SPATIAL HARVEST SCHEDULING IN THE SOUTHEASTERN UNITED STATES: ESTIMATING THE IMPACT ON LANDOWNERS OF DIFFERENT SIZES AND SPATIAL CONFIGURATION OF OWNERSHIP

by

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(Under the Direction of Pete Bettinger)

ABSTRACT

The use of spatial harvest scheduling processes has increased over the past 15 years due to regulatory and voluntary programs that affect the spatial and temporal arrangement of management activities across a landscape. A number of papers have been presented in the literature that describe and compare the performance of spatial harvest scheduling algorithms on small sets of management problems. Applications of a single planning process to a broad range of ownership sizes and spatial configuration of ownership is lacking. In this research, we assess whether there is a set of ownership patterns, ownership sizes, or initial age class distributions that will be more highly affected by potential harvest scheduling constraints than others. This research represents one of the most extensive assessments of spatial harvest scheduling constraints ever performed for southeastern U.S. forest conditions and indicates that small landowners, and landowners with young age class distributions, will be most affected by a commonly used (but voluntary at this point) set of clearcut adjacency constraints (240 acre maximum clearcut, 2-year green-up). A meta heuristic, which includes threshold accepting, 1-opt tabu search, and 2-opt tabu search performed as well, or better, than threshold accepting and tabu search by themselves. The combination of search characteristics (speed, diversification, and intensification) show that forest plans developed with heuristics will benefit from multiple search strategies. Finally, we assessed whether a recent development (raindrop heuristic) would be of value in forest planning problems that include area restriction adjacency constraints. While the modified raindrop heuristic is computationally intensive, it requires only two parameters and can produce as good, or better solutions than threshold accepting or tabu search.

INDEX WORDS: Forest Planning, Harvest Scheduling, Heuristic

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A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2006

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August 2006

DEDICATION

To my parents, Guangrong Zhu and Ruying Gao, who supported my education.

To my mother-in-law, Yumin Wang, who encourages me.

To my wife, Xiongfei Wang who trusts and loves me.

To my daughter, Chichi Zhu, who makes the world so meaningful to me.

ACKNOWLEDGEMENTS

I am extremely thankful to my major professor, Dr. Pete Bettinger for his invaluable guidance and encouragement throughout my entire research and academic years. I have benefited tremendously from his expertise and his enormous support. Over the past year, he taught me how to choose a research topic, how to give a presentation, how to write a scientific paper. My appreciation for his mentorship goes beyond my words.

I would like to thank my committee members Dr. David Newman, Dr. Walter Potter and Dr. Michael Wimberly for serving in my committee and for their advice and guidance.

My sincere gratitude is extended to my mother and mother-in-law, who have been very supportive and encouraging.

Last but certainly not least, I wish to express my sincere thanks to my wife and my daughter for their love and support.

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CHAPTER 1

INTRODUCTION

The use and evaluation of spatial harvest scheduling techniques has increased in recent years due to a variety of reasons, such as the need to develop forest plans that accommodate multiple and often conflicting management objectives (Bettinger and Chung 2004). The public worldwide are demanding sustainable forest harvesting practices that not only recognize economics, but also the preservation and maintenance of bio-diversity, aesthetic values, and public recreation areas. Long-term forest management scheduling allows all parties to determine whether sustainable forestry is actually being practiced. Federal and state regulations and polices have resulted in increasingly complex objectives for the management of forests in the United States (Bettinger and Sessions 2003). In many areas of the world, compliance with regulatory restrictions, voluntary forest certification programs, and organizational goals and policies related to landscape conditions are now important as economic objectives. These and other factors have significantly increased the complexity of harvest scheduling problems. Therefore finding efficient algorithms to assist with optimization and harvest scheduling is becoming a very practical and import issue.

An optimization process seeks to maximize certain economical and ecological objectives subject to various constraints when assigning forest management actions to management units over a period of time, in a given forest area. There are two general classes of forest harvest scheduling optimization algorithms. One is based on mathematical programming techniques and the other on heuristics. The first uses exact algorithms, which include linear programming, mixed integer programming, and integer programming (Bevers and Hof 1999, Hof et al. 1994, Hof and Joyce 1992), and dynamic programming (Synder and ReVelle 1997, Hoganson and Borges 1998). The appeal of exact algorithms is that the optimal solution to a problem (if found) will be located. To complicate matters, spatial harvest scheduling requires the use of integer decision variables. And, as a problem size increases (i.e. number of decision variables), solving a management problem may become computationally impractical (Lockwood and Moore 1993), and perhaps impossible, if integer variables are used. For example, integer programming has historically been capable of solving modest-sized problems (Jones et al. 1991). Although technology continues to advance and computers are becoming faster, the use of exact algorithms remains limited in application to small and medium-sized problems.

The second optimization method uses heuristics, such as Monte Carlo simulation (Nelson and Brodie 1990), simulated annealing (Dahlin and Sallnas 1993, Lockwood and Moore 1993, Murray and Church 1995), threshold accepting (Bettinger et al. 2003), tabu search (Bettinger et al. 1997), and genetic algorithms (Glover et al. 1995, Falcão and Borges 2001). Although heuristics can not guarantee that they can locate a global optimum solution, they can usually find good solutions to complex planning problems, making them attractive for large spatial forest planning problems.

The former method is a global procedure attempting to locate an optimal solution of the forest management model. The latter method is usually a local search process, which iteratively changes a solution without any guarantee of finding an optimal solution. A more detailed examination of mathematical approach and heuristic approaches follows.

1.1 Mathematical programming

The general forest planning problem, where harvesting is an important process, has been studied for some time. Linear programming is one of the most commonly used techniques in natural resources management. The LP-based models have been used from the 1960s, and are classic in the sense that they use the solution to linear equations to allocate resources and activities to timber stands, and to a limited extent, recognize spatial relationships.

Since LP models generally assume continuous variables are used, the solution is non-integral. Recognition of spatial features in forest planning generally requires the use of integer-decision variables, thus spatial relationships, other than management area are usually not defined in the LP model. When integer decision variables are used, the problem size of forest planning increases, the potential solution space also increases, but at a disproportionately greater rate (Lockwood and Moore, 1993). Consequently, LP-based formulations are not suitable for solving spatial harvest problem with integer decision variables, because the solutions are difficult to interpret and may be impossible to implement.

LP models make three broad assumptions. First, the linearity assumption suggests that when one unit (X1) accounts for a change of $100 in the objective function, two units of X1 will account for $200 change in the objective function. In addition, no interactions are allowed. Therefore if one unit of X1 accounts for $100, and one unit of X2 accounts for $200, together, they account for $300 in the objective function. The second LP assumption is that all variables have a value greater than or equal to zero and these can be either continuous numbers or integers, but not constrained to result in integers. The third general assumption is that the coefficients of each decision variable are known with certainty, although same work (e.g. Hof et al. 1988) has been presented to address randomness in yield coefficients.

Since LP-based models are not able to practically express spatial relationships, researchers began to study and apply mixed integer programming (MIP) models (Jones et al., 1991). An integer decision variable is often used to express a particular harvesting decision. This allows a planning model to adequately express spatial relationships such as adjacency constraints. MIP and integer programming techniques have been used to help solve contemporary management problems and generate feasible management plans. But since the MIP model uses a large number of integer variables, it is restricted to small-sized problems and theses techniques have substantive limitations when applied to large landscape (Lockwood and Moore 1993).

To explore the capability of traditional techniques, Hof and Joyce (1992) described nonlinear formulations aimed at accounting for the amount of edge, the juxtaposition of different habitat types, the dispersal distance among habitat types and the minimum size of a patch of habitat. Hof et al. (1994) also described a mixed integer programming approach that incorporates probabilistic objective functions for wildlife viability concerns and provide valuable insight into a much border range of capabilities of linear, integer and nonlinear programming methods. The limitation of these techniques persists, however, and both heuristics and simulation models are now being explored as possible alternatives.

1.2 Heuristic optimization

Heuristics are becoming more prevalent for solving harvest scheduling problems, especially when the problems involve large potential solution spaces or adjacency constraints. As mentioned earlier, there have been numerous studies exploring the use of heuristic optimization techniques to solve harvest scheduling problems. Many types of complex, nonlinear goals (e.g.

spatial and temporal distribution of elk habitat, as described in Bettinger et al. 1997), which have traditionally been considered impossible to solve with exact algorithms, are now being incorporated into heuristics. And heuristics are not confined to the three broad consumptions associated with linear programming. In addition to forest management problems, heuristics have been used to solve forest transportation problems (Murry and Church 1995), wildlife conservation and management problems (Arthaud and Rose 1996, Bettinger et al. 1997, Haight and Travis 1997), aquatic system management problem (Bettinger et al. 1998), and the problems that address biodiversity (Kangas and Pukkala 1996). The most popular heuristics used in natural resource management include Monte Carlo simulation (MC), tabu search (TS), simulated annealing (SA), threshold accepting (TA), and genetic algorithm (GA). Some efforts are also being made to integrate aspects of each into hybrid heuristic techniques.

Although using heuristics does not guarantee one will locate a global optimum solution to a scheduling problem, one can be confident that a good heuristic will generate feasible solutions to complex problems in a reasonable amount of time. Heuristics have been extensively applied in scheduling problems in the past few decades beginning with MC. Nelson and Brodie (1990) were among the first to apply a MC heuristic to solve an area-based forest planning problem. It was a biased sampling scheme that generated feasible solution alternatives, thus the greater the number of samples, the better the solution. Therefore, with this technique, optimal or near optimal solutions may only be possible if very large number of samples are generated. Unfortunately, large samples significantly increase the time required to find a solution.

Simulated annealing (SA) is a stochastic optimization technique that has been successfully used to solve combinatorial optimization problems (Kirkpatrick 1984). It is a search technique that began to be widely used during early 1980s in the operation research field

(Dowsland 1993). The foundations of SA were first published by Metropolis et al. (1953) in a scheduling algorithm that simulated the cooling of materials in a heat bath - a process known as annealing. The SA technique is a form of a Monte Carlo method that uses a localized search process, where a subset of solutions is explored by moving from one solution to a neighboring solution with a simple change of a characteristic of single-decision variable, such as timing of harvest of a management unit. Lockwood and Moore (1993) used simulated annealing to generate harvest schedules with spatial constraints and solved a large harvest scheduling problem with adjacency constraints.

Threshold accepting (TA) is similar to SA, and was introduced by Dueck and Scheuer (1990). The TA technique also uses a localized search process, but uses a slightly different and somewhat simpler set of acceptance rules for a new solution than SA. Threshold accepting accepts every new solution that is not much worse than previous solution within a preset limit of the value of current solution, whereas in SA the probability that a lower quality proposed solution would replace the current solution is a function of the quality of a solution and a stochastic element.

Tabu search (TS) has been successfully applied to a number of scheduling problems outside of forestry and wildlife management, such as those involving telecommunication, transportation, shop sequencing, machine scheduling, and layout and circuit design problems (Glover 1990). Within forestry it has been applied to timber harvest scheduling problems with adjacency constraints (Murray and Church 1995), goals for elk (Bettinger et al. 1997), and for aquatic habitat (Bettinger et al. 1998). Tabu search with 1-opt moves (changing the harvest timing of a single management unit), short-term memory, and aspiration criteria is a good scheduling technique, but generally not as good as SA or TA (Bettinger et al. 2002). Using 2-opt and greater moves have allowed TS to produce results as good as SA or TA, but at a fairly large computing cost (Bettinger et al. 2002). One advantage of TS is that it is well suited to parallel processing.

Genetic algorithms (GA) were developed initially by Holland (1975) in the 1970s. Diverse fields such as music generation, genetic synthesis, strategic planning, and machine learning have benefited from application of GAs to the scheduling of resources (Srinivas and Patnaik 1994). The GAs has been applied to a limited extent in forestry (Falcão and Borges 2000, Lu and Eriksson 2000, Mullen and Butler 1999). A hybrid GA/TS heuristic technique that utilizes 1-opt and 2-opt TS process as well as a GA crossover process (Boston and Bettinger 2002) also has shown promise for developing moderately complex forest plans.

1.3 Summary

Researchers have been working in the area of spatial harvest scheduling for about 15 years. Most of the research so far has been observational: Comparing one or more algorithms to one problem or assessing one algorithm's performance on a small set of problems. Recent attempts (e.g. Bettinger et al. 2002, Heininen and Pukkala 2004) have been made to compare the performance of several algorithms on increasingly difficult forest planning problems, but applications of these assessments to southeastern U.S are lacking. In addition, there exists a gap in the knowledge base, where no one has examined the impact of spatial constraints on landowners of different sizes or different forest conditions.

In this research I 1) Develop a set of standard harvest scheduling problems of various sizes, ownership patterns, and age class distributions; and 2) Apply heuristics to these standard problems and compare the performance. In the end, I will provide the databases I developed to the public to allow others to compare their results to those found here. The algorithms developed here will be coded in Microsoft .NET platform and will be distributed for researchers to make comparison.

In this research, two main questions will be addressed.

1. *Is there a set of ownership pattern, size, and age class distributions that will be more highly affected by potential harvest scheduling constraints than others?*

Although there are no laws regarding the maximum size of clearcuts on private land in the southeastern U.S., these laws do exist in western U.S. states. Therefore, examining the potential impact of similar management constraints in the southeastern U.S. seems like a plausible idea. This represents a new contribution to the science. A maximum clearcut size of 240 ac will be examined along with a green-up period of 2 years. These are typical assumptions for companies adhering to the Sustainable Forestry Initiative (AF & PA 2004). The null hypothesis is that all combinations of ownership pattern, size, and age class distribution will be affected in a similar manner. A statistical test, such as an analysis of variance, will be used to determine whether statistically significant differences exist and thus reject the null hypothesis.

2. *When implemented in their most basic form, do any of the heuristics perform better than others*?

One key question asked of heuristic harvest scheduling models regards the quality of results. Another regards the computational efficiency. Since these forest planning models will be quite large, with 2,000 to 200,000 integer variable needed, solving the problems exactly with integer programming will be difficult (if not impossible). Methods for estimating the global optimum solution are possible (Bettinger et al. 1998). However, statistical tests aimed at discerning statistically significant differences among the heuristics (when applied to each scheduled problem) will be used to assess the quality of results. These tests, along with statistics regarding average solution time, will allow me to reach conclusions about the computational efficiency of each technique and to determine whether to reject the null hypothesis: All of the heuristics when implemented in their basic form, perform similarly to harvest scheduling problems with area restriction adjacency constraints.

Similarly, the combination of techniques will be explored to some extent to determine whether meta heuristic approach is needed when developing forest plan with spatial constraints. The assessment of heuristic techniques (both basic forms and meta heuristics) will add to the science base and when applied to the 27 problems developed here and set a standard against which others can judge the performance of alternative planning techniques. In addition to this work, a new heuristic has recently been introduced, called the raindrop method (Bettinger and Zhu, 2006). This heuristic was found to be superior to others in a limited set of circumstances. I will attempt to formulate the heuristic to solve the same problem presented in earlier chapters, and comment on its performance and usefulness in a more complex planning situation than what was demonstrated in the initial research of Bettinger and Zhu (2006).

The simulation process of the 27 GIS databases and description of the model is presented in Chapter 2. In chapter 3, a comparison is presented of the results of applying threshold accepting, 1-opt tabu search, and a meta heuristic which consists of threshold accepting, 1-opt tabu search, and 2-opt tabu search to solve the harvest scheduling problems for the 27 GIS databases. In chapter 4, I will evaluate the null hypothesis "Is there a set of ownership pattern, size, and age class distributions that will be more highly affected by potential harvest scheduling constraints than others?" by using ANOVA analysis and other descriptive statistics. In Chapter

5, a new heuristic, a modified raindrop effect algorithm will be applied to 9 of the 27 databases, and the results will be compared to the results from threshold accepting and 1-opt tabu search.

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CHAPTER 2

METHODS

This chapter is intended to provide a detailed look at the problem formulation, and the database development processes that are not provided in subsequent chapters. Since this work uses the "manuscript option" for doctorial dissertations, subsequent chapters will not contain the detail necessary for readers to fully understand how this data was developed.

2.1 Forest planning model formulation

The forest planning problem that I investigated falls between strategic planning (long time frames, large area) and operational planning (short time frames, specific areas) in an area termed "tactical planning." The level of detail used in this research is generally greater than those used in strategic planning analyses, yet significantly lower than what is required for operational planning. The time horizon assumed is 20 years and each planning period will be one year long. This tactical planning model attempts to maximize the net present value of timber harvested. The objective function is formulated as:

Maximize:

$$\sum_{t=1}^{T}\left[\sum_{i}^{N}(V_{it}X_{it}(P-C_{it}))/1.06^{(t-0.5)}\right]+\sum_{i}^{N}(V_{i20}(P-C_{it}))/1.06^{19.5} \qquad (1)$$

Subject to:

$$\sum_{t=1}^{T} X_{it} \leq 1 \qquad \forall i \tag{2}$$

$$X_{it}A_i + \sum_{z \in N_i \cup S_i} X_{zt} A_z \leq \text{MCA} \qquad \forall_{i,\,t} \tag{3}$$

$$\sum_{i=1}^{n} V_{i20} - \sum_{i=1}^{n} \sum_{t=1}^{20} X_{it} V_{i20} > 0.9 * \sum_{i=1}^{n} V_{i1} \tag{4}$$

$$AG_c\text{-}AG_{t1}>5 \tag{5}$$

$$AG_c\text{-}AG_{t2}>5 \tag{6}$$

$$\sum_{i=1}^{n} X_{it} V_{it} > 0.9 * \sum_{i=1}^{n} \sum_{t=1}^{T} X_{it} V_{i20} / T \qquad \forall \text{ t} \tag{7}$$

$$\sum_{i=1}^{n} X_{it} V_{it} < 1.1 * \sum_{i=1}^{n} \sum_{t=1}^{T} X_{it} V_{i20} / T \qquad \forall \text{ t} \tag{8}$$

$$\sum_{i=1}^{n} X_{it} V_{it} > 0.9 * \sum_{i=1}^{n} X_{it-1} V_{it-1} \qquad \forall \text{ t} \geq 2 \tag{9}$$

$$\sum_{i=1}^{n} X_{it} V_{it} < 1.1 * \sum_{i=1}^{n} X_{it-1} V_{it-1} \qquad \forall \text{ t} \geq 2 \tag{10}$$

Where:

A_i= area of management unit *i*

AG_c=clear cut age

AG_{t1}=age when first thin happens

AG_{t2}=age when second thin happens

C_{it}= logging cost per m^3 for unit *i* harvested in time period *t*

Ht = the actual scheduled harvest volume in each time period *t*

i = a harvest unit

MCA=maximum clearcut area

N=the total number of harvest units

N_i=set of all units adjacent to unit i

P= stumpage price

S_i= the set of all management units adjacent to these management units adjacent to management unit i

t = a planning period

T = the total number of time periods in the planning horizon

V_{i20} = the unscheduled timber harvest volume at the end of period *20*, from management unit i

V_{it} = the available timber harvest volume during time period t, from management unit i

X_{it} = a binary variable, which =1 if management unit i is harvested in time period t, 0 otherwise

Equation 2 indicates that each management unit can only be harvested at most one time in all planning periods. Equation 3 ensures that the maximum clearcut size will be maintained (assuming the green-up period is 2 years). Equation 4 is an ending volume constraint. Equation 5 and 6 ensure that the separation period between thinning and clear cutting is at least six years. Equation 7 and 8 constrain the volume harvested in each time period to a proportion of the final, unscheduled and uncut volume. Equation 9 and 10 limit the deviation in harvest volume from one period to the next as a measure of harvest stability. This model formation represents a model I (Johnson and Scheurman 1977), integer programming problem. The adjacency restriction is the area restriction formulation (Murray 1999).

Standard problems used in this research are divided into three ownership size groups: small, medium and large (see Table 2.1), according to problem area acreage. Within each size class, three ownership patterns of parcels were developed: clumped, random, and dispersed.

Three age class distributions were then assigned to them: young forest, normal forest, older forest. Therefore a matrix of 27 hypothetical forests was available for analysis.

Table 2.1 Elements in harvest scheduling type databases

Size	Ownership pattern	Age class distribution
Small (1000-10,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older
Medium (10,001-20,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older
Large (20,001-100,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older

2.2 Geographic Information Systems (GIS) databases

GIS databases are integral to spatial harvest processes, as they provide the spatial relationships necessary to accommodate constraints such as those related to harvest adjacency or habitat blocks. Since I am attempting to more closely determine the impact of green-up and adjacency constraints on landowners of various sizes, spatial arrangements, and forest structures, our experimental polygons are based on an actual industrial forest land base with total area about 250,000 acres and total number of about 9,000 polygons. The forest land is located in southern part of United States. According to our design, we generated 9 GIS databases that are considered large, medium, small size and have a clumped, dispersed or random pattern. we at first visually inspected the spatial pattern, then we used an index we designed to quantitatively describe the pattern. The ownership pattern index we designated calculates the average distance of nearest *n* neighbors of a polygon (management units). The algorithms for computing this ownership pattern index are listed as following:

Step 1. Determine each centroid (P_i) for each polygon *i*.

Step 2. For each P_i, find the nearest *n* centriods, calculate distance between P_i and its nearest *n* centroids, then take average of the distances to get D_i.

Step 3. Take average of all D_is to arrive at the index.

Through trial and error, we attempted to develop large, medium, and small sized GIS databases with polygons where the ownership index was smallest under the clumped spatial distribution and largest under the dispersed spatial distribution. During this trial and error process, we manually adjusted the GIS databases by deleting and splitting polygons. The description of resulting 9 GIS databases can be found in Table 2.2.

Using the ownership pattern index, we calculated the average D_i, and report the minimum D_i for all samples when n=15, n=10, and n=5 in Table 2.3, 2.4, and 2.5. In each case, we can see that clumped pattern has the lowest ownership pattern index score, the random pattern has the highest, and the dispersed pattern falls between the two. Table 2.6 lists the average number of neighbors. The GIS maps of databases are shown in Figure 2.1 through Figure 2.9.

Table 2.2 Description of the nine main GIS databases

GIS Database	Number of units	Total area (acres)	Average polygon size (acres)	Standard error (acres)
Large, Clumped	2,946	70,546.3	26.7	27.8
Large, Dispersed	2,617	70,347.6	28.1	28.3
Large, Random	2,486	69,257.2	27.8	28.1
Medium, Clumped	516	14,090.5	28.2	27.8
Medium, Dispersed	477	14,383.6	30.1	28.7
Medium, Random	549	14,337.8	26.1	26.5
Small, Clumped	302	7,231.2	26.9	28.5
Small, Dispersed	279	7,269.1	26.7	27.1
Small, Random	308	7,220.8	23.4	25.1

Table 2.3 Average distance index of 15 neighbors

GIS Database	Index(m)	Minimum(m)	Maximum(m)
Large, Clumped	606.9	314.6	3,994.0
Large, Dispersed	1,515.3	290.8	10,765.3
Large, Random	1,003.7	337.4	12,839.0
Medium, Clumped	619.8	346.9	1,711.2
Medium, Dispersed	1,397.4	350.1	6,745.9
Medium, Random	1,001.4	434.7	3,847.8
Small, Clumped	591.6	339.4	1,082.9
Small, Dispersed	1,424.0	350.1	6,171.7
Small, Random	945.1	415.0	6,728.8

Table 2.4 Average distance index of 10 neighbors

GIS Database	Index(m)	Minimum(m)	Maximum(m)
Large, Clumped	499.1	230.7	3,448.0
Large, Dispersed	1,095.3	217.3	10,023.8
Large, Random	786.7	231.6	10,010.4
Medium, Clumped	511.5	267.8	1550.2
Medium, Dispersed	1,018.5	227.9	5,356.1
Medium, Random	774.4	328.8	3,169.8
Small, Clumped	486.0	252.3	878.3
Small, Dispersed	993.9	227.9	5,772.6
Small, Random	734.5	309.8	6,266.7

Table 2.5 Average distance index of 5 neighbors

GIS Database	Index(m)	Minimum(m)	Maximum(m)
Large, Clumped	368.4	116.6	2,151.2
Large, Dispersed	652.1	128.8	8,501.6
Large, Random	529.5	136.8	6,260.5
Medium, Clumped	379.7	158.9	1,243.6
Medium, Dispersed	630.1	140.5	3,878.6
Medium, Random	528.1	184.3	2,976.1
Small, Clumped	359.8	142.7	671.2
Small, Dispersed	608.8	140.5	4,843.3
Small, Random	489.0	206.0	5,699.1

