Staff Paper

MODELING OF AGRICULTURAL SYSTEMS

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Modeling of Agricultural Systems[1]

by

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Modeling of Agricultural Systems

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1. Introduction

Agricultural systems are diverse. In size, they range from submolecular systems to global agroclimatic systems. In character, they range from the biophysics of plant nutrient transfer across root hairs to the sociology of transhumant livestock herders. In duration, they range from hours for feed digestion or photosynthesis to centuries for soil erosion.

This chapter explores the purposes, types and applications of agricultural systems models. It begins by addressing the questions: "Why model agricultural systems?" and "For whom are these models developed?" The chapter next defines agricultural systems and develops interlocking typologies of models to address the question, "How are agricultural systems modeled?" It then explores a range of subject matter applications of agricultural systems models, closing with a review of current trends and future directions in this rapidly evolving field.

2. Why Model Agricultural Systems?

System models provide a simplified description of important system components and their interactions. Schoemaker (1982) identifies four purposes for systems models: 1) description, 2) prediction, 3) postdiction, and 4) prescription. Descriptive models are used to characterize the system; their performance, in turn, allows modelers to evaluate whether they have adequately described the important aspects. Predictive models forecast future system behavior. Descriptive models may serve a predictive purpose, but many predictive models are much simpler than descriptive ones, especially when certain system patterns repeat themselves systematically, obviating the need to describe the underlying mechanisms. For example, seasonal temperature patterns can be predicted fairly reliably from historical data, without describing the revolution of the Earth around the sun and the attendant changes in insolation, ocean currents, and jet stream activity. Postdictive models tend to be human logical constructions that allow us to explain after-the-fact what system constraints or special phenomena caused a given outcome. Prescriptive models are normative ones that offer guidance on how a system should be managed to meet some goal. Many agricultural models serve more than one of these purposes.

A secondary, but often very important, reason for modeling agricultural systems is to improve knowledge of the system. Knowledge of any given agricultural system is often uneven. Areas where knowledge of the system is sparse or missing tend to become apparent either 1) in the process of designing the model structure, or 2) in the process of finding parameters that can make empirical models operational. For example, one recent exercise in developing a weed management model revealed that in the past 30 years, North American weed scientists have focused their research so heavily on herbicide performance, that little is known about weed biology and ecology; the modeling process helped to instigate a new research effort in this area (Forcella *et al.*, 1992). Model design experiences often lead to revised priorities for future data collection research, based on data gaps defined (Dalton, 1982b; C. Mullon in ORSTOM, 1989). Hence, systems modeling may provide value not just through the end-product model developed, but also through the development process itself.

3. For Whom Are Agricultural Systems Models Designed?

The users of agricultural systems models can be grouped by the purposes of the models themselves. Researchers are the main users of descriptive and postdictive models, for these are the two classes of models whose role is to enhance understanding of the system. A much wider group of individuals seeking decision support uses the other two types of models. Predictive models are useful to those whose decisions depend upon good forecasts of future outcomes. Many farm management practices rely on good predictions of what outcomes are likely to ensue. All farmers have in their heads some heuristic predictive model of what results to expect from, say, changing a livestock feed ration or taking a position in the futures market. More sophisticated, numerical predictive models are designed with the intent of formalizing and improving upon managers' subjective predictions. At a broader level, system models may be used by policy makers to predict social welfare outcomes of proposed policies. Prescriptive models (most of which include a predictive component) have a similar audience—one which seeks to make decisions based on model recommendations.

4. Types of Agricultural Systems

Before examining in greater detail how agricultural systems are modeled, consider first how they can be classified. One approach is to classify them in space or time. Other ways are by hierarchical system level or by subject matter.

In space, the hierarchy of agricultural biophysical systems ranges in scale from micro-level plant and animal components to the individual organism to the field, to the whole farm, to multiple farm enterprises and multiple farm businesses (sometimes going beyond production to processing and some form of marketing), to larger scales such as watersheds and environmental zones. In parallel with the physical system boundaries are social systems, including rural communities and links to the larger society and macro-economy (of which the farming sector is just one part). Some of the more complicated system environments lie at the intersection of different systems. For example, the character and density of human communities affect the level of concern with the quality of their biophysical environment and public policies developed to ensure that minimum environmental quality levels are maintained. These policies, in turn, affect the management practices of farmers and others who manipulate the biophysical environment for their livelihood.

