Chapter 22

SPATIAL ENVIRONMENTAL CONCERNS

Alan T. Murray
Department of Geography, The Ohio State University, Columbus, USA

Abstract Balancing utilization and protection of the natural environment is a challenging task. Forest management in particular continues to deal with trade-offs inherent to responsible timber harvesting. This chapter focuses on harvest scheduling where one is interested in maximizing economic returns subject to maintaining a continued supply of timber in the future. This necessarily means managing resources in a sustainable manner. As such addressing spatial issues related to environmental concerns is critical. This chapter reviews approaches that have been relied upon to limit localized impacts of harvesting activity.

Keywords: Harvest scheduling, optimization, adjacency, green-up, area restrictions

1 INTRODUCTION

Human activities and their associated impacts on the environment continue to be recognized as a threat to the long-term sustainability of the Earth. Forestry represents an industry that relies on natural resources, forests and timber in particular, in a multiple-use context. Given demands for timber and wood products as well as the environmental impacts of harvest operations on flora and fauna, increasing attention has been directed to enhancing analysis and modeling detail in the management of natural resources. Of interest in this chapter is increased spatial and temporal specificity in harvest-scheduling analysis supported by optimization models.

Harvest-scheduling optimization models have characteristically focused on making decisions on how to treat standing timber over a horizon of several years to decades. Decision variables in these models relate to the sequencing of stands or blocks for harvesting to satisfy temporal timber demands and other constraining conditions. Given this, the orientation of harvest-scheduling models is to maximize economic returns in the management of a forest region.

This necessarily means minimizing management costs, such as operational overhead, transportation system development/maintenance, timber movement costs, and so on. Spatial environmental concerns arise when accounting for wildlife richness, creating habitat favorable to flora and fauna, promoting diversity, maintaining soil and water quality, preserving scenic beauty, and moving toward sustainability more generally. In order to address such concerns implicitly or explicitly, limiting spatial impacts is desired in harvest-scheduling models. Adjacency restrictions and green-up conditions have traditionally been relied upon to regulate localized activity.

2 ADJACENCY AND GREEN-UP

Avoiding concentrated harvest activity in any one area has been approached in optimization models by addressing adjacency relationships. Adjacency reflects spatial proximity of an area to another area. Typically, adjacency is defined as two areas sharing a common boarder or point, but certainly adjacency could be defined using distance between two areas as well. One way to limit localized harvest impacts is to prohibit any two adjacent areas from being simultaneously treated, as was the intent of Thompson *et al.* (1973). Consider a harvesting decision variable for management area i:

$$x_i = \begin{cases} 1 \text{ if area } i \text{ is harvested} \\ 0 \text{ otherwise} \end{cases}.$$

For two management areas i and i', we can define a condition that would limit harvesting to at most one of these adjacent areas:

$$x_i + x_{i'} \leq 1. \tag{1}$$

Thus, restrictions would be imposed for all adjacent areas N_i to area i, and these conditions would be needed for each area i. Murray (1999) has referred to harvest-scheduling problems where adjacency between management units is imposed as the unit restriction model (URM). The assumption here is that the combined area of units i and i' exceeds an acceptable threshold. That is, $\alpha_i + \alpha_{i'} > A$, where α_i is the area of unit i ($\alpha_{i'}$ similarly defined) and A is the maximum permissible harvest disturbance area. Murray *et al.* (2004) indicate that maximum area limits of 16–49 ha are common in practice.

If we also take into account temporal aspects of spatial decision making, the earlier notation can be extended as follows:

$$x_{it} = \begin{cases} 1 \text{ if unit } i \text{ is harvested in time period } t \\ 0 \text{ otherwise} \end{cases}.$$

In the context of limiting localized impacts, condition (1) can be more broadly defined to include both spatial and temporal restrictions on harvest activity as follows:

$$\sum_{t'=t-p}^{t+p} \left(x_{it'} + x_{i't'} \right) \leq 1 . \tag{2}$$

where p is a pre-specified harvesting exclusion period. Condition (2) includes the so-called green-up requirement, where an area cannot be harvested if an adjacent unit has been harvested in a pre-specified interval of time before or after the current time period t. As such, condition (2) would be necessary for each units i and adjacent units i' in every each time period t.

