Development of Spatially Feasible Forest Plans: a Comparison of Two Modeling Approaches

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Spatial goals are becoming more frequent aspects of forest management plans as regulatory and organizational policies change in response to fisheries and wildlife concerns. The combination of green-up constraints (harvesting restrictions that prevent the cutting of adjacent units for a specified period of time) and habitat requirements for red-cockaded woodpeckers (RCW) in the southeastern U.S. suggests that spatially feasible forest plans be developed to guide management activities. We examined two modeling approaches aimed at developing management plans that had both harvest volume goals, RCW habitat, and green-up constraints. The first was a two-stage method that in one stage used linear programming to assign volume goals, and in a second stage used a tabu search – genetic algorithm heuristic technique to minimize the deviations from the volume goals while maximizing the present net revenue and addressing the RCW and green-up constraints. The second approach was a one-stage procedure where the entire management plan was developed with the tabu search – genetic algorithm heuristic technique, thus it did not use the guidance for timber volume levels provided by the LP solution. The goal was to test two modeling approaches to solving a realistic spatial harvest scheduling problem. One is where to volume goals are calculated prior to developing the spatially feasible forest plan, while the other approach simultaneously addresses the volume goals while developing the spatially feasible forest plan. The resulting forest plan from the two-stage approach was superior to that produced from the one-stage approach in terms of net present value. The main point from this analysis is that heuristic techniques may benefit from guidance provided by relaxed LP solutions in their effort to develop efficient forest management plans, particularly when both commodity production and complex spatial wildlife habitat goals are considered. Differences in the production of forest products were apparent between the two modeling approaches, which could have a significant effect on the selection of wood processing equipment and facilities.

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1 Introduction

Forest planning efforts in the United States and abroad are increasingly addressing spatial goals, either regulatory or voluntary, that relate to wildlife and fisheries concerns, due to an increased awareness of the importance of landscape pattern on wildlife populations. The adoption of the American Forest & Paper Association's (AF&PA) Sustainable Forestry Initiative (SFI) (American Forest & Paper Association 2001) by more than 90% of the forest companies in the U.S. means that these companies must develop plans that restrict the average clearcut size to less than 48 ha. Furthermore, many firms voluntarily limit the maximum clearcut size; these usually range from between 60 to 90 ha. Additionally, the listing of the red-cockaded woodpecker (*Picoides borealis*) (RCW) as an endangered species mandates that private landowners follow the guidelines developed by USDI Fish and Wildlife Service (FWS). These guidelines have spatial aspects, and to follow them requires knowledge of the types of resources in specific forest locations. These circumstances encourage the use of discrete 0,1 (integer) decision variables in forest planning efforts. As the number of integer variables increases, however, it becomes more difficult, if not impossible, to develop forest plans with traditional mathematical programming approaches (e.g., linear or integer programming).

Green-up or adjacency constraints have been among the most commonly studied constraints in spatial harvest scheduling. A variety of techniques have been used to solve these problems, beginning with traditional mathematical programming (Weintraub and Navon 1976). Recently some researchers have exploited the problem structure of green-up constraints and have developed specialized optimization algorithms (Murray and Church 1996, Snyder and ReVelle 1997). Further, Hoganson and Borges (1998) used dynamic programming to develop forest plans with adjacency constraints. Several stochastic approaches have also been used, including Monte Carlo integer programming (O'Hara et al. 1989, Nelson and Brodie 1990, Clements et al. 1990), simulated annealing (Lockwood and Moore 1992, Dahlin and Sallnas 1993, Van Deusen 1999), and genetic algorithms (Mullen and Butler 1999). Finally, hill-climbing algorithms, such as tabu search, have also been used to account for spatial harvesting constraints (Murray and Church 1995, Boston and Bettinger 1999).

Wildlife habitat requirements have been included in several planning models developed during the last ten years. Hof and Joyce (1992) were among the first to combine timber production goals with edge and interior forest habitat goals into a spatial harvest scheduling problem. They solved a small problem using a branch and bound algorithm. Bettinger et al. (1997) and Bettinger et al. (1999) developed two systems that used tabu search to combine timber production goals and spatial habitat goals for elk (*Cervus elaphus roosevelti*). And Arthaud and Rose (1996) developed a system to combine aspen production with ruffed grouse goals (*Bonasa umbellus*). Most agree that a heuristic approach is required to solve the operationally-sized problems that include spatial goals, yet there is less agreement on the use of these models for large-scale forest planning problems.