In time, agricultural systems can be viewed statically or dynamically. In some systems, we care about relationships in an atemporal fashion. The comparative statics models of microeconomic theory are illustrative. A supply curve, for example, models the aggregate willingness of producers to change quantity produced in response to price changes. This model captures a relationship of predictive interest even when the inherent time lags are not explicit. Of course, time is central to evolutionary processes. Examples would include plant and animal growth, pest demographics, and disease epidemiology, as well as how humans respond to previous events as well as current events. Questions of system stability and sustainability are often of special interest in dynamic models (Conway, 1987).

Ridder (1997) proposes agro-ecosystem hierarchies that integrate space, time and organization elements. He observes that in the same space and time, different (even overlapping) organizations may coexist. For example, livestock or crop individuals may be organized into crop or animal husbandry systems, just as individual people are organized into households. Likewise, larger-scale landscape areas bound both physiographic natural resource units and human administrative units.

Subject matter may be the most common way for people to think about systems, at least judging from our language. Contemporary discourse is rife with systems: ecological systems, economic systems, political systems, social systems, and information systems, to name just a few. Within each of these, the issues of space, time, hierarchy and complexity can be explored.

5. Types of System Models

In turning from systems to their representation via models, we face not only the diverse system typologies listed above, but also diverse ways to characterize the model designs themselves. In this section, we will examine system models beginning with a general typology of model communication, and moving on to a subclassification of mathematical system models.

5.1. Communicating systems models: Iconic, analogue and symbolic approaches

System models can be communicated by three general means: iconic, analogue, and symbolic (Dalton, 1982a; Wright, 1971). Iconic models represent the system in a visual form. This can range from a miniature version of the real physical system of interest (e.g., an experimental agronomic field plot) to a pictorial representation, such as a flow chart. Analogue models are expressed in words by analogy. For example, one might describe the xylem cells in a plant as functioning like sections of plumbing pipe. Symbolic models are primarily mathematical ones; they will be discussed at length below.

Iconic and symbolic models are the ones most commonly used to represent agricultural systems. Iconic models have been used to convey visually the broad interactions within systems of many hierarchical levels and overlapping system boundaries. For example, Spedding (1988, p. 10) offers a simple but powerful pictorial model of an agricultural system, reproduced in Figure 1. The model depicts in abstract form the crop and animal production components of the system, and the various input and output flows between them, including those involving energy inputs.

INSERT FIG 1 HERE (SPEDDING FIG. 1.3, P. 10))

In a very different kind of iconic model, Pelissier (1966, cited in Upton, 1987) represents spatial agricultural fertility management in Senegal as a set of concentric circles emanating from the village; the inner circle represents fields cropped annually and manured regularly from sedentary animals in the village, the next circle fields cropped with only short, intermittent fallows and supplementary fertility restoration from itinerant livestock herds pasturing in crop stubble, and finally a third circle of fields cropped in a long fallow rotation with no reliance on animal manure for fertility enhancement.

INSERT FIG. 2 HERE (UPTON FIG. 6.8 (P. 62))

Wilson and Morren (1990, Chapter 3) offer a good summary of different flow charting iconic models applied in agricultural and natural resource modeling.

5.2. Mathematical symbolic models

Mathematical symbolic models of agricultural systems have become dramatically more important over the past forty years with the revolution in computer technology. Computing advances have allowed modelers to take advantage of three great strengths of mathematical models 1) to mimic system complexity and dynamics through detailed equations, 2) to mimic random (stochastic) processes, and 3) to do these things with precision and replicability.

Mathematical models of agricultural systems use three general techniques: simulation, optimization, and statistics. Simulation models are developed with the intent of accurately describing the evolution of the system at a given scale. They tend to be dynamic models and may describe continuous systems using differential equations or discrete ones using difference equations or Markov chains. Some continuous models admit an analytical solution. However, in their comprehensive review of the literature, Van Dyne & Abramsky (1975) found most dynamic agricultural systems models to be discrete-event models based on difference equations.

Non-optimizing dynamic simulation models serve roles for both the scientist and the decision maker. For scientific purposes of description and postdiction, they offer the potential to conduct controlled, computerized experiments by replicating natural conditions that could otherwise not be replicated, or could be replicated only at great cost. Experiments that might otherwise be destructive or excessively time-consuming can be conducted safely and quickly in a simulated setting. Moreover, since most complex systems involve random processes that cannot be described by closed-form mathematical expressions admitting an analytical solution, discrete-event simulation can be extended to model stochastic processes explicitly (Law & Kelton, 1991). While proper stochastic simulation requires careful modeling of the random processes of interest, a well-designed model can easily generate many simulated system outcomes allowing study of their probability distributions and dynamic properties.

