Decision support for temperate grasslands: challenges and pitfalls

J.R. Donnelly[1], L. Salmon[1], R.D.H. Cohen[2], ZL. Liu[3] and XP. Xin[4]
[1]*CSIRO Plant Industry, Canberra, 2601, Australia, Email:john.r.donnelly@csiro.au*
[2]*RDC Ranch Consulting, 313-10033 110 St. NW, Edmonton AB. T5K 1J5, Canada*
[3]*University of Inner Mongolia, Hohot 010021, Inner Mongolia, China*
[4]*Institute of Agricultural Resource and Regional Planning, Chinese Academy of Agricultural Sciences, No.12 South Zhongguancun Ave, Beijing 100081, China*

Key points

1. Successful adoption of decision support tools (DS tools) to address grassland management issues requires careful attention in design to ensure ease-of-use, accuracy in prediction and the flexibility to simulate actual practices.
2. DS tools must handle spatial variability and where possible include facilities for automatic sourcing of essential information for initialisation.
3. Advances in the development of DS tools will depend on resolution of scientific issues in grassland biology including investment in dedicated experiments to determine parameter values for model equations.
4. The use of mechanistic models, the integration of remote sensing technology and cooperation between research groups to develop modular simulation frameworks to share models will enhance the value of DS tools in grassland management.

Keywords: decision support tools, grazing systems, models, GrassGro

Introduction

For more than four decades computer models and decision support tools (DS tools) have been advocated for guiding the management of temperate grasslands. The first uses were for research but subsequently this has extended to farm advice, landscape management and rural policy. At best their adoption has been modest, but given their complexity and diversity this is not surprising. It is worth noting that this is similar to the uptake of many other technologies in agriculture. In a review of technology transfer in the wool industry in Australia, Vizard & Edwards (1992) point to several examples where simple but very beneficial technologies have had low adoption. However, there are some notable examples of productivity improvements with increased profits resulting from the use of DS tools, particularly where variable weather makes the outcomes of decisions uncertain (Donnelly *et al*., 2002).

Grasslands are complex biological systems. Their optimal management requires a comprehensive, systems-level approach that is best addressed using models. Modelling grasslands is indeed the “big science" recognised by Thornley (2001), but some sections of the scientific and farming communities have yet to appreciate the benefits that it can deliver. Well-tested systems models and DS tools are expensive to develop, as they require expertise in several disciplines such as biology, hydrology, mathematics, economics and computing. David et al. (2002) estimate that costs range from US$15-30M per model, but costs must be weighed against the benefits derived from their use. In Australia in 2002, an independent assessment for CSIRO by the Center for International Economics estimated a return of more than AU$70 for each dollar invested in the development of the GrazFeed DS tool (Freer *et al*., 1997).

Challenges and pitfalls

Computer-based DS tools provide an integrated framework for farm managers to identify opportunities and quantify risks to profitable livestock production from grasslands. They can help farmers integrate livestock management with other farming enterprises and policy makers can use them to evaluate alternative uses for grasslands. Moore (2005) reviewed briefly key features of a number of DS tools that have contributed to the management of grasslands at the main section of this Congress. However, there are some issues discussed below, about tool design and general requirements that must be addressed to ensure widespread use and to capture the full potential of this powerful technology.

Tool design

In practice, most models and DS tools are used for research and then only by the research groups that built them (Hook, 1997). Early ideas that farmers would be the main users of DS tools are now gradually being replaced with recognition that benefits may be delivered best by those with appropriate expertise (McCown, 2002). The more complex dynamic DS tools or simulators designed for evaluation of strategic management options are more appropriate for use by farm consultants or other professionals. Application of DS tools to day-to-day decisions by farmers may be more likely if they are installed on small, handheld devices suitable for paddock use.

