Application of Crop Simulation Models in Agricultural Research and Development in the Tropics and Subtropics

INTERNATIONAL FERTILIZER DEVELOPMENT CENTER

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Summary

Crop simulation models can be applied to management problems in numerous ways. At the field level, they can be used to investigate variety selection, fertilizer and irrigation use, the timing of planting and establishment in relation to prevailing weather and soil conditions, and long-term soil and nutrient effects on yield stability and sustainability. At the farm level, additional applications include the design and pretesting of new and improved cropping systems and their effects on household viability, together with feasible pathways for bringing about radical changes to farmers' production systems over time, and investigation into yield disparities observed between plots on the experiment station and the farmers' own fields. At the regional level, linkage to a Geographic Information System allows the aggregation of production response information for use by researchers and policymakers. In all these applications, simulation models are an adjunct to, and not a replacement for, traditional field experimentation. The objective extrapolation of field trial results across time and space enhances the efficiency of the research process. Modeling can help to ensure that scarce research resources are expended only on the most promising alternatives that fit in with smallholders' objectives and attitudes, their resource base, and their management ability. For implementing model application projects, a case study approach is recommended. Considerable research is needed in certain areas before the benefits of model use can be fully realized.

Acknowledgments

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Introduction

Substantial effort has been expended over the last 20 years or so to design and construct simulation models capable of predicting biological processes. Such simulation models involve some degree of explanatory power (statistical models and mathematical programming models are not part of this discussion). These simulation models have tended to fall into two groups: highly detailed deterministic models of important biochemical or component processes in organisms (research models) and much less detailed enterprise-oriented models, ostensibly for investigating questions related to agricultural management. To reflect biophysical uncertainty, the latter have normally included a certain number of stochastic processes, to account either for seemingly random phenomena (such as the sex of a calf at birth) or phenomena that are currently too complex to yield to a mechanistic approach to modeling (such as weather).

Modeling, as a bona fide output of research effort, seems to be recovering from a severe credibility crisis that affected it in the past (reasons for this are complex and various, but seem to stem from overenthusiasm, unrealistic expectations, and chronic user-interface problems). Evidence of simulation modeling entering the mainstream of agricultural research is afforded by the fact that major donors are now willing to risk research funds on projects whose modus operandi is almost exclusively model-related.

There is still substantial scepticism in many quarters for the claims, sometimes extravagant, that are made on models' behalf. It must be admitted that this is justified up to a point. The potential benefits of model use in the research and development process have yet to be fully (or even partially) realized, and it is a matter of concern that little work has been done on the integration of modeling activity into traditional research and development. Most modeling projects dwell on model construction and validation, very few on their actual use. A grave danger, in such a situation, is what may be termed donor burnout: claims are made for modeling, projects are funded, little real progress in enhancing the efficiency of research and development results, and over time, donors become wary of funding further related activities (for example, a case can be made that donor burnout occurred with Farming Systems Research [FSR] in the late 1980s.) Reestablishing credibility then becomes exceedingly difficult.

If donor burnout is to be avoided for modeling, then benefits to the use of modeling in development have to be demonstrated, and quickly. Crop model development is now at the stage where models are useful enough to supplement field trial work in all sorts of situations. The activities of the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) project, funded by the Agency for International Development (AID) and based at the University of Hawaii, and those of the International Fertilizer Development Center (IFDC) and other institutions have provided a solid base on which model application projects can be built. Model development is by no means complete or even at a desirable stage: the biology of cropping systems can be represented only partially. For the tropics and subtropics, there are model limitations with respect to pests and diseases, multiple cropping, and the inclusion of animal interactions at the present time (although this situation is changing).

Models, however, are still useful, even in their present state. The ideal model will never be built, and there seems little point in waiting for the next model improvements because modification is a continuous and probably never-ending process. Model applications can concentrate on the development of conceptual and practical frameworks in which models are embedded to enhance the efficiency of research and development (R&D); "better" models can always replace "worse" models in such frameworks if they are constructed in an appropriate fashion.

The purpose of this document is to consider various approaches to crop model applications, to indicate how these might be implemented, and to list priority areas of further research for successful model-related projects.

A Conceptual Framework for Using Models

The translation of research findings into technology packages that can be widely adopted by farmers constitutes a major problem in the development of agriculture in many countries. The reasons for the delay between the identification and adoption of technology include the following (Dent and Thornton, 1988):

- Some applied agricultural research is inappropriate to farmers' needs.
- The risks involved in adopting new technology are not appreciated by researchers.
- Farmers' objectives often do not coincide with those assumed by researchers and extension personnel; sometimes, farmers' objectives are not even known.
- Farmers experience management problems associated with new technology which are not always foreseen by researchers.
- Farmers operate within a set of constraints (resource-related, political, and social) that may not be fully appreciated by the researcher.

Farming Systems Research was developed in an attempt to reduce this delay and to encourage farmers to introduce new technology more quickly. It is difficult to give a precise definition of FSR because many methodologies, and thus much terminology, exist. It is perhaps more useful to list the features of what is commonly understood by the term. Some of these are as follows (Biggs, 1985):

- The activities of the farmer are analyzed holistically, implying that the approach is inter- and multidisciplinary.
- The clients of FSR tend to be small farmers, clustered in reasonably homogeneous groups.
- It is essentially applied, problem-solving research (where the problems should be specified by the farmer); feedback from such research can be used to modify basic research activities.
- It involves surveys and on-farm trials, i.e., farmer participation.
- It is a dynamic process, capable of self-correction.

Four general but sequential phases can be identified: the diagnostic phase, where existing production systems are examined with respect to constraints of all kinds; the design phase, where potential improvements are identified; the testing phase, where promising production possibilities are evaluated under local farmers' conditions; and the extension and monitoring phase, where the package is passed on to more farmers and evaluated further.

In general terms, assessment of experimental findings leads to the testing of a preliminary technology package on a small number of farms in a region. The package might involve a particular cultivar/fertilizer application/disease control program. The results from small-scale plots are monitored, usually over a number of seasons, and the appropriateness of the package may be confirmed in some sense. If so, the package may then be applied on a larger scale on a limited number of farms, with the anticipation of not only again confirming the value of the package but also now collating farmers' initial reactions and their views on management problems. Eventually, the package may be established at full farm scale on a number of reference farms in the region. The crop and the farmers' reactions are monitored. Inevitably, several more seasons must be involved. A similar procedure is necessary for other crop and livestock enterprises before the farming systems researcher can be expected finally to put together a suitable crop rotation and assess yields, their variation, and thus the expected profitability of a whole farming system package.

The advantage of the approach outlined above is that the technology is assessed in a whole farm context; interactions between the various farm activities during the whole course of the year are included in the assessment process. A full appreciation of the resource demands of the farm is possible, and the managerial and social implications for farmers and their families may be judged. Some adaptation or refinement of the technology is almost certain to take place during the testing phase. However, it is clear that time and substantial resources are involved and that, in addition, no assessment can readily be made of how the package should be modified in different districts in response to different soils and changing local climates.

Simulation modeling has considerable potential for overcoming such problems and also for speeding the transition from the design stage to the testing stage and beyond. The major benefits of using models are as follows:

- Technology packages can be designed and assessed efficiently and quickly using the computer; this can help to ensure that only the most promising actually enter field testing (with the concomitant expenditure of scarce resources that this entails).
- The same management package can be pretested in other locations simply by changing model inputs (soil and weather); the models can be used for any location where input data exist with which to run them.
- By using historical or synthetic weather sequences for many different season types, the variability associated with particular practices at a particular site can be isolated in a way that would be impossible with standard field trials (in other words, field trial results can be extrapolated through space and time).

Insofar as FSR depends on field experimentation, among other things, modeling has the potential to be used within the same framework to achieve the same ends. Of course, biological feasibility of an agrotechnology package is no guarantee of adoption. Expanding the scope of crop models to treat important nonbiological determinants of farming systems is discussed below.

Model Applications

To summarize, the value of a validated crop model derives from its ability to screen agricultural technology options so that only the most promising enter field testing; expenditure of scarce research resources on time-consuming field experimentation can thus be lessened, and field research can be made more effective and efficient (Thornton et al., 1991b). With suitable input data, the running of computer-based experiments allows extrapolation of results across sites and across seasons.

Clearly, the limit to what can be achieved depends on the sensitivity of the model to biotic factors; this sensitivity is built in by the modeler and has two components:

1. The ability of the model to react in a meaningful fashion to small changes in input conditions (such as a slightly different soil, for instance).
2. The relationships in the model designed to simulate particular biological processes (such as nitrogen uptake).

The implication of the first is that there is a well-defined accuracy to simulated output (clearly, if the results of simulations suggest that variety A outyields variety B by 5%, then this difference may not be meaningful if the model is accurate to 10%). The second component implies that there are limits to what the model is capable of simulating; there is little point in attempting to model a field trial devastated by disease if the model has no in-built capability for simulating the effects of disease on the growth and development of the plant.

Any increase in model sensitivity, in either of the senses above, generally results in increased complexity of the model and in increased data demands for running it. On the other hand, insufficient model sensitivity will allow little to be said as regards biological response to particular input conditions. The balance that the model builder achieves between these two considerations is related to a number of factors, including the use to which the model is to be put and the research resources available. The crop models are continually being modified and improved. At present, the IBSNAT crop models can be used to investigate the following (IBSNAT, 1988):

- Timing of planting and its relation to climatic conditions (such as the onset of the rainy season).
- Response to nitrogen and phosphorus fertilizer type and placement (the cereal models only).
- Variety selection.
- Planting density.
- Yield potential.
- Irrigation scheduling and yield response.
- All interactions involving the above, in any specified location.

The way in which modeling can interact with more traditional research activity is illustrated in Figure 1. Experimentation at the computer can be used to screen large numbers of production possibilities and to identify those that appear to be particularly promising for given soil-climate combinations. These promising alternatives can then be assessed further through normal field trial work. The results of such fieldwork can then provide feedback to the model,

whence fine-tuning of the appropriate management options can take place (Figure 1).

Conceptually, model applications for management problems can be considered at four levels:

1. The field level, where crop performance is assessed primarily in relation to its biophysical feasibility; limited economic analysis may be carried out at this enterprise level.
2. The farm level, where the interactions between different enterprises (which will usually be competing for scarce resources) are taken into account, in an effort to gain insight into the operation of the farm as a whole. Substantial socioeconomic analysis is necessary at this level because farmers' actions are determined by their attitudes and objectives, for example, as well as by their resource base.
3. The regional level, where individual farm response is aggregated in some way to give insight into regional production patterns.
4. The national level, where regional response is aggregated to provide information at the highest policy level.

Note that this is a bottom-up approach: some detail is omitted as higher levels are reached, in distinction to a top-down approach, where detail is added in as one moves from the higher level of organization to the lower. Given the availability of the crop models, the bottom-up approach is the obvious one to follow. Whether all the biological detail in the crop models is necessarily required at higher levels of organization is a question that needs careful answering.