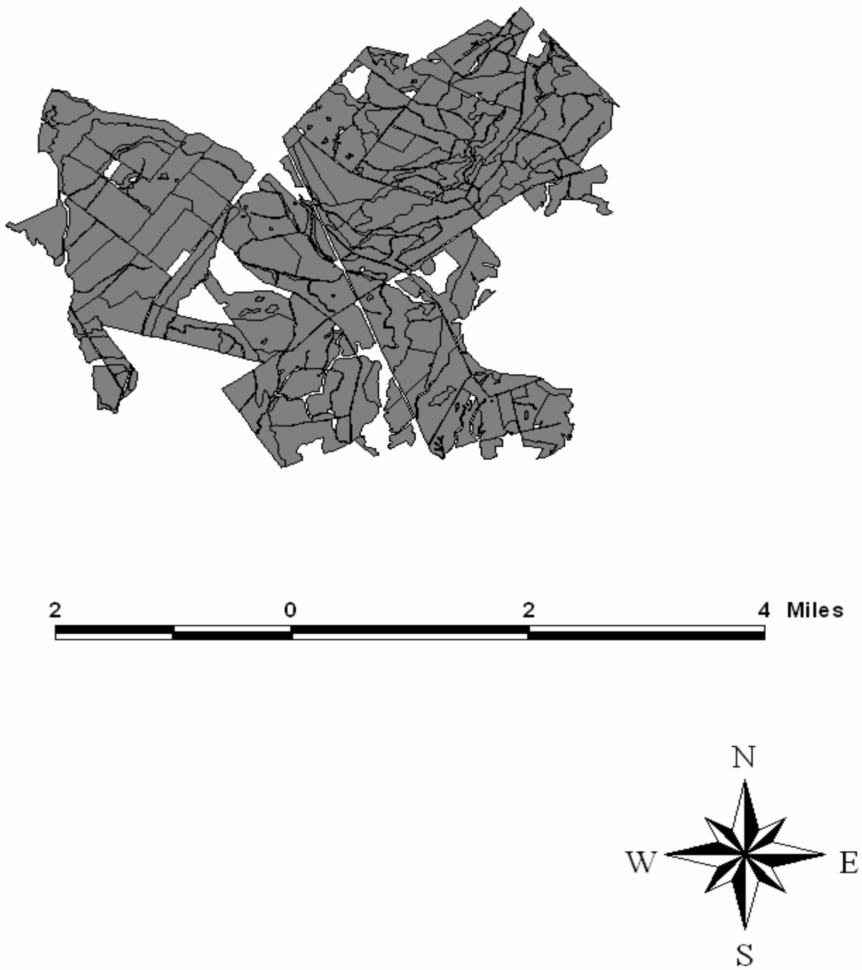

Figure 2.1 Small-sized, clumped spatial pattern

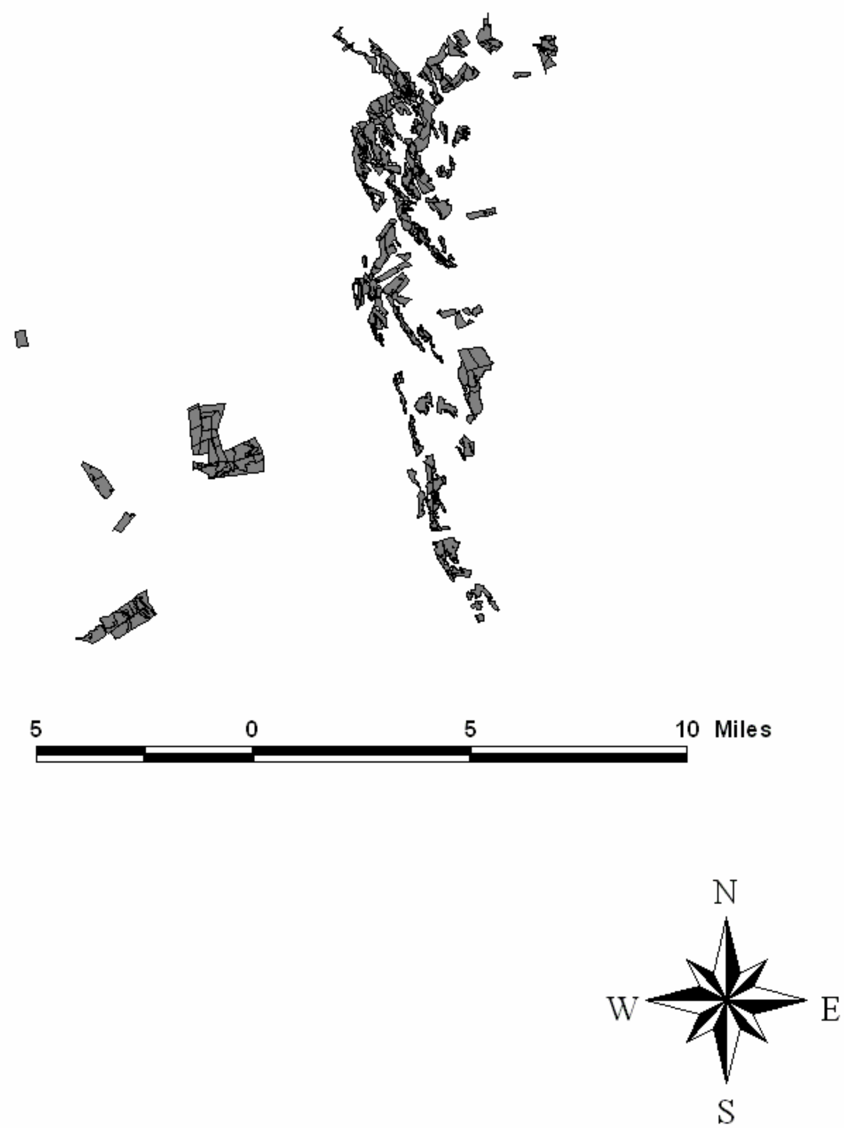

Figure 2.2 Small-sized, random spatial pattern

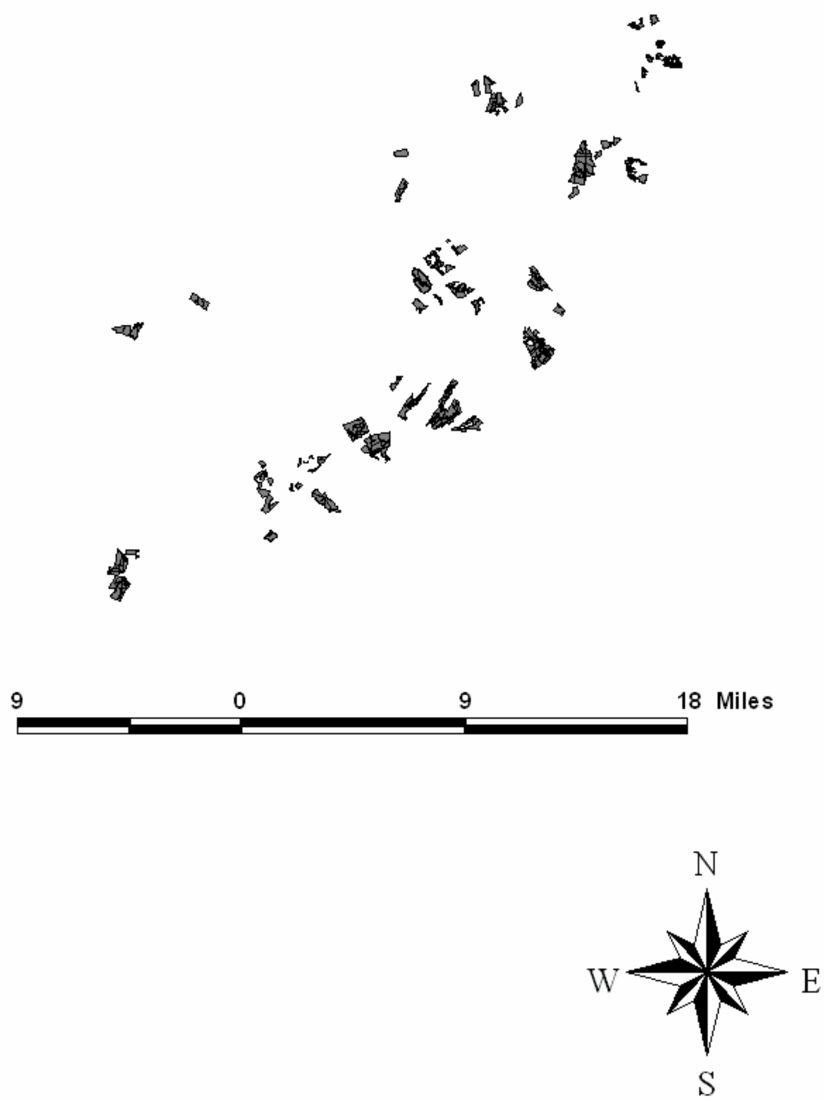

Figure 2.3 Small-sized, dispersed spatial pattern

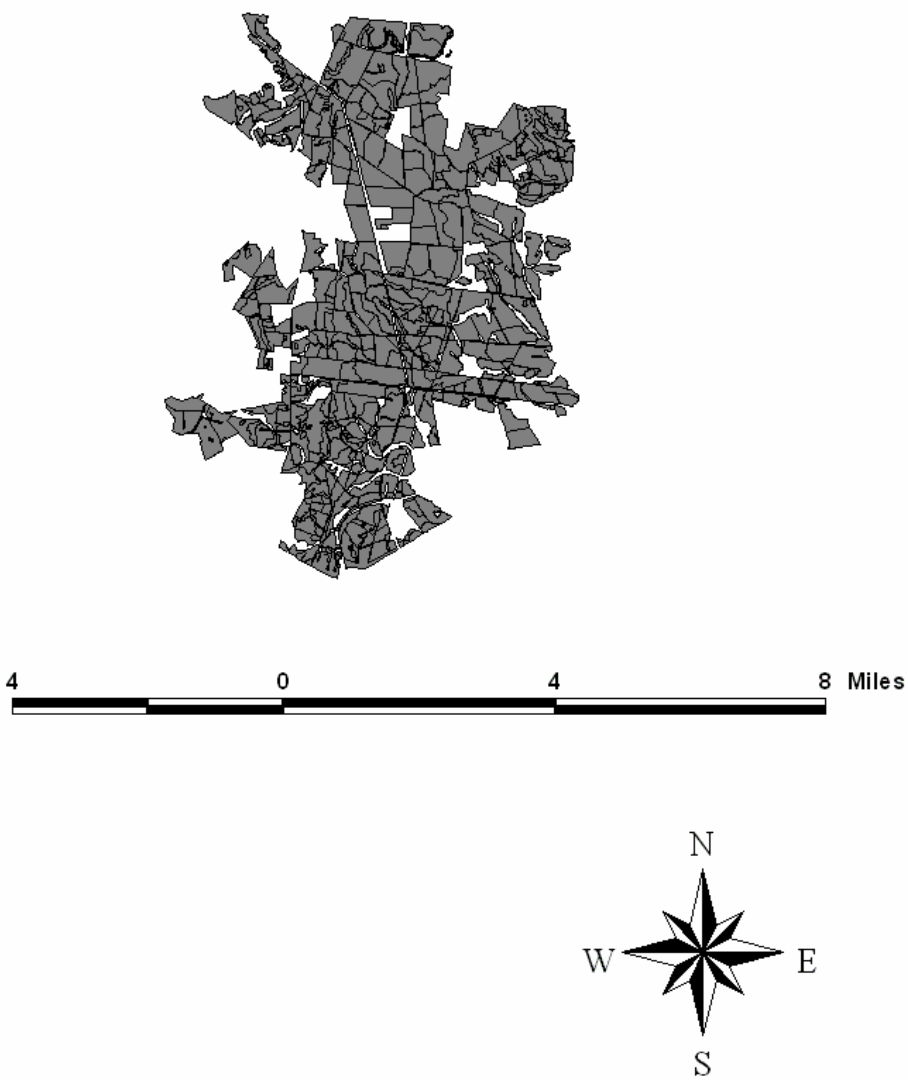

Figure 2.4 Medium-sized, clumped spatial pattern

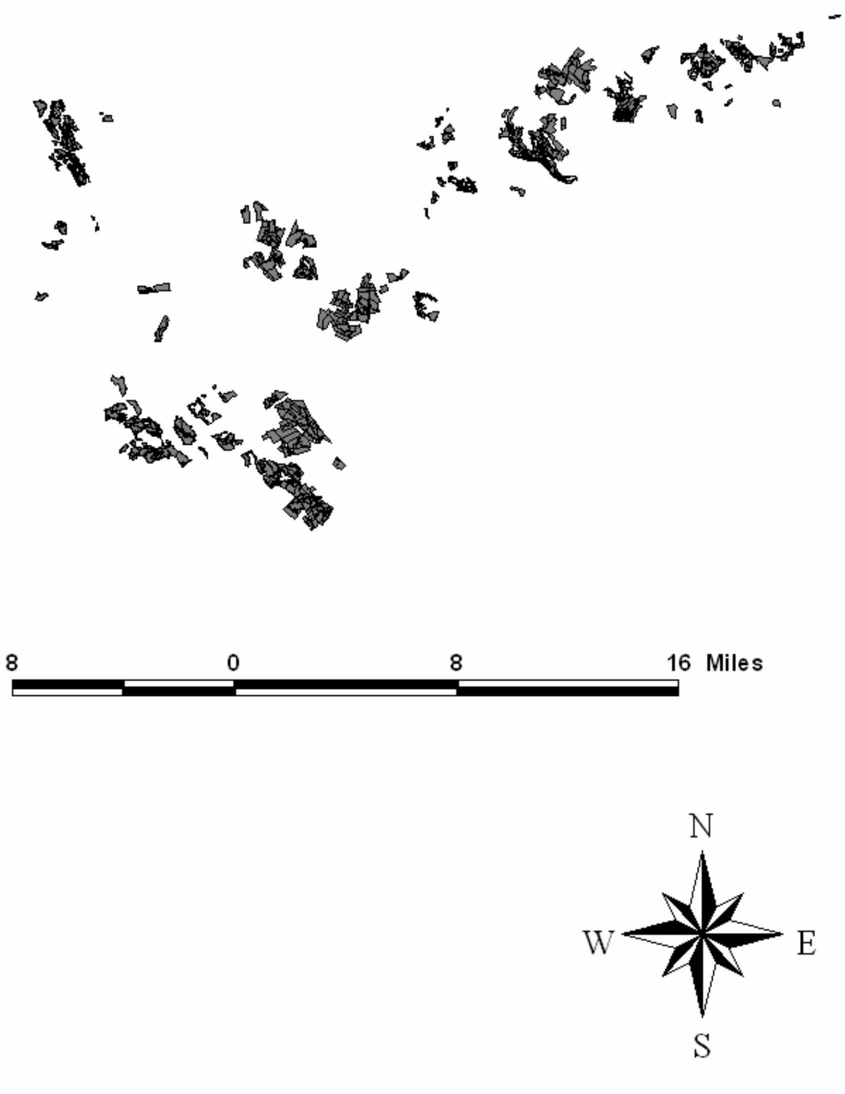

Figure 2.5 Medium-sized, random spatial pattern

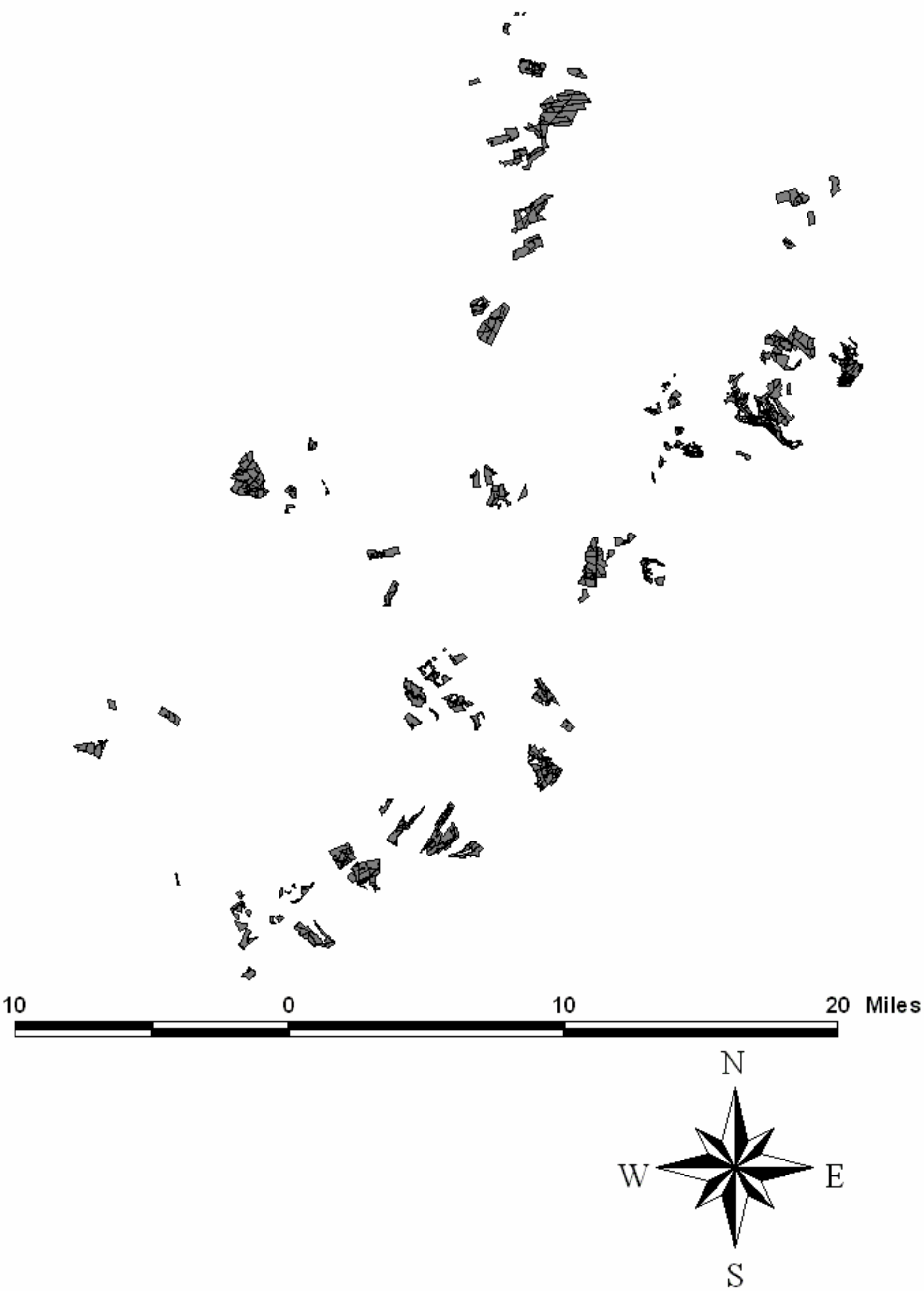

Figure 2.6 Medium-sized, dispersed spatial pattern

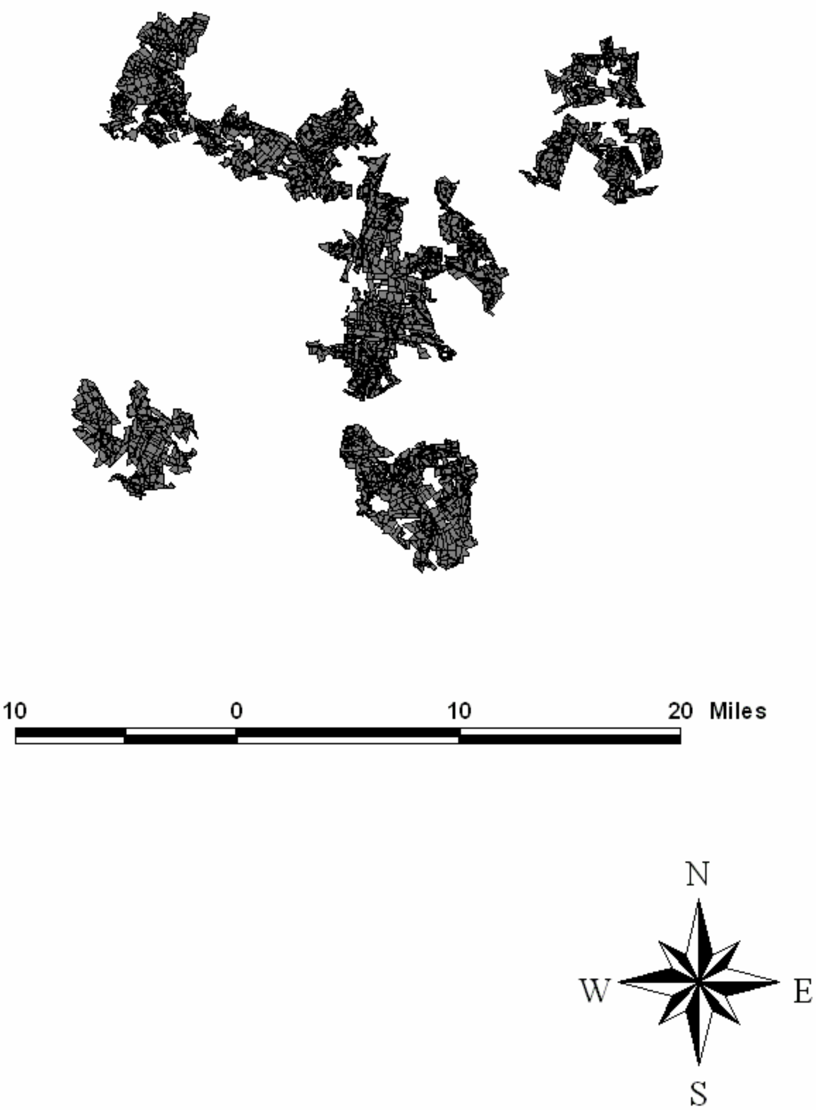

Figure 2.7 Large-sized, clumped spatial pattern

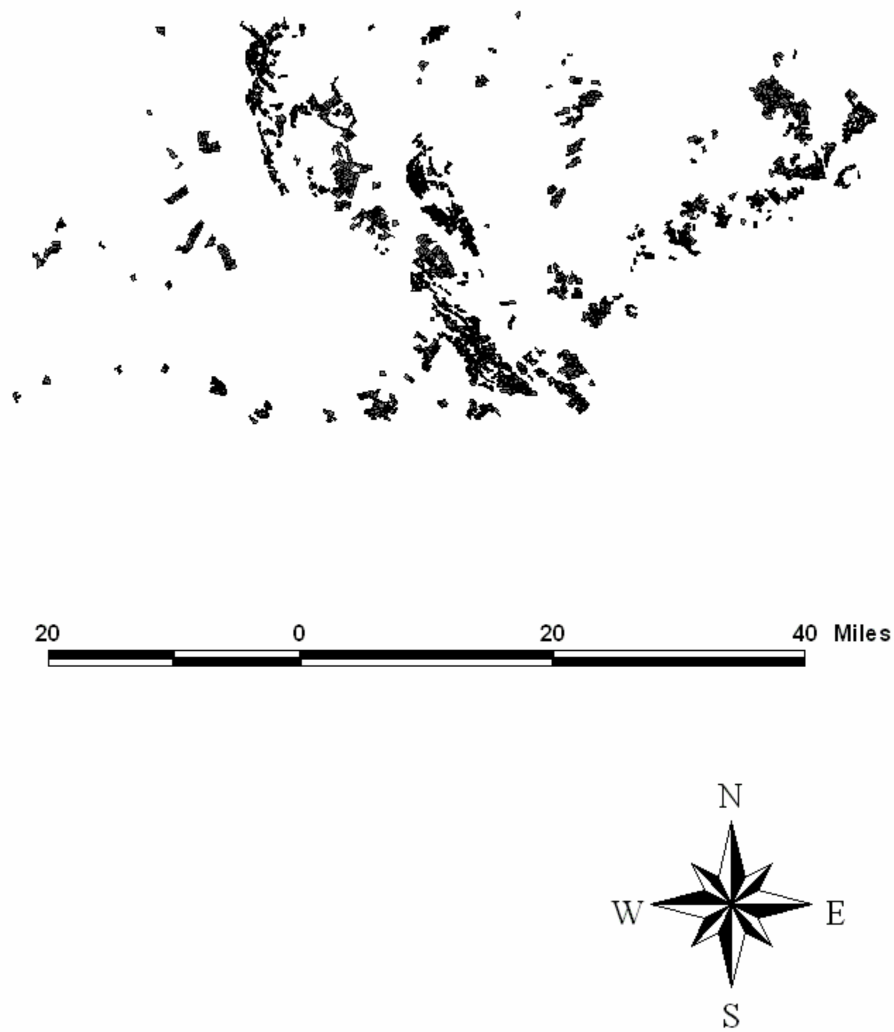

Figure 2.8 Large-sized, random spatial pattern

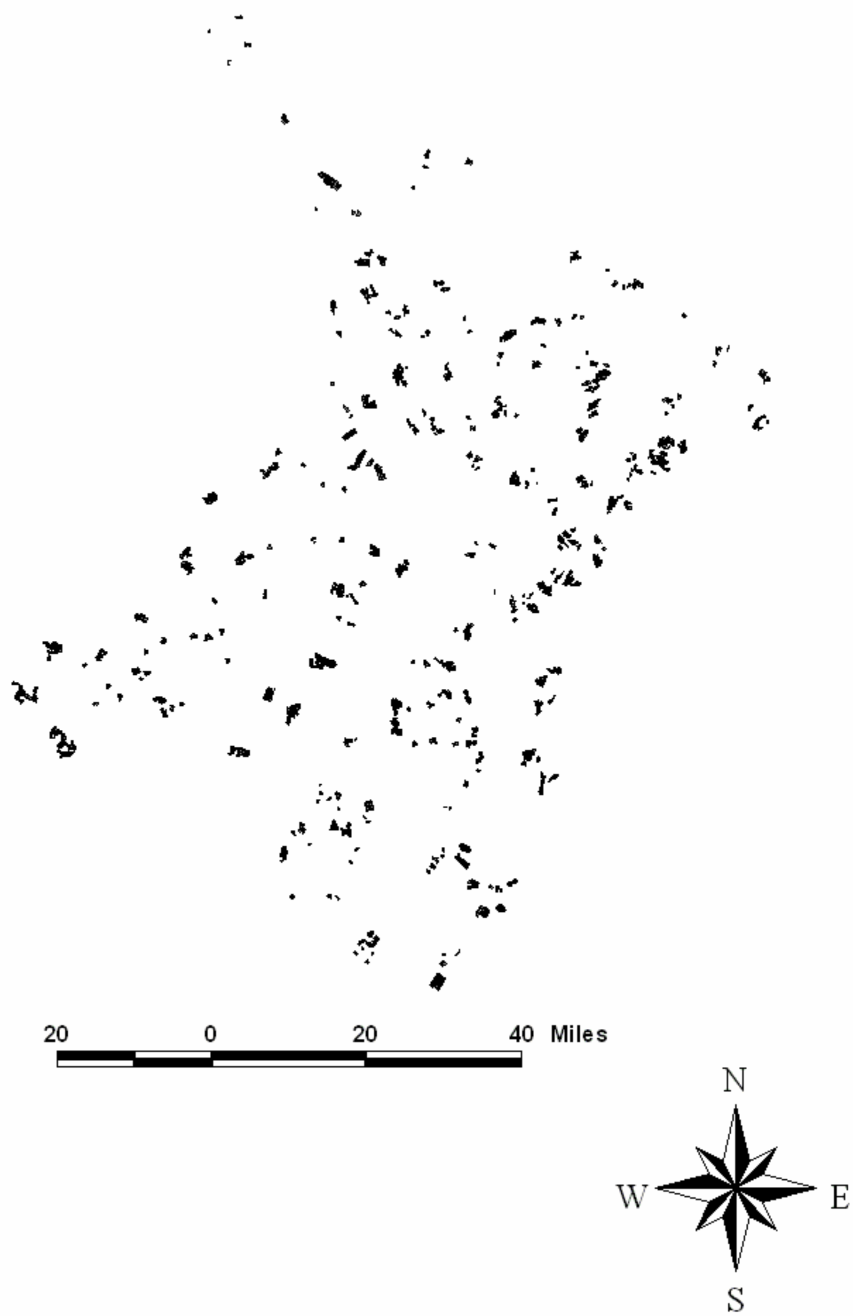

Figure 2.9 Large-sized, dispersed spatial pattern

2.3 Age class simulation

we simulated three age classes in the research, young, normal and old. In young age class, acreage of age 1 to 20 accounts for about 75% of total acreage. In normal age class distribution, each age in age 1 to 35 has very close distribution. In old age distribution acreage of age 16 to 35 represents 75% of total acreage (see Table 2.7, Table 2.8 and Table 2.9).

Based on the percentages in Tables 2.7, 2.8 and 2.9, we used the procedure in Figure 2.10 to simulate the age classes. The precondition for this simulation includes.

AGE: oldest age in the hypothetic forest

N: number of polygons in the hypothetic forest

Array *A[i]*: hold the predefined percentage of each age class. *i=1, 2 … AGE*.

Array *B[j]*: hold acreage of each polygon. *j=1, 2…N*.

After simulation we get the resulting Array *D[AGE]* which contains the age assigned to each polygon.

The age class distribution of different samples is shown in Figures 2.11 to Figure 2.37. One can see that, for normal age class distribution, the acreage has almost even distribution over all age (Figure 2.11 to Figure 2.19). For young age class distribution, the acreage has a trend to decrease as age increases. And for old age class distribution, the acreage has a trend to increase as age increases.

Table 2.6 Predefined age class distribution for young age group

Age	Percentage	Age	Percentage
1	0.056	21	0.025
2	0.054	22	0.024
3	0.050	23	0.022
4	0.046	24	0.023
5	0.048	25	0.020
6	0.044	26	0.017
7	0.043	27	0.021
8	0.040	28	0.018
9	0.038	29	0.016
10	0.037	30	0.014
11	0.035	31	0.013
12	0.036	32	0.012
13	0.034	33	0.011
14	0.030	34	0.009
15	0.030	35	0.005
16	0.028		
17	0.029		
18	0.026		
19	0.021		
20	0.025		
Total	0.750		0.250

Table 2.7 Predefined age distribution for regulated age class

Age	percentage	Age	percentage
1	0.029	21	0.028
2	0.029	22	0.028
3	0.029	23	0.028
4	0.029	24	0.028
5	0.029	25	0.028
6	0.029	26	0.028
7	0.029	27	0.028
8	0.029	28	0.028
9	0.029	29	0.028
10	0.029	30	0.028
11	0.029	31	0.028
12	0.029	32	0.028
13	0.029	33	0.028
14	0.029	34	0.028
15	0.029	35	0.028
16	0.029		
17	0.029		
18	0.029		
19	0.029		
20	0.029		
Total	0.580		0.420

Table 2.8 Predefined age class distribution for old age class

Age	percentage	Age	percentage
1	0.010	16	0.025
2	0.009	17	0.021
3	0.012	18	0.026
4	0.012	19	0.029
5	0.013	20	0.028
6	0.014	21	0.030
7	0.016	22	0.033
8	0.018	23	0.034
9	0.019	24	0.038
10	0.017	25	0.040
11	0.020	26	0.044
12	0.023	27	0.048
13	0.022	28	0.050
14	0.020	29	0.052
15	0.025	30	0.054
		31	0.048
		32	0.046
		33	0.042
		34	0.036
		35	0.026
Total	0.25		0.75

