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Operations Research Models and the Management of Agricultural and Forestry Resources: A Review and Comparison

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Operations research (OR) has helped people to understand and manage agricultural and forestry resources during the last 40 years. We analyzed its use to assess the past performance of OR models in this field and to highlight current problems and future directions of research and applications. Thus, in the agriculture part, we concentrate on planning problems at the farm and regional-sector level, environmental implications, risk and uncertainty issues, multiple criteria, and the formulation of livestock rations and feeding stuffs. In the forestry part, we concentrate on planning problems at the strategic, tactical, and operational levels, implementation issues, environmental implications, as well as the treatment of uncertainty and multiple objectives. Finally we made a comparison between the two areas in terms of problem types, problem-solving approaches, and reported applications.

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Understanding and managing systems based on agricultural or forestry resources is complex for several reasons. First, we must consider the sustainability of the underlying natural system. For agricultural and forestry resources, sustainability implies imposing constraints on the model to ensure that the harvest rate of the resource does not surpass its natural regenerative capacity and that we maintain the financial rate of growth. Second, we must take into account the underlying complexity of the growth and harvesting processes. Third, we must consider the relationship between production processes and general environmental, economic and, at times, social issues. The complexity is challenging, offering us opportunities to use operations research (OR) methods, particularly as globalized economies increase organizations' needs for efficiency.

After about 40 years of applying OR models to the management of agricultural and forestry resources, it seems sensible to review the most successful cases to evaluate past performance and to highlight current problems and future directions for research and applications. Both resources share common problems, such as scarcity, concern for the environmental effects of production, and the need for efficient production processes. The two areas differ, however, in the nature of the resources and the way they are handled, time horizons considered, planning and operational processes, and environmental impacts. We first discuss each area separately, addressing the important issues in each area, what has been accomplished in OR at a theoretical level and at an applied level, the current and future research areas, and the best opportunities for applied work.

Agriculture

Agriculture is one of the fields in which OR models were first used and have been most widely applied. Even though the number of papers published per year covering OR applications in agriculture has declined slightly over the last decade or so, the use of OR models has grown, chiefly because of the impressive development of personal commercial software programs.

Agricultural-Planning Problems (Farm Level)

Heady's (1954) work can be considered the starting point of linear programming (LP) models addressing agricultural decision making. Researchers formulated initial models at the farm level. The basic model has the following structure. The criterion function is usually gross margin (sales revenue minus variable costs). The feasible set represents the constraints that define the environment within which choices are made (for example, labor requirements, land available, and working capital requirements). Decision makers have used the basic model to (1) determine the optimum cropping pattern, (2) analyze the interdependence of parts of the farm, and (3) investigate the optimal sizes of different types of fixed equipment and machines to add to farm resources (Beneke and Winterboer 1973).

Researchers have also used LP models at the farm level to assess and to simulate the economic impact of some agricultural policies. These models are generally prospective; they try to predict the impact of policy changes on farmers' incomes and production patterns. LP models present difficulties; for example, an aggregation bias arises as one goes from farm level to regional-sector models, and identifying the real objectives farmers pursue is difficult. However, their current and future possibilities could be important. Lauwers et al. (1998) and van Huylenbroeck et al. (2001), for example, demonstrate their potential.

In some farm-planning situations, the values of the decision variables cannot be continuous (for example, the location of agricultural-processing activities) or such activities as milk production that must be undertaken at some minimum level if they are to be conducted at all. Such situations require integer or zero-one LP models. The intertemporality underlying many agricultural decisions sometimes demands the use of multiperiod LP models (Rae 1994). To deal with the risk and uncertainty that farmers encounter in real situations, we must incorporate multiple criteria into LP models.

Agricultural-Planning Problems (Regional-Sector Level)

When the analysis moves from the farm to the regional sector, the definitions of the objective function of the model and the aggregation problem change. In the regional-sector context, the objective function used at farm level (for example, gross margin) is economically unjustifiable, because, among other things, changes in the supply of outputs affect prices. As Samuelson (1952) demonstrated, the objective function of this type of model maximizes social welfare, measured by the sum of consumer and producer surpluses. This type of objective function is full of economic meaning, as it leads to a partial equilibrium. This partial-equilibrium approach was a starting point for Takayama and Judge's (1964) empirical research. Moreover, it can be extended to a case of general equilibrium (Norton and Scandizzo 1981). The partial-equilibrium method is based upon welfare economics and is beset with difficulties. Thus, the quantity and price vectors are endogenous to the model, which destroys the linearity of the objective function, creating a quadratic-programming problem. The improvement in nonlinear computer packages has reduced the impact of these difficulties. Hazell and Norton (1986) published a good survey of applications of this type of partial-equilibrium models that lead to quadratic-programming formulations. The second issue is the aggregation problem. In fact, as all farms considered in a region or sector model are not alike, it is inappropriate to treat the region or sector as a single farm. Hence, we must use the appropriate aggregation rules to minimize the aggregation bias. Day (1963) was the first to state conditions for exact aggregation that were rigorous but too strong. Kutcher and Norton (1982) and Önal and McCarl (1989) proposed weaker conditions for aggregation.

Modeling the Interaction Between Agriculture and the Environment

Until recently, agricultural managers focused on increasing yields through the intensive use of agrochemicals, fertilizers, and other inputs. This practice had many unwanted environmental side effects, some of which made the continuation of many agricultural practices doubtful. Fortunately, researchers are developing models to evaluate the economic impacts of environmental effects to achieve sustainable agriculture.

They usually use a crop-simulator model to predict the environmental effects of various management practices and then link to an optimization model to determine trade-offs between economic returns and environmental impacts. The final output is usually a sustainable compromise between economic achievements and environmental quality.

