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Developments in biophysical and bioeconomic simulation of agricultural systems: a review [1]

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Abstract

This paper reviews the features and uses of some recent biophysical and bioeconomic simulation models in agricultural economics research. Problems associated with earlier models are discussed and the extent to which recent simulators have addressed these concerns is appraised. Some salient factors that will enhance the continued relevance of simulators as research and decision support tools are indicated.

1. Introduction

Perhaps more than any other research methodology employed in agricultural economics, the growing popularity of systems approach and simulation techniques is rather exceptional judging from the reported number of applications in recent decades. The use of this technique in agricultural research, which was described as relatively novel in 1971 (Dent and Anderson, 1971), had become so widespread a few years later to the extent that two surveys of over 300 literature each did not exhaust available publications in the field (Anderson, 1974; Johnson and Rausser, 1977). Ever since, no serious attempt has been made to undertake such a comprehensive review as it is doubtful if the value of such an exercise would justify the amount of resources required. Instead, the recent trend is to narrow the focus of such studies to some specific simulation systems and/or agricultural practices (Musser and Tew, 1984; Braat and Van Lierop, 1987; Dillon et al., 1991).

In almost all the surveys of simulation use in agriculture, certain conclusions are strikingly similar regardless of the scope of such studies. The surveys have attributed the attractiveness of simulation to the dearth of feasible alternative methodologies for tackling the inherent dynamic and/or stochastic nature of agricultural problems. Also, the appeal of simulation has been enhanced by increasing computer capability at a relatively cheaper cost. However, certain concerns have been raised pertaining to the wisdom of employing simulation tools in every study. The objective of this exercise is to review some of the recent simulators [2] and their applications to physical

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[2] In this study, simulators refer to models that are developed for simulation purposes (Musser and Tew, 1984; Dillon et al., 1991). This definition contrasts with Anderson (1974) where simulators refer to the modelers (persons) and simulands are used for the models.

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and/or biological issues in agriculture. Such information will help identify the potential strengths of simulation that the modelers can build upon, as well as the possible pitfalls to avoid. Now that simulation is increasingly being used for decision support, information from such a periodic evaluation could prevent costly mistakes from being made or repeated.

In the sections that follow, some conceptual issues in simulation are first discussed. Next, factors that could enhance or limit the appeal of simulation are highlighted. Third, the distinguishing features of the class of simulators commonly used in agricultural production research are presented. Fourth, a number of common simulators and their applications are surveyed. Finally, an appraisal of these simulators and their applications is undertaken while some of the factors that could enhance the continued relevance of this methodology are indicated.

2. Certain concepts in simulation

For the sake of exposition, a brief overview of certain issues in simulation is presented as a thorough discourse of these concepts has been undertaken elsewhere (Dent and Anderson, 1971; Anderson, 1974; Johnson and Rausser, 1977). Simulation is a numerical manipulation of a symbolic model of a system with a view to generating experimental information about the systems or the model of systems (Anderson, 1974; Johnson and Rausser, 1977; Czaki, 1984). Five phases in simulation are generally recognized. These are: the model specification, parameter estimation, verification (which may also include calibration), validation and revision stages (Anderson, 1974; Johnson and Rausser, 1977; Musser and Tew, 1984). The tasks to be accomplished in these phases are somehow self-explanatory except for the verification and validation functions which are often misconstrued. As will be seen in the next section, these two steps are arguably the mostly criticized components of simulation which deserve further elucidation.

Verification is the process of establishing the truth or correctness of model's reality (Dent and Anderson, 1971). It is the process by which the investigator determines whether or not the model performs in accordance with the intended purpose (Johnson and Rausser, 1977). Verification may be undertaken at the level of programming the model (Dillon et al., 1991) and/or debugging the program (Anderson, 1974; Law and Kelton, 1991). On the other hand, validation is the process of ascertaining the closeness of the model to reality which is reflected in the model's ability to duplicate the required characteristics of the systems and fulfilling the modelling objectives (Dent and Anderson, 1971; Wright, 1971; Johnson and Rausser, 1977). Simply put, the objective of validation is to ascertain the usefulness, rather than the truthfulness, of the model (Dillon et al., 1991).

Implicit in the above concepts of verification and validation is the fact that both duties need not be performed by the same set of investigators. Often, simulators are usually not developed by the end-users. Therefore, while the function of model verification may rest with the developers, the users are certainly responsible for validating the models to establish the relevance of such simulators to the specific problems under investigation.

