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An engineering approach to modelling, decision support and control for sustainable systems

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Engineering research and development contributes to the advance of sustainable agriculture both through innovative methods to manage and control processes, and through quantitative understanding of the operation of practical agricultural systems using decision models. This paper describes how an engineering approach, drawing on mathematical models of systems and processes, contributes new methods that support decision making at all levels from strategy and planning to tactics and real-time control. The ability to describe the system or process by a simple and robust mathematical model is critical, and the outputs range from guidance to policy makers on strategic decisions relating to land use, through intelligent decision support to farmers and on to real-time engineering control of specific processes. Precision in decision making leads to decreased use of inputs, less environmental emissions and enhanced profitability—all essential to sustainable systems.

Keywords: engineering; systems models; modelling; sensors; process control; agriculture

1. INTRODUCTION

Engineering is the application of scientific and mathematical principles to practical ends. For agriculture, science continues to deliver innovation from every quarter, yet realizing practical value requires both understanding of how novelty and change impacts on the overall performance of the agricultural system and new means by which innovations can be used optimally.

Agricultural systems and processes do not produce single outputs. Though the primary goal is production of grain, meat or eggs, there are many by-products and outputs which provide inputs to other enterprises. There are also wastes and emissions to water and air, modifications to the soil and the rural community, and by-products that could be used in other markets to reduce fossil fuel demands. Farming is under pressure to reduce emissions in a competitive market place, which focuses attention on justifying the use of inputs—maximum food for minimum inputs. Sustainability sets economic arguments in the context of environmental concerns and the social implications of technology change. Simple rules to optimize inputs or justify a new machine cannot take account of the effects of complex changes in local environmental conditions or the secondary effects of the process on the environment through emissions or demands for processed inputs.

The advent of hardware that can process data rapidly allows complex descriptions to be analysed or optimizations undertaken in time spans that match the needs of customers/users. The advent of the associated mathematics and software allows the conclusions to be expressed in ways that meet concerns about uncertainty and the concept of supporting rather than making decisions. New engineering methods to collect difficult data permit control of complex real processes.

Engineering provides at least three important contributions as follows.

— Quantitative approaches to defining the whole system, so that the interacting effects of component production methods are assessed as a whole and future solutions considered in the light of economic, social and environmental impacts and policy goals.
— New tools and techniques, including machines, sensors and management methods, which enhance agricultural sustainability.
— Modelling methods and decision support tools at the level of specific processes, giving increased precision in process control.

Engineering is therefore a necessary partner with biological and other sciences in the improvement of agricultural systems and development of sustainability, providing the route to draw technologies together to achieve specific goals.

This review paper will highlight agricultural engineering science that illustrates the bridge from understanding to practice. Our purpose is to demonstrate that engineering delivers robust and relevant innovations across a range of systems and processes. An underlying concept is increased management precision whether at the policy, strategy, tactical or process level. The first part of the paper considers modelling whole systems mathematically, so that the performance of a process is evaluated and strategic decisions about machinery or management made. The systems approach provides models that address strategic issues on land use and the impacts of regulation, and also models for decision support. The latter provide sophisticated inputs to decision making by farmers, increasing the scope for reduced use of inputs without

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enhancing the risk of failure to control crop pests. The second part considers process control, modelling the process in the context of the control mechanisms available, sensing key system variables and translating system information optimally for control purposes. A more precise process management allows inputs to match production needs more closely, reducing or eliminating waste streams by automatic control. The mathematical and computational advances that have made these approaches possible are considerable—but of equal importance has been the demonstration that the application of mathematics to describe and predict complex processes and systems has been sufficiently accurate to inform and add value to the practical management of the agricultural systems concerned.

2. SYSTEMS MODELLING FOR DECISIONS

(a) *Background*

Modelling provides a logical procedure for predicting process outcomes in circumstances other than those that have been observed. Decision modelling aims to determine the optimal decision, define the trade-offs between different outcomes that are inherent in a range of decisions or predict the probable decisions that will be taken by farmers in a range of practical circumstances. Such models encapsulate knowledge of how a system is constructed of interacting processes and how each process works. They often combine experimental observations, expert knowledge and logic. In the physical world, models are frequently very precise and allow us, for example, to send probes to the moons of Jupiter. In the biological world not only are processes less well understood, often because they are made up of many sub-processes, but also the systems themselves are stochastic. Weed plants not only spread their seeds by various mechanisms—using wind, animals and birds so that their destination could be a long way from the plant—but seeds are also designed to lie dormant for times ranging from months to years so that the species can survive attacks by weather or man. Fungal spores operate in a similar fashion. Millions are launched into the air, some of these land on a leaf, some of these germinate and some of these survive the defences of plant and man to produce yet more spores. Domesticated seeds have been bred by man to germinate when planted, but this reliability is confounded by the action of wildlife such as a browsing slug finding the seed in the soil. Overlaying all is the weather and its variability and unpredictability—even with the very latest and largest computer.

Modelling to aid decision making in sustainable agriculture does not require description of all elements in fine detail—the approach needs to be tailored for the purpose. Relatively simple descriptions of specific processes are sufficient if the processes are known to respond to a limited subset of external conditions, or if other unmodelled effects can be dealt with through appropriate adjustments to accommodate drift or errors. Early attempts at decision support systems in agriculture, such as ProPlant (Frahm *et al.* 1991), relied purely on expert knowledge to instruct the user in what to do. ProPlant Expert (www.proplantexpert.com) continues to function as an expert advisory system and covers a range of crops, pests and diseases. PC-Plant Protection, developed in Denmark (Murali *et al.* 1999), also uses expert scoring rules and covers control of weeds, pests and diseases in wheat, with an emphasis on reducing chemical use. EPIPRE in The Netherlands (Zadoks 1981; Rijsdijk 1983) used empirical models to relate observed disease levels to probable losses, but use of the system has now declined as farmers have become educated about the meaning of observations. None of these approaches allows the users themselves to consider the dynamics of the diseases, interact with current weather conditions, make sequential decisions, maximize profit and compare alternatives. However, they do attempt to estimate the magnitude of losses, without which no decision is possible.

Predictive modelling of the outcomes resulting from actions enables a person to make a better decision. The methods to achieve this range from education/training so that operators better understand the consequences of their actions, through analytical studies and reports which provide the decision maker with measures of the effect of various options, to computer-based decision support systems that use the models interactively to suggest the best decisions to the operator. Modelling decisions for these systems needs to combine a probabilistic approach to the range of possible outcomes with a deterministic description. The probabilistic approach could use stochastic modelling techniques (Sells 1996), but, for systems studies, direct application of probability modelling techniques to repeated simulations is more likely, for example, using many years of weather data. The deterministic approach will generally describe component processes as logical relations or will use the fact that the overall system, the sum of the parts, often behaves in a fairly predictable way. Optimization is a powerful adjunct to predictive modelling for both the user and the modeller. In principle, its aim is to provide the farmer with the best decision. In this process, it is a very powerful test of the accuracy and completeness of a system model and, by association, of the expert knowledge.

These approaches are exemplified by a range of studies. Farming system models provide the means to assess the implications for optimal profitability and optimal environmental performance. Model outputs increase understanding of how strategic decisions, by farmer or regulator, affect system performance. Process modelling and optimization lead to decision support and optimized advice to the farmer on input management. Total system studies, in the form of life cycle assessments (LCAs), address cradle-to-grave issues in the context of global sustainability.

