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Decision Technologies for Agribusiness Problems: A Brief Review of Selected Literature and a Call for Research

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The supply chain in the food and agribusiness sector is characterized by long supply lead times combined with significant supply and demand uncertainties, and relatively thin margins. These challenges generate a need for management efficiency and the use of modern decision technology tools. We review some of the literature on applications of decision technology tools for a selected set of agribusiness problems and conclude by outlining what we see as some of the significant new problems facing the industry. It is our hope that we will stimulate interest in these problems and encourage researchers to work on solving them.

Key words: applied optimization; agriculture; crop planning

The supply chain in the food and agribusiness sector is characterized by long supply lead times combined with significant supply and demand uncertainties. Supplies are often the result of biological production processes (food crops, meat and poultry production, etc.), and the products themselves are often perishable and thus require special handling, storage, and inventory management. The industry has seen an increasing emphasis on quality with tighter specifications on consistency, safety, and traceability. Generally, margins are quite thin because most products are commodities. Producers and processors are increasingly seeking opportunities to differentiate their products in the marketplace. These challenges generate a need for management efficiency and the use of modern decision technology tools. In this paper, we will review some of the literature on applications of operations research tools for agribusiness problems. We will conclude by outlining what we see as some of the significant new problems facing the industry. It is our hope that we will stimulate interest in these problems and encourage researchers to work on solving them.

1. Review of Some Modeling Efforts

In what follows we will review a selected set of references that make use of well-known operations research tools to study crop production. In particular, our focus will be on crop planning, crop harvesting, and risk management. This focus area represents research on only a subset of the problems facing food and agribusinesses. For example, we will not discuss literature on animal and poultry production, where many interesting problems and substantial ongoing research exists. Also, we will not cover the literature on marketing or food processing, distribution, and retailing.

Our intent is not to provide a comprehensive review of all of the literature in our focus area, but instead to highlight a number of relevant issues and to discuss some of the approaches that have been taken to deal with these issues. A comprehensive survey of the pre-1985 literature on the above topics (as well as others) was provided by Glen (1987). To the best of our knowledge, no such recent survey of the literature exists.

It should be noted that many crop production issues are a series of linked operations. For example, the timing of crop planting and the harvesting of that crop affect crop yield. Also, issues such as rotation of crops are closely linked with planting and harvesting. Thus decisions such as what is to be grown and the portion of total farm land to be devoted to each crop must consider similar decisions to be made in subsequent growing seasons. In addition, a number of activities may intervene between planting and harvesting such as cultivation to control weeds and the application of fertilizers and pesticides.

1.1. Linear Programming

The early applications of formal optimization techniques to crop-planning problems involved linear programming (LP) models. Heady (1954) is frequently cited as one of the first to demonstrate that LP can be used to determine the allocation of farm land to various crops subject to operational constraints. The objective function for these models typically involves maximization of profit.

Using linear programming, Audsley et al. (1978) compare gross margins resulting from different cultivation techniques while considering crop rotations of cereals and root-crops. Four crops are modeled—winter wheat, spring barley, sugar beets, and potatoes. The model explicitly considers the fact that field operations must follow a particular sequence: harvesting, clearing, plowing, cultivating, and planting.

Resources include available land, labor, and machinery. Because of the nature of the operations, complex interactions exist between labor and machinery. Timeliness of some operations is important because, for example, crop yields will be reduced if they are not performed at optimum times. To account for the "penalty" of not performing an operation at the optimum time, the authors augment the variable cost of performing the operation where appropriate. Because equipment size is a major productivity factor, the model considers two different equipment configurations. Although some of the variables used in the model should in reality be integer, the authors use only continuous variables followed by variable rounding.

McCarl et al. (1978) report on a successful application of linear programming to assist farmers in grain crop production planning. At the time the article was prepared, the program was designed to take in descriptive data on a given farm and then create a maximum income cropping pattern subject to the available resources. The program allowed for the possibility of recommending production of corn, soybeans, wheat, or silage along with the possibility of hiring out labor and/or renting land. Resources included land availability, labor hours, field preparation time, equipment, storage capacity, etc. The effects of timeliness of planting and harvesting are handled directly by adjusting yield levels by plant/harvest schedule. To provide input for a given program run, farmers completed a 524-question document. The program has been used extensively by farmers in a series of workshops held at Purdue University. These annual workshops have been run for over 35 years with a series of enhanced farm-planning models that retain many of the features of the original model (Preckel et al. 1992, Dobbins et al. 1994).

