The Australian Journal of
Agricultural and
Resource Economics

Journal of the Australian Agricultural and Resource Economics Society

The Australian Journal of Agricultural and Resource Economics, 57, pp. 79–103

A process for the development and application of simulation models in applied economics

Graeme J. Doole and David J. Pannell†

Simulation models are widely used in applied economics to improve understanding of how a system could behave under different conditions. However, the potential degree to which such models can influence decision making depends on their ability to provide an adequate description of the important elements of a given problem. A systematic and robust procedure for the development and application of such models in agricultural, ecological, environmental and natural resource economics is presented. This process is based on the authors' experience across a broad range of model types and applications and extensive literature review. The practical impact of simulation models is argued to be greater where stakeholders and technical experts are consulted extensively throughout the modelling process.

Key words: modelling, sensitivity analysis, stakeholders, validation.

1. Introduction

A model is an abstract representation of a system that allows a person to improve their understanding of it through logical reasoning. Models serve multiple roles in applied economics – understood here to be the broad fields of agricultural, environmental and natural resource economics. They can be useful for education, highlighting primary components and interactions and identifying the impact of perturbations or interventions. Common uses in applied economics are the assessment of innovative technology or practices (e.g. Weersink *et al*. 2005) and the evaluation of alternative management policies (e.g. Grafton *et al*. 2009). Moreover, models may help to motivate data collection and the review of its quantity and quality (Jakeman *et al*. 2006). They may also be the focal point for improved communication between scientific disciplines or between the scientific community and wider society (Pannell 1996).

Economists employ a broad range of model types. This article focuses on the development of models that describe an economic system using numeri-

† Graeme J. Doole (email: gdoole@waikato.ac.nz) is at the Centre for Environmental Economics and Policy, School of Agricultural and Resource Economics, Faculty of Natural and Agricultural Sciences, University of Western Australia, 35 Stirling Highway, Crawley, Western Australia 6009, Australia and at the Department of Economics, Waikato Management School, University of Waikato, Private Bag 3105, Hamilton, New Zealand. David J. Pannell is at the Centre for Environmental Economics and Policy, School of Agricultural and Resource Economics, Faculty of Natural and Agricultural Sciences, University of Western Australia, 35 Stirling Highway, Crawley, Western Australia 6009, Australia.

doi: 10.1111/j.1467-8489.2012.00607.x

cal equations and allow its behaviour to be explored under a range of conditions. For the purposes of this study, these are broadly termed 'simulation models', with this classification including those models in which optimisation procedures are used to identify solutions to improve management (e.g. Woodward *et al.* 2005). Simulation models are broadly used by economists, particularly those in applied fields, to develop insight into sometimes-complex problems.

Despite the central role of models in economics, important factors that must be considered during their development and use are rarely discussed, either in the academic literature or in university courses. Popular text books in mathematical economics, such as Klein (2002) and Chiang and Wainwright (2005), introduce models as tools for logical inference, but do not discuss practical aspects of implementation. To some degree, this reflects the modern emphasis of academic economics on formal algebraic modelling and methodological novelty, rather than practical relevance (Malcolm 1990; Sassower 2010).

Previous work has highlighted a number of general concepts important to the construction of simulation models in economics. The importance of modelling as a craft that is developed through broad experience across different problems has been recognised previously (Lave and March 1993). Moreover, the inclusion of people in the modelling process who will be affected by decisions informed by the model is well documented. Stakeholders can gain a greater understanding of the ways that a given problem can be resolved when they are involved in the model-building process (Vennix 1996; Woodward *et al.* 2008; McCown *et al.* 2009). This is an extension of participatory research – where client interaction is used to guide the development and delivery of material more suited to their individual situations (Chambers and Ghildyal 1985; Farrington and Martin 1988; Norman *et al.* 1995). Failing to involve stakeholders in modelling exercises can substantially lower the relevance of these exercises (McCown *et al.* 2006, 2009). However, it is important to evaluate participatory modelling exercises (Jones *et al.* 2009), especially as they are commonly expensive and may have limited impact on decision makers outside of the group involved (Sinclair and Seligman 1996; Martin and Sherington 1997). The importance of participatory modelling and the iterative nature of the modelling process is further highlighted by Jakeman *et al.* (2006), who provided guidance in the context of the application of hydrological models. Various studies in operations research have also stressed the importance of interaction with system experts (Murphy 2005a), problem structuring (Rosenhead and Mingers 2001), conceptual models (Cedric 1994) and model validation (Olphert and Wilson 2004). Nevertheless, it appears that no general procedure has been developed for the development and application of models in applied economics.

The goal of this article is to discuss practical aspects of model implementation through the presentation of a rigourous, yet flexible, framework for the development and application of simulation models in applied economics.

Lessons from the diverse literature that focuses on effective model building in other disciplines is combined with the authors' collective experience in applied economic modelling across a wide range of model types and applications to develop an integrated framework developed specifically for this discipline. The procedure seeks to provide guidelines for the development and application of economic models from which output can be used to directly inform decision makers. The framework is intended to be valuable for both emerging and established modellers as a benchmark for current practice and a list of ideas for future practice.

2. A procedure for the development and application of models

A procedure for the development of economic models can take many forms. A general process for modelling to inform practical decision making is presented in Figure 1. This must be adapted to each unique situation, although the primary steps will generally remain pertinent. Experience with the process also helps an analyst gain a better understanding of the relationship between each constituent part. Implementation of strategies based on the recommendations of a modelling study, and subsequent review of the modelling process can be included (Winston 1994; Ormerod 1996). These stages are important, but are ignored here to focus on modelling in recognition that not all models may lead directly to system intervention.

The process presented in Figure 1 is intended to meet two overarching, and somewhat related, requirements: validation and input from system experts. A system expert is understood to be an individual who possesses a valuable

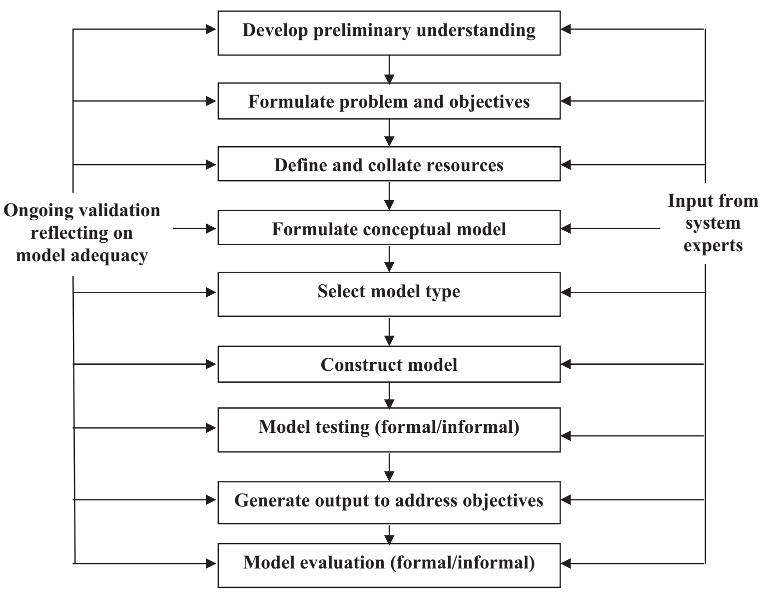

Figure 1 A process for the construction of simulation models in applied economics.

level of knowledge regarding the system being studied. In the context of agricultural applications, this group could include producers, extension officers and biophysical scientists.