(b) *Systems modelling for environmental life cycle assessments*

Environmental LCA based on agricultural system models is a holistic systems approach that assesses the overall impact of the agricultural production system. The concept of modelling required for LCA is to analyse the flows through the system to provide accurate measures of all inputs and outputs and enable comparison of alternatives. The aim is to identify all the physical resources consumed and all the (undesirable) emissions resulting from the production of a product (or functional unit). This is basically impossible, particularly in agriculture, as the input required for a given production is very uncertain. Decisions are required on what is significant and on the importance of by-products—straw for bedding from wheat, meat and manure from milk production, etc. The basic premise is to account for disposal of every input, whether an atom or a lamb.

LCA assesses the environmental aspects and potential impacts associated with a product, by compiling an inventory of relevant inputs and outputs of a system and evaluating the impacts associated with them, from raw material acquisition through production, use and disposal (Audsley *et al.* 1997; De Boer 2003). Consider comparing the national production of bread wheat by a conventional system with an alternative, for example, using lower inputs. An important part of an LCA is to define the *functional unit* being produced: in this case, wheat suitable for breadmaking with a minimum protein content of 12%. Reducing inputs of nitrogen will reduce expected protein content. (In practice, it reduces the *probability* that the output from the field will meet the requirements for breadmaking each year.) One option is to choose a very high protein variety but it is then essential to systematically analyse how much this choice reduces yield potential, hence both products are identical at the farm gate and only the farming side need be analysed.

In general, LCA analyses are comparative studies looking at alternatives to current systems. In agriculture, they frequently compare conventional and organic systems. De Boer (2003) compared conventional versus organic milk results from three studies, illustrating the large effect that small differences in assumptions can make, but with an overall message of little difference per kilogram of milk. Sandars *et al.* (2003) compared livestock manure management, showing the need to study the whole system not just the individual part being improved. It is important to remember that the functional unit is kilogram of meat not hectare of land (Halberg *et al.* 2005).

The first step is to completely define an inventory of the production systems. In particular, all flows of energy and materials entering and leaving the system, where they are different, are defined and a systematic procedure determined for measuring this difference—noting that in many cases data will be sparse or non-existent and confounded by the huge variability present in agricultural processes. Inputs consist of fertilizer (NPK), active (pesticide) ingredients, machinery, buildings and energy as fuel and electricity. The grain and straw yield also contain NPK. Outputs to air, water and landfill include carbon dioxide, ammonia, nitrous oxide, nitrate and packaging.

Although data on current systems will generally exist in some form, data on alternatives are generally sparse or non-existent and, even where they exist are likely to be transient, influenced by the preceding production system. Thus, there is a need to use or develop system models which accurately predict the future performance of alternatives.

Reduced inputs will have an effect on the soil. In studying a single commodity, it is assumed that any crop year is part of an unspecified crop rotation forming a sustainable system of production such that the soil returns to the same condition at the start of the next rotation. By comparison, experimental trials and their associated simulation models are frequently only 1 year in duration, and reduced inputs of N are not fully reflected in lower yield or lower soil N in the soil for the following crop. System simulation models can be run until a steady state is obtained, which properly predicts the (reduced) yield and soil N content. Reduced herbicide inputs present a similar problem with weeds for which the solution requires alterations to the crop rotation, cultivations or timing of drilling. An altered crop rotation, however, assumes that the market wishes to consume more of one crop and less of another! Indeed, a complete UK LCA model (which does not exist) also needs to take into account the available land area, and the impact of changed production on imports and exports. It is easy to reduce the UK's global-warming potential from the use of fertilizer in agriculture by reducing production and importing our food—but this does little for global global-warming potential.

Burdens must be allocated appropriately to the function. Thus, the energy and materials used in manufacturing a tractor are allocated in proportion to its use. Co-production is common in agricultural systems since many activities produce multiple co-products, notably cereal grain and straw. The fertilizer in manure is another example. There are a number of different approaches to allocation. A common option is *avoided burdens*, which subtracts the burdens displaced by use of the co-products. It is sometimes possible to use a property of the products. Relative economic value at the point of division in the system, which represents a measure of the incentive for production, is a final option, though a proper economic value is sometimes difficult to determine (Audsley *et al.* 1997). Cederberg & Stadig (2003) show that how you deal with products, in their case beef calves from dairy, can make a big difference to the result. Economic value gives a very different answer to expanding the system to determine the avoided burdens. It is important to consider the whole system as far as possible.

Burdens must include the production and delivery of the inputs. Thus, the energy used to produce diesel is an addition to the energy content of diesel (which is itself greater than the energy required by the task). The production generates emissions, for example, 0.016 kg N_2O is emitted from fertilizer production for each kg N in the fertilizer, and delivery of fertilizer consumes diesel (Audsley *et al.* 1997).

Field emissions are a major impact of agriculture on the environment. Generally, the model must ensure a mineral balance—total input of an element equals total output. Thus, the fate of all surplus nitrogen applied to a crop must be determined even though, in a transient situation, it is used to benefit the next crop. The application of manure provides a good example. There is more readily available nitrogen in manure than is accounted for in the adjustment a farmer makes to his fertilizer application. The organic N provides a source of N for many years, though a farmer is unlikely to make much adjustment after the year of application.

Table 1. A typical outcome of an LCA analysis of a single commodity: bread wheat production.

impacts (per tonne bread wheat produced)	conventional	organic
energy used, MJ	2361	1736
global-warming-potential, kg 100 year CO_2 equiv.	422	481
eutrophication potential, kg PO_4^{3-} equiv.	2.9	8.6
acidification potential, kg SO_2 equiv.	3.1	3.3
pesticides used, dose ha^{-1}	2.0	0
abiotic depletion, kg antimony equiv.	1.4	1.2
land use, ha grade 2	0.14	0.44

The result is increased yield and increased nitrogen emissions to the environment at a geometrically decreasing rate to infinity. This is modelled to give a difference equation for residual nitrogen: $R_{n+1}-\alpha R_n+\beta R_{n-1}=0$ and thus solved for nitrate leaching and additional yield.

Steady state does not mean that the soil contents are the same from crop to crop, only over the rotation. Weather variability means that experimental values vary from year to year but long-term averages are required. Taken together, it means that the best method to estimate losses is to derive them from an appropriate simulation model such as SUNDIAL (Smith *et al.* 1996) rather than using observations.

Steady state is less appropriate for some mineral contents. The most notable example is carbon content when comparing systems with different amounts of straw incorporated (to value straw for electricity generation). Organic matter in soil represents a significant carbon sink of the order of 40 t C ha^{-1} for cropped land, 60 t C ha^{-1} for permanent grassland and 80 t C ha^{-1} for coniferous woodland. Carbon content alters very slowly to a new steady state over 50 years, though most of the changes happen within 10 years. It is a challenge to LCA in this case to decide the rate of change to be used.

The outcome is an extensive picture of the ways in which production of the commodity impacts on the global environment, allowing systems to be compared and policy perspectives informed. A short-form summary for the example comparison of conventional and organic bread wheat production is given in table 1. This shows that there are benefits in the fossil energy of organic wheat production, due to saving on fertilizer energy, but per tonne of grain produced the conventional system produces less emission. The global-warming potential associated with the difference between conventional and organic systems is dominated (60–70%) by emissions of N_2O, which is 292 times worse than CO_2 and is a by-product of the nitrogen cycle in the soil. Organic wheat requires additional land for fertility building, with consequent emissions, and this together with the lower yield results in greater emissions per tonne of bread wheat (however, measurements are extremely variable so the figures have a large uncertainty).

(c) *Whole farm decisions and land use planning—the implications of farmers' management decisions for environmental impacts*

Policy makers are keen to assess potential impacts of probable future agricultural land use given future scenarios of climate, technology and socio-economics. Using a farm systems model to consider the combined profitability and environmental outcomes of the process by which farmers determine land use provides a new approach to realistic comparisons of policy positions.

