INTEGRATION OF GIS TECHNIQUES AND HEURISTIC ALGORITHMS TO ADDRESS SPATIAL FOREST PLANNING ISSUES IN THE SOUTHERN U.S.

by

RONGXIA LI

(Under the Direction of Pete Bettinger)

ABSTRACT

GIS techniques have been used in the natural resource field over the past few decades. As spatial analyses in forest planning are increasingly needed by forest managers and forest researchers, a high level of integration of GIS techniques and spatial forest planning is inevitable. In addition, the complexity of spatial forest planning problems requires intelligent use of heuristic methods in order to quickly generate forest plans of high quality. In this research, an extensive literature review in North American forestry journals was performed to identify trends and gaps of GIS applications in the natural resource field. Then, an informed development of meta heuristics based on several standard heuristic algorithms - Monte Carlo integer programming, simulated annealing, threshold accepting, tabu search and the raindrop method - was performed. Meta heuristics were composed by combining different standard heuristics, in an intelligent way without the need for direct human intervention. I composed 24 3-algorithm meta heuristics, and results showed that the meta heuristics presented consistently better solution qualities than standard heuristics in solving typical spatial forest planning problems for the southern U.S. region. Finally, by using both GIS and heuristic techniques, I assessed the effects of a forest planning constraint (maximum clearcut size) on forest fragmentation and found that as maximum clearcut size increased, the effects on forest fragmentation seemed to decrease. This analysis used operational GIS databases and a typical southern U.S. forest management problem formulation, each of which posed an analytical problem. First, roads in the operational GIS database were explicitly recognized, creating an artificial barrier between stands when it came to the fragmentation analysis. When roads were removed, I found that fragmentation indices changed slightly, yet the overall trend was the same. Second, I suspected that woodflow constraints in the problem formulation compounded fragmentation by spreading out harvests relatively evenly over the time horizon. By removing woodflow constraints from the analysis, I found this to be true. This work provided three advances to the forestry sciences: a published literature review illustrating the advances and gaps in the use of GIS in forestry, a novel way to integrate standard heuristics into a meta heuristic in order to develop more efficient forest plans, and an analysis of fragmentation in those forest plans for a southern U.S. landowner.

INDEX WORDS: Meta heuristics, Geographic Information Systems (GIS), Forest fragmentation, Monte Carlo integer programming, Tabu search, Threshold accepting, Raindrop method, Wood flow constraints

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DEDICATION

To my parents, Qingming Li and Lianghua Wang, who has encouraged me to set high goals and supported my education.

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CHAPTER 1

INTRODUCTION

Geographic information systems (GIS) and operations research (optimization) techniques, although developed separately over time, are closely linked together in the modern age of forest planning. Recently, a review was performed of the development of mathematical (optimization) techniques in North America (Bettinger & Chung 2004), which showed that spatial forest planning has received increasing and considerable attention over the past decade. Spatial forest planning requires the use of spatial information, such as adjacency relationships, which are derived mainly from GIS, although one could develop these independently of a GIS program. Heuristic programs have joined integer programming as logical methods for tactical forest planning involving spatial relationships. Until recently, however, most forest planners simply chose a heuristic and implemented it without understanding the quality of results it could produce. A few researchers (Bettinger et al. 2002, Heinonen & Pukkala 2004) have explored the relative quality of a set of heuristics, and have noted that perhaps a meta heuristic search structure may be necessary to produce the highest quality solutions to forest plans. Others (Boston & Bettinger 2002, Zhu 2006) have shown that meta heuristics have value, however the combination of heuristic search processes was made without any information on the characteristics or behavior of the search process, and was simply the addition of one process to another at some point in time during the search, specified by the developer of the program.

This research is aimed at addressing a few of the important areas for advancement in the forest planning science. The research represents a combination of GIS and forest planning emphases. First, an extensive literature review is performed of the use of GIS in North American forestry. Several interesting gaps in the literature are noted, providing others with a view of potential publishing opportunities. What I found was that spatial analysis has recently begun to be used widely in natural resource management to address complex issues and to facilitate decision-making needs. However, while landscape applications are widely reported for other areas of the U.S., few have been published related to the southern U.S., and most utilize satellite imagery (even though vector data is the most prevalent data structure for natural resource management GIS databases). Second, a unique contribution to the forestry sciences is made with the development and analysis of meta heuristics that operate based on recent search history (as opposed to human intervention in the process). A comparison of a large set of meta heuristics is made against standard heuristics commonly used in forestry to assess the potential improvement in solution (forest plan) quality when various search processes are integrated. This automated method for capitalizing on the strengths of different search processes can lead to more efficient forest plans and reduce the amount of time an analyst needs to develop and manipulate a solution process. Finally, GIS and optimization are brought back together to explore the effects of a common forest planning constraint (clearcut sizes) on fragmentation. Most fragmentation analyses have either (a) used objectives and constraints that are not realistic for the U.S. south, or (b) been performed completely within GIS. In addition, what I found with chapter 2 was that most landscape analyses are performed using satellite imagery rather than the more prevalently-used (in day-to day management) vector databases. The contribution of this analysis lies in both a unique analysis of potential fragmentation effects for landowners of various sizes and spatial ownership arrangements in the U.S. south, and an analysis of how fragmentation results may (or may not) change given the use of operational databases (vector GIS) for planning, and the challenges that they pose.

This dissertation is divided into five chapters: the introduction (this Chapter), a literature review on the use of GIS in North American forestry (Chapter 2), an exploration of the development of intelligent meta heuristics for forest planning (Chapter 3), an analysis of the effects of fragmentation in the U.S. south using operation databases (Chapter 4), and a summary and synthesis (Chapter 5).

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CHAPTER 2

A HISTORICAL PERSPECTIVE ON THE USE OF GIS AND REMOTE SENSING IN NATURAL RESOURCE MANAGEMENT, AS VIEWED THROUGH PAPERS PUBLISHED IN NORTH AMERICAN FORESTRY JOURNALS FROM 1976 TO 2005[1]

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[1]Li, R., P. Bettinger, S. Danskin, and R. Hayashi. 2007. Cartographica. 42 (2): 165-178.