Apart from facilitating scientific inquiry, simulation models can serve valuable predictive and prescriptive functions for farm managers and policy makers. Biophysical simulation models can predict the environmental consequences of agricultural activities, thereby providing valuable insights for policy formulation, technology design, or regulatory enforcement (Antle & Capalbo, 1993). General equilibrium models can predict repercussions of a specific system intervention in a seemingly unrelated area, for example, the effect on hog prices due to removing a subsidy on nitrogen fertilizer (which is used on corn which, in turn, is fed to hogs), or the effect of a currency devaluation on peasant household nutritional status.

Optimization models seek to optimize some criterion or set of criteria subject to a set of constraints. For example, an economist might describe a farm management problem as

$$\begin{aligned} \max_{x} \quad & U(c(y,z), h(H,x,s)) \\ s.t. \quad & h(x,s) \geq H^0 \\ & p_z z + p_s s \leq p_y y(x) - p_x x \end{aligned}$$

meaning, “Choose the level of agricultural input x that will maximize the utility derived from consumption of goods **y** and **z** and from health, **h** (which depends upon initial health status, $\mathbf{H^0}$, exposure to input **x**, and health services, **s**). Do this subject to the constraints that 1) health must remain above minimum level $\mathbf{H^0}$ and 2) enough money must be earned from selling crop **y** (which is grown using input **x**) to pay for the consumption good **z** and health services **s** required.” If **x** is a discrete source of crop nutrition, then this normative economic model could describe an individual household’s farm management problem that, in aggregate, might lead to the spatial model described by Pellisier. This kind of model can also reveal the value of unpriced resources (such as usufruct rights to land) by explicitly modeling the value of output that could be achieved if other available resources were combined with it. Conversely, such mathematical programming models can reveal the foregone income due to losing a resource, such as the impact of policies that ban an agro-chemical feared to damage the natural environment.

While many early optimization models were static and deterministic, optimization modeling has developed to embrace stepwise decision making over time and decisions in risky settings. Such models include polyperiod linear programming models (e.g., Fafchamps, 1992; Krause *et al.*, 1990; Balcet & Candler, 1982). These models also include dynamic programming models, which use an optimization technique for identifying optimal time paths for discrete-valued control variables. Applications have included longterm weed control (Taylor & Burt, 1984), machinery selection (Krause & Black, 1995), crop choice for erosion control (Van Kooten *et al.*, 1990), and agricultural policy impact analysis (Duffy & Taylor, 1993) have been used in *ex ante* analysis of agricultural technology adoption and agricultural policy impacts. Optimization models can support the decision-making objectives of agricultural managers, such as minimizing the cost of animal weight gain, enhancing weed control, or boosting farm profits (King *et al.*, 1993). As discussed below, computable general equilibrium models represent a recent innovation in the optimization modeling of nonlinear systems, typically for policy analysis. At the other extreme, the simplest optimization models budget alternative scenarios in units of money, nutrients, or some other unit of interest. Scenarios based on multiple budgets in different units (for example, net revenue and pesticide leaching budgets for the same crop system) offer one way to optimize systems where multiple objectives are sought (Roberts & Swinton, 1996).

Statistical models allow the testing of hypotheses about the behavior of agricultural systems. For example, Kislev and Peterson wished to test the hypothesis that mechanization caused U.S. farms to begin growing larger by reducing the need for labor (Kislev & Peterson, 1986). Statistical models are also frequently used to estimate parameters for simulation or input-output optimization models. Among many possible cases in point, Swinton & King (1994) used statistical models to estimate biological parameters for weed population dynamics and crop yield loss from weed competition in building a discrete-event simulation model of outcomes from alternative weed management practices. Large-scale econometric models running systems of statistically estimated equations have long been routinely used to predict macroeconomic behavior, at the agricultural sector level and more generally. Recently, statistical models have also been used to integrate results from detailed simulation models into a simplified metaproduction response function (e.g., Bouzaher *et al.*, 1993; Johnson *et al.*, 1990).

6. Model Applications at Different Scales

Like the agricultural systems they describe, models of systems can be classified according to space, time, and hierarchical organization. In fact, many conventional subject matter categories (such as biophysical-ecological, sociological-cultural, and economic) correspond to physical scale or organizational level. A useful way to organize agricultural systems models is to modify the Stomph *et al.* hierarchical classification into 1) the sub-organism, 2) the organism, 3) communities of organisms, and 4) aggregates of communities. This classification is presented in Table 1, as the basis for the text in this section describing model applications and associated spatial and temporal characteristics.