3 AREA RESTRICTIONS

Current harvest-scheduling research increasingly focuses on a variant of the earlier problem, recognizing that management units may be defined such that two or more adjacent units do not necessarily violate the maximum area limitation (see Hokans, 1983; Lockwood and Moore, 1993; Murray, 1999). That is, it is possible that $\alpha_i + \alpha_{i'} < A$, representing a feasible management possibility. In this case, rather than adjacency constraints, one needs a maximum area restriction defined for sets of units if the intended condition is to be imposed in a harvest-scheduling optimization model. Murray (1999) has referred to harvest-scheduling problems where spatial limitations apply to sets of management units as the area restriction model (ARM).

While in the general case this is a particularly formidable problem to structure (and solve) using integer programming, under certain conditions it is possible to enumerate potential feasible harvesting blocks (or areas) a priori (see Murray *et al.*, 2004; Goycoolea *et al.*, 2005). As an example, consider the forest units shown in Fig. 1, assuming a maximum allowable impact area of A=49 ha. Given this, there are 17 potential combinations of feasible blockings for these individual management units: {1}, {2}, {3}, {4}, {5}, {1,2}, {1,3}, {1,4}, {2,4}, {2,5}, {3,4}, {4,5}, {1,3,4}, {1,4,5}, {2,3,4}, {2,4,5}, and {3,4,5}. A block, then, is an area comprising spatially connect, or contiguous, management units. As such, a feasible block would need to be identified using some enumerative scheme (see Goycoolea *et al.*, 2005).

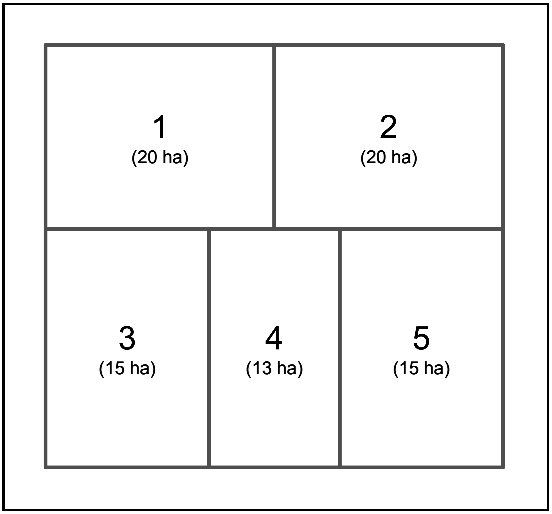

Figure 1. Forest management units.

From a modeling perspective, this somewhat changes how our problem is mathematically represented as we must account for these permissible spatial blocks. This can be done by introducing a new decision variable for each feasible block *l*:

$$y_l = \begin{cases} 1 \text{ if block } l \text{ is harvested} \\ 0 \text{ otherwise} \end{cases}.$$

Given this notation and a priori identified feasible blocks, there are two cases in which any two blocks cannot be simultaneously selected for harvest. First, if a unit *i* is common to both blocks, clearly both should not be allowed as a unit and cannot be harvested twice. Second, if two blocks are adjacent, then we assume that their combined area would result in a spatial violation. While it is true that their combined area may not actually exceed the stipulated maximum area restriction, if this combination of units is feasible it will be identified as a potential block (see Goycoolea *et al.*, 2005). Therefore, this harvesting option is present as a feasible block that can be selected. The implication of these two cases is that we can utilize an adjacency constraint to impose proscribed configurations of blocks as follows:

$$y_l + y_{l'} \le 1 \qquad \forall l, l' \in \Omega_l, \tag{3}$$

where Ω_l is the set of blocks adjacent to block *l* and those blocks which share a common management unit with block *l*.

Returning to the example shown in Fig. 1, feasible blocks {1,4} and {2} would be prohibited based on adjacency given that their combined area (53 ha) exceeds the maximum allowed disturbance area of 49 ha. Mathematically, this can be imposed as follows:

$$y_{\{1,4\}} + y_{\{2\}} \le 1.$$

Alternatively, feasible blocks {1,4} and {3,4,5} would be prohibited because they share a common area, unit 4. As such, the following additional constraint would also be needed, among others:

$$y_{\{1,4\}} + y_{\{3,4,5\}} \le 1.$$

For this example, it is possible to encapsulate the harvesting decision variables and spatial constraints as a graph of nodes and arcs. The nodes in this graph represent feasible blocks to harvest and arcs depict adjacency or block overlap restrictions. Goycoolea *et al.* (2005) refer to this as a projected graph because it is derived from the forest region. Figure 2 illustrates the projected graph for the earlier forest example. In this case, it is nearly a complete graph, with no arcs between {1} and {5}, {2} and {3}, {3} and {2,5}, and {5} and {1,3}.