Validation determines whether a model includes a sufficiently precise description of the system to provide useful insights (Miser and Quade 1988). Validation occurs throughout the entire modelling process shown in Figure 1, as practitioners are frequently encouraged to reflect on the adequacy of a model. Interaction with system experts is important during model verification and validation to aid the identification of whether the model is providing an accurate description of the system under study. Verification is the process of establishing that the model performs as intended, particularly through debugging, while validation is the determination of whether a model adequately reproduces reported behaviour. This guides revision of the model or the way it is applied; thus, each step in the process may be visited a number of times, and one step may start before the preceding stage is completed (Ackoff 1979). Nonetheless, formal/informal model testing is also an explicit step in Figure 1, as this is antecedent to conducting any analysis with the model, given the overarching goal to provide a reasonable representation of the system under study.

Brody *et al.* (1994) outline that the scientific method, as applied in the context of modelling, is characterised by statement of the research problem, evaluation of information, identification of expected responses, model development, model validation, and use of results to guide decisions. Many authors state that the implementation of a robust modelling study should be broadly based on this approach (e.g. Hillier and Lieberman 2004; Jakeman *et al.* 2006). Simulation models can be used to integrate the best available knowledge that exists about a given system and consider it to inform judgements and decisions. If such models are to provide information that is relevant to decision makers, a broader interpretation of the scientific method is required; one that involves people within all stages of the modelling process (Figure 1). This is necessary as economic systems are generally complex and characterised by a high degree of uncertainty. Moreover, economic decision processes can be complex, often involving multiple people, information sources and objectives.

Amongst the numerous people who are potentially relevant to include in a modelling investigation are:

1. Decision maker(s): those who will base decisions, at least partly, on model output. Ideally, this group would initiate the modelling study and determine its orientation.
2. Stakeholders: those who will potentially be affected by judgments formulated by the decision makers.
3. Technical experts: those who will provide information during the modelling process. These people may have expertise regarding individual components of a system, the entire system or a similar system.

4. Analysts: those who carry out the modelling exercise.

The size and composition of each group are different for each problem. One person may constitute all groups in a narrow application, while there may be multiple stakeholders with conflicting interests in another. Moreover, some decisions may affect future generations (e.g. those decisions concerning fishery management), while some may benefit or harm decision makers themselves (e.g. improved resource allocation on a farm). Moreover, some groups (e.g. technical experts) could be consulted at each stage of the modelling process, while others (e.g. stakeholders) may be consulted only at key occasions. Overall, we emphasise the importance of interdisciplinary modelling informed by broad communication with stakeholders. Broad communication is understood to involve communication with a number of people across a broad range of groups involved in a given problem context.

Broad communication with stakeholders has a number of potential benefits:

1. Improved understanding of the objectives of the different parties involved.
2. Stakeholders become more aware of their involvement in a given problem context.
3. Promoting an increased understanding of system behaviour through social learning[1] (Nicolson *et al*. 2002).
4. More appropriate information concerning input values and model structure. For example, farmers and consultants can guide the formulation of relevant price and cost estimates. Moreover, farmers may highlight those options which are not worth considering, for example, due to cost, thus informing model structure.
5. Better information for all parties regarding potential barriers to implementation, given the promotion of discussion between the different groups involved.

However, a number of practical reasons apart from cost can restrict the benefits associated with broad communication:

1. Some parties, especially the general public, may lack the appropriate skills and knowledge to provide appropriate input (Korfmacher 2001).
2. Poor quality engagement can reduce the value of a modelling application.
3. Animosity between parties, perhaps due to historical conflict, can limit cooperation and hamper progress (Coenen 2009).
4. It is difficult to involve a sample of the affected public during a modelling exercise that is truly representative of the community (Koehler and Koontz 2008).
5. Engagement with public can involve the implicit involvement of value judgements, complicating the interpretation of objective data (Korfmacher 2001).

[1] Social learning is a process whereby groups acquire knowledge through social interaction in the context of model application (Miller 2010).

Overall, these factors highlight that while it is important to involve stakeholders in modelling exercises (Reed 2008), it is important to ensure that balancing the marginal benefits and costs of this interaction are considered throughout the modelling process.

Key strategies can be employed to restrict or overcome the potential limitations listed previously. Point #1 can be mitigated through careful selection of participants, methodical project structuring to ensure that stakeholders only provide input they are qualified to present and stakeholder training. Point #2 can be ameliorated through strong investment in participatory modelling and use of established principles to maximise its effectiveness. Point #3 also requires careful management to enhance, and not diminish, decision quality through the consideration of opposing views. Vennix (1996) provided strong guidelines for effective group management in the context of poor engagement (Point #2) and conflict (Point #3). Maintaining a representative sample of the population (Point #4) can be promoted through careful selection of participants, allocation of funding to stakeholders involved in the project and the investment of effort in establishing relationships with relevant community groups. Korfmacher (2001) also highlighted the importance of widespread education, frequent feedback and promoting the need for input to involve lesser groups. Point #5 may be partly mitigated through careful consideration of the views of each party involved in the modelling process.

Group facilitation involves one person or multiple people diagnosing problems in the functioning of the group and implementing intervention strategies to more effectively promote decision making (Schwarz 2002). Effective facilitation can maximise the net benefits of stakeholder involvement. Thus, the development and application of these skills by analysts are recommended (Ormerod 1996). Greater personal awareness and emotional intelligence – the general ability to perceive, understand and manage emotions in ourselves and others (Goleman 1996) – is at the core of maximising the benefits of personal relationships and hence is highly relevant (Murphy 2005a). Many projects will benefit from having specialist facilitators, but even modellers who are weak in this area can build strength in it. The main methods available for developing such skills are reading suitable literature, speaking to effective facilitators, practice and evaluation of practice. Key texts that explore these practices further are those of Vennix (1996) and Vanclay *et al.* (2006).

Roberts *et al.* (2012) described an example of how broad stakeholder participation maximised the value of a modelling study aimed at assessing different policy approaches for reducing phosphorus (P) enrichment of the Gippsland Lakes (Victoria, Australia). The process of engagement involved:

1. Close partnership with the Gippsland Lakes Task Force (GLTF), the major investment decision-making group for the Gippsland Lakes.

2. Close partnership with a trusted consultant with previous experience in related research and strong networks.
3. Inception workshop of key stakeholders to decide on scope of analysis, baseline scenario and suggested scenarios for analysis.
4. Workshop of technical experts to identify previous research, gauge the utility of previous research, identify major knowledge gaps and identify currently recommended management practices (CRMPs) for reducing P emissions.
5. Workshop of local extension staff to identify likely adoption of different CRMPs under different incentive structures.
6. Workshop with individual technical experts and extension staff to identify cost and effectiveness of CRMPs.
7. Review of CRMP assumptions by technical experts and extension staff.
8. Ongoing discussions with GLTF regarding major decisions and concerns.
9. Presentation of interim progress report to GLTF. Additional scenarios for modelling are generated based on discussion.
10. Visual presentation to GLTF to foster engagement and discussion.
11. External review of assumptions used to underpin the analysis.

This application is indicative of how ongoing engagement with technical experts and stakeholders can aid the development of a modelling process from which output can be used to directly inform decision makers.

3. Components of the modelling process

This section provides more information regarding each step in the modelling process specified in Figure 1. Key points are illustrated through the presentation of information from a variety of modelling studies to which the authors have contributed. It is necessary to employ examples from a number of applications, as the extent to which each study is representative differs.

3.1. Develop preliminary understanding of system and stakeholders

Motivation to begin a modelling study may begin from personal interest or through a request by others. In any case, to be relevant, the analysis requires an in-depth understanding of the system under study. This is a key goal of the modelling process overall, but some preliminary knowledge is necessary to provide context to problem and objective formulation (Formulation of problem and objectives) and guide the development or selection of appropriate conceptual and simulation models. This step can involve literature review, participation in the system or personal discussions – preferably with people with different viewpoints of the system under study. It may even be beneficial to use established social research techniques – such as strategic options development and analysis (Eden 1989) or soft systems methodology

(Checkland and Scholes 1990) – to gain a greater appreciation of problem context (Ormerod 1996).