Because most of the early LP models associated with crop planning were targeted toward maximizing profit, some researchers realized that objectives other than profit maximization were relevant. Barnett et al. (1982) use goal programming with multidimensional scaling to model a Senegalese subsistence farmer's decision problem. The authors point out that a multi-objective approach is particularly relevant for subsistence farmers because they are frequently said to possess conflicting objectives such as profit maximization, risk avoidance, and maintenance of minimum food requirements. The chosen goals in their study are: (1) produce sufficient food to feed the entire family, (2) spend less on farm inputs, (3) earn more income to purchase livestock, and (4) organize work to have more leisure time. To develop objective function weights for the goal program, the authors elicited preferences through a survey. A sample of 80 individuals was drawn from a census of farmers. The individuals were selected from all social strata. Each respondent was then asked to make a comparison of various goals to describe his/her current objectives. From the results of these survey questions, the authors were able to construct appropriate weights for the goal program. The resulting model, according to the authors, performed satisfactorily in that it generated results consistent with previously observed Senegalese farmer behavior.

Whan et al. (1978) utilize a Markov decision process to model the problem of scheduling sugar cane crops in Australia. An optimization problem arises in scheduling due to the affect that a crop's age has on its value at the time of harvesting. Once a crop is planted, up to three harvests of sugar cane can be obtained from the same root-stock. Thus the time of harvest of one crop in a given cycle defines harvest parameters for the next cycle. However, in a given cycle there is an optimal time to harvest the cane because sugar content reaches a peak and then declines if not harvested. In defining the Markov transitions, the authors modeled discrete levels of crop quality: good, average, or bad. Decisions in the problem correspond to actions regarding harvesting of the current crop along with decisions regarding next actions, e.g., continue to grow on the same root-stock, replant, allow the ground to remain idle during the next cycle, etc. The problem was modeled and solved as a linear program. Both discounted and undiscounted versions of the model were considered.

1.2. Stochastic Programming

To include the likely situation where some parameters, e.g., commodity prices, resource needs, are not known with certainly in the crop-planning problem, Cocks (1968) suggests the use of stochastic programming as an appropriate tool for such problems. Cocks discusses various approaches to formulating linear programs when parameters are uncertain, and he devotes most of the paper to formulating a profit maximization model involving two crops (wheat and sugar beets) where labor requirements and the margin per acre are probabilistic at the planning moment but become known with certainty at a later date. Cocks then shows that the stochastic programming approach is superior to other linear programming approaches where all decisions must be made prior to knowledge of the outcome of the stochastic problem parameters.

Rae (1971) provides an empirical implementation of the model suggested by Cocks that focuses on a fresh-vegetable farm. Nine vegetable crops were considered, some of which have alternative harvesting schedules. Both weather (and thus indirectly yields) and prices are treated as random variables. He demonstrates that the value of the optimal strategy relative to the strategy determined from a deterministic model was substantial for the application.

Featherstone et al. (1990) develop a stochastic programming formulation to examine the capital structure of a farm. Their analysis reflects liquidity risk, collateral risk, and credit-reserve risk in determining optimal investment decisions. They conclude that in a multiyear context, the inclusion of constraints on borrowing reflecting the typical behavior of financial institutions has important consequences for near-term investment decisions.

A more recent example of stochastic programming applications to crop planning can be found in Jones et al. (2001). Their paper reports on an implementation of stochastic programming for a major hybrid seed-corn company to help determine the number of acres to plant for production of the seed. The seed company has the option of producing seed in North America during May–September, and in South America during November–March. Supply is uncertain because yield (harvested sales units per acre) is uncertain. Also, obviously demand for the seed the following spring is uncertain because the customer (farmer) has a choice of several hybrids offered by several seed companies. The model involved a two-stage optimization procedure with recourse (depending on the outcome of yield in North America).

Maatman et al. (2002) model a typical farmer's strategies on the Central Plateau in Burkina Faso, West Africa. This area of West Africa experiences highly variable rainfall, and serious food shortages are possible. The authors report on a stochastic program with recourse that considers the situation where farmers have three decision-making periods, depending on weather conditions. The first period is at the beginning of the season during the first rains—given the rainfall thus far, what agricultural production decisions to make in the face of uncertainty about future rainfall patterns. The second period occurs later in the growing season conditioned on observed rainfall. In the last period, following harvest, decisions regarding consumption, storage, selling, or purchasing must be made. The model allows for different combinations of crop-types, land location, landownership conditions, fertilization, and crop-sowing dates. The objective function of the model is to minimize deficits of nutrients available to the household minus revenues (that can change due to the sale or purchase of crops). Separate models are developed for each realization of the first period rainfall so that two recourse stages are used. The authors then compare results of their stochastic programming approach with results derived from a pre-existing static model.