Naylor and Finger (1971) proffer three methodological concepts of validation in economics which can be extended to validation in computer simulation. Law and Kelton (1991) expatiate on these concepts by providing specific recommendations on how these concepts can be implemented. The first concept, rationalism, holds that economic models are simply a system of logical deductions from synthetic premises of unquestionable truth that are not themselves open to empirical validation (Naylor and Finger, 1971). Thus the role of validation is to identify a set of basic assumptions governing the behavior of the system being modeled. For this concept, the operational framework proposed by Law and Kelton (1991) is that the model should possess high face validity that seems reasonable to people who are knowledgeable about the system being modeled. These underlying assumptions may be identified by using any combination of these methods: conversations with system experts, observation of the system, studying the results from earlier attempts, checking the existing theories, the use of experience and intuition.

The second concept, empiricism is in complete opposition to rationalism as it refuses any assumptions that cannot be independently verified. To implement this concept, Law and Kelton (1991) recommend the testing of model's assumptions empirically by using either the goodness of fit statistics, sensitivity analyses or other testing parameters. Finally, the last concept, positive economics holds that a satisfactory validation is the one that demonstrates an efficient ability of the model to predict the dependent variables that are treated by the model regardless of whether the underlying assumptions are valid or not.

Naylor and Finger (1971) further argue that a satisfactory validation is one that incorporates basic elements of the three concepts in a multistage validation (MV) fashion. In MV, each of the three conceptual positions is regarded as a necessary but not sufficient procedure for validating simulation experiments (Naylor and Finger, 1971; Ray and Richardson, 1978). The first stage in MV calls for the formulation of a set of hypotheses or postulates underlying the model. The second stage attempts to validate the postulates subject to the limitations imposed by existing statistical tools. The third and final stage in MV tests the model's ability to predict the behavior of the system under investigation. For this definitive test, when real systems exist, validation may be a relatively easy task of comparing the simulated data to real, out of sample data (King et al., 1993). If the population distribution of the real systems is known, the generated data can be tested statistically to see whether they could come from such a distribution (Anderson, 1974). However, if information on the real systems is not available, which is the common reason for most ex ante simulation analyses, validation becomes subjective and the expert opinion plays a key role in determining the credibility of the model (Law and Kelton, 1991). In all cases, an acid test of satisfactory validation is the ability to show that the simulation model leads to a better decision which cannot be readily obtained with alternative techniques (Wright, 1971).

3. Strengths and weaknesses of simulation

Numerous factors have contributed to the widespread use of simulation in agricultural economics research. First, by training, economists are generally not equipped to undertake physical experimentation that would produce needed information for economic studies. Therefore, when satisfactory experimental data can not be sourced from physical scientists, simulation becomes inevitable because of the relative ease of generating the input–output data that are needed. Also, simulation provides a means for incorporating certain stochastic variables (e.g., states of nature) that are not easily observable but can facilitate a better understanding of the system being modeled. Simulation becomes a more powerful tool when the generated data lead to sound management decisions that cannot be outclassed by using alternative techniques. Simulation can substitute for large scale physical experimentation while ex ante simulation can aid the understanding of a system that does not exist or that is currently impracticable to experiment (Anderson, 1974; Johnson and Rausser, 1977).

Another factor that is responsible for the explosive use of simulation is the increasing computer power and affordability (Dillon et al., 1991; King et al., 1993). One of the early concerns of simulation is its high cost. For this reason, Dillon (1971) notes that simulation, once started, will continue until available funds are exhausted. The observation of Anderson (1974) that a study through simulation always absorbs more resources than anticipated a priori duly complements this position. Therefore, It is not surprising to see an increased use of simulation as technological advances lower computation costs and make it very competitive when compared to physical experimentation or other methods.

The bulk of systems simulation has been used to address complex stochastic and/or dynamic problems in agriculture. Application to irrigation projects represents a substantial component of simulation (Anderson, 1974; Johnson and Rausser, 1977; King et al., 1993). In general, simulation has been used primarily as a research tool with little consideration for its credibility where credible models are simulators that have been widely accepted to the extent of being used as an aid in making decisions (Law and Kelton, 1991). However, the increasing demand for such credible models is now stimulating interest in the development of specialized simulators that meet these needs (King et al., 1993).

The criticisms of simulation are also worthy of consideration. Virtually all empirical applications have not placed much premium on the importance of model validation (Johnson and Rausser, 1977; King et al., 1993). Since a majority of these simulators are usually developed by parties that are external to their subsequent usage, validation is a prerequisite for discerning whether the predetermined model assumptions and the resultant model prescriptions are transportable and applicable to the new environment or problem under investigation. Also, some users may need to strengthen their justification for employing simulation tools as it is possible that feasible, cost-effective alternative techniques that can yield superior results are available.