There are basically two approaches to predicting future agricultural land use. One approach (top-down) is to determine the prices and production at a national level and allocate to land (Hossell *et al.* 1996). The alternative (bottom-up) seeks to determine what individuals would do and aggregate to the level of a region or country (Veldkamp & Verburg 2004). Within this, a geographic information system (GIS) and agent-based approach is more frequently used for non-agricultural land use planning, but in agriculture the neighbour does not have a major effect in general, although the neighbour is likely to have very similar soil and climate and thus behave the same.

A traditional approach analyses past aggregated data to predict future outcomes. Even if valid for normal situations, it is clearly not appropriate for novel situations. The engineering approach (Annetts & Audsley 2002) to predicting the impact of future agricultural policies, socio-economics or climate on agriculture land use and its environmental impact is based on estimating the decisions of individual farmers. The underlying hypothesis is that farmers are 'profit maximizers' (Oglethorpe & O'Callaghan 1995). The main differences in the choice of which crops to grow occur as farmers attempt to maximize their long-term profit, constrained by the physical attributes of their land—soil type, climate and slope—and their perceptions of the future profitability of crops. Climate determines how well a crop will perform. Owing to variability in yields and prices, each farmer given the same information will process it differently due to perceptions, experiences and attitude to risk. The model simulates this by randomly selecting yields and prices based on their variability. Aggregated at the regional level, the cumulative decisions show how agriculture may adapt to accommodate changes in climate or socio-economics, technology or legislation (Audsley *et al.* 2006*a*,*b*). Combined with the environmental emissions calculated above, the MEASURES project showed the economic and environmental impact of possible policy choices on sustainable farming (Williams *et al.* 2003).

The Silsoe whole farm model (figure 1) is a multiple objective linear programming model developed for a variety of farming scenarios including UK and European arable, livestock and mixed farms (Annetts & Audsley 2002). The model optimizes a weighted sum of component objective functions which calculate annual net profit and environmental outcomes, subject to a set of constraints. In particular, the model determines the best strategic farm plan of cropping and machinery for given farm, economic and climate details. The crop rotation, timing of

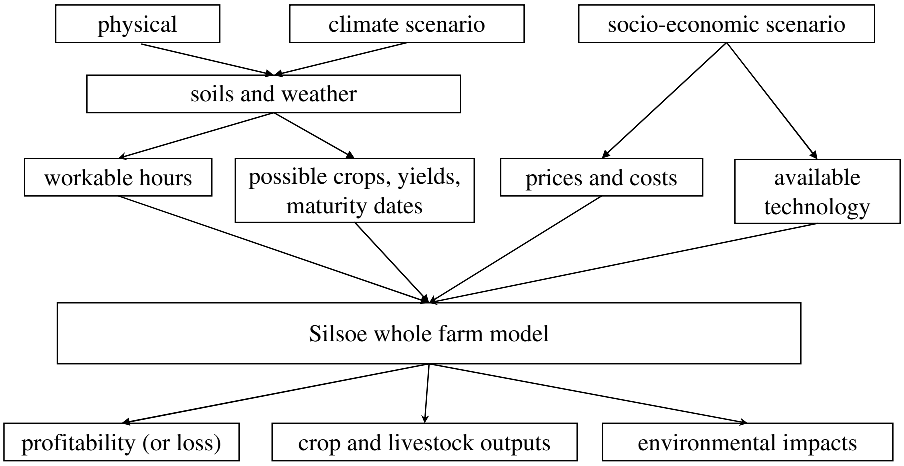

Figure 1. The linkages in the Silsoe whole farm model.

operations and machinery systems used will affect the profitability in terms of potential crop yields, cost of machinery, fuel use, machinery repairs, inputs (e.g. fertilizer and herbicides), etc. The plan must be sustainable over the long term not just for a single year. The hours available in each period are operation dependent, since weather and soil conditions impact the amount of time the farmer can plough, drill, harvest, etc. in differing amounts; for example, spraying requires good weather and low wind speeds, whereas ploughing is possible in wind, rain or shine, provided the soil is workable. Thus, some operations are more restricted in terms of the time available than others.

Any human activity has effects on the environment, but different choices have different effects. A particular example is the choice of when an operation is carried out, e.g. planting winter wheat. There is a time which will give the farmer the highest yield from that crop. The crop could be planted a few weeks later for a loss of yield and a decreased need for chemicals (such as herbicide to control grass weeds). However, later sowing increases the risk of leaching of nitrate which the crop would otherwise have taken up. The model incorporates the effects of changes in crop, method or timing on yield, costs and environmental outcomes.

For livestock, the model considers feed and bedding requirements, and waste production and subsequent disposal to land. The major environmental outcomes are associated with waste disposal, which may lead to large emissions of ammonia to the atmosphere and nitrate leaching to water courses, depending on the method and the timing. Constraints describe the feeding of the animals from foodstuffs, such as straw, grazed grass, grass silage, maize silage and various manufactured concentrates, some of which can be grown on the farm or are by-products of growing crops.

The systems model needs to predict changes in yields as a function of soil, fertilizer rate and climate; to estimate soil workability as a function of climate; to estimate environmental emissions; and to model changes to livestock production with changes in feeds and the availability of forages with climate. Thus, it brings together many models from different sources. The models should be only as complex as necessary for the purpose, but equally they should include all the important parameters. Many crop simulation models predict the average crop yield using weather data, but these are normally soil–water and development stage models, do not include disease, and mostly model just wheat. Complex nitrate leaching models also exist, again usually well tested only for major crops, often transient models and not designed to model the steady-state situation over a prolonged crop rotation. However, these models provide a foundation from which more comprehensive system-level models can be developed.

As an illustration, let us consider how an environmental policy option to reduce herbicide use by taxation compares to a conceptual approach in which the farmer chooses practices which are likely to result in less use while maximizing profit. Data for herbicide use were estimated using a weed control model (Sells 1996), and attached to appropriate crops, rotations and operations. Figure 2 shows results from modelling a typical arable farm (Sells 1999). Applying a tax regime that increases herbicide price reduces the optimum net profit of the farm system, but makes only a small saving in the amounts of herbicide applied, largely through small changes in cropping patterns. When an increasing weighting is applied in the optimization to minimizing the herbicide use while maximizing the net profit, there is a much greater impact on the herbicide use. Trebling herbicide price (200% tax) reduces profit by 5%, and decreases wild oat and blackgrass herbicide use by 13 and 21%, respectively. For the same profit reduction, the goal-driven scenario achieves herbicide reductions of at least three times as much, i.e. 37 and 100%. This shows that there are a number of near-optimal solutions which have lower environmental burdens and tax is not an efficient means of control.

Similar effects have been shown with attempts to reduce nitrate leaching by limiting fertilizer, in this case using the nitrogen turnover model Sundial (Smith *et al.* 1996) as the source for estimates of leaching. In this case, the farmer's reaction is to grow nitrogen-fixing crops and the result is actually an increase in nitrate leaching! The model predicts the probable reactions of optimizers to proposed interventions.