1.3. Risk Programming

Another approach to crop planning under uncertainty is to select crop plans that lie on the E-V efficient frontier where E reflects expected profit and V represent the variance of profit. In his classical approach to the E-V problem, Markowitz (1959) suggests the use of quadratic programming to construct the efficient frontier—finding the minimum variance portfolio subject to a lower bound on expected return. This approach was placed in the context of determining an E-V-efficient acreage allocation to crops by Scott and Baker (1972). Scott and Baker demonstrate the approach for four crops and include the corn-supply-control government program of the day, allowing the model to choose not only the crop mix, but also the level of participation in the government program.

Contemporary to Scott and Baker, Hazell (1971) suggest that an alternative to farm planning using quadratic programming is to instead use the minimization of total absolute deviation (MOTAD) model. This formulation provides an approximation to the mean-variance model and has the advantage that the resulting problem is a linear program. Hazell demonstrates the use of MOTAD on a crop-planning problem for four crops, subject to constraints on land availability, labor requirements, and corporation specifications. Comparisons are then made on the MOTAD-derived solution versus a solution using quadratic programming.

The motivation for the E-V problem finds its origins in von Neumann-Morgenstern expected utility theory (see, e.g., Keeney and Raiffa 1976). Lambert and McCarl (1985) suggest direct solution of the expected utility problem where the distribution of random events is discrete. They demonstrate the model for portfolio problems under alternative distributional assumptions. However, other authors use the method for production-related problems (e.g., Randhir and Lee 2000).

1.4. Dynamic Programming

Among the earliest works using dynamic programming (DP) for crop production decisions are Burt and Allison (1963), for the deterministic case, and Burt (1965), for the stochastic case. Burt and Allison apply DP to the problem of determining when to grow wheat versus fallow in the western United States. Fallowing (idling the land) allows moisture to accumulate, resulting in higher wheat yields in the future. Thus, if soil moisture is sufficiently low, it may be economically optimal to forego planting in the current year in anticipation of higher future yields. Subsequently, Burt formulates the general optimal replacement model for productive agricultural assets (farm machinery, buildings, livestock, etc.) as a stochastic DP model. While an empirical application is not presented in the paper, several subsequent papers made use of the general model in analyzing asset replacement decisions.

Allocation of irrigation to competing crops is an important farm-planning issue when water is scarce. Yaron and Dinar (1982) present a systems approach for a water-allocation and irrigation-scheduling problem. The overall system is composed of a linear programming model coupled with a dynamic programming model. The LP model has the objective of maximizing farm income subject to technology constraints. The LP considers several possible irrigation alternatives that are gradually introduced into the problem. The analysis starts with a solution of an LP from a given set of water prices. Using dual variables from the LP, the dynamic program is used to construct new irrigation alternatives. New alternatives are then inserted into the linear program and it is re-solved. This iterative process continues until no new improvements can be made. The authors then apply their system to a water-allocation problem on a typical cotton-growing farm in Israel.

Stoecker et al. (1985) develop a dynamic programming model for measuring the economic benefits of an irrigation system development over a depleting aquifer. The setting is in the Texas High Plains area and involves the Ogallala Aquifer. This aquifer is isolated from significant recharge sources, and thus water is not replaced quickly as it is being drawn down. The authors derive the model and use it to determine optimal investments in resources as well as cropping plans.

Their study is developed in two phases. In Phase 1, linear programming is used to generate optimal one-year water allocation and farm plans, as well as irrigation decisions. The operational mode of the irrigation system can be changed each year by such actions as drilling additional wells, etc. The output of

Phase 1 is a series of tables reflecting the one-year net farm income obtainable from each possible state and stage of the dynamic program, as well as the decision variables.

Phase 2 uses the Phase 1 tables in the dynamic program where optimal temporal decisions are made. The constructed dynamic program is deterministic in the sense that benefits as well as appropriate changes in the states are assumed to be known with certainty.