Literature review helps to assess how previous analysts have studied the system or similar systems and summarise their key insights. It is especially pertinent in economic systems that interface with natural systems, as scientific principles not familiar to the modeller are often relevant. Participation promotes a greater depth of understanding through experiential learning (Murphy 2005a; Merriam *et al.* 2007). If the opportunity for participation is unavailable – perhaps due to time constraints or the scale of systems – then it is imperative to interact with people that have a good understanding of the system and its individual elements. One example was that an enduring relationship with the Pastures Group at the Department of Agriculture and Food Western Australia (DAFWA) promoted the relevance of a detailed assessment of the profitability of pasture sequences in Western Australia (Doole *et al.* 2009; Doole and Revell 2010). This is inherently difficult, given the multiple pressures on most researchers. However, it can be promoted through alignment with supportive staff, careful diplomacy, clear communication, exploitation of networks, reciprocal aid, strategic selection of interdisciplinary teams and investment of time in understanding the general objectives of the relevant staff, who are sometimes located across different research institutions possessing different goals (e.g. financial return versus industry-good considerations).

3.2. Formulation of problem and objectives

Problem definition is a critical part of a modelling investigation. It increases awareness of the key focus of the analysis and its scope. Formulation of a problem statement and a problem structure allows an analyst to appreciate the different facets of the problem. Problem structure requires identification of (i) the decision maker(s), (ii) their objectives, (iii) their decision criteria, (iv) their decision variables, (v) the relationship between decisions and outcomes, (vi) constraints on decisions, (vii) who benefits from decisions and (viii) who are negatively affected by decisions. It is important to recognise the important relationship between decisions and outcomes in Step #v to reflect on the logic of the proposed intervention. System complexity and risk/uncertainty may have a significant impact on this association. However, a distinct benefit of simulation modelling is that these links can be explored, particularly through sensitivity analysis (Generate model output to address objectives).

Doole *et al.* (2012) presented a formal evaluation of diverse policy instruments targeted at reducing nonpoint emissions into the Waikato River of New Zealand. This work involved the application of a large catchment model linking together 332 individual farm models. A problem statement and problem structure for this application are presented in Table 1. These were constructed based on discussions with the local environmental regulator, Environment Waikato. Formulation of such a table is beneficial, as it requires an analyst to make the different components of the problem explicit. This promotes reflection by the analyst and perhaps others. The relationships between the interdependent components that determine the implications of changes in management for the outcomes of interest (profit and pollution in the example illustrated) are often complex. Thus, as stated in this example, it can be useful to summarise some links between decisions and outcomes in a list or a figure.

Some problems may be so complicated that a structured problem definition cannot be formulated (Ackoff 1973). These 'wicked problems' (Churchman 1967) typically involve a high level of physical and social complexity (Jackson 2000). Physical complexity is characterised by a high number of interdependent parts in a dynamic system containing multiple indeterminacies and uncertainties. In contrast, social complexity is characterised by diverse, and often conflicting, values and objectives. Such complex problems complicate the application of models, as defined

Table 1 Problem statement and problem structure derived for the modelling study concerning the regulation of dairy farms to improve water quality in the Waikato River, New Zealand

Element of problem	Characteristic of problem
Problem statement	The environmental regulator is uncertain of the costs to dairy farmers associated with different policies targeted at reducing nitrate leaching from dairy farms in the Waikato region of New Zealand
Problem structure	
Decision maker(s)	Environmental regulator (Waikato Regional Council)
Objective(s) of decision makers	Identify ways to reduce the cost of environmental regulation
Decision criterion of decision makers	Meeting environmental constraints at lowest cost is the main policy goal
Decision variables	Manipulate production through changes in stocking rate, fertiliser application and use of supplementary feed Adopt discrete mitigation strategies, such as improved effluent management, nitrification inhibitors and use of stand-off pads
Relationship between decisions and outcomes	Dairy farms are complex systems containing many components that could be affected (e.g. see Figure 2) Broad farm heterogeneity exists Farm emissions are difficult to observe
Constraints on decisions	Confidence in process used to identify cost-effectiveness of alternative instruments
Who benefits	Environmental regulator gains knowledge regarding least-cost regulation Regional cost of regulation is reduced
Who suffers	Meaningful policies will likely impact income distribution

in this article, as the formulation of concise and tractable frameworks is not straightforward.

A potential strategy in this situation is the application of problem-structuring methods (Rosenhead and Mingers 2001), in which facilitation is used to gain an understanding of stakeholder values, identify a common understanding of the problem and approach an incomplete resolution based on partial consensus (Mingers and Rosenhead 2004). Problem-structuring methods may provide enough indication of problem structure to define scope for the application of models. Indeed, models will often be valuable tools in complex problems, primarily to help stakeholders gain greater understanding of the system, the consequences of their actions and potential impacts of different interventions (Vennix 1996; Voinov and Bousquet 2010). However, models can only provide appropriate input into decision making if they represent the true complexity of a given problem (Ackoff 1979).

A structured problem definition allows the statement of concise objectives that state the proposed, practical outcomes that the modelling study seeks to achieve. Objectives should also be specific, measurable, achievable, relevant and time-bound (SMART). This ensures that:

1. The scale and scope of the project is defined.
2. The precision of model output is explicitly outlined.
3. The intended outcomes of the analysis can be rigourously stated such that the degree to which these are achieved can be ascertained.
4. Objectives are directly focused at the alleviation of the issue defined by the problem statement.
5. The project plan is feasible in terms of methods and time.

Thus, overall, the list of objectives provides an opportunity to identify whether the modelling project will provide adequate information to the decision maker in the context of a given problem.

The following objectives flow from the problem characteristics listed for a sample application in Table 1:

1. Construct a bioeconomic model of the dairy farms in the Upper Waikato catchment of the Waikato River, New Zealand, within 12 months from project initiation.
2. Evaluate the cost (dollars per ha) associated with alternative nitrate-leaching targets and different proposed methods of achieving these targets using the bioeconomic model. The proposed policies are listed in Table 2.
3. Compare and contrast the impact of this set of policy instruments on the income distribution of farmers in the study region.

The definition of the problem statement, problem structure and objectives reveals the boundaries of the system, as recognised by the modelling team. These boundaries are often subject to conjecture among people as they reflect different perceptions of the problem and the system itself. Thus, identification of the problem statement, problem structure and objectives is often an

Table 2 Details of policy instruments evaluated in the sample application

Policy	Description
1. Uniform cap on stocking rates	Every dairy farm in the catchment must limit stocking rates to a specified level
2. Ban nitrogen fertiliser, 1 Mar–31 July	Dairy farms are prohibited from applying N fertiliser between 1 March and 31 July
3. Ban nitrogen fertiliser application	Dairy farms are prohibited from applying N fertiliser at any time
4. Uniform cap on nitrogen emissions	Every dairy farm in the catchment must limit average N emissions to 22, 26 or 30 kg N ha^{-1} or less
5. Cap on nitrogen emissions, trading allowed	Total N emissions across the catchment equal 22, 26 or 30 kg N ha^{-1}, but abatement varies over farms depending on farm characteristics
6. Replace dairy with sheep and beef farms	Specific farms are selected for conversion out of dairying to achieve emission targets at least cost

Source: Doole *et al*. (2012).

iterative process involving the modelling team and other parties. Moreover, these features may change over the course of an analysis as more is learnt of the characteristics of a problem. These can be revisited at the completion of a modelling project to ascertain how they have evolved and how this can inform future, perhaps related, research. Indeed, review and reflection as a part of structured learning and adaptation are key characteristics of expert modellers (Murphy 2005b).