Various researchers have conducted studies in this direction. Johnson et al. (1991) linked CERES, a crop-simulator model, to a dynamic optimization model to determine the optimum applications of water and fertilizers needed to maximize gross margin. Zekri and Herruzo (1994) combined NTRM, a crop-simulator model, and a mathematical mixed multiobjective programming model to assess the effects of an increase in nitrogen prices and a reduction in drainage irrigated water, thus inducing the adoption of best management practices. Finally, Teague et al. (1995) used the EPIC-PST simulation model to predict the environmental risks of using pesticides and nitrates. They combined the results with a Target MOTAD optimization model that minimizes the sum of negative deviations from a prefixed income target (Tauer 1983). In this way, they evaluated the trade-offs between income and an index measuring the risks associated with using pesticides and nitrates.

Including environmental constraints in agricultural programming models dates back to the early 1970s, but environmental concerns are increasingly important. Thus, the multiobjective modeling of joint production processes that combine private goods sold on the market place and public goods without established markets, such as environmental protection, is an important line of research (Nalle et al. 2004).

Risk and Uncertainty Analysis

Managing agricultural activities is characterized by risk and uncertainty. Because farmers' incomes vary with weather conditions, market price changes, and crop and animal diseases, decision-support models in agriculture should include risk and uncertainty.

Game theory models of games against nature are conventional means of analyzing agricultural decisions under uncertainty. Their purpose is to find a pure or mixed strategy that optimizes the decision maker's aspirations according to a certain behavioral criterion (for example, maximizing the minimum outcome, minimizing the largest regret, or maximizing the minimum benefit). McInerney (1967) introduced the use of game theory in agriculture, whereas Hazell (1970) and Kawaguchi and Maruyama (1972) introduced the idea of parametric games, optimizing one criterion (for example, maximizing the minimum outcome) while considering another criterion as a parametric constraint (for example, minimizing the largest regret). These models establish a trade-off frontier between the criteria considered. The game-theory approach can be generalized with the help of goal programming, leading to compromise games (Romero and Rehman 2003, Chapter 7).

The oldest approach to risk programming in agriculture is a direct application of the Markowitz (1952) approach to portfolio theory, as was initially suggested by Freund (1956). In his approach, the model defines the risk of an agricultural enterprise through the variability of its returns, measured by variance. Then the model establishes an efficient frontier by minimizing the variance of the cropping pattern, treating the expected return as a parametric constraint. To avoid the use of parametric quadratic programming, Hazell (1971) suggested minimizing the mean absolute deviation instead of the variance.

The second phase of Markowitz's approach consists of maximizing the expected utility of the decision maker over the efficient frontier. However, this maximization can be rigorous only when returns follow a normal distribution of probability or when the decision maker's utility function is quadratic. However, the normal distribution of returns is a hypothesis, which has not been widely corroborated empirically, and quadratic utility functions have many logical flaws (for example, absolute risk aversion increases with wealth). Some analysts (for example, Tew et al. 1992) have proposed mitigating this problem by approximating the maximum expected utility over the efficient frontier.

Anderson et al. (1977, p. 204) criticized the application of game-theory rules on the grounds that the decision criteria used are incompatible with the axioms of rational choice. However, analysts are reviving the games-based approach and criticizing the axioms of rational choice underlying Markowitzean approaches (for example, Zeleny 1982, pp. 437–438). Despite the preponderance of these two approaches, analysts have proposed and applied other methods to deal with risk and uncertainty in agriculture. They include safety-first models, chance-constraint programming, and stochastic programming. With safety-first models, the decision makers lexicographically satisfy their preference for safety and then might take profit-driven approaches. In chance-constraint programming, the analyst deals with the uncertainty of the available resources by assuming that their distribution probability is known and by fixing a lower limit on the probability of the respective constraint being satisfied. Finally, with stochastic programming, some or all coefficients of the constraint set are random variables. Hardaker et al. (1997) reviews the technical aspects, potentials, and limitations of these approaches.

Dealing with Multiple Criteria in Agriculture

Nowadays analysts recognize that multiple criteria are the rule in agriculture management at the farm level and at the regional-sector level. In fact, several sociological studies demonstrate that farmers do not seek to optimize a single well-defined objective function but usually seek an optimal compromise between several conflicting objectives or try to establish satisfactory levels for their goals (Gasson 1973, Harper and Eastman 1980). Hence, analysts must formulate decision-support models for agriculture management that can recognize multiple objectives and goals in the farmers' objective functions. In a pioneering piece of work, Wheeler and Russell (1977) planned a 600-acre mixed farm in the United Kingdom using a goal-programming model, that included the goals of gross margin, seasonal cash exposure, and provision of stable employment.

Since the 1980s, researchers have published extensively, mostly in case studies, on several agriculture-management problems from a multicriteria perspective. Most used goal programming, although a number used multiobjective programming and compromise programming. Romero and Rehman (2003) provided a comprehensive reference on multicriteria analysis in agriculture, and Hayashi (2000) surveyed applications, extensively.

Formulating Livestock Rations and Feeding Stuffs

In the first successful application of mathematical programming in agriculture, Waugh (1951) used LP models to determine the least-cost combination for the feeding-stuffs industry and livestock rations at the farm level that would meet specified nutritional requirements. Since the early 1950s, many farmers and most feed mixers have relied on LP for the optimum design of livestock diets.

Analysts have extended the original analytical LP framework in several directions. They use parametric LP to study the effect of price changes in ingredients (coefficients of the objective function) on the optimum mix. By analyzing the dual models, they establish the shadow price of each constraint (nutritional requirement) of the model. Incorporating chance-constraint programming increases the realism of the model when the real content of some ingredients is uncertain. Analysts have extended the approach in this field in various ways, including investigating the relationship between the bulk and cost of the ration and using the technique within a practical environment.