This paper describes two different modeling approaches for developing spatially feasible forest plans that include the green-up constraints and habitat guidelines for the recovery of the RCW on private forestlands in the southeastern United States. The first approach, Model A, is a two-stage approach (Fig. 1) that begins by developing a continuous solution using linear programming (LP), with the goal of determining timber volume targets. These targets become goals for the second stage, which uses a heuristic optimization technique to develop a tactical forest plan. The heuristic technique accounts for the green-up and spatial RCW constraints while simultaneously maximizes the net present value and minimizes deviations from the volume targets. The advantage of the two-stage approach is that the second stage contains knowledge of the upper-bound on the potential solution values generated by the first stage (albeit we are solving a relaxed problem that does not contain the RCW or green-up spatial constraints). The second approach, Model B, used only one stage to develop the spatially feasible forest plans. This approach assumes that the achievement of volume goals is implicit in the heuristic search process,

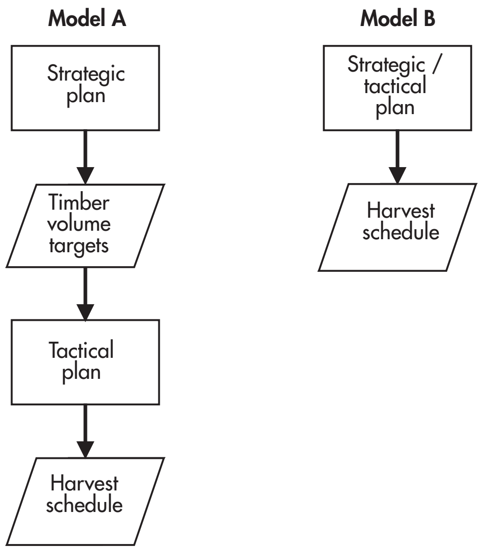

Fig. 1. Model A and Model B approaches to strategic and tactical planning.

rather than being set by a prior process. It has the goal of maximizing net present value while minimizing the desired differences between harvest levels, and while meeting the green-up and RCW constraints. The advantage of Model B is that the volume levels are computed while simultaneously considering the spatial constraints. The objective of this research was to determine the benefits and challenges involved with each modeling approach (two- or one-stage) to guide the development of spatially feasible tactical forest plans that incorporate spatial constraints for wildlife.

2 Methods

We first summarize the problem statement we used for meeting the objectives of this analysis, then briefly describe a spatial database. We then describe the development of the LP-based forest plan used in Model A, followed by the development of the heuristic process used in both models to develop the spatially-feasible forest management plan. The LP-based forest plan provided volume goals for Model A but did not include green-up and RCW constraints, which were incorporated into the spatially feasible forest plans.

2.1 Problem Statement and Data Assumptions

We are assuming in this discussion that some forest landowners and managers associated with forest products firms in the southeastern United States have commodity production as well as wildlife habitat goals. The managers' goals are twofold: to maximize net present value of the forest resource, and to adhere to the restrictions placed on them by government and voluntary regulations. The RCW habitat guidelines came from Lipscomb and Williams (1998), who suggest the establishment of two zones around each RCW nest to meet the habitat requirements for RCWs on private lands. The inner zone, the cluster zone, was created with a 61.0 m buffer (1.2 ha) around each nest, with the goal of maintaining the basal area between 11.5 and 18.4 m^2 ha^{-1}. It is assumed that a combination of precommercial thinning and prescribed burning will be used to maintain the open-pine habitat, and no commercial timber harvesting will be scheduled in this zone. The outer zone, the forage zone, is the area between 61.0 and 804.6 m of the nest location (representing 203.4 ha). Within this zone, a minimum of 24.3 ha of pine forests are to be maintained for RCW forage purposes. This zone requires a minimum total pine tree basal area of 278.7 m^2, with tree diameters averaging at least 25.4 cm. Within each time period, no harvest is allowed in the forage zone until the structural goals are met.