3.3. Define and collate resources

The ultimate formulation of the simulation model – including its type, size, structure and parameterisation – is influenced greatly by the quantity and quality of available resources. The modelling process is itself a constrained optimisation problem, in which the analyst seeks to provide knowledge at the required resolution, subject to constraints of available data, expertise, funding, software and time. The demand and supply of these scarce resources are interdependent, and efficient allocation requires continued consideration of such factors as the time required to correctly develop, validate and apply simulation models – especially those of a type that an analyst has not used previously – and the cost of external expertise, required software, and collecting and maintaining data. Many analysts apply methods that they are familiar with, as this reduces the need for additional resources, such as training and new software. Nevertheless, the adopted technique should be consistent with the objectives of the analysis to maximise the value of the study.

Data collection is a primary component of many modelling studies and can exhaust more than half of the time available for an analysis. Compilation, analysis and evaluation of existing data are undertaken to provide suitable input values and provide for satisfactory model validation. Interaction with system experts is a key opportunity to review the quality of these data. Indeed, interaction with biophysical scientists at DAFWA was critical to the estimation of growth dynamics for a new plant species, *Bituminaria bituminosa*, in the study of Doole (2012). The goal is to ensure, as far as is possible, that data are accurate, appropriate, complete, sufficient and unbiased (Landry *et al*. 1983). More information about the impact of input assumptions on model results is gained during sensitivity analysis (Generate model output to address objectives).

The complexity of a model should be largely guided by the processes that are being modelled and the precision of the model outputs that are required. Rapid improvements in theory and computational power have allowed simulation models to grow larger and more complex (Chwif *et al*. 2000; Doole 2010). However, the scarcity of high-quality information can restrict the marginal value of such additional sophistication, as extensions may be reliant on weak data (Doole and Pannell 2008).

3.4. Formulation of conceptual model

Formulating a concise description of the structure or framework of the simulation model prior to its construction provides some *a priori* insight into whether the simulation model will:

1. adequately address the objectives of the analysis,
2. be completed subject to any expected resource constraints (Define and collate resources), and
3. possess any potential limitations that may need to be addressed.

The first point reflects the crucial need to make a strong connection between the problem and the structure of the model. It provides another opportunity to ensure these two factors are consistent with one another. The second and third points motivate reflection on the suitability of the model, especially in the context of available resources.

Formulation of the conceptual model requires analysts to make explicit preliminary descriptions of:

1. the problem boundary (i.e. which system factors are included/excluded),
2. the main components of the problem,
3. the characteristics of those components,
4. relationships between components,
5. how components will be represented in the simulation model,
6. the resolution with which each component will be described,
7. the nature of inputs,
8. the nature of outputs,
9. key data sources, and
10. key assumptions.

The characteristics of the simulation model must be strongly related to the problem definition if output is to provide useful insights for decision makers. The conceptual model plays a central role through providing a preliminary, and preferably clear and accessible, description of its structure. This allows analysts to reflect on whether a model will meet the objectives of the study, which flow from the problem definition (Develop preliminary understanding of system and stakeholders). Furthermore, abstraction can allow people to recognise the dependence of the model on several important parts – promoting the parallel development of these individual components – or to recognise the need to refine elements of the conceptual model that are more coarsely described (Cedric 1994). This is necessary as it is often difficult to discern the relative importance of model components when a study is initiated (Nicolson *et al.* 2002). Refinement of the conceptual model will typically continue alongside the process of identifying and collating available resources, such as data and relevant software. However, a conceptual model can also guide the acquisition of resources (e.g. computer hardware and software, data needs, training).

A conceptual model can take many forms, but diagrams are often useful. Available diagrammatic tools are activity cycles, bond graphs, block diagrams, digraphs, event graphs, influence diagrams, object models, petri nets, process flow diagrams and simulation activity diagrams (Sterman 2000; Jakeman *et al.* 2006; Robinson 2008). Although a broad range of tools are available, simple block diagrams are often helpful, as they are straightforward to learn and generate, can be easily interpreted by others and are simple to expand or decompose as the degree of system complexity represented in the model changes.

Figure 2 is an example of such a block diagram, in which the blocks represent principal components and lines represent relationships between these components. Figure 2 presents a conceptual model of a dairy-farming system. This was utilised to construct a farm-level model for the evaluation of optimal producer responses to different nitrate-leaching targets in Doole and Parangahawewa (2011). The conceptual model provides very broad detail for improved clarity. However, more detailed conceptual models are typically described, especially as a greater understanding of different components develops. The complexity of the problem, which motivates the use of a modelling analysis, is evident in that multiple factors affect both profit and pollution and many components are interdependent.

A distinct benefit of block diagrams is their flexibility, as conceptual models are typically continually revised as a greater understanding of the problem is attained. Such revision is common as formulation of the problem structure, conceptual model and simulation model are strongly interlinked and should inform one another continually in an iterative sequence. Less-structured models, such as mind maps or rich pictures, may also be useful in complex systems (Checkland and Scholes 1990; Checkland and Poulter 2006), particularly those involving multiple stakeholder groups.

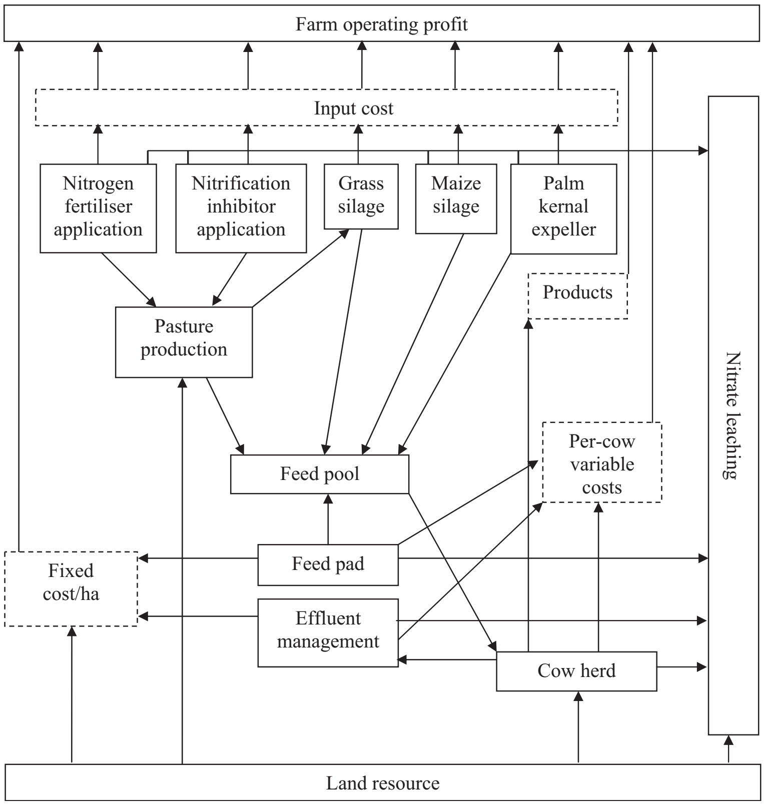

Figure 2 A conceptual framework outlining the structure of a model representing a New Zealand dairy farm. This framework uses a block diagram structure, in which principal components appear as blocks and lines indicate relationships. Variables that aggregate similar items before their inclusion in the profit function are shown in dashed boxes.

3.5. Select model type

An understanding of the strengths and limitations of a method in the context of a given problem ensures that the solution method is appropriate and that its limitations have been minimised through appropriate procedures. The suitability of a method is determined by its capacity to describe important features of the problem structure, the type of inputs available, the type of outputs required and proposed level of abstraction.