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ABSTRACT

Since the introduction of Geographic Information Systems (GIS) to natural resource management in the 1970's, there has been a logical and increasing use of GIS in natural resource management organizations. An assessment is made of the literature in applied North American forestry journals that are read mainly by forest practitioners, along with an illustration of the trends of technological adoption by natural resource management organizations. We conclude that the diversity of GIS technology use in forestry is increasing and evolving to a high and complex level. While small-scale (local) and site-specific natural resource applications predominate the use of GIS in these papers, landscape applications have obtained more attention and importance in recent years, mainly in the western and north central United States. Although several of the journals we reviewed emphasize the practical nature and value of information, few papers were located that illustrate GIS implementation in natural resource organizations, or advances in GIS technology. The professions associated with natural resource management have traditionally been adopters of technology (rather than developers), yet since GIS is so closely tied to the management and assessment of landscapes, it is possible that the issues that arise in natural resource management have had a significant impact on the development of GIS analytical techniques. We suggest that surveys be performed frequently (every 5 years) so that the natural resource management field can stay current with changes in technology and in expectations of employers. The assessment of the literature has pointed out the trends and gaps in the forestry-related literature, and suggests opportunities for future dissemination of information. Research papers lead the widespread adoption of technology by a decade or more, thus with this work one could envision what might become commonplace a decade from now. Those unaware of the

relatively short history of the technology and how it has evolved may gain some understanding with this brief history of the use of GIS in natural resource management.

Keywords: Geographic Information Systems(GIS), Natural resource management, Landscape applications, Vector, Raster, Education

INTRODUCTION

Maps are a critical management tool in natural resource management. Historically, natural resource managers had to be able to both create and interpret maps to facilitate management decisions. Prior to digital mapping, those few foresters, biologists, and other professionals who possessed significant cartographic skill were generally called upon to create and update maps needed by others. However, with the advent of geographic information systems (GIS), many employers now view map creation and development as a necessary skill for all practitioners.

Almost forty years have passed since the concept of Geographic Information Systems (GIS) was introduced. One of the first large-scale systems was the Canadian Geographic Information System (Aronoff 1989). Since then, the use and application of GIS has changed considerably, particularly in natural resource management. GIS is a technology that involves integration of spatial information and computer algorithms for the display and management of databases. Natural resource management activities have an inherent spatial context, which is why GIS can be used to address many management issues, such as those related to tree planting, harvesting, intermediate silvicultural treatments (e.g., herbicide applications), and fire management. In fact, since the early 1990's, almost every moderately-sized natural resource organization has used GIS as an important mapping and management tool. In this review we illustrate how the use of GIS has evolved in the forestry literature, describe the trends that are recognizable, and draw conclusions about where GIS may be headed in the future. This historical perspective will help natural resource managers obtain an understanding of not only the cartographic uses of GIS, but also the advanced spatial assessments that have been performed, and where these and other trends may be leading.

METHODS

The review that follows focuses on a particular technical and cultural area of employment: forest and natural resource management. In order to obtain a historical perspective on the use of GIS in forestry, we performed a literature review of seven of the main North American forestry journals: *The Forestry Chronicle, Canadian Journal of Forest Research, Northern Journal of Applied Forestry, Southern Journal of Applied Forestry, Western Journal of Applied Forestry, Forest Science, and Journal of Forestry*. While the aims and scope of these journals have evolved over the years, they currently emphasize assisting field practitioners and other researchers by keeping them informed about significant developments in the forest sciences, communicating professional and scientific management of forest resources to forest managers, and reporting significant new advancements and understanding of forests and related resources. Perhaps the most widely distributed forestry journal is the *Journal of Forestry*, which is available to over 15,000 members of the Society of American Foresters. While these journals may vary in their methodological rigor, they are applied in nature and are read by many natural resource management practitioners and researchers in North America.

A concentration on the seven main forestry journals was preferred over other options because these are the most likely journals that are read by forestry professionals. This could be viewed as a limitation of the analysis, as advancements in GIS use and integration in the forest sciences might also be found in other journals. However, the papers published in these seven journals represent a large portion of the basic and applied forestry research performed in North America. Other journals, such as *Photogrammetric Engineering & Remote Sensing*, *International Journal of Forest Engineering, Ecological Modelling, Silva Fennica, and Forest Ecology and Management* (and others), also are important, but do not necessarily have a North American forestry emphasis.

The time period considered ranges from 1976 to 2005, except where journals were not introduced until later years (e.g., the *Northern Journal of Applied Forestry* began publishing papers in 1984). In this analysis, papers are included which describe GIS technology or development, or use GIS technology as one of the main tools in a case study. In addition, those purely technological papers are included, as long as GIS concepts are recognized in the paper, the paper explicitly mentions the use of GIS, or describes the progress or implementation of GIS.

As with previous reviews of natural resource-related research (e.g., Bettinger and Chung 2004; Newman 2002), a set of criteria were developed to classify each of the papers we chose to include in the review. For each qualified paper, information regarding the publication date, the journal name, the research objective and geographic data structure employed were recorded. We also grouped the many application areas into four main categories according to the goals or purpose of each paper. These categories were: (1) overviews, which are subdivided into the three sub-categories of education, implementation of GIS, and reviews of GIS; (2) natural resource management applications, which include those related to aquatic resources, entomology, environment, fire, wildlife, and so on; (3) landscape applications, which are subdivided into the three categories of land cover-land use change, vegetation classification, and land classification; and (4) technology applications, which are subdivided into accuracy assessments, algorithms, analytical tools, and sensors. We limited *natural resource management* to areas related to forest planning activities, because we assumed the *landscape applications* generally involved more than one or two landowners (i.e., the entire landscape), are more complex, and are gaining more emphasis as an independent area of study. However, in a more general context, it is arguable that *landscape applications* can be grouped into the *natural resource management* category.

In this review we also focused on how GIS technology was employed in natural resource applications. More specifically, we wanted to determine what the real role or purpose of GIS was in each application, such as whether GIS was used mainly for cartographic purposes (mapping), land classification, landscape visualization, or spatial analysis. Different uses would reflect varying levels of emphasis on GIS, and a chronological analysis of GIS use would help understanding how GIS has evolved in the forestry field.