The GIS database, acquired from a forest products firm in Georgia (USA), represents a typical industrial ownership in the southeastern United States. The database contains mostly pine plantations, plus a mixture of hardwood areas not managed for timber production. It also contains approximately 700 potential logging units, resulting in approximately 10 000 0–1 decision variables. Sixteen RCW nest locations were randomly assigned to the area, with an assumption that there were enough large pine trees in the random locations to serve as RCW nest sites in the inner circles. Harvesting will be permitted in the forage circles only if the habitat requirements can be met. Timber yields were estimated with equations developed by Harrison and Borders (1996) for three types of wood products: sawlogs, chip-and-saw logs, and pulpwood. Basal areas were estimated by using Bulletin 19 from the Georgia Forestry Association (Saucier et al. 1981). Assumed product prices are shown in Table 1. We assumed a logging cost of US$ 0.27 per ft^3, and an 8% real discount rate to derive net present value. All penalty values associated with not achieving a volume target for a particular timber product were discounted using an 8% real discount rate. Since we have less certainty regarding the information in the later periods, penalty values are discounted to reflect less certainty regarding the goals.

2.1.1 Model A

Model A is a two-stage method for generating a forest plan: first a continuous (strategic) plan is developed, then a tactical plan is developed to address the spatial restrictions. The continuous forest plan, formulated as a linear programming problem, was solved by using the Forestry-Oriented Linear Programming Interpreter (Garcia 1984). The goal was to maximize the discounted net present value over 15 1-year periods; minimum harvest age was assumed to be 19 years. It was assumed that all stands were regenerated to meet the AF&PA SFI guidelines (American Forest & Paper Association 2001) which require immediate regeneration. The continuous forest plan provides the target harvest goals for the tactical plan, and it can be considered a "relaxed" problem, since the green-up constraints and RCW constraints were absent. The results from the continuous forest plan provide a theoretical upper bound on the solution. The maximum harvest volume from the forest over a 15-period planning horizon is generated with the LP solution, and is attempted to be implemented with the tactical solution. This is difficult, because a highly intensive management objective can lead to a large the difference between the results of the continuous, non-spatial solution and the discrete, spatially-constrained solution. The objective function consists of maximizing the net present value of revenue from harvests less logging costs:

Table 1. Prices assumed for forest products.

Product	Price ($/ cf^3)
Pulpwood	0.34
Chip-and-saw logs	1.00
Sawlogs	1.15

$$\text{maximize} \sum_{j=1}^{J}\sum_{n=1}^{N}\sum_{t=1}^{T}(\text{Rev}_{nt} - \text{Lc}_{nt})\text{V}_{jnt}\text{X}_{nt} / (1.08^{t}) \quad (1)$$

where J = number of products; j = product type; N = number of harvest units; n = harvest unit; T = number of time periods; t = time period; Rev_{nt} = revenue per cubic meter for unit n harvested in time period t; Lc_{nt} = logging cost per cubic meter for unit n harvested in time period t; V_{jnt} = volume per hectare of product j in unit n harvested during time period t; X_{nt} = proportion of unit n harvested during time period t.

A minimum harvest age of 19 years was assumed for each timber stand, and except for sawlog volumes, which were set to 10% per period, individual product volumes could not change by more than 5% per time period.

$$\left| 1 - \left(\left(\sum_{n=1}^{N}(\text{V}_{jnt}\text{X}_{nt}) - \sum_{n=1}^{N}(\text{V}_{jnt+1}\text{X}_{nt+1}) \right) / \left(\sum_{n=1}^{N}(\text{V}_{jnt}\text{X}_{nt}) \right) \right) \right| \le \text{deviation}_j \quad \forall j, t = 1,...,t-1 \quad (2)$$