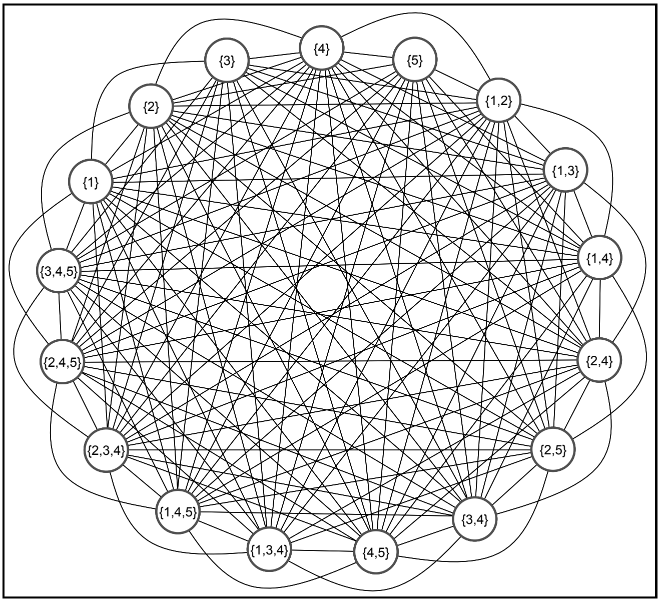

Figure 2. Graph depicting blocks and restrictions in the five unit-forest.

Given the projected graph, it is possible to structure the harvest-scheduling optimization problem as an integer program by restricting spatial impacts between blocks using the ARM.

4 SOLVING THE AREA RESTRICTION MODEL (ARM)

The remainder of this chapter will focus on the ARM, as the URM has been shown to be a special case of the ARM (see Murray, 1999). Murray and Weintraub (2002) provide an empirical examination of the relationship between the URM and ARM. The ARM can be formally stated as follows:

$$\text{Maximizes } \sum_{l}\sum_{t}\beta_{lt}y_{lt}, \tag{4}$$

subject to

$$\sum_{t'=t-p}^{t+p}\left(y_{lt'}+y_{l't'}\right)\leq 1 \qquad \forall l,l'\in\Omega_l,t, \tag{5}$$

$$\sum_{l}v_{lt}y_{lt}\leq U_t \qquad \forall t, \tag{6a}$$

$$\sum_{l}v_{lt}y_{lt}\geq L_t \qquad \forall t, \tag{6b}$$

$$\sum_{t}y_{lt}\leq 1 \qquad \forall l, \tag{7}$$

$$y_{lt}=\{0,1\} \qquad \forall l,t, \tag{8}$$

where

β_{it} is the benefit of harvesting block l in period t,
v_{it} is the volume produced by harvesting block l in period t,
U_t is the upper bound on total volume harvested in period t, and
L_t is the lower bound on total volume harvested in period t.

The objective (4) maximizes net return in selecting blocks for harvest. Constraints (5) impose adjacency and incompatibility restrictions on the simultaneous selection of blocks. Constraints (6) establish upper and lower bounds on harvesting productivity in each time period. Constraints (7) allow a block to be harvested at most once over the planning horizon. Finally, constraints (8) indicate integer requirements on decision variables.

Common extensions to this basic model include road network construction and maintenance, minimum revenue requirements, age structure, and preservation of habitat (see Kirby *et al.*, 1986; Murray and Church, 1995; Caro *et al.*, 2003).

Solving the ARM has proven to be a challenge. Much of the initial work on solving the ARM utilized heuristic solution methods. Hokans (1983) detailed an artificial intelligence-based heuristic for the ARM. Following this were approaches based on simulated annealing and tabu search developed by Lockwood and Moore (1993), Clark *et al.* (2000), and Richards and Gunn (2000). Recent work in this area includes the evolutionary approach (genetic algorithm) of Falcao and Borges (2002) and the tabu 2-opt heuristic of Caro *et al.* (2003).

Murray *et al.* (2004) and Goycoolea *et al.* (2005) detail an approach for solving the ARM exactly using commercial integer-programming software. The idea behind the approach is to exploit properties of the projected graph. In particular, constraints (5) in the ARM are not particularly strong in the sense of inducing facets beneficial to integer-programming techniques. Specifically, integer-programming typically relies on linear programming (LP) coupled with branch-and-bound, where integer restrictions on decision variables are initially relaxed then systematically resolved in the branching phase. When constraints (5) are utilized, highly fractional LP solutions often result, if a relaxed solution can be obtained at all, requiring substantial effort to resolve fractions and prove optimality, again if this can even be done at all. To address this issue, Goycoolea *et al.* (2005) proposed higher-ordered cliques and other facet-defining constraints in the projected graph. A clique is a set whose members share a mutually exclusive relationship with all other members in the set. The cliques suggested in Goycoolea *et al.* (2005) are structurally similar to those developed for the URM by Murray and Church (1996).

