was unnecessary to have more than 40 adult age-classes, confirming Birch's (1948) conclusions that the contributions to the population growth rate of adults much older than the duration of the developmental period are insignificant. The computational consequences of this were considerable, with the matrix model being reduced in size from 173x173 to 70x70, thereby reducing computer memory requirements by 83%. A further enhancement was the inclusion of a variable developmental period, since the emergence pattern of many species, including *S. oryzae,* has been shown to be log-normal. This model was used to investigate the consequences of combining grain fumigation and grain-cooling, showing that, if fumigation were followed by cooling, the perceived period of protection would be approximately doubled before retreatment would be necessary.

One of the unfortunate features of the classical Leslie matrix formulation is the presence of a large number of zeros in the matrix. In a large model, such as that for *Sitophilus*, this will impose a significant computational overhead. To overcome this, Longstaff (1987, 1988a) further revised the model by splitting the matrix into vectors for survivorship, fecundity, and maturation, and thus eliminating the zeros. This meant that the total number of model elements was reduced from over 6000 to 131, or less than one half of one per cent of the

TABLE 1. Suitable situations for implementation of the *Sitophilus* model, where temperature manipulation will swamp the metabolic effects of the insects on their environment.

1.	The effect of rate of cooling upon insect population growth
2.	The effect of using grain cooling to follow fumigation
3.	The use of grain cooling with the admixture of residual insecticides
4.	The role of grain cooling in the management of insecticide resistance

original Cuff-Hardman model, with no loss of detail but with a substantial improvement in the level of sophistication and the domain of applicability.

The current version of this demographic model has now been used to investigate the consequences of various alternative integrated approaches to pest control. As we are unable, as yet, to adequately describe the temperature changes in the grain brought about by the metabolic activities of the insects, use of the model has been limited to situations where this is relatively unimportant, i.e. where the control measure involves temperature manipulation (Table 1). Longstaff(1987, 1988a) took a more detailed look at the impact of grain-cooling upon population growth and found that, whilst it was generally beneficial for pest control, the rate of cooling was very important. This study quantified an effect found in earlier studies (e.g. Desmarchelier *et al.* (1979). By itself, cooling is unable to provide adequate control under Australian conditions and, therefore, would need to be used in combination with another control measure. For example, the use of cooling to follow fumigation will limit any damage resulting from subsequent reinfestation, be it due to immigration, poor fumigation practice, or resistance (Figure 2). The combined use of cooling and insecticide application would result in reductions in the application rates of insectides, due to lower rates of chemical breakdown and temperature-related demographic phenomena. The level of the reductions was found to depend on the nature of the temperature-toxicity relationship of the particular insecticide. For example, the model predicted that the use of a synergised pyrethroid together with rapid cooling could reduce the required application rate by as much as 90%.

The logical extension of this last study was to consider the consequences of such an integrated approach for the management of insecticide resistance. In the grain storage system, particularly where grain is stored in bulk, the traditional pest control strategy requires that the grain be treated with a long-lasting residual insecticide at intake. This is contrary to the conventional wisdom for the management of resistance, which suggests that it is best to treat with a very potent but short-lived insecticide (e.g.Taylor and Georghiou, 1982). Sinclair and Alder (1985) developed a simulation model to look at the role of farm practices, including hygiene and insecticide usage upon the development and spread of resistance. Muggleton (1986) used a general genetic model to investigate the nexus between insecticide dose (i.e. selection pressure) and the rate of spread of resistance, whilst White *et al.* (in press) used another general model to consider the consequences for resistance of heterogeneous application of insecticide. Longstaff (1988b) added a genetic sub-model of insecticide resistance to the general demographic model, based on simple but realistic