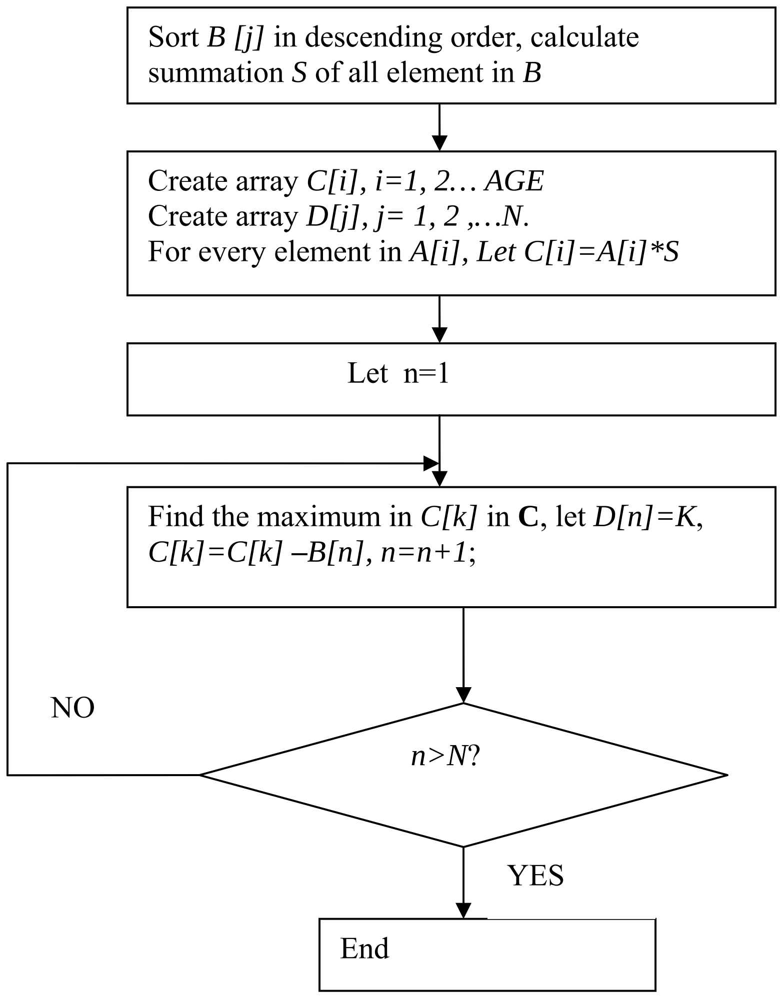

Figure 2.10 Flow chart for age class distribution simulation

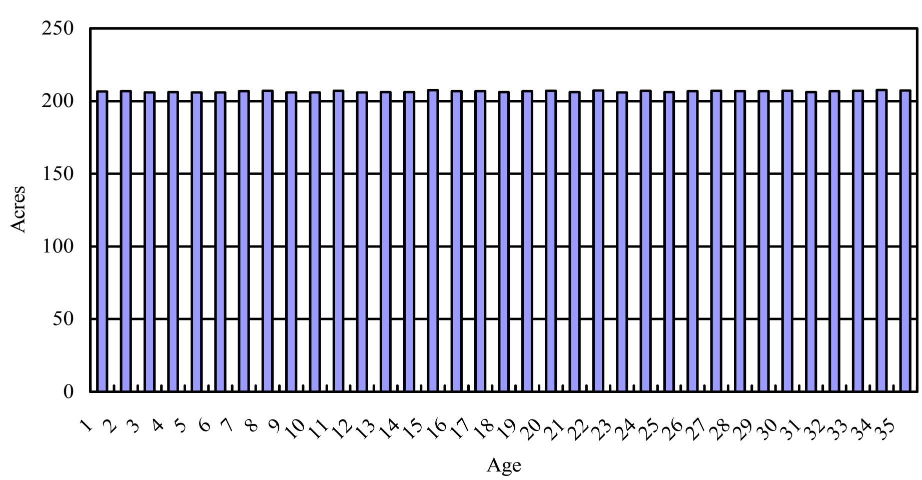

Figure 2.11 Small-sized, clumped, normal age class distribution

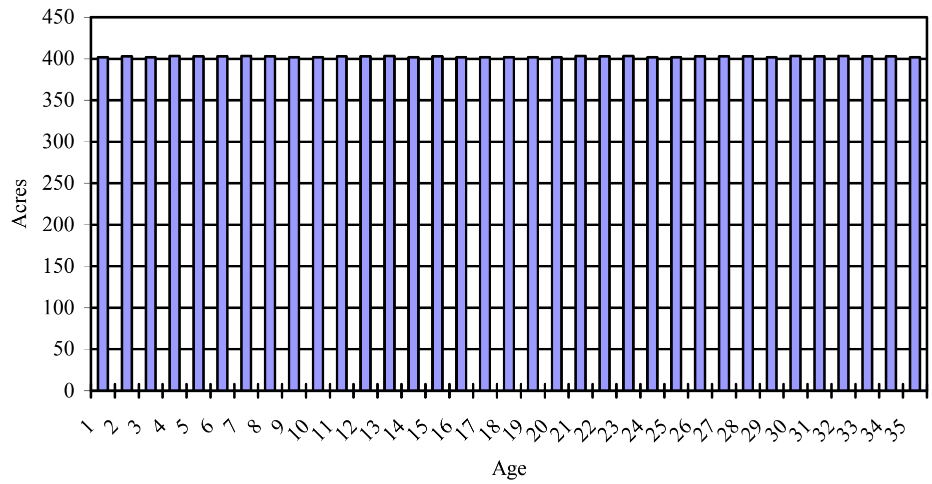

Figure 2.12 Medium-sized, clumped, normal age class distribution

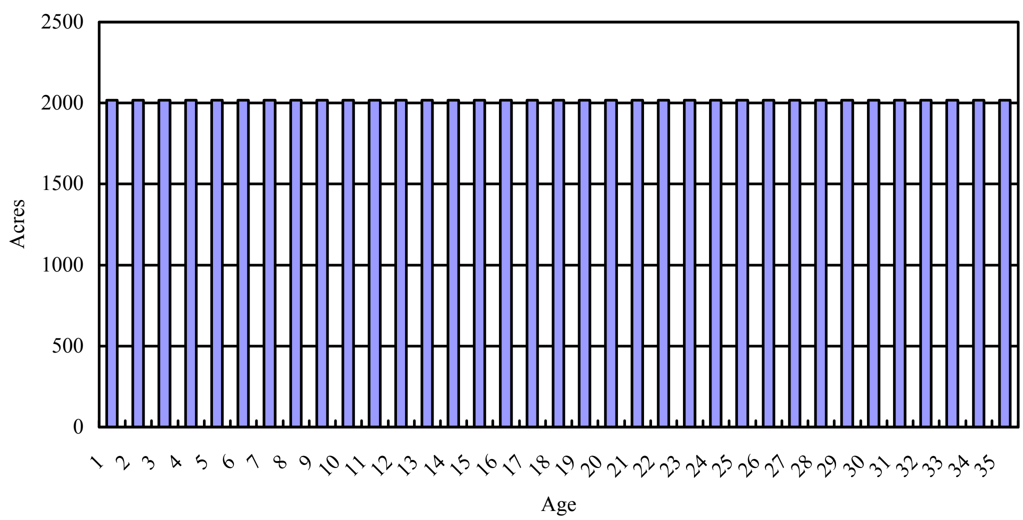

Figure 2.13 Large-sized, clumped, normal age class distribution

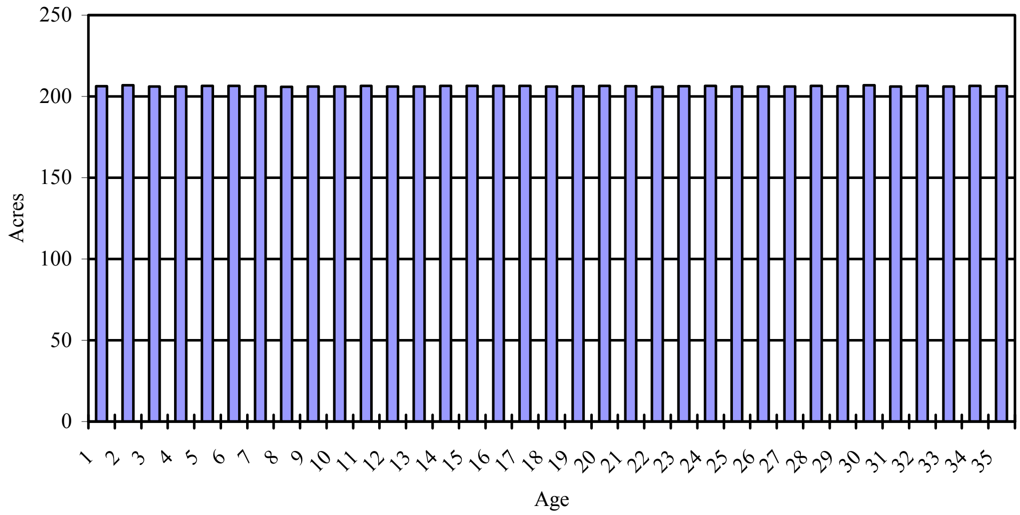

Figure 2.14 Small-sized, random, normal age class distribution

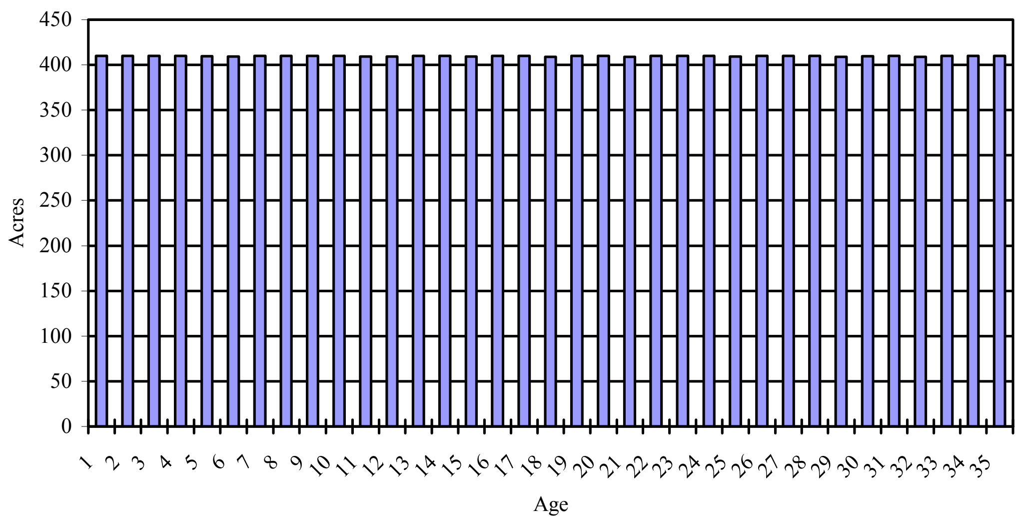

Figure 2.15 Medium-sized, random, normal age class distribution

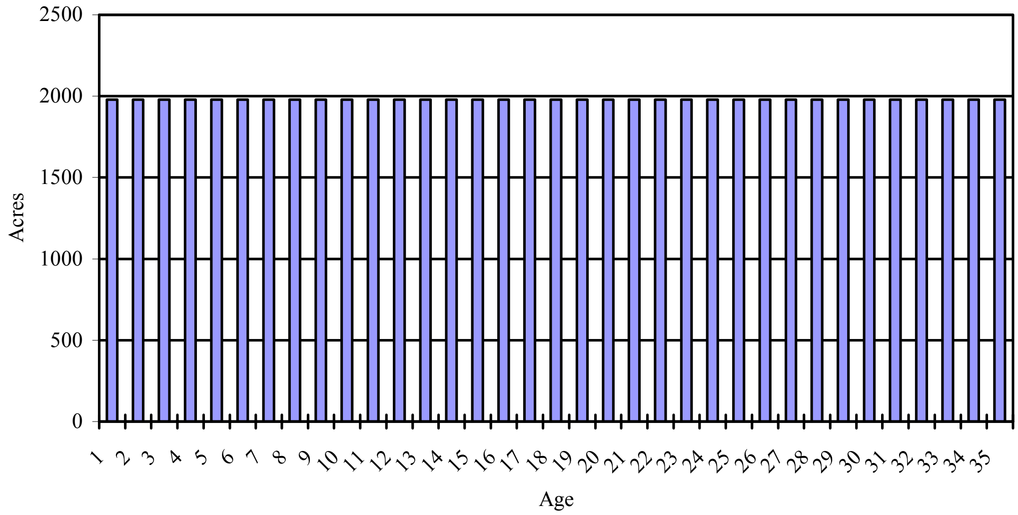

Figure 2.16 Large-sized, random, normal age class distribution

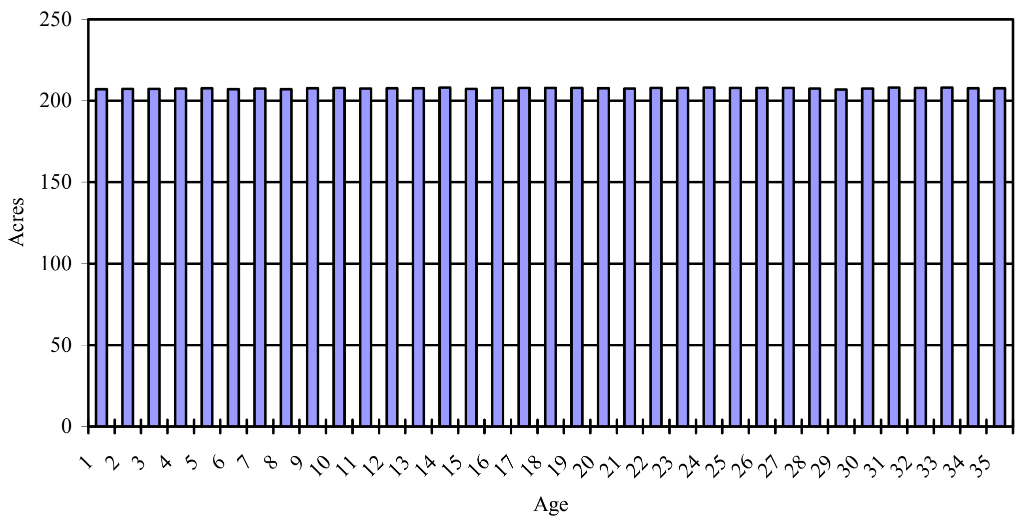

Figure 2.17 Small-sized, dispersed, normal age class distribution

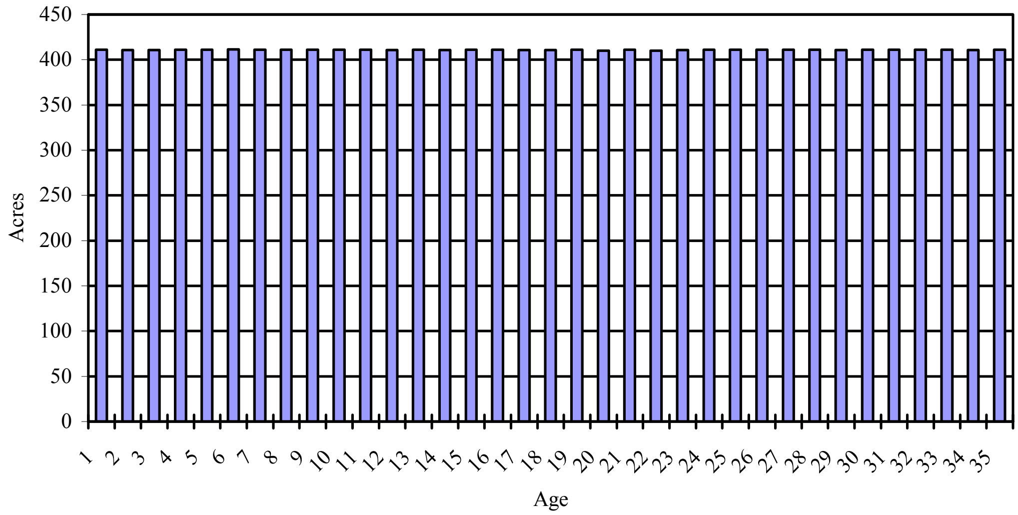

Figure 2.18 Medium-sized, dispersed, normal age class distribution

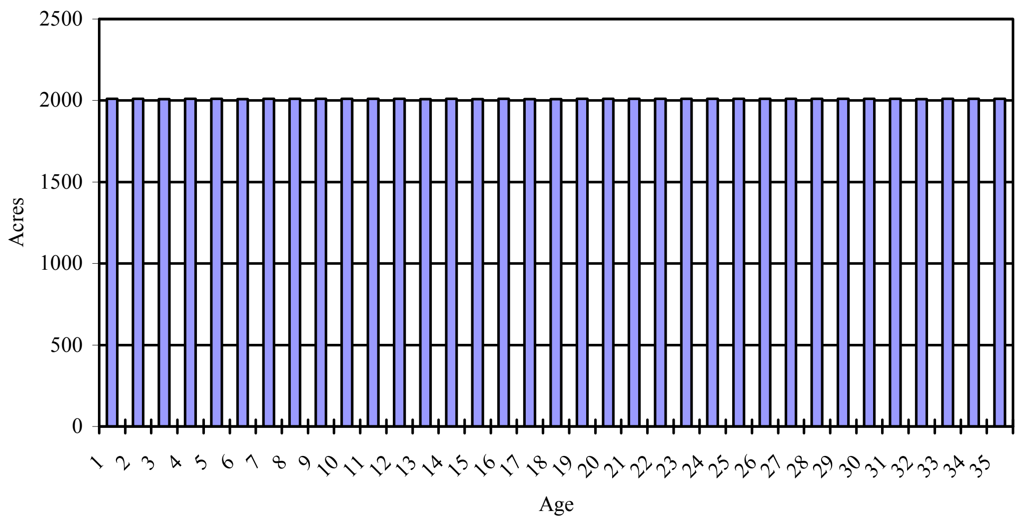

Figure 2.19 Large-sized, dispersed, normal age class distribution

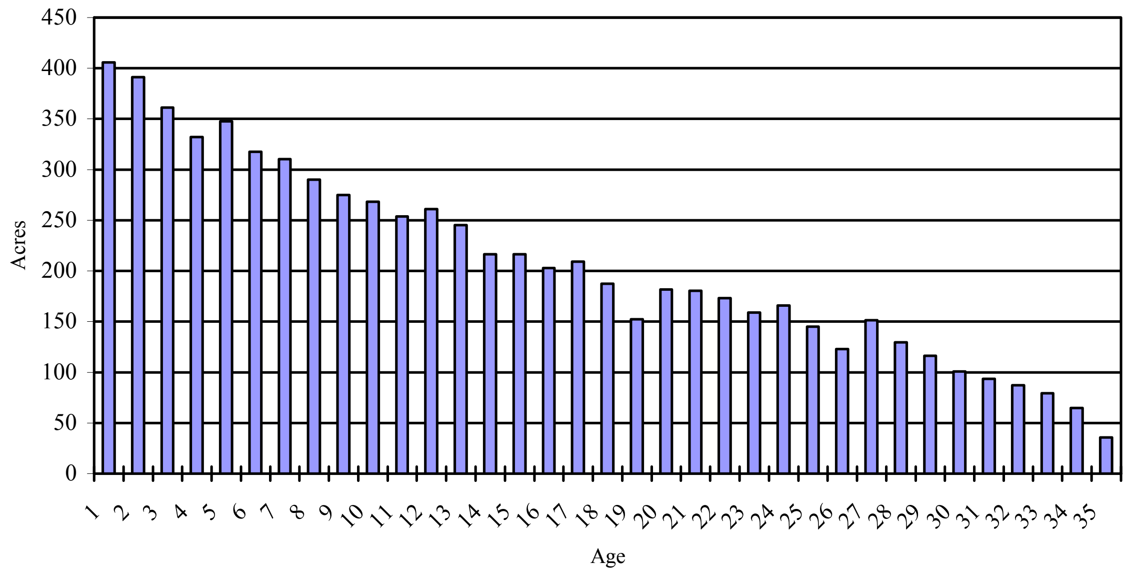

Figure 2.20 Small-sized, clumped, young age class distribution

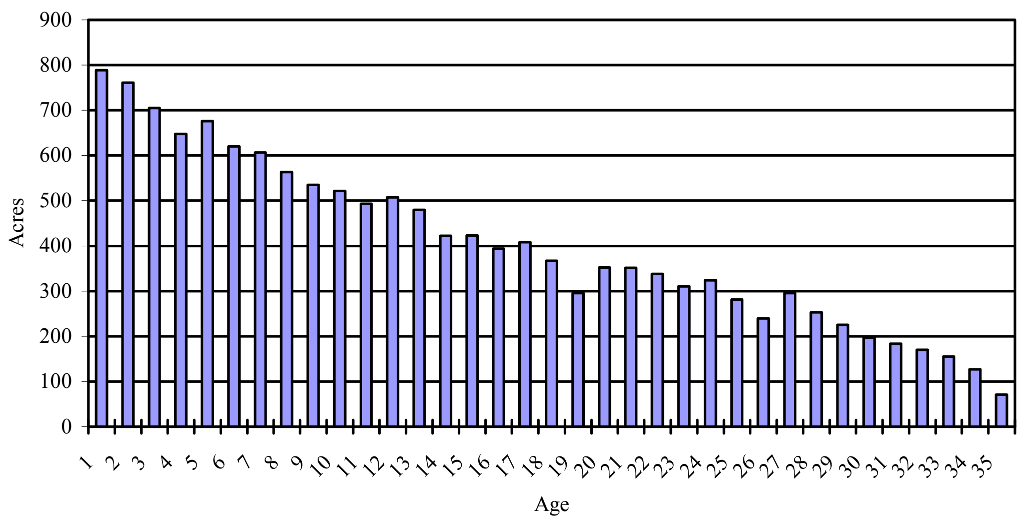

Figure 2.21 Medium-sized, clumped, young age class distribution

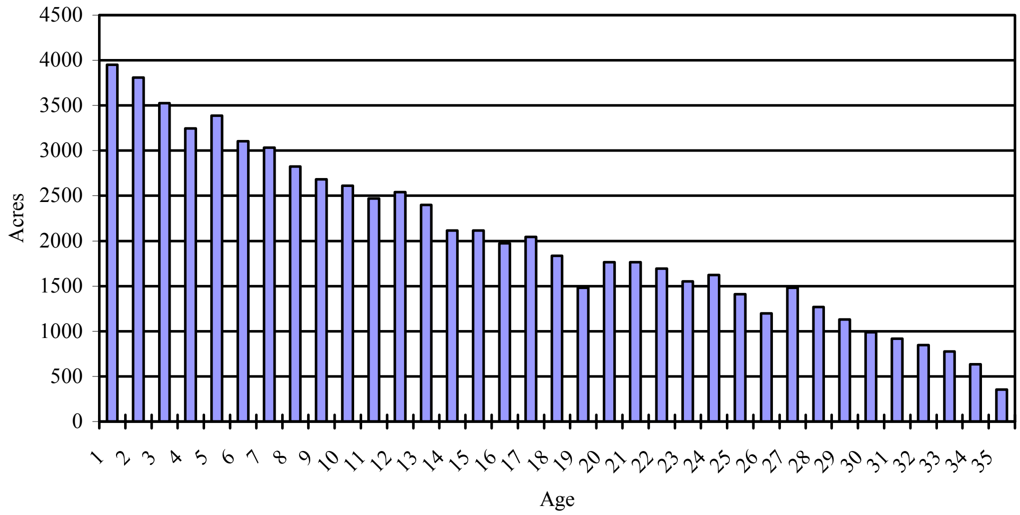

Figure 2.22 Large-sized, clumped, young age class distribution

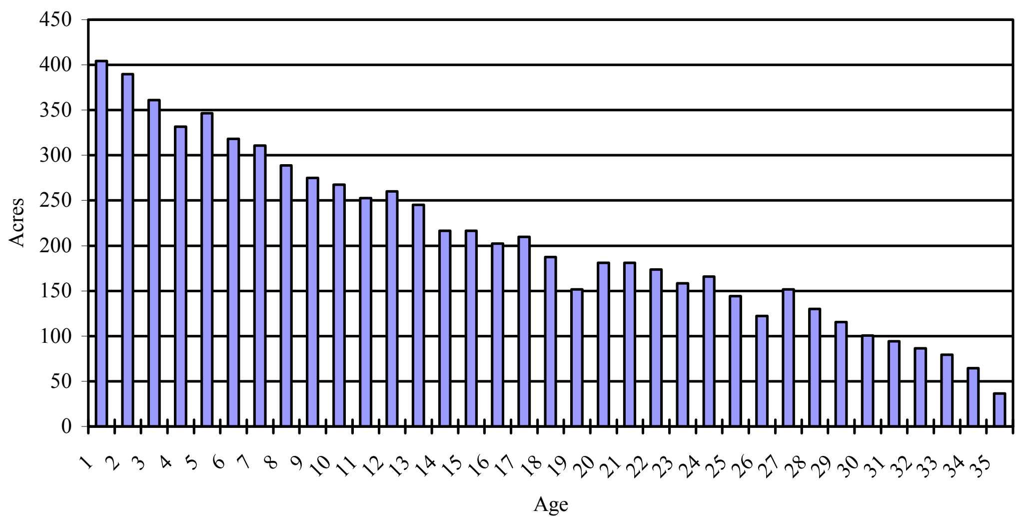

Figure 2.23 Small-sized, random, young age class distribution

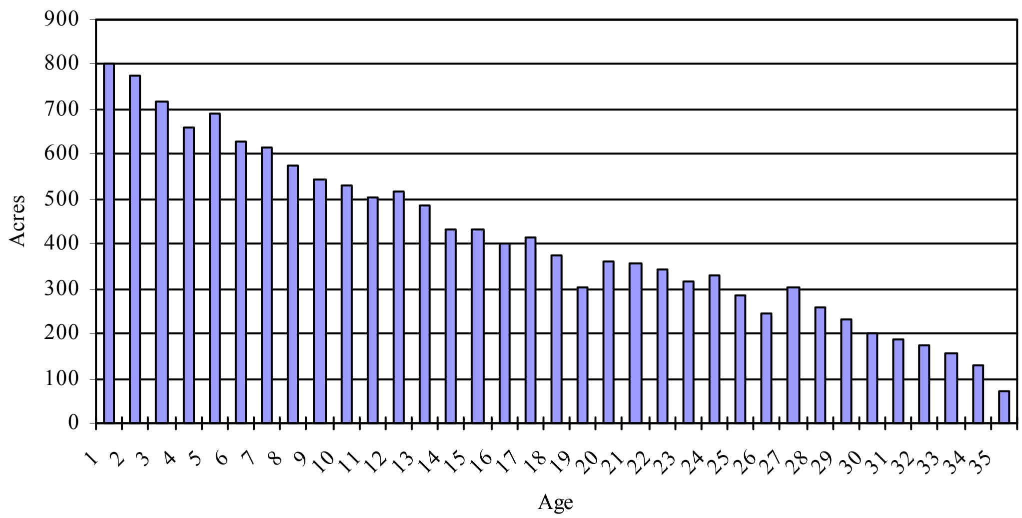

Figure 2.24 Medium-sized, random, young age class distribution

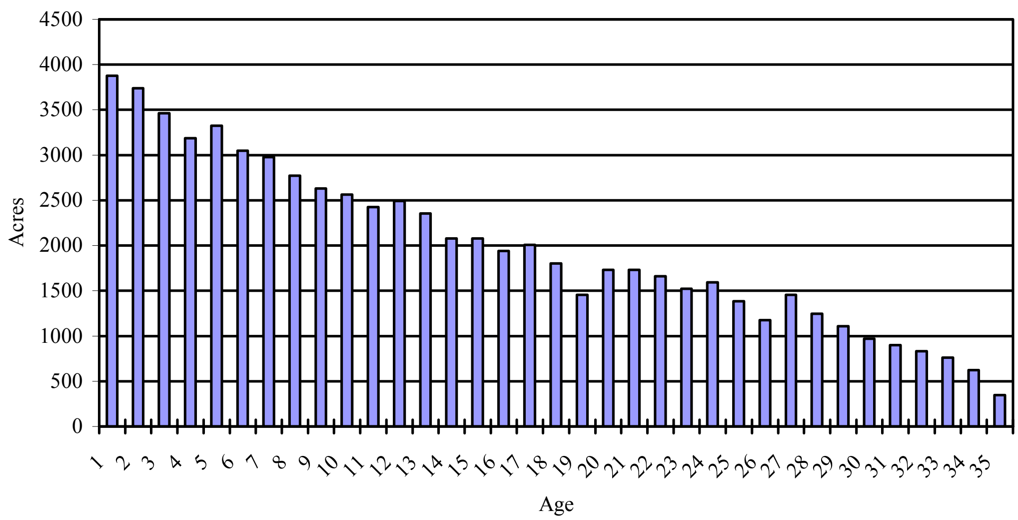

Figure 2.25 Large-sized, random, young age class distribution

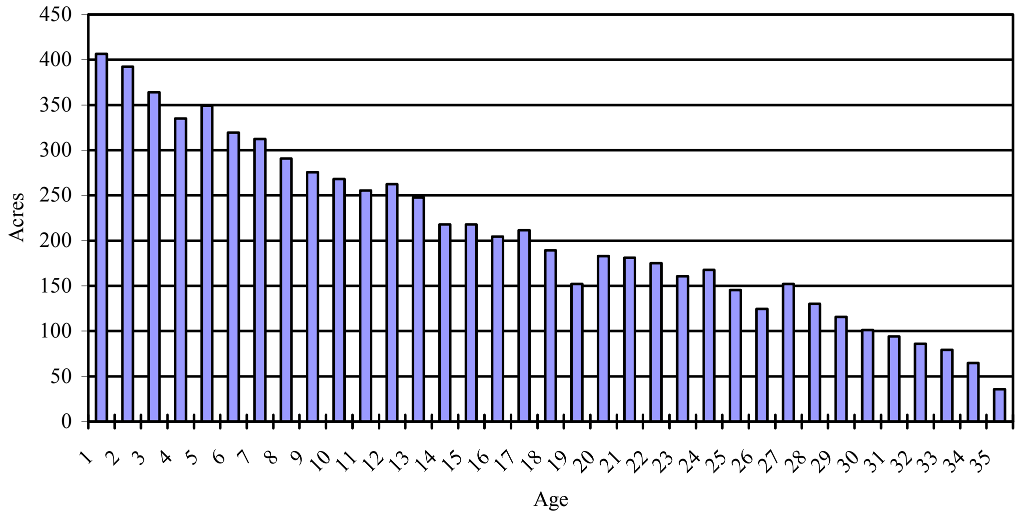

Figure 2.26 Small-sized, dispersed, young age class distribution

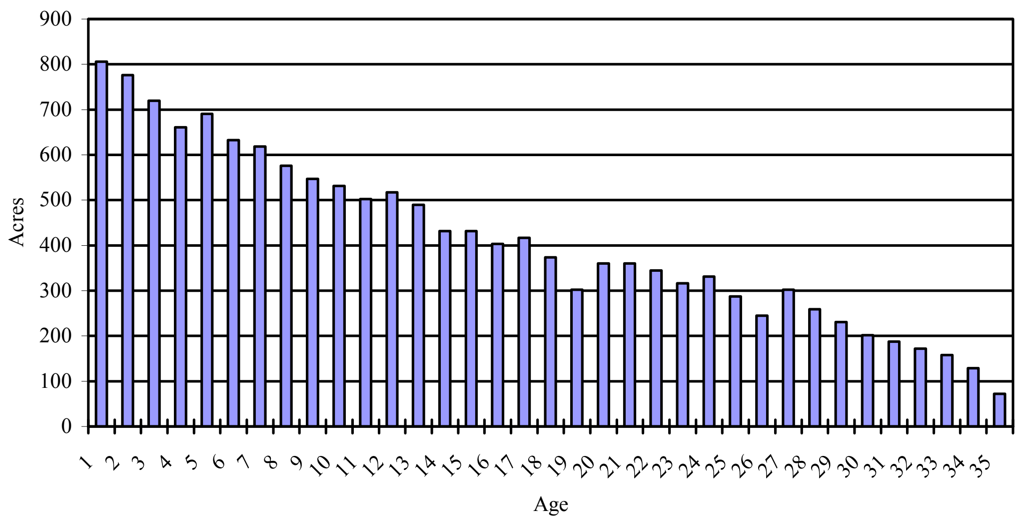

Figure 2.27 Medium-sized, dispersed, young age class distribution

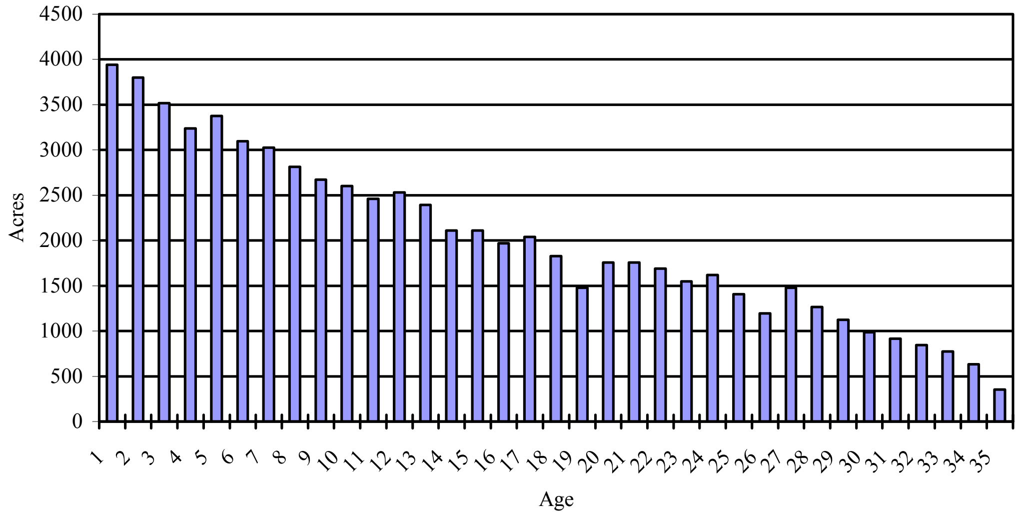

Figure 2.28 Large-sized, dispersed, young age class distribution

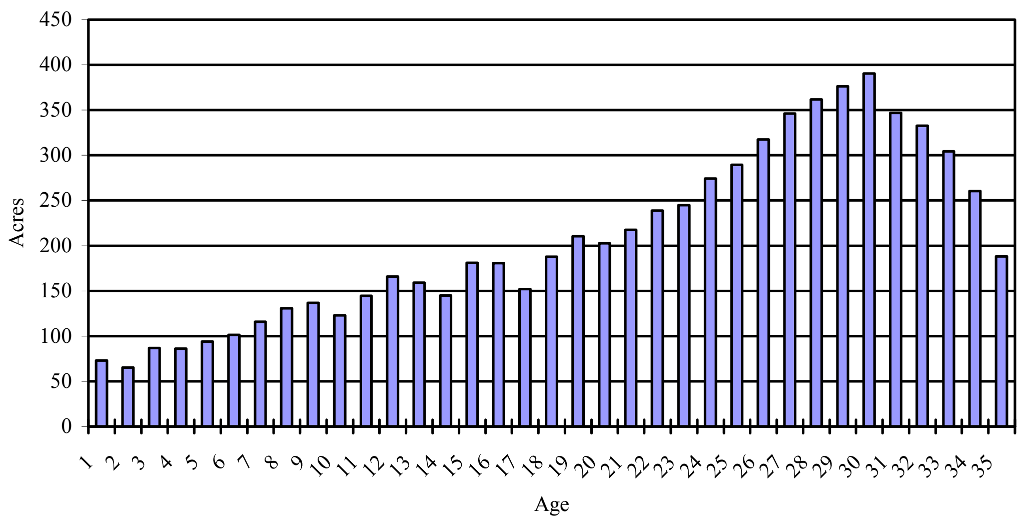

Figure 2.29 Small-sized, clumped, old age class distribution

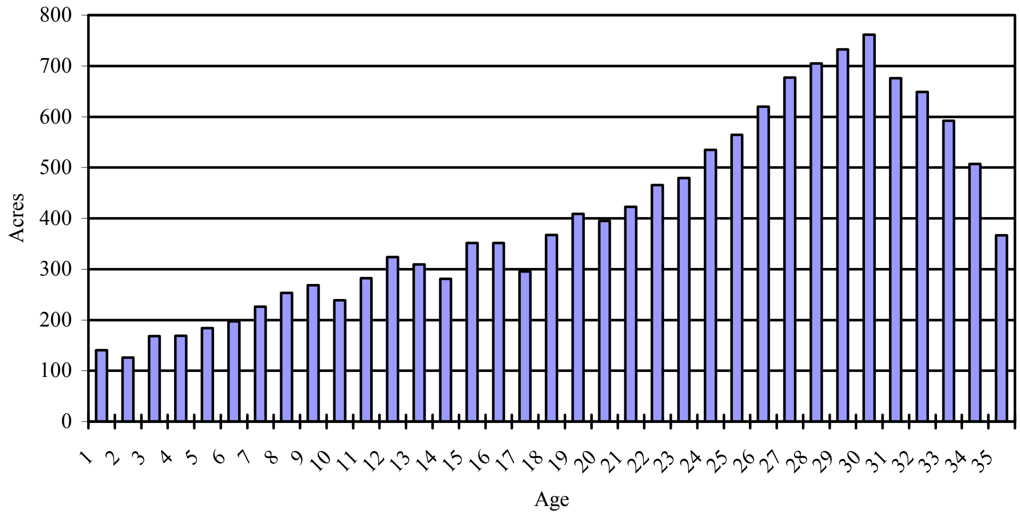

Figure 2.30 Medium-sized, clumped, old age class distribution

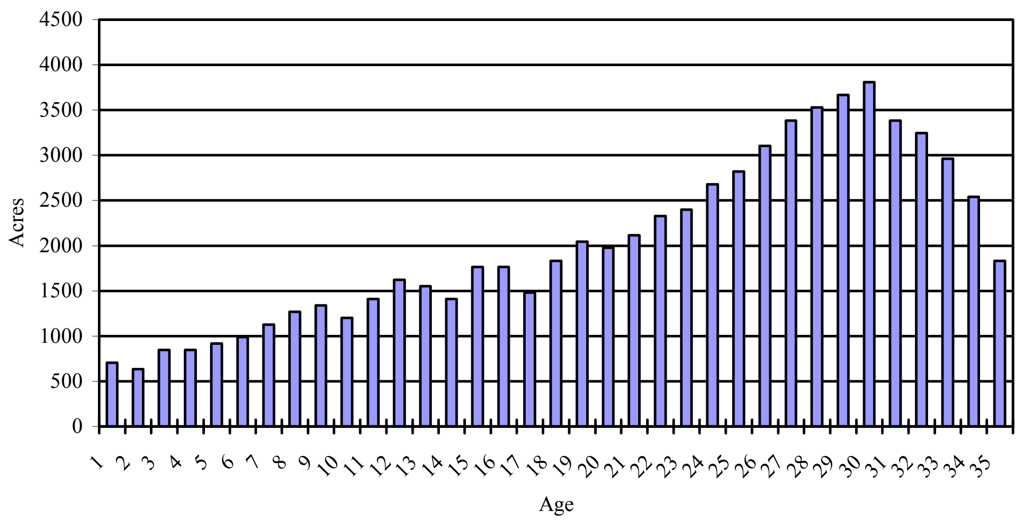

Figure 2.31 Large-sized, clumped, old age class distribution

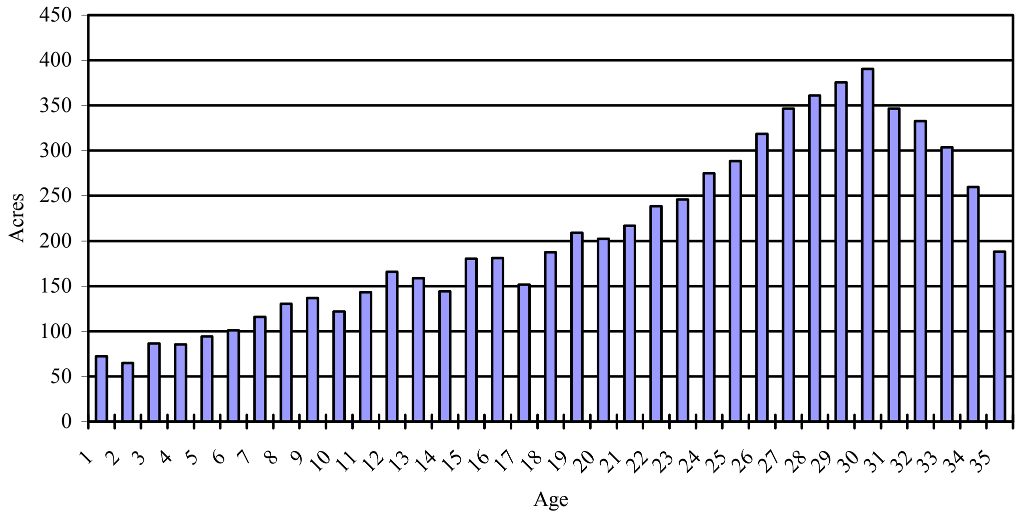

Figure 2.32 Small-sized, random, old age class distribution

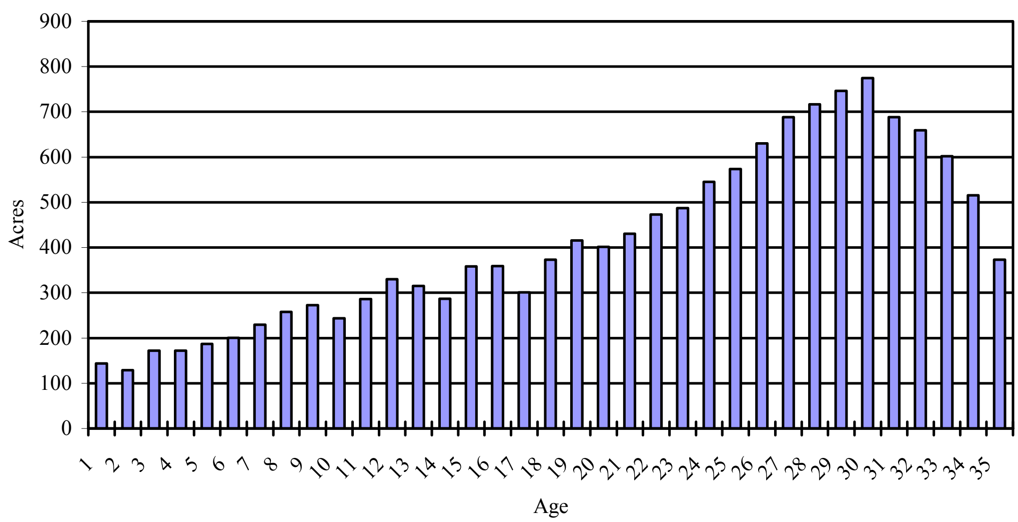

Figure 2.33 Medium-sized, random, old age class distribution

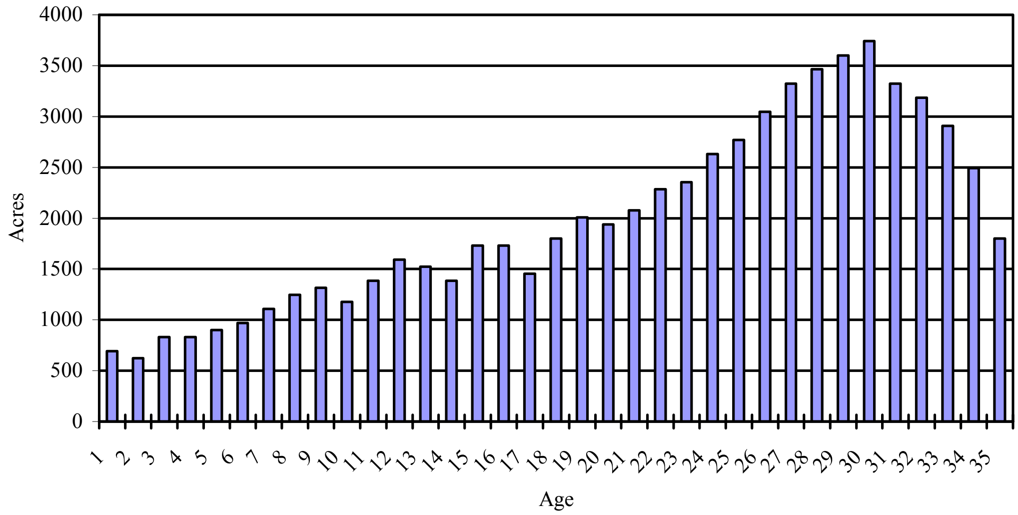

Figure 2.34 Large-sized, random, old age class distribution

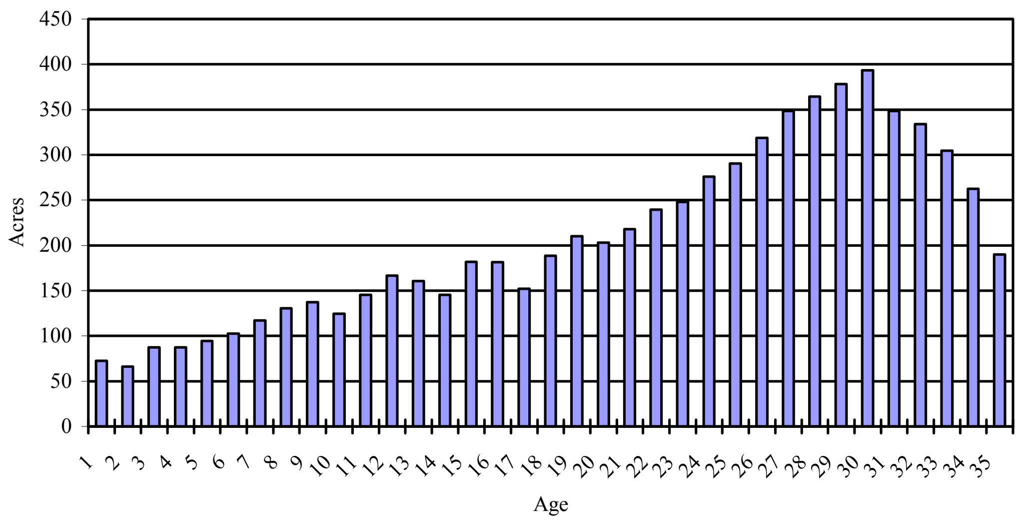

Figure 2.35 Small-sized, dispersed, old age class distribution

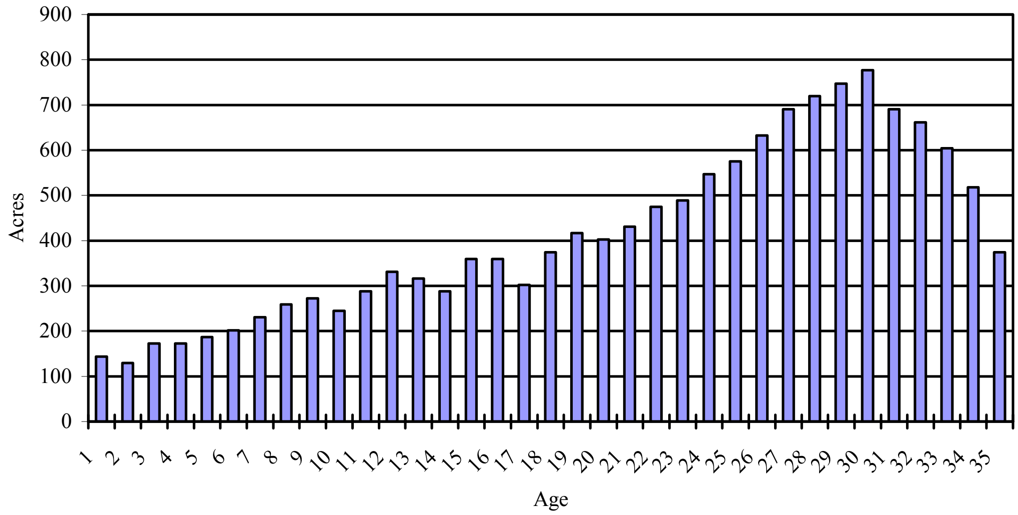

Figure 2.36 Medium-sized, dispersed, and old age class distribution

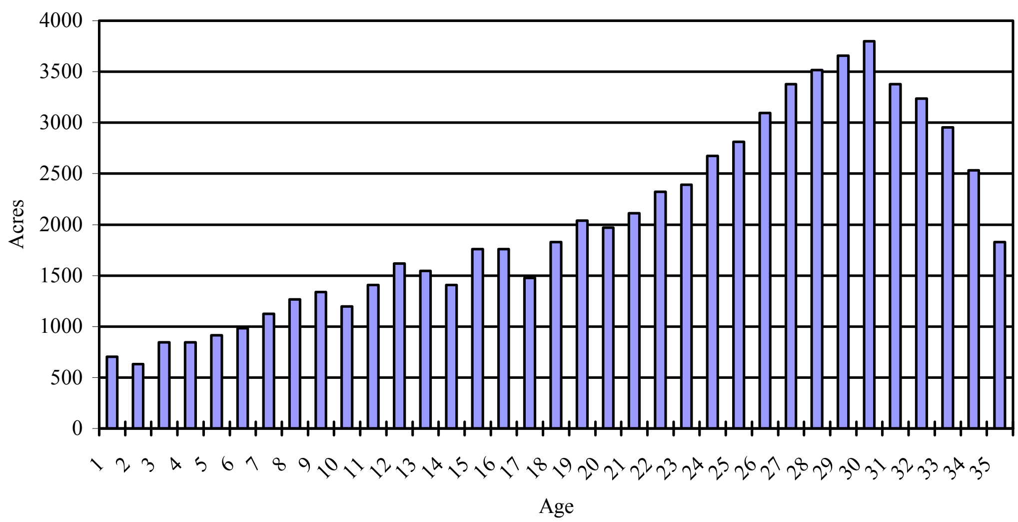

Figure 2.37 Large-sized, dispersed, old age class distribution

2.4 Growth and yield model

The growth and yield model developed by the Plantation Management Research Cooperative, Daniel B. Warnell School of Forest Resources, University of Georgia was used in this research. we used the model of lower coastal area for regions of South Carolina, Georgia, and Florida for loblolly pine. The detailed information can be found in their internal publication (Plantation Management Research Cooperative, 1996).