Model development and interpretation can also benefit from previous modelling efforts if close similarities between model types are identified at an early stage (Polya 1945; Ackoff 1956; Murphy 2005a). For example, the economic theory of fishery management is based on the interpretation of a fish population as a capital stock, which allows the application of financial theory to identify key results (Clark 2010). Moreover, the application of optimisation in the policy evaluation example discussed earlier exploits the close relationship between economic theory and mathematical programing, given that the latter computes the shadow prices of constrained resources in the process of solution (Chiang and Wainwright 2005).

3.6. Construct model

Model construction is a stage that is visited often in the modelling process. The development of a valid model that provides useful insights rests on the enhancement of model formulations in response to their capacity to describe observed behaviour (Model validation). Frequent iteration through the phases of model construction, validation and use are often required to achieve this. This is underpinned by a focus on the identification of the apparent limitations of a model and ways to improve its structure or inputs (Hillier and Lieberman 2004). However, a model is a simplification of reality; thus, trying to provide an exact description of the system of interest is flawed and should be resisted. Rather, one aims to achieve a balance between the marginal benefits and costs of including further detail and complexity in the model.

The gradual evolution of a model from a small, simple framework to a larger, more complex framework allows efficient identification of limitations of the model structure and its coding. Systematic and deliberate expansion of the model helps to identify apparent modelling errors. Indeed, rapid extension can delay model development considerably by complicating the identification of errors (Pannell *et al.* 1996). Optimisation can be useful here as optimal solutions are rapidly generated and can show errors in logic that were not apparent during model development (Audsley and Sandars 2009).

Another key benefit of systematic model development is that preliminary results provide a general indication of the nature of model output that will be obtained in the final version of the model. Results will change as the model becomes more sophisticated, but this preliminary information allows tactical decisions to be made regarding the sufficiency of model type, structure and inputs. Early results may motivate the use of another method, thus reducing the investment of resources in a flawed system description. Alternatively, they may reveal a simpler model specification to be sufficient.

Large models can also benefit from the simultaneous, independent development and validation of separate components (validation is covered in Model validation). Identification of such opportunities is a key benefit of conceptual modelling (Define and collate resources). It is more efficient to identify errors and limitations of each component in this disaggregated state than when the model is fully integrated. It also aids the allocation of labour in an interdisciplinary team, allowing modellers to focus more strongly on their area of specialisation. However, the overall focus of the modelling study should remain on the adequate description of the whole system, discouraging the tendency for scientists to remain confined within their disciplines.

Stepwise model development should continue until the model is at its smallest, meaningful size. Consistent with the principle of Ockham's Razor, models that require fewer parameters are often preferable to large models that are less transparent, provided both approaches provide the same degree of insight. Smaller models can require restrictive assumptions that severely reduce their practical relevance (Caswell 2001; Doole 2010). However, they are also typically more efficient to use as it is generally easier to obtain required data, and they are easier to plan, develop, review, verify, validate, use and interpret. They are also more easily integrated with other models, in part because they are more straightforward to document (Innis and Rexstad 1983). These facets are important as they promote the efficiency of model development and application. Smaller models may also be more attractive to decision makers because they can be more transparent. Large-scale models also require significant resources to maintain them. For example, Pannell (1996) suggested that half a year of a person's time is required to maintain for ongoing active use a model of reasonable size through verification, documenting, review and updating. Larger models can also become obsolete owing to a lack of funding or expertise, in which case a smaller model or model(s) may be preferable. Overall, the analyst should continually weigh the marginal benefits and costs of greater complexity together and recognise that increased sophistication can have diminishing, or even negative, marginal returns (Robinson 1994).

3.7. Model validation

Establishing the validity of a model is critical to maintain the relevance of a modelling exercise (Landry *et al*. 1983). There is no general consensus of what constitutes adequate model validation (McCarl 1984). Rather, the process of validation is specific to the context of an application and the purpose of model development (Olphert and Wilson 2004).

Three necessary, but not sufficient, conditions for effective model validation are (Naylor and Finger 1967):

1. Model structure to be consistent with the stylised facts of important system processes.
2. Input data to be consistent with expected or reported values.
3. Output to be consistent with expected or reported values for a range of scenarios.

Steps 1 and 2 are dealt with initially during the early stages of the modelling process. However, they are revisited in the cycle of model construction, validation and use as greater precision is sought. Some simplifying assumptions are required for a problem to be tractable within a modelling framework. These can be difficult to validate, so must be stated clearly to help people better appreciate the model's structure and limitations. Step 3 above concerns evaluating the capacity of the model to describe the system at a level of precision consistent with the objectives of the study (Balci 1994). Validation of model output is best established through simulation of historical scenarios and comparison against quantitative or qualitative data. Step 3 determines whether changes in model structure, input data or validation scenarios

(scenarios in which model output is tested against expected or reported outdcomes) are necessary. If no changes are required, then analysis begins (Generate model output to address objectives).

Validation exercises vary broadly in their level of completeness. As highlighted previously, the important components to consider are model structure, inputs and outputs. Key sources of validation information are unpublished/published literature (quantitative data) and peer review (qualitative data). Each combination of these components and types of information may be investigated with different levels of effort. Low levels of effort can correspond to informal discussions, while high levels of effort may be invested in statistical comparisons of the model's results against available data. Many simulation models used in economics are difficult to validate, particularly if they involve optimisation of large, complex systems. Indeed, output validation is extremely rare in this discipline. Thus, most effort is usually directed towards improving the consistency of model structure with economic theory and the quality of input assumptions. Nevertheless, output validation indicates a model's ability to adequately describe reality and thus is an important activity that practitioners should seek to practice, where possible.

Table 3 presents unpublished validation output that compares output from a detailed optimisation model of a New Zealand dairy farm model (the Integrated Dairy Enterprise Analysis (IDEA) model) and output from FARMAX – a system-level model that farmers and consultants use to guide production decisions on New Zealand dairy farms (Bryant *et al*. 2010). The FARMAX modelling is based on survey data obtained from farmers in the Waikato region, but provides an integrated set of data for comparison with output from the optimisation model (A. Adler, pers. comm.). There is a close symmetry between computed and reported outcomes in Table 3, with the maximum deviations being around 10–12 per cent. These results give

Table 3 Comparison of output from a detailed optimisation model of a New Zealand dairy farm (the IDEA model) and from FARMAX

Variable	Units	FARMAX	IDEA	Diff. (%)
Imported feed	% diet	10	10.38	3.8
Farm profit	$ ha^{-1}	1201	1235	2.8
Stocking rate	cows ha^{-1}	3.08	3.13	1.6
Milk production	kg MS cow^{-1}	333	342	2.7
Lactation length	Days	271	275	1.5
Grazed pasture eaten	t DM ha^{-1}	12.1	13.2	9
Grass silage eaten	t DM ha^{-1}	0.35	0.34	−2.9
Maize silage eaten	t DM ha^{-1}	0.37	0.41	10.8
Bought-in feed eaten	t DM ha^{-1}	1.46	1.63	11.6
N fertiliser applied	kg N ha^{-1}	105	118	12.4
Crop area	{type, % area}	{maize, 2.15}	{maize, 2.2}	2.3
Replacement rate	%	23	21.6	−6

Notes: MS denotes milksolids, DM denotes dry matter and N denotes nitrogen. IDEA, integrated dairy enterprise analysis.

increased confidence that the model provides a suitable description of important processes in this study region. However, if a model is calibrated to represent a given validation scenario too closely, then it may impair the ability of a model to adequately represent scenarios outside of those used for calibration. A practical strategy to prevent this is through cross-validation, where one set of data is used to calibrate the model and another is used for validation (Olphert and Wilson 2004).