Most model applications to date have dealt with the first of these levels, although regional applications are currently underway. The higher levels of organization do not necessarily require a more complex overall model; nor, assuming applications are built around detailed biological crop simulation models, is the same type of model ideally suited to each level. In fact, there are strong reasons to suppose that the farm-level model is likely to be the most complex, in view of the necessity of incorporating the biology, sociology, and economics of the farming household. There are certainly severe problems in aggregating farm response to regional and higher levels of organization, but these are likely to be comparatively tractable compared with the problems of assembling a farm model in the first place. These issues are discussed further below.

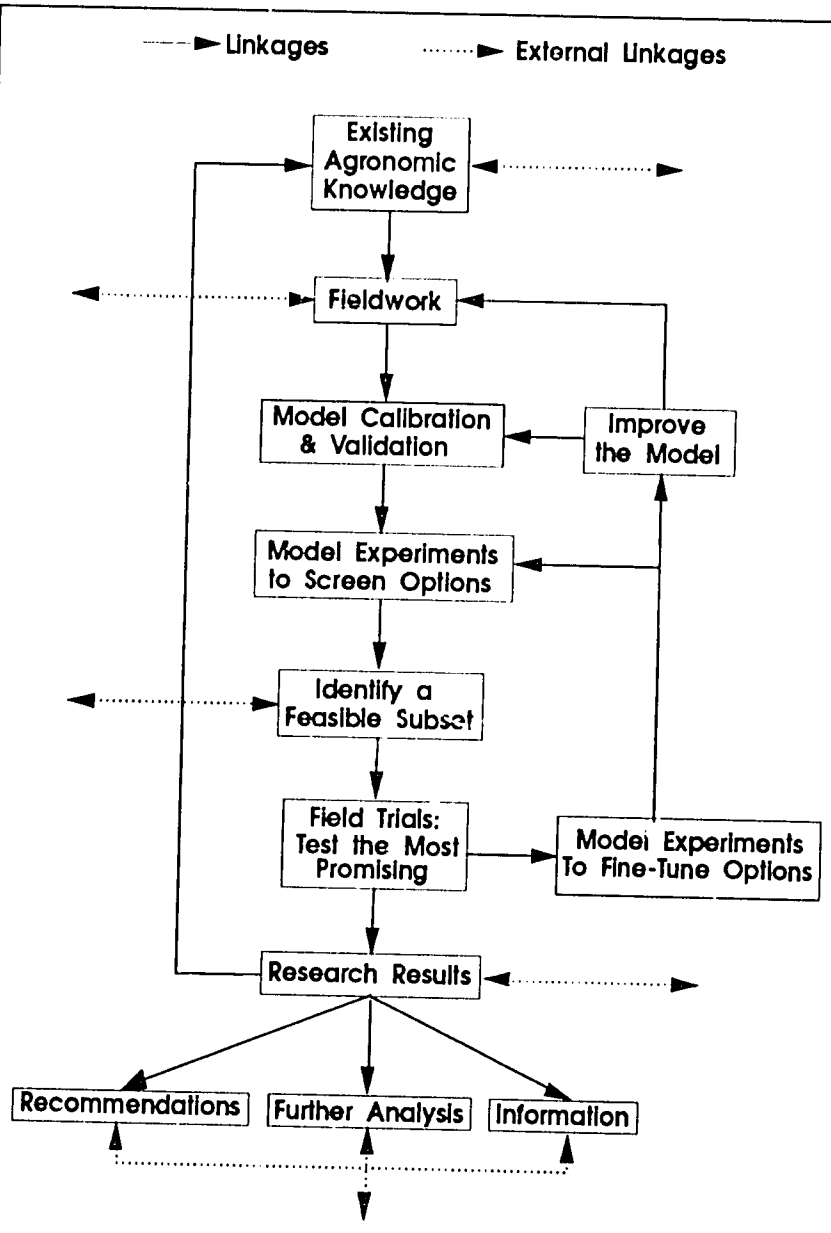


Figure 1. Modeling and the Research Process.

The Field Level

Variety Selection—Computer-based experiments to assess the suitability of particular varieties for particular locations can be carried out in three ways:

Table 1. Cultivar-Specific Coefficients for CERES-WHEAT: Sample Values for Wheat Genotypes Adapted to Different Environments (from Godwin et al., 1989).

Adaptation	Cultivar-Specific Coefficients					
	P1V	P1D	P5	G1	G2	G3
Spring Wheats						
Northern Europe	0.5	3.5	2.5	4.0	3.0	2.0
North American Prairies	0.5	3.0	2.5	3.5	3.5	2.0
Australia	0.5	2.0	2.5	2.5	2.0	4.0
India	0.5	1.5	3.5	4.0	2.0	2.0
Winter Wheats						
America, Pacific	6.0	3.0	2.0	3.0	2.0	2.0
America, N. Plains	6.0	2.5	2.0	4.0	2.0	1.5
America, S. Plains	4.0	3.0	2.5	3.0	3.0	2.0
America, East	6.0	3.0	2.0	4.0	2.0	2.0
West Europe	6.0	3.5	4.0	4.0	3.0	2.0
East Europe	6.0	3.0	5.0	4.5	3.0	2.0

These "scale" values are guides only; they are converted to biological values in the model.

The vernalization values do not represent the full range of values present within the species (see Godwin et al. [1989] for more details).

P1V VERNALIZATION COEFFICIENT: relative amount that development is slowed for each day of unfulfilled vernalization, assuming 50 days is sufficient for all varieties (range 0-9)

P1D PHOTOPERIOD COEFFICIENT: relative amount that development is slowed when plants are grown in a photoperiod 1 hour shorter than the optimum, assumed to be 20 hours (range 1-5)

P5 DURATION OF GRAIN FILL STAGE COEFFICIENT: degree days above a 1 degree C base from 20 degrees C days after anthesis to maturity (range 1-5)

G1 KERNEL NUMBER COEFFICIENT: kernel number per unit weight of stem (less leaf blades and sheaths) plus spike at anthesis (range 1-5)

G2 KERNEL WEIGHT COEFFICIENT: kernel filling rate under optimum conditions, mg per day (range 1-5)

G3 SPIKE NUMBER COEFFICIENT: dry weight of a single stem (excluding leaf blades and sheaths) and spike, under no stress, when elongation ceases, g (range 1-5)

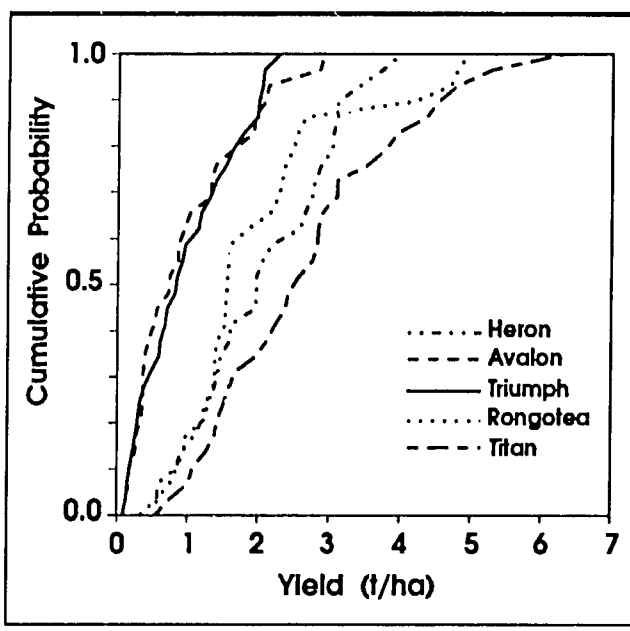


Figure 2. Variety Screening: Rainfed Wheat in Australia Over 21 Simulated Seasons.

1. Varieties can be characterized using detailed field experimentation to derive the necessary cultivar-specific coefficients as accurately as possible (examples for the CERES wheat model are presented in Table 1).
2. Varieties can be clustered on the basis of broad types to produce cultivar "homologues" that behave similarly in a particular environment.
3. A cultivar coefficient blueprint can be identified for a particular location; on the basis of experimentation at the computer, the coefficients can be adjusted, and simulated results over many seasons can be compared to define suitable cultivar characteristics for the situation under investigation and for other locations.

Detailed characterization has the advantage of accuracy but involves substantial expenditure of research resources. For situations where such experimentation is not feasible, perhaps because of the number of lines of interest, one option is to attempt to match cultivars with those that have already undergone detailed characterization. IBSNAT's Decision Support System for Agrotechnology Transfer (DSSAT) contains a data base of all varieties of each crop that have been extensively characterized; some 100 varieties of wheat, for example, have undergone this process (Jones, 1986; IBSNAT, 1989). The illustration in Figure 2 shows various wheat varieties grown in rainfed conditions in New South Wales, Australia; these yield curves were obtained from simulations over 21 years, using synthetic weather sequences. The enormous variability in yield, primarily a function of rainfall variability under Australian low-input conditions, is particularly noteworthy.

A slightly different approach involves the clustering of varieties.

The first step in such characterization might reasonably involve duration of the entire growing season by identifying planting windows for particular varieties. This would allow a number of groups to be established. Further subdivision could then be carried out by attempting to maximize the duration of particular growth stages for each group; in maize, for example, this might involve silking to maturity. Once a suitable group has been identified for a location, then again the data base of varieties can be inspected in an attempt to match the group type with a variety that has already been characterized fully.

The blueprint approach can be used in a number of situations: for example, where improved varieties have not previously been grown or where a need is identified for a new improved variety to be introduced to an area. Through inspection of the variety data base and comparison with the coefficients generated using the model, the cultivar and the situation may be successfully matched; then standard field testing procedures can follow. Full and detailed characterization need be done only for those varieties that have some potential.

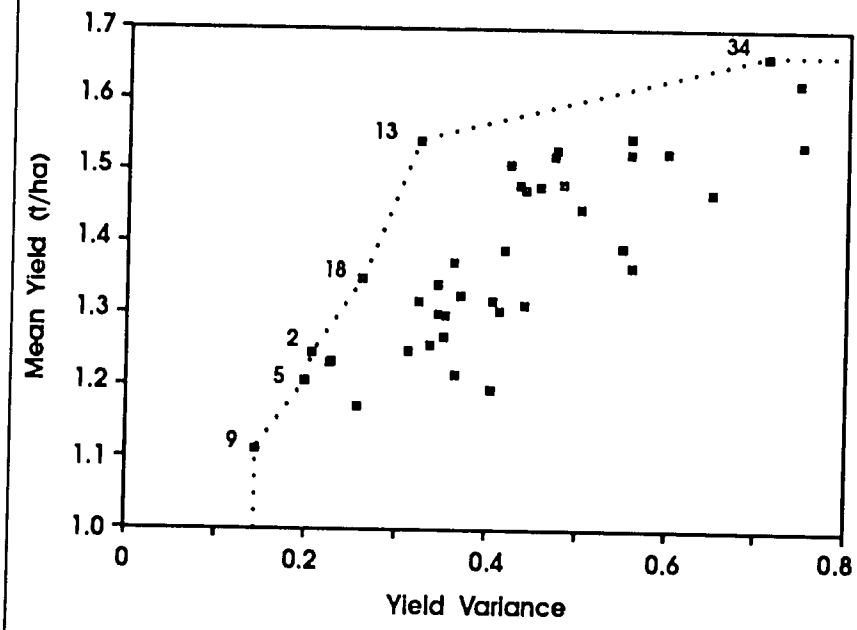
Of course, varieties are by no means fully characterized in terms of the cultivar-specific coefficients required by the model; nothing is said about the ability to withstand disease and pest attack, for example; such characteristics are likely to be added at a future date for many of the models. Nevertheless, agronomic performance of varieties can be assessed initially by using the models.