These models may also address the potential effects of future scenarios such as climate change (Rounsevell *et al.* 2003). The REGIS decision support system

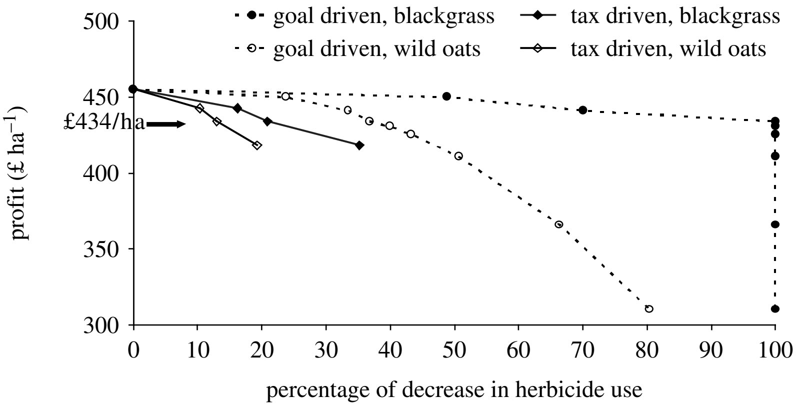

Figure 2. The effect on profit of encouraging decreased herbicide use (filled symbols, blackgrass; open symbols, wild oats), either by taxation (each point on the solid lines represents 100, 200 and 300% herbicide price increases) or by land users making decisions that put increasing weighting on reduced use (dotted line), for a typical sandy loam soil, arable and roots farm.

allows a user to study interactively the regional impact of a wide range of economic and climate variables (Holman *et al.* 2005). This modelling has required metamodels to replace the complex system models. The metamodels, in addition to being representations of the full models, must exhibit the same robustness-to-data characteristics.

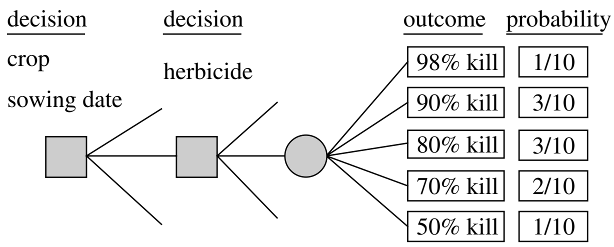

Figure 3. The key determinants of the weed control in an arable system.

(d) *Decision support for complex uncertain systems—stochastic dynamic programming and weed control strategies*

Many of the driving forces in agricultural systems, for example, the levels of weed seed production and the weather conditions that may influence the timing of their germination, are highly variable and uncertain. Specific modelling strategies are required where a strategic decision demands that an array of possible outcomes are considered and weighted. Consideration of options for weed control and subsequent decision support provides an important example.

One of the major criteria in weed control is future losses, illustrated by the maxim: 'one year's seeding is seven years' weeding'. The farmer wishes to maintain a low level of weeds and hence seeds, because the weed may be difficult to control in some future crops (Bastiaans *et al.* 2000). Dynamic programming (DP) is a valuable modelling technique for optimizing such a multi-annual strategy for weed control (Sells 1996). The method is now being implemented as part of the weed management support system (WMSS) in the arable decision support (ArableDS) system (Davies *et al.* 2004). Figure 3 shows the problem and the main variable element of the system, the herbicide effectiveness each year. Control can be achieved by changing crop, cultivation method and sowing date, and by choosing one of a number of herbicides and doses. However, the level of control achieved becomes more variable as one tries to reduce costs.

The formulation of the stochastic dynamic programme is

$$f_t(i) = \max_k \left\{ \sum_{j=1}^{N} p_{ij}^k \left(R_{ij}^k + \alpha f_{t+1}(j) \right) \right\}, \tag{2.1}$$

where $f_t(i)$ is the optimal expected reward for years t and beyond given that at the beginning of year t the number of seeds in the seedbank is described by state i; p_{ij}^k is the transition probability of going from state i to j given the actions described by k; $R_{ij}^k$is the associated reward; and α is a discount factor.

For the DP model, the seedbank number is divided into discrete states on a logarithmic scale owing to the exponential nature of population growth. It is usually necessary to define the seedbank by two state variables for the surface and deep levels, ploughing moving the seeds between levels and deep seeds suffering higher mortality. One of the major problems with any DP formulation is always the time required to solve a realistic problem. Needing two soil levels and hence n^2 states is a classic example.

To use stochastic DP, we need to calculate the transition probability p_{ij}^k of moving from one state i to another j for a given set of actions defined by the index k. Actions k define crop, cultivation, sowing time and weed control. In general, it is possible to describe the control achieved in experiments by a lognormal or similar distribution function. The reward function is the loss of yield and cost of treatments, and also needs to include allowance for loss of value or cleaning costs from having weed seeds in the grain. Once the dynamic programme is formulated, we can solve it to optimize profits over an infinite time horizon.

As part of WMSS, the system allows the user to specify the weeds of concern and their current levels, examine the impact of alternative options manually and then optimize. For a complete system, it is necessary to parametrize the seed and herbicide models for every arable weed of concern. This is rather a challenge for experimental data, but by having a model for which the expert provides parameters by reference to known weeds, performance can be simulated and optimized, the results tested against reasonableness and the parameters adjusted if necessary.

(e) *Linking process and system models to support on-farm decision making—an example for fungicide dose optimization*

Though processes like weed control may, to some degree, be considered in isolation when developing optimal decisions, others are so intimately linked to the whole growth and development of the crop that an integrated approach is necessary. A key example is the optimization of fungicide treatment, where development of the leaf canopy and the timing in relation to grain formation are key interactions with the effect of any disease development, and require a joined up approach to modelling the component processes.

In cool temperate climates, farmers typically spray intensively managed wheat two or three times during April to June to control fungal diseases. At present, the UK farmer has a choice of approximately 20 active ingredients, formulated in combinations into hundreds of products. These in turn can be mixed and applied at different doses and timings. Wheat varieties have different susceptibility to various diseases and weather is very variable. The choice of what, when and how much to spray is complex, and this complexity together with the variability in disease attacks creates a common perception that farmers use too much chemical because they choose a minimal-risk, insurance approach. It is also the basis of a huge and continuing amount of field experimentation as diseases rapidly adapt, new chemicals are discovered and new more- or less-resistant crop varieties are introduced.

Research under the banner ArableDS has developed models (Milne *et al.* 2003; Parsons & Te Beest 2004; Audsley *et al.* 2006*a*,*b*) that bring together agronomic expertise, biological reasoning and experimental information on disease growth and fungicide performance into a decision support tool. The wheat disease manager (WDM) seeks to improve chemical use by transferring this knowledge to users, providing advice on the best choices of timing and product. The model is not prescriptive but instead calculates and demonstrates to the user the probable outcome of choices of chemicals and timing. The user is free to study the alternatives and examine the consequences in yield, cost and reliability of control or ask for the optimum. Decisions can be refined progressively through the season as the effect of weather, earlier sprays and new observations become available. This approach provides a considerable challenge to the expert knowledge as the modelling process rapidly highlights inconsistencies and incompleteness, and is thus a major benefit to decision making.

WDM predicts disease control on winter wheat using a hierarchy of semi-mechanistic models simulating canopy growth, development of the four main foliar fungal diseases (namely *Septoria tritici*, yellow rust, powdery mildew and brown rust), the effect of sprays applied and disease-induced yield loss (figure 4). Foliar diseases reduce yield by destroying green leaf area which would otherwise intercept light energy (Bryson *et al.* 1997). The models respond to

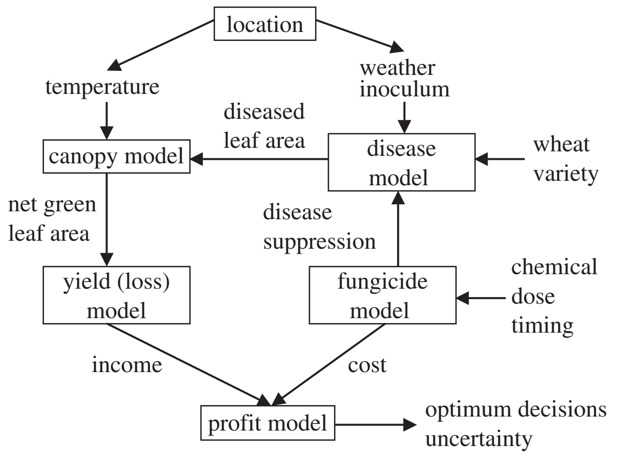

Figure 4. Hierarchy of models used in the WDM to lead to optimal decisions on disease control.

differences in location, sowing date, varietal disease susceptibility, weather data, climatic data, and user observations of crop and disease, etc. The potential development of the crop, disease and yield are predicted using future weather scenarios appropriate to that location.