Important output often exists for which little suitable information is available for comparison. One example is the temporal energy consumption of cows on dairy farms, which may be reported in experiments but have little relevance to commercial management. In such cases, qualitative review may be relied on to provide sound judgement regarding whether model output is broadly representative. Moreover, peer opinion can promote context-specific discussion of alternative formulations, subjective decisions made during the modelling process (e.g. regarding the functional form selected for a given relationship), the degree and management of uncertainty and what constitutes sufficient validation. Key peers to consult are technical experts with relevant experience and people who manage components of a system, the entire system or a similar system. People with modelling experience or who have worked with modellers previously are invaluable, as they may be more likely to have a good understanding of what is required. An example is that the authors have recently interacted with farm consultants and biophysical scientists throughout north–central Victoria to validate the suitability of estimated farm gross margins.

Evaluation of the model is enhanced through maintaining clear and concise documentation of model assumptions, logic, validation and output. It can be difficult to maintain motivation for maintaining clear documentation, but there are various benefits from doing so. Documenting the model in stages, rather than at completion, helps to make the task less onerous and promotes ongoing review. Documenting the model in both a text file and in the model code promotes evaluation and aids interpretation of the model by different analysts, particularly when the model has not been used for some time. A text file can contain extensive information regarding key assumptions, justifications and results (Risbey *et al.* 1996). In comparison, model code may just contain information regarding a description of data and their standard values. Model code is generally easier to understand if practitioners use longer names and descriptions, include comments on the nature and sources of data, include raw data as opposed to that which has been manipulated and format code to improve readability (McCarl *et al.* 2010).

3.8. Generate model output to address objectives

Evaluation of scenarios that address research objectives follows validation. The optimal allocation of effort between validation and analysis varies between studies given disparity in available resources (especially time), purpose and subjective judgement (Gass 1983). Time constraints often limit extensive validation; however, this activity does enhance the value of the analysis by increasing confidence in model outcomes.

Modellers should aim for presentation of the analysis scenarios that convey the key results of the research in a clear and concise fashion. Indeed, Murphy (2005b) identifies this as the key role of a simulation modeller. Key limitations to effective presentation are presenting overly complex figures and tables and/or too many of them. Decision makers should be presented with key output of the model achieved with standard assumptions (standard analysis) and assumptions that differ from standard values to a reasonable extent (sensitivity analysis). Sensitivity analysis has many uses, including improving a decision maker's understanding of the relationship between input and output values in the model, the implications of parametric and structural uncertainty, stability of the baseline strategy in response to parameter changes and how management could best respond to uncertainty (Pannell 1997). Overall, these factors help a decision maker develop a greater understanding of the system being studied.

Unstructured and simplistic approaches to sensitivity analysis often constrain its value. An example is the common, but misplaced, strategy of evaluating the impacts of arbitrary proportional perturbations to key parameters (e.g. plus and minus 20 per cent) rather than making changes that reflect the perceived distributions of individual parameters. A comprehensive approach to sensitivity analysis, suited to a broad range of applications, is outlined by Pannell (1997). This method considers the relative elasticity, correlations and expected distribution of input data.

Monjardino *et al.* (2010) applied the procedure for sensitivity analysis outlined by Pannell (1997) in an application exploring the value of forage shrubs for mixed farming systems in the Central Wheatbelt of Western Australia. Table 4 presents the subjective probabilities generated for a range of parameters in this study. These were drawn from a combination of literature review and expert opinion. Table 4 contains symmetric changes to all parameter

Table 4 Values of uncertain parameters used in the sensitivity analysis (model default values in boldface) and probability of occurrence for each parameter value

Parameters	Units	Minimum		Standard		Maximum	
		Value	Prob.	Value	Prob.	Value	Prob.
Biomass production	kg edible DM/plant	1	0.15	**2**	0.7	3	0.15
Nutritive value	MJ ME/kg edible DM	7	0.05	**8**	0.9	9	0.05
Wheat price	($/t)	100	0.2	**200**	0.6	300	0.2
Wool price	c/kg clean wool	520	0.2	**720**	0.6	920	0.2
Prime lamb price	$/kg	2	0.1	**3**	0.8	4	0.1
Carbon sequestration	t of CO_2-e/ha/yr	0	0.1	**5**	0.8	10	0.1

Notes: Output of sensitivity analysis is shown in Figure 3. DM denotes dry matter, and MJ ME denotes megajoules of metabolisable energy.
Source: Monjardino *et al.* (2010).

values, although the percentage deviation of each key parameter from its baseline varies. These symmetric changes are justified as they are not considered in isolation, but in a process of structured sensitivity analysis and because there is a distinct lack of information suggesting other formulations are more appropriate. To illustrate the application of these probabilities, Figure 3 shows cumulative distribution functions for the net benefits of the novel farming practice for farms that are made up of 7 or 15 per cent of poor soils. (This figure is generated based on an assumption that the uncertain parameters are distributed independently.) The cumulative distribution functions shown in Figure 3 present the probability that the net value of shrubs on the Western Australian farm is less than a given amount.

Most applications of sensitivity analysis do not present the implications of alternative specifications for describing system components. This can be restrictive as key output is often sensitive to reasonable changes in model structure. An example is illustrative. Economic evaluations of environmental management frequently incorporate a limited set of key mitigation practices. Figure 4 demonstrates the differences in estimated abatement cost from a modelling study in which farmers could reduce nitrate leaching through production decisions only (Scenario 1), as simulated by Ramilan *et al.* (2011), or through both production decisions and the adoption of discrete management practices (Scenario 2). The figure shows that failure to include all relevant decision options can result in substantial errors in the outputs. Another key factor is that the addition of stochastic processes will typically affect model output (e.g. Kingwell 1994; Shortle and Horan 2001). Accordingly, the inclusion of randomness in models can help identify the impact of risk on key model output. However, the relevance of including risk and risk aversion in economic models has been questioned (Pannell *et al.* 2000), as these facets complicate model formulation and use, but seldom provide added insight into

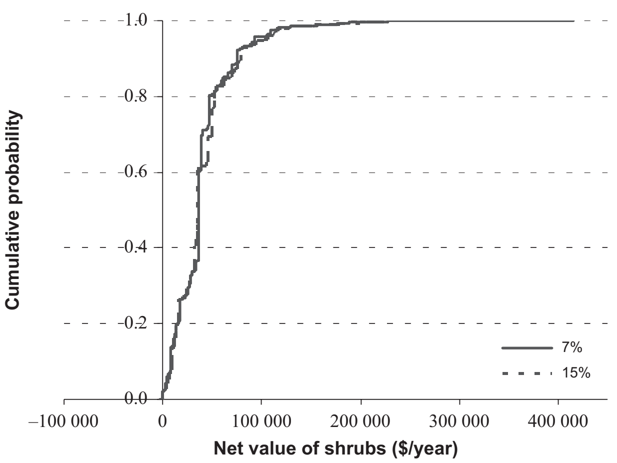

Figure 3 Cumulative distribution function for the profit gain achieved through inclusion of shrubs on a Western Australian mixed cropping farm with different proportions of poor soil (7 and 15 per cent). Source: Monjardino *et al.* (2010).

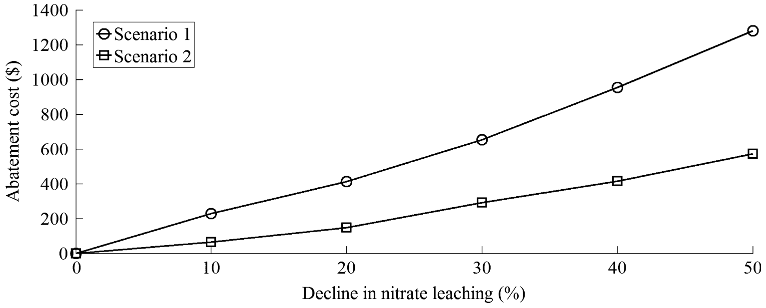

Figure 4 Abatement cost computed in a model of a New Zealand dairy production system when a producer can reduce nitrate leaching through production decisions only (Scenario 1) or through both production decisions and the adoption of currently recommended mitigation practices (Scenario 2).

significant value, especially given that tactical management in response to observed variation is often ignored.