Fertilizer and Irrigation Use— The crop models can be used to assess and compare traditional and new varieties in their response to different fertilizer regimes and irrigation schedules. Factors suitable for computer experimentation with regard to fertilizer use include the following:

- Source of nitrogen and phosphorus (rock phosphate, super phosphate, urea, etc).
- Timing and optimum levels of application (single or split applications, etc).
- Placement (broadcast or side-banded applications, etc).

For particular locations, experiments can be run on the computer, involving numerous combinations of variety, source, timing, application level, and placement, and these can each be replicated many times using different simulated weather sequences. In the first instance, analysis of each treatment run under different climate scenarios will involve the comparison of yield distributions. A simple economics model can then be added to estimate appropriate gross margins for each treatment, since there may be substantial differences in cost between treatments involving one or more applications of fertilizer. Well-documented procedures that can be used for comparing distributions include mean-variance analysis, stochastic dominance analysis (Anderson et al., 1977), and mean-Gini stochastic dominance (see Appendix). Similar analyses can be carried out for particular irrigation strategies.

An example of mean-variance analysis is shown in Figure 3. Yield



Treatment

2 May 1 planting, 30 Kg N applied at planting
5 May 1 planting, 30 kg N applied at planting + 30 days
9 May 1 planting, 60 kg N applied, split application
13 May 15 planting, 60 kg N applied at planting
18 May 15 planting, 30 kg N applied, split application
34 June 15 planting, 90 kg N applied at planting

Figure 3. Mean-Variance Diagram for a Nitrogen Experiment on Wheat.

mean is plotted against yield variance for a 40-treatment nitrogen experiment, involving four levels of N and three dates of application (this experiment was run on the Supercomputer at the University of Edinburgh, United Kingdom, and involved 2000 separate season-long simulations; the entire experiment was simulated in less than 770 seconds). The efficient treatments are numbered and described in the figure.

Yield variability is only one estimate that will be of interest to a smallholder farmer, and it may not even be the major source of variation in determining the economic return to the household. Price and market risk may be of greater concern when a farmer contemplates changing his management or introducing new technology.

The importance of including even a simple economic analysis is illustrated in Figure 4. A traditional variety might be outyielded over the entire probability interval by an improved variety; agronomically, the improved variety is far superior (see Figure 4A). However, assume that the improved variety requires better seed-bed preparation and matures somewhat later than the traditional variety. The first assumption means that the variable costs of production will be increased with respect to the traditional variety; for the second, assume further that mean crop price decreases as time to harvest increases and that price variability increases concomitantly (see Figure 4B).

The yield and price distributions can be combined to produce a value of output (money per hectare). Subtracting the respective variable costs of production produces a gross margin for the crop. The cumulative probability curves for gross margin per hectare present a very different picture compared with the yield curves (Figure 4C):

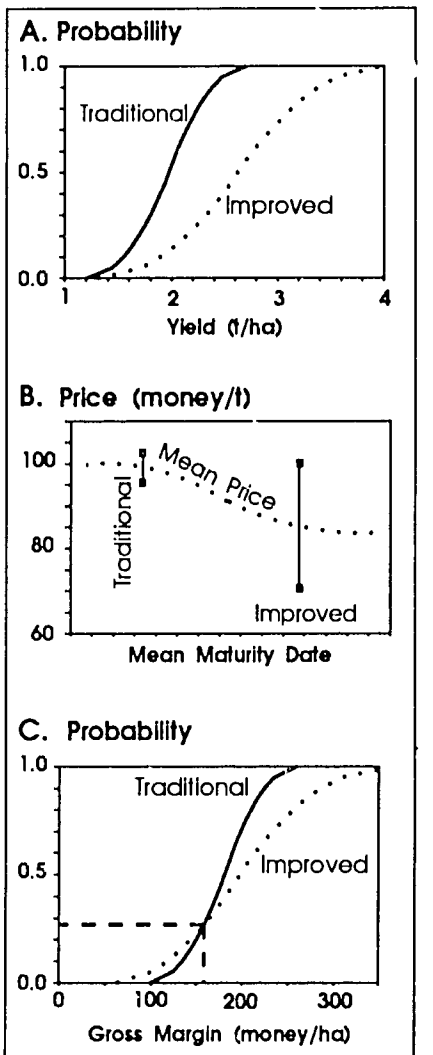


Figure 4. Improved and Traditional Technology: A Simple Analysis.

- The traditional variety produces more stable gross margins.
- In approximately 3 years out of 10, the traditional variety does better (as a long-term strategy, not necessarily in any particular 3 years in 10) than the improved variety.
- If this cash crop is required to produce 100 units of money from the 1 ha that the household grows, as an absolute necessity and without fail, then clearly the improved variety is not suitable because of the strong probability that income will be less than 100 units (about 1 year in 10).

Agronomic performance is thus not always a good indicator of economic performance. Even a simple analysis such as this cannot be carried out without the generation of the frequency distributions by way of a crop model because field-generated data to represent the outcomes for a crop management strategy over a sample of season types would clearly take too long to produce.

As noted above, given limitations to model accuracy, the objective is not to identify a single optimum practice, but rather to prescreen the available possibilities; it might be that some 80% of treatments assessed using the computer could be discarded as being clearly inferior agronomically and economically, leaving a more manageable number of treatments that could then be examined more closely. Ultimately, it might be decided that two or three were worthy of actual testing through field experimentation in each location of interest.

Timing of Planting and Establishment—A similar procedure can be anticipated for investigating the effect of timing of planting and density of plants on establishment and subsequent yield. The interest in this case derives from the interaction between plant growth and establishment and simulated weather sequences. A large number of planting decision rules can be investigated (such as, plant when the ratio of actual to potential evapotranspiration first reaches 0.75 for 3 consecutive days or when local practices can be followed), and probabilities of crop failure can be established for different planting rules. Analysis of yield distributions can follow that

outlined above. An alternative presentation is shown in Figure 5, where yield is plotted against planting date, in terms of the mean and the 25th and 75th percentile of the yield probability distribution (from the nitrogen simulation experiment described above).

Such investigations can be carried out on a regional basis because changes in variety, soil conditions, and weather are likely to have profound effects on the identification of optimal or near-optimal fertilizer practices, planting windows, and planting densities. Such computer experimentation can then lay the groundwork for the derivation of regional fertilizer and planting recommendations. This is discussed further below.

Long-Term Soil and Nutrient Effects on Yield Stability—The IBSNAT crop models are currently being modified to allow the investigation of soil water and nutrient effects on production variability over multiple seasons. Thus, instead of looking at single growing seasons and the between-season effects of climate, as outlined above, it becomes possible to investigate sequences of two or more years run together, with carryover effects in terms of soil status being incorporated directly in the analysis. By modeling the soil processes that occur during the dry season with a fallow component or with another crop, and taking account of cropping history in a field, researchers can investigate the performance and variability of varieties and management practices over a longer period.

In such investigations, the unit of replication is not the season but the season sequence. Care has to be exercised that errors, particularly with regard to soil nutrient status, do not build up over time, but this problem could be minimized by considering relatively short season sequences or by some form of mid-sequence updating. Again, management can be imposed by the model user, and replication can be carried out to assess output distributions both within and between replicates. The identification and screening of stable production systems that make minimal use of external inputs is likely to be one of the major areas where the models could contribute substantially.

An important output of such simulations is the performance of biological descriptors over time. Two examples are shown in Figure 6 (these are purely hypothetical). In the top graph, yield is plotted over 21 consecutive seasons, together with the 10th and 90th percentile of the yield distributions. Note that variability increases as the sequence goes on and that yields are decreasing over time. A trend line for mean yield is plotted over the time series, and it is clear that this system is in the process of crashing, unless action is

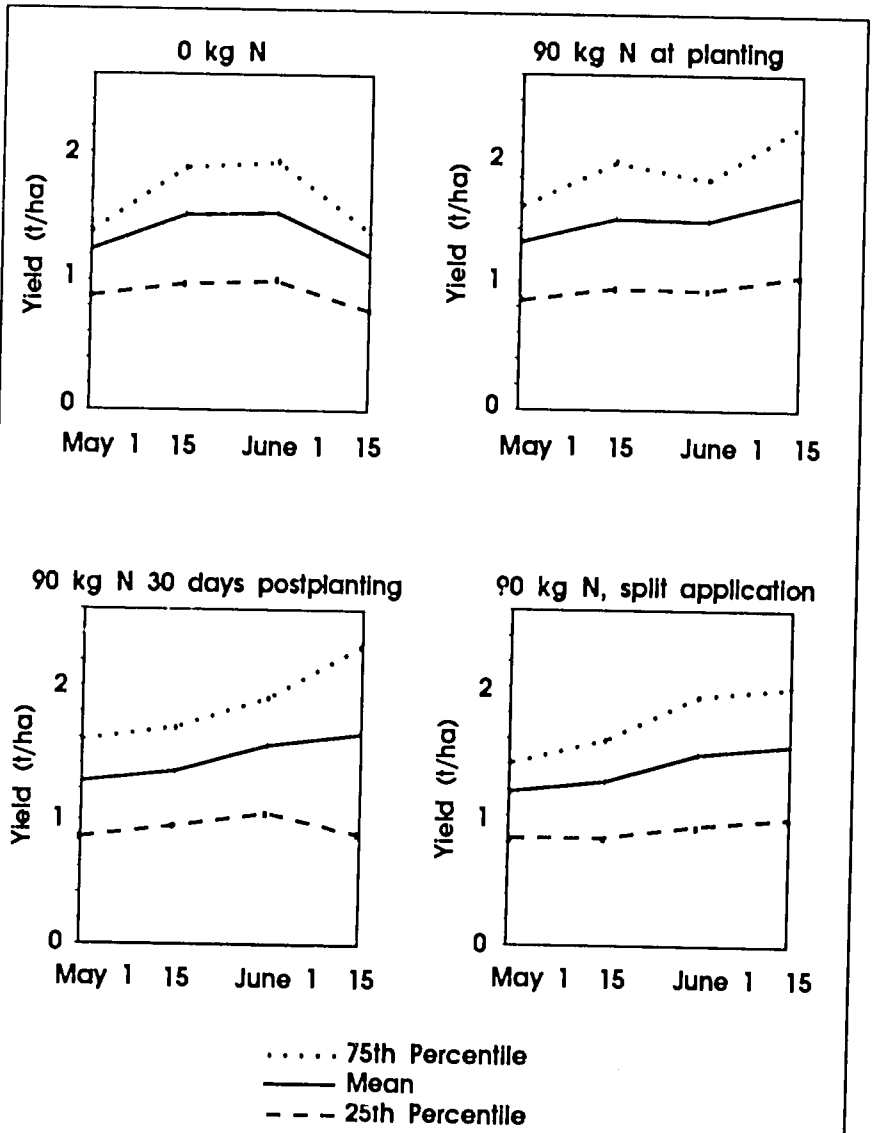


Figure 5. Interaction of Planting Date and N Fertilizer on Simulated Yield.

taken. In the bottom of Figure 6, a different picture is obtained; for a variable such as Total Soil Nitrogen (TSN), initial conditions mean that the variance at year 1 is nearly zero. This increases to year 5, after which variability remains approximately the same. No fall-off in mean TSN is indicated, suggesting adequate replenishment of soil nitrogen reserves. Although the examples in Figure 6 are manufactured, it is clear that the types of response that may be obtained can give valuable insight into cropping system sustainability.