INSERT TABLE 1 HERE

At the sub-organismal scale, most agricultural systems models are biophysical. These include sub-cellular models (or even smaller), attempting to describe such phenomena as how food is converted into mechanical energy by mitochondria or how root hairs differentially absorb plant nutrients.

A much larger number of agricultural systems models have been developed at the organismal level. One major grouping is the growth models. These are almost exclusively discrete-event dynamic simulators. An important group describe crop and livestock growth in response to key inputs (e.g., Hanks & Ritchie, 1991; Meynard, 1998; Peart & Curry, 1998; Tsuji *et al.*, 1994; Rotz *et al.*, 1989). Many of these are employed to test new technology or policy scenarios, since they can predict crop and livestock yield results due to changes in management, including generating probability distributions of outcomes that result from random weather.

In agricultural economic systems, the individual productive enterprise is analogous to the organism. It represents a formal conceptual way of viewing an economic subsystem in terms of financial costs and benefits. Crop and livestock enterprise budgets represent a time-honored way of doing this (e.g., Brown, 1979). “Green budgets” represent a variation on these that attempts to incorporate nonmarket environmental costs and benefits (Roberts & Swinton, 1996; Faeth, 1993). A different perspective on agricultural economic systems comes from looking at the marketing chain. Analogous to the enterprise budget from a production perspective is the commodity subsector from the marketing perspective. In the production-marketing chain, the subsector tracks a particular commodity from production to first-handler to processing to distribution and final consumption. Subsector models are typically analogue or iconic in structure.

Farmer decision-support computer models constitute yet another enterprise-level class of agricultural systems models. Papy (this volume) suggests that such models can provide a foundation for management consultations between experts and farmers. A variety of such mathematical models have been developed in the United States and Europe to support such decisions as whether to control crop or livestock pests (e.g., Swinton & King, 1994; Wilkerson *et al.*, 1991; Kells & Black, 1991; Renner & Black, 1991), whether to invest in new farm machinery (Cerf *et al.*, 1995), or whether to participate in government commodity price support programs (Gardner *et al.*, 1992).

Moving up to aggregates of individual organisms and their interrelationships, we encounter models of agricultural ecology and economics. The ecological models describe relationships among species in specific habitats or farming systems. In agriculture, many of these are mathematical models that come out of the pest sciences (entomology, plant pathology, and weed science) or efforts to model environmental fate and transport of hazardous substances. At the field scale, models include: for soil erosion, RUSLE and EPIC (Williams *et al.*, 1989); for chemical fate, EPIC-PST; for surface runoff, CREAMS; for nitrate leaching, NLEAP (Shaffer *et al.*, 1991). Other iconic models of aggregates come from technology development research in developing countries under the farming systems research or action-research methodologies in specific agro-climatic zones (e.g., McIntire *et al.*, 1992).

If enterprises represent the organisms in agricultural production economics, then farms represent the fundamental aggregates of these organisms. Due to the well-developed neoclassical economic theory of the firm, household-level agricultural economic models are more common than intra-household or village-level models (Fleming & Hardaker, 1993). The simplest of these household models are whole-farm budgets, which integrate a set of enterprise budgets in the context of limited farm resources. There exist several computerized accounting models for developing consistent whole-farm budgets either for evaluating farm plans (Hawkins *et al.*, 1995, 1993) or for *ex ante* policy analysis at the farm level (Richardson & Nixon, 1986). These models are best classified as simulation models.

Mathematical programming models have been widely used for static whole-farm planning and farm-level policy analysis. A general purpose, deterministic example is the Purdue Crop/Livestock Linear Program (PC-LP) (Dobbins *et al.*, 1994). In the research literature, there are many other mathematical programming models that have incorporated risk, including both measures of variability in the objective function (e.g., Hazell, 1971; Tauer, 1983) as well as constraints on acceptable probabilities of undesired outcomes (Atwood *et al.*, 1988; Teague *et al.*, 1995).

In the past two decades, the household has been studied econometrically using systems of equations that jointly estimate production and consumption activities. These models have assumed the household's objective to be maximization of utility due to consumption, with that constrained by a budget in which farm production and employment determined the revenue available (Singh *et al.*, 1986).

At the highest level of aggregation, examining groupings of aggregates, there are higher-level models from ecology, economics, and sociology. Here we encounter environmental models at a regional scale, such as the watershed, aquifer or airshed (e.g., Adams *et al.*, 1990). Some models were designed to study processes, while others were designed specifically to support decisions, such as government regulatory decisions on environmental compliance of agricultural producers. The U.S. government has been particularly interested in supporting models for tracking environmental fate and transport of agricultural chemicals and soil erosion. At the landscape scale, the Agricultural Non-Point Source (AGNPS) pollution and SWAT spatial simulation models and GRASS spatial erosion models have played roles in policy analysis if not enforcement. To date, this is the only major category of models that explicitly include spatial characteristics.