RESULTS

To begin the findings of our assessment, we first provide a simple chronology of research as it has been presented. According to the methods we employed, 230 papers were selected from papers published over the past 30 years. The entire list can be obtained from the corresponding author. During the first ten years (1976-1985) of the assessment period, when GIS was initially being developed, only a few papers related to the potential capabilities of GIS were found in the forestry journals (Figure 1). From 1986 onward, on a year-by-year basis, there appears an increasing trend in the reporting of technological advances and applications of GIS in natural resource management. From 2000 to 2005 the extent of the increase is significant, with the highest rate of publication noted in 2005 (38 papers). Initially, most GIS-related papers were published in only one of the seven main North American forestry journals, the *Journal of Forestry* (Figure 2), although two of the journals (*Western Journal of Applied Forestry*, *Northern Journal of Applied Forestry*) only began publishing research in the mid-1980's. The *Journal of Forestry* still maintains a leadership role in providing technological advances to natural resource professionals, more recently, however, the *Canadian Journal of Forest Research* and *Forest Science* have come to the forefront in publishing GIS-related papers.

While it may be difficult to characterize the preference of each journal for GIS-related papers, results suggest that the seven journals exhibit some differences. For example, very few GIS-related papers were found in the applied journals of forestry: the *Southern Journal of Applied Forestry*, the *Western Journal of Applied Forestry*, and the *Northern Journal of Applied Forestry*. The three regional applied journals publish sporadic papers related to GIS, whereas *The Forestry Chronicle*, a Canadian journal similar in scope to the three applied journals, publishes a relatively consistent number each year. In addition, the *Canadian Journal of Forest Research*, *Forest Science*, and the *Journal of Forestry* all contained numerous papers that related to GIS. This dichotomy is curious since the regional applied journals would be the likely outlets for papers describing practical applications of GIS-related analyses. Upon further examination we found most papers that were published in the *Canadian Journal of Forest Research* and *Forest Science* used GIS in conjunction with other algorithms or modeling applications, demonstrating relatively complex and rigorous scientific methods.

We paid close attention during the review process to the data structure used in each paper. Most raster data used in natural resource management are derived from satellites, particularly

Landsat Thematic Mapper (TM), while most vector data are obtained from land surveys, air photo interpretation, or map digitizing. Among the 230 papers we reviewed, about one-quarter of the papers either did not explicitly refer to one of the two main data structures (vector or raster), or failed to mention which one(s) they employed. Most of these papers either present an overview of GIS, or describe general GIS technological advances. Of the other 175 papers we reviewed, 51 only used vector data, 70 only used raster data, and 54 used both vector data and raster data. These numbers reveal that while vector data dominate the practical applications of day-to-day natural resource management, raster data are as important, mainly due to relative availability over large areas (i.e., Landsat data), and ease of use in landscape analysis and research. In practice, however, it is hard to argue against vector data being more prevalent for making natural resource management decisions. However, the trends indicate that perhaps one single data structure can not satisfy the needs of more complex research and management applications, particularly when it comes to assessing spatio-temporal change across the landscape.

Across the entire period covered, papers that emphasized small-scale (local) or site-specific applications of GIS were predominant. While a number of examples of natural resource applications were published prior to 2000, a significant increase in applications can be seen in the seven North American forestry journals since 2002 (Figure 3). Wildlife applications (17 papers, e.g., Bosakowski and Vaughn 1996, McComb and others 2002, Betts, Franklin, and Taylor 2003) represent one of the largest groups of papers, followed by entomology (12 papers, e.g., Liebhold and Elkington 1989; Hall, Volney, and Wang 1998; Magnussen, Boudewyn, and Alfaro 2004), fire (14 papers, e.g., Burgan and Shasby 1984, Barrett, Jones, and Wakimoto 2000, Zhai, Munn, and Evans 2003), inventory (13 papers, e.g., Monty 1987, Kleinn 2000, Fournier and others 2003), harvest scheduling (11 papers, e.g., Batten, Bettinger, and Zhu 2005), and environment (11 papers, e.g., Goebel Wyse, and Corace 2005). Fields associated with the management of forested landscapes that have received little attention in the seven main forestry journals include aquatic resources (e.g., Bettinger, Johnson, and Sessions 1998), tree physiology (Sampson and others 2000, Sampson and others 2003), and recreation (Becker 1976, Boxall, McFarlane, and Gartrell 1996, Queen and others 1997, Wing and Shelby 1999). Some plausible reasons for the lack of papers emphasizing these associated resource management fields include: (1) management issues in these areas have not been as contentious nor litigious, (2) less research has been placed on the spatial aspects of management, as compared to the other fields, (3) papers related to these fields can be found in other journals, (4) some research areas may be inherently less spatial in nature, (5) some aspects of certain disciplines may be only poorly developed, and (6) some fields of study may be limited by expensive instrumentation needs.

While the focus of the natural resource application research papers is somewhat uneven, the geographic location of these research papers has been relatively evenly spread across North America. From Canada, the applications include those from Alberta (Flannigan and Vonder Haar 1986, Boxall, McFarlane, and Gartrell 1996), British Columbia (e.g., Sandmann and Lertzman 2003, Cerda and Mitchell 2004), Ontario (e.g., Gillis, Pick, and Leckie 1990, Sampson and others 2003), Quebec (e.g., Bilodeau, Bédard, and Lowell 1993, D'Aoust, Kneeshaw, and Bergeron 2004), New Brunswick (Betts, Franklin, and Taylor 2003), and Newfoundland (McLaren and Mahoney 2001). Applications from across the United States (U.S.) include those from the northeast (e.g., Becker 1976, MacFaden and Capen 2002), the north central region (e.g., Hall, Volney, and Wang 1998, Carver and others 2004), the interior west (e.g., Burgan and Shasby 1984, Dodds and others 2004), the west (e.g., Zack and Minnich 1991, Wimberly 2002), Alaska (Dissing and Verbyla 2003), and the south (e.g., Doggett 1993, Zhai, Munn, and Evans

2003). A few GIS papers describing applications outside of North America have also been published in the seven main forestry journals. These include applications from the United Kingdom (Foody, Jackson, and Quine 2003, Gilbert and others 2003), Korea (Kang, Kim, and Lee 2002), Costa Rica (Kleinn 2000), Finland (Katila and Tomppo 2002), The Netherlands (van Oort and others 2005), Spain (García-Gigorro and Saura 2005), Brazil (Neeff and others 2005), Russia (McRae and others 2005), and Cameroon (Robiglio and Mala 2005).