Real-Time Simulation—In general, crop management can be thought of as a sequence of decision points that build up into a decision tree. The crop models can be used in real time to help the researcher identify appropriate management regimes, based on particular soil and climate conditions, such as irrigation scheduling.

At sowing, there is a particular probability distribution for yield associated with any particular variety, soil, and climate. This distribution is essentially unchanging from year to year. As time progresses and the crop starts to develop in the field, more and more weather becomes known or fixed. The distribution of crop yield, if simulated using historical weather data up to a particular point and generated weather thereafter, may be very different from the preseason yield distribution: the earlier part of the season may have been unusually dry so that the probability of a poor yield is much increased.

This process is illustrated in Figure 7. The mean yield of the crop is initially 1.3 t/ha, for all possible season types, depending on the characteristics of the particular historical season used; for a good season, mean yield increases to 2.7 t/ha, whereas for a poor season, yield decreases to 0.6 t/ha (Figure 7A and C, respectively). In all cases, the variance of the simulated yield distribution gradually falls away to zero as all the simulated weather is replaced by historical weather.

Real-time simulations are useful not only for making tactical decisions through the life of the crop but also for other purposes, such as the following.

1. They act as a validation check on the performance of the model; although yield variability cannot be checked directly from one trial grown in one season, the behavior of the yield distribution as more and more becomes known about the season in question should afford some insight as to the performance of the model. From a consideration of the biological relationships in the model, it can be expected that variance should decrease in a

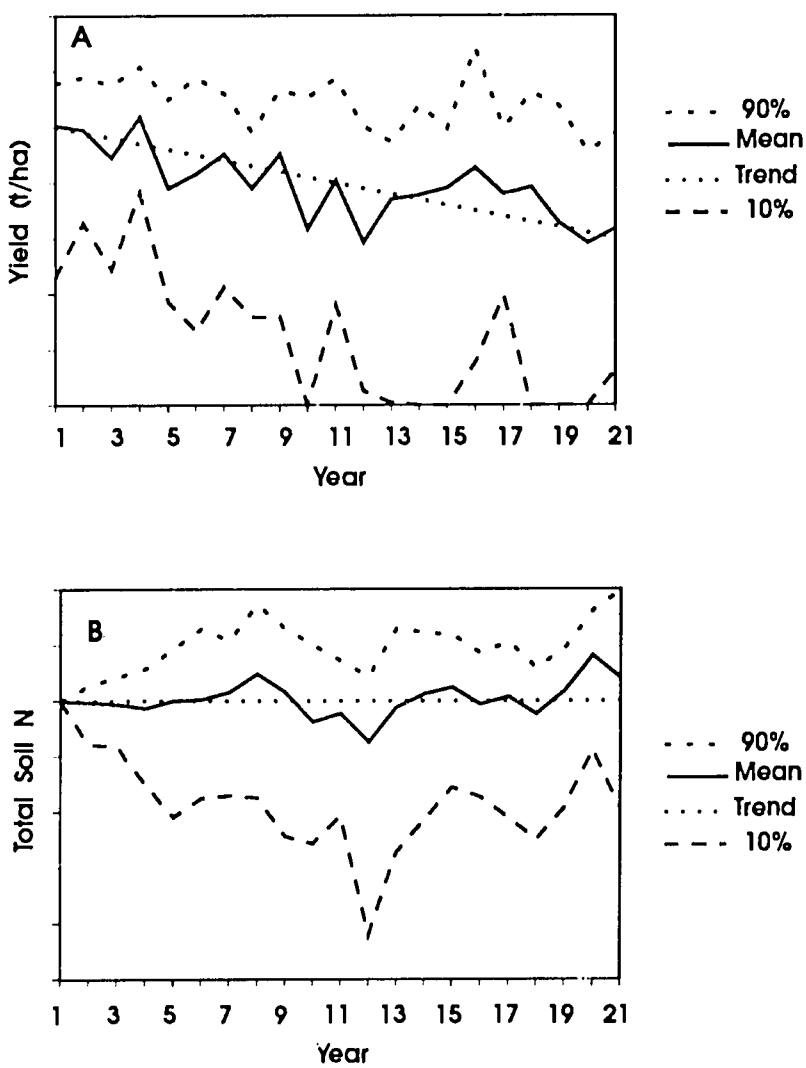


Figure 6. Analysis of Long-Term Simulations Using Crop Sequencing.

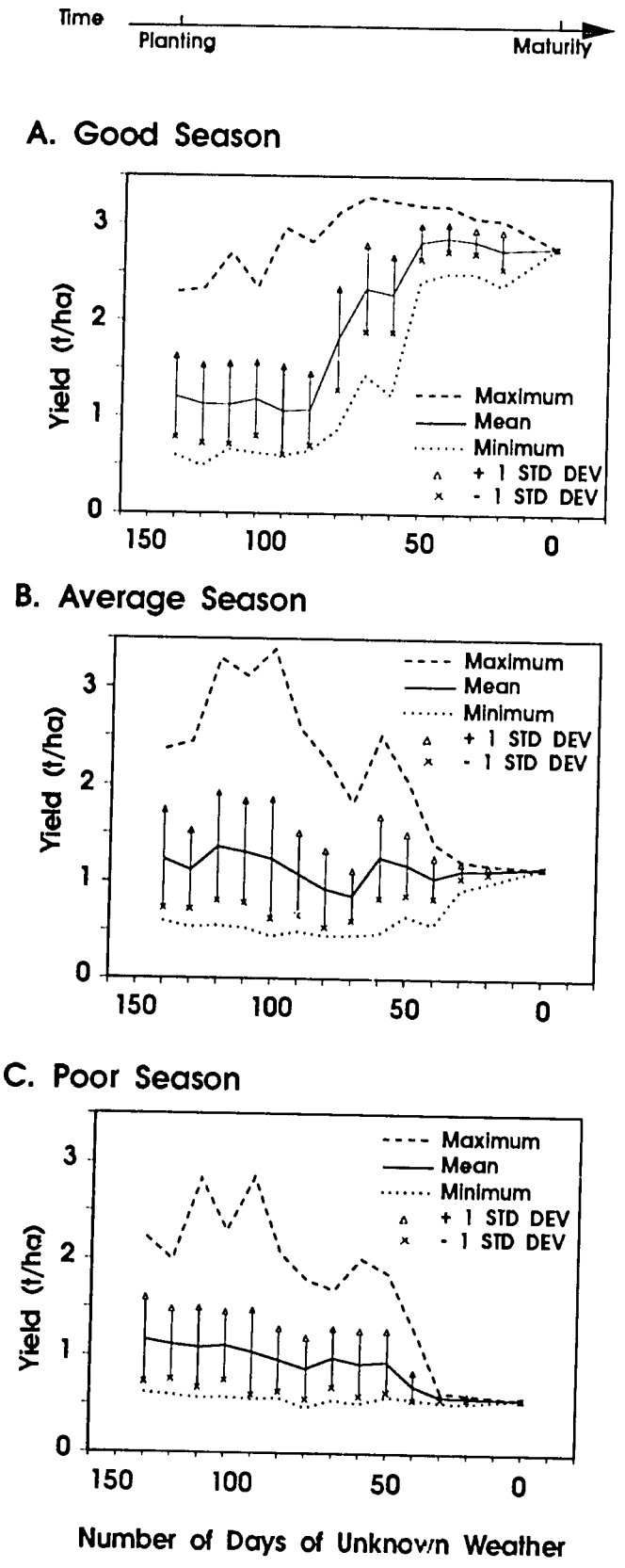


Figure 7. Real-Time Simulation:Movement of Yield Mean and Variance.

somewhat predictable fashion (for example, as one by one the yield components become set as the season progresses). In general, the shape of the variance curve over time may be a valuable tool for analyzing the reasonableness of the model; work is starting to be done on this type of analysis.

2. It is not only the movement of the variance that is important, but also the mean, the maximum, and the minimum values of the yield distribution over time. The ability of the model to act in an early-warning capacity (e.g., a sudden preponderance of very low yields presaging a disastrous season) would add considerably to its use as a research tool; obviously, the earlier in the season it can be accurately indicated that the current season is going to be bad, the more time there is to take compensatory action.
3. In a more research-oriented role, real-time simulations can be expected to be of use in monitoring the progress of the trial, especially with respect to the possibility of disease attack and its effects on the crop. Useful information could be gleaned from a comparison of actual (infected) and simulated (noninfected) leaf areas, for instance, in an attempt to take account of the effects of disease on final yield and its components. Similarly, it may be possible to forestall and ameliorate, to a degree, the effects of unforeseen water or nutrient stress on the crop in the field before too much damage is done.

The issue of tactical as opposed to strategic decisionmaking is discussed in more detail in a later section.

Modeling in Extreme Environments—One further role of the crop models is their use at a rather more basic level of research. Most of the IBSNAT crops are grown in such a diversity of locations and conditions that there are limitations to the way the associated models will perform in extreme environments. Crop scientists' knowledge of plant growth and development is not perfect, and there are gaps where little is known about particular processes that may only come into play in certain conditions.

An important role of the crop models is to generate information on such gaps so that ultimately this knowledge can be built back into the model, thereby increasing its sensitivity to peculiar or marginal conditions in which the crop is grown. Once a model has been validated for a particular location, then any inability of the model to simulate reasonably successfully a particular field trial in that location can be ascribed to the occurrence either of something outside the model's predictive capacity (potassium deficiency or disease attack, for example) or of something outside the range of the relationships built into the model, such as might occur under conditions of extreme stress. The CERES Sorghum model, for example, has been adapted to take account of seed scorching in the Northern Territory of Australia (Carberry and Abrecht, 1990); soil surface temperatures can reach 60°C, causing total loss of seed. A new function has been built into the model, involving a linear decrease in seed survival above soil surface temperatures of 40°C; simulated sorghum plant establishment densities and yields now more accurately reflect experimental results in this particularly harsh environment. In this way, data sets can be collected from the field and used to extend the applicability of particular relationships in the crop models.

The Farm Level

In considering model applications at the farm level, two aspects have to be borne in mind: the necessity of considering all the enterprises in which the farmer is engaged, because these are competing for scarce resources, and the desirability of quantifying the economic and social framework within which the farmer operates.