Constraints (5) actually are low-ordered cliques, fundamentally containing two decision variables, for example, Eq. 3 and a right-hand side coefficient value of one. Interestingly, higher ordered cliques typically exist in projected graphs, making it possible to have many decision variables in one constraint while retaining a right-hand side coefficient of one. Thus, Eq. 3 can be generalized as follows:

$$\sum_{l \in C} y_l \leq 1, \tag{9}$$

where C is the set of blocks forming a clique (all blocks in the clique are mutually prohibited from being harvested together). Such a constraint in the ARM provides the facet-inducing property important for optimally solving integer-programming problems in practice.

For the forest example previously discussed, only three cliques are needed to impose all projected graph restrictions:

$$\begin{aligned} & y_{\{1\}} + y_{\{1,2\}} + y_{\{1,3\}} + y_{\{1,4\}} + y_{\{1,3,4\}} + y_{\{1,4,5\}} \\ & + y_{\{2\}} + y_{\{2,4\}} + y_{\{2,5\}} + y_{\{2,3,4\}} + y_{\{2,4,5\}} \\ & + y_{\{4\}} + y_{\{3,4\}} + y_{\{4,5\}} + y_{\{3,4,5\}} \leq 1 \end{aligned}, \tag{10a}$$

$$\begin{aligned} & y_{\{1\}} + y_{\{1,2\}} + y_{\{1,3\}} + y_{\{1,4\}} + y_{\{1,3,4\}} + y_{\{1,4,5\}} \\ & + y_{\{3\}} + y_{\{3,4\}} + y_{\{2,3,4\}} + y_{\{3,4,5\}} \\ & + y_{\{4\}} + y_{\{2,4\}} + y_{\{4,5\}} + y_{\{2,4,5\}} \leq 1 \end{aligned}, \tag{10b}$$

$$\begin{aligned} & y_{\{2\}} + y_{\{1,2\}} + y_{\{2,4\}} + y_{\{2,5\}} + y_{\{2,3,4\}} + y_{\{2,4,5\}} \\ & + y_{\{4\}} + y_{\{1,4\}} + y_{\{3,4\}} + y_{\{4,5\}} + y_{\{1,3,4\}} + y_{\{1,4,5\}} + y_{\{3,4,5\}} \\ & + y_{\{5\}} \leq 1 \end{aligned}, \tag{10c}$$

Assuming that an enumerative scheme is developed to identify all necessary cliques in a projected graph, a constraint for each clique k may be structured as follows:

$$\sum_{l \in C_k} \sum_{t'=t-p}^{t+p} y_{lt'} \leq 1 \qquad \forall k,t, \tag{11}$$

where k is the index of cliques. These constraints would replace constraints (5) in the ARM. The rationale for this replacement is that there will be substantially fewer constraints (11) than (5). Further, the facet inducing structure of constraints (11) is far superior to (5).

Goycoolea *et al.* (2005) provide computational experience using commercial integer-programming software to solve the ARM using constraints (11) for a range of harvest-scheduling problems. The largest problem solved had 1,363 management units and a planning horizon of 7 periods, resulting in some 9,500 scheduling decision variables alone. Extensions of the ARM to account for average area considerations were detailed in Murray *et al.* (2004), readily solving scheduling problems with 351 planning units. The point here is that the projected graph and higher-ordered cliques make it possible to solve fairly large ARM-based harvest-scheduling problems with modest computational effort.

5 TEMPORAL RESTRICTIONS

While much progress has been made in the development of optimization approaches to support harvest scheduling, a relatively under investigated area of research in modeling spatial environmental concerns is the impacts of temporal output requirements. This is not particularly surprising given that spatial restrictions have been challenging to represent and impose, and they have had substantial impact on model solvability (Murray and Church, 1996; Goycoolea *et al.*, 2005). Recent work by Vielma *et al.* (2007) has found that merely adding a temporal dimension to an ARM with a requirement on productivity in each time period greatly increased computational complexity. As an example, for a problem with 1363 management units and 15 time periods the addition of volume restrictions, constraints (6a) and (6b) increased computational effort by more than 200% just to find a solution within 1% of optimality. Thus, addressing both space and time presents difficulty, but is fundamentally important to responsible natural resource management practices (see Ware and Clutter, 1971; Bettinger *et al.*, 2003).