DS tools must be able to represent attributes of the system that the user considers important (such as the legume content of pastures), otherwise they will not be adopted. They must be easy to use with a minimum investment of time to solve a problem and they must facilitate access to in-built or web-accessible databases such as soil properties or climate if these data are required. The interface must guide the user in deconstruction of a problem and in identification of the key controlling variables so that analysis is feasible. The DS tool must help interpret the information generated and produce a report. Analysis of more complex problems may require a factorial design. Such facilities need to be in-built and linked to smart ways to extract critical information from output, which can otherwise be unmanageable. Moore (2005) describes the redevelopment of the GrassGro interface to focus on problem solving, so that pre-configured formats for analyses are available and the simulation results linked with customised reporting. The analyses can also be stored for later use. The objective is to make tailor-made advice more effective and affordable.

Estimating coefficients for equations

Precision and accuracy in prediction is important for widespread acceptance of DS tools. A key issue is the generality and reliability of coefficients in the equations within the underlying models. Since the coefficients can vary with environmental and other conditions, estimating their values is one of the most difficult problems in modelling (Ahuja & Ma, 2002). Estimation by experiment is costly and the lack of standard methodology means it is difficult to achieve. Simplification of biophysical processes in models sometimes frustrates experimental measurement; for example, the artificial partitioning of soil organic matter into recalcitrant and labile pools and the uncertainty in the organic matter turn-over times between pools.

Most pasture plant models have a structure based on a water budget, assimilate production and distribution, reproduction and senescence. A major issue, however, is the lack of a standard approach to quantifying the parameters of the equations for plant growth and development. A relatively large number of parameters are required to discriminate the patterns of growth, reproduction and senescence of different plant species (Moore *et al.*, 1997) and obtaining estimates of these parameters is demanding even when data are available; for many species there are no data. In practice, the relative values for these parameters are far more important than their absolute values as their purpose is to discriminate between species.

This pragmatic approach has enabled continued tool development despite the lack of precise data. As the parameter sets describing pasture species are external to the model, few coding changes are generally required. This model design, has enabled GrassGro to be used in more extreme environments than those of temperate Australia. Rapid parameterisation of 19 species common to the Canadian prairie (Cohen *et al.*, 2003) and descriptions of 7 species common to the steppe of Mongolia and Inner Mongolia (*Leymus chinensis, Stipa grandis, S. krylovii, Agropyron michnoii*, *A. cristatum, Cleistogenes squarrosa* and *Artemisia frigida*) have been possible (Figure 1).