Beginning in the early 1990's, a concentration of work in landscape applications began to separate as an independent area of research in natural resource management. In our review, 51 papers were found which illustrate or advance techniques for classifying land, vegetation, or land-use change (Figure 4). While most papers regarding the use of satellite imagery in GIS may be published in journals such as *Photogrammetric Engineering & Remote Sensing*, *Remote Sensing of Environment*, or the *International Journal of Remote Sensing*, a number have also been published in forestry journals to expose forestry professionals to the opportunities associated with using satellite imagery. The use of satellite imagery far outweighs the use of other GIS databases for these types of applications, due to its spatially broad and temporally repeatable coverage. Landsat databases are the most prevalent satellite-derived data used (36 papers, e.g., Dodge and Bryant 1976, Bolstad and Lillesand 1992, Ohmann and Gregory 2002, Pocewicz, Gessler, and Robinson 2004). However, IKONOS imagery (Mallinis and others 2004), SPOT imagery (Salajanu and Olson 2001), AVHRR imagery (Zhu and Evans 1992), MODIS imagery (Bergen and others 2003), aerial scanner imagery (Befort and Evans 1988), aerial photography (Hove and others 1989, Pitt, Runesson, and Bell 2000, Rhemtulla and others 2002, Heyman and others 2003), digital aerial images (Lachowski and others 1997), and other vector databases (Radeloff and others 1999, Schulte, Mladenoff, and Nordheim 2002, Nadeau, Li, and Hans 2004) have been used for classifying the landscape in a GIS-based environment.

The geographic locations of the landscape applications have been centered mainly in the western U.S. (e.g., Fox, Mayer, and Forbes 1983, Ripple 1994, Ohmann and Gregory 2002) and north central U.S. (e.g., Hove and others 1989, Bolstad and Lillesand 1992, Riitters, Coulston, and Wickham 2003). However, considerable work has also been reported from applications in Alberta and the northeastern U.S. Other areas of North America, such as Ontario (Pitt, Runesson, and Bell 2000), New Brunswick (Wardoyo and Jordan 1996), British Columbia (Sachs, Sollins, and Cohen 1998, Franklin and others 2000), the interior western U.S. (Pocewicz, Gessler, and Robinson 2004), and the southern U.S. have been represented by relatively few examples of landscape classification. Landscape applications from other areas of the World are increasingly being represented in the seven main North American forestry journals. These include China (Shao and others 1996, Dai, Shao, and Xiao 2003), Greece (Mallinis and others 2004), Sweden (Wallerman and others 2002), and Russia (Bergen and others 2003).

One of our interests was in locating papers that provided a perspective on using GIS in the classroom, and several that we located are notable. First, results of surveys of U.S. and Canadian forestry schools, describing the status of the integration of remote sensing and GIS in undergraduate forestry curricula, as well as trends in graduate research, can be found in Sader and Vermillion (2000), Sader and Winne (1990), and Sader, Hoffer, and Johnson (1989). Second, Berry (1986) described some fundamental tools required of students that might help them to understand the mechanics of GIS. Weir (1989) described a number of challenges to implementing GIS in forestry curricula. Finally, Hess and Cheshire (2002) describe how GIS is being implemented in a basic forest measurements course, and provide suggestions of how to integrate GIS in other upper-level forestry courses. Most of these papers related to the educational aspects of GIS were published in the *Journal of Forestry*.

We located 18 papers that described the implementation of GIS, and not surprisingly most were centered on U.S. or Canadian examples. Only a few describe the implementation challenges and opportunities in other parts of the World, such as Mexico (Bocco and others 2001) and Zambia (Polansky and Heermans 2004). The organizations that were the focus of these papers varied as well, from non-industrial private landowners (Blinn and Vandenberg-Daves 1993), to industrial landowners (Bettinger 1999, Winkle 1991), state (Marshall, Johnson, and Hann 1997), and federal entities (Smart and Rowland 1986). Some of the major themes addressed with these papers include system design, training, development of spatial databases, and personnel. Other papers have described the integration of GIS with remote sensing (Lachowski, Maus, and Platt 1992), inventory systems (Bonner and Magnussen 1987), with a larger forest management information system (Bulger and Hunt 1991, Leggat and Buckley 1991), and with other forestry models (Fournier and others 2000). Queen and Arthaud (1994) were among the few who described the development of a multi-owner GIS system. The challenges and benefits related to the implementation of GIS are particularly outlined in Leggat and Buckley (1991), Leckie and Gillis (1995), and Bettinger (1999). Given the emphasis of several of the journals on the practical application of technology, it is somewhat surprising that more papers on these topics were not available.

Of the 25 papers that we determined were reviews of GIS technology, de Steiguer and Giles (1981) provided perhaps the first paper in the seven main North American forestry journals on the classical elements of GIS, followed by Devine and Field (1986). Although de Steiguer (1978) wrote an early paper on remotely sensed data and its application to natural resource management, a number of other papers describing remote sensing technology and its advances over time were provided by Woodham (1985), Schwaller and Dealy (1986), Green (1992), Brown (2000), and King (2000). Wynne and Carter (1997) described the advantages and disadvantages of remote sensing in forestry applications. As for reviews that specifically centered on the use and application of GIS technology, Congalton and Green (1992) provided readers a basic understanding of the underpinnings of GIS, and Wing and Bettinger (2003) and Bernard and Prisley (2005) gave an update on the significant developments in the field. In addition, Kessler (1992) supplied readers with a glossary of GIS terminology. Dangermond (1991) speculated on the direction that GIS was heading, as did Smith and others (2003). It is clear from a review of the content of these papers that natural resource management organizations are adopters, not developers, of the technology. However, the distinct challenges faced by natural resource managers could arguably inspire advances in GIS technology and associated systems. A few of the advances that have been provided by natural resource organizations include specialized applications such as Xtools (Oregon Department of Forestry 2003), developer toolkits such as Xgen (Goran 1998), and broader educational and programmatic advances that occur when large natural resource organizations invest in GIS technology (Greenlee and Guptill 1998).