Social scientists have characterized several kinds of human organizations into iconic or analogue models. Agricultural economists have long monitored the evolution of "farm size structure" in the United States and other countries and its meaning for the quality of rural life and income distribution (U.S. Department of Agriculture 1979). U.S. farms in the 20th Century have divided between fewer large full-time farms and more small, part-time farms. Rural sociologists have tracked changes in the size, number, and vitality of rural communities (e.g., Flora, 1990). In the United States, important applications have been the effect of large discount department stores and shrinking populations in many agricultural areas. Efforts have been made to draw general conclusions about minimal characteristics needed to support rural communities that are viable in the sense of being able to keep their schools and certain local businesses. Regional models have been employed to study the interaction between location of agribusinesses and farms which require their services.

Agricultural markets have been modeled more mathematically, since the questions of interest are often quantitative ones, such as "How will price change in response to a change in technology or policy?" Agricultural sector models attempt to characterize the interactions between production and consumer demand, including substitutions across inputs and products. Most comprehensive agricultural sector models have been econometrically estimated from time series data (e.g., Huang, 1988) or constructed as elaborate mathematical optimization models (e.g., Taylor, 1994; Norton & Solis, 1983). Although historically these have been restricted to marketed commodities, early proposals to account more fully for human use of natural resources (e.g, Boulding, 1981) are beginning to be heeded (Norton & Solis, 1983).

During the past decade, simulation has been applied through computable general equilibrium (CGE) models. These nonlinear optimization models have the potential to capture feedback relationships between agricultural and nonagricultural activity at the household, village, regional, and national level. CGE models have chiefly been used for fiscal and trade policy analysis (De Janvry *et al.*, 1991; Hertel & Tsigas, 1988; Robinson *et al.*, 1990; Sadoulet & de Janvry, 1995), although they have also been applied to regional economic development (Kilkenny & Otto, 1994). In a few instances, they have been used to model decisions at the village or household level (Adelman *et al.*, 1987). Although dynamic models are possible at all these levels, they have been most common in the sub-organismal and organismal biophysical models. Dynamic models have been little used in routine economic applications.

7. Agricultural Modeling Applications Today and in the Future

7.1. New developments

While some observers have expressed dismay that agricultural systems simulation has not been used as much as early its proponents expected in the 1970's (Malcolm, 1990; Doyle, 1990), a number of innovative uses of agricultural systems models have emerged. A major area of recent growth is the linking of simulation with optimization models (called for by Van Dyne & Abramsky over 20 years ago [1975]). This has been most notable in analyses of environmental management problems in agricultural production economics research that link biophysical simulations of the natural system with economic optimization of one or more objectives (Teague *et al.*, 1995; Xu *et al.*, 1995; Antle & Capalbo, 1993; Johnson *et al.*, 1991; Bouzaher *et al.*, 1992; Jourdain, 1995; Flichman & Jourdain, 1998; Malik, 1998).

The declining cost of and increasing capacity to do computer calculations is encouraging more computationally-intensive agricultural models. This is particularly true in optimization models. Optimization models with nonlinear objective functions and constraints are increasingly easy to develop using commercial software. Techniques like CGE are proliferating as a result. Dynamic programming models, while not automated, have become more numerous in part due to increasing computing power that helps to overcome their extravagant computer memory requirements.

Expansion of computer power has also led to increasing integration of related agricultural models. For example, twelve crop growth discrete-event simulation models sharing a daily time step and a single-season simulation period have been assembled into the "Decision Support System for Agro-technology Transfer" model (DSSAT, Tsuji *et al.*, 1994). The group of models share similar input data requirements and can be used to simulate crop rotations under alternative management scenarios. Similarly, the SWAT (Soil and Water Assessment Tool) model is the offspring of EPIC-PST, a field-level dynamic erosion and pesticide fate soil and yield impact predictor, and a surface water movement model at the subwatershed level (Arnold & Allen, 1992).

A new area ripe for growth is in spatial models. The growing power of geographic information systems (GIS) provides a mechanism for organizing data appropriately. At the same time, the rapid growth in many countries of site-specific environmental regulations and farming technologies is creating increasing motive for studying systems spatially. So far, simulation of environmental movement of eroded soil and agricultural chemical runoff (e.g., SWAT, among others) have been early applications. But more are likely to follow in hand with rapid advances in spatial statistics and optimization methods.