Despite its proven success, using LP models to determine optimum animal diets is not without difficulties. Decision makers cannot rely on the cost of the blend as the only relevant criterion, especially in calculating livestock rations at the farm level. Farmers seek economically optimal rations that achieve a compromise among such conflicting objectives as cost, bulkiness of the mix, and nutritional imbalances. These objectives introduce multiple criteria in the traditional LP approach. Analysts have formulated multicriteria models for the optimum design of animal diets within a multiple criteria context (for example, Rehman and Romero 1984, Neal et al. 1986, Czyzak and Slowinski 1991, Zhang and Roush 1999).

Another problem underlying the traditional LP approach is the overrigid specification of nutritional requirements. Some relaxation of the constraints would not seriously affect the animals' performance. Such relaxation would increase the size of the feasible set, allowing a reduction in the cost of the ration. Some analysts have tackled this problem. Thus, Rehman and Romero (1987) have addressed the overrigid specifications of nutritional requirements by incorporating a system of penalty functions into a goal-programming model. Czyzak (1989) used fuzzy mathematical programming. Although use of such methods in the feeding-stuffs industry is still rare, they merit research.

A problem methodologically related to formulating livestock rations is determining fertilizer combinations (Minguez et al. 1988). Finally, analysts use dynamic programming and Markov models to address other problems in livestock production, such as optimum replacement or culling policies (Houben et al. 1994, Kristensen 1994) and assessing the adoption of new reproductive technologies (Yates and Rehman 1996).

Even though LP and parametric LP models are still the most widely used models in the feeding-stuffs industry, advanced approaches, such as chance-constraint programming, have led to important savings in this industry (Roush et al. 1994).

Forestry

Analysts started using OR models in forest planning in the 1960s, for example, in the well-known Timber RAM (Navon 1971) LP model the US Forest Service used for long-range harvest planning. In the 1970s, 1980s, and 1990s, they incorporated multiple use and other forestry concerns in the models. In developed countries, such concerns as ecological issues, biodiversity, wildlife, and preservation took precedence over timber production, particularly in native forests, where preservation of original species of trees is a goal. For their plantations of, say, pine or eucalyptus, producers in North America, New Zealand, South Africa, and Chile emphasize efficient production but increasingly take into account such environmental concerns as protecting soil, water quality, and scenic beauty. Analysts have developed interesting, mostly combinatorial algorithms to provide the spatial properties needed to characterize environmental constraints. They have incorporated uncertainty and multiple objectives in this context but have focused largely on methodological propositions and case studies. They have also developed models to support decisions for private plantations.

Decision-Making Levels

Decisions in forestry are often divided into strategic or long range, tactical or medium range, and operational or short range.

Strategic decisions deal with long-range plans to obtain sustainable yields at the aggregate level, both in terms of land specification and timber products. Thus, analysts aggregate forest areas that are similar in site quality, tree species, and age, and they usually consider the total volume of timber. LP models have been the basic planning tools for native forests, which have multiple species coexisting in any area, standard tree rotations of 60 to 80 years, and planning horizons of several rotations. For example, the US Forest Service explicitly introduced multiple uses and concerns, such as recreation, concern for indigenous populations and historical sites, and such environmental considerations as sustainability, wildlife, scenic beauty, and soil and water quality, through its LP models FORPLAN (Johnson et al. 1986) and SPECTRUM (Martell et al. 1998).

Plantation owners have relied on LP models for about two decades in many countries, including, Brazil, Canada, Chile, Sweden, and the United States. The models vary, considering basic forest management in New Zealand (Garcia 1990), environmental concerns in the United States (Fletcher et al. 1999), and vertical integration with pulp plants and sawmills, with 0–1 variables to account for plant investments (Cea and Jofré 2000).

Tactical medium-range models concern horizons that run only to the next harvest (Church et al. 2000). They are more detailed than strategic models in terms of spatial resolution, specifying actions for each area, roads for access, and other spatial details due to environmental issues. Their recommendations on harvesting and other actions are usually aggregated. Models give timber production as total volume or as a few classes based on eventual use, such as sawmill lumber or pulp for paper. Kirby et al. (1986) developed mixed-integer LP models, integrating harvesting decisions with road building.

These are mixed-integer problems of network design, often difficult to solve. Analysts have used commercial packages (accepting suboptimal solutions for the more difficult problems) and heuristics mixed with LP solutions (Weintraub et al. 1994). By adding logical inequalities, lifting, and Lagrangean relaxation, they have improved problem-solving processes (Andalaft et al. 2003). Richards and Gunn (2000) and Clark et al. (2000) proposed heuristic algorithms based on local search approaches.

The use of OR tools has increased for operational decisions on harvesting and transportation:

(1) Short-term harvesting requires decisions about which areas to harvest each week and how to cut up stems into logs of defined quality, length, and diameter to meet demand at various destinations. Analysts use LP models to match the supply of standing timber with demand for specific products in such countries as Brazil, Chile, New Zealand, Sweden, and the United States (Martell et al. 1998, Epstein et al. 1999, Carlsson and Rönnqvist 2001). In some cases, the problem of how best to cut up stems is solved at the plant, which has more equipment and information available to make better use of each tree than lumberjacks in the woods. Plant managers base such decisions on the characteristics of each stem (length, shape, diameter, and quality) and the products demanded and their market prices, and use dynamic programming (Briggs 1989), Tabu search (Laroze and Greber 1997), and other heuristics (Sessions et al. 1989). To integrate decisions about areas to harvest and products to produce, analysts have used LP with column generation, reducing wasted timber (Epstein et al. 1999).