The initial planting density for our hypothetical forests is 726 trees per acre. At age 10, there were 500 trees per acre. There are three management schemes for this research. The first scheme is to have no thinning over the entire management period. The second scheme is to have one thinning and third scheme is to have two thinnings. The thinning ages are shown in Table 2.9. A fertilization will occur the following year after every thin. Tables 2.10 to 2.19 list the simulated results of growth and yield models.

Table 2.9 Site index and thinning ages

Site Index	Age of first thinning	Age of second thinning
50	20	30
55	19	29
60	18	28
65	17	27
70	16	26
75	15	25
80	14	24

Table 2.10 Simulated results of chip-n-saw (tons) with no thinning

	Site Index						
Age	50	55	60	65	70	75	80
10	0	0	0	0	0	0.03	0.28
11	0	0	0	0	0.03	0.33	1.50
12	0	0	0	0.03	0.29	1.42	4.38
13	0	0	0.01	0.20	1.14	3.80	9.07
14	0	0	0.10	0.76	2.92	7.58	15.30
15	0	0.04	0.41	1.97	5.79	12.61	22.54
16	0.01	0.17	1.12	3.98	9.69	18.58	30.23
17	0.04	0.51	2.39	6.82	14.43	25.07	37.84
18	0.16	1.18	4.28	10.41	19.76	31.70	44.97
19	0.44	2.28	6.79	14.59	25.39	38.13	51.34
20	0.96	3.86	9.87	19.18	31.06	44.10	56.81
21	1.78	5.91	13.40	24.00	36.53	49.43	61.31
22	2.95	8.39	17.26	28.83	41.63	54.03	64.87
23	4.48	11.25	21.32	33.53	46.21	57.86	67.55
24	6.35	14.39	25.43	37.95	50.22	60.94	69.43
25	8.53	17.73	29.47	41.99	53.62	63.30	70.62
26	10.97	21.17	33.34	45.59	56.42	65.01	71.20
27	13.61	24.61	36.95	48.72	58.63	66.14	71.28
28	16.39	27.98	40.24	51.36	60.30	66.77	70.95
29	19.24	31.20	43.17	53.53	61.48	66.97	70.28
30	22.10	34.22	45.73	55.25	62.23	66.8	69.34
31	24.91	36.99	47.92	56.55	62.61	66.34	68.19
32	27.62	39.49	49.73	57.48	62.66	65.64	66.89
33	30.19	41.70	51.20	58.07	62.44	64.74	65.48
34	32.59	43.62	52.34	58.38	62.00	63.70	63.99
35	34.79	45.25	53.18	58.43	61.36	62.54	62.45
36	36.78	46.61	53.76	58.26	60.59	61.30	60.88
37	38.55	47.71	54.10	57.91	59.69	60.00	59.31
38	40.10	48.58	54.23	57.41	58.70	58.67	57.75
39	41.45	49.22	54.18	56.79	57.65	57.32	56.22
40	42.58	49.66	53.98	56.07	56.56	55.97	54.71
41	43.52	49.93	53.65	55.27	55.43	54.63	53.24
42	44.28	50.05	53.21	54.41	54.28	53.30	51.82
43	44.88	50.03	52.68	53.51	53.14	52.01	50.44
44	45.32	49.89	52.07	52.58	51.99	50.74	49.11
45	45.62	49.65	51.41	51.63	50.86	49.50	47.83
46	45.81	49.32	50.71	50.67	49.75	48.30	46.60
47	45.88	48.92	49.97	49.71	48.65	47.15	45.42
48	45.85	48.47	49.21	48.75	47.59	46.03	44.29
49	45.75	47.96	48.43	47.81	46.55	44.95	43.21
50	45.56	47.42	47.65	46.88	45.54	43.92	42.18

Table 2.11 Simulated results of chip-n-saw (tons) with 1 thinning

	Site Index						
Age	50	55	60	65	70	75	80
10	0	0	0	0	0	0.03	0.27
11	0	0	0	0	0.03	0.32	1.48
12	0	0	0	0.03	0.28	1.40	4.33
13	0	0	0.01	0.19	1.12	3.75	9.00
14	0	0	0.10	0.75	2.88	7.51	10.21
15	0	0.04	0.40	1.94	5.73	8.45	16.31
16	0.01	0.17	1.11	3.94	6.55	13.56	36.40
17	0.04	0.51	2.37	4.69	10.7	32.69	43.18
18	0.16	1.18	3.02	7.89	28.77	39.81	44.81
19	0.44	1.68	5.33	24.66	36.29	41.82	44.97
20	0.74	3.18	20.40	32.59	38.74	42.30	44.78
21	1.57	16.11	28.65	35.49	39.53	42.34	44.51
22	11.88	24.47	32.00	36.61	39.82	42.28	44.22
23	20.04	28.23	33.45	37.13	39.96	42.19	43.91
24	24.10	29.97	34.19	37.46	40.05	42.07	43.55
25	26.09	30.91	34.68	37.71	40.10	41.90	43.12
26	27.18	31.52	35.07	37.91	40.10	41.65	42.59
27	27.87	32.00	35.40	38.08	40.05	41.32	41.97
28	28.37	32.42	35.70	38.19	39.91	40.90	41.25
29	28.81	32.81	35.97	38.24	39.68	40.37	40.45
30	29.23	33.19	36.18	38.21	39.35	39.75	39.56
31	29.66	33.54	36.34	38.09	38.93	39.05	38.61
32	30.09	33.87	36.42	37.87	38.42	38.27	37.61
33	30.54	34.15	36.43	37.57	37.82	37.42	36.58
34	30.98	34.37	36.35	37.18	37.15	36.53	35.53
35	31.40	34.52	36.18	36.70	36.42	35.61	34.48
36	31.79	34.60	35.93	36.15	35.64	34.67	33.43
37	32.12	34.59	35.59	35.55	34.83	33.72	32.39
38	32.38	34.51	35.19	34.89	34.00	32.77	31.37
39	32.58	34.35	34.72	34.20	33.16	31.83	30.37
40	32.70	34.11	34.21	33.49	32.31	30.91	29.41
41	32.74	33.81	33.65	32.75	31.47	30.00	28.48
42	32.70	33.45	33.06	32.01	30.63	29.12	27.59
43	32.60	33.04	32.44	31.26	29.81	28.27	26.72
44	32.44	32.60	31.81	30.52	29.02	27.45	25.90
45	32.22	32.12	31.17	29.79	28.24	26.65	25.11
46	31.95	31.62	30.53	29.07	27.48	25.89	24.35
47	31.64	31.10	29.89	28.36	26.75	25.16	23.63
48	31.29	30.57	29.25	27.68	26.05	24.45	22.95
49	30.92	30.03	28.62	27.01	25.37	23.78	22.29
50	30.53	29.49	28.01	26.36	24.71	23.14	21.66

Table 2.12 Simulated results of chip-n-saw (tons) with 2 thinnings

	Site Index						
Age	50	55	60	65	70	75	80
10	0	0	0	0	0	0.03	0.27
11	0	0	0	0	0.03	0.32	1.48
12	0	0	0	0.03	0.28	1.40	4.33
13	0	0	0.01	0.19	1.12	3.75	9.00
14	0	0	0.10	0.75	2.88	7.51	10.21
15	0	0.04	0.40	1.94	5.73	8.45	16.31
16	0.01	0.17	1.11	3.94	6.55	13.56	36.40
17	0.04	0.51	2.37	4.69	10.70	32.69	43.18
18	0.16	1.18	3.02	7.89	28.77	39.81	44.81
19	0.44	1.68	5.33	24.66	36.29	41.82	44.97
20	0.74	3.18	20.40	32.59	38.74	42.30	44.78
21	1.57	16.11	28.65	35.49	39.53	42.34	44.51
22	11.88	24.47	32.00	36.61	39.82	42.28	44.22
23	20.04	28.23	33.45	37.13	39.96	42.19	43.91
24	24.10	29.97	34.19	37.46	40.05	42.07	10.88
25	26.09	30.91	34.68	37.71	40.10	9.95	9.79
26	27.18	31.52	35.07	37.91	9.07	8.99	6.61
27	27.87	32.00	35.40	8.24	8.28	6.02	4.97
28	28.37	32.42	7.43	7.66	5.53	4.47	4.08
29	28.81	6.64	7.11	5.14	4.05	3.64	3.56
30	5.83	6.61	4.86	3.73	3.27	3.15	3.23
31	6.12	4.70	3.51	2.99	2.82	2.85	3.00
32	4.65	3.40	2.80	2.57	2.55	2.65	2.83
33	3.40	2.71	2.40	2.32	2.36	2.50	2.70
34	2.72	2.33	2.17	2.15	2.23	2.38	2.58
35	2.34	2.10	2.01	2.04	2.13	2.29	2.48
36	2.12	1.96	1.91	1.95	2.05	2.20	2.38
37	1.99	1.87	1.84	1.88	1.98	2.11	2.28
38	1.91	1.80	1.78	1.82	1.90	2.03	2.18
39	1.85	1.75	1.73	1.76	1.83	1.94	2.08
40	1.81	1.71	1.68	1.70	1.76	1.85	1.98
41	1.78	1.67	1.62	1.63	1.68	1.77	1.89
42	1.75	1.62	1.57	1.57	1.61	1.69	1.80
43	1.71	1.57	1.51	1.50	1.54	1.61	1.71
44	1.67	1.52	1.45	1.44	1.47	1.53	1.63
45	1.62	1.47	1.39	1.37	1.40	1.46	1.55
46	1.57	1.41	1.33	1.31	1.33	1.39	1.47
47	1.52	1.36	1.28	1.25	1.27	1.32	1.40
48	1.46	1.30	1.22	1.19	1.21	1.26	1.34
49	1.40	1.24	1.16	1.14	1.15	1.20	1.28
50	1.35	1.19	1.11	1.08	1.10	1.15	1.22

Table 2.13 Simulated of pulpwood (tons) with no thinning

	Site Index						
Age	50	55	60	65	70	75	80
10	0.38	1.75	4.47	8.56	13.98	20.75	28.75
11	1.50	4.21	8.37	13.92	20.83	28.95	37.73
12	3.44	7.44	12.89	19.74	27.82	36.56	45.11
13	6.00	11.16	17.77	25.67	34.34	42.90	50.51
14	8.97	15.17	22.77	31.31	39.93	47.70	54.07
15	12.19	19.33	27.64	36.31	44.34	51.02	56.10
16	15.58	23.48	32.13	40.46	47.57	53.07	56.97
17	19.03	27.46	36.04	43.67	49.74	54.11	56.98
18	22.46	31.10	39.26	46.01	51.00	54.36	56.38
19	25.75	34.29	41.78	47.55	51.55	54.03	55.34
20	28.79	36.96	43.62	48.43	51.53	53.27	54.00
21	31.50	39.09	44.87	48.77	51.08	52.20	52.47
22	33.84	40.69	45.59	48.67	50.31	50.91	50.81
23	35.76	41.83	45.88	48.23	49.30	49.49	49.09
24	37.29	42.54	45.82	47.53	48.13	47.98	47.35
25	38.43	42.89	45.47	46.64	46.84	46.42	45.61
26	39.23	42.95	44.90	45.61	45.48	44.84	43.90
27	39.72	42.75	44.16	44.48	44.09	43.28	42.24
28	39.94	42.35	43.30	43.28	42.68	41.74	40.62
29	39.94	41.79	42.34	42.05	41.28	40.24	39.06
30	39.75	41.11	41.31	40.80	39.90	38.78	37.57
31	39.40	40.33	40.25	39.56	38.55	37.37	36.15
32	38.93	39.49	39.16	38.33	37.23	36.03	34.79
33	38.36	38.6	38.07	37.12	35.96	34.73	33.50
34	37.71	37.68	36.98	35.93	34.74	33.50	32.28
35	37.01	36.74	35.90	34.79	33.57	32.33	31.12
36	36.26	35.79	34.85	33.68	32.44	31.21	30.03
37	35.48	34.85	33.82	32.61	31.37	30.15	28.99
38	34.69	33.91	32.81	31.59	30.35	29.15	28.02
39	33.88	33.00	31.85	30.61	29.37	28.20	27.09
40	33.08	32.1	30.91	29.67	28.45	27.29	26.22
41	32.28	31.23	30.01	28.77	27.57	26.44	25.40
42	31.49	30.38	29.15	27.91	26.73	25.64	24.63
43	30.71	29.56	28.32	27.09	25.94	24.87	23.90
44	29.95	28.76	27.52	26.32	25.19	24.15	23.21
45	29.21	28.00	26.76	25.58	24.48	23.47	22.56
46	28.49	27.26	26.04	24.87	23.80	22.83	21.95
47	27.79	26.56	25.34	24.20	23.16	22.22	21.37
48	27.11	25.88	24.68	23.57	22.55	21.64	20.82
49	26.46	25.23	24.05	22.96	21.98	21.09	20.31
50	25.83	24.60	23.45	22.39	21.43	20.58	19.82

Table 2.14 Simulated results of pulpwood (tons) with 1 thinning

	Site Index						
Age	50	55	60	65	70	75	80
10	0.38	1.75	4.45	8.51	13.92	20.68	28.68
11	1.50	4.21	8.34	13.86	20.76	28.87	37.66
12	3.44	7.44	12.86	19.68	27.74	36.49	45.06
13	6.00	11.16	17.73	25.61	34.28	42.84	50.48
14	8.97	15.17	22.73	31.25	39.87	47.66	30.34
15	12.19	19.33	27.60	36.26	44.30	28.59	31.56
16	15.58	23.48	32.09	40.42	26.68	29.87	29.05
17	19.03	27.46	36.01	24.56	28.06	27.75	26.34
18	22.46	31.10	22.19	26.09	26.50	25.22	24.59
19	25.75	19.53	23.89	25.26	24.18	23.59	23.47
20	16.56	21.38	23.99	23.18	22.67	22.58	22.74
21	18.48	22.64	22.20	21.80	21.75	21.93	22.21
22	21.12	21.20	20.97	20.98	21.19	21.49	21.80
23	20.15	20.14	20.25	20.50	20.83	21.15	21.44
24	19.28	19.53	19.86	20.22	20.57	20.87	21.08
25	18.80	19.23	19.66	20.04	20.36	20.58	20.72
26	18.60	19.11	19.56	19.90	20.15	20.29	20.33
27	18.57	19.09	19.50	19.77	19.92	19.96	19.91
28	18.63	19.11	19.43	19.61	19.66	19.60	19.46
29	18.73	19.13	19.35	19.41	19.36	19.21	19.00
30	18.83	19.12	19.22	19.18	19.02	18.80	18.52
31	18.90	19.07	19.05	18.90	18.66	18.36	18.03
32	18.93	18.97	18.84	18.59	18.27	17.92	17.54
33	18.91	18.82	18.59	18.25	17.87	17.46	17.06
34	18.84	18.63	18.29	17.89	17.45	17.01	16.58
35	18.72	18.40	17.98	17.50	17.02	16.55	16.11
36	18.55	18.13	17.63	17.11	16.60	16.11	15.65
37	18.34	17.83	17.28	16.72	16.18	15.67	15.21
38	18.10	17.52	16.91	16.32	15.76	15.25	14.78
39	17.83	17.18	16.54	15.92	15.36	14.84	14.37
40	17.54	16.84	16.17	15.54	14.96	14.44	13.97
41	17.24	16.50	15.80	15.16	14.58	14.06	13.60
42	16.92	16.15	15.44	14.79	14.21	13.70	13.24
43	16.60	15.80	15.08	14.43	13.86	13.35	12.90
44	16.28	15.46	14.74	14.09	13.52	13.02	12.57
45	15.96	15.13	14.40	13.76	13.19	12.70	12.26
46	15.64	14.81	14.08	13.44	12.88	12.39	11.96
47	15.33	14.49	13.76	13.13	12.58	12.10	11.68
48	15.02	14.18	13.46	12.84	12.30	11.82	11.41
49	14.72	13.89	13.17	12.56	12.02	11.56	11.15
50	14.43	13.60	12.89	12.29	11.76	11.30	10.90

Table 2.15 Simulated results of pulpwood (tons) with 2 thinnings

	Site Index						
Age	50	55	60	65	70	75	80
10	0.38	1.75	4.45	8.51	13.92	20.68	28.68
11	1.50	4.21	8.34	13.86	20.76	28.87	37.66
12	3.44	7.44	12.86	19.68	27.74	36.49	45.06
13	6.00	11.16	17.73	25.61	34.28	42.84	50.48
14	8.97	15.17	22.73	31.25	39.87	47.66	30.34
15	12.19	19.33	27.60	36.26	44.30	28.59	31.56
16	15.58	23.48	32.09	40.42	26.68	29.87	29.05
17	19.03	27.46	36.01	24.56	28.06	27.75	26.34
18	22.46	31.10	22.19	26.09	26.50	25.22	24.59
19	25.75	19.53	23.89	25.26	24.18	23.59	23.47
20	16.56	21.38	23.99	23.18	22.67	22.58	22.74
21	18.48	22.64	22.20	21.80	21.75	21.93	22.21
22	21.12	21.20	20.97	20.98	21.19	21.49	21.80
23	20.15	20.14	20.25	20.50	20.83	21.15	21.44
24	19.28	19.53	19.86	20.22	20.57	20.87	4.46
25	18.80	19.23	19.66	20.04	20.36	4.17	3.84
26	18.60	19.11	19.56	19.90	3.94	3.55	2.57
27	18.57	19.09	19.50	3.76	3.31	2.31	2.01
28	18.63	19.11	3.64	3.13	2.09	1.78	1.72
29	18.73	3.58	3.02	1.93	1.59	1.51	1.55
30	3.57	2.97	1.81	1.44	1.34	1.35	1.44
31	2.99	1.76	1.34	1.20	1.19	1.25	1.36
32	1.75	1.28	1.11	1.07	1.10	1.18	1.31
33	1.28	1.06	0.98	0.98	1.04	1.13	1.26
34	1.05	0.93	0.90	0.93	1.00	1.09	1.22
35	0.92	0.86	0.85	0.89	0.96	1.06	1.18
36	0.85	0.81	0.82	0.86	0.93	1.03	1.15
37	0.81	0.78	0.80	0.84	0.91	1.00	1.11
38	0.78	0.76	0.78	0.82	0.88	0.97	1.08
39	0.76	0.74	0.76	0.80	0.86	0.94	1.04
40	0.75	0.73	0.74	0.78	0.83	0.91	1.01
41	0.74	0.72	0.72	0.75	0.81	0.88	0.97
42	0.73	0.70	0.70	0.73	0.78	0.85	0.94
43	0.71	0.69	0.69	0.71	0.76	0.82	0.91
44	0.70	0.67	0.67	0.69	0.73	0.80	0.88
45	0.68	0.65	0.65	0.67	0.71	0.77	0.85
46	0.67	0.63	0.63	0.64	0.68	0.74	0.82
47	0.65	0.61	0.61	0.62	0.66	0.72	0.79
48	0.63	0.59	0.59	0.60	0.64	0.69	0.77
49	0.61	0.58	0.57	0.58	0.62	0.67	0.74
50	0.60	0.56	0.55	0.56	0.60	0.65	0.72

Table 2.16 Simulated results of sawtimber (tons) with no thinning

	Site Index						
Age	50	55	60	65	70	75	80
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0.01
14	0	0	0	0	0	0.01	0.08
15	0	0	0	0	0	0.04	0.32
16	0	0	0	0	0.02	0.18	0.93
17	0	0	0	0	0.08	0.53	2.11
18	0	0	0	0.03	0.25	1.25	4.02
19	0	0	0.01	0.09	0.63	2.47	6.76
20	0	0	0.02	0.26	1.32	4.30	10.34
21	0	0	0.08	0.59	2.42	6.79	14.74
22	0	0.02	0.20	1.16	4.01	9.96	19.87
23	0	0.05	0.44	2.05	6.12	13.77	25.64
24	0.01	0.12	0.85	3.30	8.76	18.18	31.94
25	0.02	0.26	1.48	4.96	11.93	23.11	38.66
26	0.05	0.51	2.38	7.04	15.58	28.47	45.68
27	0.12	0.90	3.58	9.53	19.65	34.19	52.92
28	0.23	1.46	5.09	12.42	24.10	40.17	60.28
29	0.43	2.23	6.93	15.66	28.86	46.35	67.71
30	0.73	3.23	9.09	19.23	33.86	52.67	75.13
31	1.15	4.47	11.54	23.07	39.05	59.05	82.50
32	1.71	5.95	14.27	27.14	44.38	65.45	89.78
33	2.44	7.67	17.24	31.40	49.79	71.84	96.94
34	3.34	9.62	20.43	35.79	55.25	78.16	103.95
35	4.42	11.78	23.79	40.29	60.71	84.41	110.81
36	5.67	14.13	27.30	44.85	66.15	90.54	117.48
37	7.10	16.66	30.93	49.45	71.54	96.56	123.98
38	8.69	19.33	34.64	54.06	76.87	102.44	130.28
39	10.43	22.12	38.41	58.65	82.11	108.18	136.40
40	12.31	25.01	42.22	63.21	87.25	113.77	142.34
41	14.32	27.99	46.04	67.71	92.28	119.21	148.08
42	16.43	31.02	49.86	72.15	97.20	124.49	153.65
43	18.63	34.09	53.66	76.52	102.00	129.62	159.04
44	20.91	37.19	57.43	80.80	106.68	134.60	164.26
45	23.25	40.30	61.15	85.00	111.23	139.43	169.31
46	25.64	43.40	64.82	89.10	115.66	144.12	174.21
47	28.06	46.49	68.43	93.10	119.97	148.66	178.95
48	30.51	49.56	71.97	97.01	124.16	153.07	183.55
49	32.97	52.60	75.45	100.82	128.22	157.35	188.01
50	35.43	55.59	78.85	104.53	132.17	161.50	192.33

Table 2.17 Simulated results of sawtimber (tons) with 1 thinning

	Site Index						
Age	50	55	60	65	70	75	80
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0.01
14	0	0	0	0	0	0.01	0.07
15	0	0	0	0	0	0.04	0.38
16	0	0	0	0	0.02	0.22	9.10
17	0	0	0	0	0.10	6.85	24.64
18	0	0	0	0.04	4.82	19.79	38.81
19	0	0	0.01	3.11	15.25	31.87	49.77
20	0	0	1.79	11.16	25.34	41.21	58.03
21	0	0.88	7.64	19.36	33.17	48.18	64.52
22	0.35	4.79	14.04	25.75	38.93	53.56	69.99
23	2.64	9.52	19.10	30.40	43.29	58.04	75.03
24	5.85	13.33	22.71	33.82	46.85	62.13	80.00
25	8.52	15.99	25.27	36.54	50.07	66.18	85.14
26	10.34	17.80	27.24	38.96	53.26	70.39	90.57
27	11.50	19.10	28.94	41.36	56.61	74.90	96.35
28	12.25	20.18	30.63	43.92	60.25	79.75	102.49
29	12.82	21.24	32.45	46.73	64.22	84.96	108.97
30	13.37	22.43	34.52	49.87	68.54	90.51	115.75
31	14.02	23.81	36.87	53.33	73.19	96.36	122.77
32	14.82	25.45	39.53	57.13	78.15	102.48	130.00
33	15.83	27.35	42.49	61.23	83.38	108.80	137.36
34	17.05	29.54	45.75	65.59	88.83	115.29	144.82
35	18.51	31.99	49.28	70.19	94.46	121.89	152.33
36	20.20	34.70	53.04	74.98	100.22	128.56	159.86
37	22.12	37.63	57.00	79.92	106.07	135.26	167.37
38	24.24	40.77	61.12	84.97	111.98	141.97	174.83
39	26.56	44.07	65.37	90.09	117.91	148.66	182.23
40	29.05	47.52	69.72	95.26	123.84	155.30	189.55
41	31.69	51.09	74.13	100.44	129.75	161.88	196.78
42	34.46	54.74	78.58	105.63	135.61	168.38	203.90
43	37.34	58.45	83.05	110.79	141.41	174.80	210.90
44	40.30	62.21	87.52	115.91	147.14	181.11	217.79
45	43.32	65.98	91.97	120.97	152.79	187.33	224.56
46	46.38	69.77	96.39	125.98	158.36	193.44	231.20
47	49.48	73.54	100.77	130.92	163.83	199.44	237.73
48	52.59	77.29	105.09	135.78	169.21	205.33	244.13
49	55.70	81.01	109.36	140.57	174.50	211.11	250.41
50	58.81	84.69	113.56	145.27	179.69	216.79	256.57

Table 2.18 Simulated results of sawtimber (tons) with 2 thinnings

	Site Index						
Age	50	55	60	65	70	75	80
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0.01
14	0	0	0	0	0	0.01	0.07
15	0	0	0	0	0	0.04	0.38
16	0	0	0	0	0.02	0.22	9.10
17	0	0	0	0	0.10	6.85	24.64
18	0	0	0	0.04	4.82	19.79	38.81
19	0	0	0.01	3.11	15.25	31.87	49.77
20	0	0	1.79	11.16	25.34	41.21	58.03
21	0	0.88	7.64	19.36	33.17	48.18	64.52
22	0.35	4.79	14.04	25.75	38.93	53.56	69.99
23	2.64	9.52	19.10	30.40	43.29	58.04	75.03
24	5.85	13.33	22.71	33.82	46.85	62.13	17.57
25	8.52	15.99	25.27	36.54	50.07	13.30	23.64
26	10.34	17.80	27.24	38.96	9.80	18.71	42.82
27	11.50	19.10	28.94	6.98	14.56	35.91	56.33
28	12.25	20.18	4.77	11.09	29.96	48.03	65.86
29	12.82	3.08	8.22	24.86	40.81	56.55	72.61
30	1.84	5.84	20.49	34.58	48.41	62.55	77.47
31	3.90	16.72	29.20	41.34	53.72	66.82	81.10
32	13.43	24.55	35.22	46.02	57.45	69.96	83.98
33	20.46	29.90	39.33	49.26	60.14	72.40	86.47
34	25.22	33.51	42.13	51.55	62.19	74.47	88.79
35	28.37	35.91	44.06	53.25	63.89	76.38	91.10
36	30.41	37.51	45.44	54.62	65.43	78.27	93.49
37	31.72	38.62	46.52	55.84	66.95	80.23	96.00
38	32.58	39.44	47.46	57.03	68.53	82.30	98.67
39	33.18	40.14	48.37	58.27	70.21	84.51	101.49
40	33.66	40.81	49.32	59.61	72.01	86.85	104.45
41	34.12	41.52	50.36	61.05	73.93	89.33	107.53
42	34.62	42.30	51.51	62.62	75.98	91.92	110.72
43	35.19	43.19	52.76	64.29	78.13	94.60	113.98
44	35.86	44.17	54.11	66.07	80.38	97.36	117.30
45	36.61	45.25	55.56	67.92	82.69	100.17	120.65
46	37.46	46.42	57.09	69.85	85.06	103.02	124.03
47	38.40	47.67	58.68	71.83	87.47	105.90	127.40
48	39.40	48.98	60.32	73.85	89.90	108.78	130.77
49	40.47	50.33	62.01	75.89	92.33	111.65	134.11
50	41.58	51.73	63.71	77.95	94.77	114.51	137.42

In addition to these assumptions, the following are used throughout my dissertation, unless otherwise stated: Prices of timber products are from Timber Mart-South (2004) based on the average prices in Georgia. The price for pine sawtimber is $43.57 per ton, for pine chip-n-saw is $25.60 per ton, for pine pulpwood is $6.73 per ton. In addition we use a discount rate of 6 percent. The regeneration costs used in this research are from Smidt and Mark (2004). The costs include mechanical site preparation at the cost of $115.7 per acre, machine and hand planning cost at $47.14 per acre and a chemical treatment cost $63.04 per acre. The fertilization cost, which happens a year after thinning, is $49.23 per year. The maximum clear cut size is 240 acres and the green-up period is 2 years.

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CHAPTER 3

A COMPARISON OF THREE ALGORITHMS FOR SOLVING A WIDE RANGE OF COMMODITY-PRODUCTION SPATIAL HARVEST SCHDULING PROBLEMS[1]

[1] Zhu, J., P. Bettinger. To be submitted to *Forest Science*.

ABSTRACT

Spatial harvest scheduling has been a hot topic for the last 15 years. Researchers have attempted to find fast and efficient ways to schedule land management activities with traditional mathematical approaches as well as heuristics. Due to limitations on the use of traditional methods for large planning problems, heuristics are an alternative, although the qualities of heuristic solutions is always a concern. In this study, three heuristics were developed and applied to a wide range of forest planning problems to assess the quality of results that can be obtained, and the time required to obtain them. The three heuristics include threshold accepting, 1-opt tabu search, and a meta heuristic which consists of threshold accepting, 1-opt tabu search, and 2-opt tabu search. The three heuristics are tested in a wide range of forest planning problems, which include 27 GIS databases of different sizes, ownership patterns, and age class distributions. The meta heuristic found the best solutions to most problems with older and normal age class distributions. In problems with young age class distributions, the meta heuristic produced slightly lower solutions. The variation in solution quality was lowest when using the meta heuristic for all problems, however, thus the model seems to be of value for optimal harvest scheduling efforts.

INDEX WORDS: Forest Planning, Harvest Scheduling, Heuristics, Tabu Search, Threshold Accepting

3.1 Introduction

The use and evaluation of spatial harvest scheduling techniques has increased in recent years due to a variety of reasons, such as the need to develop forest plans that accommodate multiple and often conflicting management objectives (Bettinger and Chung 2004). The public worldwide are demanding sustainable forest harvesting practices that not only recognize economics, but also the preservation and maintenance of bio-diversity, aesthetic values, and public recreation areas. Long-term forest management scheduling allows all parties to determine whether sustainable forestry is actually being practiced. Federal and state regulations and polices have resulted in increasingly complex objectives for the management of forests in the United States (Bettinger and Sessions 2003). In many areas of the world, compliance with regulatory restrictions, voluntary forest certification programs, and organizational goals and policies related to landscape conditions are now as important as economic objectives. These and other factors have significantly increased the complexity of harvest scheduling problems. Therefore finding efficient algorithms to assist with optimization and harvest scheduling is becoming a very practical and import issue.

An optimization process seeks to maximize certain economical and ecological objectives subject to various constraints when assigning forest management actions to management units over a period of time, in a given forest area. There are two general classes of forest harvest scheduling optimization algorithms. One is based on mathematical programming techniques and the other on heuristics. The first uses exact algorithms, which include linear programming, mixed integer programming, and integer programming (Bevers and Hof 1999, Hof et al. 1994, Hof and Joyce 1992), and dynamic programming (Snyder and ReVelle 1997, Hoganson and Borges 1998). The appeal of exact algorithms is that the optimal solution to a problem (if found) will be located. But, as a problem size increases, solving it may become computationally impractical (Lockwood and Moore 1993), and perhaps impossible, if integer variables are used. For example, integer programming has historically been capable of solving modest-sized problems (Jones et al. 1991). Although technology continues to advance and computers are becoming increasingly fast, the use of exact algorithms remains limited in application to small and medium-sized problems. The second optimization method uses heuristics, such as Monte Carlo simulation (Nelson and Brodie 1990), simulated annealing (Dahlin and Sallnas 1993, Lockwood and Moore 1993, Murray and Church 1995), threshold accepting (Bettinger et al. 2003), tabu search (Bettinger et al. 1997, Batten et al. 2005), and genetic algorithms (Glover et al. 1995, Falcão and Borges 2001). Although heuristics can not guarantee that they can locate a global optimum solution, they can usually find good solutions to complex planning problems, making them attractive for large spatial forest planning problems.

The former method is a global procedure attempting to locate an optimal solution of the forest management model. The latter method is usually a local search process, which iteratively changes a solution without any guarantee of finding an optimal solution. A more detailed examination of mathematical approach and heuristic approaches follows.

Many heuristics have been applied to forest planning problems. Heuristics perform differently under different management problems. Bettinger et al. (2002) compared eight heuristics on three increasing difficult wildlife planning problems. They found that threshold accepting, simulated annealing and tabu search with 2-opt moves worked the best in most cases. Heinonen and Pukkala (2002) did a comparison of 1-opt and 2-opt compartment neighborhoods on five test forests and confirmed the notion that 2-opt were important. In this chapter we will compare three heuristics on 27 GIS databases with different sizes, ownership patterns, and age class distributions. The goal is to determine which algorithm works best for the management problem under consideration here, one which is different from the previous assumptions. However, knowledge gained from the previous research will inform the selection of test heuristics. For example, threshold accepting is a relatively fast heuristic. It can move an inferior solution to a problem to a very good solution in a fraction of the time that tabu search requires. Tabu search, on the other hand, uses deterministic choices to refine the quality of solutions. My hypothesis is that a combination of the two can be developed to produce a even better solutions than when used alone.