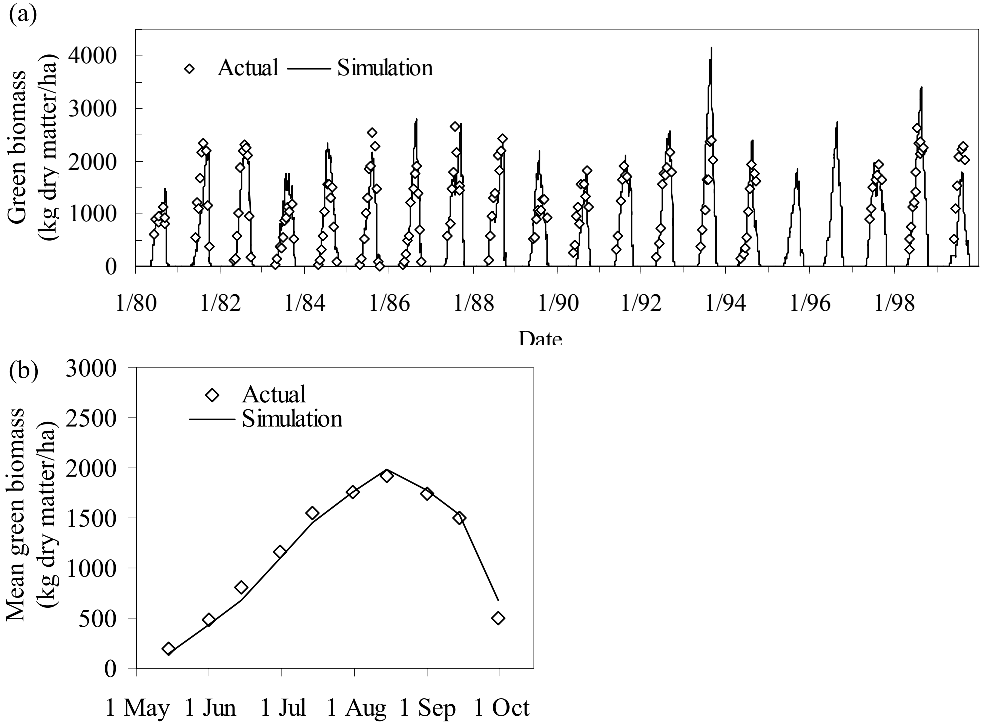

Figure 1 a. Comparison of simulated pasture biomass of 7 species common to the steppe of Mongolia and Inner Mongolia (line) with observed green pasture biomass (circles) at Xilingol, Inner Mongolia, 1980-1999. Measurements were not available for 1995-1996. **b**. Mean values for the same period (1980-1999).

Validation

Although estimation of the coefficients for equations is the most difficult problem in modelling, validation of the predictions of a model or DS tool is the most contentious. Validation generally refers to the accurate prediction of results observed in a particular experiment. It is contentious because of uncertainty about i) the accuracy of the experimental data, ii) the precise environmental conditions under which the data were collected, iii) possible differences in calibration of methods used for measurement, iv) the correct use of the model and v) the precision and accuracy of the model for the particular circumstances of the experiment. Conclusions about the validity of a model ultimately depend on its correct application, the accuracy of any data used for checking predictions and the accuracy and precision of its predictions.

Validation can be hampered by uncertainty about initialisation of the model (see below), particularly if initialisation values are based on a spatially limited sample and the data used for validation are measured at a larger scale. For example, soil core samples are expensive to collect, so minimal numbers of cores taken from a representative site are often used to initialise the soil profile for a whole paddock, or even a whole farm. In reality it is unknown if the sample is truly representative. If the initialisation values do not represent the actual properties of the predominant soil of the paddock or farm, then model predictions, for example, of herbage yields are unlikely to match actual observations. In this case, if predictions diverge from observations, the model is not necessarily in error and the initialisation could be inadequate.

Errors in model predictions may also be introduced by the time scales used for measurement of driving variables. If daily rainfall is used as a driver of plant growth, no account can usually made for rainfall intensity, which operates at a much finer scale. Infiltration and runoff values can differ markedly for the same daily rainfall measurement with very significant consequences for plant growth.

Given that most DS tools designed for use in grassland management are based on deterministic models, it is generally not feasible to calculate an error of prediction. However, the plausibility of output values and the sensitivity of the overall model can be checked by varying initialisation values for key variables. For example, inputs for soil depth can be varied over the measured range of values. This is usually a lengthy process generating large amounts of information, so additional tools or facilities are essential to help the user efficiently assess the response surface. Alternatively, the response of individual equations to changes in parameter values can be checked externally, for example, in a spreadsheet such as that available for the animal model used in GrazFeed (Freer *et al.*, 1997; www.pi.csiro.au/grazplan). The SGS pasture model developed recently in Australia (Johnson et al., 2003) was designed with an in-built facility to test the effect of parameter values on model responses.

All users of DS tools require accuracy and precision in the underlying models, but the level required depends on the intended application. Validation can be very difficult if small errors, when accumulated, lead to large errors at a higher level of the system. As McNamara (2004) points out, precise measures (1-5% error) of daily feed intake of even housed dairy cows, for example, are not available and may never be, but over a 300d lactation this small measurement error could potentially lead to a large cumulative error in predicted energy retention perhaps amounting to 30kg of body fat.