(2) Locating harvesting machinery to carry felled trees to roads is another problem. Workers use skidders or tractors on flat terrain and towers or cable logging machinery to bring stems in steep areas up to a loading area. The company must build access roads to the loading areas and roads on flat terrains so the slow-moving tractors do not have to travel long distances. The traditional manual approach to solving this problem using topographic graphs has often been replaced by computational tools, which interact with geographic information systems (GISs) that collect and manage detailed terrain and forest inventory data. The USDA Forest Service's PLANS (Twito et al. 1987) and New Zealand's PLANZ (Cossens 1992) are simulation tools that define the access roads and timber operations needed for the machine locations the user specifies using a visual interactive approach based on the GIS. Another system, PLANEX (Epstein et al. 2005), used by Chilean forest firms uses a heuristic algorithm that interacts with the GIS to determine the best locations for the machines, saving costs and the environment by reducing the number of roads needed.

(3) Transportation is usually an important cost in global logistics. Typically logs are carried by truck from forest locations to such destinations as pulp plants, sawmills, and ports for overseas transport. Trucks scheduled manually typically queue at loading and unloading points and overall have higher costs than those scheduled by computerized systems. ASICAM (Weintraub et al. 1996), used by forestry firms in Argentina, Brazil Chile, South Africa, Uruguay, and Venezuela, supports daily scheduling decisions for all trips. The system is based on a deterministic simulation model with heuristic decision rules to assign trips. The system reduced the number of trucks needed and overall costs by 10 to 25 percent.

Carlsson and Rönnqvist (2001) developed a system based on heuristic LP column generation to support truck routing in Sweden, where many trucks visit several loading areas before delivering the accumulated logs at a destination. As communication technology prices fall and the devices become more accessible, transportation scheduling will increasingly involve real-time decisions. One such system, based on a heuristic column-generation LP model (Rönnqvist and Ryan 1995), was used in New Zealand for a time.

A remaining problem is the interaction of decisions at different hierarchical levels for horizons ranging from a day to many decades and areas ranging from a few hectares to hundreds of thousands of hectares. Analysts have developed and implemented models to deal with different levels separately and linked them mostly in ad hoc ways. The remaining problems include ensuring consistency between levels of decisions, which means aggregating and disaggregating information and decision variables between decision levels, which is difficult with 0–1 variables, as is the case, for example, when building roads or investing in plants (Weintraub and Bare 1996). Another problem is considering multiple forest owners within global governmental policies (Martell et al. 1998).

Implementation Issues

Why have OR applications in forestry succeeded over the last decades? Based on our experience in industry and government, papers reporting applications, and discussions with many colleagues, we believe the following factors drive OR applications:

Suitability. Despite uncertainties in future forestry characteristics, statistical models have proved surprisingly precise in predicting aggregate timber yields and other parameters.

Need for efficiency. Partly because of globalization, competition is strong and promotes efficiency.

Sophistication of users. In most successful implementations, some managers have knowledge of OR and are innovative.

Scale. Firms using OR are large enough to benefit from using OR. Small firms probably lack sophisticated users and also face simpler problems. Manual solutions of small firms' problems may be quite adequate. In many countries, large firms own most of the timberland and can benefit from using OR models. In Sweden, small land owners dominate, and large plant owners drive the use of models for coordinating timber supply to plants.

Participation of OR experts. OR professionals and academics have collaborated with forestry specialists in many successful applications, and forestry schools are teaching OR, creating synergy between the two areas.

Implementation strategy. Many successes may be based on involving the users and getting their commitment and that of upper management. Users' participation in developing models insures that they will correspond to the real problems and creates long- term relationships.

Improvement of PCs and software. Constantly improving software and PCs permit solution of larger and larger problems.

Given all these factors driving successful applications, analysts should still be realistic about what data is available and reliable, what can be modeled and what is best left to the decision maker, and what makes models easy to use and valuable in decision making.

The Environmental Question

Because of environmental issues, forest managers must consider increasingly stringent conditions:

(1) The amount of habitat protected requires decisions on which areas to leave unharvested in a compromise between economic and wildlife-protection goals. This problem can be defined as the minimal reserve set, that is, what is the minimal number of areas to reserve to ensure that each protected species is represented in at least one reserved area (Clements et al. 1999). Church et al. (1996) developed a maximal-covering-location problem to identify sets of sites to best represent specific species. Cocks and Baird (1989) and Rosing and ReVelle (1986) showed how to use OR models to solve the reserve-selection problem. Because different species require different habitat types defined by levels of growth of trees (or seral stages), this specification is a simplification of the real problem.

(2) Habitat patches or areas with no grown trees can have both minimum or maximum area constraints. Planning for them matches the so-called adjacency problem, where no two adjacent cutting units in a forest can be harvested in the same period. Cutting units typically measure about 40 hectares. This leads to a chessboard pattern, where only the white cells can be harvested in a single period. Analysts can model this hard combinatorial problem as a 0–1 integer problem but can solve only moderate size problems using conventional branch-and-bound algorithms. North American and European forest management typically includes these constraints. In actual applications, analysts are using heuristic approaches, such as tabu search, simulated annealing, and Monte Carlo simulation (Martell et al. 1998). They have proposed exact approaches for solving the adjacency problem, including strengthening the LP formulation using LP column generation coupled with heuristics (Barahona et al. 1992), clique representations of adjacency (Murray and Church 1996), and dynamic programming (Hogason and Borges 1998).

In the last few years, analysts have been seeking ways to better define the cutting units. Foresters form cutting units of 40 hectares from basic cells of five to 20 hectares through GIS-assisted analysis. Murray (1999) showed that they could improve solutions by taking one step back and introduce the building of cutting units into the decision models. Barret et al. (1998) have solved large instances of the resulting complex combinatorial problems using local search heuristics only. Goycoolea et al. (2005) have solved medium-sized problems of up to 1,300 cells with models of 10,000 to 15,000 0–1 variables by strengthening the LP formulations. Foresters must provide large blocks of old trees for some animal species or establish corridors between patches, problems which have typically been approached via metaheuristics (Caro et al. 2003a).