3.2 Methods

3.2.1 Problem formulation

The forest planning problem that we investigated falls between strategic planning (long time frames, large area) and operational planning (short time frames, specific areas) in an area termed "tactical planning." The level of detail used in this research is generally greater than those used in strategic planning analyses, yet significantly lower than what is required for operational planning. The time horizon assumed is 20 years and each planning period will be one year long. This tactical planning model attempts to maximize the net present value of timber harvested. The objective function is formulated as:

Maximize:

$$\sum_{t=1}^{T}\left[\sum_{i}^{N}(V_{it}X_{it}(P-C_{it}))/1.06^{(t-0.5)}\right]+\sum_{i}^{N}(V_{i20}(P-C_{it}))/1.06^{19.5} \qquad (1)$$

Subject to:

$$\sum_{t=1}^{T} X_{it} \leq 1 \qquad \forall i \tag{2}$$

$$X_{it}A_i + \sum_{z \in N_i \cup S_i} X_{zt} A_z \leq \text{MCA} \qquad \forall_{i,\, t} \tag{3}$$

$$\sum_{i=1}^{n} V_{i20} - \sum_{i=1}^{n}\sum_{t=1}^{20} X_{it} V_{i20} > 0.9 * \sum_{i=1}^{n} V_{i1} \tag{4}$$

$$AG_c - AG_{t1} > 5 \tag{5}$$

$$AG_c - AG_{t2} > 5 \tag{6}$$

$$\sum_{i=1}^{n} X_{it} V_{it} > 0.9 * \sum_{i=1}^{n}\sum_{t=1}^{T} X_{it} V_{i20} / T \qquad \forall\ t \tag{7}$$

$$\sum_{i=1}^{n} X_{it} V_{it} < 1.1 * \sum_{i=1}^{n}\sum_{t=1}^{T} X_{it} V_{i20} / T \qquad \forall\ t \tag{8}$$

$$\sum_{i=1}^{n} X_{it} V_{it} > 0.9 * \sum_{i=1}^{n} X_{it-1} V_{it-1} \qquad \forall\ t \geq 2 \tag{9}$$

$$\sum_{i=1}^{n} X_{it} V_{it} < 1.1 * \sum_{i=1}^{n} X_{it-1} V_{it-1} \qquad \forall\ t \geq 2 \tag{10}$$

Where:

A_i= area of management unit i

AG_c=clear cut age

AG_{t1}=age when first thin happens

AG_{t2}=age when second thin happens

C_{it}= logging cost per m^3 for unit i harvested in time period t

Ht = the actual scheduled harvest volume in each time period t

i = a harvest unit

MCA=maximum clearcut area

N=the total number of harvest units

N_i=set of all units adjacent to unit i

P= stumpage price

S_i= the set of all management units adjacent to these management units adjacent to management unit i

t = a planning period

T = the total number of time periods in the planning horizon

V_{i20} = the unscheduled timber harvest volume at the end of period *20*, from management unit i

V_{it} = the available timber harvest volume during time period t, from management unit i

X_{it} = a binary variable, which =1 if management unit i is harvested in time period t, 0 otherwise

Equation 2 indicates that each management unit can only be harvested at most one time in all planning periods. Equation 3 ensures that the maximum clearcut size will be maintained (assuming the green-up period is 2 years). Equation 4 is an ending volume constraint. Equation 5 and 6 ensure that the separation period between thinning and clear cutting is at least six years. Equation 7 and 8 constrain the volume harvested in each time period to a proportion of the final, unscheduled and uncut volume. Equation 9 and 10 limit the deviation in harvest volume from one period to the next as a measure of harvest stability. This model formation represents a model I (Johnson and Scheurman 1977), integer programming problem. The adjacency restriction is the area restriction formulation (Murray 1999).

Standard scheduling problems used in this research are divided into three ownership size groups: small, medium and large (see Table 4.1), according to problem area acreage. Within each size class, three ownership patterns of parcels were developed: clumped, random, and dispersed. Three age class distributions were then assigned to them: young forest, normal forest, older forest. Therefore a matrix of 27 hypothetical forests was available for analysis.

The time horizon is 20 years, divided into twenty 1-year time periods. The interest rate assumed is 6 percent. The stumpage prices were obtained from Timber Mart-South (2004), and are \$43.57 per ton for pine sawtimber, \$25.60 per ton for chip-n-saw, and \$6.73 per ton for pine pulpwood. The costs assumed are \$115.70 per acre for mechanical site preparation, \$47.14 for planting, and \$63.40 for a herbaceous weed control treatment. The maximum clearcut size is 240 acres, and the green-up period is assumed to be 2 years.

3.2.2 Modified Monte Carlo simulation

Random search is the baseline method used for initiation of the forest harvest scheduling search process and its purpose is to generate a feasible initial solution. In general, the method is used to generate an initial solution by randomly choosing a unit and a period to schedule, and then checking the constraints (Figure 3.1). If the constraints are not violated, the activity is scheduled. If it is constrained, another unit or period is scheduled. This process is repeated until all units and periods are explored. An initial feasible solution is guaranteed to be generated in this way. But in the problem, because there is a lower bound constraint, every time when a unit is assigned to a period, a period with the least total harvest volume is scheduled. If the schedule breaks the constraints, a period with second least volume will be scheduled. If after scheduling all periods, no feasible solution is generated, the process will restart until it finds a feasible solution.

Table 3.1 Elements in harvest scheduling type databases

Size	Ownership pattern	Age class distribution
Small (1000-10,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older
Medium (10,001-20,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older
Large (20,001-100,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older

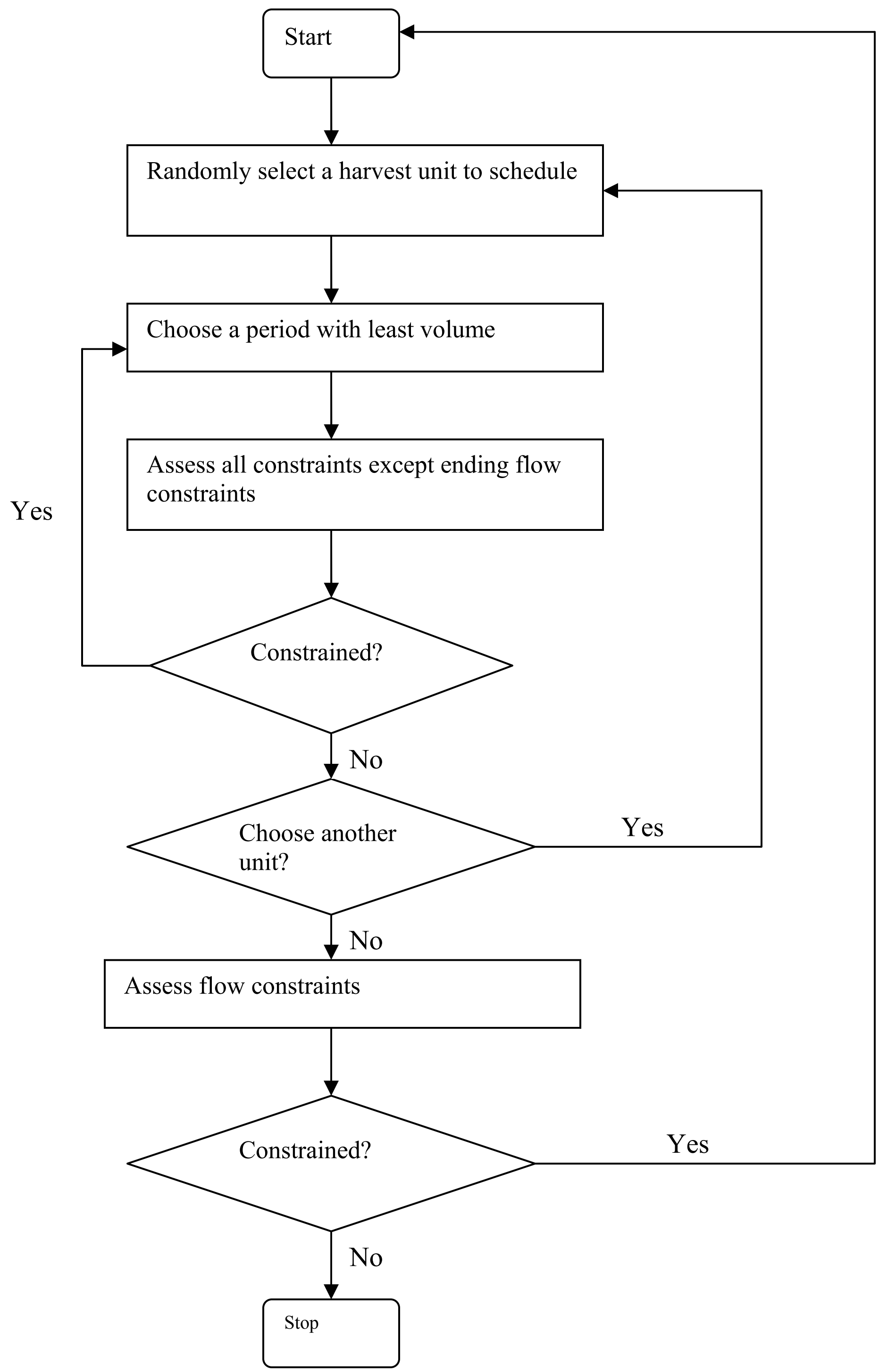

Figure 3.1 The revised Monte Carlo simulation process

3.2.3 Threshold accepting

In threshold accepting (Figure 3.2), one first needs to generate an initial solution and set it as the current solution. The modified Monte Carlo simulation described above is used to do this. The parameters needed for threshold accepting include the initial threshold, number of total iterations, and change per threshold, and unsuccessful iterations per threshold. Threshold accepting is a stochastic local process. Here, a management unit (polygon) and a prescription are selected at random, and temporarily inserted into the current forest plan. Because the process to check the adjacency constraint is very time consuming, it is the last constraint assessed. If the choice results in an infeasible plan, it is rejected. If the choice results in a feasible plan, and which is also an improvement on the best solution that had been stored in memory, the adjacency constraints are then assessed. If adjacency is not violated, the choice is formally accepted into the solution, and a new "best solution" is recorded in memory. Otherwise the choice will be rejected. If the choice results in a feasible solution, yet does not result in the best solution, it may be formally accepted as well. The decision, in this case, depends on whether the new solution is within some tolerance (threshold) from the best solution stored in memory.

Threshold accepting usually begins with a large threshold level, which is decreased as the number of iterations pass, until it is so small that the program stops. The large initial threshold allows the search process to move around the solution space easily, which is necessary in the beginning phase of threshold accepting. As the threshold gets smaller, the search process focuses on a small area of the solution space, and tries to find the best solution.

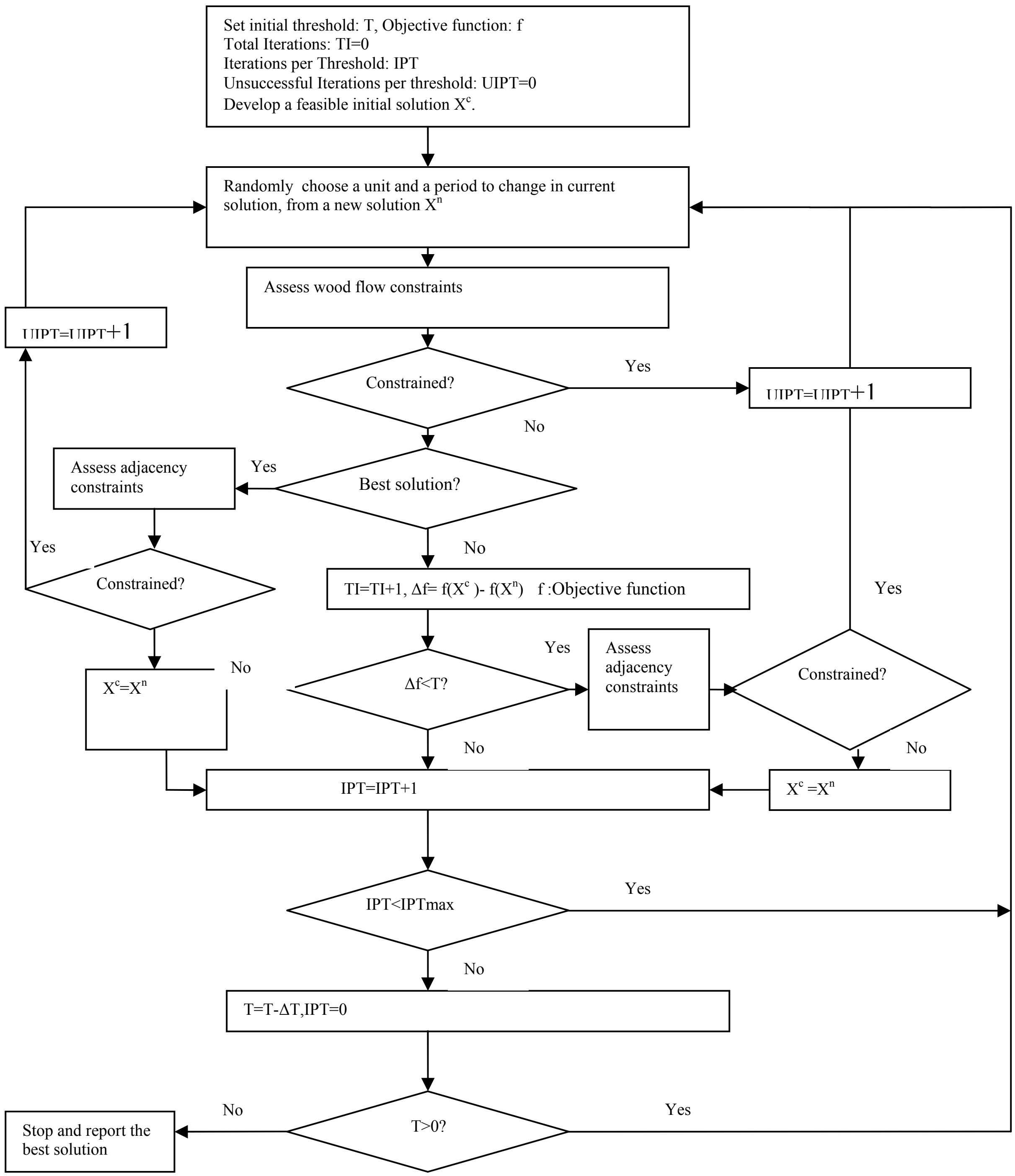

Figure 3.2 The threshold accepting process that is incorporated into the spatial forest planning model

Threshold accepting requires several parameters to run effectively: the total number of iterations (choices) to select in a run of the model, an initial threshold level, the number of iterations (choices) to make at each threshold level, the amount that the threshold will change each time the number of iterations per threshold has passed, and the stopping criteria. In our implementation of this heuristic, for a number of trial runs, we tested total iterations between 100,000 and 10,000,000, iteration per threshold between 100 and 1,000, threshold change between 100 and 1,000, unsuccessful iterations per threshold between 100 and 1,000. Based on those runs we selected following parameters for all problems (Table 3.2). The effects of the best parameters on the different size problems of GIS databases are illustrated in Figures 3.3, 3.4 and 3.5.

Table 3.2 Parameters for different size of GIS databases (TA)

Size	Number of total iterations	Iterations per threshold	Threshold change	Unsuccessful iterations per threshold
Small	1,000,000	500	200	500
Medium	1,000,000	500	200	500
Large	1,000,000	500	200	500

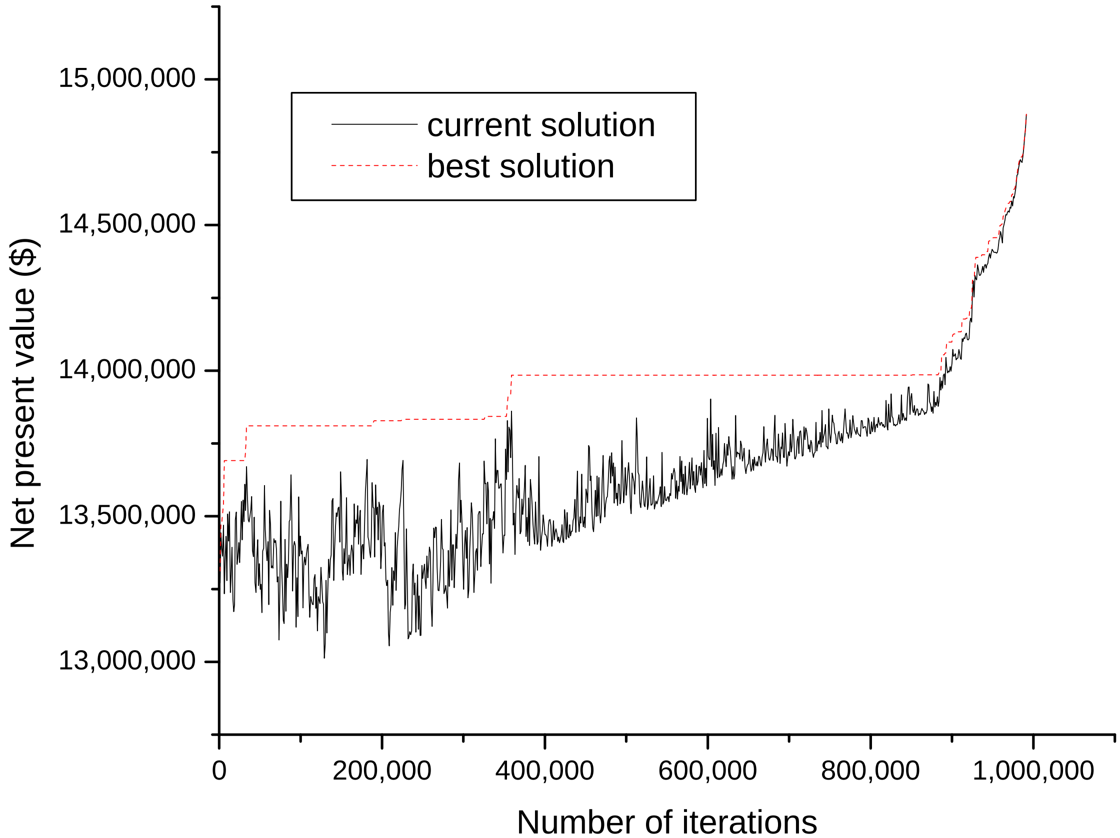

Figure 3.3 Behavior of the TA search process using best parameters for the small-sized GIS database

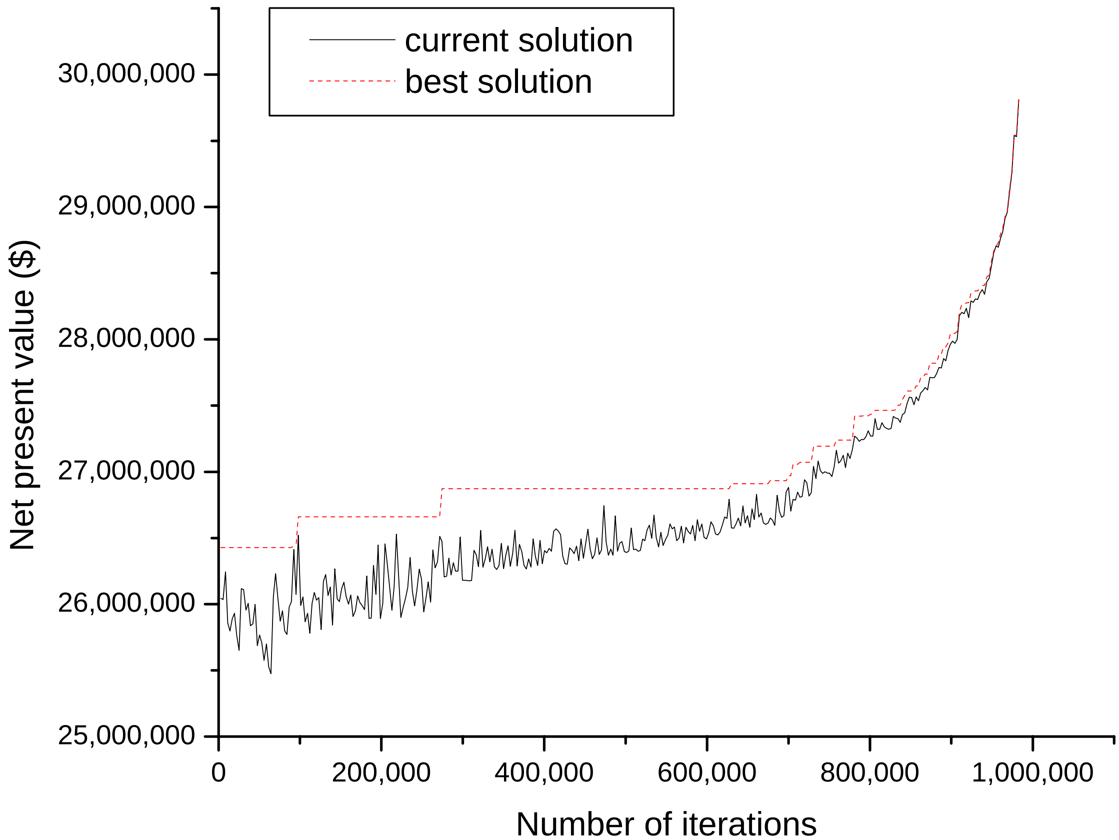

Figure 3.4 Behavior of the TA search process using best parameters for the medium-sized GIS database

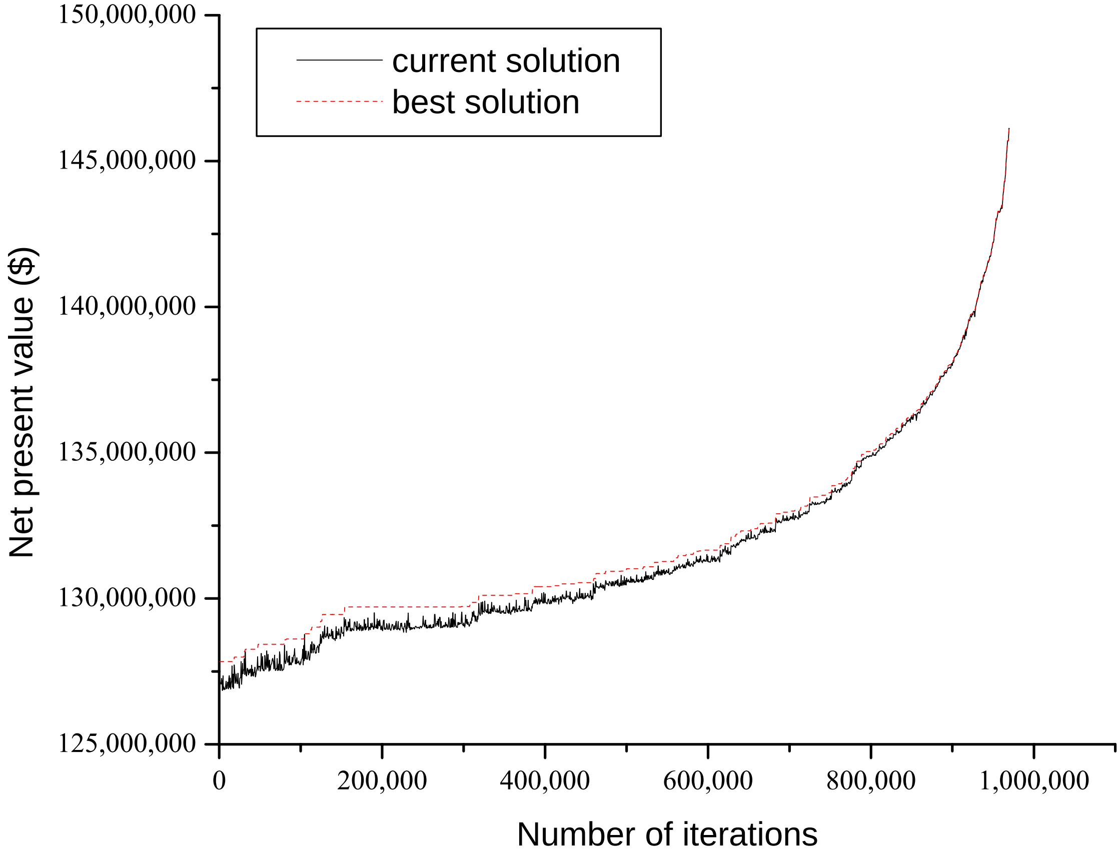

Figure 3.5 Behavior of the TA search process using best parameters for the large-sized GIS database

3.2.4 1-opt tabu search process

In 1-opt tabu search (Figure 3.6), an initial feasible solution is generated using the modified Monte Carlo simulation. The main parameters for a 1-opt tabu process are the total number of iterations and tabu state. A tabu choice is one that has been made recently in the search process. A "tabu state" is assigned to each choice that is made. This tells the search process that a choice is "off limits" for some period of time or some number of future iterations of the process. The choice can still be selected if it leads to a solution that is better than the best solution stored in memory. This is termed the "aspiration criteria."

Tabu search is a deterministic process. In this process, a unit and a prescription are selected from a set (neighborhood) of potential changes to the current solution. A neighborhood of potential changes to the current solution represents the potential net present value of a new solution if any one of the potential changes represented in the neighborhood is selected. Therefore, the neighborhood of potential changes is computed, and the search process then examines the neighborhood for the best change to make to the current solution. Just as in TA process, after finding the best change, the wood flow constraints are assessed. If they are not violated and the choice is an improvement on the current solution, and the choice that is selected from the neighborhood is either not tabu, or tabu but passes the aspiration criteria, the adjacency constraints are then assessed. If the constraints fail, the choice is rejected and the next-best choice is considered from the neighborhood. If all of the constraints are satisfied, the choice is formally accepted into the current solution.

Tabu search with 1-opt moves requires two parameters to run efficiently: the total number of iterations and the length of tabu state. In this implementation of the algorithms, for a number of trial runs, we tested total iterations of run from 10,000 to 50,000 and tabu status from 100 to 1000. Based on the results of trial runs, we selected a set of the parameters (Table 3.3) for all problems. The effects of the best parameters for different sizes of GIS databases are illustrated in Figures 3.7, 3.8, and 3.9.

Table 3.3 Parameters for different size of GIS databases (TS 1-opt)

Size	Total number of iterations	Length of tabu status
Small	20,000	600
Medium	20,000	600
Large	20,000	500

3.2.5 2-opt tabu search process

In a 2-opt tabu search process (Figure 3.10), a 2-opt neighborhood is developed by switching the prescriptions in two units, and recording the potential change in a 2-opt neighborhood (represented by a two dimensional matrix). Because calculating the potential net present value change is a very computationally expensive process, it is too time-consuming to perform with large problems. Therefore in my implementation, we use a window of 100 sequentially numbered units. For example, if we randomly choose unit 50 as starting point, the first 2-opt move selection comes from the set of potential management prescription swaps among stands numbered 50-99, the second 2-opt move selection comes from a set of stands numbered 51-100 and so on. The 2-opt tabu search process requires two parameters to run effectively: the total number of iterations (choices) to select in a run of the model, and the tabu state assigned to each polygon combination that is made. The parameters for 2-opt move are listed in Table 4. With these parameters, the number of potential times a management unit is considered will be relatively consistent between small, medium, large sizes. For example, the small sized GIS database has approximately 200 polygons, therefore every polygon can potentially be selected 25 times (100*50/200). A medium size GIS database contains approximately 400 polygons, hence every polygon can potentially be selected 25 times (100*100/400) as well (Figure 3.4).

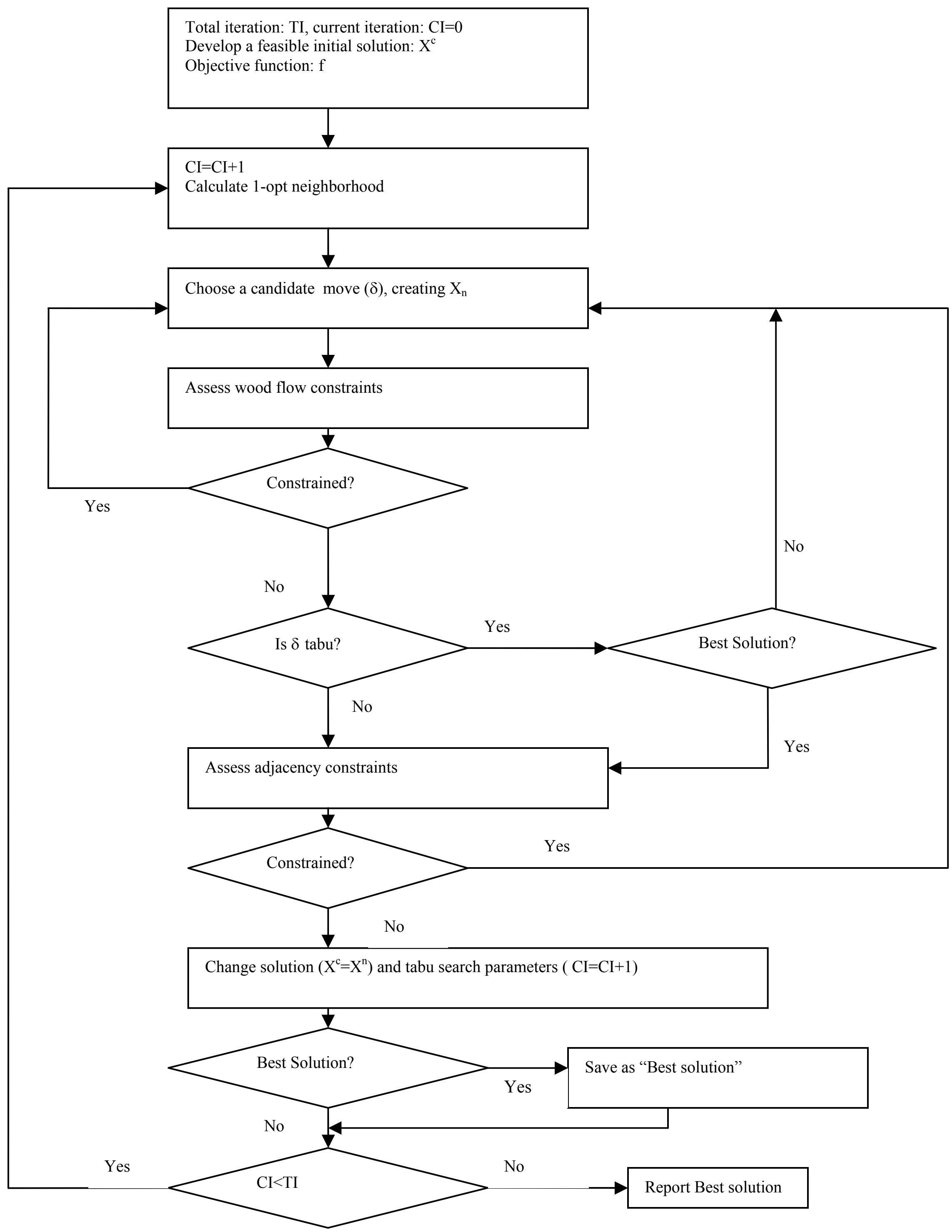

Figure 3.6 The 1-opt tabu search process that is incorporated into the spatial forest planning model.

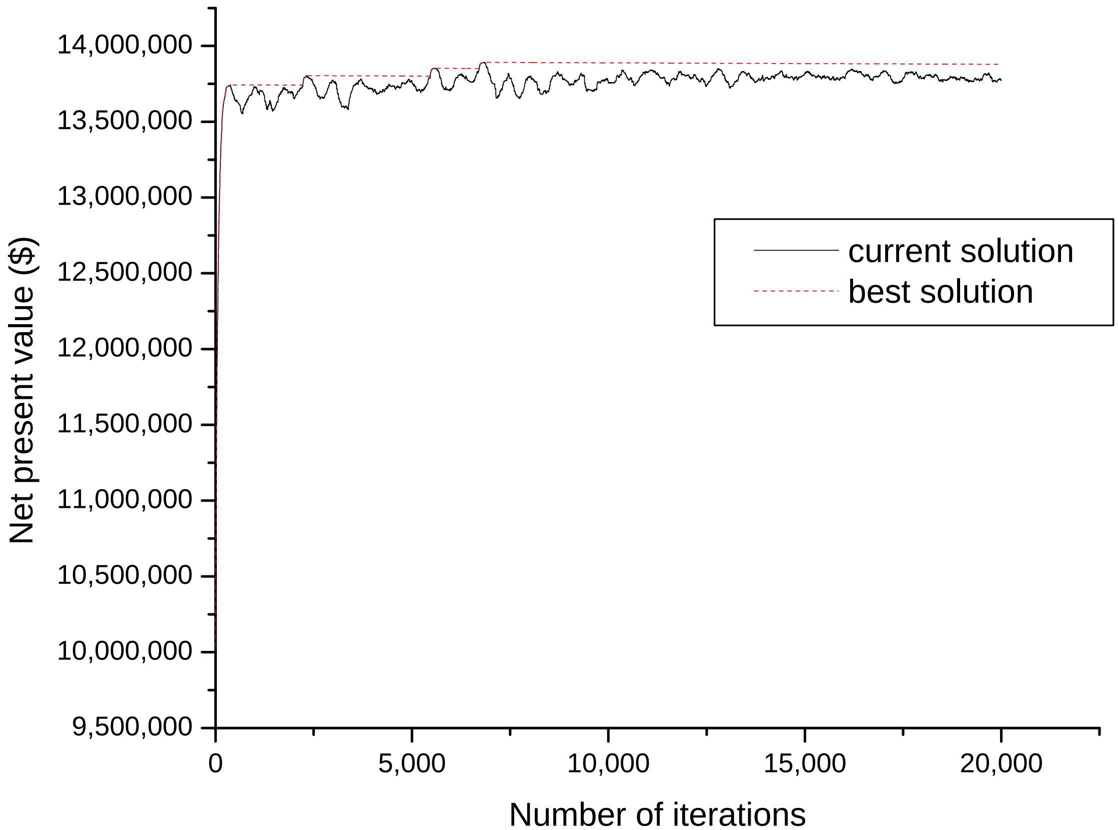

Figure 3.7 Behavior of TS search process using best parameters for the small-sized GIS database

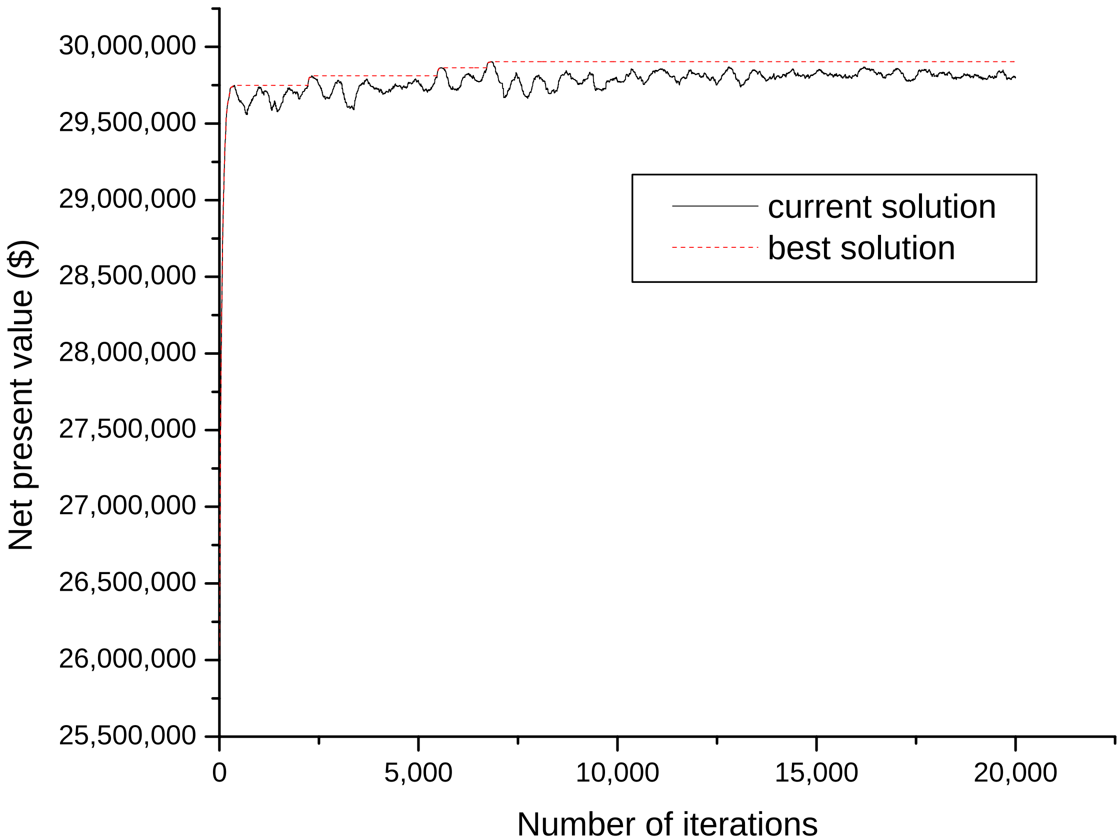

Figure 3.8 The behavior of TS search process using best parameters for the medium-sized GIS database

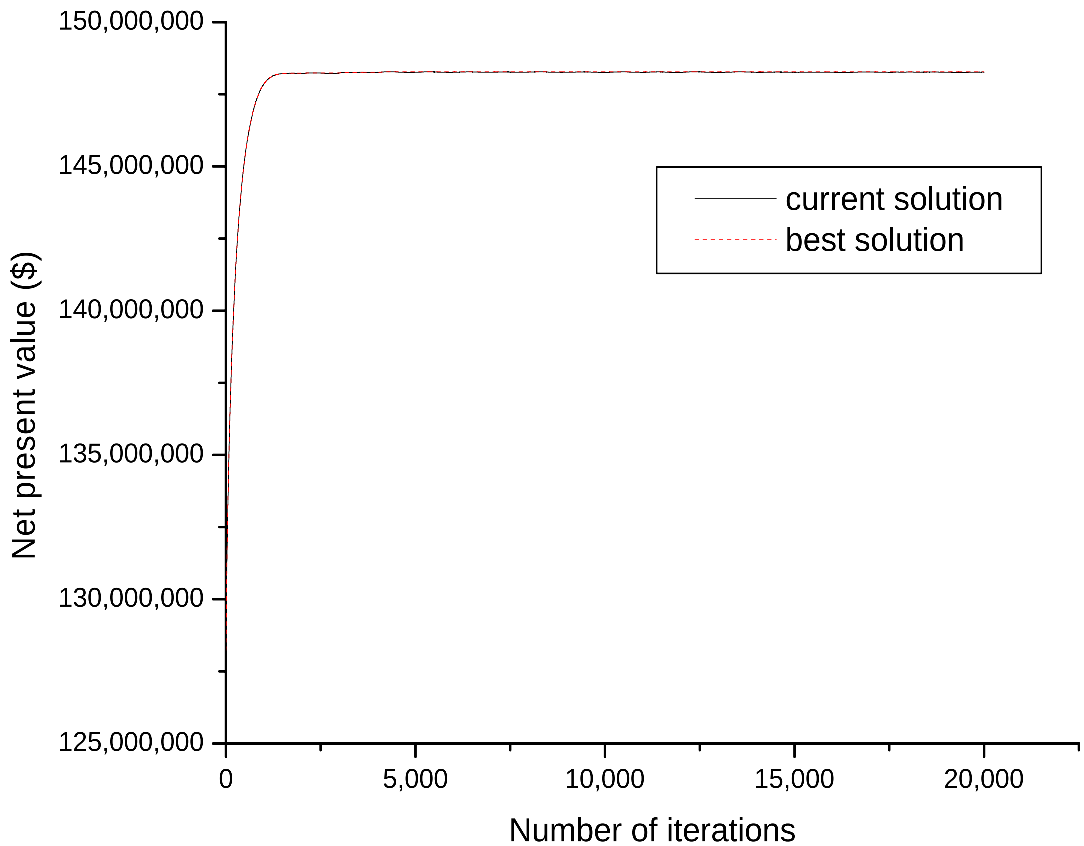

Figure 3.9 Behavior of TS search process using best parameters for the large-sized GIS database

As with the 1-opt tabu search process, a neighborhood of potential changes to the current solution represents the potential net present value of a new solution if any one of the potential changes represented in the neighborhood is selected. Therefore, the neighborhood of potential changes is computed, and the search process then searches the neighborhood for the best change to make to the current solution. This choice can either be an improvement on the current solution (i.e., one that leads to a higher net present value), or not (one that leads to the least decrease in net present value from the current solution).