While the modelling objectives of economists often involve some optimization, potential developers and users sometimes fail to recognize that simulation is not necessarily an optimal procedure and its application to a problem does not automatically lead to an optimal solution. While the search for an efficient way of using simulation as a means of optimization is an area deserving attention, few approaches have been suggested to deal with optimization of systems through simulation modelling (Anderson, 1974; Czaki, 1984; Azadivar and Lee, 1988). According to Azadivar and Lee (1988), these are: the Response Surface Methodology (RSM), direct search, and Stochastic Approximation Method (SAM). RSM entails the estimation of the regression parameters of linear or quadratic form of simulation outcomes (Box and Wilson, 1951; Smith, 1976). If the number of feasible simulation outcomes is limited, direct search for optimal results may be possible either with repeated iterations (Anderson, 1974; Czaki, 1984) or by careful enumeration and evaluation of all possible outcomes (King et al., 1993; Swinton and King, 1994). However, since a sizeable number of simulation models are often stochastic and more complicated in nature, the third category, SAM, which is a group of statistically convergent search methods, may be more appropriate (Kushner and Clark, 1978). A heuristic procedure developed by Azadivar and Lee (1988) for optimizing complex stochastic systems modeled by simulation is a good example of the SAM method. However, users need to balance the gains of optimization with the extra costs of pursuing any of these optimization procedures.

Other criticisms of simulation include: the need to validate the simulator in every application which makes its use time-consuming and expensive (Harnos, 1987), the divergence between model results and real world situations (Anderson, 1974), the fact that many simulation decisions and inputs are predetermined and uncontrollable thus necessitating an interdisciplinary cooperation for the simulators to be adaptable for other research (Musser and Tew, 1984).

4. Biophysical and bioeconomic simulation

Surveys of simulators and their applications have usually been conducted by subject area (Dent and Anderson, 1971; Johnson and Rausser, 1977; Czaki, 1984; Musser and Tew, 1984). Although there is no consensus as to the appropriate jargon for this classification, the categories provided by Johnson and Rausser (1977) will suffice. Their five broad classes are the firm and process, the market, the aggregate, the development and the natural resource models.

In agricultural production, a sub-set of firm and process models, otherwise known as biophysical simulators, are very common (Boggess, 1984; Musser and Tew, 1984). Biophysical simulators (BPS) are process models that explicitly account for the biological and/or physical components of agricultural production (Musser and Tew, 1984). These simulators provide the means of generating production response surfaces required for empirical production research (Boggess, 1984).

Often, BPS and bioeconomic simulators or models have been used interchangeably. A bioeconomic model is a mathematical representation of a biological system which describes biological processes and predicts the effects of management decisions on those processes (King et al., 1993). In practical applications, there seems to be no clear distinction between BPS and bioeconomic models (BEMS). For instance, the literature cited in BPS and BEMS surveys often overlap (see, e.g., Musser and Tew, 1984; Dillon et al., 1991; King et al., 1993). However, a few attempts have been made to distinguish between both classes of simulators. In general, BPS, by themselves, do not include an economic component. Musser and Tew (1984) contend that it is the magnitude of physical processes that differentiates BPS from BEMS. However, this distinction fades as BPS is intensively used to solve economic problems.

A more definitive difference between BPS and BEMS can be gleaned from King et al. (1993). They notice that BEMS generally fall within the class of predictive models where biological processes are represented by a relatively small number of equations relating current state and control variable levels to future states of the system. Conversely, BPS belong to a class of process models where relatively detailed subsystems of physical and biologically processes are linked in an overall representation of plant (or animal) growth in such a way that the structure and parameters of component subsystems are based on general theoretical models of specific physical or biological processes. Nevertheless, it is rather difficult to distinguish between both simulators in practice and the remainder of this survey will focus on both sets of simulators jointly.

5. Survey of BPS and BEMS simulators

The simulators reviewed in this section are neither representative nor exhaustive of all relevant models. Rather, the choice was influenced either by their acceptance, as reflected in the number of applications, or by the extensive involvement of agricultural economists in their development. Even with these criteria, it is conceivable that some important simulators would have been inadvertently left out.

SOYGRO (Wilkerson et al., 1983) and CERES (Ritchie and Otter, 1985) models are among the most famous process models that have been used in simulating whole crop–soil systems. Although SOYGRO was developed as a decision support tool for irrigation and pest management, it has been largely used for research purposes (Hoogenboom et al., 1992). SOYGRO simulates the yield, growth and development of soybeans (*Glycine max* L. Merr) as a function of soil, weather and management variables (Wilkerson et al., 1983). From its early version in the early 80's, SOYGRO has undergone substantial modifications such that it now ranks among the most flexible models whose validity of results is no longer location-specific or environment-dependent. Hoogenboom et al. (1992) describe the measures that were taken to ensure that the predictions of the model are reliable. During verification, the code was checked so as to ensure that the programming logic was consistent and a true reflection of the system being modeled. This was accomplished with the aid of debugging tools of FORTRAN compilers and some static program analyzers. For calibration, data from experimental sites in Gainesville, Florida were compared to model predictions. SOYGRO has been extensively validated in various locations in USA and Europe (Hoogenboom et al., 1992; Moulin and Beckie, 1993; Nagarajan et al., 1993; Savin et al., 1994; Gabrielle et al., 1995). Unlike many simulators, transportability of SOYGRO is enhanced by the generic format that was adopted for data entry so that site-specific information can be used for model predictions.