(3) The movement of wildlife species and their dispersion over time (a way of controlling population) require corridors of mature trees between feeding areas (Hof and Bevers 2002). Typical problem-solving procedures include linear and nonlinear programming, integer programming, heuristics, and Monte Carlo simulation.

(4) Forest edges juxtapose trees of different ages, which many species require for cover, feeding, and foraging. Such species cannot travel far through unbroken forest without eating. Water quality is also important; harvesting operations cause warming and increase sediment.

The algorithms and systems developed for these problems rely on GIS linkages to databases and heuristic approaches. Analysts are investigating more complex approaches, such as the use of 0–1 LP models for wildlife habitats or edge effects.

In managing plantations, foresters have used models to evaluate the costs of implementing environmentally sensitive harvesting policies, such as not using heavy machinery on fragile soils or leaving riparian strips to avoid polluting rivers (Weintraub et al. 2000, Caro et al. 2003b). Nalle et al. (2004) combined a wildlife-simulation model and an optimization model and used a heuristic algorithm to obtain efficient solutions and analyzed the trade-offs between timber production and preservation of two animal species. This approach proved superior to analyzing each aspect separately.

The increasing severity of international-environmental-certification processes compel foresters to cope with environmental issues and will provide analysts with modeling challenges. Analysts have developed decision-support models to help foresters understand and control forest fires. They have used simulation to estimate fire propagations and LP and 0–1 LP models to support decisions on fire prevention and short-term suppression operations (Martell et al. 1998).

Uncertainty and Multiple Objectives

Uncertainty and multiple objectives are important in forest planning, just as they are in agricultural planning. Few of the important theoretical developments in the two areas have been applied, largely because of difficulties in implementation and lack of reliable data. Most of the uncertainty is in future prices and future timber production, which are affected by fires and pests, also uncertain elements. The techniques for coping with uncertainty range from traditional conservative estimates to stochastic dynamic programming, chance-constrained models, stochastic-programming models, scenario analysis, Markov decision models, and optimal control theory (Weintraub and Bare 1996, Martell et al. 1998). Environmental factors add further dimensions of uncertainty and should lead to novel modeling issues. Insley (2002) is applying the concept of real options to forestry.

Objectives increased as people derived multiple uses for forests. Typical techniques for handling multiple objectives in forestry are goal programming, multiple-objective LP, and compromise programming (Diaz-Balteiro and Romero 1998), and interest in such techniques is increasing in importance. Diaz-Balteiro and Romero (2006) describe the techniques developed for different purposes. For harvest-scheduling problems, the techniques include goal programming, multiobjective programming, and compromise programming. For conserving forest biodiversity, the techniques include the analytical hierarchy process (AHP), goal programming, and multiobjective programming. For forest sustainability, the techniques include such multicriteria methods as ELECTRE, binary goal programming, and the AHP.

Most of these models are continuous, but in some cases, analysts introduce integer variables to handle spatial specifications. While the techniques published are increasing, few have been applied.

Comparative Analysis

The OR models for agricultural resources and those for forestry resources have similarities and differences.

The Problems

In both areas, the two types of decision makers are regulatory agencies and managers. Government or other agencies set constraints for the exploitation of resources. In agriculture, analysts need to predict the impact of agricultural policies, such as price supports. In forestry, agencies set regulations for managing forests, including government-owned forests.

In agriculture, researchers have done some work to support managers and work to plan livestock rations at the farm level and blends for the feeding-stuffs industry, which are extensions of the classical diet problem. In forestry, analysts have developed OR models to support various long- and short-term management decisions.

Data

To develop and use models, analysts need good quality data to input as coefficients. In agriculture, most decisions are short term, for which managers need data on yields, costs, and prices.

Generally, analysts can obtain reasonable estimates of costs based on prior experience. The main sources of uncertainty are weather and pests, which affect yields, market prices, and other disturbances, such as flooding. Shortages of reasonable data are not a deterrent to the use of OR models.

For forestry, acquiring data is not straightforward, and a great deal of effort has gone into collecting data. Simulation models based on sample plots provide good estimates of product yields for standing timber, while statistical regression analysis is used to predict tree growth under different management options. Analysts have collected data concerning the environmental impacts of forest managers' decisions. Thus, with good data based mainly on timber yields, OR models are used at different decision-making levels and horizons.

The main sources of uncertainty are future prices, tree growth, and disasters, such as fires and pests, which are discussed in case studies.

Environmental Issues

Environmental issues are increasingly important because of the increase in practices that damage the environment and the increase in public demands to protect the environment.

In agriculture, people are concerned about the use of fertilizers, pesticides, and water. Researchers are beginning to model their interactions and effects because excessive use of them can jeopardize future agricultural sustainability.

In forestry, environmental issues play a major role. In native forests in developed countries, sustainability, wildlife, biodiversity, and preservation of nature often play more important roles than timber production. In plantations, managers are increasingly concerned with protecting soil and water quality (Weintraub et al. 2000). Analysts have formulated new models in response and incorporated existing models.

The Impact of OR Models

Generally, how important OR models are in decision making depends on several factors:

—The quality of data,
—The competitiveness of markets,
—Ownership, and
—The culture of the application area and peoples' understanding of OR's advantages.

In agriculture, use of OR models is increasing with advances in hardware and software. The most commonly used OR techniques are LP models, simulation, risk programming, and multiple-criteria programming. People use models at two levels and for two purposes. They use them to improve decisions at the farm level, and they use them to help policy makers predict the impact of policy changes on farmers' behavior.

In forestry, the use of OR models is widespread for problems ranging from long-term forest planning to short-term harvesting and transportation decisions. The models also cover environmental constraints and fire dangers. Forestry managers see the applicability and advantages of OR models and exchange information about the models they use, which encourages their use. They rely on such OR techniques as LP and mixed-integer LP models, simulation, and various heuristic approaches, in particular, metaheuristics.