It has been reported that wild oats are one of the most significant weeds that plague cereal crop producers worldwide. This is particularly true for growing small cereal grain such as wheat because the physical characteristics of the two plants are quite similar. To complicate matters, wild oat seed can reside in the soil for several growing seasons before sprouting and creating a problem for the grain farmer. To manage this weed problem while trying to maximize profit, the cereal grain farmer can grow a crop without the use of an herbicide, apply a pre-emergent herbicide, apply a post-emergent herbicide, or leave the land fallow (not plant).

Taylor and Burt (1984) develop a multiperiod dynamic program to assist in making best decisions. State variables in the dynamic program are the density of wild oat seed in the soil, whether the land last period was used to grow the crop or was fallow, the soil moisture level if it was not fallow last period, and the market price of the grain once harvested. Several interesting relationships between the state variables are included in the model, e.g., the carryover of wild oat seed from one period to the next. The objective function of the dynamic program is to maximize long-term discounted profit. The paper derives a "near optimal" set of decision rules.

Taylor (1993) edited a book that focused on applications of DP to decision problems in agriculture. One chapter in this book applies DP analysis to the optimal replacement of farm machinery (Gustafson 1993). Machine failures are the stochastic variable, and the probability of failure, cost of repair, and net cost of replacement are all treated as varying with the age of the machine. The model was applied to the decision to replace a combine harvester on a typical cash grain farm in western Minnesota. Another chapter in this book applies DP analysis to the problem of pest control in wheat (Danielson 1993). The pest of interest is a yield-damaging fungus. The control strategy is to periodically alternate the wheat crop with either fallow or a different crop that does not serve as a host for the wheat fungus. The stochastic variable in the problem is the level of infestation (fraction of plants infected). Results indicated that either fallowing or planting barley could be optimal depending on crop prices. The author suggests that the model could be improved by the inclusion of an additional state variable for soil moisture.

1.5. Simulation

Simulation is another well-known decision-support tool that has been found to be useful in decision making in agribusiness. Chen and Yang (1980) develop a simulation model to help determine the optimum day to start harvesting sweet potatoes. Using data gathered from field experiments, the authors determine the relationship between growing days (number of days between planting and harvesting), and (1) the yield of Number 1 potatoes (most desirable potato grade) and (2) the yield of three other less desirable potato grades. For example, a potato becomes less desirable if it is too large. Thus the yield of Number 1 potatoes, as a function of growing days, first increases and then decreases. However, yield of the "too large" grade is an increasing function of growing days.

Once all functional relationships were established, the authors simulate growing seasons using stochastic parameters such as market price of sweet potatoes, weather, harvesting rate, etc. Model outputs were used to construct expected relationships between harvesting dates and gross profit.

Biophysical simulation models are based on modeling the physical growth of plant tissues as a function of weather (e.g., available light, moisture, nutrients). These models are often used as a means to investigate production strategies. For example, Dillon et al. (1989) use a biophysical simulation model to generate yield data that serve as input to an acreage-allocation model based on quadratic programming. They use the resulting model to evaluate crop mix. Saseendran et al. (1998) use a biophysical simulation model for rice (CERES Rice Version 3.0) to directly determine the optimal transplanting dates to move rice seedlings from nurseries to the field.

As is suggested above, a significant body of literature exists regarding the application of decision-support tools to agribusiness problems. Much of this work continues today as new problems emerge. Fortunately, the development of improved software and increased computing power will accommodate the modeling and solution of more complex problems in the future.

2. Emerging Issues—Future Research Needs

Agriculture is currently undergoing changes on several fronts that create a need for new approaches to efficient management. Boehlje et al. (2003) identify several dimensions or themes of the current structural changes in agriculture. Here, we re-examine several of those themes with an eye toward the research needed to support the efficient operation of the agricultural production and processing enterprises.

Two of these themes are related to product differentiation. For example, consider corn. Historically, the distribution system for corn has been organized into two primary channels. The main, high-volume channel was for commodity corn, and the secondary, low-volume channel was for high-value specialty crops such as organic corn (Bender 2003). With the advent of genetic engineering, the number of differentiated corn types has greatly increased, and now even commodity corn is differentiated. These changes have created the need for a redesign of the transportation and distribution systems and a re-examination of inventory management strategies.

Because of product proliferation, agriculture-supply businesses face significant inventory/product-variety management challenges. For example, corn and soybean seed companies now have many more varieties to offer in the marketplace. (A partial explanation for this phenomenon is the aforementioned introduction of genetic engineering.) In addition to seed variety, the number of different seed treatment options has grown significantly over the past few years. This explosion in product variety has led to increased aggregate inventory levels for seed producers. Decisions such as determining appropriate inventory levels become much more complex as product substitution becomes more prevalent. Also, life-cycle issues such as when to "retire" an existing product become more important as new products enter the marketplace.