Any economic analysis of a single season's returns remains incomplete: nothing is said about what happens to the household's livelihood in the event of a sequence of poor years, for example. Cash or resource carryover effects from one season to another may be of paramount importance (in broad terms, the farming system's economic sustainability); low but dependable cash income may allow the household to subsist from one year to the next, whereas high but variable cash income may spell disaster if poor years are experienced in succession. Smallholders rarely if ever operate only one farm enterprise. One of the central tenets of systems philosophy is that improvements to one component of the system cannot be presumed in an isolated analysis to lead to enhancement of the overall system; perhaps the new technology has increased labor demands which, when seen in a whole farm setting, put a labor squeeze on other enterprises. To take such factors into account, the modeling concept may be taken a stage further (Thornton and Dent, 1987).

This next stage involves integrating a number of crop simulation models with elements representing the most important socioeconomic factors that constrain, or otherwise impinge upon, agricultural production and decisionmaking in a particular place. With such a structure, it becomes possible to examine alternative technologies within the total production framework of the farmer. If the farm model is set up for a representative farm household in a district, technology can be designed with a much clearer notion of the overall impact it may achieve on production.

Socioeconomic modeling can be based on a variety of optimizing and nonoptimizing techniques, but it is essential, within the whole farm framework, to take into account consumption behavior, attitudes to risk and to borrowing and investment, and seasonal labor availability. In any farm model, revenue will be a function of farm production, which can be derived from simulations with the crop models and a knowledge of the costs and prices involved and their seasonal variation, for example. This revenue is used for family consumption, for farm operating expenses, and for servicing any debt; the balance, whether negative or positive, results in reserves being built up or depleted and investment or disinvestment on the farm, which affects subsequent production. The prices and costs of production may be generated stochastically and then combined with the yield distributions to produce distributions of net revenue or gross margin, for example.

A further layer to this framework consists of factors of two broad types: socioeconomic constraints and the most important of the host of nontechnical factors that impinge on farmers' decisionmaking. For example, labor use might depend on such things as the division of labor between the sexes and household attitudes and objectives, as well as the availability of labor for hire in the district and the household's ability to hire it.

A farm model constructed around these notions could be used in two major ways:

1. To assess the agronomic and socioeconomic feasibility of changes to farmers' production practices, such as the introduction of a particular agricultural

technology or of a new cropping rotation.

2. To investigate the effects of possible government policy initiatives on the adoption of new technology through an assessment of household responses to different scenarios.

Such assessments would involve investigation of the sustainability and variability of proposed changes and the effects that these would have on the long-term performance of smallholders.

Modeling Socioeconomic Factors—It is difficult to include in a modeling framework the important socioeconomic factors that affect decisionmaking; some will act as constraints to production, which are comparatively easy to treat, while others may be much harder to quantify. One approach to such factors is to use sets of rules that, it is hypothesized, govern farmers' behavior. Some examples follow.

1. Consider the household's treatment of a cash surplus or deficit; this will inevitably reflect cultural and societal norms, in addition to household objectives and biophysical constraints. The illustration in Figure 8 is taken from a New Zealand context (Beck and Dent, 1987) and shows a typical set of priorities for disposing of a cash surplus or meeting a cash deficit. A cash deficit can be allayed by drawing from cash reserves; if these are exhausted, then routine farm maintenance expenditure can be put off until a better year; if no more expenditure can be put off, then borrowing has to be increased. Similarly, a cash surplus might first be used to pay off some of the farm's debt; if debt is reduced to a reasonable level, then any deferred farm maintenance can be carried out; after this, liquid reserves will be built up to reach some specified level, and then on- or off-farm investment can take place. The priorities themselves may be rather different in a smallholder context, but the concept remains the same.

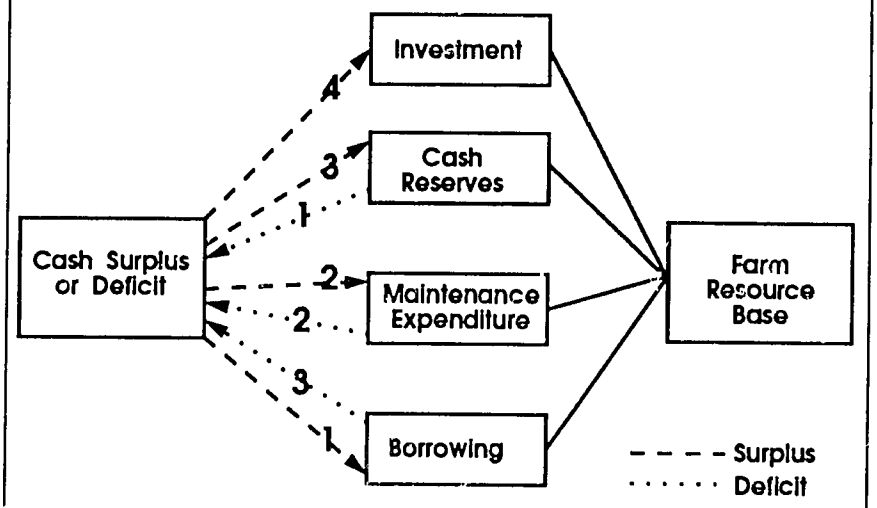


Figure 8. Priorities for Dealing With a Cash Surplus or Deficit in a New Zealand Hill Farming System.

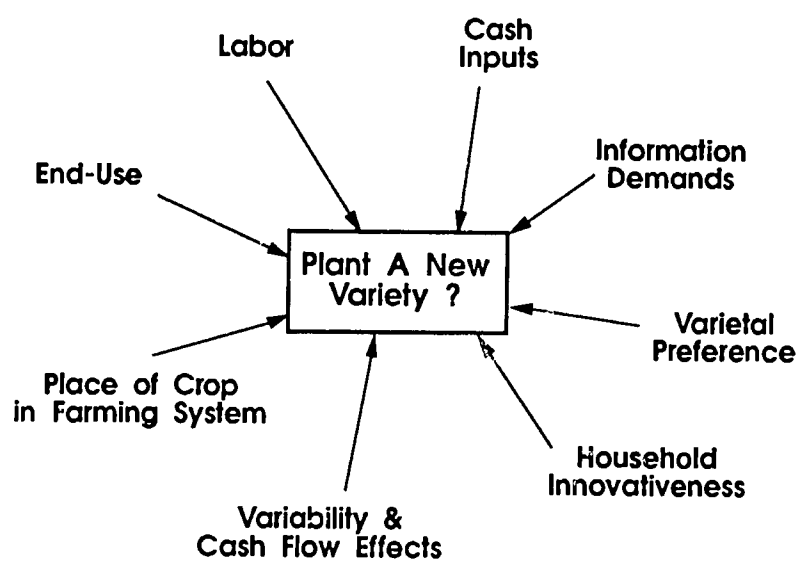


Figure 9. Factors Affecting the Decision to Plant a New Variety.

2. Consider the set of factors that determine whether a new bean variety will be adopted in Guatemala (Figure 9, from Thornton and Dent, 1990). Such factors will include labor, cash inputs, access to information (if unfamiliar husbandry techniques

Level				
1	Landowner		Tenant	
2	Low	High Cash Reserves	Low	High
3	Risk Aversion	Income Level	Risk Aversion	Social Aspirations
4	Social Aspirations	Age	Household Size	Income Level
5	Household Size	Education Access to Information	Discretionary Consumption	Age
6	Income Level Age Cash Growth Off-Farm Acitivity	Risk Aversion Social Aspirations		Risk Aversion Household Size
	1	2	3	4
	Farm Type			

Figure 10. A Hypothetical Farm Classification.

have to be used), varietal preferences, household innovativeness, yield stability and effects on household cash flow, and the end-use of the beans (are they to be consumed by the household or sold off-farm?). Yield stability, for example, can be investigated directly using the bean growth simulation model. Some of these other factors can be treated as constraints to production: hired labor may not be available; beans must be black and must have a short cooking time to be acceptable to most consumers in Guatemala. Other factors are more difficult to quantify: household innovativeness, in particular, may itself depend on factors such as type of land tenure, attitudes to risk, and social aspirations. For these, sets of rules can be assembled to allow such constructs to be described.

3. How might household innovativeness be represented in a modeling framework? A hypothetical classification of farm households is presented in Figure 10. This suggests a primary classification of farm households into those owning land and those farming land belonging to others. At the second level of classification, the figure distinguishes between households on the basis of high or low cash reserves. For the four resulting farm household types, a ranking of other attributes is provided for their relative importance in influencing household innovativeness. Thus, for example, for tenant farming households with high cash reserves (farm type 4, Figure 10), it might be hypothesized that social aspirations will be the major motivating force for innovation followed by income levels in recent years. Risk attitudes will play a part in determining innovativeness in such households, but these are ranked below age considerations and equivalent to household size in importance. This kind of classification can be handled in a rule-based framework to determine the potential for innovation of a

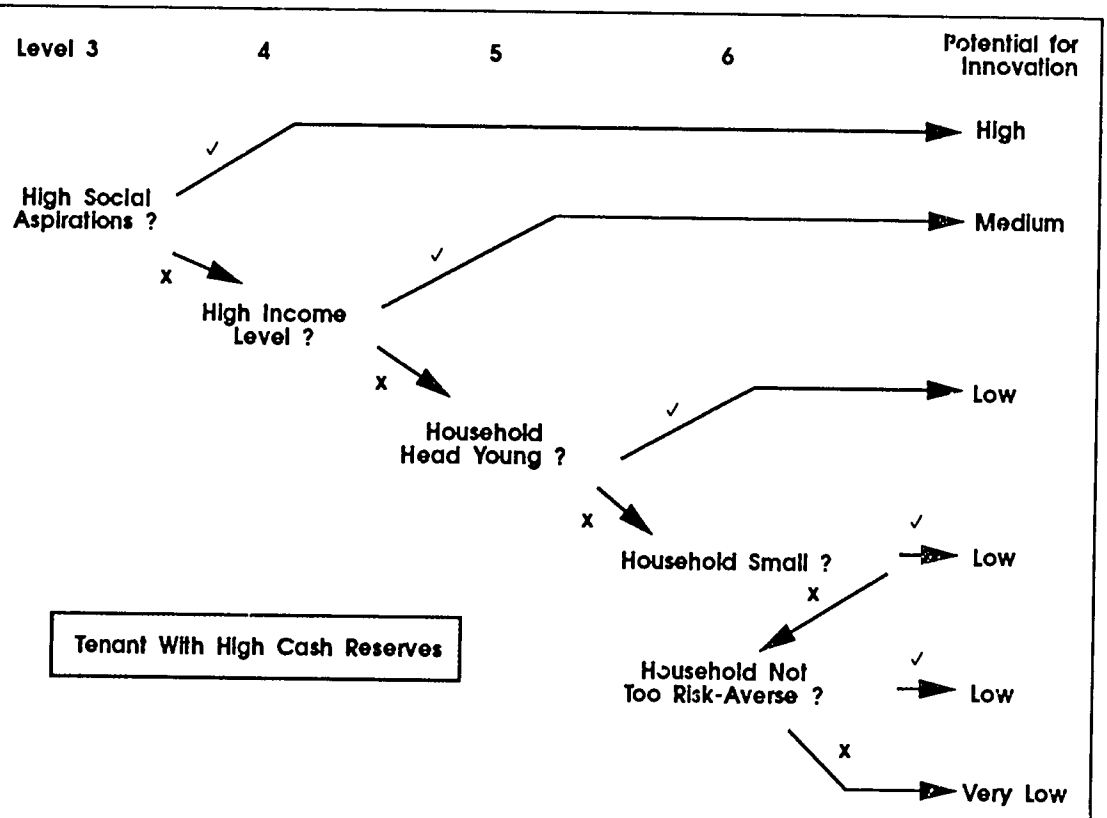


Figure 11. Household Innovativeness Potential.

particular household type. Thus in the scheme of Figure 11, a tenant farmer with high cash reserves and with high social aspirations might be expected to have a high potential for innovation. If, however, the farmer does not have particularly high social aspirations, but household income levels in recent years have been relatively high, then the household's potential for innovation might be expected to be medium. Such a structure involves trade-offs between ranked attributes (in the example just given, high income levels in recent years partly offset lack of social aspirations). At the other end of the scale, a tenant farmer who has low cash reserves and low social aspirations, who has achieved low income levels in recent years, and who is no longer young and is at least moderately risk averse might be expected to have a very low potential for innovation.