7.2. More intensive computer models for farm management

As information processing and acquisition costs decline, the use of computer models for farm management decision support is expanding rapidly in North America. The models are designed for two purposes: 1) record keeping and 2) decision support. Farmers keep records both voluntarily (for comparative and trend analysis of farm performance in production, marketing, and financial management) and because they are required to. In the United States, farmers are required to keep detailed records on pesticide use, employees, and taxable income, among others. The emerging nutrient accounting systems for livestock and crop farms in parts of Europe—notably the Netherlands (Breembroek *et al.*, 1996)—are analogous to financial accounting in the sense that they can be audited to insure that nutrient losses to water and air fall within legal bounds.

Decision support models are increasingly popular because farming is becoming more competitive and because data collection is becoming cheaper or mandatory. In the United States, the national association of soybean growers is supporting research to adapt a soybean crop growth model to use for in-season soybean management decisions such as when to irrigate or how much fertilizer to apply given growing conditions up to the present. Electronic sensors can now monitor yields of many crops at harvest, just as they can identify individual cows at milking time. Remote sensors can monitor crop conditions during the growing season from satellites or airplanes. So in addition to more traditional uses, farm-level decision support models are now being developed to make “real time” recommendations such as to administer variable fertilizer rates as applicators move across a farm field (Pierce & Sadler 1997). Other applications include recent work in managing animal nutrition and physiology to meet acceptable manure nutrient output levels while achieving farm profitability.

7.3. Modeling environmental value

As human populations rise, the implicit value of unpopulated natural and agricultural locales rises. This, in turn, is creating more demand for spatial models to guide public policy in zoning land uses. A key step in the process is to develop values for lands in different uses. Agricultural land valuation is another area ripe for new systems models. Values derive only in part from market economic land uses; the greater challenge is to simulate environmental quality under alternative uses and the associated benefits and costs. Some of these come from direct consumption values associated with market economics or closely related values such as cost of avoiding an environmental hazard. But other areas will be more demanding of systems modelers, such as quantifying the amenity value of farm landscape, or identifying optimally mixed uses for government lands. In many instances, governments will not care to intervene directly in environmental management, but will wish to instill in citizens a set of incentives that encourage socially desirable behavior. Research today into environmentally responsible contract designs between private parties is in its infancy (Segerson, 1988; Swinton *et al.*, 1999).

7.4. Institutional economic and sociological models of agrarian structure and rural communities

The structure of socio-economic relationships is changing—both along the production-marketing-retail supply chain and in rural communities. In North America, the trend toward a bifurcation of farm size and more distinct differentiation between large full-time and small part-time farms has been underway for over 50 years. But a new trend toward the “industrialization of agriculture” is generating a new set of iconic and analogue models of increasing vertical coordination of agricultural production (Wolf, 1998; Boehlje, 1998). The North American livestock industries have led in this trend, first with poultry, now with swine. One outgrowth is an upsurge in research on the economic benefits and costs of vertical coordination in a society where information flows from consumer to producer are daily becoming greater and faster. Another outgrowth is an inquiry into the division of labor that is emerging, with growing concern that vertical coordination and information-intensive farming may lead to a proletarianization of farmers (Lowenberg-DeBoer & Swinton, 1997). Related to this are new attempts to model spatial patterns of farm specialization (e.g., clusters of swine farms) as well as the effects on rural communities of fewer, larger farms which may require fewer services from local sources.

7.5. Modeling interactions among systems

Agricultural systems models will also be needed to improve our understanding of how production system components interact if the systems are to be optimized. Three issues motivate the need for better information to optimize agricultural systems: environmental quality, product quality control, and ecosystem management. In most regions of the world, the environmental quality issue is now clear: The side effects of certain farming practices impose costs on others that must be reckoned with if sustainable systems are to be developed. Examples include water pollution due to manure runoff from intensive livestock production, threats to animal welfare, soil erosion that fills waterways with silt and reduces crop yields, salinization from irrigation systems, and pesticide misuses.

The second motivation for better modeling interactions is to enhance product quality control. As agriculture in many industrialized countries progresses toward closer integration of production with marketing and retailing, it becomes essential to be able to link end-product quality to detailed knowledge of production system components and how they interact. For more and more products (e.g., fresh fruits and vegetables, branded meats), the range of permissible tolerances for quality deviation is narrowing. With the emerging use of ecolabels that describe environmental characteristics of production conditions (Van Ravenswaay & Blend, 1999), modeling will become important to determine the risks of producing in more environmentally benign ways that may attract premium product prices.