The formulation for the discrete (tactical) planning problem is similar to the continuous plan and to the objective function found in Boston and Bettinger (1999). The objective function for the problem is:

$$\text{maximize} \sum_{j=1}^{J}\sum_{n=1}^{N}\sum_{t=1}^{T}(\text{Rev}_{nt} - \text{Lc}_{nt})\text{V}_{jnt}\text{X}_{nt} / (1.08^{t}) - \sum_{j=1}^{J}\sum_{t=1}^{T}(\text{Vp}_{jt}\,\text{du}_{jt}) / (1.08^{t}) - \sum_{j=1}^{J}\sum_{t=1}^{T}(\text{Vp}_{jt}\,\text{dl}_{jt}) / (1.08^{t}) \quad (3)$$

where X_{nt} = 0,1 variable indicating whether unit n is harvested during time period t; Vp_{jt} = volume penalty per cubic meter of product j during time period t; du_{jt} = positive deviation from volume goal of product j during time period t; and dl_{jt} = negative deviation from volume goal of product j during time period t. The volume goals we used were those that resulted from the strategic plan. Penalties were used to guide the heuristic search process towards solutions that would emulate the continuous forest planning solution. Table 2 illustrates the penalty values for the tactical plan portion of Model A.

Table 2. Penalty values (Vp_{jt}) used in the tactical forest plans (price = product price).

	Volume deviation (%)				
Product	0–5	5–10	10–15	15–20	20+
Pulpwood	0	price	price^2	price^2	price^2
Chip-and-saw logs	0	price	price^2	price^2	price^2
Sawlogs	0	0	price	price	price^2

$$\sum_{n=1}^{N}(\text{V}_{jnt}\text{X}_{nt}) - \text{du}_{nt} + \text{dl}_{nt} = \text{volume goal} \quad \forall\, j,t \quad (4)$$

Where du_{nt} and dl_{nt} are the upper and lower deviation variables from the volume goal in each period.

The first constraint in the discrete planning problem is a singularity constraint, which limits each unit to one treatment during the planning horizon.

$$\sum_{t=1}^{T}\text{X}_{nt} \le 1 \quad \forall n \quad (5)$$

Four policy constraints were considered. Two methods for controlling green-up sizes were used: controlling the maximum opening size, and controlling the average opening size. As these represent the green-up constraints faced by the forest industry in the southeastern US. We first defined a maximum opening size for each logging unit n and its set of adjacent neighbors (U_n). For the 3-year green-up constraints used in this model, we defined a set (T_m) of near-time periods (m_z, where m_1 = t–3, m_2 = t–2, m_3 = t–1, m_4 = t, m_5 = t+1, m_6 = t+2, and m_7 = t+3; all m_z (0 otherwise not in T_m; all m_z (T otherwise not in T_m). Therefore, an opening is not just the harvests that occur in time period t, but also those around each unit n that have occurred during the near-time periods. The maximum opening size constraint is:

$$\left[\sum_{z=Nn\cup Sn}^{Z}(\text{A}_z W_{zt})\right] + (\text{A}_n\text{X}_{nt}) \le \text{Maximum opening size} \quad \forall\, n \text{ where } \text{X}_{nt} = 1;\, t \quad (6)$$

If X_{nt} = 1, W_{nt} = 1 $\quad \forall\, t \in T_m$
Else W_{nt} = 0

where Nn = the set of adjacent neighbors to unit n; Sn = subset of adjacent units to the neighbors of unit n, and all units adjacent to neighbors of neighbors, etc. as per Murray (1999); W_{zt} = 0,1 variable indicating whether unit z was harvested during a time period near t defined in T_m; T_m = the set of near-time periods; m = a near-time period; A_z = area of unit z; A_n = area of unit n; and X_{nt} = 0,1 variable indicating whether unit n is harvested during time period t. For this problem, the maximum opening size used was 91 ha.

A maximum average opening size can be defined for each time period. If each opening is centered around a focal unit (f) during a time period (t), we can define the size of the opening (O_{ft}) as:

$$\left[\sum_{z=Nf\cup Sf}^{Z}(A_z W_{zt})\right]+(A_f X_{ft}) = O_{ft} \tag{7}$$

A_f = area of focal unit f; and X_{ft} = 0,1 variable indicating whether focal unit f is harvested during time period t.