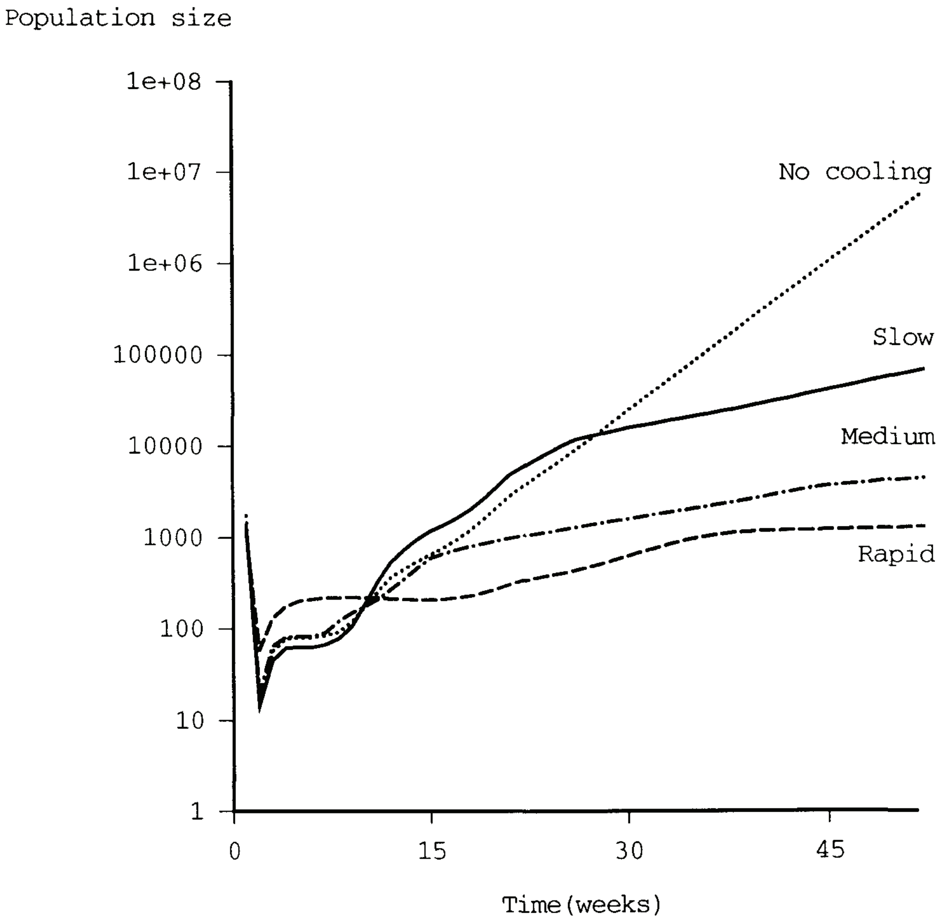

Figure 2. The predicted responses of *Sitophilus oryzae* populations exposed to an imperfect fumigation followed by grain cooling at different rates (after Longstaff, 1988a).

assumptions. Results from the simulations suggested that grain-cooling is likely to have a pronounced effect upon the rate of spread of a resistance gene in a population, largely as a result of the effect on the developmental rate and, thus the generation time (Table 2).Such a conclusion supports the theoretical studies of May and Dobson (1986), who showed that the rate of spread of resistance was linearly dependent on generation-time but only logarithmically on other factors, such as initial gene frequency or selection strength. The results emphasize the fact that the integrated use of grain-cooling with insecticide application has several benefits for the manager. Firstly, insecticide breakdown is slowed and so less insecticide is necessary, with obvious cost-savings. Secondly, the slowing-down of population growth rate, as temperature is lowered, further reduces the amount of insecticide needed. Not only are costs reduced still further, but the residue levels are also reduced. Finally, such a strategy provides the manager with a substantial 'cushion' of safety should control fail for any reason. Any damage to the commodity will be much reduced and, if the failure was due to insecticide resistance, the spread of the resistance gene is restricted. The simulations also highlight the importance of rate of cooling. A major assumption of the

TABLE 2. The proportional increase in the population of *S. oryzae* after one year of storage where insecticide was applied at a rate sufficient to achieve control in the absence of resistance. The initial frequency of the resistance gene is 0.01 and the resistance factor is 64X.