Important insights that aid model interpretation may also arise from a review of previous work. Important sources in economics are smaller, analytical frameworks whose output can guide the application of simulation models. For example, Doole (2008) highlighted the importance of evaluating the relationship between herbicide resistance severity and the value of lucerne pasture in a small, conceptual model, which was subsequently explored further in a large, simulation model by Doole and Pannell (2008).

Input from technical experts and decision makers can also help to guide model application by outlining scenarios of interest and/or allowing several iterations of presentation and review of key output. This is evident in the application of Roberts *et al.* (2012) discussed in A procedure for the development and application of models.

3.9. Evaluation of modelling process

The goal of this stage is to establish whether the modelling study has satisfied the requirements outlined by decision makers. Evaluation may identify that the analysis is sufficient or that previous steps in the process need to be revisited. Strong evaluation potentially involves input from many of the parties involved in the modelling exercise (A procedure for the development and application of models). In particular, decision makers can discuss whether the recommendations are adequate, while technical experts can comment on the quality of the specific decisions made during the modelling process. Both approaches are evident in the application of Roberts *et al.* (2012) discussed in A procedure for the development and application of models. The presentation of results is facilitated if, as discussed in A procedure for the development and application of models, the decision maker has been involved throughout the preceding stages in the idealised modelling process, as this reduces the chance that model output strongly contrasts expectations.

4. Conclusions

A systematic procedure for the development and application of simulation models in applied economics is described to encourage reflection by practitioners on how they can improve their modelling practice. Explicit identification of these elements allows informal and formal evaluation of modelling practice, potentially improving the ability of future applications to better guide decision making.

References

Ackoff, R.L. (1956). The development of operations research as a science, *Operations Research* 4, 265–295.

Ackoff, R.L. (1973). Science in the systems age: beyond IE, OR, and MS, *Operations Research* 21, 661–671.

Ackoff, R.L. (1979). The future of OR is past, *Journal of the Operational Research Society* 30, 93–104.

Audsley, E. and Sandars, D.L. (2009). A review of the practice and achievements from 50 years of applying OR to agricultural systems in Britain, *OR Insight* 22, 2–18.

Balci, O. (1994). Validation, verification, and testing techniques through the life cycle of a simulation study, *Annals of Operations Research* 53, 121–173.

Brody, T.A., De La Pena, L. and Hodgson, P.E. (1994). *The Philosophy Behind Physics*. Springer Verlag, New York.

Bryant, J.R., Ogle, G., Marshall, P.R., Glassey, C.B., Lancaster, J.A.S., Garcia, S.C. and Holmes, C.W. (2010). Description and evaluation of the Farmax Dairy Pro decision support model, *New Zealand Journal of Agricultural Research* 53, 13–28.

Caswell, H. (2001). *Matrix Population Models*. Sinauer Associates, Sunderland.

Cedric, V. (1994). Heirarchical abilities of diagrammatic representations of discrete event simulation models, in Tew, J.D., Manivannan, S., Sadowski, D.A. and Seila, A.F. (eds), *Proceedings of the 1994 Winter Simulation Conference*. IEEE, Piscataway, pp. 589–594.

Chambers, R. and Ghildyal, B.P. (1985). Agricultural research for resource-poor farmers: the farmer-first-and-last model, *Agricultural Administration* 20, 1–30.

Checkland, P.B. and Poulter, J. (2006). *Learning for Action*. Wiley, Chichester.

Checkland, P.B. and Scholes, J. (1990). *Soft Systems Methodology in Action*. Wiley, Chichester.

Chiang, A.C. and Wainwright, K. (2005). *Fundamental Methods of Mathematical Economics*. McGraw Hill, Columbus.

Churchman, C.W. (1967). Wicked problems, *Management Science* 14, 141–142.

Chwif, L., Barretto, M.R.P. and Paul, R.J. (2000). On simulation model complexity, in Joines, J.A., Barton, R.R., Kang, K. and Fishwick, P.A. (eds), *Proceedings of the 2000 Winter Simulation Conference*. IEEE, Piscataway, pp. 449–455.

Clark, C.W. (2010). *Mathematical Bioeconomics*. Wiley, New Jersey.

Coenen, F.H. (2009). *Public Participation and Better Environmental Decisions*. Springer, New York.

Doole, G.J. (2008). Optimal management of annual ryegrass (*Lolium rigidum* Gaud.) in lucerne-wheat rotations in the Western Australian wheatbelt, *Australian Journal of Agricultural and Resource Economics* 52, 339–362.

Doole, G.J. (2010). Indirect instruments for nonpoint pollution control with multiple, dissimilar agents, *Journal of Agricultural Economics* 61, 680–696.

Doole, G.J. (2012). Evaluation of an agricultural innovation in the presence of severe parametric uncertainty: an application of robust counterpart optimisation, *Computers and Electronics in Agriculture* 84, 16–25.

Doole, G.J. and Pannell, D.J. (2008). Optimisation of a large, constrained simulation model using compressed annealing, *Journal of Agricultural Economics* 59, 188–206.

Doole, G.J. and Parangahawewa, U. (2011). Profitability of nitrification inhibitors for abatement of nitrate leaching on a representative dairy farm in the Waikato region of New Zealand, *Water* 3, 1031–1049.

Doole, G.J. and Revell, C.K. (2010). Delayed pasture germination improves rigid ryegrass (*Lolium rigidum*) control through grazing and broad-spectrum herbicide application, *Crop Protection* 29, 153–162.

Doole, G.J., Pannell, D.J. and Revell, C.K. (2009). Economic contribution of French serradella (*Ornithopus sativus* Brot.) pasture to integrated weed management in Western Australian mixed-farming systems: an application of compressed annealing, *Australian Journal of Agricultural and Resource Economics* 53, 193–212.

Doole, G.J., Marsh, D. and Ramilan, T. (2012). Evaluation of agri-environmental policies for reducing nitrate pollution from New Zealand dairy farms accounting for firm heterogeneity, *Land Use Policy* 30, 57–66.

Eden, C. (1989). Using cognitive mapping for strategic options development and analysis (SODA), in Rosenhead, J. (ed.), *Rational Analysis for a Problematic World. Problem Structuring Methods for Complexity, Uncertainty and Conflict*. Wiley, Chichester, pp. 21–42.

Farrington, J. and Martin, A.M. (1988). Farmer participatory research: a review of concepts and recent fieldwork, *Agricultural Administration and Extension* 29, 247–264.

Gass, S.I. (1983). Decision-aiding models: validation, assessment, and related issues for policy analysis, *Operations Research* 31, 603–631.

Goleman, D.G. (1996). *Emotional Intelligence*. Bantam, New York.

Grafton, R.Q., Kompas, T. and Ha, P.V. (2009). Cod today and none tomorrow: the economic value of a marine reserve, *Land Economics* 85, 454–469.

Hillier, F.S. and Lieberman, G.J. (2004). *Introduction to Operations Research*, 8th edn. McGraw Hill, Columbus.

Innis, G. and Rexstad, E. (1983). Simulation model simplification techniques, *Simulation* 41, 7–15.

Jackson, M.C. (2000). *Systems Approaches to Management*. Kluwer, New York.

Jakeman, A.J., Letcher, R.A. and Norton, J.P. (2006). Ten iterative steps in development and evaluation of environmental models, *Environmental Modelling and Software* 21, 602–614.