To a large extent, the above features of SOYGRO are shared by other -GRO models for grain legumes. They are PNUTGRO for peanuts (*Arachis hypogea* L.) and BEANGRO for common beans (*Phaseolus vulgaris* L.). Also, these attributes characterize CERES (an acronym for crop estimation through resource and environment synthesis) class of models for cereals. The purpose of CERES models is to generate yield estimates by modelling factors that were considered to be most relevant in yield determination. These factors include plant growth and development, soil water and nutrient status (Ritchie and Otter, 1985). Random factors that could be controlled by management such as pest and disease infestations were not considered. CERES Wheat and CERES Maize are the common types of CERES models. CERES and -GRO models are among the models within the framework of IBSNAT-DSSAT (the International Benchmark Sites Network for Agrotechnology Transfer Project Decision Support Systems for Agrotechnology Transfer) whose goal was to standardize the structure of these models in order to enhance their suitability for any region (Hoogenboom et al., 1992). Validation results for all or any components of SOYGRO and CERES models have generally shown a satisfactory level of correspondence between observable data and simulated variates, although certain sub-routines often require some recalibration before realistic model estimates are obtained (Moulin and Beckie, 1993; Nagarajan et al., 1993; Savin et al., 1994; Gabrielle et al., 1995).

FLIPSIM (Richardson and Nixon, 1986) is a FORTRAN computer simulation model that was developed for analyzing the probable consequences of alternative policies and income tax developments on typical farms. It is a firm level, recursive, simulation model which generates the annual production, farm policy, marketing, financial management, growth, and income tax components of a farm over a planning horizon of up to ten years (Richardson and Nixon, 1986). FLIPSIM identifies the optimal path of crop enterprises by systematically enumerating and evaluating the outcomes of all feasible alternatives. Verification and validation of FLIPSIM was fashioned after the multistage approach suggested by Naylor and Finger (1971).

HERB (Wilkerson et al., 1991), WEEDSIM (Swinton and King, 1994) and WEEDCAM (Lybecker et al., 1994) are all recent BEMS which are handy decision support systems for the management of agricultural pests (mainly weeds). HERB was first in the series of these pest management models to be developed. HERB is a computer-based, interactive, menu-driven program that can generate post-emergence herbicide recommendations for profitable soybean production (Wilkerson et al., 1991). Using the field-specific information supplied by the user, the model provides a number of feasible weed control alternatives and their associated impacts on weeds and returns (King et al., 1993). Data obtained from North Carolina experiments were used to calibrate HERB model. Information on the specific procedures employed for model verification and validation is rather scanty but satisfactory results with HERB applications have been reported (Wilkerson et al., 1991; Wiles et al., 1992). WEEDCAM is similar to HERB except it is a bioeconomic model for managing both pre- and post-emergence weeds in irrigated corn (*Zea mays* L.). It is a spreadsheet-based computer software which was developed and validated in Colorado. Its format assumes the knowledge of spreadsheet data management. This novel approach enhances the flexibility and robustness of the model with its liberal data entry and manipulation procedures.

WEEDSIM extends the frontiers of the above weed management models by recognizing a more plausible scenario of multiple weeds and multiple control strategies within a dynamic setting. It is a computer-based, dynamic, bioeconomic weed management model for corn and soybeans that identifies a two-year path of weed control treatments that maximize net returns per acre. The two-year horizon enables the model to track the carryover effects of current weeds and control measures in subsequent season. WEEDSIM, like the other two pest management models, identifies the weed control strategies that maximize returns by systematically enumerating and evaluating profits under all possible sequences of feasible weed control actions, rather than using dynamic programming or other optimization procedures. For verification, the steps described in Law and Kelton (1991) were followed while statistical tools and expert opinions were used in model validation. Evidence from on-field validation trials suggests that WEEDSIM is a promising tool for enhancing returns and/or reducing herbicide use when compared to farmers' conventional practices (Buhler et al., 1996; Forcella et al., 1996). A related model, GWM (Wiles et al., 1994), which has a better users' interface and which is considerably more flexible than WEEDSIM in terms of its data entry capabilities is presently being field-tested in several locations.

GLEAMS (Groundwater Loading Effects of Agricultural Management Systems) (Leonard et al., 1987) is a simulation model for evaluating the effects of different management systems on the movement of agricultural chemicals. It is a suitable tool for addressing the groundwater quality concerns of chemical usage. Another related model is AGNPS (Agricultural NonPoint Source) (Young et al., 1989) which is an event-based water quality model for analyzing nonpoint-source pollution in agricultural watersheds. Since a major constraint to the widespread use of these water quality models is their time-consuming input data demands, geographic information systems (GIS) have been successfully integrated with AGNPS (Tim and Jolly, 1994). This development has proved to be an effective way to collect, manipulate, visualize and analyze the input and output data of AGNPS (Srinivasan and Arnold, 1994). GLEAMS and AGNPS have ben found to be useful tools for environmental planning in various locations (Bingner et al., 1992; Sugiharto et al., 1994; Foltz et al., 1995; Rode and Frede, 1997).