The third reason for need for better modeling component interactions is to advance ecosystems management in lieu of the conventional, more industrial approach to production management. Sustainable agriculture is based more on the manipulation of the basic biological system. For example, pest and weed management are based not on application of purchased external chemical inputs, but instead on fostering biological controls that are already part of the agroecosystem. In order to accomplish this more effectively, two advances are needed. First, we need a better understanding of interactions among system components. Second, we need more efficient experiential learning methods, since annual experiments with uncontrolled weather make for slow learning.

Improved modeling of interactions within and among agricultural systems can help address all three of these needs—better environmental quality, better product quality control, and better ecosystem management.

7.6. Modeling challenges

The rapid expansion of information technology in agriculture will call for more, better computerized models of agricultural systems. The precision agriculture revolution has begun with low-cost data collection (e.g., yield monitors, remote sensing), GIS software, and hardware controllers to allow variable rate input control. The logical next phase will be an explosion in computerized decision support models that can make sound input recommendations site-specifically, interacting with a spatial database of field characteristics. As computer models become more accessible over the Internet, both for downloading and for direct access using languages such as Java, other simulation and decision support uses will also proliferate.

The new demands for computerized agricultural models will bring new challenges. The growing user audience for computerized decision support will require more user-friendliness and data updating than the research community that was the main audience for earlier generations of agricultural models. This will likely call for new ways to share model design and support between public and private sector institutions. Universities and governments may be good at generating new modeling concepts, but they are poorly suited to the continual updating and customer support that are hallmarks of successful private software companies.

Certain aspects of good model development will continue to be as challenging as always. Finding the appropriate trade-off between versatility in model output information and reasonably parsimonious data input requirements is never easy. The best model designs will realistically envision model uses and will be designed to accommodate them flexibly. The trend toward object-oriented computer programming may make it more practical to construct large models from fairly simple building blocks. But up to the present, there has always been a painful trade-off between model robustness, data requirements, and adaptability to new uses. This problem is nowhere more true than for the adaptation of research models for field decision support purposes (King *et al.,* 1993). Critics of past agricultural decision support models stress that successful models are developed by researchers with close links to the field and used for the specific purposes intended (Molle & Valette, 1995; Meynard, 1998).

The exponential growth of computerized mathematical symbolic models will not end the need for iconic and analogue models to conceptualize agricultural systems. The new uses of iconic and analogue models to describe the economic transformation of the food system supply chain is a case in point. Nonetheless, the easy manipulation and replication of computerized system models will cause them to continue expanding in use for the foreseeable future.

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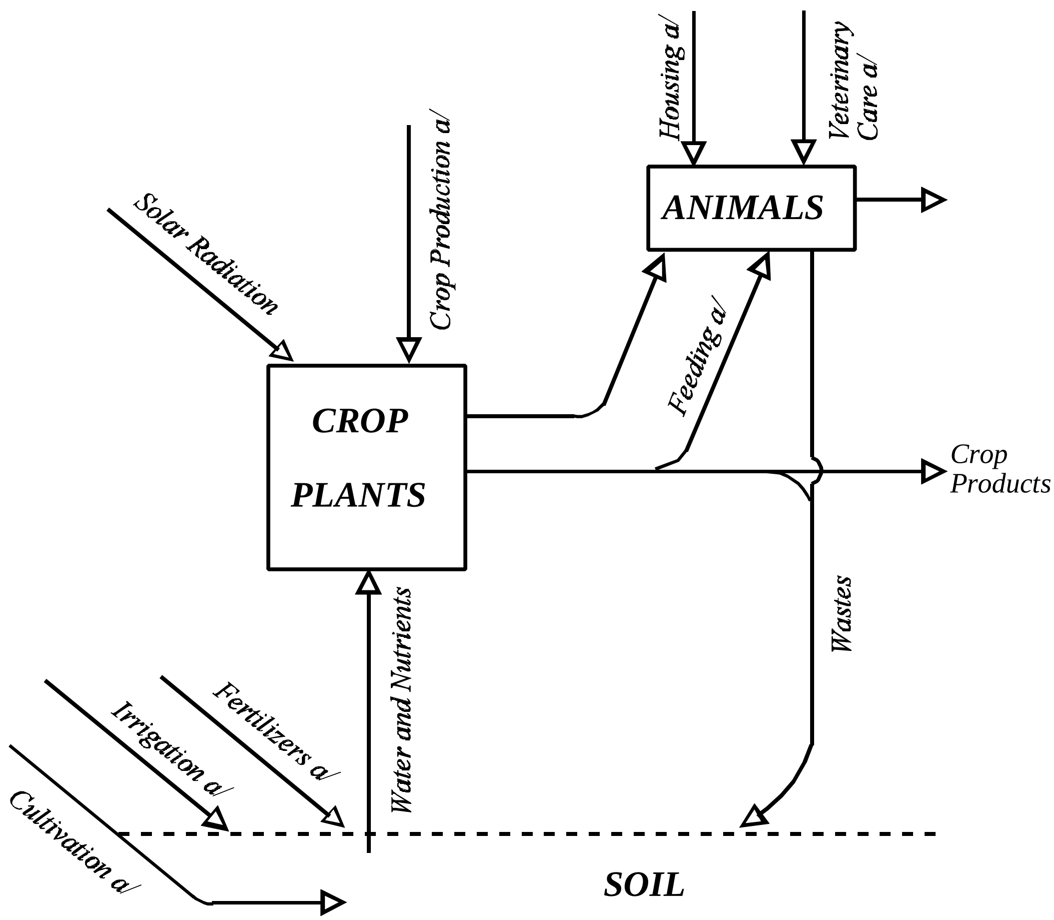
Table 1: Hierarchical classification of agricultural systems models.