Temperature regime	Population increase	Frequency of resistance gene
No cooling	15000X	0.94
Slow cooling	200X	0.73
Rapid cooling	2X	0.16

genetic sub-model was that the only effect of resistance was upon adult survival. The literature suggests that this is probably not the case but the lack of adequate data has prevented further investigation. We are in the process of investigating some of the demographic consequences of resistance .

There are many areas in which our knowledge of the biology of *Sitophilus* is insufficient to allow us to develop appropriate mathematical descriptions. In particular, we know that such insects respond to physical and biological stimuli in non-random ways but we are not able to quantify these responses. By way of an example, we carried out a moderately large experiment where we infested small silos (5t) with *S. oryzae* and monitored the development and distribution of the population over a period of 8 months. Some of these silos were aerated, others not, and it became clear that the insects in the aerated silos were behaving differently to those not exposed to aeration. Aeration appeared to be having an additional effect upon the insects other than that attributable to a simple reduction in temperature. We are now about to carry out a series of experiments to investigate this, with the hope that we will be able to incorporate it into the general model. And so the story goes on.....

The basic structure of the demographic model for *S. oryzae* has thus evolved from a single general equation, through a complex algorithmic system of equations, lacking any explicit mathematical structure, to a detailed simulation model, derived from a conceptual mathematical model, that is able to describe demographic phenomena in terms of key environmental variables. Each stage in the development of the model has prompted further experimentation to provide more data in particular areas, as the question being asked is rephrased. Thus, in the case of the *Sitophilus* model, the objectives of the modelling exercise have evolved from a need to describe population growth to a desire to investigate alternative control strategies that may seek to target a particular part of the life-cycle, perhaps through the manipulation of certain physical parameters. This evolutionary process illustrates the feedback relationships shown in Figure 1.

GENERAL PEST MANAGEMENT MODELS

The analytical and simulation models described thus far have dealt with single species and have been used to investigate only one or two aspects of pest management. The further development of such models to encompass broader management issues, with the same level of detail, is constrained by the lack of appropriate data sets and the amount of time and enormous computing resources needed to run them. Because of this, a number of research and industry bodies are seeking alternative methods of using existing expertise to develop rational pest management strategies. The ultimate goal is to combine detailed experimental, theoretical, *and* experiential information into a computer-based decision-support system. The user will be able to describe a particular grain-storage system and the objectives and constraints of the management plan, be able to investigate alternative control strategies and be advised of the consequences and costs of the course(s) of action. Such decision-support systems are frequently referred to as "Expert" systems.

Expert systems are intended to mimic, as closely as possible, the decision-making logic that a human expert would employ when solving a particular problem. The knowledge contained in an expert system can be contrasted with that in a systems model in a number of ways. In particular, the knowledge base of an expert system is usually constructed from the special knowledge of one or more experts, who have gained their understanding from experience, whereas a systems model is generally based upon the interpretation of scientifically-controlled observations and experiments, as we have already seen. The knowledge base is the explicit functional associations between items of information and/or data in a particular application and is functionally equivalent to the equations in a systems model. The knowledge is most frequently represented in the form of simple or complex rules (Table 3). The knowledge base for an expert system will typically consist of from a few hundred to a few thousand rules.

TABLE 3. Examples of rules that might be included in an "Expert System"

- IF facility is not sealed or sealable THEN no fumigation
- IF facility is sealed THEN fumigate
- IF moisture content is < 10.0% THEN do not treat for weevil
- IF initial moisture content is > 12% THEN aerate
- IF aeration must be carried out THEN no fumigation

Knowledge acquisition is usually done by a process of successive approximations. A "knowledge engineer" interviews the expert, gains access to any appropriate documentation, and then produces a prototype. This is then reviewed by the expert and subsequently refined. The same iterative procedure portrayed in Figure 1. The design of the knowledge base is a crucial stage in the development process because decisions made at this stage will have consequences for the subsequent maintainability of the system by third parties. This stage is, or should be, independent of the mechanism of implementation, which may be a commercially available "shell", such as EXSYS or NEXPERT, or a programming language, such as PROLOG or LISP.