If the choice that is made is "tabu," it could be rejected. A tabu choice is one that has been made recently in the search process. A "tabu state" is assigned to each choice that is made. This tells the search process that a choice is "off limits" for some period of time (some number of future iterations of the process). If the selected choice is considered tabu, it can still be chosen if it leads to a solution that is better than the best solution stored in memory. This is termed the "aspiration criteria."

If the choice that is selected from the neighborhood is either not tabu, or tabu (yet passes the aspiration criteria), the constraints are then assessed. If any one of the constraints fails, the choice is rejected. As in threshold accepting and 1-opt tabu search, the wood flow constraints are first assessed, then, if feasible, the adjacency constraints. If all of the constraints are satisfied, the choice is formally accepted into the current solution.

Table 3.4 Tabu search parameters for different size GIS database (2-opt)

Size	Total number of iterations	Length of tabu status
Small	50	100
Medium	100	100
Large	400	100

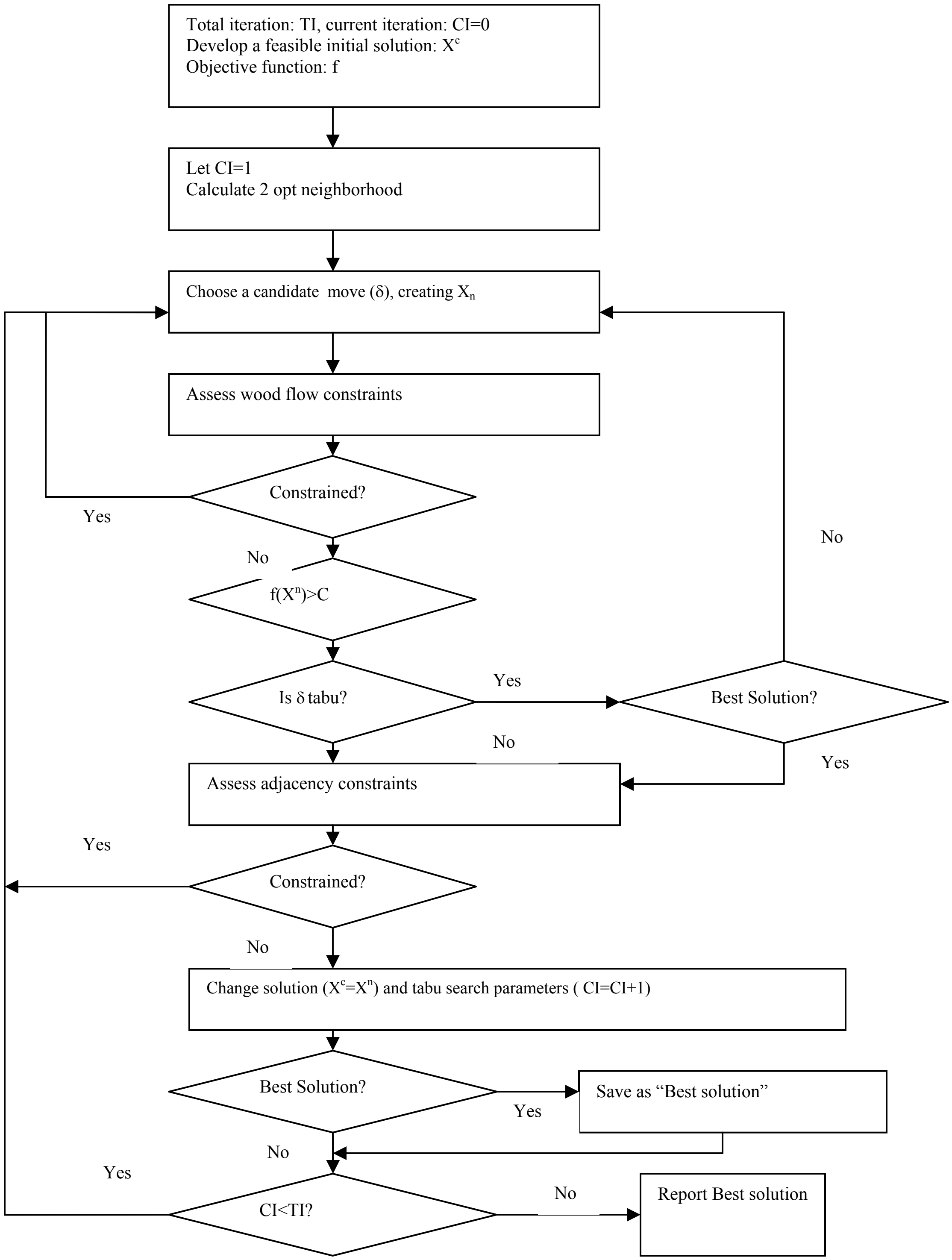

Figure 3.10 Illustration of the 2-opt tabu search process.

3.2.6 Meta heuristic: threshold accepting, 1-opt tabu search, 2-opt tabu search

The meta heuristic (Figure 3.11) consists of threshold accepting, 1-opt tabu search and 2-opt tabu search. The main tabu search processes applied in the spatial forest planning models are ones that use 1-opt moves, and 2-opt moves. In the meta heuristic, threshold accepting is carried on first with all the parameters described earlier. The 1-opt tabu process is carried out using the result of threshold accepting. The 2-opt process uses the result of 1-opt search and is last step refining the result (Figure 3.11). The 1-opt move process assesses the new solution after a change to a "current solution" by modifying the prescription assigned to a single polygon. The 2-opt process assesses the new solution after a change to the current solution by switching the prescriptions assigned to two polygons.

The reasons for developing this process are, first, that threshold accepting has been shown to quickly move a solution from an inferior state to a very good state. Tabu search with 1-opt moves can do this too, but takes much longer to do so, given the computations necessary to develop the neighborhood of choices during each iteration. Tabu search with 1-opt moves is employed prior to tabu search with 2-opt moves to further refine the solution prior to the computationally–expensive 2-opt process. However, the 2-opt process further refines the solution by intensifying the search around a very good solution (Bettinger at al. 1999, 2002). The parameters from Table 3.2, Table 3.3, and Table 3.4 for threshold accepting, 1-opt tabu search and 2-opt tabu search respectively in the meta heuristic. The 1-opt and 2-opt loop runs once in this implementation.

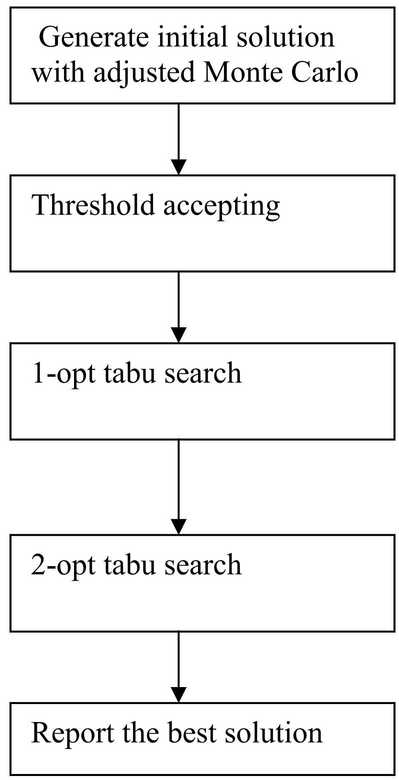

Figure 3.11 Basic illustration of the meta heuristic

3.3 Results and discussion

In order to compare the results, 30 solutions for each of the 27 GIS databases were generated by each of the three heuristics (81 sets of 30 solutions). Each of the solutions can be considered independent to each other because the starting point of each search was a random solution. A series of statistics are employed to evaluate the mean, maximum, minimum, standard deviation of each set of 30 solutions.

The best solution generated by the three heuristics for the 27 hypothetical landowners is shown in Table 3.5. The meta heuristic provides the best solutions for most of the problems involving normal and old forest age classes. In the three (of 18) instances where it did not, the best solution generated by the meta heuristic was within 0.5% of the best solution generated by other either tabu search or threshold accepting. In general, the meta heuristic and threshold accepting produced similar solutions, although in a few cases, the meta heuristic was $200,000 or higher in net present value. On the downside, the meta heuristic was out performed in most cases including the young forest age class structures. The time required to generate a meta heuristic solution was also about 2 times as long as the others, mainly due to the inclusion of 2-opt procedure.

The threshold accepting heuristic performed reasonably well on its own and much better than the 1-opt tabu search heuristic on the large forest problems. 1-opt tabu search was out performed both threshold accepting and the meta heuristic on the small and medium young forest age class structures. The time required for both threshold accepting and tabu search to develop their best solutions was very similar, and about one-half that need for meta heuristic.

On average, the meta heuristic produced the better solutions to most of the 27 problems (Table 3.6) with the exception of medium and small young forests. The worst solutions (minimum solution) generated by the meta heuristic were about as poor as the worst solution generated by threshold accepting (Table 3.7), and better (significantly in old forest cases) than those produced by 1-opt tabu search (Table 3.8). The variation in results for each of the 27 problems was highest when use 1-opt tabu search was used and was similar between threshold accepting and the meta heuristic.

While it required more time to generate a solution, the meta heuristic produced the most favorable solutions to many of the problems. One could characterize their quality as being slightly better, on average, and containing similar variation as solution generated by threshold accepting.

Table 3.5 Quality of the best solution generated and associated time spent by three heuristics

	TA		TS		Meta	
Databases	Best Solution (NPV)	Time spent (hrs)	Best Solution (NPV)	Time spent (hrs)	Best Solution (NPV)	Time spent (hrs)
Large, Clumped, Normal	147,186,443	1.89	137,015,302	0.74	147,290,260	2.81
Large, Dispersed, Normal	147,334,415	1.13	137,158,893	0.77	147,346,731	2.02
Large, Random, Normal	144,666,346	1.11	135,479,598	0.73	144,853,289	2.09
Medium, Clumped, Normal	30,221,224	0.48	30,174,932	0.21	30,247,567	0.68
Medium, Dispersed, Normal	30,930,636	0.11	30,950,206	0.18	30,919,281	0.28
Medium, Random, normal	31,969,564	0.15	31,929,358	0.21	31,999,744	0.35
Small, Clumped, Normal	15,104,291	0.19	15,045,319	0.22	15,236,543	0.28
Small, Dispersed, Normal	14,848,688	0.05	14,873,803	0.09	14,908,719	0.14
Small, Random, Normal	15,100,433	0.06	15,070,506	0.10	15,104,362	0.18
Large, Clumped, Old	177,738,163	1.97	165,980,503	0.83	177,929,303	3.09
Large, Dispersed, Old	180,763,163	1.15	169,524,278	0.79	180,772,764	2.16
Large, Random, Old	175,671,888	1.18	160,694,543	0.80	175,818,338	2.19
Medium, Clumped, Old	36,273,572	0.61	36,357,071	0.23	36,321,728	0.83
Medium, Dispersed, Old	36,928,728	0.14	36,668,719	0.19	36,928,773	0.33
Medium, Random, Old	39,241,724	0.19	39,021,044	0.22	39,270,258	0.40
Small, Clumped, Old	18,252,713	0.20	17,958,838	0.17	18,172,697	0.29
Small, Dispersed, Old	17,902,145	0.06	17,895,195	0.10	17,986,656	0.15
Small, Random, Old	18,410,390	0.08	18,100,495	0.09	18,548,123	0.19
Large, Clumped, Young	111,407,076	1.46	97,978,198	0.70	111,543,510	2.27
Large, Dispersed, Young	111,813,398	0.79	98,906,388	0.71	111,716,500	1.59
Large, Random, Young	107,838,819	0.79	94,714,039	0.68	107,780,975	1.57
Medium, Clumped, Young	22,657,789	0.29	22,867,632	0.33	22,708,003	0.46
Medium, Dispersed, Young	23,045,952	0.07	23,395,161	0.15	23,083,192	0.21
Medium, Random, Young	23,553,600	0.09	23,882,224	0.17	23,696,948	0.27
Small, Clumped, Young	11,033,854	0.13	11,116,497	0.18	11,050,164	0.21
Small, Dispersed, Young	11,404,357	0.04	11,551,906	0.08	11,364,717	0.11
Small, Random, Young	11,495,767	0.04	11,612,310	0.10	11,497,653	0.13

TA=Threshold accepting TS=tabu search meta=meta heuristics

Table 3.6 In-depth statistics regarding the meta heuristic solution (n=30 in each of the 27 cases)

Databases	Maximum solution (NPV)	Minimum solution (NPV)	Mean solution (NPV)	Standard deviation solution (NPV)	Mean time (hrs)	Standard deviation time (hrs)
Large, Clumped, Normal	147,290,260	146,723,151	147,059,301	127,051	2.81	0.0145
Large, Dispersed, Normal	147,346,731	146,896,254	147,174,121	105,526	2.02	0.0056
Large, Random, Normal	144,853,289	144,449,642	144,604,831	104,956	2.09	0.0073
Medium, Clumped, Normal	30,247,567	30,063,669	30,154,847	44,830	0.67	0.0191
Medium, Dispersed, Normal	30,919,281	30,720,674	30,837,965	50,187	0.28	0.0023
Medium, Random, normal	31,999,744	31,648,001	31,883,998	70,009	0.35	0.0022
Small, Clumped, Normal	15,236,543	14,697,447	14,923,503	149,222	0.19	0.0046
Small, Dispersed, Normal	14,908,719	14,382,119	14,660,931	131,756	0.15	0.0395
Small, Random, Normal	15,104,362	14,663,604	14,892,017	104,775	0.16	0.0029
Large, Clumped, Old	177,929,303	177,537,484	177,731,345	95,325	3.08	0.0113
Large, Dispersed, Old	180,772,764	180,491,134	180,620,684	88,593	2.15	0.0056
Large, Random, Old	175,818,338	175,232,872	175,587,872	125,244	2.16	0.0078
Medium, Clumped, Old	36,321,728	36,021,862	36,159,711	80,795	1.26	2.2898
Medium, Dispersed, Old	36,928,773	36,680,344	36,806,826	71,169	0.33	0.0015
Medium, Random, Old	39,270,258	38,817,947	39,135,416	101,482	0.40	0.0022
Small, Clumped, Old	18,172,697	17,430,700	17,829,542	194,847	0.30	0.0048
Small, Dispersed, Old	17,986,656	17,132,688	17,528,644	221,654	0.15	0.0030
Small, Random, Old	18,548,123	17,638,789	18,082,608	234,744	0.18	0.0026
Large, Clumped, Young	111,543,510	111,109,842	111,330,420	99,753	2.26	0.0086
Large, Dispersed, Young	111,716,500	110,839,308	111,384,933	185,811	1.60	0.0090
Large, Random, Young	107,780,975	107,079,886	107,420,979	161,272	1.56	0.0097
Medium, Clumped, Young	22,708,003	22,456,251	22,575,653	65,597	0.46	0.0084
Medium, Dispersed, Young	23,083,192	22,710,915	22,908,212	85,830	0.21	0.0022
Medium, Random, Young	23,696,948	23,260,553	23,446,960	95,355	0.26	0.0030
Small, Clumped, Young	11,050,164	10,728,465	10,869,645	88,369	0.20	0.0048
Small, Dispersed, Young	11,364,717	11,066,177	11,243,817	69,042	0.11	0.0020
Small, Random, Young	11,497,653	11,203,025	11,377,452	79,960	0.13	0.0020

Table 3.7 In-depth statistics regarding the threshold accepting solution (n=30 in each of the 27 cases)

Databases	Maximum solution (NPV)	Minimum solution (NPV)	Mean solution (NPV)	Standard deviation solution (NPV)	Mean time (hrs)	Standard deviation time (hrs)
Large, Clumped, Normal	147,186,443	146,751,316	147,002,635	88,967	1.88	0.0057
Large, Dispersed, Normal	147,334,415	146,969,954	147,112,537	84,064	1.12	0.0021
Large, Random, Normal	144,666,346	144,350,357	144,512,074	92,151	1.11	0.0030
Medium, Clumped, Normal	30,221,224	30,014,957	30,127,954	47,366	0.48	0.0046
Medium, Dispersed, Normal	30,930,636	30,679,421	30,838,991	58,995	0.12	0.0009
Medium, Random, normal	31,969,564	31,803,717	31,889,503	45,005	0.15	0.0009
Small, Clumped, Normal	15,104,291	14,533,705	14,861,849	163,707	0.37	0.5352
Small, Dispersed, Normal	14,848,688	14,346,198	14,632,945	122,556	0.05	0.0015
Small, Random, Normal	15,100,433	14,473,625	14,881,778	141,381	0.06	0.0019
Large, Clumped, Old	177,738,163	177,447,465	177,603,823	75,778	1.97	0.0061
Large, Dispersed, Old	180,763,163	180,376,325	180,529,460	95,645	1.14	0.0047
Large, Random, Old	175,671,888	175,358,330	175,496,600	90,659	1.18	0.0018
Medium, Clumped, Old	36,273,572	35,903,645	36,150,274	92,493	0.62	0.0137
Medium, Dispersed, Old	36,928,728	36,606,934	36,792,688	88,160	0.14	0.0011
Medium, Random, Old	39,241,724	38,892,874	39,124,263	87,638	0.19	0.0010
Small, Clumped, Old	18,252,713	17,259,523	17,742,594	214,780	0.20	0.0074
Small, Dispersed, Old	17,902,145	17,129,740	17,534,926	178,391	0.06	0.0015
Small, Random, Old	18,410,390	17,671,206	18,033,118	173,453	0.07	0.0021
Large, Clumped, Young	111,407,076	110,851,961	111,211,343	118,331	1.46	0.0062
Large, Dispersed, Young	111,813,398	111,094,584	111,335,915	163,674	0.79	0.0040
Large, Random, Young	107,838,819	106,888,262	107,336,658	179,559	0.79	0.0041
Medium, Clumped, Young	22,657,789	22,385,192	22,547,999	68,416	0.30	0.0057
Medium, Dispersed, Young	23,045,952	22,482,869	22,888,484	112,586	0.07	0.0017
Medium, Random, Young	23,553,600	23,143,970	23,389,789	111,854	0.10	0.0016
Small, Clumped, Young	11,033,854	10,646,339	10,875,570	99,936	0.13	0.0033
Small, Dispersed, Young	11,404,357	11,066,898	11,209,577	79,117	0.04	0.0010
Small, Random, Young	11,495,767	11,191,102	11,355,753	69,681	0.04	0.0015

Table 3.8 In-depth statistics regarding the tabu search solution (n=30 in each of the 27 cases)

Databases	Maximum solution (NPV)	Minimum solution (NPV)	Mean solution (NPV)	Standard deviation solution (NPV)	Mean time (hrs)	Standard deviation time (hrs)
Large, Clumped, Normal	137,015,302	130,533,201	133,256,055	1,773,852	0.75	0.0083
Large, Dispersed, Normal	137,158,893	128,927,649	133,307,132	2,364,256	0.76	0.0131
Large, Random, Normal	135,479,598	129,084,195	131,271,568	1,568,620	0.73	0.0098
Medium, Clumped, Normal	30,174,932	29,916,595	30,049,159	73,680	0.21	0.0118
Medium, Dispersed, Normal	30,950,206	30,535,196	30,714,628	109,727	0.18	0.0012
Medium, Random, Normal	31,929,358	31,533,289	31,744,262	109,815	0.21	0.0017
Small, Clumped, Normal	15,045,319	14,488,736	14,805,761	152,787	0.51	1.7154
Small, Dispersed, Normal	14,873,803	14,460,635	14,682,829	109,904	0.10	0.0008
Small, Random, Normal	15,070,506	14,533,776	14,873,310	144,157	0.10	0.0108
Large, Clumped, Old	165,980,503	155,871,381	159,045,287	2,564,128	0.80	0.0113
Large, Dispersed, Old	169,524,278	156,449,432	160,670,152	3,231,045	0.78	0.0106
Large, Random, Old	160,694,543	152,914,446	157,029,872	2,115,883	0.79	0.0067
Medium, Clumped, Old	36,357,071	35,625,570	35,946,897	181,383	0.23	0.0020
Medium, Dispersed, Old	36,668,719	36,066,760	36,431,426	150,379	0.19	0.0009
Medium, Random, Old	39,021,044	38,139,481	38,593,633	208,488	0.22	0.0007
Small, Clumped, Old	17,958,838	17,299,992	17,637,117	161,302	0.14	0.0723
Small, Dispersed, Old	17,895,195	17,222,862	17,528,975	183,045	0.10	0.0007
Small, Random, Old	18,100,495	17,220,148	17,623,001	214,823	0.09	0.0012
Large, Clumped, Young	97,978,198	93,771,947	95,980,164	1,133,977	1.23	2.8181
Large, Dispersed, Young	98,906,388	94,158,779	95,649,607	1,161,243	0.71	0.0035
Large, Random, Young	94,714,039	90,731,400	92,024,471	951,334	0.69	0.0020
Medium, Clumped, Young	22,867,632	22,516,404	22,719,244	84,507	0.32	0.1275
Medium, Dispersed, Young	23,395,161	23,086,176	23,217,040	74,480	0.15	0.0021
Medium, Random, Young	23,882,224	23,610,096	23,770,549	74,031	0.18	0.0017
Small, Clumped, Young	11,116,497	10,632,425	10,926,773	105,491	0.12	0.0629
Small, Dispersed, Young	11,551,906	11,212,807	11,376,069	70,280	0.08	0.0007
Small, Random, Young	11,612,310	11,049,938	11,481,927	121,623	0.09	0.0079

Another way to evaluate heuristic performance is to compare the results they generate to the results provided by relaxed linear programming. One can measure the reduction in solution quality (percentage reduction) as the cost of implementing the adjacency and green-up policy. The percentage reductions using the meta heuristic were 0.3% to 4.5% below the linear programming situations. This is consistent with the results found by others (e.g. Boston and Bettinger, 2001).

One might argue that the improvement in solutions generated by meta heuristic is simply because the meta heuristic takes much longer time to generate a solution. However, because the parameters for threshold accepting and tabu search were carefully selected, the comparison among result is valid. Even if the number of iterations for threshold accepting and 1-opt tabu search were increased, we hypothesize that the results would not change significantly. The reason why the meta heuristic performs better in most cases is that it uses 2-opt tabu search process to switch the schedule for two units simultaneously. A 2-opt heuristic is also an intensification (rather than diversification) scheme which has been shown to refine solutions very well (Bettinger et al. 1999).

This intensification process works well for small forest planning problems (Bettinger et al 2002), and has shown promise for larger management problems (Bettinger et al. in press). What remains to be determined is whether the sequence of scheduling techniques (TA, 1-opt TS, 2-opt TS) needs adjusting to further enhance the performance of the meta heuristic. When it comes to young age class problems (where 1-opt TS excelled), the addition of 2-opt TS may not have been of value, since the earlier study (Bettinger et al. in press) suggested its usefulness in planning problems which maximized even-flow of timber harvest volume (not NPV), with random or older forest age class structures.

While the concentration here has been on the assessment of a meta heuristic with threshold accepting and tabu search processes, other types of heuristics could provide processes to help diversify (avoid becoming stuck in local optima) or intensify the search (carefully search a good area of the solution space). TA was selected based on previous research (Bettinger et al 2002). 1-opt tabu search has some advantageous characteristics (deterministic moves made, regardless of decrease in solution value). And 2-opt tabu search has been suggested as a worth-while addition to tabu search algorithms even though the processing time requirements may be high. Other heuristics such as genetics algorithms have been included in forest planning meta heuristics (e.g. Boston and Bettinger, 2001). However, the effect of the crossover routine on the maintenance of adjacency is generally so high that a number of constraint violations must be attended to (usually by unscheduled harvests) to maintain feasibility at each iteration of the search.

3.4 Conclusions

While threshold accepting can provide very good solutions to a variety of forest planning problems, and produce them relatively quickly, the addition of tabu search procedures (to form a meta heuristic) allows one to produce high quality solutions, on average to many type of forest planning problems. The additional time required (0.5 hr to 1 hr) to generate a solution that has a \$50,000-200,000 increase in net present value seems moot, given that the plan will be implemented over a series of years.

This work has shown that the cost of typical adjacency constraints (2 year green-up and 240 acres maximum clear cut size) is consistent with current knowledge: 1-5% reduction in NPV from relaxed case. What remains to examine is the impact on the various hypothetical landowners to determine which may be more highly affected by policies that restrict the timing and placement of clearcuts. In addition, one further recent advancement in spatial harvest scheduling (Bettinger and Zhu, 2006) may be useful in developing even better solutions. However, this new technique, called the raindrop effect, has only been tested on a limit set of small, even-flow maximization problems.

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CHAPTER 4

ESTIMATING THE EFFECT OF GREEN-UP CONSTRAINTS ON DIFFERENT TYPES OF LANDOWNERS[2]

[2] Zhu, J., P. Bettinger. To be submitted to *Canadian Journal of Forest Research*.

ABSTRACT

The Sustainable Forestry Initiative (AF & PA 2004) recommends a maximum clearcut size of 240 acres for members who have voluntarily agreed to adhere to its standards. Some states of United States have laws that indicate the maximum clearcut size. The impact of actual and hypothetical clearcut size restrictions is therefore a concern for forest landowners who have acquired land and intend to practice forestry for profit. In this research, the effect of a 240 acre clearcut size constraint with a green-up period of 2-years is assessed for forest landowners with different forest land sizes, ownership patterns, and age class distributions. A meta heuristic which consists of threshold accepting, 1-opt tabu search, and 2-opt tabu search is used to develop spatially-constrained forest plans for 27 hypothetical forest landowners. These results are compared to a relaxed solution produced with linear programming, and statistical analyses are used to determine differences in impact on the hypothetical landowners. The null hypothesis is that each of hypothetical landowners is affected in a similar manner when adjacency constraints are imposed. ANOVA analysis gave us enough evidence to reject the null hypothesis which means that at least there exists two factors (size of ownership pattern and age class distribution), and one interaction factor (size×age class discussion) which have significant different mean values across different levels. One can conclude from this analysis that landowners of small forests with young age class distributions will be significantly more affected by adjacency and green-up restrictions in the southern U.S. than other types of landowners.

INDEX WORDS: Forest Planning, Harvest Scheduling, Heuristics, Tabu Search, Threshold Accepting, Meta Heuristic

4.1 Introduction

Tactical forest harvest scheduling problems typically include temporal and spatial constraints, due to voluntary and regulatory forest based programs (Bettinger and Sessions 2003). Nowadays, forest planning problems are becoming increasingly complex because of the need to integrate ecological, economical and management objectives into a planning process. As a consequence, heuristic techniques are increasingly used in forest planning, rather than exact methods (i.e. linear programming). A number of studies (e.g. Boston and Bettinger 2001) have illustrated the cost of adjacency on forest landowners in the U.S. These studies typically utilize a single hypothetical landowner as an illustrative case to determine the percent reduction in land value between a relaxed case (i.e. no adjacency constraints) and a constrained case. The purpose of this work is to move beyond the determination of the cost of adjacency for southeastern U.S. landowners and to determine which landowner groups (defined by size, spatial configuration of parcels, and age class distribution) are most affected by a typical green-up and adjacency policy.

Some states have laws that stipulate that the maximum clearcut size should below a certain size. Currently, none of the states in the southeastern U.S. have these types of laws, however, landowners who agree to adhere to the Sustainable Forest Initiative (AF & PA 2004) must keep clearcut below 240 acres. In this research, we will evaluate the effect of a 240 acre clearcut area constraint with a 2-year period on forest landowners with different forest land size, ownership pattern, and age class distributions.

4.2 Methods

In this methods section, we describe the solution processes used to generate the forest plans that will be assessed. In addition, the problem formulation and the 27 hypothetical databases that are examined are described along with the statistical analyses that will be performed to determine whether one or more of these hypothetical landowners are more affected by adjacency and green-up constraints than the others.

4.2.1 Mathematical programming

The general forest planning problem, where harvesting is an important process, has been studied for some time (Bettinger and Chung 2004). Linear programming has traditionally been used and still is one of the most commonly used planning techniques in natural resources management. LP-based models were used from the 1960s to 1990s on U.S. National Forests and are classic in the sense that they use linear programming to allocate resources and activities to timber stands, and to a limited extent, recognize spatial relationships. LP is still used today on many industrial lands, and Canadian provinces.

Since LP models generally assume continuous variables are used, the solution is non-integral. Recognition of spatial features in forest planning generally requires the use of integer-decision variables, thus spatial relationships, thus other than management spatial relationship are usually not defined in an LP model. When integer decision variables are used, the problem size of forest planning increases, the potential solution space also increases, but at a disproportionately greater rate (Lockwood and Moore, 1993). Consequently, LP-based solutions are not suitable for solving spatial harvest problems with integer decision variables, because they are difficult to interpret and may be impossible to implement.

LP models make three broad assumptions. First, the linearity assumption suggests that when one unit (X1) accounts for a change of $100 in the objective function, two units of X1 will account for $200 change in the objective function. In addition, no interactions are allowed.

Therefore if one unit of X1 accounts for \$100, and one unit of X2 accounts for \$200, together, they account for \$300 in the objective function. The second LP assumption is that all variables have a value greater than or equal to zero and these can be either continuous numbers or integers, but they do not necessarily have to be integers. The third general assumption is that the coefficients of each decision variable are known with certainty, although same work (e.g. Hof et al. 1988) has been presented to address randomness in yield coefficients.

Since LP-based models are not able to express spatial relationships in a practical manner, researchers began to study and apply mixed integer programming (MIP) models (Jones et al. 1991) in the late 1980's and early 1990's. An integer decision variable is often used to express a particular harvesting or road management decision. This type of variable allows users a planning model to accommodate spatial relationships and allows uses of control adjacency restrictions. MIP and integer programming techniques have been used to help solve natural resource management problems and to generate feasible management plans. But since the MIP model uses a large number of integer variables, it is restricted to medium-sized natural resource management problems, thus these techniques are not used for broader landscapes (Lockwood and Moore 1993).

To explore the capability of traditional mathematical techniques, Hof and Joyce (1992) described nonlinear formulations that account for the amount of edge, the juxtaposition of different habitat types, the dispersal distance among habitat types, and the minimum size of a patch of habitat. Hof et al. (1994) also described a MIP approach that incorporates probabilistic objective functions for wildlife viability concerns, and provides valuable insight into a much border range of capabilities of linear, integer and nonlinear programming methods. However, the limitation of these techniques persists, and both heuristics and simulation models are now being considered as possible alternatives for the development of natural resource management plans with spatial relationships.

4.2.2 Heuristic optimization

As noted earlier, heuristics are becoming more prevalent for solving forest harvest scheduling problems, especially when the problems involve large potential solution spaces or adjacency constraints. There have been numerous studies exploring the use of heuristic optimization techniques to solve harvest scheduling problems. Many types of complex, nonlinear goals (e.g. spatial and temporal distribution of elk habitat, as described in Bettinger et al. (1997), which have traditionally been considered impossible to solve with exact algorithms, are now being incorporated into heuristics. In addition, heuristics are not confined to the three broad assumptions associated with linear programming. Heuristics have been used to solve forest transportation problems (Murry and Church 1995), wildlife conservation and management problems (Arthaud and Rose 1996, Bettinger et al. 1997, Haight and Travis 1997), aquatic system management problems (Bettinger et al. 1998), and the problems that deal with the achievement of biodiversity goals (Kangas and Pukkala 1996). The most popular heuristics used in natural resource management include Monte Carlo simulation (MC), tabu search (TS), simulated annealing (SA), threshold accepting (TA), and genetic algorithms (GA). Some efforts are also being made to integrate aspects of each into hybrid heuristic techniques.