Two of the Boehlje et al. (2003) themes relate to the globalization of agriculture. Production of agricultural products in one hemisphere for consumption or use in the other can now be economically achieved for a large number of commodities. At the same time, increasing global competition creates pressure for lower prices. Efficient management of the transportation, distribution, and inventory management of these products, many of which are perishable, is essential to profitability and provides additional research opportunities.

Another of these themes, precision production, refers to technology and information-driven approaches to agricultural production that focus control efforts on much smaller units than was possible in the past. For example in the past, crop production was typically managed at the level of a field—a contiguous, multiacre tract of land. The advent of global-positioning-system technology in conjunction with inexpensive computers and sensor technology has resulted in an ability to manage crop production within the field. These technologies allow producers to monitor yields within-field and apply chemicals at rates that vary within fields. In a recent survey, Griffin et al. (2004) reports that some form of precision agriculture was used on over one third of all corn acres and over one quarter of all soybean acres in the United States in 2000. Lowenberg-Deboer (2004) cites the development of three systems for real-time sensors for soil nitrogen—an essential nutrient for crop growth. Another opportunity for research involves determining how to best use precision production data to increase farm profitability.

Another of these themes relates to the increasing use of contracting and accountability at various stages in the agricultural product supply chain. Historically, transactions in these supply chains have been based primarily on spot markets. At present, an increasing variety of longer-term relationships are springing up between the various agents in the chain. Boehlje et al. (2003) suggest these longer-term relationships increase efficiency by improving the scheduling of material flow and capacity utilization, improving quality control, reducing food-safety risks for consumers, and providing for more rapid response to consumer desires. Identifying sustainable contractual arrangements and designing effective systems for tracing both up and down stream along the agricultural supply chain also represent potentially fertile areas for research.

3. Summary

As mentioned at the beginning of this paper, our intent is to stimulate interest among the operations management research community in tackling some of the many problems facing the management of agribusinesses. To provide examples of previous work, we have reviewed selected applications of decision-support tools to a narrow slice of agribusiness management, namely crop planning. In addition, we have outlined what we see as some of the emerging issues that will benefit from research by our colleagues. It is our hope that they will accept the challenge.

References

Audsley, E., S. Dumont, D. Boyce. 1978. An economic comparison of methods of planting cereals, sugar beets and potatoes and their interactions with harvesting, timeliness and available labour by linear programming. *J. Agricultural Engrg. Res.* **23** 283–300.

Barnett, D., B. Blake, B. McCarl. 1982. Goal programming via multidimensional scaling applied to Senegalese subsistence farms. *Amer. J. Agricultural Econom.* **64** 720–727.

Bender, K. 2003. Product differentiation and identity preservation: Implications for market developments in U.S. corn and soybeans. *Sympos. Product Differentiations Market Segmentation Grains Oilseeds: Implications Indust. Transition*, Economic Research Service of the U.S. Department of Agriculture and the Farm Foundation, Washington, D.C. (January 27–28, 2003).

Boehlje, M., J. Fulton, A. Gray, T. Nilsson. 2003. Strategic issues in the changing agricultural industry. Purdue University Cooperative Extension Service, CES Paper #341, West Lafayette, IN.

Burt, O. R. 1965. Optimal replacement under risk. *J. Farm Econom.* **47** 324–346.

Burt, O. R., J. R. Allison. 1963. Farm management decisions with dynamic programming. *J. Farm Econom.* **45** 121–136.

Chen, L., Chi-Chen Yang. 1980. Optimum starting date for the harvest of sweet potatoes. *Trans. Amer. Soc. Agricultural Engineers* **23** 284–287.

Cocks, K. 1968. Discrete stochastic programming. *Management Sci.* **15** 72–79.

Danielson, J. 1993. Optimal crop rotations to control cephalosporium stripe in winter wheat. C. Taylor, ed. *Applications of Dynamic Programming to Agricultural Decision Problems.* Westview Press, San Francisco, CA, 39–54.

Dillon, C. R., J. W. Mjelde, B. A. McCarl. 1989. Recommendations on the implementation and development of biophysical simulation models in agricultural economic research. J. K. Clema, ed. *Proc. 1989 Summer Comput. Simulation Conf.*, Austin, TX (July 24–27).