Because we are attempting to calculate the average opening size, we do not wish to count openings more than once. This miscounting could occur if we allowed each unit (n) in an opening (composed of multiple units n) to be considered the "center". Therefore, only one unit (n) can be delineated as the focal center (f) of the opening in any time period, and the total number of openings equals the number of focal centers of openings. Thus,

$$\sum \mathrm{f} \le \sum \mathrm{n} \quad \text{and} \quad \sum X_{ft} \le \sum X_{nt} \tag{8}$$

The average opening size for a set of openings in a time period (t) can then be constrained with the following equation:

$$\left[\sum_{f=1}^{F} O_{ft}\right] / \mathrm{F} \le \text{average opening size} \quad \forall t \tag{9}$$

where F = the total number of openings; f = the focal center of an opening, or an opening; and O_{ft} = an opening centered around a focal unit f during time period t. For this problem, the maximum average opening used was 48 ha., the limit set by the AF&PA (American Forest & Paper Association 2001).

The last constraints are for units contained within the RCW forage areas, the area between 61.0 and 804.6 meters of the nest tree. Constraint 10 requires a minimum of 278.7 m^2 of total pine basal area within the forage area. Constraint 11 requires a minimum average diameter of 25.4 cm for the pine trees within the forage area.

$$\sum_{n\in Rp} BA_{nt} A_n \ge \text{minimum basal area} \qquad \forall t; Rp, p = 1,...,P \tag{10}$$

Where R_p = the p^{th} RCW forage area, from the set of R_p ranging from R_1 to R_P, containing units n; BA_{nt} = the basal area of unit n during time period t.

$$\frac{\sum_{n\in Rp}[D_{nt} A_n]}{\sum_{n\in Rp}[A_n]} \ge \text{minimum diameter} \qquad \forall t; Rp,\ p = 1,...,P \tag{11}$$

Where D_{nt} = the average tree diameter of unit n during time period t.

2.1.2 Model B

The product of Model B is a forest plan that considers both the harvest levels and spatial constraints simultaneously. The goals and constraints used in Model B are exactly the same as those in Model A, except that Equation 3 is altered and Equation 4 is not used. First, a set of equations to define the deviations between periods is developed:

$$\left|1-\left(\left(\sum_{n=1}^{N}(V_{jnt}X_{nt})-\sum_{n=1}^{N}(V_{jnt+1}X_{nt+1})\right)/\left(\sum_{n=1}^{N}(V_{jnt}X_{nt})\right)\right)\right| = \text{deviation}_{jt} \quad \forall j, t = 1,...,t-1 \tag{12}$$

where deviation$_{jt}$ represents the variation between harvest volume for product j during time periods t and t+1. No penalty was incurred if the volume produced of chip-and-saw and pulp logs varies less than 5 % between periods. Sawlog volumes were allowed to vary up to 10% without incurring a penalty value. The original Equation 3 is altered to become Equation 13:

$$\text{maximize} \sum_{j=1}^{J}\sum_{n=1}^{N}\sum_{t=1}^{T}(\text{Rev}_{nt} - \text{Lc}_{nt})\text{V}_{jnt}\text{X}_{nt} / 1.08^{t} - \sum_{j=1}^{J}\sum_{t=2}^{T}(\text{Vp}_{jt})\text{ deviation }_{jt} / 1.08^{t} \qquad (13)$$

where deviations in volume levels, by product, from one period to the next are penalized. This retains the intent of Equations 2 and 3, which were devised to produce a flow of volume with some allowable variation between periods but were given some slack to allow the achievement of the goals. These were the same allowable variations to the volume goals that were used in the continuous model in approach A.

2.2 Heuristic Technique

The heuristic technique used for stage 2 of Model A and for the entire Model B process is a hybrid algorithm consisting of five components. The first is a Monte Carlo integer programming algorithm that randomly develops an initial solution. This process selects a logging unit, determines whether it meets the minimum harvest age requirement, and ensures that its incorporation into the solution does not violate the green-up constraints or the RCW habitat guidelines. This selection process continues until 20 units have been scheduled in each period. Because each new run of the heuristic technique uses a new seed for use in a random number generator, this component allows an increase in the proportion of the solution space explored when the program is executed repeatedly.