Jones, N., Perez, P., Measham, T., Kelly, G., Aquino, P., Daniell, K., Dray, A. and Ferrand, N. (2009). Evaluating participatory modelling: developing a framework for cross-case analysis, *Environmental Management* 44, 1180–1195.

Kingwell, R.S. (1994). Risk attitude and dryland farm management, *Agricultural Systems* 45, 191–202.

Klein, M.W. (2002). *Mathematical Methods for Economics*. Addison Wesley, Boston.

Koehler, B. and Koontz, T.M. (2008). Citizen participation in collaborative watershed partnerships, *Environmental Management* 41, 143–154.

Korfmacher, K. (2001). The politics of participation in watershed modelling, *Environmental Management* 27, 161–176.

Landry, M., Malouin, J.L. and Oral, M. (1983). Model validation in operations research, *European Journal of Operational Research* 14, 207–220.

Lave, C. and March, J. (1993). *An Introduction to Models in the Social Sciences*. University Press of America, Lanham.

Malcolm, L.R. (1990). Fifty years in farm management in Australia: survey and review, *Review of Marketing and Agricultural Economics* 58, 24–55.

Martin, A. and Sherington, J. (1997). Participatory research methods—implementation, effectiveness and institutional context, *Agricultural Systems* 55, 195–216.

McCarl, B.A. (1984). Model validation: an overview with some emphasis on risk models, *Review of Marketing and Agricultural Economics* 52, 153–173.

McCarl, B.A., Meeraus, A., van der Eijk, P., Bussieck, M., Dirkse, S. and Steacy, P. (2010). *Extended GAMS User Guide*. GAMS Development Corporation, Washington D.C.

McCown, R.L., Brennan, L.E. and Parton, K.A. (2006). Learning from the historical failure of farm management models to aid farm management practice. 1. The rise and demise of theoretical models of farm economics, *Australian Journal of Agricultural Research* 57, 157–172.

McCown, R.L., Carberry, .P.S., Hochman, Z., Dalgliesh, N.P. and Foale, M.A. (2009). Re-inventing model-based decision support with Australian dryland farmers. 1. Changing intervention concepts during 15 years of action research, *Crop and Pasture Science* 60, 1017–1030.

Merriam, S.B., Caffarella, R.S. and Baumgartner, L.M. (2007). *Learning in Adulthood*. Wiley, New York.

Miller, P. (2010). *Theories of Developmental Psychology*. Worth, Richmond.

Mingers, J. and Rosenhead, J. (2004). Problem structuring methods in action, *European Journal of Operational Research* 152, 530–554.

Miser, H.J. and Quade, E.S. (1988). Validation, in Miser, H.J. and Quade, E.S. (eds), *Handbook of Systems Analysis: Craft Issues and Procedural Choices*. North Holland, New York, pp.527–565.

Monjardino, M., Revell, D. and Pannell, D.J. (2010). The potential contribution of forage shrubs to economic returns and environmental management in Australian dryland agricultural systems, *Agricultural Systems* 103, 187–197.

Murphy, F.H. (2005a). The art and science of practice: elements of a theory of the practice of operations research: a framework, *Interfaces* 35, 154–163.

Murphy, F.H. (2005b). The art and science of practice: elements of a theory of the practice of OR: expertise in practice, *Interfaces* 35, 313–322.

Naylor, T.H. and Finger, J.M. (1967). Verification of computer simulation models, *Management Science* 14, 92–101.

Nicolson, C.R., Starfield, A.M., Kofinas, G.P. and Kruse, J.A. (2002). Ten heuristics for interdisciplinary modelling projects, *Ecosystems* 5, 376–384.

Norman, D.W., Worman, F.D. and Siebert, J.D.M. (1995). *The Farming Systems Approach to Development and Appropriate Technology Generation*. FAO, Rome.

Olphert, C.W. and Wilson, J.M. (2004). Validation of decision-aiding spreadsheets: the influence of contingency factors, *Journal of the Operational Research Society* 55, 12–22.

Ormerod, R. (1996). On the nature of OR—entering the fray, *Journal of the Operational Research Society* 47, 1–17.

Pannell, D.J. (1996). Lessons from a decade of whole-farm modelling in Western Australia, *Review of Agricultural Economics* 18, 373–383.

Pannell, D.J. (1997). Sensitivity analysis of normative economic models: theoretical framework and practical strategies, *Agricultural Economics* 16, 139–152.

Pannell, D.J., Kingwell, R.S. and Schilizzi, S. (1996). Debugging mathematical programming models: principles and practical strategies, *Review of Marketing and Agricultural Economics* 64, 86–100.

Pannell, D.J., Malcolm, L.R. and Kingwell, R.S. (2000). Are we risking too much? Perspectives on risk in farm modelling, *Agricultural Economics* 23, 69–78.

Polya, G. (1945). *How to Solve it*. Princeton University Press, Princeton.

Ramilan, T., Scrimgeour, F., Levy, G., Marsh, D. and Romera, A. (2011). Simulation of alternative dairy farm pollution abatement policies, *Environmental Modelling and Software* 26, 2–7.

Reed, M. (2008). Stakeholder participation for environmental management: a literature review, *Biological Conservation* 141, 2417–2431.

Risbey, J., Kandlikear, M. and Patwardhan, A. (1996). Assessing integrated assessments, *Climatic Change* 34, 369–395.

Roberts, A.M., Pannell, D.J., Doole, G.J. and Vigiak, O. (2012). Agricultural land management strategies to reduce phosphorus loads in the Gippsland Lakes, Australia, *Agricultural Systems* 106, 11–22.

Robinson, S. (1994). Simulation projects: building the right conceptual model, *Industrial Engineering* 26, 34–36.

Robinson, S. (2008). Conceptual modelling for simulation. Part II. A framework for conceptual modelling, *Journal of the Operational Research Society* 59, 291–304.

Rosenhead, J. and Mingers, J. (eds) (2001). *Rational Analysis for a Problematic World Revisited*. Wiley, New York.

Sassower, R. (2010). Is *Homo Economicus* extinct?, *Philosophy of the Social Sciences* 40, 603–615.

Schwarz, R.M. (2002). *The Skilled Facilitator*. Jossey-Bass, San Francisco.

Shortle, J. and Horan, R. (2001). The economics of nonpoint pollution, *Journal of Economic Surveys* 15, 255–290.

Sinclair, T.R. and Seligman, N.G. (1996). Crop modelling: from infancy to maturity, *Agronomy Journal* 88, 698–704.

Sterman, J.D. (2000). *Business Dynamics: Systems Thinking and Modelling for a Complex World*. McGraw-Hill, Massachusetts.

Vanclay, J.K., Prabhu, R. and Sinclair, F. (2006). *Realising Community Futures: A Practical Guide to Harnessing Natural Resources*. Routledge, Florence.

Vennix, J.A.M. (1996). *Group Model Building: Facilitating Team Learning Using System Dynamics*. Wiley, New York.

Voinov, A. and Bousquet, F. (2010). Modelling with stakeholders, *Environmental Modelling and Software* 25, 1268–1281.

Weersink, A., Llewellyn, R.S. and Pannell, D.J. (2005). Economics of pre-emptive management to avoid weed resistance to glyphosate in Australia, *Crop Protection* 24, 659–664.

Winston, W.L. (1994). *Operations Research*. Wadsworth, Belmont.

Woodward, R.T., Wui, Y.-S. and Griffin, W.L. (2005). Living with the curse of dimensionality: closed-loop optimisation in a large-scale fisheries simulation model, *American Journal of Agricultural Economics* 87, 48–60.

Woodward, S.J.R., Romera, A.J., Beskow, W.B. and Lovatt, S.J. (2008). Better simulation modelling to support farming systems innovation: review and synthesis, *New Zealand Journal of Agricultural Research* 51, 235–252.