Dobbins, C. L., Y. Han, P. V. Preckel, D. H. Doster. 1994. Purdue crop/livestock linear program (PC/LP) Version 3.2. Cooperative Extension Service, Purdue University, West Lafayette, IN.

Featherstone, A. M., P. V. Preckel, T. G. Baker. 1990. Modeling farm financial decisions in a dynamic and stochastic environment. *Agricultural Finance Rev.* **50** 80–99.

Glen, J. J. 1987. Mathematical models in farm planning: A survey. *Oper. Res.* **35** 641–666.

Griffin, T. W., J. Lowenberg-Deboer, D. M. Lambert, J. Peone, T. Payne, S. G. Daberkow. 2004. Adoption, profitability, and making better use of precision farming data. Staff Paper 04-06, Department of Agricultural Economics, Purdue University Site Specific Management Center, West Lafayette, IN.

Gustafson, C. R. 1993. Optimal stochastic replacement of farm machinery. C. Taylor, ed. *Applications of Dynamic Programming to Agricultural Decision Problems.* Westview Press, San Francisco, CA, 39–54.

Hazell, P. 1971. A linear alternative to quadratic and semivariance programming for farm planning under uncertainty. *Amer. J. Agricultural Econom.* **53** 53–62.

Heady, E. O. 1954. Simplified presentation and logical aspects of linear programming technique. *J. Farm Econom.* **36** 1035–1048.

Jones, P., G. Kegler, T. Lowe, R. Traub. 2001. Matching supply and demand, the value of a second chance in producing hybrid seed corn. *Manufacturing Serv. Oper. Management* **3** 122–137.

Keeney, R. L., H. Raiffa. 1976. *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. John Wiley & Sons, New York.

Lambert, D. K., B. A. McCarl. 1985. Risk modeling using direct solution of nonlinear approximations to the utility function. *Amer. J. Agricultural Econom.* **67** 846–852.

Lowenberg-Deboer, J. 2004. The management time economics of on-the-go sensing for nitrogen application. *SSMC Newsletter* (May).

Maatman, A., C. Schweigman, A. Suijs, M. Van Der Vlerk. 2002. Modeling farmer's response to uncertain rainfall in Burkina Faso: A stochastic programming approach. *Oper. Res.* **50** 399–414.

Markowitz, H. 1959. *Portfolio Selection: Efficient Diversification of Investments*. John Wiley & Sons, New York.

McCarl, B., W. Candler, D. Doster, P. Robbins. 1978. Experience with mass audience linear programming for farm planning. *Math. Programming Stud.* **9** 1–14.

Preckel, P. V., Y. Han, C. L. Dobbins, D. H. Doster. 1992. Purdue crop/livestock linear program formulation. Purdue University Agricultural Experiment Station Bulletin 634 (April).

Rae, A. N. 1971. An empirical application and evaluation of discrete stochastic programming in farm management. *Amer. J. Agricultural Econom.* **53** 625–638.

Randhir, T. O., J. G. Lee. 2000. Effect of water quality standards on farm income, rise, and NPS pollution. *J. Amer. Water Resources Association* **36** 595–608.

Saseendran, S. A., K. G. Hubbard, K. K. Singh, N. Mendiratta, L. S. Rathore, S. V. Singh. 1998. Optimum transplanting dates for rice in Kerala, India, determined using both CERES Version 3.0 and ClimProb. *Agron. J.* **90** 185–190.

Scott, J. T., Jr., C. B. Baker. 1972. A practical way to select an optimum farm plan under risk. *Amer. J. Agricultural Econom.* **54** 657–660.

Stoecker, A., A. Seidmann, G. Lloyd. 1985. A linear dynamic programming approach to irrigation system management with depleting groundwater. *Management Sci.* **31** 422–434.

Taylor, C., ed. 1993. *Applications of Dynamic Programming to Agricultural Decision Problems*. Westview Press, San Francisco, CA.

Taylor, C., O. Burt. 1984. Near-optimal management strategies for controlling wild oats in spring wheat. *Amer. J. Agricultural Econom.* **66** 50–60.

Whan, B., C. Scott, T. Jefferson. 1978. A stochastic model of sugar cane crop rotation. *J. Oper. Res. Soc.* **29** 341–348.

Yaron, D., A. Dinar. 1982. Optimal allocation of farm irrigation water during peak seasons. *Amer. J. Agricultural Econom.* **64**(4) 681–689.