Besides GIS technology review papers, we located 20 papers from North American forestry journals that probe into specific GIS technology implemented in the forestry field. A large proportion of these focus on developing and analyzing GIS analytical tools. For example, Liu (1982) described a semi-automated mapping system for forest resource mapping and data management, and Blinn, Martodam, and Queen (1994) developed a stand-alone system called EPPL Shell macro which provided convenient access to a forest inventory database within the

Minnesota Department of Natural Resources, and facilitated spatial analyses. Stoltman, Radeloff, and Mladenoff (2004), McCarter and others (1998) and McGaughey (1998) all integrated GIS with other computer image technology to provide visualization tools for landscape or forest management. Gimblett, Richards, and Itami (2001) discussed a simulation tool (RBSim) to simulate recreation behavior. With advances in technology, one also expects that the accuracy of data used in GIS and natural resource management fields will be assessed, thus papers were located from this area of interest, and include spatial data accuracy assessment (Bolstad and Smith 1992), geometric error correction (Bolstad 1992), and comparisons of data transfer methods (Bilodeau and Lowell 1997). The remaining papers that focused on the technology category mainly relate to sensors for data acquisition, including airborne digital camera (Haddow and others 2000), airborne video imagery (Bobbe, Reed, and Schramek 1993), and remote sensing sensors (Wynne and others 2000). About half of the papers that described advances in GIS technology were published in the *Journal of Forestry*.

While most people envision the applications of GIS across broad landscapes, a number of papers published in the seven main forestry journals used GIS to study and map individual trees within small areas. Raster databases derived from LIDAR imagery (McCombs, Roberts, and Evans 2003) or digital video imagery (Maltamo, Tokola, and Lehikoinen 2003) have been used to pinpoint tree crowns. Vector databases have also been developed to facilitate the mapping of individual stems to estimate how the species and spatial distribution of trees affects canopy structure (Song, Chen, and Silbernagel 2004), to quantify forest structure and growth (Biondi, Myers, and Avery 1994, Battaglia and others 2002, Kint and others 2003), or to associate the spatial distribution of trees to biomass distributions (Chen and others 2004). A number of geostatistical methods were demonstrated and used to assess the spatial relationships among trees mapped in the vector GIS databases.

Finally, we located several papers that could not easily be included within one of the categories we pre-defined. These include papers that address forest pathology issues (White, Brown, and Host 2002), policy analysis (Hann and others 1998), forest fuel classification or treatments (Riaño and others 2002), wood procurement (Brinker and Jackson 1991), and early technological descriptions of input devices and their use in forestry, such as scanning devices (Fleet 1986).

DISCUSSION

Historically, foresters and other natural resource managers used spatial information to develop maps that guided the management of the resources under their control. In the early years of our analysis (from 1976 to 1990) the emphasis was on advances in techniques which facilitated the development and display of databases. Here, digitizing and mapping were the main GIS-related tasks in the research applications. The need for developing maps to guide natural resource management remains, but the required cartographical skill has evolved from one that required a steady hand and precise handwriting to one that now requires knowledge of a computerized mapping system. While the ability to make clear and concise maps may be a central need of a GIS program, it barely taps into the wealth of spatial analysis tools available. Until recently, spatial analysis has been reserved for GIS analysts to perform, however, as entry-level managers are increasingly being equipped with GIS knowledge from college-level courses, it is not unreasonable to assume that some of these tasks will eventually shift from a select group of analysts to the field personnel. In fact, from our analysis we see a changing trend in the way GIS is portrayed in the research papers from the North American forestry journals. In recent years, spatial analysis and visualization have begun to stand out as methods for addressing more complex analytical and decision-making needs.

GIS technology has been in development for more than 30 years, and will likely continue to evolve during our careers in the natural resource management field. Based on our assessment of the literature of the past thirty years, we can see a clear developing trend - that more specific areas in natural resource management are beginning to use GIS in a wider and more integrated manner. However, these applications of GIS are not evenly distributed in each natural resource area. For example, fifteen papers focused on wildlife applications, while only four papers discussed recreational applications. In some areas of natural resource management (e.g., fisheries), we did not locate any GIS-related literature (although there are research papers in these areas in forestry journals). Since forestry and forest management can encompass all of the associated natural resource issues (i.e., recreation, wildlife, fisheries, soils, and so on), and since research papers that involve these other natural resource areas were found in forestry journals, it was not unreasonable to assume that if there were advances or applications in the use of GIS that were related to the other areas of natural resource management, they too would be found in the forestry journals we selected to review. Several reasons were mentioned earlier for the apparent absence of these types of papers, including: they are published in other journals, the applications are not much different from other applications in similar fields (thus not new), or the amount of research in these areas (e.g., GIS in recreation management) is limited. In addition to this opportunity to explore and report the use of GIS in fields related to forestry, we suggest that economic research on the costs and benefits of GIS would be a fertile and important area of research. Many natural resource managers question the need for the resources necessary to implement a successful GIS program. An analysis that clearly demonstrates the costs and benefits of using GIS to support management decisions might be viewed as a seminal paper in natural resource management. While an expanded review of the literature is needed to assess the gaps in GIS-related research, the results indicate that GIS analysis has been heavily applied to forest land management decision making, although publication of research does not necessarily lead to uptake of technology in resource management organizations.

With the long history of continuous data collection and data policies, it is not surprising that Landsat raster data are widely used in natural resource GIS applications and research, although the spatial or spectral resolution may be inappropriate for some applications that are presented in the literature. However, given that the papers we have reviewed have themselves been peer reviewed, we are confident that the influence of Landsat on advancing the application and research associated with geographic information systems is high.

From this assessment of GIS-related papers in North American forestry journals, two educational concerns arise. First, some scientists and policy makers debate whether GIS should be viewed as a tool or a science. Many natural resource managers consider GIS a useful and powerful tool for cartographic purposes (making maps of proposed activities, habitat, etc.). Others view GIS as an area of science, and thus use it to assist with the testing of scientific hypotheses. Many of the papers we reviewed suggest that GIS is simply an analysis tool that facilitates a spatial analysis of resources. Other papers suggest that GIS represents an area of science in itself, that provides a fertile ground for advancements in spatial analysis and visualization algorithms. The evolution of papers, from the initial description of advances in GIS techniques to the illustration of uses of GIS in natural resource management problems, is similar to the evolution of the adoption of other fields of work in natural resource management, such as operations research. Natural resource management has historically been an adopter of technology developed in other areas (herbicides, operations research techniques, etc.). However, since GIS is so closely tied to the management and assessment of landscapes, it is possible (although we have not tested it) that natural resource management has had a significant impact on the development of GIS analytical techniques.