Despite these issues, a grassland farmer using a model primarily wants an affordable and useable tool with acceptable predictions, even though there may be few accurate records against which to test the predictions. In the absence of data, the predictions must at least approximate the user's expectations. Formal validation of the model is rarely possible on a farm and it may not matter that some processes are estimated by a relatively simple approximation. An example from GrassGro, which can model swards of mixed species, is the option to specify a fixed legume content for a pasture rather than to explicitly model the competition between grasses and legumes. Since the legume component of a pasture has a marked effect on animal food intake and production, the inclusion of a legume component is important. If species competition cannot be modeled with confidence, then under some circumstances specifying the legume content is a reasonable although crude approximation that ensures a more realistic simulation.

Initialisation

Before a DS tool can be used it must be initialised to represent the conditions on the farm or part of the farm that is under study. Initialisation can be time-consuming and expensive and where possible, the essential information should be automatically sourced from geo-referenced databases stored with the DS tool or accessed from the web. For example, local soil information and weather data should be accessible simply by specifying the geographic location of the paddock, enterprise or farm under study. Real progress towards achieving this is now possible by advances in computing and communications technology, although there may be IP issues that still require resolution to gain general access to web databases.

Spatial variability across paddocks or farms and temporal variability can cause non-uniform plant growth and development that requires integration for accurate initialisation (Ahuja & Ma, 2002). There are several approaches to simulating a highly variable site: averaging, sensitivity testing, integration of simulations of different spatial units (Beverley *et al*., 2003) or stochastic modelling using probability distributions. Remote sensing holds promise as a method for measuring variability across landscapes. Initial values may also be obtained from a preliminary simulation run. As discussed above, the most common problems with estimating initial values are the cost and difficulty of measurement.

Technical support

The adoption of a DS tool is rarely a matter of selling a piece of software "off the shelf". Documentation, on-going technical support and some form of training for effective use are essential and must be funded. However, some tools are easy to use, require little training for familiarization and are suitable for distribution as software products. Other tools designed to set or evaluate strategic objectives, such as GrassGro, usually require significant training for effective use. An alternative to distributing software is the sale of comprehensive, regionally-specific analyses undertaken by an expert user working within a consultancy firm and perhaps with web-based delivery.

Web-based delivery of DS tools may also help contain the cost of technical support and ensure that only the latest versions of software are used for analyses. The University of New England has implemented technology to distribute slightly modified versions of the GRAZPLAN DS tools (Donnelly *et al*., 2002) on a fee for service basis at educational institutions throughout Australia (Daily *et al*., 2005).

Combining laboratory and software analyses is another approach to providing analyses using DS tools. The NUTBAL nutritional management system is operated by the Grazingland Animal Nutrition Laboratory at Texas A&M University (Stuth *et al*., 2002). Clients collect fresh dung deposits from the field and submit the faecal sample to the laboratory, together with information describing the animals and grazing environment. The laboratory uses near infra-red (NIR) spectral analysis of faeces to estimate dry matter intake and diet quality. The estimates are used with the NUTBAL model to calculate the nutritional balance of the herd and advise modification to the animal's feed if necessary.

Funding

The scarcity of funds for production-based agricultural research and extension is now a major constraint to technological progress in farming and it is becoming more severe as resources are redirected to biotechnology, natural resource management and other important national priorities, such as the effects of climate change. It is ironic that endeavours in these disciplines could be enhanced with the use of appropriate DS tools. The problem is becoming more severe as the contribution of agriculture to employment and GDP of major economies is declining worldwide (Marsh, 2004; Keogh, 2004; Freshwater, 2004). Access to farming technology used to be free, primarily through public extension services, but these are being progressively withdrawn and advice is becoming more costly. The environment for research into model and DS tool development is particularly unfavorable, as it is largely funded by public outlays and the non-government sector provides only minor support for application of the technology to solve industry problems. A further major constraint is a worldwide shortage of biological scientists with training in applied mathematics and system analysis, who are willing to work in a field that is poorly resourced.