EPIC (Erosion-Productivity Impact Calculator) (Jones et al., 1991) was developed by a multidisciplinary team of USDA researchers at the Blacklands Research Center in Temple, Texas. EPIC is a dynamic model that can be used to estimate soil erosion and its impacts on crop production. The nine major components of EPIC are: weather, hydrology, erosion, nutrient cycling, soil temperature, tillage, crop growth, crop and soil management, and economics. EPIC has been extensively used and the model appears to give acceptable results with minimal calibration (Bryant et al., 1992; Rosenberg et al., 1992; Foltz et al., 1995; Hughes et al., 1995).

CEEPES (the Comprehensive Environmental Economic Policy Evaluation System) (Bouzaher et al., 1995) is an integrated system of simulation models and policy appraisal tools that facilitates a systematic evaluation of trade-offs from alternative agroenvi-

Table 1
Some simulators and their applications

Simulator	Description	Examples of Application
AGNPS(Young et al., 1989)	Water quality model for analyzing nonpoint-source pollution in agricultural watersheds.	Kozloff et al., 1992;Sugiharto et al., 1994;Rode and Frede, 1997.
CEEPES(Bouzaher et al., 1995)	Integrated system for evaluating trade-offs from alternative agroenvironmental policies	Bouzaher et al., 1995.
CERES models(Ritchie and Otter, 1985)	Process models for predicting growth, development and yield of respective cereal grains.	Parsch et al., 1991;Johnson et al., 1991;Moulin and Beckie, 1993.
CIM(Brown et al., 1983)	A computer-based model for managing insect pests in cotton	Szmedra et al., 1991.
CORNF(Stapper and Arkin, 1980)	A biophysical simulation model for corn	Dillon et al., 1989.
COTTAM(Jackson et al., 1988)	A model for simulating the growth, development and yield of cotton. Similar to GOSSYM.	Dillon et al., 1989.
EPIC(Jones et al., 1991)	Dynamic model for estimating soil erosion impacts on crop production	Foltz et al., 1993;Hughes et al., 1995;Sabbagh et al., 1992.
FLIPSIM(Richardson and Nixon, 1986)	A firm level, simulation model for generating production, financial and marketing data.	Duffy et al., 1986;Bailey and Richardson, 1985;Perry et al., 1986;Salassi et al., 1987.
GAFS(Hutton and Hinman, 1968)	A general agricultural firm simulator	Harris and Mapp, 1986.
GLEAMS(Leonard et al., 1987)	Model for evaluating effects of management systems on movement of agricultural chemicals	Foltz et al., 1993.
GOSSYM(Baker et al., 1986)	A model for simulating the growth of cotton.	Misra and Spurlock, 1991.
GRAZE(Loewer et al., 1980)	Dynamic model for simulating beef-forage production as a function of both management and environmental variables.	Parsch and Loewer, 1987.
HERB(Wilkerson et al., 1991)	A bioeconomic model for post-emergence control of weeds in soybeans.	Wiles et al., 1992.
SORGF(Maas and Arkin, 1978)	A biophysical simulation model for sorghum.	Harris and Mapp, 1986; Dillon et al., 1989.
SOYGRO(Wilkerson et al., 1983)	A process-oriented computer-based model for predicting growth, development and yield of soybeans	Boggess and Amerling, 1983; Boggess et al., 1985; Szmedra et al., 1991; Parsch et al., 1991; Nagarajan et al., 1993.
SWAT(Brown and Hollis, 1996)	A semi-empirical model for predicting concentrations of pesticides entering surface water from agricultural land.	Arnold and Allen, 1996;Brown and Hollis, 1996.
SWRRB(Williams et al., 1985)	A hydrology model for simulating water balance and related processes in rural basins	Arnold and Williams, 1987;Singer et al., 1988;Savabi et al., 1988.
TAMW(Maas and Arkin, 1980)	A Biophysical simulation model for wheat. It is very similar to CERES-Wheat	Dillon et al., 1989.
WEEDSIM(Swinton and King, 1994)	A dynamic bioeconomic model for multiple weed management in corn and soybean.	Swinton et al., 1995;Buhler et al., 1996;Forcella et al., 1996;Oriade et al., 1996.

ronmental policies. This is a useful policy evaluation model especially with the growing concern regarding the potential environmental and health effects of agricultural chemicals. The four major components of CEEPES are: policy, agricultural decision, fate and transport, and health and environmental risk.