The canopy simulation (Milne *et al.* 2003) predicts developmental stages as a function of photo-vernal thermal time, and upper culm leaves are set to emerge at a constant rate in thermal time. The foliar disease model (Audsley *et al.* 2006*a*,*b*) simulates the growth of daily infections and differs from other models in three respects. Variables (such as weather, host resistance and inoculum pressure) which affect disease risk are integrated in their effect on disease progress—the agronomic and meteorological data called for are restricted to those commonly available to growers by their own observations and from meteorological service networks. Field observations during the growing season may be used both to correct current estimates of disease severity and to modify parameters which determine predicted severity. Pathogen growth and symptom expression are modelled to allow the effects of fungicides as protectants (reducing infections which occur post-application) and eradicants (reducing growth of pre-symptomatic infections).

Diseased leaves and ears intercept less solar energy proportional to the area of disease, and this is the basis of predicted yield loss. An important aspect of the system is to make use of information on disease levels obtained from field walking, while allowing for the limited accuracy of disease observations. A typical example is yellow rust which is difficult to observe at low levels, but may rapidly explode if not controlled. Bayes' theorem is used to update a prior estimate based on site and variety, using observation. Thus, for example, a zero observation at a high-risk site is effectively not believed!

A genetic algorithm procedure (Parsons & Te Beest 2004) finds a list of the best solutions for a fungicide application plan that optimizes profit margin over fungicide spray cost. This meets a user demand that the decision model should give a ranked list of near-optimal spray programmes, not just the best. The allowable set of solutions consists of legal combinations of products at one-quarter, one-half, three-quarters

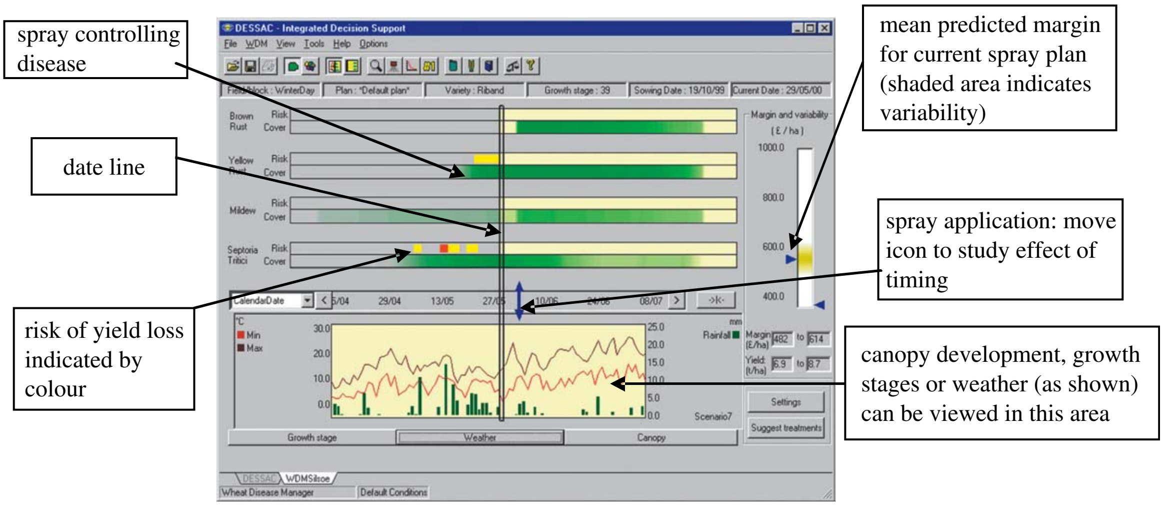

Figure 5. The main user interface screen of the WDM, with explanation of main features.

and full (label-recommended) doses. The user can choose to apply up to four sprays, each of which contains up to three products, subject to restrictions on permitted mixtures, timing and doses. The product database is large and complex. Products are combinations of active ingredients in a bewildering range of different concentrations. By concentrating on actives, it is possible to reduce the problems of parametrizing them—experimental data are very variable and must be collected over several years—using parameters which effectively compare the performance of actives.

The system is accessed through a feature-rich user interface (figure 5). This allows the user to investigate scenarios by altering model settings and observing the effect on disease and margin as predicted by the model, as well as to request a list of the optimized spray plans for the scenario under consideration. The system has been used by farmers for several years and forms a part of the ArableDS decision support system. Its recommendations have proved generally effective (Parsons *et al.* 2004). In 2003, it achieved the twin 'sustainability successes' of suggesting lower doses than the experts and achieving the same control giving higher profits. Conversely, in 2004, it was suggesting high doses 'in a tricky *Septoria* season'—its target is the most appropriate dose—while farmers were applying lower doses. Validating the correctness of the decisions is an interesting challenge since the post-harvest optimum is not the same as the optimum decision at spray time when future weather is unknown.

3. CONTROL ENGINEERING APPROACHES TO BIOLOGICAL SYSTEMS

(a) *Background*

Responsibility for the outcome of the many interlinked and complex processes that comprise agricultural production is largely in the hands of the farmer. Farmers need to control inputs to achieve a particular set of production targets. At present for most systems, decisions are based on experience and intuition, rather than measurements. Though sensors could provide the measurements, sensing technology is only a partial solution to improving production control. Sensors produce large amounts of data which are only useful once the information content is available, and when the farmer has the means to take decisions from that information. In the case of animal nutrition, sensors of animal size or weight might indicate that an animal is growing too slowly, suggesting that it is given more food, but how much more protein, how much more energy and how quickly should the diet be changed? The wrong diet might produce unwanted fat rather than valuable muscle. Is the increased cost of providing more food justified by the increased value of the animal? The development of sensing systems, their linkage to control via models and the ability of these control approaches to incorporate factors beyond production alone, including emissions to the environment, demonstrate the potential for precision approaches to be integral to future sustainable agriculture.

Automatic closed-loop control systems have the potential to control such complex processes. Any control system will include: a reference signal, or input, which sets the desired value of the controlled variable; a controller, which produces an appropriate control signal; an actuator, which acts on the system in response to the control signal; the process that is to be controlled; and the controlled variable, or output, from the system. In its simplest form, this constitutes an open-loop control system, so-called because there is no way in which the value of the output variable influences the input signal. Most agricultural production processes operate in this way. For example, in the case of rearing animals for meat, the input is a desired growth rate; the controller is the farm manager; the actuator is the feed supply system, which is operated by the manager; the process is the animal; and the output is the resulting growth rate.

Open-loop control is prescriptive. The nutritional inputs (protein and energy) for the animals to realize their potential growth are calculated in advance—in a well-managed enterprise by growth models. However, there are many factors (e.g. disease or unfavourable environment) that may prevent the animals from achieving their potential, and growth targets may be missed. These problems are reduced by introducing a feedback loop in which the value of the output is measured, compared with the input and the difference between them (the error) used to control the actuator. An example from agriculture is the system that controls the temperature in livestock housing by switching on a variable number of fans in response to signals from temperature sensors inside and outside the house. The detailed design of the controller determines how the input is modified in response to a given output error. For many applications, a simple on/off controller may suffice. This will switch the actuator on when the controlled variable exceeds a limit, and off when the error is back within the limit.