Support for grassland modelling, with or without agricultural applications, may have to come from non-agricultural sources. A partial solution to boost funding is to link DS tool development with well-funded public initiatives for landscape management or climate change and seasonal weather forecasting. The DS tools provide a powerful way to extend and evaluate these initiatives. The following example shows how application of a DS tool to a grazing system enables the value of a weather forecast to be assessed.

Case study: DS tools and evaluation of 3-monthly seasonal rainfall forecasts – how good does a seasonal rainfall forecast have to be to warrant action by a farmer?

Seasonal rainfall forecasts are routinely issued for many regions of the world and farmers can use them to guide weather-sensitive management decisions. However, the actual weather outcomes are subject to great uncertainty, so it is reasonable to question the reliability of decisions based on the forecasts. The question that must be answered is: what is the "break-even" probability for taking action in response to a forecast? This probability can be estimated by calculating the expected monetary value (EMV) of the alternative decisions (Vizard, 1994) and is equivalent to the cost:loss ratio (Wilks, 2001). If the monetary values of these management options are not known, then a DS tool like GrassGro, which is driven by the climatological record, can provide these as financial outcomes for a defined set of seasonal conditions; for example, the average gross margin of years with summers in the driest tercile. Combining the predictive capacity of GrassGro with calculation of the "break-even" probability (or cost:loss ratio) gives a unique and powerful way to determine whether a farmer should respond to a seasonal forecast for a particular enterprise. The following example demonstrates this approach for a bull-fattening enterprise in south-eastern Australia (Salmon *et al*., 2003).

A beef producer at Branxholme, Victoria, (mean annual rainfall of 655mm) wanted to use surplus pasture at the end of the growing season in December 2002 by purchasing cheap bulls weighing 330kg and fattening them to 525kg for sale in the following November. Before making the decision to buy the bulls two questions needed answers. First, how many bulls should be purchased to make maximum profit? Second, what was the risk of the failure of autumn rains increasing the need to feed expensive grain to the bulls? The first step to answer these questions was to use GrassGro to simulate the perennial ryegrass, annual grass and subterranean clover pasture sown on the farm. The model was initialised to represent the yield and quality of the pasture and the condition of the bulls at the end of December 2002. Then, daily pasture production, intake of pasture and supplement and weight gain of the bulls were simulated for six stocking rates (1.5 to 4.0 bulls/ha) between December and the following November, using daily weather data from the climatological record from each of 46 years from 1957 to 2002. Annual gross margins were calculated for the bull fattening enterprise (Figure 2).

The simulation results indicate that on average the optimum number of bulls to buy would be 2.5/ha as this stocking rate achieved the highest mean gross margin without excessive risk of financial loss (Figure 2).

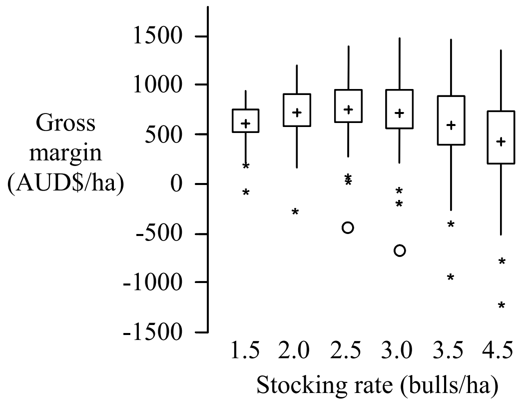

Figure 2 Boxplots showing the distribution of predicted annual gross margins at six stocking rates over the period 1957-2002 for a bull beef enterprise in Victoria, Australia. The mean gross margins are indicated by a cross symbol and outliers by an asterisk or open circles.