During the operation of the expert system, the rules are managed by a special program called an *inference engine,* which accepts input from the user, fetches data from the data base, performs the logical reasoning required by the rules, and presents the system's response to the user. In many applications of expert systems the consequences of an incorrect or misunderstood recommendation may be serious. It is, therefore, essential that such systems have an explanation facility so that the user can question the system's action. A good explanation facility will provide a controlled depth of response, with the option to further explain elements of the earlier explanation.

In the context of the current paper, the most complete application of this technology to the management of stored grain pests is that of Denne (1988), who developed a system that included cost-benefit analyses and risk assessment to provide the user with sufficient information to make rational decisions. Other groups are actively involved in developing such systems (e.g. USDA, Manhattan and CSIRO, Canberra) and we must look forward to their maturation. The idealized expert system would seek to combine all aspects of the pest management problem and provide appropriate costings (Table 4). A daunting task indeed!

TABLE 4. Features of the ideal "Expert System"

1.	Must cater for the complete spectrum of insect pests
2.	Must allow for all types of treatments
3.	Must be able to provide costs for alternative recommendations
4.	Must encompass practices for the management of insecticide resistance
5.	Must cater for the range of customer requirements
6.	Must encompass all physical types of storage
7.	The development of a good graphical user-interface to provide both interrogation of the client and good explanatory performance
8.	Should include available simulation models as "black boxes", so that alternative integrated strategies may be compared without the need to understand the details of the models involved

As a word of caution, it worth pointing out that not all problems should be seen as candidates for expert system development. It is necessary that the problem be reasonably well-defined and, because of the high cost of development, the perceived benefits should be considerable.

THE FUTURE

This paper has attempted to provide a historical perspective of the developing role of modelling in the management of pests of stored products. Where do we go from here? It seems to me that the future for modelling as a management tool will see a melding of the simulation and expert systems modelling approaches. Such hybrid systems will have to be