Second, given the recent advances in GIS and increased adoption by natural resource management organizations, we recommend periodic surveys of the needs of employers are necessary. It seems, from our experiences, that employers and academia have a different vision of the tools students need to obtain while studying for their degrees. We can see from the literature review, for example, a significant emphasis placed on the use of satellite imagery in forestry and natural resource applications. However, our practical experience suggests that field foresters and other resource managers would be better suited learning and mastering vector-based GIS techniques. This suggests that at least two surveys are needed: one that describes the GIS tools desired for entry-level natural resource managers (foresters, biologists, etc.), and a second that describes the tools desired for those who will quickly become GIS analysts or GIS managers. The former survey is for students pursuing bachelor's degrees, the latter for students pursuing advanced degrees. These surveys should be performed frequently (every 5 years) to stay consistent with changes in technology and (perhaps highly correlated) changes in expectations of employers.

Most public and private forest management organizations now use GIS operationally for many management-related issues, such as mapping, to manage inventories, or to perform spatial analyses. Many of the uses of GIS in practice today are not the types of processes normally reported in journal articles, they are adoptions of basic processing techniques to common management problems. However, in reviewing the history of GIS in forestry journals, one can see that the research papers lead the widespread adoption of technology by a decade or more. Thus one could potentially project recent publication trends into the future to understand what might become commonplace a decade from now. This is one main point of the paper. The other point of the paper is to illustrate the history of the use of GIS in natural resource applications. Young professionals are often unaware of the relatively short history of the technology, and how it has evolved along with advances in computer technology.

We acknowledge that other research methods may be useful in assessing the trends in GIS use in natural resource organizations. These include surveys of seasoned researchers and professionals, and assessments of "seminal" papers in other related geography, remote sensing, and natural resource journals. The latter approach may lead to significant bias, based on one's judgement of the contribution of research papers. Our basic methodology was to focus on the number of papers published each year in the seven most commonly used forestry journals in North America, across a time frame that encompassed the period of development and adoption of GIS. Our analysis is informative and could provide forest and natural resource managers with an assessment of the scope of the literature presented in forestry journals and the trends of technological adoption by natural resource management, research, and educational organizations. We would argue that there is value in looking back in time and assessing the trends associated with GIS use in natural resource management. Our approach was but one way to do so, however, papers published in other journals could also be viewed as advancing the science and use of GIS, because they could be more significant contributors than the ones we have assessed in this review. This concern is problematic, since the assessment of "significance" is difficult, and perhaps should be pursued using another research instrument (surveys, for example). Further, the time involved in reviewing papers published in the 20-30 international remote sensing and

GIS journals was prohibitive, and we assumed that these journals are not as widely read by forestry professionals.

This review only covers papers published in the seven main North American forestry journals, and as a consequence, books, book chapters, proceedings papers, theses, dissertations, and other reports (e.g., U.S. Forest Service General Technical Reports) were not examined. The process for selection of papers to examine for any literature review is subjective, and reflects the biases and special interests of the reviewers (Current and Marsh 1993).

CONCLUSIONS

From its inception, GIS technology has been a particularly useful tool in forestry and natural resource management, which has been verified through an examination of the papers from the seven main applied North American forestry journals. Our analysis of these papers indicates that in the past 30 years, GIS has been heavily and widely used in many diversified areas and will continue to delve deeper and further based on current development trends and the needs of its customers. The evolution and improvement of GIS science and technology seems to drive the expanded application of GIS in natural resource management, and similarly, developments within natural resource management (e.g., habitat suitability models, resource policies) provide a strong impetus for advances in GIS analytical capabilities. Broad-scale landscape analysis is one of the recent trends in the literature that will likely facilitate natural resource management in the future, as will web-based GIS technology and remote mapping, as others have suggested (Bernard and Prisley 2005), and new sensors such as LIDAR. Research into the cost-effectiveness of these tools would be necessary prior to wide-spread acceptance and use.

The journals we have evaluated are applied in nature, and are read mainly by forest practitioners. While the broader scope of geomatics and spatial analysis has evolved along many fronts, the advances in GIS and remote sensing that are being adopted by natural resource management today are focused on land use and land cover change and other large-scale spatial analyses using satellite imagery, as well as the integration of quantitative multi-resource evaluation systems and protocols (wildlife, fire, etc.) with GIS. The literature also suggests that as a profession, forestry and natural resource management continues to cope with organizational and educational issues of technological advances in this area.