What about the producer’s concerns of a delayed start to autumn growth with limited pasture feed? Should the number of bulls be reduced to say 1.5 rather than 2.5 bulls/ha, given that the seasonal rainfall forecast for the next 3 months (January to March) predicted a “dry” season (rainfall in the lowest tercile)? What is the required level of probability for the forecast being correct that would justify reducing the number of bulls purchased? This decision requires the calculation of the “break-even” probability or cost:loss ratio.

If p and (1-p) are the probabilities of a season being dry or not dry and v1 and v2 are the respective financial outcomes of purchasing the optimum number of bulls (2.5/ha), then

$$EMV_{2.5} = p*v1 + (1-p)*v2$$

Likewise, if v3 and v4 are the financial outcomes for reducing the number of bulls to 1.5/ha, then

$$EMV_{1.5} = p*v3 + (1-p)*v4$$

At the break-even probability $EMV_{2.5} = EMV_{1.5}$, that is

$$p*v1 + (1-p)*v2 = p*v3 + (1-p)*v4$$

So relative to v2 (not dry and buy 2.5 bulls/ha)

$$p = v4/(v1+ v4 – v3)$$

The ratio v4/(v1 + v4 – v3) is also known as the cost:loss ratio (Wilks, 2001).

The EMVs for calculating the break-even probability were obtained from the gross margins generated by GrassGro. For each stocking rate, gross margins for the 46 years simulated were ranked according to the amount of rain that fell in January to March of the same year. The mean gross margin was then calculated for the driest 33% of years and for the remaining 67% of years ("not dry"). The gross margins for each stocking rate (2.5 or 1.5 bulls/ha) under "dry" or "not dry" conditions were used to calculate the break-even probability (Table 1).

Table 1 Relative expected monetary values for calculation of the break-even probability for reductions in stocking rate from 2.5 to 2.0 or 1.5 bulls/ha.

	Effect on gross margin (AUD$/ha)	
Stocking rate (bulls/ha)	"Dry"	"Not Dry"
1.5	-395 (v3)	-192 (v4)
2.0	-333 (v3)	-57 (v4)
2.5	-360 (v1)	0 (v2)

Substituting the values for a stocking rate of 1.5 bulls/ha in Table 1 into the cost:loss ratio (-92/(-360 -192 + 395)) gives an illogical value of 1.22 for the break-even probability. This indicates that reducing the number of bulls purchased to 1.5/ha will always result in a financially worse outcome even if the forecast is correct and the January to March period turns out to be "dry". This is because (a) a stocking rate of 1.5 was less profitable than a stocking rate of 2.5 in all but one year (for the grain costs and beef prices used in the analysis), (b) summer rainfall did not greatly affect the distribution of pasture growth over the rest of the year in this environment and (c) the bulls were able to exhibit compensatory growth during spring. Reducing the number purchased to 2.0 bulls/ha gives a break-even probability for action of 0.68. This means that the probability of a seasonal rainfall forecast for January to March rainfall in the driest tercile must exceed 0.68 before the farmer should reduce the number of bulls purchased to 2.0/ha. In reality, the Australian Bureau of Meteorology rarely issues such forecasts that deviate from the underlying probability value of 0.33 (Bureau of Meteorology, 1997). The Canadian Meteorological Centre has concluded that the seasonal rainfall forecasts for that country have little or no value for decisions with the current forecasting system based on dynamical and empirical models (Gagnon & Verret, 2002).

Lags in biological processes mean that short-term outcomes are in large part determined by the current state of the biological system. A decision support tool like GrassGro is extremely powerful because it can describe difficult-to-measure attributes of the current system and capture the impact of important drivers of system response e.g. soil moisture, pasture mass and quality, root depths and plant growth stages, seed banks, livestock condition and reproductive status. Of equal importance is the way the GrassGro analysis of the tactical management decision takes into account the distribution of relevant weather events in the historical record. In this example the January to March forecast was not a good predictor of autumn growth. To be useful to a farmer, a seasonal weather forecast must: (a) predict the seasonal outcome for a period that is relevant to the particular grazing enterprise and (b) do so with a greater probability than can be obtained from analysis of the enterprise with a DS tool that accurately captures the current state of the grazing system and uses climatology. Perhaps the shift of resources away from agricultural research to climate forecasting in this case, falls within the umbrella of "failed themes in grassland science" referred to by L.R. Humphreys in his final address summing up the XIX IGC in Brazil in 2001 (Humphreys, 2001). There is certainly cause for concern.