Other simulators that have featured in literature include SORGF (Maas and Arkin, 1978), CORNF (Stapper and Arkin, 1980), TAMW (Maas and Arkin, 1980), COTTAM (Jackson et al., 1988), GOSSYM (Baker et al., 1986), CIM (Brown et al., 1983), GRAZE (Loewer et al., 1980), GAFS (Hutton and Hinman, 1968), SWRRB (Williams et al., 1985) and SWAT (Brown and Hollis, 1996). Features of these simulators are summarized in Table 1.

6. A survey of selected applications

As with simulators, this survey does not consider all empirical work involving some simulation. Instead, the few that were selected only serve to illustrate the breadth of issues for which simulation methods have been deemed appropriate. The categories include irrigation, crop management, pest management, livestock management and agriculture and environment.

6.1. Irrigation

BPS and BEMS have been used extensively to determine the optimal allocation of irrigation water without over-exploiting the aquifers. Mapp and Eidman (1976) employed GAFS to simulate a representative farm and estimate returns under alternative duration and severity of soil moisture and atmospheric stresses during the critical stages of crop development. Simulated farm incomes under alternative strategies facilitated the recommendation of strategies and policy initiatives that are optimal under various water resource situations. Bernardo et al. (1987) used a biophysical simulation model, SPAW-IRRIG, to generate yield response to irrigation schedules. The irrigation activities so generated were later employed in a mathematical programming model that identified irrigation strategies for constrained profit maximization under limited water supply. Bernardo (1988) employed SORGF to evaluate the effects of spatial variability of irrigation applications on the efficiency of irrigation. The growth and yields of sorghum were simulated under both the assumption of uniformity and non-uniformity in water application. This formed the basis for comparing benefits under spatial variability to returns from conventional practice of uniform sprinkler irrigation.

On irrigation and risk, Boggess and Amerling (1983) employed SOYGRO to explore the implications of irrigation investments on risk and returns to irrigation strategy. This crop model was used to estimate yield response of crops to irrigation with seventeen years of historical weather data. Using cost estimates for alternative irrigation practices generated by a computer-based irrigation cost generator program, irrigation strategies that could maximize present value of returns under various weather conditions were identified. Harris and Mapp (1986) employed SORGF to simulate sorghum returns to stochastic soil water and other production and environmental conditions. The returns were later subjected to stochastic dominance comparisons in order to identify the water-conserving irrigation strategies for grain sorghum farmers that depend on the Ogallala aquifer in Oklahoma. Bosch and Eidman (1987) utilized a bioeconomic model to explore the value of soil and weather information for choosing optimal irrigation strategies when risk preferences of decision makers are not neutral. The study simulated the value of information for an expected utility maximizing decision maker whose representative farm comprises both irrigated and non-irrigated acreage under corn, soybean and rye production in Minnesota. Although the irrigation scheduling strategy was examined, the model proposed can be employed to analyze the returns to any production input under risk.

6.2. Crop management

With FLIPSIM, Duffy et al. (1986) evaluated the effects of alternative farm programs and levels of price variability on the survival and growth of Texas cotton farms. Five levels of price variability and three farm policy options under 1981 Farm Bill were simulated for two representative cotton farms. Perry et al. (1986) employed the model to evaluate alternative cropping patterns and share leasing arrangements that can enhance the economic viability of tenant rice and soybean farmers in Texas. FLIPSIM was used to simulate probability distributions of returns to a typical producer. Stochastic dominance techniques were later applied to these returns in order to identify efficient strategies and establish the relationship between crop rotation practices and the nature of share-leasing arrangements. Against the backdrop of declining acreage under rice production in the Mississippi River Delta region of the United States, Salassi et al. (1987) also used FLIPSIM to determine the economic survivability of rice farms if the prevailing economic conditions persist. The study led to the identification of enterprise mix and production practices that would sustain a higher level of production.

With CERES models, Johnson et al. (1991) predicted crop yields under different input levels to facilitate their evaluation of on-farm effects of cropping strategies that could reduce nitrate groundwater pollution. These crop yields were in turn employed in optimization and linear programming models from which inferences concerning leaching-profit tradeoffs of representative farms were drawn. Parsch et al. (1991) developed an amalgam of CERES-wheat and SOYGRO models which they used to assess the risk–return tradeoffs of double-cropped wheat–soybean producers such that the costs of early harvest of winter wheat are compensated by improved returns of early soybean plantings. With other models, Misra and Spurlock (1991) utilized GOSSYM to generate yield information required for the identification of efficient cotton cropping systems that balance the dual objective of maximizing whole-farm returns while reducing the risk of scarce fieldwork time. In a study that investigated the optimal crop mixes as risk preferences of farmers change in the Blackland prairies of Texas, Dillon et al. (1989) employed four crop simulation models (i.e., CORNF, SORGF, TAMW and COTTAM) to generate the needed input–output data. The economic decision problem was solved by applying mean-variance programming to the simulated returns.