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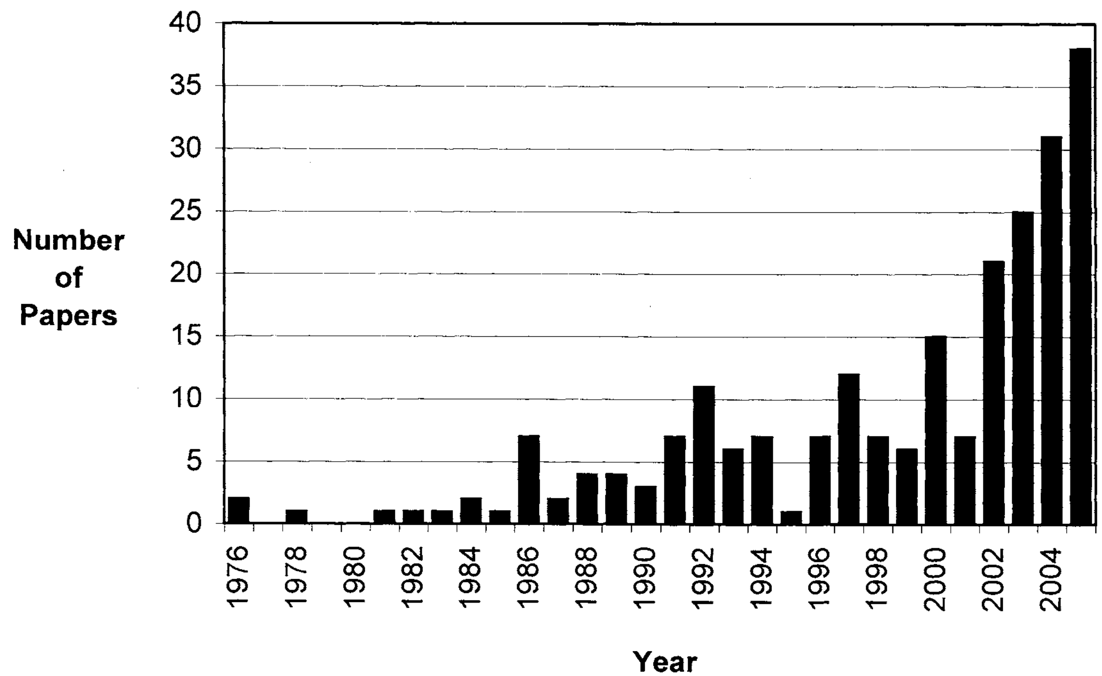
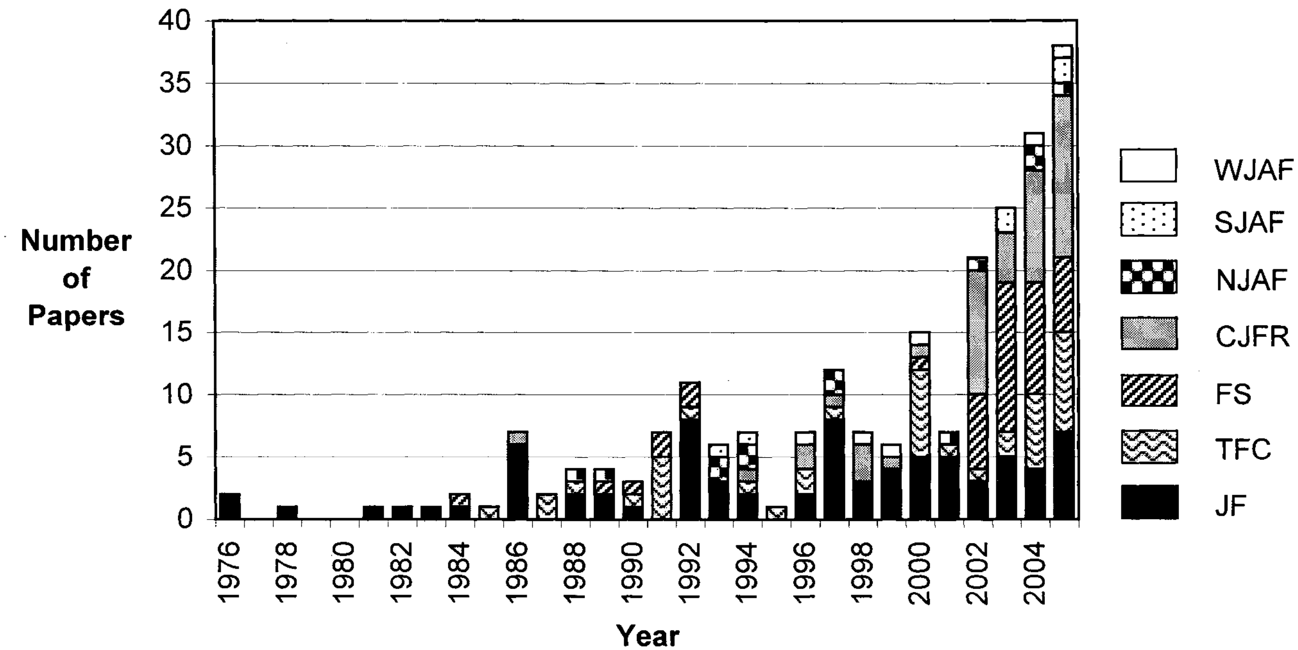


Figure 2.1 Number of papers in North American forestry journals that contained GIS-related analysis or topics, 1976-2005.



CJFR = Canadian Journal of Forest Research
FS = Forest Science
JF = Journal of Forestry

NJAF = Northern Journal of Applied Forestry
SJAF = Southern Journal of Applied Forestry
TFC = The Forestry Chronicle
WJAF = Western Journal of Applied Forestry

Figure 2.2 Number of papers, by journal, in North American forestry journals that contained GIS-related analysis or topics, 1976-2005.