The two areas can learn from each other. Agriculture uses models to analyze the equilibrium of systems and the impact of governmental or sectorial measures, and potential changes in agricultural policy. Forestry could use models for similar purposes.

In forestry, few centralized decisions are based on models. For example, the timber assessment market model (Adams and Haynes 1980) uses a partial-equilibrium model for calculating prices and US timber supplies and demands under the Resource Planning Act of 1974.

In the 1980s, the Chilean government subsidized forest firms that planted industrially to compensate for the risks involved in long-term investments.

Today, environmental issues affect the exports of firms, which must be certified to secure markets. These firms can use OR models for global analysis and decision support.

Private forest firms and public organizations use OR tools to support strategic, tactical, and especially operational decisions.

Conclusions

Managers of agricultural and forestry resources have applied OR models massively and successfully and should continue to do so as global, competitive markets increase productivity.

Environmental issues seem to be increasing in importance. So far, biologists' and silviculturalists' views of environmental problems have not been compared to those of forest engineers and agronomists. Ecological modelers often use stochastic simulation to assess how spatial ecosystems will evolve over time given particular exogenous factors (Mladenoff and Baker 1998). Strengthening the link between biological simulation models and multicriteria optimization approaches should facilitate calculating the trade-offs among different indicators of sustainability. OR tools, particularly mathematical-programming techniques, seem suitable for incorporating environmental externalities in decision making. Finally, incorporating risk and uncertainty in OR models in agriculture and forestry is crucial. Most approaches for dealing with risk and uncertainty are straightforward adaptations from financial portfolio theory. We need to develop concepts and methods for dealing with risk and uncertainty specifically conceived for the particulars of the agricultural and forestry sectors. In forestry operations, we can expect to manage the whole supply chain, from standing timber to plants and sawmills to final delivery of wood-based products, in real time.

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References

Adams, D., R. Haynes. 1980. The 1980 softwood timber assessment market model: Structure, projections, and policy simulations. *Forest Sci.* **26**(3) 1–64.

Andalaft, N., P. Andalaft, M. Guignard, A. Magendzo, A. Wainer, A. Weintraub. 2003. A problem of forest harvesting and road building. *Oper. Res.* **51**(4) 613–628.

Anderson, J. R., J. L. Dillon, J. B. Hardaker. 1977. *Agricultural Decision Analysis.* Iowa State University Press, Ames, IA.

Barahona, F., A. Weintraub, R. Epstein. 1992. Habitat dispersion in forest planning and the stable set problem. *Oper. Res.* **40**(S1) S14–S21.

Barret, T., T. Gilles, L. Davis. 1998. Economic and fragmentation effects of clear cut restrictions. *Forest Sci.* **44**(4) 569–577.

Beneke, R. R., R. Winterboer. 1973. *Linear Programming Applications to Agriculture.* Iowa State University Press, Ames, IA.

Briggs, D. G. 1989. Tree value system: Description and assumptions. General technical report PNW-239, USDA Forest Service, Portland, OR.

Carlsson, D., M. Rönnqvist. 2001. Wood flow problems in Swedish forestry. M. Palmgren, M. Rönnqvist, eds. *Proc. Logistic and Optimization in Forestry.* Åre, March 11–14, LiTH-MAT-R-2001-16, Linköping University, Linköping, Sweden.

Caro, F., M. Constantino, I. Martins, A. Weintraub. 2003a. A 2-opt tabu search procedure for the multi-period forest harvesting problem with adjacency, green-up, old growth, and even flow constraints. *Forest Sci.* **49**(5) 738–751.

Caro, F., R. Andalaft, X. Silva, A. Weintraub, P. Sapunar, M. Cabello. 2003b. Evaluating the economic cost of environmental measures in plantation harvesting through the use of mathematical models. *Production Oper. Management* **12**(3) 290–306.

Cea, C., A. Jofré. 2000. Linking strategic and tactical forestry planning decisions. *Ann. Oper. Res.* **95**(28) 131–158.

Church, R. L., A. T. Murray, K. H. Barber. 2000. Forest planning at the tactical level. *Ann. Oper. Res.* **95**(16) 3–18.

Church, R. L., D. M. Stoms, F. W. Davis. 1996. Reserve selection as a maximal covering location problem. *Biol. Conservation* **76**(2) 105–112.

Clark, M., R. Meller, T. McDonald. 2000. A three stage heuristic for harvest scheduling with access road network development. *Forest Sci.* **46**(2) 204–218.

Clements, M., C. Revelle, J. Williams. 1999. Reserve design for species preservation. *Eur. J. Oper. Res.* **112**(2) 273–283.

Cocks, K. D., I. A. Baird. 1989. Using mathematical programming to address the multiple reserve selection problem: An example from the Eyre Peninsula, South Australia. *Biol. Conservation* **49**(2) 113–130.

Cossens, P. 1992. Planning and control of short-term log allocation in New Zealand. *Integrated Decision-Making in Planning and Control of Forest Operations. Proc. IUFRO Conf., January 27–31.* New Zealand School of Forestry, University of Canterbury, Christchurch, New Zealand, 46–56.

Czyzak, P. 1989. Multicriteria agricultural problem solving under uncertainty. *Foundations Control Engrg.* **14**(2) 61–80.

Czyzak, P., R. Slowinski. 1991. Solving the multiobjective diet optimization problem under uncertainty. P. Korhonen, A. Lewandowski, J. Wallenius, eds. *Multiple Criteria Decision Support.* Springer-Verlag, Berlin, Germany, 273–282.

Day, R. 1963. On aggregating linear programming models of production. *J. Farm Econom.* **45**(4) 797–813.