What is significant about the work of Vielma *et al.* (2007) is that the fraction-inducing behavior of temporal volume constraints becomes apparent. That is, temporal volume constraints do not tend to be integer-friendly. As a result, approaches for dealing with this aspect of modeling difficulty in harvest scheduling is necessary, which is precisely what was done in Vielma *et al.* (2007). Specially, Vielma *et al.* (2007) discussed approaches for constraint branching and relaxing strict volume constraints.

6 CONCLUSIONS

Spatial environmental issues are of central concern in forest management. Harvest scheduling has long been focused on using optimization models to support management and decision making. There has been an evolution of sorts in harvest-scheduling where greater spatial and temporal specificity is expected with increases in geographic data and a better understanding of ecological processes. To support this, harvest scheduling models have moved from unit-based to area-based approaches, such as the ARM. While many of the initial ARM applications made use of heuristic solution methods, recent work has demonstrated increased capabilities for optimally solving such problems. Improvements facilitated by the use of projected graphs and cliques necessarily exploit spatial problem structure. Along the temporal domain, advances are being made associated with the ARM, but there appears to be substantial opportunity for improvements based on space–time insights.

Future research addressing spatial environmental concerns will no doubt continue to push the envelop of computational capabilities for solving harvest-scheduling models. One can anticipate advances in both exact and heuristic approaches. It seems reasonable as well to expect research focusing on the impacts of temporal volume restrictions. Beyond this, extension of the basic ARM to address roading and other operational concerns is no doubt an important future area of work with real potential for significant contributions.

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7 REFERENCES

Bettinger, P., D.L. Johnson and K.N. Johnson (2003). Spatial forest plan development with ecological and economic goals. *Ecological Modelling* 169: 215–236.

Caro, F., M. Constantino, I. Martins and A. Weintraub (2003). A 2-opt tabu search procedure for the multiperiod forest harvesting problem with adjacency, greenup, old growth and even flow constraints. *Forest Science* 49: 738–751.

Clark, M.M., R.D. Meller and T.P. McDonald (2000). A three-stage heuristic for harvest scheduling with access road network development. *Forest Science* 46: 204–218.

Falcao, A.O. and J. Borges (2002). Combining random and systematic search heuristic procedures for solving spatially constrained forest management scheduling models. *Forest Science* 48: 608–621.

Goycoolea, M., A.T. Murray, F. Barahona, R. Epstein and A. Weintraub (2005). Harvest scheduling subject to maximum area restrictions: exploring exact approaches. *Operations Research* 53: 490–500.

Hokans, R.H. (1983). Evaluating spatial feasibility of harvest schedules with simulated stand-selection decisions. *Journal of Forestry* 81: 601–603, 613.

Kirby, M., W. Hager and P. Wong (1986). Simultaneous planning of wildland management and transportation alternatives. *TIMS Studies in the Management Sciences* 21: 371–387.

Lockwood, C. and T. Moore (1993). Harvest scheduling with spatial constraints: a simulated annealing approach. *Canadian Journal of Forest Research* 23: 468–478.

Murray, A.T. 1999. Spatial restrictions in harvest scheduling. *Forest Science* 45: 45–52.

Murray, A.T. and R.L. Church (1995). Heuristic solution approaches to operational forest planning problems. *OR Spektrum* 17: 193–203.

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

Murray, A.T., M. Goycoolea and A. Weintraub (2004). Incorporating average and maximum area restrictions in harvest scheduling models. *Canadian Journal of Forest Research* 34: 456–464.

Murray, A.T. and A. Weintraub (2002). Scale and unit specification influences in harvest scheduling with maximum area restrictions. *Forest Science* 48: 779–789.

Richards, E.W. and E.A. Gunn (2000). A model and tabu search method to optimize stand harvest and road construction schedules. *Forest Science* 46: 188–203.

Thompson, E.F., B.G. Halterman, T.S. Lyon and R.L. Miller (1973). Integrating timber and wildlife management planning. *Forestry Chronicle* 47: 247–250.

Vielma, J.P., A.T. Murray, D.M. Ryan and A. Weintraub (2007). Improving computational capabilities for addressing volume constraints in forest harvest scheduling problems. *European Journal of Operational Research*, 176: 1246–1264.

Ware, G.O. and J.L. Clutter (1971). A mathematical programming system for the management of industrial forests. *Forest Science* 17: 428–445.