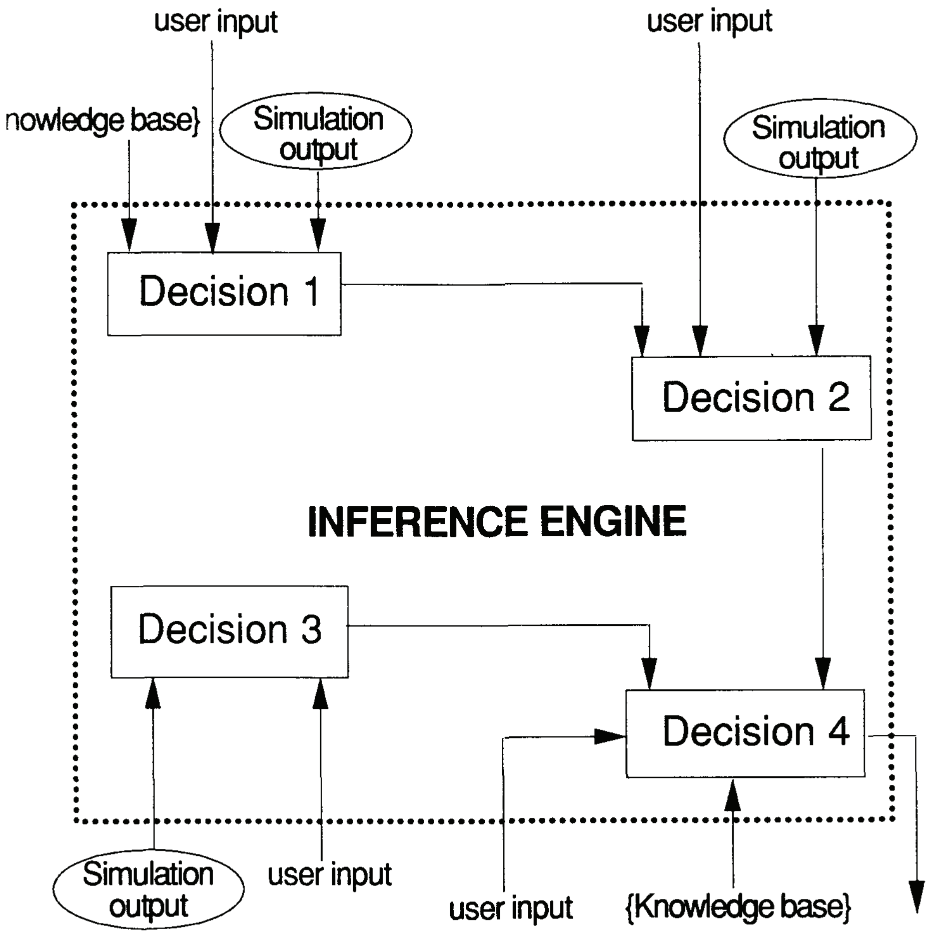

Figure 3. The breakdown of management into a system of decisions linked by information flow in the form of a) user input of data, b) knowledge stored in the knowledge base, c) output from simulation models, d) previous decisions that reflect the opinion of experts (adapted from Coulson *et al.,* 1987).

very "user friendly", having good graphical user-interfaces, and will allow the user to quantify the potential consequences of certain actions, and ask questions like: "How much synergised deltamethrin should be applied to grain that has an initial temperature of 34°C, a moisture content of 11.5%, and will be stored in an unsealable structure at terminal x, with aeration facilities, for at least four months before being shipped to country y?". (Figure 3). Expert systems may well be used to help design and build simulation models, by using a generic form into which the user enters information specific to the application (Logan, 1988). In addition to their management role, expert systems have already shown their potential as training aids, where the explanatory capability is particularly important (Heong, 1990). The additional dimension provided by the hybrid system will obviously further enhance its value as an instructive aid. Finally, the potential exists for these hybrid systems to aid research by identifying weaknesses in existing knowledge (Norton, 1987). To date, expert systems have not been used in this context.

REFERENCES

Bartlett, M. S. (1957) On theoretical models for competitive and predatory biological systems. Biometrika, 44:27-42.

Bellows, T. S. (1982a) Analytical models for laboratory populations of *Callosobruchus chinensis* (L.) and *C. maculatus* (F.) (Coleoptera, Bruchidae). J. Anim. Ecol., 51:263-287.

Bellows, T. S. (1982b) Simulation models for laboratory populations of *Callosobruchus chinensis* and *C. maculatus*. J. Anim. Ecol., 51:597-623.

Birch, L. C. (1948) The intrinsic rate of natural increase of an insect population. J. Anim. Ecol.,17:15-26.

Birch, L. C. (1953a) Experimental background to the study of the distribution and abundance of insects. I. The influence of temperature, moisture and food on the innate capacity for increase of three grain beetles. Ecology, 34:698-711.

Birch, L. C. (1953b) Experimental background to the study of the distribution and abundance of insects. II. The relation between innate capacity for increase in numbers and the abundance of three grain beetles in experimental populations. Ecology, 34:712-726.

Caswell, H. (1988) Theory and models in ecology: a different perspective. Ecol. Modelling, 43:33-44.

Chapman, R. N. (1928) The quantitative analysis of environmental factors. Ecology, 9:111-122.

Coulson, R. N., Folse, L. J., and Loh, D. K. (1987) Artificial Intelligence and Natural Resource Management. Science, 237:262-267.

Cuff, W. R. and Hardman, J. M. (1980) A development of the Leslie matrix formulation for restructuring and extending an ecosystem model: the infestation of stored wheat by *Sitophilus oryzae*. Ecol. Modelling, 9:281-305.

Denne, T. (1988) *An expert system for stored grain pest management.* Unpublished Ph.D. thesis. University of London, U. K.