Diaz-Balterio, L., C. Romero. 1998. Modelling timber harvest scheduling problems with multiple criteria: An application in Spain. *Forest Sci.* **44**(1) 47–56.

Diaz-Balterio, L., C. Romero. 2006. Multiple criteria decision making in forest planning: Recent results and current challenges. A. Weintraub, T. Bjorndal, R. Epstein, C. Romero, eds. *Management of Natural Resources: A Handbook of Operations Research Models, Algorithms and Implementations.* Kluwer Academic Publishers. Forthcoming.

Epstein, R., R. Morales, J. Serón, A. Weintraub. 1999. Use of OR in Chilean forest industries. *Interfaces* **29**(1) 7–29.

Epstein, R., E. Nieto, A. Weintraub, P. Chevalier, J. Gabarró. 2005. A system for short term harvesting. *Eur. J. Oper. Res.* **119**(2) 427–439.

Fletcher, R., H. Alden, D. Holmen, M. Etzenhouser. 1999. Long term forest ecosystem planning at Pacific Lumber. *Interfaces* **29**(1) 90–111.

Freund, R. J. 1956. The introduction of risk into a programming model. *Econometrica* **24**(2) 253–264.

Garcia, O. 1990. Linear programming and related approaches in forest planning. *New Zealand J. Forest Sci.* **20**(31) 307–331.

Gasson, R. 1973. Goals and values of farmers. *J. Agricultural Econom.* **24**(3) 521–537.

Goycoolea, M., A. Murray, F. Barahona, R. Epstein, A. Weintraub. 2005. Harvest scheduling subject to maximum area restrictions, exploring exact approaches. *Oper. Res.* **53**(3) 490–500.

Hardaker, J. B., R. B. M. Huirne, J. R. Anderson. 1997. *Coping with Risk in Agriculture.* CAB International, Wallingford, UK.

Harper, W. H., C. E. Eastman. 1980. An evaluation of goal hierarchies for small farm operators. *Amer. J. Agricultural Econom.* **62**(4) 742–747.

Hayashi, K. 2000. Multicriteria analysis for agricultural resource management: A critical survey and future perspectives. *Eur. J. Oper. Res.* **122**(2) 486–500.

Hazell, P. B. R. 1970. Game theory—An extension of its application to farm planning under uncertainty. *J. Agricultural Econom.* **21**(2) 239–252.

Hazell, P. B. R. 1971. A linear alternative to quadratic and semivariance programming for farm planning under uncertainty. *Amer. J. Agricultural Econom.* **53**(1) 53–62.

Hazell, P. B. R., R. D. Norton. 1986. *Mathematical Programming for Economic Analysis in Agriculture.* Macmillan Publishing Company, New York.

Heady, E. O. 1954. Simplified presentation and logical aspects of linear programming technique. *J. Farm Econom.* **24**(5) 1035–1048.

Hof, J. G., M. Bevers. 2002. *Spatial Optimization in Ecological Applications.* Columbia University Press, New York.

Hogason, H. M., J. G. Borges. 1998. Using dynamic programming and overlapping subproblems to address adjacency in large harvest scheduling problems. *Forest Sci.* **44**(4) 526–538.

Houben, E. H. P., R. B. M. Huirne, A. A. Dijkhuizen, A. Kristense. 1994. Optimal replacement of mastitis cows determined by a hierarchic Markov process. *J. Dairy Sci.* **77**(10) 2975–2993.

Insley, M. 2002. A real options approach to the valuation of a forestry investment. *J. Environ. Econom. Management* **44**(3) 471–492.

Johnson, K., T. Stuart, S. Crimm. 1986. FORPLAN, Version 2: An overview. USDA Forest Service, Land Management Planning Systems Section, Washington, D.C.

Johnson, S. L., R. M. Adams, G. M. Perry. 1991. Assessing the on-farm costs of reducing groundwater pollution: A modelling approach and case study. *Amer. J. Agricultural Econom.* **73**(5) 1063–1073.

Kawaguchi, T., Y. Maruyama. 1972. Generalized constrained games in farm planning. *Amer. J. Agricultural Econom.* **54**(4) 591–602.

Kirby, M. W., W. Hager, P. Wong. 1986. Simultaneous planning of wildland transportation alternatives. *TIMS Studies in the Management Sciences,* Vol. 21. Elsevier Science Publishers, New York, 371–387.

Kristensen, A. R. 1994. A survey of Markov decision programming techniques applied to the animal replacement problem. *Eur. Rev. Agricultural Econom.* **21**(1) 73–93.

Kutcher, G. P., R. D. Norton. 1982. Operations research methods in agricultural policy analysis. *Eur. J. Oper. Res.* **10**(4) 333–345.

Laroze, A., B. J. Greber. 1997. Using tabu search to generate stand-level, rule-based bucking patterns. *Forest Sci.* **43**(2) 157–169.

Lauwers, L., G. van Huylenbroeck, L. Martens. 1988. A systems approach to analyse the effects of Flemish manure policy on structural changes and cost abatement in pig farming. *Agricultural Systems* **56**(2) 167–183.

Markowitz, H. 1952. Portfolio selection. *J. Finance* **7**(1) 77–91.

Martell, D., E. Gunn, A. Weintraub. 1998. Forest management challenges for operational researchers. *Eur. J. Oper. Res.* **104**(1) 1–17.

McInerney, J. P. 1967. Maximum programming: An approach to farm planning under uncertainty. *J. Agricultural Econom.* **18**(2) 279–290.

Mínguez, M. I., C. Romero, J. Domingo. 1988. Determining optimum fertilizer combinations through goal programming with penalty functions: An application to sugar beets in Spain. *J. Oper. Res. Soc.* **39**(1) 61–70.

Mladenoff, D. J., W. L. Baker, eds. 1998. *Spatial Modeling of Forest Landscape Change: Approaches and Applications.* Cambridge University Press, Cambridge, UK.