For improved control, controllers such as proportional + integral + derivative are used. The proportional element provides a control action proportional to the error, the integral element removes steady-state error and the derivative term controls output oscillation. The controller consequently contains three parameters for which suitable numerical values are required for the particular process to be controlled. These parameters are fixed. If the process changes with time, or differs in its behaviour from the one for which the controller was designed, the resulting control of the process will be degraded since there is no mechanism for adapting the controller to the revised process. Examples of control degradation include increased delay in the output reaching the target value, the output overshooting the target, and the output becoming unstable and oscillating around the target value.

One solution to this problem is to incorporate a model of the process in the controller. Continuous revisions of the model can then reflect changes in the real process and be used to recalculate suitable controller parameters. The model of the process, which is driven by the process input and output, is used to calculate suitable values for the controller parameters. Thus, controller characteristics become responsive to process behaviour—if the process changes, the controller changes accordingly.

(b) *Incorporating models in the control loop*

Animals are increasingly grown to tight market specifications for unit weight, lean and fat composition, and meat distribution on the animal. The farmer chooses the diets for the animal so that it produces an acceptable yield of meat. It is clearly useful to be able to weigh a growing animal periodically if one is aiming at a target final weight and especially if the market demands (and it frequently does) achievement of the target on a particular date. An obvious solution is a weighing platform that an animal would stand on, and these have been developed (Turner *et al.* 1984) and are available commercially for smaller animals like broiler chickens.

Although models of most agricultural processes including animal growth have been developed, few are suitable for direct incorporation into a control system. Most models have been developed to demonstrate a scientific understanding of the process valid in a wide range of contexts. They are expensive to develop since they involve dissecting the process into many subprocesses, and they are generally mathematically complex, making implementation in a real-time controller difficult. In contrast, the controller model is required to provide predictions which need only be valid for a given place and time. If process

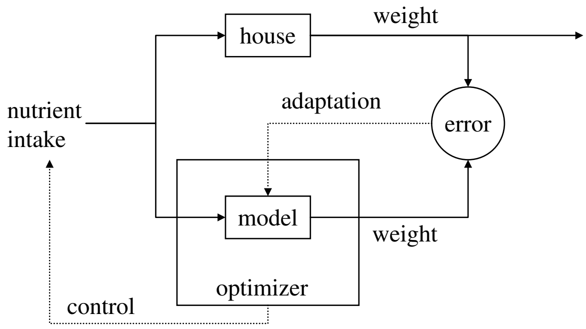

Figure 6. Model-based control for broiler production.

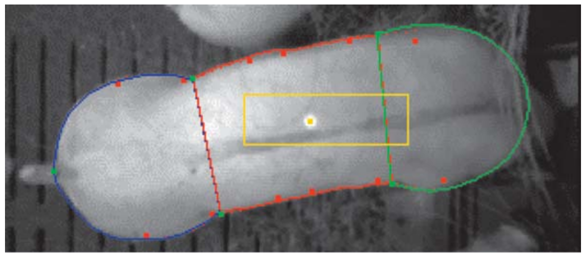

Figure 7. Processed image of a pig showing areas identified and measured by the image analysis system.

characteristics change so that the model is no longer valid, it should be possible to develop a new model to fit the changed process easily and cheaply, for example, when a new strain of animal is developed. Similarly, if the animals' growth patterns were modified by local conditions, for example, environmental conditions, it should be possible to modify the model easily to take these changes into account. In summary, the requirements of a model for use in a model-based controller (figure 6) are that it is specific, easy to develop and mathematically simple.

Using system identification techniques to develop models of agricultural processes is one way to meet these requirements. These techniques use online measurements of process inputs and outputs to estimate the parameters of an adaptive abstract mathematical model. The approach has, for example, been used to produce a model of the growth response of broilers to feed intake (Aerts *et al.* 2003*a*). The model was derived solely from measurements of the process output (broiler growth) in response to changes in the process input (feed intake), and did not require knowledge of the biological processes involved. The accuracy of prediction achieved by the model was similar to that of three traditional static empirical growth models. The model has been used in a feed control system (Aerts *et al.* 2003*b*) to grow birds along different growth curves with promising accuracy.

An alternative approach to the modelling problem was taken by Frost and colleagues (Frost *et al.* 2003; Stacey *et al.* 2004). They judged that a detailed mechanistic model would be too slow for practical implementation in the controller, and instead developed and used a semi-mechanistic growth model predicting broiler growth from feed intake and feed composition (lysine, protein, organic matter, lipid and energy content, and nutrient digestibility) each day. Having satisfied the requirement for maintenance, the limiting nutrient (lysine or energy) determines the protein growth rate. The model assumes that excess energy is deposited as lipid and excess protein is excreted at an energy cost. This is based on established models and principles. A single parameter of the model, effectively representing digestibility of the food, is optimized online in response to past and present values of the process inputs and outputs by minimizing the r.m.s. error between target weight and actual weights plus the growth predicted by the model for the remainder of the growth period.

A prototype system was used in trials to calculate the daily diet for the birds in two broiler houses. At the same time, in two other houses on the same farm, birds were grown by an experienced manager using the traditional prescriptive diet calculation procedure. For operational reasons, the new controller could only change the diet three times a week over the six-week growth period, rather than once a day which would have been preferable, and there was a 24-hour lag in delivering the recalculated diet. Despite these limitations, both of which have been overcome in a fully developed commercial system, the performance of the controller was comparable to that of the experienced manager, using the criteria of deviation from the final target bird weight, and feed conversion ratio. It is well established that the performance of human managers in all areas of livestock production is very variable with some producing consistently better results than others. Novel controllers of this type have the potential to reduce this variation, raising the overall standards of performance and allowing managers to focus on animal husbandry.

The main prerequisite for these approaches is the availability of input and output data, updated at a frequency matched to the speed of the process. In the case of broiler growth control, this means that up-to-date bird weight and feed intake data must be available every day. These studies have demonstrated that practical systems can achieve this reliably, leading towards practical adoption.

A criticism sometimes directed at this process control approach is that it excludes the farmer, thus losing the benefit of his experience. This should not be the case. The process control system informs the farmers so that they are able to take a supervisory role, for example, to approve the animal diet calculated by a nutrition control system and are able to override it. Freed from routine tasks by automation, the farmer would have more time to devote to the skilful aspects of animal and crop husbandry.

(c) *Control of multiple outputs—target growth but with limited emissions*

Animal production has multiple outputs that include the animal product itself, the financial outturn, environmental emissions and animal welfare. All are affected by process inputs which include the animals, their nutrition and their environment. These multiple inputs and outputs are interconnected, for example: changing the animal's diet to achieve a target growth rate may have an undesirable effect on emissions by providing excess protein leading to increased nitrogen excretion; it may produce no economic benefit because the increased value of the animal does not justify the increased feed cost; or compromise animal welfare because the new diet does not meet basic requirements. The ideal control system would regulate all of the inputs so that all output targets are met simultaneously. In practice, this might prove impossible. The most useful system is likely to target profitability as the priority, but with limits that protect welfare and the environment.