Such socioeconomic analysis, including the classification of farm types and the ranking of attributes, occurs as a result of socioeconomic data collection through formal and informal surveys. Such activity is of no less importance to the whole farm model builder than biological experimentation is to a crop modeler. Considerable work remains to be done on this type of modeling, however.

The Use of Farm Models— Model applications at the farm level can involve the same set of experimental factors as were considered for the field level, only now packages are assessed in relation to the household's resource base and the objectives and attitudes of household members. In this way, both biological and economic feasibility of particular production practices can be investigated, and their suitability for representative farming households can be explored. Three applications in particular at the farm level are discussed briefly: the design of cropping systems, identification of on-farm constraints, and analysis of agropastoral production systems.

1. **Cropping System Design**: Once the individual crop models have been strung together to allow cropping sequences to be simulated over multiple seasons, with concomitant carryover effects of soil water and nutrient status, it becomes possible to investigate the feasibility of changes to cropping systems. In general terms, such experimentation follows that outlined above with reference to variety selection: crop types can be defined explicitly by the user, or gaps in the cropping sequence

can be filled by varying the crop-specific cultivar coefficients. In either case, the effects on household viability can be observed over a number of seasons using historical or simulated weather sequences for given economic scenarios.

2. **On-Farm Constraints:** A problem that is often cited as a hindrance to the rapid adoption of new technology is the disparity that sometimes arises between yields obtained in plots on the experiment station and those commonly achieved in the fields of resource-poor farmers. In some cases, it is not only the yield levels that will differ substantially, but also the relative rankings of different technology packages. In a broad sense, such disparities can be attributed to differences in the resource base between the two situations: on the experiment station, soil nutrients will not usually be limiting and labor is freely available for weeding and for planting at the optimum time, for example. The situation in the farmer's field may be very different. A farm model can be used to help identify the root causes of this yield differential problem in a particular situation by focussing directly on farmers' crop husbandry techniques and by attempting to simulate farmers' yield levels rather than those obtained in field plots.
3. **Agropastoral Farming Systems**: The ubiquity of mixed farming in many parts of the tropics and subtropics represents a potential resource of enormous implications for the design and operation of low-input, sustainable production systems. Unfortunately, the interactions between animal and crop enterprises are not always well-understood and consequently are difficult to model satisfactorily. Soil incorporation of crop residues, feeding of residues to animals, and the return of nutrients to the soil by the animal, are all areas that require considerable research, some of it basic, if much progress is to be made in modeling agropastoral systems.

With multiple cropping systems, crop-livestock systems share the following characteristic: there are so many combinations and permutations of experimental variables that traditional experimentation involving such systems is unlikely ever to unravel the complexities to the point where useful management recommendations can be made. Modeling is probably the only realistic way of examining such systems.

The Regional Level

A further step in the scope of crop modeling is to make a contribution at the regional level. Policymakers work with a broad brush; they need to articulate agricultural policies concerning not only farmers' incomes and regional development but also macrosocial and macroeconomic factors involving income distribution, public welfare, balance of payments, and trade.

The data bases for soils, weather, and crops, the simulation models, and simplified farm-level models, can be integrated with a Geographic Information System (GIS). This is shown in Figure 12 (adapted from King, 1989). The top three overlays constitute a traditional GIS, with a graphics base on the left-hand side of the figure and a data base of spatially organized information on the right-hand side. Two further overlays are added, involving types of agricultural systems and representative farm types within the agricultural zones, characterized in terms of important determinants. In Figure 12, two such determinants are included for illustrative purposes: household size and income level. There will be others, such as type of land tenure.

The crop models can then be run, alone or in sequence to simulate crop rotations, using the spatially organized data in the GIS. For a particular location, the following information is extracted:

- The appropriate soil profile description.
- The appropriate set of coefficients to allow statistical generation of weather sequences.
- The appropriate farm type, in terms of cropping patterns and land use.
- The appropriate representative farm and household description.

For each location, the crop models can then be run to produce information on production levels and stability and on resource use. Model results from many such locations can then be aggregated to produce estimates of regional response to particular input combinations. Such simulations can be carried out over many simulated season types, with or without stochastic cost-price variables, to produce distributions of the outputs of interest.

A regional agrogeographic information system could be used in a number of ways:

1. As a store of information on farming systems that can be updated continually, mainly by survey, to produce timely statistics of current land use patterns and production levels and how these are changing over time.
2. As a short-term policy tool, in relation to forecasting for the coming year or the current

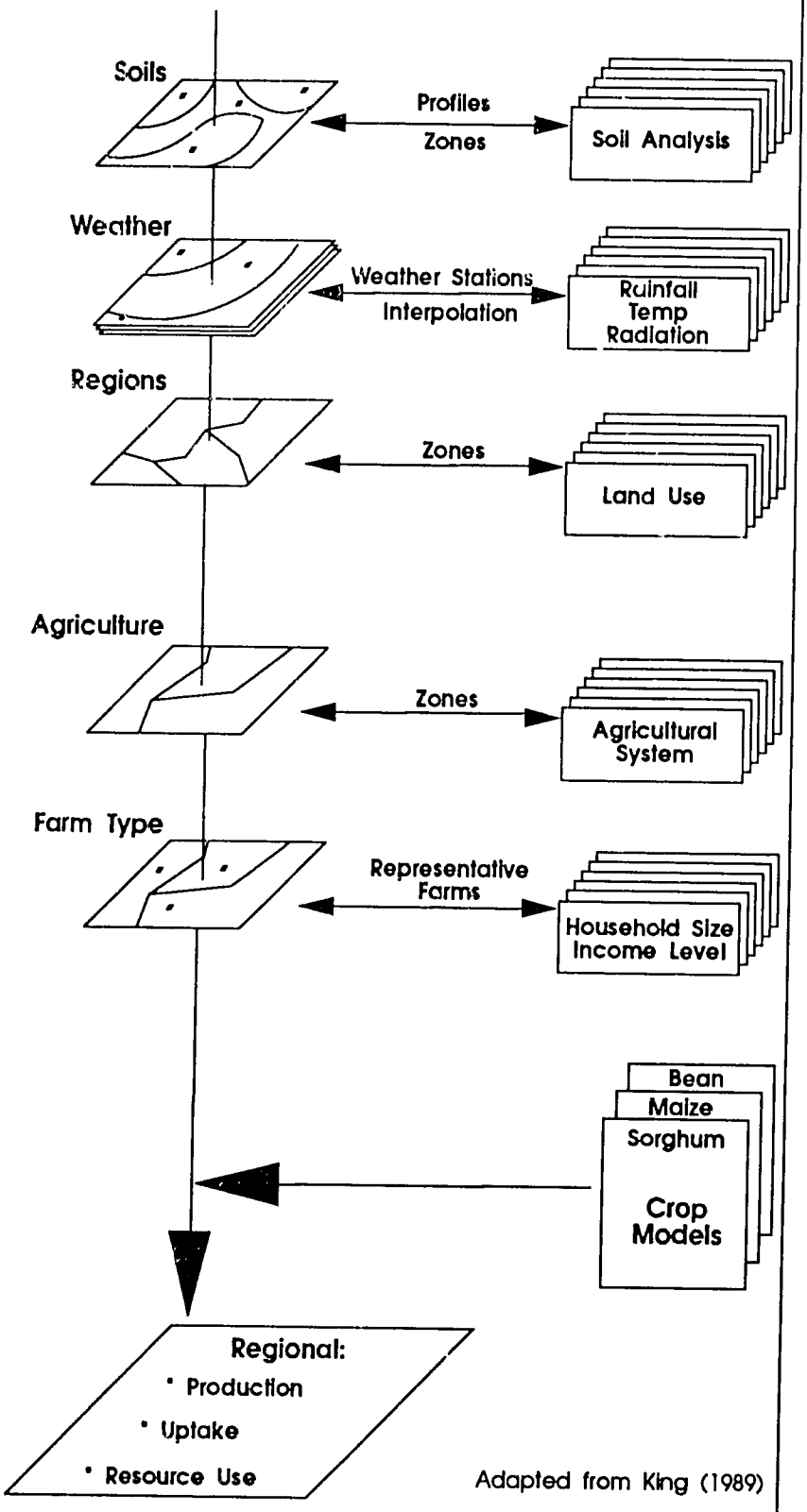


Figure 12. Integration of an Agricultural GIS and Crop Simulation Models.

season. Here, regional simulations of yield and resource use would give an estimate of requirements for imports of agricultural inputs and exports of commodities, any aid requirements in response to a bad season, and likely international loan requirements, for example.

3. As a long-term policy tool, to investigate the effects of change on regional production and resource requirements. Such changes might be economic, technological, or climatic, or they might be substantial policy or trade changes to the economic environment within which farmers operate.

An Example of Spatial Variation of Biological Response—One of the key issues which can be addressed with a GIS that has crop simulation models linked to its data base is the effect of spatial soil variability on agricultural production. The physical characterizations available from the International SCS soil data base for Guatemala (Table 2), for example, have been used to study potential bean production of these soils (Hoogenboom et al., 1990). The bean model uses 14 years of historical weather data for a site in southeastern Guatemala, and the simulated response of two varieties of phaseolus bean, planted on June 1, shows a strong variation as a function of the various soil characteristics (Figure 13). Soil 3, which has the least depth (0.5 m) and the smallest amount of extractable soil water, produces the lowest yield, with a standard deviation as large as the average yield for the 14 years of this study. Soil 12, which has the greatest depth (1.50 m) and the largest amount of extractable soil water, produces the highest yield and the smallest standard deviation of all the soils used in this study.