Desmarchelier, J. M., Bengston, M., Evans, D. E., Heather, N. W., and White, G. G. (1979) Combining temperature and moisture manipulation with the use of grain protectants. In "Australian Contributions to the Symposium on the Protection of Grain Against Insect Damage During Storage, Moscow, 1978" (Ed. D. E. Evans), pp 61-73, CSIRO Division of Entomology, Canberra, Australia.

Hagstrum, D. W. and Throne, J. E. (1989) Predictability of Stored-Wheat Insect Population Trends from Life History Traits. Environ. Entomol. 18:660-664.

Hall, C. A. S. (1988) An assessment of several of the historically most influential theoretical models used in ecology and of the data provided in their support. Ecol. Modelling, 43:5-31.

Hardman, J. M. (1978) A logistic model simulating environmental changes associated with the growth of populations of rice weevils, *Sitophilus oryzae*, reared in small cells of wheat. J. Appl. Ecol., 15:65-87.

Heong, K. L. (1990) Computer expert systems for improving insect pest management. Rev. Agricultural Entomology, 78, 1-11.

Jeffers, J. N. R. (1978) *An Introduction to Systems Analysis: with ecological applications.* London: Edward Arnold. 198pp.

Kawamoto, H., Woods, S. M., Sinha, R. N., and Muir, W. E. (1989) A simulation model of population dynamics of the rusty grain beetle, *Cryptolestes ferrugineus* in stored wheat. Ecol. Modelling, 48:137-157.

Landahl, D. H. (1955) A mathematical model for the temporal pattern of a population structure, with particular reference to the flour beetle. Bull. Math. Biophys., 17:63-77.

Leslie, P. H. (1958) A stochastic model for studying the properties of certain biological systems by numerical methods. Biometrika, 45: 16-31.

Leslie, P. H. (1962) A stochastic model for two competing species of *Tribolium* and its application to some experimental data. Biometrika, 49:1-25.

Levins, R. (1966) The strategy of model building in population biology. American Scientist, 54:421-431

Lewontin, R. C. (1960) Models, mathematics and metaphors. Synthese, 15:222-244

Logan, J. A. (1988) Toward an expert system for development of pest simulation models. Environ. Entomol., 17:359-376.

Longstaff, B. C. (1981a) The manipulation of the population growth rate of a pest species: an analytical approach. J. Appl. Ecol., 18:727-736.

Longstaff, B. C. (1981b) Density-dependent fecundity in *Sitophilus oryzae* (L.) (Coleoptera:Curculionidae). J. Stored Prod. Res., 17:73-76.

Longstaff, B. C. (1987) Environmental manipulation as a physiological control measure. Proc. 4th Int. Working Conf. Stored Product Protection, Tel Aviv, Israel, Sept. 1986. (Eds. E. Donahaye and S. Navarro) pp47-61.

Longstaff, B. C. (1988a) A modelling study of the effects of temperature manipulation upon the control of *Sitophilus oryzae* (Coleoptera:Curculionidae) by insecticide. J. Appl. Ecol., 25:163-175.