Frost *et al.* (2003) linked their experimental studies of growth control in broiler production to intensive monitoring of ammonia emissions. Dietary control, or strategic feeding, has been identified as a technique offering good overall prospects for abatement of ammonia from livestock production (Phillips *et al.* 1998). Frost *et al.*'s study showed that some aspects of the production regime were associated with higher emissions of ammonia, dust or odours. In related studies reported by Robertson *et al.* (2002), there were observable correspondences between the ammonia emission from each house and the actual total protein intake in that house, being highest for the house where the highest total protein diet was consumed, and generally lowest for the house with the lowest protein intake.

With appropriate models of emissions associated with excretion, the above semi-mechanistic modelling approach can be extended to seek to change the animal's diet to achieve a target growth rate while also constraining emissions within specified limits. Improved systems for managing large animal production facilities to constrain environmental emissions are part of Integrated Pollution Prevention and Control regulations in the UK and EU and may become a global requirement for environmental management.

(d) *Advanced sensing techniques—a route to more complex control opportunities*

The scope of advances in sensing to contribute new approaches to sustainable control of agricultural systems is enormous. For the purpose of this chapter, we will just reflect on two areas: machine vision and biological sensors.

(i) *Machine vision*

Though weighers for heavier animals are available, they are rarely used owing to their capital cost, the labour involved in ensuring that the animals stand on them (there are many examples of innovative technology not being adopted owing to its impact on workloads) and reliability (the floor under an animal is an especially hostile environment).

A more practical solution is to apply the science of machine (computer) vision—video cameras linked to computers that analyse the image to produce definitive information on the size of the animal. Overhead cameras collect plan view images (figure 7) from which specific body dimensions are extracted by PC-based image analysis algorithms. These dimensions have been found to correlate well with weight (Wathes & Schofield 2004). Cheap hardware is available, most farms already have a PC, and mass-produced webcams provide adequate quality images. The software extracts the data automatically so that, with the cameras positioned such that images of the

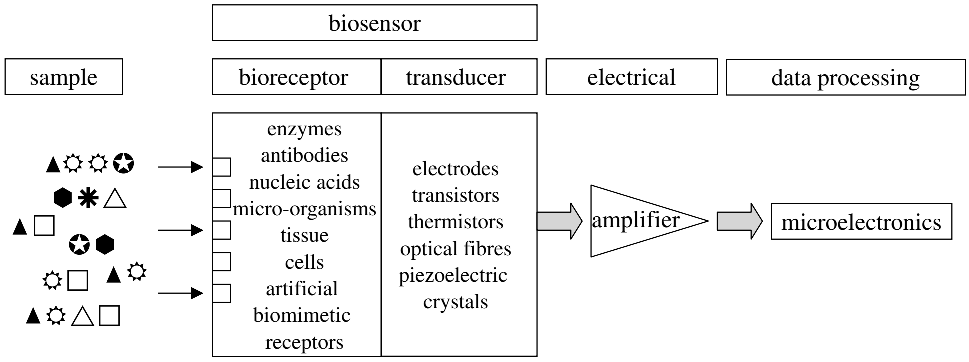

Figure 8. Biosensors offer a key opportunity to introduce engineering control to a wide range of biological processes.

animals are collected during a normal day (e.g. over a feeder), the system is fully automatic (Schofield *et al.* 1999). This general principle of using mass-produced sensors together with advanced software to interpret the signals that they produce is more likely to succeed commercially than one based on developing special-purpose, and therefore expensive, sensors. White *et al.* (2004) developed a prototype practical system for incorporation into an integrated management system for pig production (Parsons *et al.* 2005).

In contrast to applications in manufacturing industry, agricultural machine vision must operate robustly in unstructured environments and, owing to biological variability, can make fewer assumptions about the nature of the subject. A vision system has to cope with the variation in the apparent shape of plants or animals of given species due to inherent variability, changing viewpoint or variable lighting. For example, the presence of shadows in external scenes can pose serious problems for rapid and robust image interpretation. Because daylight is of variable spectrum, the colour of any scene component sensed by a computer vision system will vary, making discrimination based on colour difficult. Marchant & Onyango (2002) have overcome this problem using the fact that sunlit areas receive more light at the red end of the spectrum than shaded areas. They have developed a transformation for colour images that is invariant to daylight spectral changes. The result is a more robust sensing mechanism that can control outdoor processes resiliently, in scenes with sun and shade. This has direct relevance to real-time field machine control, discussed at the end of this chapter.

(ii) *Biological sensors*

Engineering to apply biosensor science in special-purpose sensors has considerable potential (figure 8). A biosensor may be defined as incorporating a biological or biomimetic sensing element connected to a transducer that produces an electrical output. Biosensor research and development has hitherto been mainly directed at healthcare, for example, the hand-held glucose meter used by diabetics. Progress in agricultural applications has been made in detecting pollutants in crops and soils (Palmer *et al.* 1998; Starodub *et al.* 1999), identifying diseases in crops and animals (Schutz *et al.* 2000) and monitoring animal fertility (Velasco-Garcia & Mottram 2003). The latter is a particularly important example for on-farm process control as the economic performance of a dairy farm is heavily dependent on predicting cow ovulation, to allow insemination on the optimal day for conception. Traditionally, the farmer observes cow behaviour, looking for signs of increased activity associated with oestrus. This method is very unreliable. It is known that monitoring progesterone levels in milk is a very effective means of predicting ovulation. ELISA test kits have been available for some time, but are not widely used, at least in part because they require the farmer to take samples of milk and carry out a procedure culminating in observing a colour change. This is another example of the failure of labour-intensive sensor technology to make an impact, indicating that new technology must be labour-saving and preferably automatic. Biosensing can provide such a solution for progesterone monitoring. A prototype electrochemical biosensor, based on screen-printed carbon electrodes modified by immobilization of appropriate monoclonal antibodies, able to detect progesterone at the required concentrations, has been assessed for automatic on-farm monitoring systems (Velasco-Garcia & Mottram 2001). The approach could reduce culling, with obvious profitability, waste and welfare benefits. The scope to incorporate other non-invasive sensing heralds the future for precision animal management.

A radical approach to sensing for process control uses the crop or animal itself as the sensor. Thus, the main purpose of a temperature control system in an animal house should be to make the animals comfortable rather than to control temperature itself. At a given temperature, thermal comfort depends on other environmental variables such as humidity and airspeed, and on animal-related variables such as stocking density and coat length. Animal behaviour may be a better indicator of their comfort. For example, Xin (1999) used automatic analysis of images of groups of pigs to monitor their thermal comfort, based on the observation that a group of pigs will lie huddled closely when they are feeling cold, spread out when they are warm and just touching when they are comfortable. A similar approach is being used to determine an animal's well being from the noises that it makes. It has been shown, for example, that the pig huddling behaviour mentioned earlier is accompanied by an increase in high-frequency vocalizations (Hillmann *et al.* 2004), suggesting an automatic acoustic monitoring system for temperature regulation. Direct monitoring of plant temperature, using thermal imaging, has also been used in greenhouse production to enhance the precision of control, potentially saving energy and enhancing the quality of the crop (Langton *et al.* 2004).

(e) *Real-time machine control*

At the extreme short end of the time scale for making decisions, the challenge for control is to operate at time scales and frequencies that are not attainable by even the most proficient person, and this is exemplified by control of field machinery. Traditionally, arable operations such as cultivation, crop spraying and harvesting have been carried out as if the field were homogeneous. Precision agriculture aims to control operations in response to the spatial variability of soil, crop or pest infestations. The first principle is to measure the variable properties and then to tailor inputs or actions to local needs or conditions. For some systems, this is possible in real time, adjusting the machine to local conditions as immediately measured. The definition of needs may again be based on a model of crop or pest performance that interprets local data to determine the appropriate action. For other systems, past knowledge of the field—the soil type variation or past years' crop performance—may determine the actions. In these circumstances, field maps and Global Positioning System (GPS) referencing of the equipment are an integral part of the control system.