Hierarchical scale	**Natural**	**Human**
Aggregated communities	Natural resource or agricultural region - Watershed models (spatial-M) - Aquifer (spatial-M) - Airshed models (spatial-M)	Political/economic region - Farm structure (A-I) - Agric. sector/prices (M) - Computable general equilibrium (M)
Community	Field or herd - Soil erosion (M) - Nutrient/pesticide leaching, runoff (M)	Farm household - Whole-farm budgets (M) - Whole-farm linear programming (M) - Household econometrics (M)
Organism	Plant or animal - Growth simulation (M)	Individual farm activities - Enterprise budgets (M) - Input decision support models (M)
Sub-organism	Plant/animal components - Metabolic simulation (M)	

Notes: M = mathematical model
A-I = analogue or iconic model

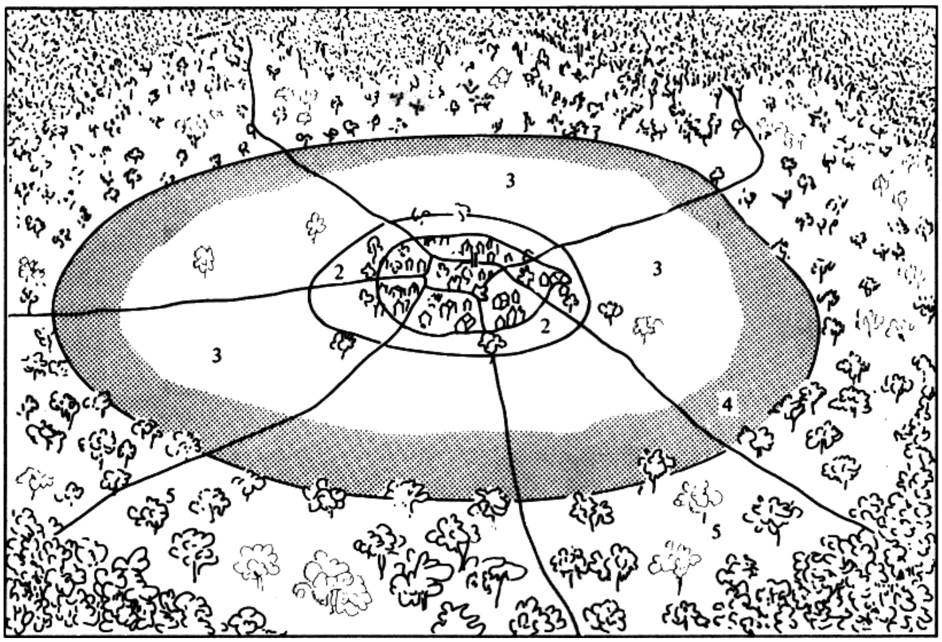
(Classification modified from Stomph *et al.*, p. 246)

Figure 1. A Model of Agriculture



a/ Involves inputs of support energy.
Reprinted with permission from Spedding, 1988.

Figure 2. Spatial Organization of Land Use in N'Gayene, Senegal.



1 = Houses and gardens; 2 = permanent cultivation; 3 = intensive fallow systems; 4 = intensive shifting cultivation; 5 = bush and extensive shifting cultivation. Reprinted with permission from Upton, 1987.