Longstaff, B. C. (1988b) Temperature manipulation and the management of insecticide resistance in stored grain pests: a simulation study for the rice weevil, *Sitophilus oryzae*. Ecol. Modelling, 43:303-313.
Longstaff, B. C. and Cuff, W. R.(1984) An ecosystem model of the infestation of stored wheat by *Sitophilus oryzae:* a reappraisal. Ecol. Modelling, 25:97-119.
Longstaff, B. C. and Evans, D. E. (1983) The demography of the rice weevil, *Sitophilus oryzae* (L.) (Coleoptera: Curculionidae) : submodels of adult survival and fecundity. Bull. Entomol. Res., 73:333-344.
May, R. M. and Dobson, A. P. (1986) Population dynamics and the rate of evolution of pesticide resistance. In: "Pesticide Resistance: Strategies and Tactics for Management". National Academic Press, Washington, DC., pp170-193.
Mertz, D. B. (1972) The *Tribolium* model and the mathematics of population growth. Ann. Rev. Ecol. and Syst., 3:51-78
Muggleton, J. (1986) Selection for malathion resistance in *Oryzaephilus surinamensis* (L.) (Coleoptera:Silvanidae): fitness values of resistant and susceptible phenotypes and their inclusion in a general model describing the spread of resistance. Bull. ent. Res., 76:469-480.
Niven, B. S. (1967) The stochastic simulation of *Tribolium* populations. Physiol. Zool., 40:67-82
Norton, G. A. (1987) Developments in expert systems for pest management at Imperial College, U. K. Review of Marketing and Agricultural Economics, 55:167-170.
Nuttall, R. M. (1989) Simulated population dynamics of a stored-products' pest (*Ptinus tectus* , Coleoptera). Ecol. Modelling, 48:291-313.
Onstad, D. W. (1988) Population-dynamics theory: the roles of analytical, simulation, and supercomputer models. Ecol. Modelling, 43: 111-124.
Rosenblueth, A. and Wiener, N. (1945) The Role of Models in Science. Philosophy of Science, 12:316-321.
Sinclair, E. R. and Alder, J. (1985) Development of a computer simulation model of stored product insect populations on grain farms. Agricultural Systems 18:95-113.
Singh, N. B., Campbell, A., and Sinha, R. N. (1976) An energy budget of *Sitophilus oryzae* (Coleoptera: Curculionidae). Ann. Entomol. Soc. Am., 69:503-512.
Smith, R. H. and Lessells, C. M. (1986) Oviposition, ovicide and larval competition in granivorous insects. In: "Ecological consequences of Adaptive Behaviour: The 25th Symposium of the British Ecological Society, Reading, 1985", (Eds. R. H. Smith and R. M. Sibly) pp 423-448.
Stanley, J. (1932) A mathematical theory of the growth of populations of the flour beetle, *Tribolium confusum*, Duv. Can. J. Res., 6:632-671.
Taylor, C. E. and Georghiou, G. P. (1982) Influence of pesticide persistence in the evolution of resistance. Environ. Entomol., 11: 746-750.
Taylor, N. W. (1967) A mathematical model for *Tribolium confusum* populations. Ecology, 48:290-294.
Thorpe, G. R., Cuff, W. R., and Longstaff, B. C. (1982) Control of *Sitophilus oryzae* infestation of stored wheat: an ecosystem model of the use of aeration. Ecol. Modelling, 15:331-351.
White, G. G., Mayer, D. G., and Chant, D. C. (in press) Survival Resulting from Uneven Application and its Consequences for Resistance: a General Model Applied to Stored Grain Pests. J. Econ. Entomol.

LE ROLE DE LA MODELISATION DANS LA GESTION DES RAVAGEURS DES PRODUITS STOCKES

B.C. LONGSTAFF

SCIRO Division of Entomology
GPO Box 1700, Canberra
ACT 2601, Australia

Résumé

Le terme de "modélisation" évoque des concepts différents chez différentes personnes. Cet exposé cherche à survoler son processus : la connaissance cachée derrière la modélisation, les différents types d'approches disponibles et les situations dont elle relève et auxquelles elle s'applique, comme la gestion des écosystèmes de stockage. Les deux formes traditionnelles de modélisation mathématiques, théorie et simulation, sont des outils de valeur dans la conception des stratégies et des tactiques à appliquer aux problèmes à résoudre, bien que les bénéfices qu'on en retire soient plutôt différents. Une forme relativement nouvelle de modélisation, développée dans le secteur de l'intelligence artificielle, est celle du "système expert". Cette approche cherche à combiner l'information dérivant des méthodes expérimentales plus traditionnelles avec celles dérivant de l'expérience, et délivre une prévision ou une décision sous forme verbale qui peut être interprétée par des non-experts. Les bénéfices et les inconvénients de ces diverses approches sont discutés.