Pesticide application provides examples of precision approaches using maps, where applied dose is calculated according to local variations in pest infestation, rather than using a standard rate for the whole field (Miller 2003). For many species, weed distributions in fields are patchy and it has been shown that patch spraying can deliver savings of up to 40% in herbicide use. Weed patch detection is the main problem. In widely spaced row crops such as vegetables, there is considerable scope for developing fully automated detection systems based on image analysis, and for the development of accurate guidance systems that apply pesticides only to the weeds. This may not be feasible for crops with higher plant density, in which case providing the spraying machine with weed maps, produced in advance by human observation, is a more practical approach. It is impossible to use real-time observation when using pre-emergence herbicides or when the crop or weeds are very small, preventing accurate identification. In these circumstances, maps of past infestations have been shown to provide sufficiently accurate information for a patch spraying system (Paice *et al.* 1996).

Matching applications to crop canopy structure may also reduce pesticide use. In crops such as cereals, studies have demonstrated potential savings in fungicide, particularly at earlier stages of growth, by adjusting spray delivery to measured canopy characteristics. This approach is particularly important in bush and tree crops where savings of up to 75% in pesticide use have been estimated (Miller 2003). It presupposes that relevant crop canopy measurements are possible. A light detection and ranging system has been used to provide such measurements in an apple orchard (Walklate *et al.* 2002). The canopy measurements have been used as input to a spray deposition model which estimates required pesticide application rates. Reductions in pesticide applications through improved precision have direct benefits both to improved profitability and to reduced environmental contamination.

Pressures on pesticide availability due to more stringent regulation and approval processes are challenging the sustainability of production systems for some crops. Precision in non-chemical interventions has the potential to provide effective solutions. For example, in many intensive farming systems, though mechanical weed control is feasible, it is slow and expensive. In organic systems, the limitations to the performance of mechanical weed control constrain important aspects of the crop rotation. Significant environmental and economic benefits would be available from precision mechanical control of weeds. The difficulty is in guiding the hoe or cultivator so that its blades do not damage the rows of crop but do uproot or bury weeds across most of the inter-row. The required lateral positioning accuracy of typically ± 25 mm is not reliably achievable by manual guidance or by mapping techniques or by GPS-based technology at the kind of forward speeds necessary for a competitive weed control technique.

This guidance problem has been addressed by applying the science of vision analysis in real time (Tillett *et al.* 2002). The novel position control system adjusts the lateral position of the hoe relative to the tractor, using hydraulic cylinders. Inter-row cultivator units were mounted on the hoe frame at separations corresponding to the crop row spacing. The vision system consisted of a standard monochrome CCD camera mounted on the centre of the hoe frame so that four rows of crop were in view (hoe widths and seed drill bouts need to be equal). Contrast between the plants and soil was enhanced using a near infrared filter. The image analysis system must locate the crop rows as the crop grows from small discrete plants to continuous rows of vegetation, accommodate the presence or absence of weeds between the crop rows and tolerate varying lighting conditions. This was achieved by dividing each image into eight horizontal bands and using a mathematical filter to detect the periodic component of the amplitude in each band due to the crop rows (Hague & Tillett 2001). To allow for unreliability in observation of row position obtained from a particular image band due to the presence of weeds or absence of crop plants, information from each band was compared with an idealized template and assigned a confidence term between one, indicating a good fit, and zero. To track hoe position with respect to crop rows, a mathematical filter was provided with observed row position from each image band and row positions predicted from knowledge of previous positions and the machine's kinematics. The observed and predicted positions were compared, and if the difference exceeded a given value the new position observation was ignored. Otherwise, it was used in the calculation of the next prediction. The latest estimate of position was used to control the lateral position of the hoe. Field trials with the guidance system in sugar beet showed encouraging accuracy with standard deviation in hoe lateral position relative to crop rows within 16 mm and a mean bias of not more than 10 mm. The system demonstrated robustness with respect to plant growth stage, missing crop and varying lighting conditions. Good weed control was achieved and it was possible to operate at twice the target forward speed of 6 km h^{-1} without crop damage (Hague & Tillett 2001).

Developments in this area are likely to increase work rates by the guidance of multi-component (wider) machines. For example, the system described by Tillett *et al.* (2002) relies on all rows covered by the hoe being parallel, which is only true for the rows planted by a single drill pass. This restricts the width of an automatic hoe to that of the drill, typically 4 m. A hoe with several independently guided 4 m wide sections would solve this problem and make the technology more economically attractive. This first embodiment of automatic hoe control only targets weeds in the inter-row—hoeing weeds within the row of spaced row crops will follow.

4. CONCLUSIONS

These concepts and examples of developments in engineering science directed at agricultural systems demonstrate the scope for quantitative mathematical approaches within an engineering framework to target key concerns of sustainable agriculture. The overall impact of a farming system can be understood better, the options for management decisions that address both profit and environmental impacts can be presented, and the implications of regulation assessed. In addition, specific techniques for automatic process control provide benefits from precision in use of inputs or management of unwanted outputs.

The critical engineering challenge with systems models is to provide approaches that address real and practical problems and provide information that will improve performance. The performance could be in the context of policy decisions, assessing the impact of regulation on how land use and environmental impacts may change, or at the other extreme in immediate and day-to-day decisions on uses of inputs that influence profitability and the environmental footprint of agriculture. High-level models and simplified descriptions of processes are essential if the models are to be tractable and the outputs available to practical effect.

It is important to have techniques for mathematical optimization of the models so that the best solutions or a range of near-optimal solutions and associated probabilities are provided to support decision makers. However, optimization also provides a very valuable test of the reliability of any system model. Optimization will identify and exploit errors and omissions in the model or parametrization and lead to unrealistic optima. Thus, in the fungicide model, it is unnecessary to force a spray at growth stage 39, since if it has been correctly constructed and parametrized, the optimized model will nearly always choose to spray at or near that time. Not to do so indicates an error. In the weed model, sensible levels of control must be suggested by the optimization for any combination of weeds. In the land-use model, the optimization should give a reasonable prediction of current cropping given soils, climates, yields and prices, all without being constrained to do so.

The engineering developments for real-time control are not only relevant to intensive agriculture. For example, the automatic process control techniques that are currently being applied to intensive livestock farming are equally applicable to extensive systems. It may be more difficult to develop sensors for monitoring free-ranging animals than those confined in a building and to control the nutrient intake of a grazing animal, but these problems are amenable to engineering research. The need for advanced process control in agriculture will increase as production priorities move from simple requirements to maximize outputs and profit to more complex multiple targets involving compromises between, for example, economic performance and environmental impact. The example of the automatically guided hoe shows that advanced engineering science is able to provide systems that have less direct environmental impact than their predecessors. Engineering development in agriculture is proving itself flexible to changing priorities.

Other disciplines continue to provide new challenges for engineering to translate innovation into practice. The potential for biosensors that detect key indicators of disease or physiological status will increase as the benefits of post-genomics are realized. The potential from continuing increases in computing performance will enable new mathematical modelling methods and permit more effective approaches that accommodate the temporal and spatial variability of biological and agricultural processes, and thus a more robust and confident realization of precision agriculture. Integrated approaches to communication of extensive and complex data and decisions will be an important part of the development of model-based decision support, providing the farmer with technical precision at his fingertips, ready at the moment a decision is required. The natural world's uncertainty and variability have always created key challenges for the timeliness, accuracy and precision of decision making and control in agriculture and new mathematical and engineering approaches are providing the means to meet them.

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