The second component is the core tabu search routine, similar to the algorithms described in Murray and Church (1995), Bettinger et al. (1997), and Boston and Bettinger (1999). It is composed of two elements: (1) a tabu list that maintains a record of the recent moves, and (2) aspiration criteria. After experimentation, 100 iterations was selected as the tabu list length. For this application, the aspiration criterion was assumed to be the overall best objective function value. The best move from the neighborhood of moves is considered first, whether or not it improves the current solution. If the move is not tabu, it is accepted into the solution. In addition, if the move is tabu yet exceeds the aspiration criteria, it is accepted into the solution. If a move is tabu and does not exceed the aspiration criteria, it is rejected.

The third component is the intensification routine. The objective of an intensification routine is to search for better solutions within a portion of the neighborhood that has already yielded a good solution. This intensification routine begins by recalling the current best solution from the core tabu search routine. By using a 2-opt neighborhood (where the harvest timing of one unit is swapped with that of another) described in Bettinger et al. (1999), two units can simultaneously change their status. This process, however, only considers non-forage-area units. The intensification routine has the same short-term memory features as the core tabu search routine, but the tabu list has been reduced from 100 to 20 iterations.

Tabu search finds good solutions to large combinatorial problems, but the solutions tend to be concentrated in a small portion of the solution space (Glover et al. 1995). Thus, the fourth and fifth components of the heuristic technique have the goal of changing the neighborhood considered by the core tabu search algorithm. The fourth component is a diversification routine that schedules those units with the lowest frequency of entering the solution, while maintaining the minimum harvest age requirement and not violating the green-up constraints. This diversification forces the algorithm to the least explored portion of the solution space. The resulting solution becomes the starting point for a return to the core tabu search routine.

The last component aims to combine two good solutions to find a superior solution. It is based on a crossover routine used in genetic algorithms. The best solutions from the 1-opt and 2-opt tabu search processes are selected for the genetic crossover routine, which treats the solutions to the forest planning problems as if they were chromosomes, with each unit being a gene on a chromosome. The values for the genes–the alleles–become the periods when the unit is harvested. By using a random number generator that selects the crossover point, the two "chromo-

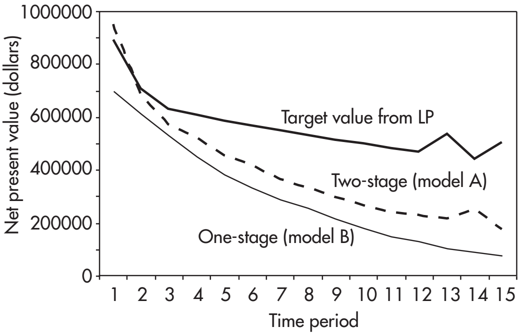

Fig. 2. Net present value per time period from LP, Model A heuristic, and Model B heuristic forest plans (discounted revenue, with no penalty values included).

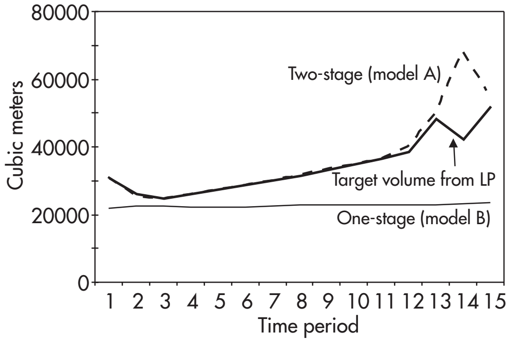

Fig. 3. Pulpwood volume from LP, Model A heuristic, and Model B heuristic forest plans.

somes" are recombined into two new solutions. The solution with the highest objective function value survives the crossover and becomes the starting solution for a continuation of the core tabu search routine.

This heuristic technique has produced good results for similar spatial harvest scheduling problems with 3000 to 5000 0–1 integer variables (a companion paper on validation of the heuristic technique is in preparation); the current heuristic technique uses 2-opt moves, which should provide even better results (Bettinger and Boston 1999). Extending the use of this solution method to larger scheduling problems therefore seems reasonable, although its performance cannot be directly compared against known optimal solutions. The results we provide from the heuristic technique are the best solution from a set of twenty generated for stage 2 of Model A, and the best solution from a set of twenty produced for Model B.