Future developments

DS tools clearly have a valuable role in providing a highly structured and consistent framework of analysis for making informed decisions about the management of grasslands, but there is substantial room for improvement in their design and accuracy. Many of the limitations outlined above will be addressed by future technical developments and a new approach to model building.

Modular simulation frameworks and object oriented modelling

Multidisciplinary models are expensive to build, so eliminating duplication of effort to reduce costs is being attempted independently by several modelling groups throughout the world (Neil *et al*., 1999; Moore *et al*., 2001; David *et al*., 2002). The objective is to reuse well-tested, component modules and supporting tools possibly developed by other scientific groups. This development is a significant technical advance in simulation capability and is based on module connectivity made possible by a software interface layer or "wrapper" that generates code to allow communication between modules (Figure 3). The technique is especially powerful because it permits connectivity between modules written in different computer languages, so even those modules do not have to be rewritten. Furthermore, relatively small development teams will be able to build comprehensive DS tools that use the best scientific modules developed by expert teams from other disciplines and perhaps even located in other countries. With internet facilities it should be possible to build, at will, tailor-made DS tools for specific applications drawing on worldwide expertise. The technology will provide the only likely cost-effective way to evaluate the integration of multiple enterprises on mixed farms over a range of seasons. Salmon et al. (2005) used this approach to provide a preliminary analysis of mixed farming for sheep meat and grain cropping in Australia using a model incorporating these features.

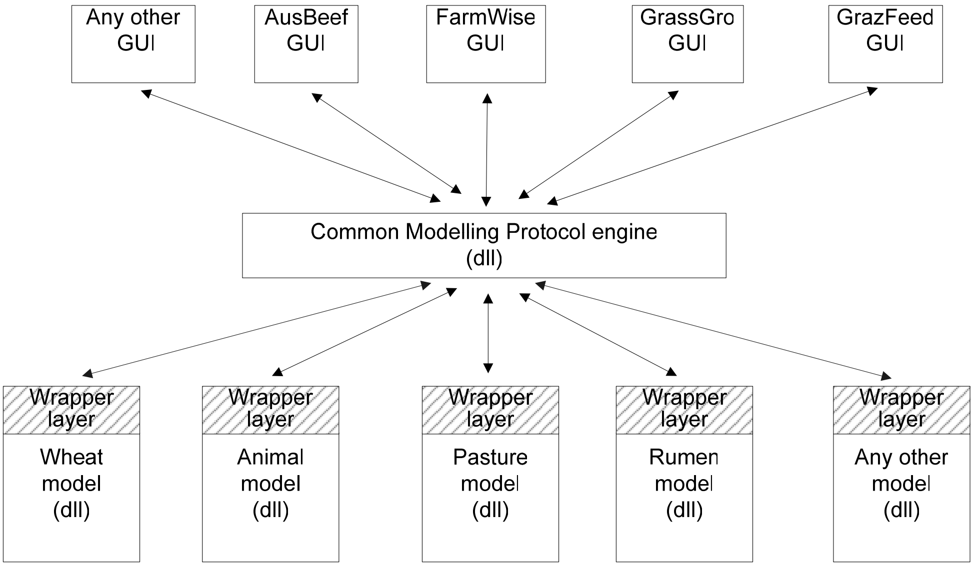

Figure 3 The CSIRO common modelling protocol is an example of a modular simulation framework that permits connectivity between models written in any language and complied as dynamic linked libraries (dll). The content of the models remains private at the cost of a relatively small code fragment or "wrapper layer" that allows relevant models to be linked together in a graphical user interface (GUI) through the Common Modelling Protocol engine to provide purpose-specific, tailor-made DS tools such as FarmWi$e or GrassGro.