Table 2. Guatemalan Soils in the International Soil Conservation Service Soils Data Base.

Pedon[a]	Depth (m)	E-W[b] (mm)	Soil Type	Soil Classification
83P0511	1.40	169.1	clay loam	Fine montmorillonitic isohyperthermic typic Hapludoll
83P0512	1.75	204.7	clay	Fine mixed isohyperthermic typic Humitropept
83P0513	0.50	43.8	clay	Fine mixed isohyperthermic shallow typic Haplustoll
83P0514	1.50	167.0	clay	Loamy-skeletal mixed isohyperthermic typic Ustifluvent
83P0515	1.40	165.6	clay	Very fine mixed isohyperthermic udic Chromustert
83P0516	1.40	168.4	clay	Very fine montmorillonitic isohyperthermic udic Pellustert
83P0517	0.50	57.9	clay loam	Clayey halloysitic isohyperthermic lithic Argiustoll
83P0518	1.45	152.6	clay loam	Clayey-skeletal mixed isohyperthermic Ustifluvent
83P0519	1.20	139.8	clay	Very fine kaolinitic isohyperthermic fluventic Haplustox
83P0520	1.20	142.5	clay	Very fine halloysitic isohyperthermic typic Argiustoll
83P0521	1.28	105.8	clay loam	Sandy mixed nonacid isohyperthermic aquic Tropofluvent
83P0522	1.50	215.9	sandy loam	Fine-loamy mixed nonacid isohyperthermic aquic Tropofluvent

a. Soil Conservation Service Pedon Number
b. Extractable water

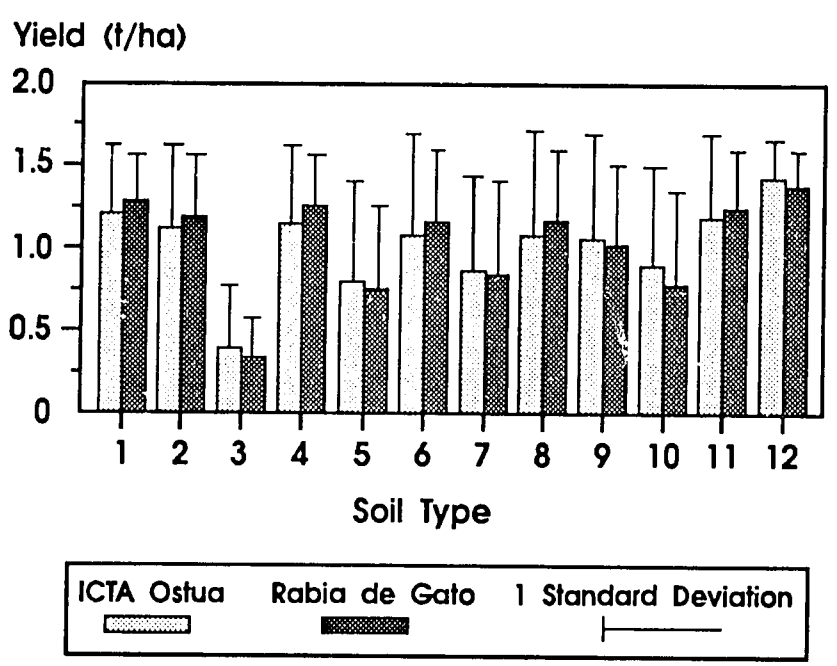


Figure 13. Mean Yield and Standard Deviation for Two Varieties of Bean on 12 Soils in Southeast Guatemala.

This example clearly demonstrates that the total amount of extractable soil water is crucial for bean production, although the planting date coincided with the regular growing period during the normal rainy season. Other soil factors, however, can limit bean production as well. Soil 7, with only 57.9 mm extractable soil water, produces a higher yield than both soil 5 and soil 10, with 165.6 mm and 142.5 mm extractable water, respectively. For the highest yielding conditions, Rabia de Gato outperforms ICTA Ostua, except for soil 12. For lower yielding conditions, however, ICTA Ostua performs better.

Regional Yield Response Potential—In this section, a purely hypothetical region is used to illustrate model use. The biophysical environment hypothesized for this region (Figure 14) includes four soil types, which are mapped as shown. Daily weather data with which to run the crop models are available for three sites. Physical relief is uniform over the region, so no interpolation of weather records is attempted; instead, the region is divided into three zones using Dirichlet tessellations (i.e., boundaries are drawn such that each point within a polygon is nearer to the associated weather station than to any other weather station), and the weather is assumed to be uniform within each polygon. A high percentage of the region is currently arable.

Assume that it is planned to release a new variety of maize. The new variety outyields the variety traditionally grown in most years, but it also exhibits a higher yield variability; response depends on weather and soil type. For each combination of weather and soil type, the maize model is run over 30 seasons using both the traditional and the new variety.

Potential yield response to the use of the new variety is shown in

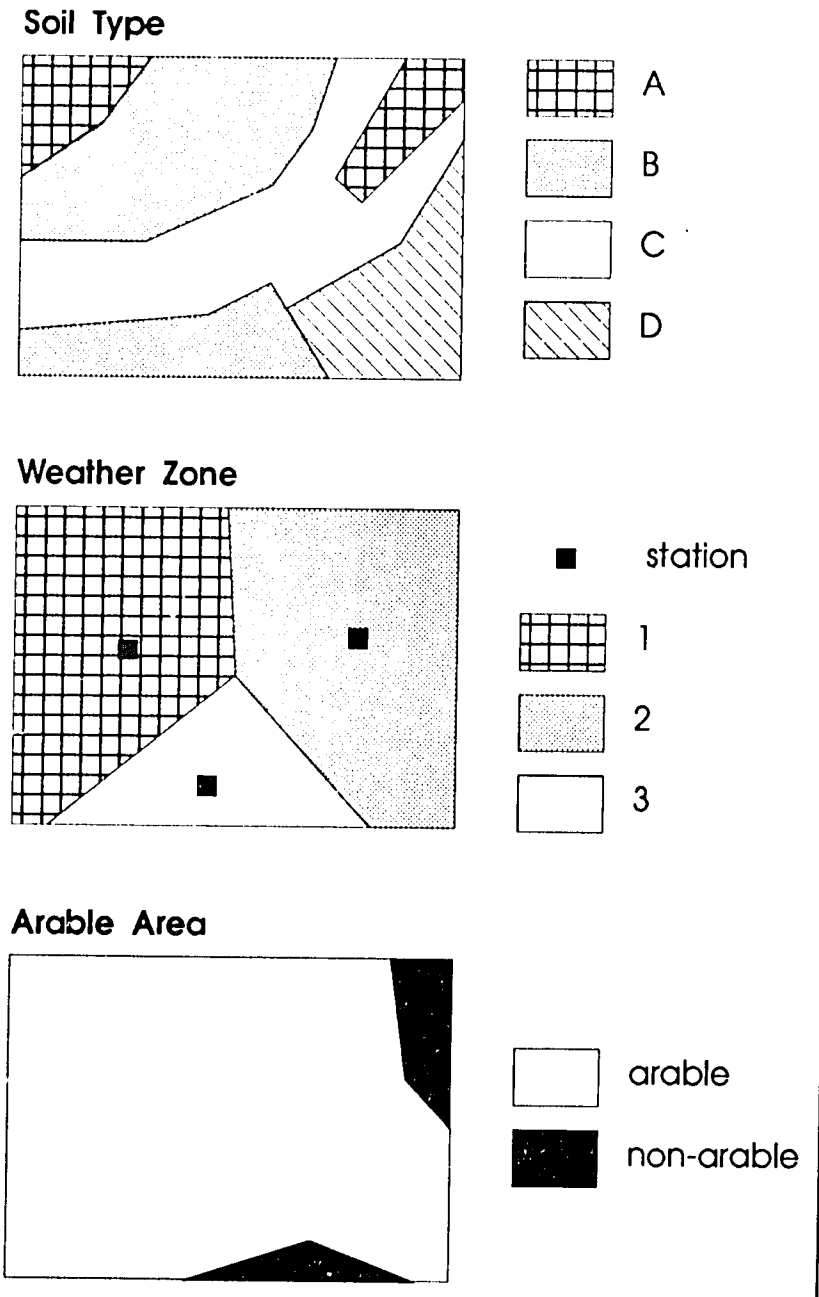


Figure 14. Simple Biophysical Descriptors of a Hypothetical Region.

Figure 15, where polygons are assigned percentage differences as shown, in terms of the mean and the 10th and 90th percentile of the yield distributions. By combining this yield information with the arable area mapped in each polygon, the modeler can estimate regional yield response in three season types that correspond approximately to good, average, and bad years. Such maps can then be used to identify regional fertilizer recommendations that are economically and environmentally appropriate, for example.

Technology Design and Assessment—The crop models can be used within such a GIS framework to investigate a whole range of effects; the limits of the experimental domain are imposed solely by the sensitivity of the relevant models to biological and management inputs. For example, the models can provide regional fertilizer recommendations, tailored to the specific soil and climatic conditions within a region. Optimization techniques for use with the crop models are still under development. Deriving output distributions for all polygons of a realistic spatial data base requires substantial computation. The use of faster computers, either serial or parallel, is also under investigation (Thornton et al., 1991a).

Regional nutrient budgeting is also possible, by running simulations of cropping sequences over a number of seasons. For many such uses, economic analyses can be carried out, as for single sites, to produce estimates of regional impact on enterprise gross margins or changes to net farm income. These responses can then be mapped in a manner similar to that shown in Figure 15.

Adoption Dynamics—The integration of the crop models, spatial physical data bases, and representative farm models poses considerable problems, but the potential payback is the ability to model adoption patterns of particular agrotechnology packages over time and to identify feasible pathways for step-wise farming system development where substantial changes are proposed.

For example, assume that, in addition to the biophysical information in Figure 14, the region has been characterized by farm type. Farms might be specified in terms of factors similar to those shown in Figure 10. The various farm types have different potentials for adoption of the new variety, ranging

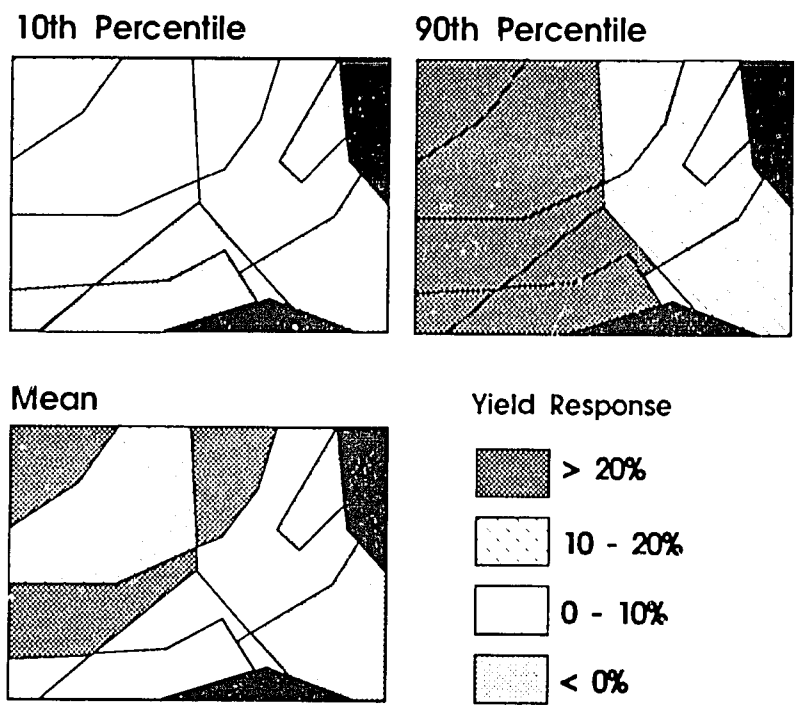


Figure 15. Regional Potential Yield Response.

from no potential to high potential. For each polygon of the relevant farm type, probability of adoption in any year might be related to an appropriately shaped adoption curve and to the potential yield response: thus the probability of adoption in year 1 for one farm type is zero, whereas that for another type in a high-yield response polygon might be 0.2 in year 1 and 0.5 in year 2, for example. Integrating all this information would allow simulated adoption patterns to be tracked over time, and maps could be produced, one for each year for a number of years after variety release, showing areas where adoption has occurred and areas where it has not.