3 Results

The linear programming solution (stage 1 of Model A, the "relaxed" solution to the planning problem) indicates that when spatial constraints are not considered and non-integer solutions allowed, the optimal strategy for this land base is to primarily produce chip-and-saw logs and pulpwood logs. As we will soon see, however, once the spatial constraints are considered, harvests become delayed due to green-up constraints and RCW habitat requirements, causing an increase in the percentage of sawlogs and chip-and-saw logs produced, reducing the percentage of pulpwood logs. In terms of net present value produced per time period, the two-stage modeling approach (Model A) produced better results than the one-stage approach (Model B, Fig. 2). This only considers the revenue produced from the forest, and do not include the remaining the forest's residual asset value, since the goal was to develop a plan that maximizes the income from the property over a 15-yr planning horizon. In fact, the net present value for Model A was more than that for Model B in every time period. Incorporating a residual value calculation therefore would not change the result of this analysis. Solution values for both Model A and Model B are generally less than the LP results, since the LP solution is a relaxed version of the forest planning problem.

In terms of actual products produced, Model A closely follows the LP solution for the first 12 periods for pulpwood production (Fig. 3) and the first 13 periods of chip-and-saw production (Fig. 4). Model B drops in production of pulpwood after period 12, yet it produces a nearly even flow for chip-and-saw logs. Both modeling approaches show large variations in sawlog production (Fig. 5), although Model A more closely reflects the targets derived from the LP solution as would be expected. Neither model produces, over the 15-year planning horizon, the mix of products

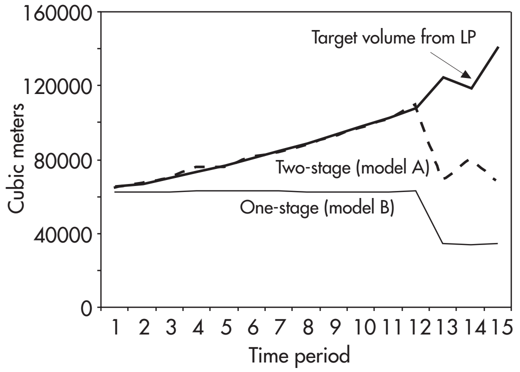

Fig. 4. Chip-and-saw log volume from LP, Model A heuristic, and Model B heuristic forest plans.

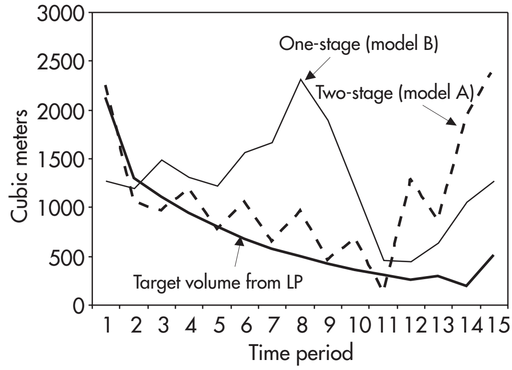

Fig. 5. Sawlog volume from LP, Model A heuristic, and Model B heuristic forest plans.

suggested by the relaxed LP solution: larger quantities of smaller products in the later time periods. Both models generally show more sawlog production over time, suggesting the harvest delays caused by the spatial constraints and the implied integer constraints with the removal of fractional solutions lead to production of a larger quantity of sawlogs and chip-and-saw logs.

The solution time for Model A required 10 hours for this problem (700 logging units, 10 000 0–1 variables), while Model B required 20 hours for the same number of iterations, each on a Pentium 233 with Windows NT operating system. We anticipate more efficient programming techniques would lead to a substantial improvement in the computer time required to generate a solution, therefore these time commitments should not be seen as a deterrent to the development of spatially feasible forest plans.