Remote sensing

Linking models and DS tools with remote sensing techniques has potential to add value to farm decision making, especially where spatial scales can make model initialisation a difficult and expensive operation. The rapid development of remote sensing using spectral analysis to monitor forage resources, has potential to generate cheaper time series of plant data for validation and to provide digestibility estimates of forage quality which are essential inputs for DS tools. Comprehensive databases relating spectral analysis to herbage characteristics could be built for a wide range of pasture species at different stages of their growth cycle. Plant phenological stages predicted by a model could then be used to access estimates of herbage quality from the database.

Science

Many areas of grassland biology still require scientific resolution before a modelling approach can be considered totally adequate. Modelling grasslands is a complex multidisciplinary activity and requires substantial data. The need for comprehensive experiments conducted by skilled scientific teams was foreseen as an essential requirement more than 35 years ago by Morley (1968). His vision contrasts with current trends for trials that are more demonstration than research and located on farmer properties where careful monitoring is nearly always compromised. These studies are often intended to get the farming community involved in "research", which is desirable, but they contribute relatively little information of the type that is critically needed for model building and DS tool development. An exception is the commitment to long-term detailed observations at the whole-farm level combined with modelling at the "De Marke" experimental farm (Aarts, 2000). This should lead to the design of more sustainable nutrient management systems for dairy farming in the Netherlands.

For animal nutrition and production, some areas where information is insufficient for modelling include prediction of nutrient intake, the partitioning of absorbed and recycled nutrients, and the effect of nutrition on the quality or value of the product produced. For pasture plant production, the most urgent need is the parameterisation of additional important plant species sown or naturally occurring in pastures. The description of a plant genotype can be as broad as a plant functional type, for example, a generic annual grass that gets around the problem of describing all annual grasses. If warranted and if the information is available, the description can be more specific to represent a particular grassland species or cultivar. Since there are no standard procedures to guide this process, in practice a pragmatic choice is made about the level of information required for the intended use.

A successful analogue of this approach is used in the animal model in GrassGro and GrazFeed (Freer *et al*., 1997) where breed names imply nothing more than a convenient reference to a functional animal type representing the genetic potential, which is scaled through the standard reference weight. This approach using functional types is very powerful as it leads to an ability to use the potential of generic models for predicting plant and animal production in any temperate region.

Second generation models

Market demands for timely delivery of quality products from grassland-based enterprises are increasing the need for DS tools with more accurate and flexible models to represent nutritional management. Estimating the voluntary food intake of grazing ruminants is still a challenge for the development of reliable DS tools. Models like that used in GrazFeed and which are suitable for use in advisory situations predict the intake and partitioning of dietary protein and energy but do not model the processes of tissue metabolism which control product quality. Considerable progress has been made with detailed mechanistic models for voluntary intake of grain diets operating through controls which act on metabolic functions, rumen fill and food breakdown rate (Nagorcka *et al*., 2000). This opens the way to modelling fermentation in the rumen and the resulting concentration of individual volatile fatty acids and amino acids, which can then be used to predict the composition of weight, gain of lot-fed animals. The approach makes it possible to use models to explore opportunities for targeted feeding to meet precise carcase specifications, but it is not yet suitable for use in DS tools designed for grazing situations because initialisation of variables is too demanding. However, advances with NIR spectral analysis of feeds may provide a solution to this obstacle.

Conclusion

This paper has identified challenges and proposes actions essential for continued development and improvement of DS tools in a hostile funding environment. The actions include designing tools that are sensitive to the needs of users and model-developers and which do not compromise the integrity of the underlying biophysical models. This international Congress provides a unique opportunity to initiate this process and address the challenges.

Acknowledgements

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