6.3. Pest management

Reichelderfer and Bender (1979) developed a simulation model that described the physical production relationships between Mexican bean beatles, control inputs and soybean yields under different conditions. The simulation model was later used to investigate the relative social and economic advantages of alternative methods of controlling these insect pests in soybeans. Boggess et al. (1985) developed and employed a multi-species bioeconomic simulation model, the Florida Soybean Integrated Crop Management Model (SICM), that could prescribe optimal pest management strategies for soybeans within a deterministic, multiple species setting. SICM, which has been incorporated into SOYGRO, was used to simulate the population dynamics (fecundity, development and mortality) for common insect pests of soybeans and under varying weather, cultural and soil conditions.

Szmedra et al. (1991) used the Cotton Insect Management (CIM) simulation model to study the impact of extending the boll weevil eradication (BWE) program to Mississippi River Delta region of the United States on producers‘ returns and the efficacy of such pest control actions. The model aided the determination of the effectiveness of BWE participation and non-participation under low and high levels of integrated pest management (IPM). Nyangito et al. (1996) employed a whole farm simulation model, the Technology Impact Evaluation System, to assess the impact of alternative disease control methods on the economic viability of dairy cattle production among small holder farmers in East Africa. Returns under various alternative immunization programs were simulated and stochastic dominance tools facilitated the identification of efficient strategies for resource poor, risk averse farmers in the study area.

For site-specific management of weeds, Wiles et al. (1992) used HERB to investigate the value of information about weed patchiness for improving the recommendations of HERB that were based on non-patchy weed distributions. In a related study, Oriade et al. (1996) employed a modified version of WEEDSIM to examine the potential economic and environmental benefits of site-specific weed management relative to the conventional uniform control of weeds. Simulations with this model were carried out within a dynamic but deterministic framework.

For assessing the implications of pesticide policy on returns to pest control, Swinton et al. (1995) used

WEEDSIM to simulate the effect of local bans and taxes on triazine herbicide use in corn (*Zea mays* L.).

6.4. Livestock management

Brorsen et al. (1983) developed and utilized a stocker cattle growth simulation model to estimate physical and economic results of alternative stocker production systems. The model was used to calculate energy requirements, dry matter intake, and stock gains and weights of alternative production systems in Oklahoma. Parsch and Loewer (1987) utilized a biophysical model, GRAZE, to determine whether rotational or continuous grazing results in optimal performance for steers pastured on Bermuda grass (*Cynodon dactylon* L. Pers.) in western Arkansas and when faced with weather uncertainty. The pasture growth and animal weight gain under nine rotational grazing strategies were simulated with the model. Strategies were compared on the basis of net returns while variance and other measures of dispersion were used to gauge the riskiness of each grazing strategy.

6.5. Agriculture and environment

Sabbagh et al. (1992) developed and used EPIC-PST model to simulate the effects of different agricultural management practices on crop yields and pesticide losses by surface runoff, sediment movement, and leaching under irrigation in the High Plains region of Oklahoma. Kozloff et al. (1992) used AGNPS in a Minnesota watershed to simulate the relative effectiveness of alternative cropland retirement schemes with respect to budget outlays for annual payments to landowners, reduction in downstream sediment yield and nutrient loss, and reduction in on-site erosion. Foltz et al. (1993) combined output from EPIC and GLEAMS with a farm level linear programming model to assess the economic and environmental implications of selected eastern Corn Belt farming systems. Sugiharto et al. (1994) used EPIC and AGNPS to simulate the effects of selected management practices on associated sediment and phosphorus yields originating from agricultural land used for dairy operations. They simulated 1990–1991 land management alternative practices on three soils in the Upper Bower Creek area of Wisconsin and compared the quality of effluents from fields and watersheds to current standard practices. Bouzaher et al. (1995) used CEEPES to assess the economic and environmental implications of atrazine ban in the Corn Belt region of United States. Hughes et al. (1995) employed EPIC and budgeting tools to evaluate both the short-run profitability and long-run sustainability of a number of agricultural practices in the Barley cropping area of Jordan.

6.6. Miscellaneous

Other applications of BPS and BEMS include the determination of optimal timing of harvests, evaluation of research productivity and marketing analysis. Kellogg et al. (1988) developed a bioeconomic model which they used, in conjunction with optimal control techniques, to determine the optimal time periods for opening the harvest season for Bay Scallop fishery in North Carolina. Bosch and Shabman (1990) developed a bioeconomic model which they later used to study the effects of alternative types of research information on the returns to oyster production. The model results provide an insight into the nature of research priorities that is appropriate for enhancing productivity in the oyster industry. Finally, in marketing, Bailey and Richardson (1985) have used FLIPSIM to evaluate alternative marketing strategies for cotton. Daily features and cash cotton prices were simulated by the model and the impact of alternative marketing strategies to the farm's survival and economic success was determined within a whole-farm framework.