Although such an example would be simple to construct, substantial problems would need to be overcome before a real problem could be tackled. Adoption potential may be the final outcome of a large amount of data collection and analysis, the nature of which is largely unknown. More importantly, how can nonspatial attributes be represented spatially? In a soil classification, for example, soil zones tend to be contiguous. In a classification of farm type, there may be little clustering for attributes such as risk aversion, and perhaps not much even for attributes such as farm size. For most regions, a complete survey of all farming households is out of the question; therefore, how to sample the population and how to represent the results spatially as one of a number of well-defined farm types are questions that need some attention.

The implications of taking modeling to such a level are obvious: not only can biophysical and socioeconomic feasibility be assessed, likely impacts on the resource inputs and outputs of the region can also be judged in response to a new agrotechnology package. An adoption model capable of reacting to biological and economic risk and to farmers' likely behavioral patterns represents an enormously powerful tool for ex ante analysis by researchers, extensionists, and policymakers, if it can be constructed: the chances of unsuccessful agrotechnology release would be reduced, and the effects on the efficiency of research and development would be profound.

How site-specific such a model would be is an interesting question. Although there are undoubtedly similarities between diverse production systems in the way that farmers can react to change, the differences would appear to be larger than the similarities. It is possible that future research may lead to the identification of suitable paradigms that could form the generic core of all such adoption models, no matter where the location, but this is by no means certain.

The National Level

If the problems of the regional level prove tractable, then there are few reasons for supposing that, conceptually, aggregation to the national level presents insuperable difficulties. National- and even global-level studies using crop simulation models are already underway, notably to investigate the effects of carbon dioxide-induced climatic change on crop production (see, for example, Smith and Tirpak, 1989; Parry, 1990). The biophysical aspects present few problems, although the current status of the general circulation models used to generate new climate scenarios is far from ideal. Impact assessment at the national level, however, is subject to the same problems as outlined above at the regional level.

Strategic and Tactical Decisionmaking

Almost all of the applications considered above involve the provision of information for helping to make strategic or long-term decisions. Some of the decisions that farmers routinely face are of this nature, such as deciding what crop to plant this season and when to plant it. Farmers have to live with the consequences of such decisions for the duration of the growing season; in general, such decisions do not need to be taken again until the start of the season cycle the following year. There are many other decisions, however, that are taken within a particular season that will have ongoing impacts on yield, such as when to irrigate or when and how to take action against weeds and pests that appear in the crop during the growing season. In the more developed areas of the world, the use of computer models in aiding such tactical decisions is an area of rapid expansion (see, for example, Batchelor et al., 1989; McKinion et al., 1989). These decisions are usually the preserve of the individual farmer and are taken with reference to his or her own particular conditions.

There are obvious reasons why such on-farm tactical decisionmaking tools are inappropriate for small farmers in the tropics: these decision aids are prohibitively expensive, and for resource-poor farmers, there are few options available for reacting to external factors during the growing season (which may well obviate their need anyway). The bias towards the use of models for strategic decisionmaking purposes in development is thus understandable.

At the policy level, however, tactical information may be very important. Some idea of this is given in Figure 7, where the distribution of yield is modified throughout a growing season. These changes in the shape of the yield distribution may be the result of a number of factors: weather, weeds, and pest or disease attack, for instance, or combinations of such factors. This ability of a crop simulation model to act as an early-warning system is potentially of great utility and importance. The early identification of regional shortfalls or surpluses in agricultural production would allow planners to take appropriate action very much quicker than would normally be the case. The prediction of relatively narrow bands within which yield is likely to fall in a particular season can also be used to forecast likely commodity prices at the end of the season. The benefits to planners (and, for that matter, entrepreneurs in the agricultural sector) are obvious.

Despite the patent absurdity of the concept of on-farm computer-based tactical decision aids for resource-poor farmers in the tropics, there are potential benefits from the use of such tools that can be passed on to the farmer through extension services. In particular, the tailoring of fertilizer recommendations, and of pest and disease management recommendations, to specific season types is worthy of investigation. Such recommendations, which need not be complex even though the tools used to derive them may well be, could help to increase the efficiency of resource use, either by reducing inputs in seasons when yield potential is very low (and would thus be largely wasted) or by increasing returns to smallholder farmers in seasons when yield potential is high and low input but timely and effective management options can be exercised.

Conclusions

The various levels at which crop simulation models may be applied are summarized in Table 3. Whether models can be used successfully in the near future in some of these applications depends heavily on finding solutions to some difficult problems. In particular, researchers need to find ways of increasing crop model sensitivity to factors such as multiple cropping, residue incorporation, pests and diseases, and crop-livestock interactions. Until this is done, crop simulation models will be incapable of representing the biology of important classes of agricultural systems in any general fashion.

Of the applications listed in Table 3, those at the farm level can be expected to be the most problematic because of the difficulties associated with farmers' decisionmaking behavior. A key research area here is the feasibility of using rule-based methodologies to represent important qualitative factors that impinge on farmers' decisionmaking processes.

A number of these model applications are being pursued at IFDC, including the following:

- Fertilizer use efficiency for maize, wheat, and sorghum at locations in Latin America (Argentina, Uruguay, and Brazil) and Africa (Malawi and Kenya) at the field and region levels.
- Use of crop models to investigate the effects on production of carbon dioxide-induced global warming, using a variety of general circulation models to generate possible future weather scenarios.

- Crop model development of the following: wheat, maize, rice, sorghum, millet, barley, and the modeling of nitrogen and phosphorus dynamics.
- The investigation of yield and nitrogen dynamics (uptake and efficiency) for maize and sorghum on a regional basis in the semiarid tropics.
- A farm-level project concerned with modeling the bean-maize-sorghum systems found in southeastern Guatemala; model validation and calibration are being carried out. An expected output is a prototype whole farm model as outlined in the discussion of applications at the farm level.
- Fertilizer use and soil fertility issues for the maize crop in Malawi, for the major agroecological zones in which maize is grown.

In all such activity, model applications need to be problem-driven; if there are more efficient or better ways of solving particular problems, they should be used. Modeling is a tool like any other; it is highly suitable for solving some types of problems and totally inapt for solving others. However, models can contribute substantially to some of the global research areas of the age: the environment, sustainability, and low-input agriculture, to name but three. With care, modern information technology can be used to generate and collate information that can be passed on in various ways to benefit the resource-poor farmer of the tropics and subtropics.

Table 3. Uses of Biological Models by Level, With Examples of Relevant Applications

Level	Research or Development Objectives
FIELD:	
- biological	biological feasibility and stability
FARM:	
- biological	biological feasibility and stability
- economic	economic feasibility and stability
- socioeconomic	adoption of new technology; reaction to change
REGIONAL:	
- infrastructural	land use capability; regional adoption patterns and dynamics
- environmental	environmental impact
NATIONAL:	
- macropolitical	resource use; effects of government policy; human nutrition
- macroecosystemic	climate change

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APPENDIX
Stochastic Efficiency Criteria

The stochastic efficiency rules are an important class of decision criteria, which are particularly suited to the analysis of simulation model output. They have their basis in Bernoullian utility theory, and they differ in the assumptions that are made about the decisionmaker's attitude to risk. Developed to tackle the problem of portfolio selection in investment theory, they are now firmly entrenched tools for risk analysis in all sorts of applications. All involve a pair-wise comparison of random variables, and strictly speaking, these should relate to financial gains and losses. The result of the analysis is an efficient set. The efficient set contains a subset of treatments that are superior (there may be one only, but usually there will be more than one efficient treatment). Three variations are described briefly (for a full treatment, consult Anderson et al. [1977] for the first two and Buccola and Subaei [1984] or Fawcett and Thomton [1990] for the third).

1. Mean-variance (EV) analysis

For two risky prospects, A and B, with means E(.) and variances V(.), respectively, A dominates B if

$$E(A) = E(B) \text{ and } V(A) < V(B)$$
$$\text{or if}$$
$$V(A) = V(B) \text{ and } E(A) < E(B) .$$

A is then said to be EV-efficient. If prospects are plotted in EV space (V the ordinate, E the abscissa), then utility increases in a north- westerly direction. EV analysis assumes that the decisionmaker has a quadratic utility function for gains and losses, and/or that the risky prospects are distributed normally (or at least distributed symmetrically). These are often untenable assumptions, and the EV criterion has fairly weak discriminatory power (i.e., the efficient sets tend to be large).

2. Stochastic Dominance (SD) analysis

For two risky prospects, A and B, A dominates B by first-order stochastic dominance (FSD) if the Cumulative Distribution Function (CDF) of gains from A lies to the right of the CDF of B over the entire probability interval 0 to 1.

If the CDFs of A and B intersect, then no dominance by FSD can be established. If, however, the area between the two CDFs below the point of intersection is greater than the area between the two CDFs above the point of intersection, then A dominates B by second-order stochastic dominance (SSD); otherwise, no dominance can be established, and both A and B are second-order efficient.

For FSD, no assumptions are made about the attitude of the decisionmaker to risk; for SSD, it is assumed the decisionmaker is averse to risk to some unknown degree. No assumptions need be made about the distributional properties of the random variables either.

3. Mean-Gini Dominance (MGD) analysis

For two risky prospects, A and B, A dominates B by MGD if

$$E(A) >= E(B) \text{ and } E(A) - g(A) = E(B) - g(B)$$

with strict inequality for one of these expressions, where E(.) is the mean, and g(.) is the gini coefficient of distributions A and B (which is half the value of Gini's mean difference: the absolute expected difference of a pair of randomly selected values of the variable).

MGD, like SSD, assumes that the decisionmaker is averse to risk, but unlike SSD, it excludes the morbidly risk-averse from the analysis. It is thus a more discriminating decision rule than SSD (because the MGD efficient set is usually smaller), and, computationally, MGD is generally much easier to establish than SSD.