Although using heuristics does not guarantee one will locate a global optimum solution to a scheduling problem, one can be confident that a good heuristic will generate feasible solutions to complex problems in a reasonable amount of time. Heuristics have been extensively applied in scheduling problems in the past few decades. For example, Bettinger and Chung (2004) illustrate a number of other efforts in North America and Nelson and Brodie (1990) applied MC heuristic to solve an area based forest plan problem. It is a biased sampling scheme that generates feasible solution alternatives, thus the greater the number of samples, the better the solution. Therefore, with this technique, optimal or near optimal solutions may only be possible if very large number of samples are generated. Unfortunately, large samples significantly increase the time required to find a solution.

Threshold accepting (TA) was introduced by Dueck and Scheuer (1990). The TA technique also uses a localized search process, but uses a slightly different and somewhat simpler set of acceptance rules for a new solution than simulated snnealing (SA). Threshold accepting accepts every new solution that is not much worse than previous solution within a preset limit of the value of current solution, whereas in SA the probability that a lower quality proposed solution would replace the current solution is a function of the quality of a solution and a stochastic element.

Tabu search (TS) has been successfully applied to a number of scheduling problems outside of forestry and wildlife management, such as those involving telecommunication, transportation, shop sequencing, machine scheduling, and layout and circuit design problems (Glover 1990). Within forestry it has been applied to timber harvest scheduling problems with adjacency requirements (Murry and Church 1995), as well as to forest plans that have landscape goals for elk (Bettinger et al. 1997), and aquatic habitat (Bettinger et al. 1998). Tabu search with 1-opt moves (changing the harvest timing of a single management unit), short-term memory, and aspiration criteria is a good scheduling technique, but generally not as good as SA or TA (Bettinger et al. 2002). Using 2-opt and greater moves have allowed TS to refine solutions and produce results as good as SA or TA, but at a fairly large computing cost (Bettinger et al. 1999, 2002). One advantage of TS is that it is well suited to parallel processing.

It has been shown in previous work (Zhu 2006) that a combination of threshold accepting and tabu search heuristics can improve most solutions generated to a NPV maximization, area restriction adjacency management problem, when compared to basic tabu search and threshold accepting. In cases where meta heuristic produced solution of lower quality, the difference was small. In all cases, the variation in solution results from the meta heuristic was the smallest. Therefore, to solve the problem that is described next, a meta heuristic that uses threshold accepting, 1-opt tabu search, and 2-opt tabu search, in that order, will be used.

4.2.3 Forest planning model formulation

The forest planning problem that we investigated falls between strategic planning (long time frames, large area) and operational planning (short time frames, specific areas) in an area termed "tactical planning." The level of detail used in this research is generally greater than those used in strategic planning analyses, yet significantly lower than what is required for operational planning. The time horizon assumed is 20 years and each planning period will be one year long. This tactical planning model attempts to maximize the net present value of timber harvested. The objective function is formulated as:

Maximize:

$$\sum_{t=1}^{T}\left[\sum_{i}^{N}(V_{it}X_{it}(P-C_{it}))/1.06^{(t-0.5)}\right]+\sum_{i}^{N}(V_{i20}(P-C_{it}))/1.06^{19.5} \tag{1}$$

Subject to:

$$\sum_{t=1}^{T}X_{it}\leq 1 \qquad \forall i \tag{2}$$

$$X_{it}A_i + \sum_{z\in N_i \cup S_i} X_{zt}A_z \leq \text{MCA} \quad \forall_{i,\, t} \tag{3}$$

$$\sum_{i=1}^{n} V_{i20} - \sum_{i=1}^{n}\sum_{t=1}^{20} X_{it}V_{i20} > 0.9 * \sum_{i=1}^{n} V_{i1} \tag{4}$$

$$AG_c\text{-}AG_{t1}>5 \tag{5}$$

$$AG_c\text{-}AG_{t2}>5 \tag{6}$$

$$\sum_{i=1}^{n} X_{it}V_{it} > 0.9 * \sum_{i=1}^{n}\sum_{t=1}^{T} X_{it}V_{i20} / T \qquad \forall \text{ t} \tag{7}$$

$$\sum_{i=1}^{n} X_{it}V_{it} < 1.1 * \sum_{i=1}^{n}\sum_{t=1}^{T} X_{it}V_{i20} / T \qquad \forall \text{ t} \tag{8}$$

$$\sum_{i=1}^{n} X_{it}V_{it} > 0.9 * \sum_{i=1}^{n} X_{it-1}V_{it-1} \qquad \forall \text{ t}\geq 2 \tag{9}$$

$$\sum_{i=1}^{n} X_{it}V_{it} < 1.1 * \sum_{i=1}^{n} X_{it-1}V_{it-1} \qquad \forall \text{ t}\geq 2 \tag{10}$$

Where:

A_i= area of management unit i

AG_c=clear cut age

AG_{t1}=age when first thin happens

AG_{t2}=age when second thin happens

C_{it}= logging cost per m^3 for unit i harvested in time period t

Ht = the actual scheduled harvest volume in each time period t

i = a harvest unit

MCA=maximum clearcut area

N=the total number of harvest units

N_i=set of all units adjacent to unit i

P= stumpage price

S_i= the set of all management units adjacent to these management units adjacent to management unit i

t = a planning period

T = the total number of time periods in the planning horizon

V_{i20} = the unscheduled timber harvest volume at the end of period 20, from management unit i

V_{it} = the available timber harvest volume during time period t, from management unit i

X_{it} = a binary variable, which =1 if management unit i is harvested in time period t, 0 otherwise

Equation 2 indicates that each management unit can only be harvested at most one time in all planning periods. Equation 3 ensures that the maximum clearcut size will be maintained (assuming the green-up period is 2 years). Equation 4 is an ending volume constraint. Equation 5 and 6 ensure that the separation period between thinning and clear cutting is at least six years. Equation 7 and 8 constrain the volume harvested in each time period to a proportion of the final, unscheduled and uncut volume. Equation 9 and 10 limit the deviation in harvest volume from one period to the next as a measure of harvest stability. This model formation represents a model I (Johnson and Scheurman 1977), integer programming problem. The adjacency restriction is the area restriction formulation (Murray 1999).

4.2.4 Spatial and non-spatial data

Standard problems used in this research are divided into three ownership size groups: small, medium and large (see Table 4.1), according to problem area acreage. Within each size class, three ownership patterns of parcels were developed: clumped, random, and dispersed.

Three age class distributions were then assigned to them: young forest, normal forest, older forest. Therefore a matrix of 27 hypothetical forests was available for analysis. The characteristics of the databases are illustrated in Table 4.2.

The time horizon is 20 years, divided into twenty 1-year time periods. The interest rate assumed is 6 percent. The stumpage prices were obtained from Timber Mart-South (2004), and are \$43.57 per ton for pine sawtimber, \$25.60 per ton for chip-n-saw, and \$6.73 per ton for pine pulpwood. The costs assumed are \$115.70 per acre for mechanical site preparation, \$47.14 for planting, and \$63.40 for a herbaceous weed control treatment. The maximum clearcut size is 240 acres, and the green-up period is assumed to be 2 years.

Table 4.1 Elements in harvest scheduling type databases

Size	Ownership pattern	Age class distribution
Small (1000-10,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older
Medium (10,001-20,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older
Large (20,001-100,000 ac)	Clumped	Young
		Normal
		Older
	Random	Young
		Normal
		Older
	Dispersed	Young
		Normal
		Older

Table 4.2 Description of the nine main GIS databases

GIS Database	Number of units	Total area (acres)	Average polygon size (acres)	Standard error (acres)
Large, Clumped	2,946	70,546.3	26.7	27.8
Large, Dispersed	2,617	70,347.6	28.1	28.3
Large, Random	2,486	69,257.2	27.8	28.1
Medium, Clumped	516	14,090.5	28.2	27.8
Medium, Dispersed	477	14,383.6	30.1	28.7
Medium, Random	549	14,337.8	26.1	26.5
Small, Clumped	302	7,231.2	26.9	28.5
Small, Dispersed	279	7,269.1	26.7	27.1
Small, Random	308	7,220.8	23.4	25.1

4.3 Results and discussion

Thirty solutions for each of the 27 problems were generated using the meta heuristic. Since each started with a randomly-defined solution, the resulting NPV varies, and each is assumed to be an independent sample from a very large population of potential solutions. One solution to each of the 27 problems was also generated using linear programming. These solutions should be viewed as relaxed solutions to the planning problems since the adjacency constraints were ignored.

4.3.1 Statistical summary analysis

The difference in the results between the meta heuristic and the linear programming solutions divided by the results from linear programming solutions represents the reduction percentage of implementing the green-up and adjacency policies (Table 4.3). It needs to be pointed out that this is just a approximation, because heuristics can not guarantee one will generate a global optimal solution. If technology advances to such an extent in future that one can solve the problem with integer programming or other techniques which can guarantee to generate a global optimum, one will be able to more accurately assess the cost of adjacency and green-up policies.

The largest percentage reduction in spatially constrained problems are for small clumped forest land with a young age class distribution and small dispersed forest land with young age class distribution, each is 4.48% lower in net present value compared to the result from linear programming. The lowest reduction is the medium clumped database with normal age distribution which represents 0.26% reduction in NPV compared to the result from linear programming.

To investigate further for the effect of size, ownership pattern, and age class distributions to forest landowners when applying in the green-up constraints, one can view the average of the percentage reduction among all different sizes. One can see (Figure 4.1) that the average reduction for the 90 small-sized forest solutions is about 3.61% which is much higher than that of the 90 medium size (1.33%) and large size forest solutions (1.43%). When one investigates the effect of ownership pattern by taking average of percentage reduction among all ownership patterns, one can see (Figure 4.2) that the average percentage reduction over different ownership pattern is 2.01% for random pattern, 2.17% for dispersed pattern and 2.10% for compact pattern which are fairly close to each other. Finally, one can take a look at the effect of age class distribution. It can be seen (Figure 4.3) that the average percentage reduction for 90 young class distributions is the highest, which is 2.78%. Next to it is the average percentage reduction for old age class which is 1.93% and the lowest is that for normal forest age class distribution. One can conclude from this analysis that the percentage reduction for young age group is different from other age class distributions, and the small-sized problems are more affected by the green-up and adjacency polices than the medium- and large-sized problems.

In order to further investigate the effect of three factors, we need to determine if there is interaction effect between the three factors (size, spatial pattern, and age class distribution). Figure 4.4 shows the co-effect of size and ownership pattern, in which the three curves are not parallel to each other, thus the differences between three forest sizes on each ownership pattern, which indicate that there exists interactions between the two factors. Figure 4.5 shows the co-effect of forest size and age class distribution. One can see that the three curves are also not parallel, which means that there exists an interaction between size and age class distribution. Figure 4.6 shows the co-effect ownership pattern and age class distributions. Although the curves for different age class distributions under different ownership pattern are not parallel to each other, the difference between them is small. Further investigation is needed to make a final conclusion whether there are interactions between age class distribution and ownership pattern.

Table 4.3 the ratio reduction of net present value from the meta heuristics to linear programming solution

Databases	Ratio reduction
Large clumped normal	1.35
Large dispersed normal	1.20
Large random normal	1.16
Medium clumped normal	0.26
Medium dispersed normal	1.51
Medium random normal	1.00
Small clumped normal	2.84
Small dispersed normal	3.34
Small random normal	2.39
Large clumped old	0.99
Large dispersed old	1.03
Large random old	1.00
Medium clumped old	0.77
Medium dispersed old	0.91
Medium random old	1.20
Small clumped old	4.42
Small dispersed old	3.28
Small random old	3.78
Large clumped young	1.97
Large dispersed young	2.15
Large random young	2.07
Medium clumped young	1.83
Medium dispersed young	2.56
Medium random young	1.95
Small clumped young	4.48
Small dispersed young	4.48
Small random young	3.55
Average	2.13

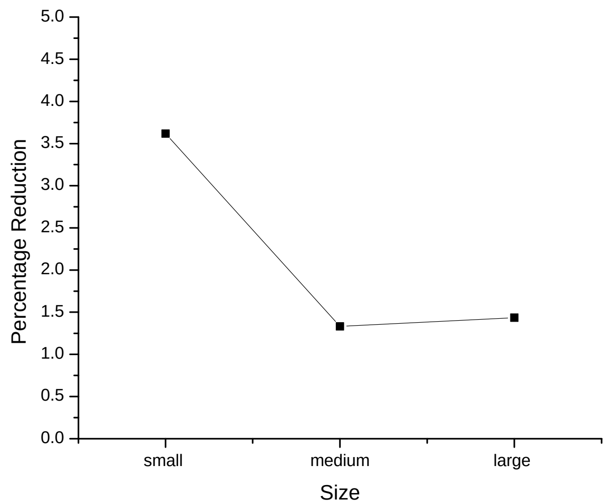

Figure 4.1 Percentage reduction of net present value over different size

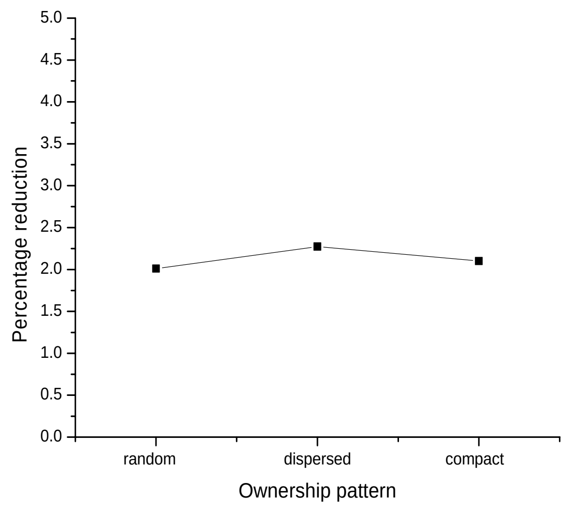

Figure 4.2 Percentage reduction of net present value over different ownership pattern

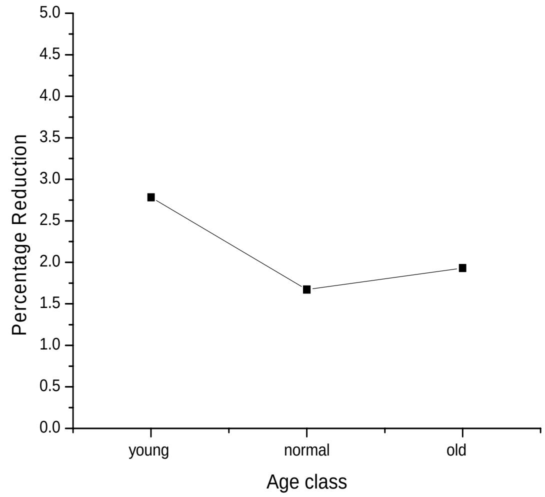

Figure 4.3 Percentage reduction of net present value over different age class

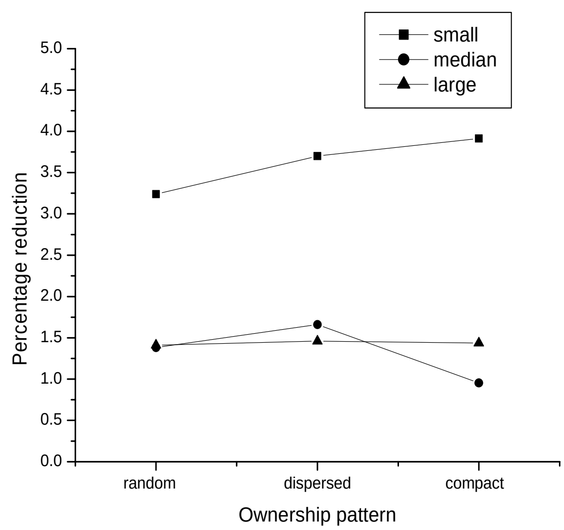

Figure 4.4 The interaction effect of ownership pattern and size

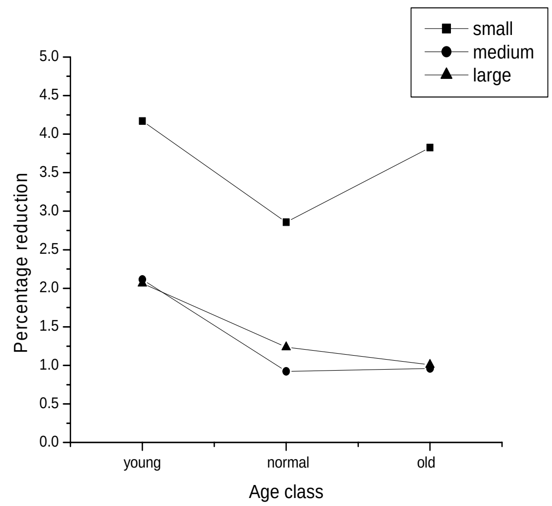

Figure 4.5 The interaction effect of age class and size

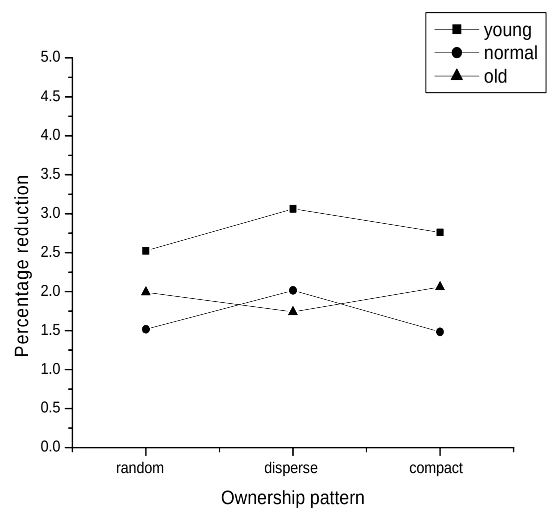

Figure 4.6 The interaction effect of ownership pattern and age class

4.3.2 ANOVA analysis

In the study design, there are three factors (sizes, ownership pattern, and age class distribution) and each factor has 3 levels (for size: small, medium, and large; for ownership pattern: random, dispersed and clumped; for age class: young, normal and old). An ANOVA (Analysis of Variance) is used to further analyze the effect quantitatively.

The ANOVA model is:

$Y_{ijk}=\mu+\alpha_i+\beta_j+\gamma_k+(\alpha\beta)_{ij}+(\alpha\gamma)_{ik}+(\beta\gamma)_{jk}+\varepsilon_{ijk}$

where

Y_{ijk}= the percentage reduction for 27 GIS databases

μ= main effect

α_i=Effect of ith level of size

β_j=Effect of j^{th} level of ownership pattern

γ_k= Effect of k^{th} level age class

$(\alpha\beta)_{ij}$=The interaction effect of i^{th} level of size and j^{th} level of ownership pattern

$(\alpha\gamma)_{ik}$= The interaction effect of i^{th} level of size and k^{th} level of age class

$(\beta\gamma)_{jk}$= The interaction effect of j^{th} level of size and k^{th} level of ownership pattern

ε_{ijk} = Residuals which are normally distributed with mean 0 and constant variance

i= 1, 2, 3

j= 1, 2, 3

k= 1, 2, 3

After fitting the model, one can see (Table 4.4) that the overall model is significant at level 0.0001, which means at least there exists two factors and one factor interaction which have significant different mean values across different levels. The treatment effect and treatment interaction effect model analysis (Table 4.5) indicates that factors of size, age class and the interaction of size and age class are significant at level 0.05. A further investigation shows that (Table 4.6), the p-value for interaction of size and ownership pattern is 0.0515 which is larger than 0.05. By re-examining the graph (Figure 4.4), it can be seen that there is an interaction and it is significant. For the factor of size, the difference between small and other two are significant at level 0.05 but the difference between medium and large are not significant at level 0.05. For that factor of age class distributions, the difference between young age class distributions and normal age class distribution, young age class distributions and old age class distributions are significant at level 0.05 but the difference between normal age class distributions and old age class distributions is not significant at level 0.05. In all, it can be concluded that, for interaction, there are interactions between size and ownership pattern, and size and age class distributions. For factor effects, the small size forest results are different from large and medium size. Young age class distribution is different from normal age class distribution and old age class distribution. This conclusion drawn from ANOVA model matches the conclusions arrived at earlier when viewing the graphs.

Table 4.4 ANOVA of entire model

Source of variance	Degree of Freedom	Sum of Square	Mean Square	F-value	p-value
Model	18	39.675	2.204	28.93	0.0001
Error	8	0.610	0.076		
Corrected Total	26	40.285			

Table 4.5 Treatment effect and treatment interaction effect

Source	DF	Mean Square	F Value	Pr > F
size	2	14.994	196.79	<.0001
pattern	2	0.159	2.10	0.1853
Age class dist.	2	3.035	39.84	<.0001
size×pattern	4	0.288	3.79	0.0515
size×age class dist.	4	0.328	4.31	0.0377
pattern×age class dist.	4	0.206	2.71	0.1072

Table 4.6 Contrast of size and age class at different level

Contrast	DF	Mean Square	F Value	Pr > F
Small size vs. medium size	1	23.506	308.51	<.0001
Small size vs. large size	1	21.429	281.24	<.0001
Large size vs. medium size	1	0.048	0.63	0.4500
Young age vs. normal age class	1	5.544	72.77	<.0001
Young age vs. old age class	1	3.259	42.78	0.0002
Normal vs. old age class	1	0.301	3.96	0.0818

4.3.3 Model validation

One assumption for an ANOVA model to be valid, which needs to be tested, is the normality of the residuals. The quantile-quantile (q-q) plot is a standard graphical technique for determining if two data sets come from populations with a common distribution.

A q-q plot is a plot of the quantiles of the first data set against the quantiles of the second data set. By a quantile, this implies the fraction (or percent) of points below the given value. That is, the 0.2 (or 20%) quantile is the point at which 20% percent of the data fall below and 80% fall above that value.

If the two sets come from a population with the same distribution, the points should fall approximately along a 45 degree reference line. The greater the departure from this reference line, the greater the evidence for the conclusion that the two data sets have come from populations with different distributions. In our case, the plot of standard normal distribution vs. our observed data the result shows that it is approximately a 45 degree line (Figure 4.7). The histogram of residuals also shows the normality assumption holds (Figure 4.8). Another assumption needs to be checked is that the residuals have constant variance. This is can be verified in Figure 4.9 which shows the plot of residuals vs. predicted value of Y_{ijk}. Here the residuals have constant variance and mean zero.

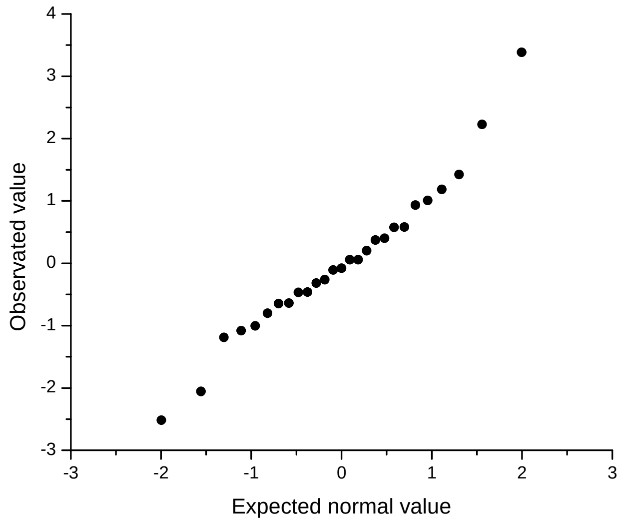

Figure 4.7 q-q plot of the quantiles

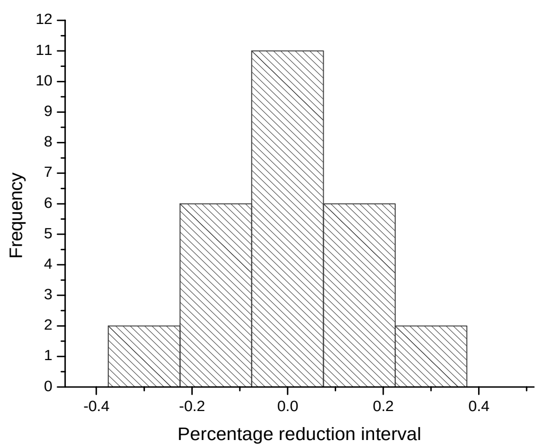

Figure 4.8 Histogram of the residuals

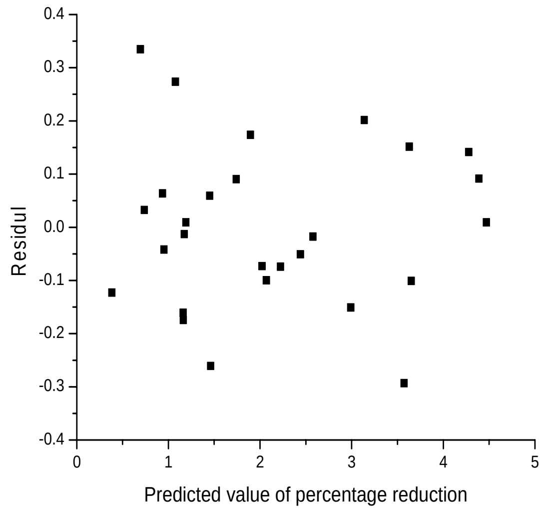

Figure 4.9 Plot of residuals vs. predicted values of Y_{ijk}

4.4 Conclusions

Through the statistical and graphical analysis of the difference between forest plans developed with meta heuristic (the spatially-constrained problems) and linear programming (the relaxed problems), one can conclude that small forest landowners and landowners with young age class distributions will be most affected by an adjacency and green-up policy. Small landowners have less flexibility to re-arrange harvest schedules when the adjacency policy is modeled. Young age class forests face a similar problem- there is less flexibility, in the earlier years of a forest plan, to generate timber volumes that meet wood flow requirements. This work represents the first insight into the type of landowners that maybe most affected by sustainability (i.e., green-up and adjacency) policies.

Our analysis has centered on a maximum clearcut size of 240 acres for a 2-year green-up period. This is the policy inherent in the Sustainable Forestry Initiative. One natural question extension of the work is to examine the effect of a change in the maximum clearcut size and green-up period. Some possible combination include: 240 aces vs. 3 years, 240 acres vs. 4 years, 120 acres vs. 2 years, 120 acres vs. 3 years, and 120 acres vs. 4 years. The 120 acre clearcut size is the average recommended in the Sustainable Forestry Initiative, and the maximum allowed in the Oregon Forestry Practices Act. These seem to be reasonable scenario to access in the future.

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CHAPTER 5

A MODIFIED HEURISTIC METHOD FOR SOLVING SPATIALLY CONSTRAINED FOREST PLANNING PROBLEMS BASED ON RAINDROP EFFECT[3]

[3] Zhu, J., P. Bettinger. To be submitted to *Silva Fennica*.

ABSTRACT

The raindrop method of searching a solution space for feasible and efficient forest management plans has been demonstrated as being useful under a limited set of circumstances, mainly where adjacency restrictions are accommodated using the unit restriction model. Here, a modified raindrop algorithm is described and applied to the area restriction adjacency model, then tested on 6 GIS databases of different sizes and age class distributions. The modified raindrop method is then tested against threshold accepting and tabu search. The modified raindrop heuristic's performance was better on small-sized problems with older forests or normal forests, than 1-opt tabu search and threshold accepting, but it takes a longer time to locate the best solution. For medium-sized problems, the raindrop heuristic is as good as threshold accepting and 1-opt tabu search, in general. The variation in results, for small-sized problems, is similar, as results from the three heuristics have similar standard deviations. For the medium-sized problems, the raindrop heuristic has the smallest standard deviation, in general. On average, the raindrop heuristic produced higher quality solutions to most of the problems. A big advantage of the raindrop heuristics is that it uses only two parameters in the search process and does not require extensive testing to determine the appropriate value to use.

INDEX WORDS: Forest Planning, Harvest Scheduling, Heuristics, Raindrop Heuristic

5.1 Introduction

Contemporary forest harvest scheduling problems are combinatorial optimization problems by nature, which means as the problem size increases, the complexity of the problem will increase at a disproportional rate. Generally, forest management plans maximize certain economical and ecological objectives subject to various constraints, and the task is to assign forest management actions to management units over a period of time, in a given forest area. Early forest management plan models are based on mathematical programming techniques and some are still used today. These include linear programming, mixed integer programming, and integer programming (Bevers and Hof 1999, Hof et al. 1994, Hof and Joyce 1992). Nowadays, forest planning problems are becoming increasingly difficult to solve due to adjacency and green-up constraints, which require the use of binary integer decision variables. Thus as problem size increases, solving it may become computationally impractical (Lockwood and Moore 1993), and perhaps impossible if traditional mathematic programming is used. Many researchers have turned to heuristics, such as Monte Carlo simulation (Nelson and Brodie 1990), simulated annealing (Dahlin and Sallnas 1993, Lockwood and Moore 1993, Murray and Church 1995), threshold accepting (Bettinger et al. 2003), tabu search (Bettinger et al. 1997) and genetic algorithms (Glover et al. 1995, Falcão and Borges 2001, Boston and Bettinger 2002) to address spatially-constrained forest planning problems. Heuristics can not guarantee that they can locate a global optimum solution, but usually can find good solutions to complex planning problems in a reasonable amount of time.

In this study, we take the raindrop heuristic introduced by Bettinger and Zhu (2006) and apply it to a forest management model. In Bettinger and Zhu (2006), the raindrop heuristic was shown to be highly preferable than other heuristics for locating solutions for maximizing the even-flow of harvest volume, while constraining the solution using a unit restriction model of adjacency (Murray 1999). Here, the objective is to maximize net present value of a forest plan while constraining the solution using an area restriction model of adjacency (Murray 1999). The difference between the two models of adjacency is that the unit restriction model restricts the scheduling of adjacent units (regardless of size) during the green-up period, while the area restriction model allows adjacent units to be scheduled during the green-up period as long as the total size of the clearcut does not exceed the maximum clearcut size that is assumed. Thus this second method of modeling adjacency is more complex to both formulate and solve.

This new heuristic, the raindrop method, has only been tested on one forest management problem, thus the contribution of this research is to determine whether it is useful, as a search process, in broader applications. The heuristic will be compared against standard heuristics (threshold accepting, tabu search) to determine its effectiveness in solving a more complex management problem. My hypothesis is that the raindrop method will be as effective in solving a net present value maximization problem, which contains area restriction adjacency constraints, as other standard heuristics are in solving the same problem. In addition, some insight will be gained in attempting to use the heuristic on a more complex problem. Initial consideration of the model suggests that there will be some difficulties in using it in conjunction with the area restriction adjacency constraint formulations.

5.2 Methods

The methods section will first address the problem formulation for the forest planning model. Then the 6 GIS databases that are modeled will be briefly described, along with the non-spatial economic assumptions pertinent to this research. Finally, the new heuristic will be described along with the modifications necessary to implement with the forest planning model.

5.2.1 Forest planning model formulation

The forest planning problem that we investigated falls between strategic planning (long time frames, large area) and operational planning (short time frames, specific areas) in an area termed "tactical planning." The level of detail used in this research is generally greater than those used in strategic planning analyses, yet significantly lower than what is required for operational planning. This tactical planning model attempts to maximize the net present value of timber harvested. The objective function is formulated as:

Maximize:

$$\sum_{t=1}^{T}\left[\sum_{i}^{N}(V_{it}X_{it}(P-C_{it}))/1.06^{(t-0.5)}\right]+\sum_{i}^{N}(V_{i20}(P-C_{it}))/1.06^{19.5} \qquad (1)$$

Subject to:

$$\sum_{t=1}^{T}X_{it}\leq 1 \qquad \forall i \qquad (2)$$

$$X_{it}A_i+\sum_{z\in N_i\cup S_i}X_{zt}A_z\leq \text{MCA} \qquad \forall i, t \qquad (3)$$

$$\sum_{i=1}^{n}V_{i20}-\sum_{i=1}^{n}\sum_{t=1}^{20}X_{it}V_{i20}>0.9*\sum_{i=1}^{n}V_{i1} \qquad (4)$$

$$AG_c\text{-}AG_{t1}>5 \qquad (5)$$

$$AG_c\text{-}AG_{t2}>5 \qquad (6)$$

$$\sum_{i=1}^{n}X_{it}V_{it}>0.9*\sum_{i=1}^{n}\sum_{t=1}^{T}X_{it}V_{i20}/T \qquad \forall\ t \qquad (7)$$

$$\sum_{i=1}^{n} X_{it}V_{it} < 1.1 * \sum_{i=1}^{n}\sum_{t=1}^{T} X_{it}V_{i20} / T \qquad \forall\ t \qquad (8)$$

$$\sum_{i=1}^{n} X_{it}V_{it} > 0.9 * \sum_{i=1}^{n} X_{it-1}V_{it-1} \qquad \forall\ t \geq 2 \qquad (9)$$

$$\sum_{i=1}^{n} X_{it}V_{it} < 1.1 * \sum_{i=1}^{n} X_{it-1}V_{it-1} \qquad \forall\ t \geq 2 \qquad (10)$$

Where:

A_i= area of management unit *i*

AG_c=clear cut age

AG_{t1}=age when first thin happens

AG_{t2}=age when second thin happens

C_{it}= logging cost per m^3 for unit *i* harvested in time period *t*

Ht = the actual scheduled harvest volume in each time period *t*

i = a harvest unit

MCA=maximum clearcut area

N=the total number of harvest units

N_i=set of all units adjacent to unit *i*

P= stumpage price

S_i= the set of all management units adjacent to these management units adjacent to management unit *i*

t = a planning period

T = the total number of time periods in the planning horizon

V_{i20} = the unscheduled timber harvest volume at the end of period *20*, from management unit *i*

V_{it} = the available timber harvest volume during time period *t*, from management unit *i*

X_{it} = a binary variable, which =1 if management unit *i* is harvested in time period *t*, 0 otherwise

Equation 2 indicates that each management unit can only be harvested at most one time in all planning periods. Equation 3 ensures that the maximum clearcut size will be maintained (assuming the green-up period is 2 years). Equation 4 is an ending volume constraint. Equation 5 and 6 ensure that the separation period between thinning and clear cutting is at least six years. Equation 7 and 8 constrain the volume harvested in each time period to a proportion of the final, unscheduled and uncut volume. Equation 9 and 10 limit the deviation in harvest volume from one period to the next as a measure of harvest stability. This model formation represents a model I (Johnson and Scheurman 1977), integer programming problem. The adjacency restriction is the area restriction formulation (Murray 1999).

5.2.2 Spatial and non-spatial data

Standard GIS databases used in this research harvest scheduling problems are divided into three ownership size groups: small, medium (see Table 5.1), according to problem area acreage. One ownership pattern is assumed (dispersed arrangement of parcels). Three age class distributions were then assigned to the 6 problems: young forest, normal forest, older forest. Therefore a matrix of 6 hypothetical forests was available for analysis. The resulting GIS databases are derived from an actual landownership in the southern U.S. (Figures 5.1 and 5.2).