7. Critique and appraisal

Although earlier surveys (Anderson, 1974; Johnson and Rausser, 1977; Musser and Tew, 1984) point to a preponderance of simulation applications in irrigation studies, simulators are now being richly applied to pest management, animal and crop production, risk and environmental issues. Traditionally, simulators have been used to resolve dynamic and/or stochastic problems. However, its use in static and deterministic cases has been increasing. Also, while the primary objective of simulation is to forecast crop (or livestock) yields, evidence suggests that its potential for estimating pollutants and in generating certain inputs and intermediate products is being explored.

Recent BPS and BEMS have improved considerably as serious attempts have been made to avoid pitfalls associated with earlier systems. Model builders have capitalized on technological advances in making their systems more robust, flexible and portable. Programming modules are increasingly being standardized and it is not uncommon to find simulation programs that, in addition to being somehow user-friendly, possess advanced graphic capabilities. In some cases, quality documentation that is typical of commercial software is now being provided. However, a sizeable proportion of simulators are still cumbersome and poorly-designed to the extent that their developers often insist on formal training of potential users before permitting the use of such systems.

There is evidence of improved interdisciplinary collaboration between physical and social scientists which has resulted in the development of more robust and widely-tested simulators. However, this contradicts one of the reasons often adduced for developing new simulators which is the lack of certain desirable features in the earlier models. For instance, the motivation for developing SOYGRO, instead of using the then existing soybean models, is the need for a simpler model that has the ability to simulate crop growth in response to daily microclimate and stress factors (Wilkerson et al., 1983). Also, WEEDSIM was developed because of the inability of earlier pest management models to account for the more plausible dynamic nature of weed problems within a multiple species and multiple control setting (Swinton and King, 1994). Since these simulators were developed without any commercial intent, it is possible for more robust and widely applicable models to emerge from collaborative efforts that lead to the upgrade of existing systems instead of developing new ones. With this approach, desirable features that are lacking in earlier models can be incorporated in later versions.

The structure of funding model-building projects sometimes has implications on the shelf-life and popularity of the resultant simulators. Model developers often rely on research grants for developing their systems and interest in such models wanes once grant funds are exhausted. A system of archiving models and the associated resource personnel is germane in ensuring maximum returns to model-building ventures and avoid unnecessary duplication of efforts.

The verification and validation aspects of existing models both during system development and subsequent applications have improved considerably. Users now regard validation as a key component of project implementation. Virtually all studies now incorporate some elements of validation. However, in most cases, on-field validation trials were carried out at locations close to where initial data for calibrating the systems were sourced. Rather than attesting to the robustness of the simulators, this location bias may account for the high degree of correspondence between the simulated and experimental results. For instance, models that were validated outside the immediate model-building environment often have to be recalibrated in order to obtain acceptable model results (Moulin and Beckie, 1993; Nagarajan et al., 1993; Savin et al., 1994; Gabrielle et al., 1995).

Still on validation, there seems to be no consensus as to how validation steps should proceed. For validation of BPS and BEMS, some modellers have relied heavily on basic comparisons of simulated and observed results. Occasionally, subjective expert opinion is sought to determine the acceptable level of congruence. It is certain that disagreement on what constitutes an acceptable form of validation procedures will continue until generally agreeable standards are set. Until then, Naylor and Finger (1971) multi-stage approach as augmented by Law and Kelton (1991) which was described earlier may serve as a convenient starting point.

Simulation seems like a methodology of convenience. Some studies that employed simulation tools failed to investigate whether alternative strategies that could produce similar or superior results were readily available. Also, simulation results are sometimes interpreted as optimal solutions. This conclusion is valid only if simulation routines have incorporated an optimization search technique such that the resultant simulation outcomes have converged to the results of any optimization process. Some of the possible optimization search methods were highlighted in an earlier section of this review.

8. Conclusion

Simulation, econometric and mathematical programming methods rank among the best known methodologies for tackling the various questions in applied economic research. However, the review shows how simulation is a unique method that can facilitate the resolution of certain complex and/or dynamic problems that might otherwise remain intractable. Therefore, the continuous relevance of BPS and BEMS as suitable research tool is certainly not in doubt despite the minimal instances of their misuse and abuse.

The importance of simulation to management decision making is reflected in the increasing number of simulation-based decision support systems that is now in use. This represents a shift from the conventional role of simulation as a purely research tool. It also places a higher premium on the precision of simulation results as the acceptable margin of error disappears. Consequently, in order to ensure the usefulness of simulation methods in facilitating optimal management decisions, the residual concerns that are highlighted in this and similar studies should be addressed.

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