Murray, A. 1999. Spatial restrictions in harvest scheduling. *Forest Sci.* **45**(1) 45–52.

Murray, A. T., R. L. Church. 1996. Analyzing cliques for imposing adjacency restrictions in forest models. *Forest Sci.* **42**(2) 166–175.

Nalle, D. J., C. A. Montgomery, J. L. Arthur, S. Polasky, N. H. Schumaker. 2004. Modeling joint production of wildlife and timber. *J. Environ. Econom. Management* **48**(3) 997–1017.

Navon, D. I. 1971. Timber RAM: A long-range planning method for commercial timber lands under multiple-use management. Research paper PSW70, USDA Forest Service, Berkeley, CA.

Neal, H. D., J. France, T. T. Treacher. 1986. Using goal programming in formulating rations for pregnant ewes. *Animal Production* **42**(1) 97–104.

Norton, R. D., P. L. Scandizzo. 1981. Market equilibrium computations in activity analysis models. *Oper. Res.* **29**(2) 243–262.

Önal, H., B. McCarl. 1989. Aggregation of heterogeneous firms in mathematical programming models. *Eur. Rev. Agricultural Economics.* **16**(4) 499–513.

Rae, A. N. 1994. *Agricultural Management Economics.* CAB International, Wallingford, UK.

Rehman, T., C. Romero. 1984. Multiple-criteria decision-making techniques and their role in livestock ration formulation. *Agricultural Systems* **15**(1) 23–49.

Rehman, T., C. Romero. 1987. Goal programming with penalty functions and livestock ration formulation. *Agricultural Systems* **23**(2) 117–132.

Richards, W., E. Gunn. 2000. A model and tabu search method to optimize stand harvest and road construction schedules. *Forest Sci.* **46**(2) 198–203.

Romero, C., T. Rehman. 2003. *Multiple Criteria Analysis for Agricultural Decisions*. Elsevier, Amsterdam, The Netherlands (original publication 1989).

Rönnqvist, M., D. Ryan. 1995. Solving truck dispatch problems in real time. *Proc. 31st Annual Conf. Oper. Res. Soc. New Zealand, August 31–September 1*. Wellington, New Zealand, 165–172.

Rosing, K. E., C. S. ReVelle. 1986. Optimal clustering. *Environ. Planning A* **18** 1463–1476.

Roush, W. B., R. H. Stock, T. L. Cravener, Th. H. D'Alfonso. 1994. Using chance-constrained programming for animal feed formulation at Agway. *Interfaces* **24**(2) 53–58.

Samuelson, P. A. 1952. Spatial price equilibrium and linear programming. *Amer. Econom. Rev.* **42**(2) 283–303.

Sessions, J., E. Olsen, J. Garland. 1989. Tree bucking for optimal stand value with log allocation constraints. *Forest Sci.* **35**(1) 271–276.

Takayama, T., G. G. Judge. 1964. Spatial equilibrium and quadratic programming. *J. Farm Econom.* **46**(1) 67–93.

Tauer, L. W. 1983. Target MOTAD. *Amer. J. Agricultural Econom.* **65**(3) 606–610.

Teague, M. L., D. J. Bernardo, H. P. Mapp. 1995. Farm-level economic analysis incorporating stochastic environmental risk assessment. *Amer. J. Agricultural Econom.* **77**(1) 8–19.

Tew, B. V., D. W. Reid, G. T. Rafsnider. 1992. Rational mean-variance decisions for subsistence farmers. *Management Sci.* **38**(6) 840–845.

Twito, R. H., S. E. Reutebuch, R. J. McGaughey, C. N. Mann. 1987. Preliminary Logging Analysis System (PLANS), Overview. General technical report PNW-199, USDA Forest Service, Portland, OR.

van Huylenbroeck, G., E. M. Ureña Campos, I. Vanslembrouck. 2001. A (recursive) multiple objective approach to analyse changes in the utility function of farmers due to policy reforms. *Appl. Math. Comput.* **122**(3) 283–299.

Waugh, F. V. 1951. The minimum-cost dairy feed. *J. Farm Econom.* **33**(3) 299–310.

Weintraub, A., B. Bare. 1996. New issues in forest land management from an operations research perspective. *Interfaces* **26**(5) 9–25.

Weintraub, A., R. Epstein, G. Murphy, B. Manley. 2000. The impact of environmental constraints on short term harvesting: Use of planning tools and mathematical models. *Ann. Oper. Res.* **95**(26) 41–66.

Weintraub, A., R. Epstein, R. Morales, J. Serón, P. Traverso. 1996. A truck scheduling system improves efficiency in the forest industries. *Interfaces* **26**(4) 1–12.

Weintraub, A., G. Jones, A. Magendzo, M. Meacham, M. Kirby. 1994. Heuristic system to solve mixed integer forest planning models. *Oper. Res.* **42**(6) 1010–1024.

Wheeler, B. M., J. R. M. Russell. 1977. Goal programming and agricultural planning. *Oper. Res. Quart.* **28**(1) 21–32.

Yates, C. M., T. Rehman. 1996. Integration of Markov and linear programming models to assess the farmgate and national consequences of adopting new bovine reproductive technologies in the United Kingdom agriculture. *J. Oper. Res. Soc.* **47**(11) 1327–1342.

Zekri, S., A. C. Herruzo. 1994. Complementary instruments to EEC nitrogen policy in non-sensitive areas: A case study in southern Spain. *Agricultural Systems* **46**(3) 245–255.

Zeleny, M. 1982. *Multiple Criteria Decision Making*. McGraw Hill, New York.

Zhang, F., W. B. Roush. 1999. Multiple objective programming models for feed formulation. *Poultry Sci.* **78**(Supplement 1) 76–84.

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