The time horizon is 20 years, divided into twenty 1-year time periods. The interest rate assumed is 6 percent. The stumpage prices were obtained from Timber Mart-South (2004), and are \$43.57 per ton for pine sawtimber, \$25.60 per ton for chip-n-saw, and \$6.73 per ton for pine pulpwood. The costs assumed are \$115.70 per acre for mechanical site preparation, \$47.14 for planting, and $63.40 for a herbaceous weed control treatment. The maximum clearcut size is 240 acres, and the green-up period is assumed to be 2 years.

Table 5.1 Elements in harvest scheduling type databases

Size	Ownership pattern	Age class distribution
Small (1000-10,000 ac)	Dispersed	Young
		Normal
		Older
Medium (10,001-20,000 ac)	Dispersed	Young
		Normal
		Older
Large (20,001-100,000 ac)	Dispersed	Young
		Normal
		Older

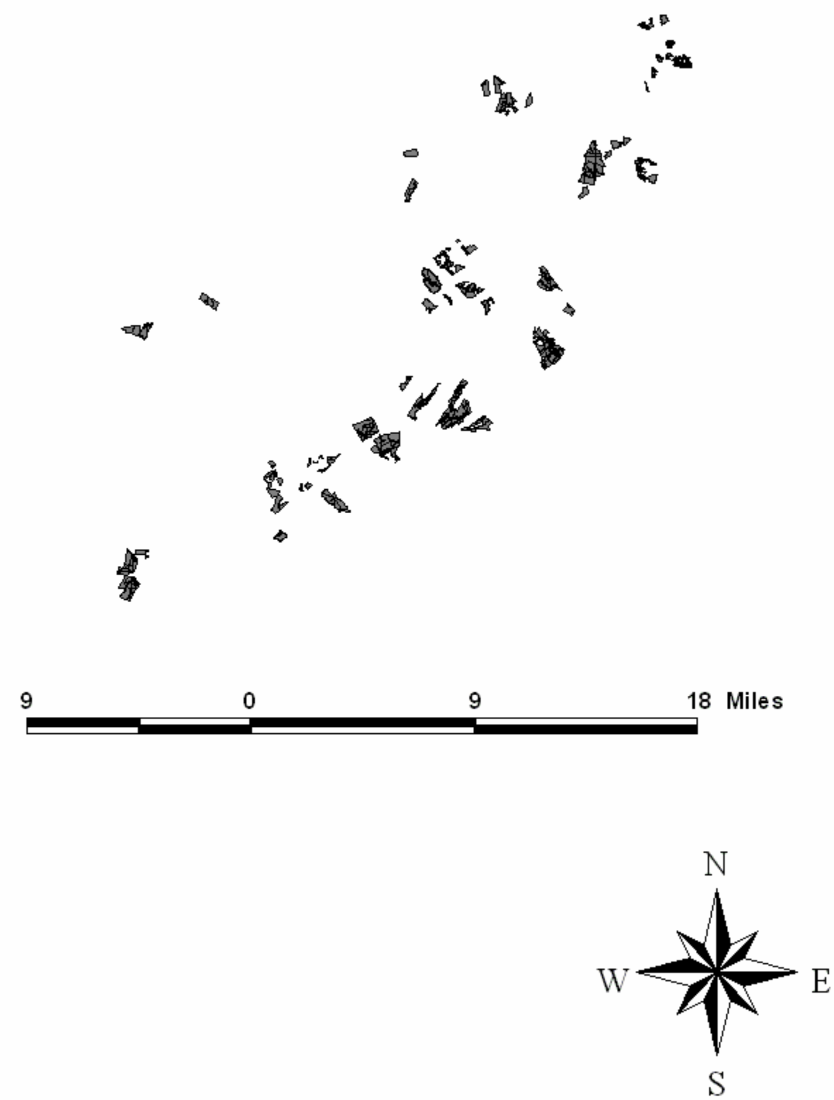

Figure 5.1 Small-sized, dispersed parcel forest landbase

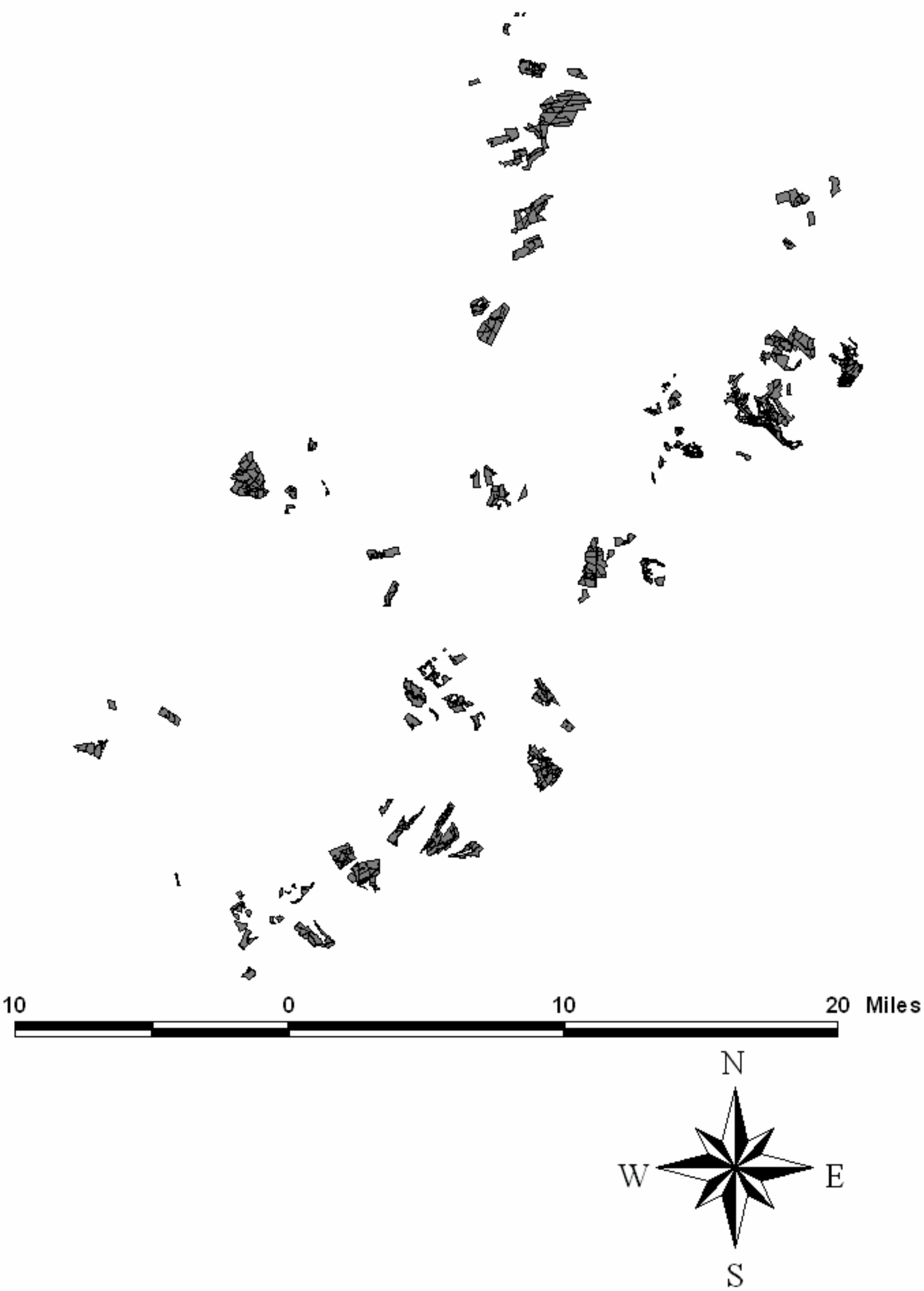

Figure 5.2 Medium-sized, dispersed parcel forest landbase

5.2.3 Modified raindrop effect algorithm

A new heuristic was recently introduced (Bettinger and Zhu, 2006) based on raindrop impact. In this new heuristic, the search process starts with a random feasible solution. Then it randomly picks one unit and a period which is not in the current solution and forces it into current solution regardless any potential constraint violations. If there are adjacency constraint violations, the algorithm fixes the constraints using a radiating wave motion. All the units which are affected by the constraint are added to a list and checked in order of distance from their centroid to the centroid of the original unit, and the closest unit is corrected first. The next best alternative for the affected unit is then inserted into the solution. Any harvest units that are subsequently affected by this change to the solution are added to the list of affected units. The next unit which is closest to the original unit is checked and next best alternative which does not result in constraint violation is again selected and forced into the solution space. This process continues until all constraint violations have been fixed. Any mitigation must prevent subsequent violations with management units which are nearer to the originally modified (randomly picked) unit, thus the impacts radiate outward from the initial choice. Once all infeasibilities have been mitigated, a single iteration of the model ends.

The main advantage of the algorithm is that it only uses two parameters and can locate a very good solution for unit restriction problems. The two parameters are: (1) the total number of iterations to model, and (2) the number of iterations that pass before search process reverts to the best solution (stored in memory). Bettinger and Zhu (2006) showed that reverting every 3 or 4 iterations to the best solution produces results that are superior to other heuristics. Simply modeling the raindrop without reversion does not lead to better solutions to complex problems. As pointed out by the authors "one could speculate that as the number of constraints grows, the ability of the heuristic to mitigate the infeasibilities that arise may become cumbersome." we speculate that for area restriction models with lower bound wood flow constraints, it may become very hard to implement this heuristic, and maybe computationally infeasible to apply the idea of mitigating infeasibilities related to the area restriction model the same way as introduced in the original raindrop algorithm. In unit restriction models, after making a change, if constraints are violated, the infeasibilities are fixed one unit at a time in outward radiating fashion. In area restriction model, it is very possible that several units work together to cause the violation. This situation is illustrated in Figure 5.3. Suppose the green-up period is 2 years and unit F is changed from period 14 to 4. F's green up window is period 3 to period 5 (assuming a 2-year green-up). If one starts from F, one can find that F, B, and A are in the same green-up window. In other way, if one starts from H, one can find H, D, G and F are in the same green-up window. So simply assuming one adjacent unit is affected does not hold, others in proximity to unit F may also be affected. This means that if we try to conquer the violation starting from F, using radiating fashion, the search for all affected units becomes time-consuming and makes the problem difficult to solve, since the area restriction model must check the clearcut size numerous times with one change to a solution.

A 5	B 3	C 8	D 4
E 8	F 14	G 6	H 5
I 9	J 10	K 18	L 17
M 6	N 3	O 2	P 1

Figure 5.3 Illustration of a situation of using the area restriction model. Each letter represents a unit, each number represents a clearcut period

Instead of trying to fix the infeasibility one by one unit and putting the new units which might cause a new violation into the list, the modified algorithm (Figure 5.4) puts all units that potentially can cause the violation into a list, then tries to fix the violation by simply setting the units to “no cut” one by one for all units in the list. The detailed working mechanisms are described in following paragraph.

As usual, the scheduling process starts with the modified Monte Carlo simulation to get a initial feasible solution. After generating the initial solution, a random unit and clearcut period are selected and the result (without checking constraints) is assessed. If the change results in a better solution, the wood flow and adjacency constraints are assessed. If constraints are violated, all units associated with the area restriction adjacency constraint violations are added to a list. For example, if unit A is proposed to change to period 8, all units which have a clearcut period from 7 to 9 in the same patch as unit A will be added to the list. A unit (B) which is closest to unit A (based on the centroid of each unit) is then selected and the clearcut period to set to “no cut” and the adjacency constraint is again assessed. If the violation has not been fixed, unit B’s solution is changed back to the original status and the next closest unit to unit A, in terms of centroid distance, is assessed. This is repeated until the area restriction constraint is once again not violated. Thus the modification is not to select the next best choice for the affected unit (as modeled in Bettinger and Zhu (2006)), but to unschedule units until the clearcut blocks are smaller than the maximum clearcut size.

The last step in each iteration is to check to see whether the best solution has been located and whether the stopping criterion (number of iterations) has been reached. If it is the time to stop, the best result solution is reported.

There are two parameters for this algorithm, the total number of iterations and the total number of iterations that pass before reverting back to the best solution (stored in memory). By trial and error, we found the following parameters to be best for the algorithm in the different situations.

Small size databases: 100,000 iterations

Medium size databases: 200,000 iterations

Large size databases: 1,000,000 iterations.

In addition, based on what was learned in Bettinger and Zhu (2006), the search process reverts back to the best solution every 4 iterations.

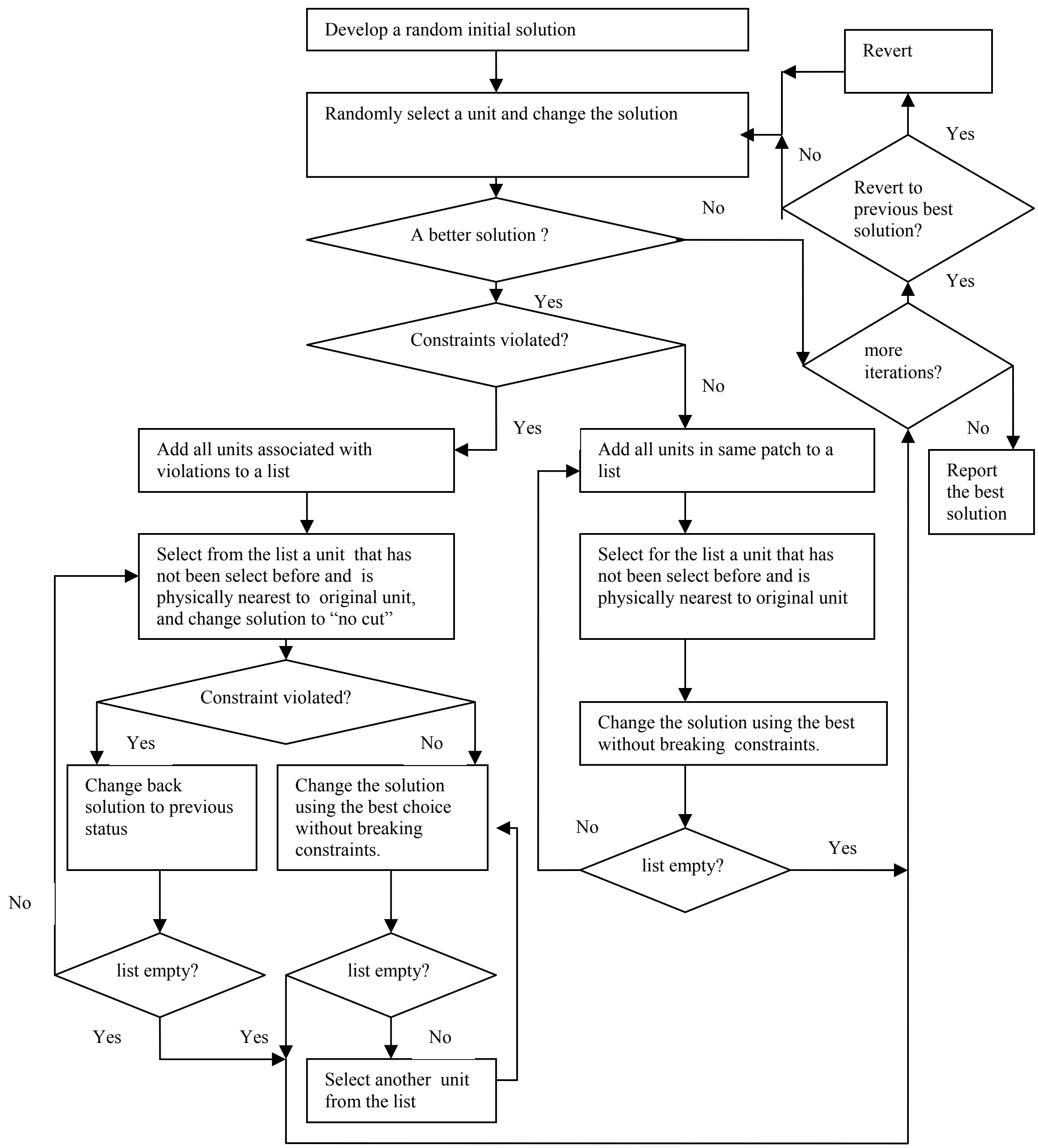

Figure 5.4 A flow chart of the modified raindrop search process for area restriction model

The new modified heuristic was compared to threshold accepting and 1-opt tabu search. Threshold accepting was initially described by Dueck and Scheuer (1990), and has been applied to forest problems (Bettinger et al. 2002, 2003) with a high level of success. In complex forest planning problems, it has been shown to be as good as simulated annealing and other heuristics, and it is relatively simple to implement, although some parameterization is required. Tabu search was introduced by Glover (1990), and has also been successfully applied to forestry problems (Bettinger et al. 1997, 1998, 2002). Tabu search with 1-opt moves involves simply changing the status (clearcut period) of one management unit. The change is made deterministically, whereas in threshold accepting the change is made randomly.

In order to compare the results, 30 solutions were generated for each of the GIS databases. Each of the 30 solutions can be considered independent to each other because the initial solution is randomly defined. A series of statistics are employed to evaluate the quality of the solutions (mean, maximum, standard deviation).

5.3 Results

For two of the three problems that involved small-sized of the GIS databases (Table 5.3), the best solutions were found by the raindrop heuristic. Tabu search located the best solution that involved the young forest age class distribution. For medium-sized GIS databases, the raindrop heuristic found the best solution for the normal age class distribution. Tabu search found the best solution for the young age class distribution, and threshold accepting found the best solution for the old age class distribution. For old and young age class distributions, the best solution found by the raindrop heuristic is within 1.5% of the best solution generated by other either tabu search or threshold accepting. In terms of time spent to find the best solution, the raindrop is the most expensive one and costs twice as much time as the time consumed by tabu search.

Table 5.2 Quality of the best solution generated and associated time spent by three heuristics

	TA		TS		Raindrop	
Databases	Best Solution (NPV)	Time spent (hrs)	Best Solution (NPV)	Time spent (hrs)	Best Solution (NPV)	Time spent (hrs)
Small, Dispersed, Normal	14,848,688	0.05	14,873,803	0.09	14,888,572	0.25
Small, Dispersed, Old	17,902,145	0.06	17,895,195	0.10	18,194,232	0.27
Small, Dispersed, Young	11,404,357	0.04	11,551,906	0.08	11,507,865	0.22
Medium, Dispersed, Normal	30,930,636	0.11	30,950,206	0.18	31,083,463	0.41
Medium, Dispersed, Old	36,928,728	0.14	36,668,719	0.19	36,888,317	0.43
Medium, Dispersed, Young	23,045,952	0.07	23,395,161	0.15	23,069,865	0.39

To evaluate the overall quality of the solutions, one can examine the mean solution and standard deviation of the 30 solutions generated by each heuristic (Table 5.3, Figures 5.5-5.11). The mean solutions found by the raindrop heuristic are the best among three heuristics for four of the six problems. Threshold accepting found the best average solution for the medium-sized problem, old age class distribution. Tabu search found the best average solution for the medium-sized problem, young age class distribution. For all databases the raindrop algorithm is the most expensive one in terms of time to find a solution. For small-sized databases, three heuristics have very similar variation of solutions. For medium-sized problems, the raindrop heuristic has the smallest standard deviation, in general.

Table 5.3 Quality of the mean solution generated and mean time spent by three heuristics

	TA		TS		Raindrop	
Databases	Average Solution	Average Time	Average Solution	Average time	Average Solution	Average time
Small, Dispersed, Normal	14,632,945	0.05	14,682,829	0.10	14,720,781	0.24
Small, Dispersed, Old	17,534,926	0.06	17,528,975	0.10	17,770,583	0.26
Small, Dispersed, Young	11,209,577	0.04	11,376,069	0.08	11,395,723	0.21
Medium, Dispersed, Normal	30,838,991	0.12	30,714,628	0.18	30,805,705	0.42
Medium, Dispersed, Old	36,792,688	0.14	36,431,426	0.19	36,737,841	0.46
Medium, Dispersed, Young	22,888,484	0.07	23,217,040	0.15	22,943,418	0.39

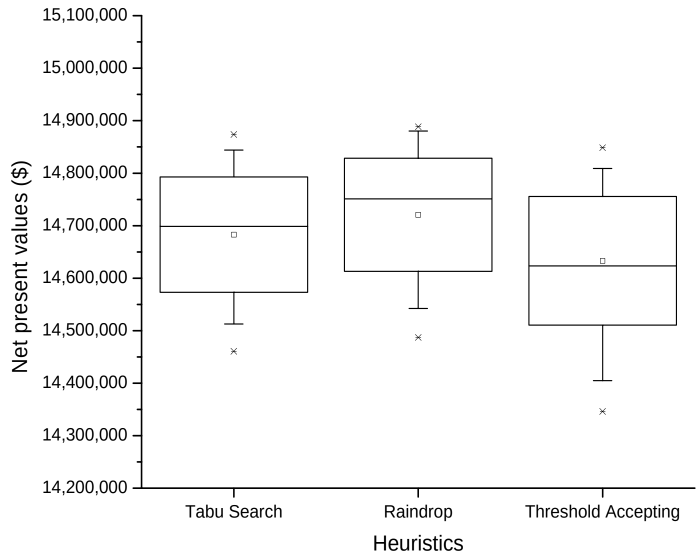

Figure 5.5 Box-Cox plot for small, dispersed, normal age class distribution databases

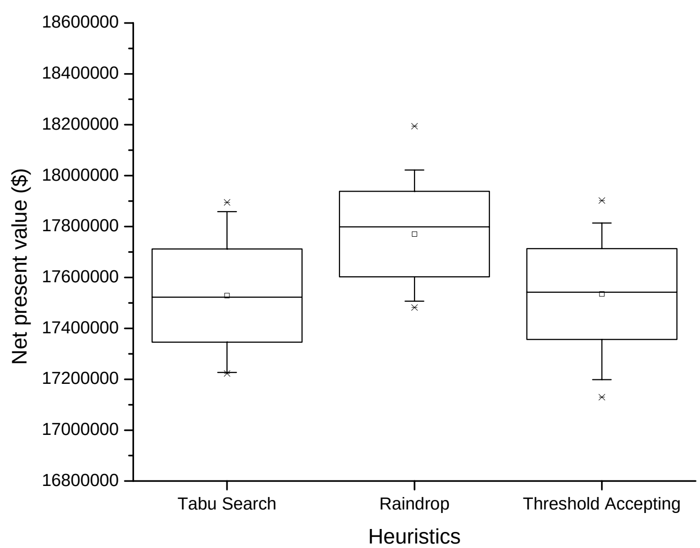

Figure 5.6 Box-Cox plot for small, dispersed, old age class distribution databases

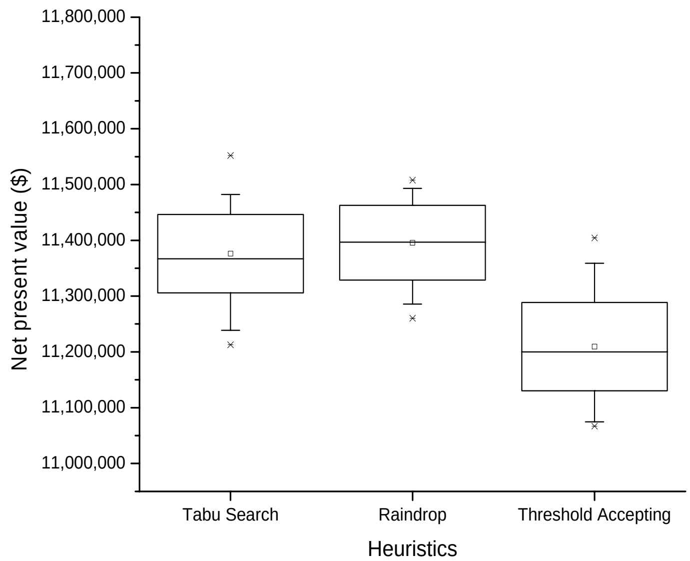

Figure 5.7 Box-Cox plot for small, dispersed, young age class distribution databases

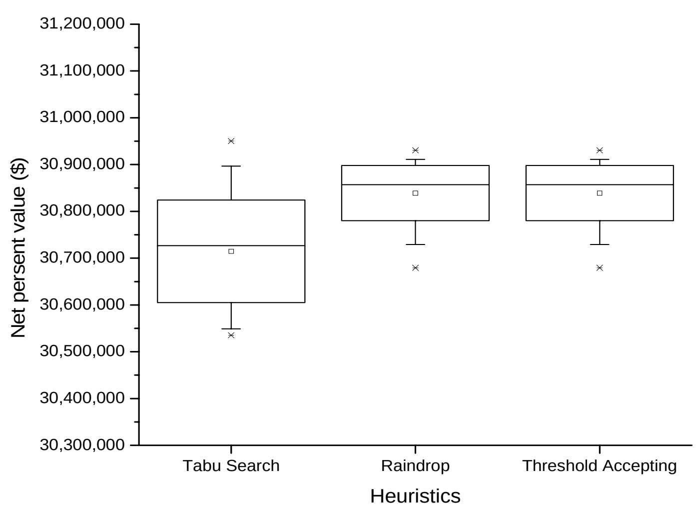

Figure 5.8 Box-Cox plot for medium, dispersed, normal age class distribution databases

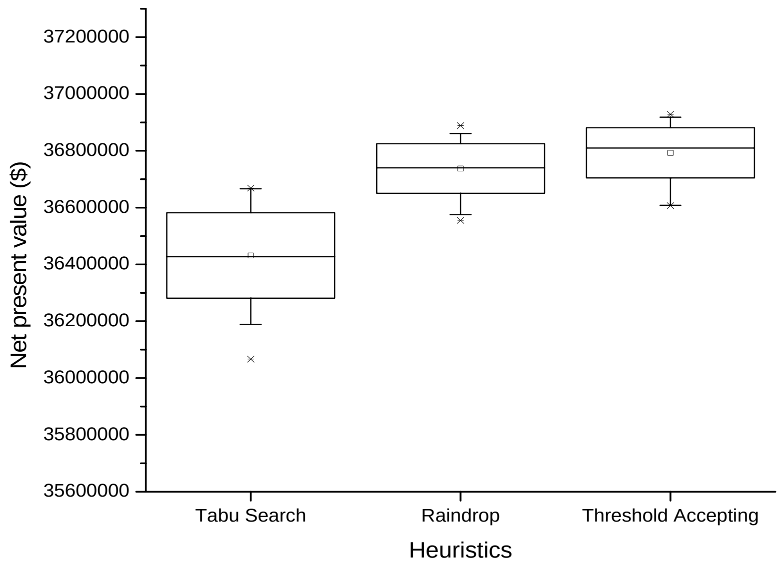

Figure 5.9 Box-Cox plot for medium, dispersed, old age class distribution

Database

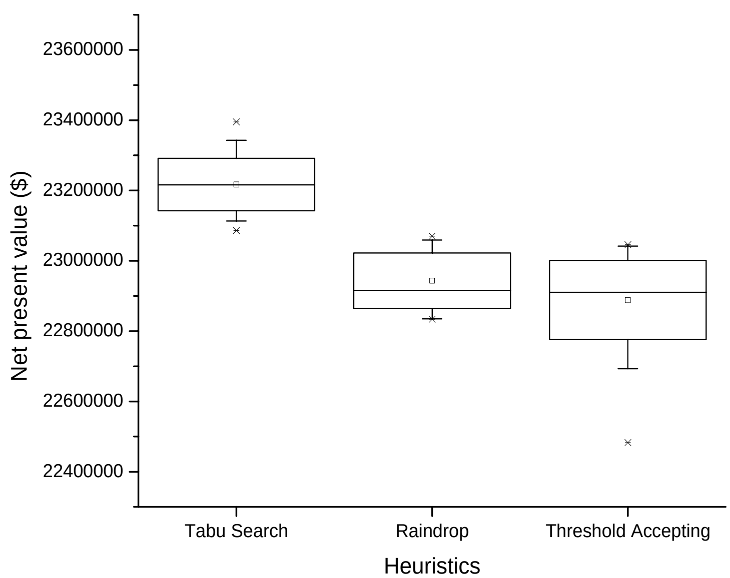

Figure 5.10 Box-Cox plot for medium, dispersed, young age class distribution databases

A final way to evaluate the raindrop heuristic is to compare the results generated to the results from relaxed linear programming. The difference between the best raindrop heuristic solution and the linear programming solution, divided by the linear programming solution represents the reduction percentage of implementing the policy of green-up constraints. Table 5.4 shows the reduction percentage for all 6 databases. One can find from the table that the largest percentage reduction is for small-sized, dispersed, normal age class distribution which is 3.60% of total net present value compare to the result from linear programming. The lowest reduction is for medium-sized, dispersed, normal age class distribution database which represents 0.99% reduction comparing to the result from linear program. These results are consistent with previously published research (e.g., Boston and Bettinger 2001).

Table 5.4 Comparison of the result from raindrop to results from linear programming

Database	Raindrop (NPV)	Linear Programming (NPV)	Percentage reduction
Small, Dispersed, Normal	14,888,572	15,424,070	3.60
Small, Dispersed, Old	18,194,232	18,596,600	2.21
Small, Dispersed, Young	11,507,865	11,568,480	3.39
Medium, Dispersed, Normal	31,083,463	16,256,394	0.99
Medium, Dispersed, Old	36,888,317	36,928,773	1.03
Medium, Dispersed, Young	23,069,865	23,689,660	2.69

5.4 Discussion

Over the past 15 years, researchers have been exploring alternatives to traditional mathematic search processes (i.e., linear programming, mixed integer programming) to solve spatial harvest scheduling forest planning problems. One avenue of research has been the development of testing of heuristic search methods. A number of heuristics have shown promise for addressing the development of spatially complex forest management plans. These heuristics can produce near-optimal solution very quickly (in most cases). However, the main limitation of many heuristics is the extensive testing of parameters which must be performed prior to their use.

Bettinger and Zhu (2006) introduced a new heuristic that requires very limited testing, and has shown to be superior to other heuristics on small problems, where the objective is to maximize ever-flow of timber harvest volume subject to unit restriction adjacency constraints. When this search process was modified to address larger problem, and problems with more typical southeastern U.S. character (e.g., maximizing net present value, subject to a 240 acre maximum clearcut size modeled using area restriction methods), the heuristic was as good as or better than, other standard heuristics.

The raindrop method needed to be modified to accommodate the modeling of area restriction adjacency. Since this model uses a spatially-sprawling method to determine all of the sizes of all of the clearcuts, within their respective green-up windows, the preferred method of mitigating the constraint violation was to unschedule the clearcuts of some units until the constraints were again satisfied (i.e., not violated). This modification may have led to suboptimal results, since as Bettinger and Zhu (2006) suggest, the next best choice for an affected unit should be selected. However, to explore other options for affected units (those that are a part of adjacency violation) would require much more processing time, as the area restriction adjacency constraints would need to be accessed repeatedly until it was no longer violated. In any event, the raindrop heuristic produced as good, or better solution to most problems studied, although the time to generate a solution was much greater than that required by threshold accepting and tabu search.

As found in earlier work (Zhu 2006), tabu search found the best solution to the medium-sized problem that used the young age class distribution. The ability of other heuristics to locate good solutions to young age class problem may therefore be better handled by standard 1-opt tabu search, particularly when larger landscapes are modeled, since the raindrop heuristic found better solutions to the small-sized, young age class distribution problem. Threshold accepting continued to find very good solutions to all problems, and if one were concerned about the time required to generate a solution, this method may be preferred.

The advantages of the raindrop method lie in solving smaller, spatially constrained forest planning problems. If a landowner were to model smaller areas, rather than entire districts, this method may be preferred. In addition, only two parameters are required, and they do not need extensive tests to determine the appropriate values. However, to accommodate area restriction adjacency constraints required an extensive and complex set computer code, which is the main disadvantage of using this heuristic to these types of problems.

5.5 Conclusions

This modified raindrop heuristic is still shares the same core idea of using radiating, spatially sprawling process to find better solutions that was demonstrated with the original raindrop algorithm. Some modification of the heuristic is required to accommodate area restriction adjacency constraints. Just like the original raindrop heuristic, the main advantage is that it only uses two parameters and it has been shown to generate as good, or better results compared to TA and 1-opt TS for the 6 GIS databases studied here. The disadvantage for this method is that it takes longer time than the other algorithms examined to generate solution to a spatial harvest scheduling problems. One could conclude from this work that it may be advantageous to use this heuristic for small problems (10,000 ac or less), and problems that do not involve young age class distributions.

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CHAPTER 6

SUMMARY

The research here, to the best of our knowledge, represents one of the most extensive assessments of spatial harvest scheduling constraints ever performed for southeastern U.S. forest conditions. In this research, a forest planning model is developed to maximize net present value of forest production given certain spatial and temporal constraints and the model is applied to assess the impact of a forest management policy (green-up period and maximum clearcut size) on forest landowners of various ownership patterns, sizes, and initial age class distributions. Based on a comparison of three heuristics, a meta heuristic which consists threshold accepting, 1-opt tabu search, and 2-opt tabu search was selected to generate the forest plans that were used to estimate the impact of the policy on different hypothetical landowners. The difference of the result from the meta heuristic and the result from linear programming was used to estimate the effect of green-up and maximum clearcut size constraints. The research provides a good platform for other researchers to carry on further research.

There are several contributions of this research. First, we simulated 27 GIS databases based on a real landscape in southeastern United States. The 27 GIS databases include different sizes, ownership patterns, and age class distributions. With those 27 GIS database, most forest landowners may be able to associate themselves with one or more hypothetical situations. These databases can be seen as standard problems which will be accessible for other researchers in this field to use.

Second, a meta heuristic which consists of threshold accepting, 1-opt tabu search, and 2-opt tabu search, was selected out of three heuristics. The meta heuristic performed as well, or better than the other two in terms of best solution and variation of the all the solutions. However the meta heuristic takes more time to locate the best solution than threshold accepting or standard tabu search.

Third, an ANOVA model is employed to answer the question: "Is there a set of ownership patterns, sizes, and age class distributions that will be more highly affected by potential harvest scheduling green-up constraints than others?" Based on the best solutions found by the meta heuristic, we used the ANOVA model to test the null hypothesis, which is that all combinations of ownership patterns, sizes, and age class distributions will be affected in a similar manner. The results from the ANOVA analysis reject the hypothesis at level 0.0001, which means at least there exists one factor which has significant different mean values across different levels. Thus there are combinations of ownership patterns, sizes, and age class distributions that are affected in a different manner. The treatment effect and treatment interaction effect model analysis indicate that factors of landowner size, age class distribution the interaction of size and age class distribution are significant at level 0.05. For the factor of size, the difference between the small landowner and other two are significant at level 0.05, but the difference between medium and large are not significant at level 0.05. For the factor of age class distribution, the difference between young age class distribution and both the normal and older age class distributions is significant, but the difference between the normal and old age class distributions is not significant.

Finally, we modified the raindrop heuristic, which was shown to be valuable for unit restriction adjacency problems, and applied it to the area restriction model. This modified algorithm continued to use the core idea of using a radiating, spatially sprawling process to find better solutions. Just like the original raindrop method, the main advantage of this algorithm is that it only uses two parameters. While the modified raindrop heuristic is computationally intensive, when applied to the area restriction adjacency problems, it can provide as good, or better, solutions to forest planning problems as threshold accepting or tabu search.

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