4 Discussion and Conclusions

The comparison of solutions from Models A and B, while important, must be made with a caveat in mind. Model B actually utilized higher penalty values for non-smooth harvest levels, since the deviations of harvests from period-to-period are incorporated directly with the spatial constraints in the problem formulation. For example, should the spatial constraints force the solution far from the original LP solution (the first stage of Model A), the solution of Model A may not reflect the original harvest level smoothness criteria. Given the complexity of the formulations, and our attempt to adequately formulate the problem in both one-stage and two-stage processes, one could argue that the resulting formulations are not exactly the same, and the resulting comparisons should be viewed in this manner.

The impact of including spatial constraints along with the resulting integer requirements in forest plans is clarified by examining the difference between the spatially feasible forest plans (the resulting spatial forest plans for Models A and B) and the relaxed LP solution (generated as stage 1 of Model A). Incorporating spatial constraints led to longer rotations, which produced a lower percentage of pulpwood logs and a higher percentage of chip-and-saw logs and sawlogs in the long-run. However, the magnitude of the difference between the relaxed LP solution and spatially feasible solutions generated by the heuristic technique will depend on the arrangement of stands in a particular forest and the degree at which the continuous forest solution is converted to an integer solution. A forest with highly aggregated stands (e.g., small ranges of age classes in concentrated areas) will probably show a larger difference between a relaxed LP solution and a spatially feasible solution than a forest with a dispersed age-class distribution. Thus the results shown here should not be viewed as being the universal effects of the RCW and green-up constraints applied to all forests in the southeastern

USA. To assess the impacts of spatial constraints on particular areas of the Southeast, we recommend the inclusion of spatial constraints in forest plans, particularly is the results will lead to the support (or non-support) of wood processing equipment, based on the anticipated raw material produced from a forest.

The problem formulations could easily be adapted to include other silvicultural treatments, such as thinning operations. Since these treatments are not primarily used in the short-rotation plantation forests of the southeastern US, they were not included in the models presented here. Their inclusion would simply require the addition of other decision variables reflecting the opportunity to choose those activities in the scheduling process.

Tabu search is a scheduling model that generally considers the impact of iterative, single changes in a solution to a problem, such as changing the harvest timing of a single management unit. These potential moves may shift the value of the resulting solution considerably. Using a 2-opt procedure and a genetic crossover routine reduces these impacts, fine-tuning the solution values and allowing a more efficient search of the solution space. The guidance provided by the LP solution in Model A, however, allows the heuristic technique to find higher valued solutions than when used alone (in Model B). As a result, a two-stage approach (LP and heuristic) seems, at least with this problem, to produce more efficient spatially feasible forest plans than a one-stage approach.

We recommend those considering a variety of forest product goals and wildlife habitat goals as joint products to pay close attention to the quality of resulting solutions generated by heuristic techniques, and at a minimum, compare them, where possible, with relaxed LP solutions. The forest planning problem evaluated here, with three forest products that were mainly a function of stand age, were greatly influenced by delays in harvesting caused by the achievement and maintenance of wildlife habitat goals. Model A provided some guidance about these products to the heuristic, allowing the heuristic to find better solutions when no guidance was provided (Model B). This is one of the problems with heuristics such as tabu search, they are unable to consider the entire production surface when solving a problem. The guidance from the LP solution produces a better result than allowing the tabu search heuristic to develop a harvest schedule that simultaneously meets the spatial constraints while minimizing the deviations from the desired volume levels.

With the likelihood that governmental regulations and internal policies of forest companies will increasingly emphasize wildlife habitat goals, the resulting situation will be one where companies increasingly ask their planners "what if" questions about the short- and long-term prospects of management on their land. For example, planners may be called upon to examine the effect on harvest levels and cash flow if the required size of RCW habitat areas is increased (or decreased). To fully explore the potential effects of policies, which include spatial constraints, heuristic techniques will more than likely be required, and the planning process may require a one- or two-stage approach as described here. The benefit of the two-stage approach is that some guidance is given the heuristic from the results of a "relaxed" solution to the problem. The benefit of the one-stage approach is that it considers the harvest levels while simultaneously meeting the spatial constraints. While the two-stage approach seems more appropriate for the green-up and RCW constraints we described, planners and managers will need to assess for themselves the relative benefits and costs to their organizations of these two planning processes, particularly if decisions are to be made, based on these results, regarding the development of wood processing facilities or selection of wood processing equipment.

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