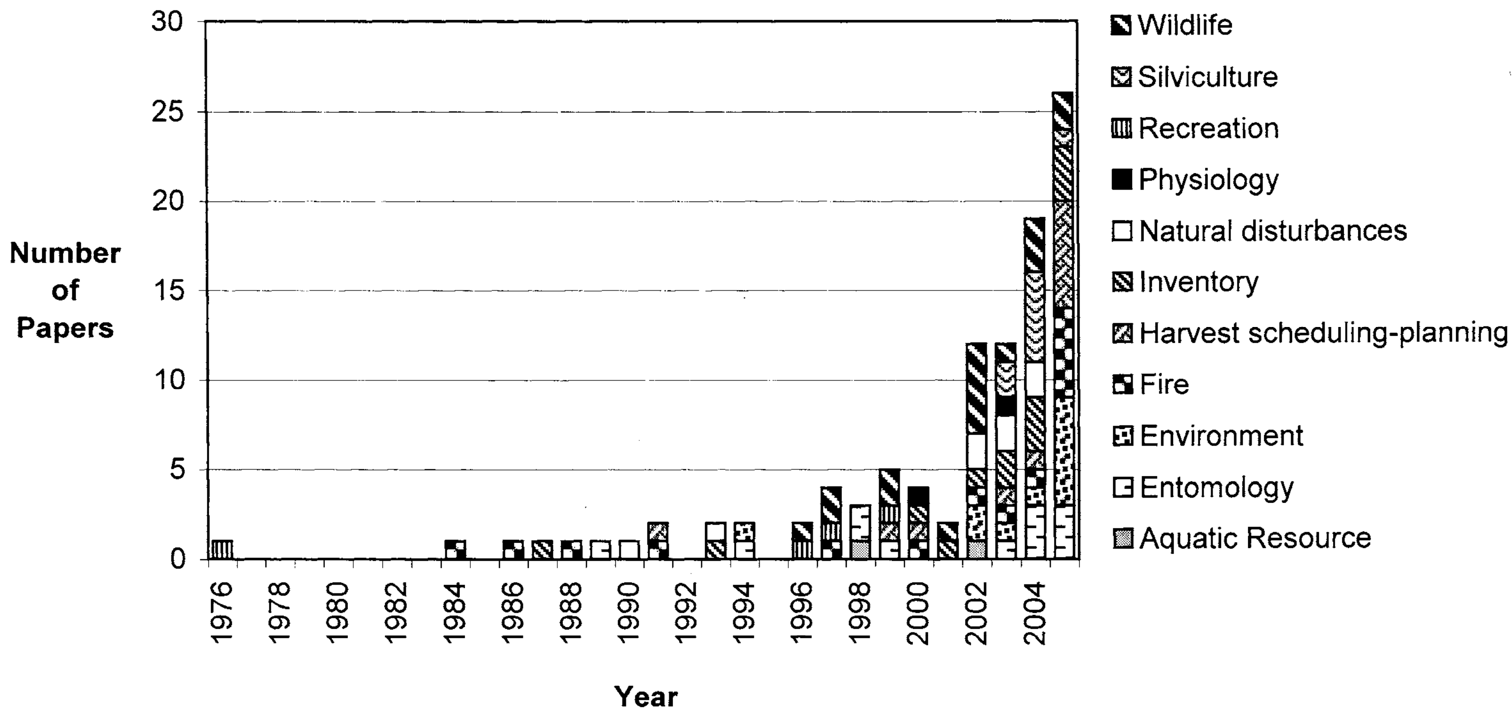


Figure 2.3 Natural resource management applications described in GIS-related papers in North American forestry journals, 1976-2005.

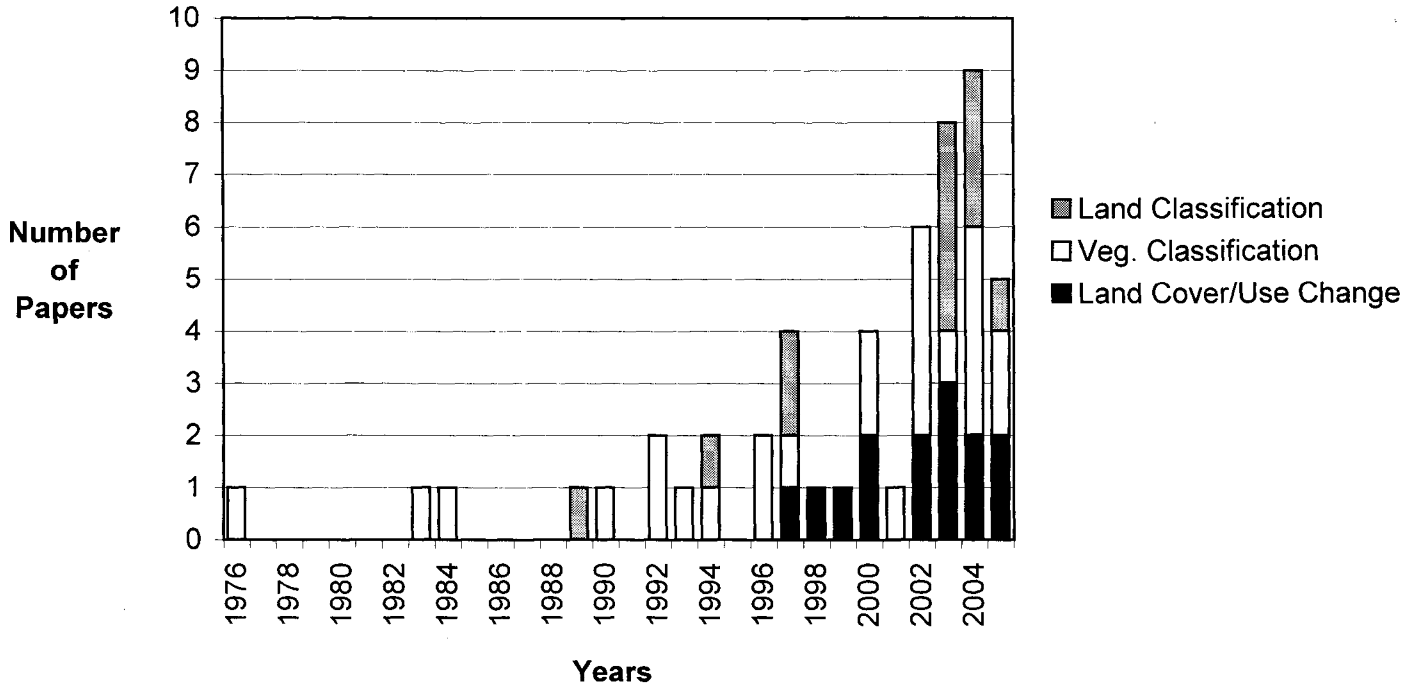


Figure 2.4 Landscape analysis applications described in GIS-related papers in North American forestry journals, 1976-2005.

CHAPTER 3

INFORMED DEVELOPMENT OF META HEURISTICS TO SOLVE SPATIAL FOREST PLANNING PROBLEMS[1]

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[1]Li, R., P. Bettinger, and K. Boston. To be submitted to *Forest Science*.

ABSTRACT

Each heuristic algorithm has a distinct behavior when it attempts to solve a forest planning problem — e.g. some use stochastic processes, some use deterministic processes. In this research, standard heuristics, including Monte Carlo integer programming, simulated annealing, threshold accepting, tabu search and the raindrop method, were used to compose 24 3-algorithm meta heuristics to solve a large spatial forest planning problem. An intelligent mechanism of combining standard algorithms was developed based on search behavior of each standard algorithm, using the cubic spline smoothing technique. Twelve 2-algorithm meta heuristics were examined first to determine the best integration positions to link two different algorithms. We then used this information to determine how to build a 3-algorithm meta heuristic that employed different intensification and diversification search strategies. We found that more than 75% of the 3-algorithm meta heuristics presented consistently better solution qualities than the best standard heuristic in terms of mean solution values and maximum solution values, and a 2-algorithm meta heuristic (threshold accepting + tabu search) performed the best in terms of the maximum solution value, improving solution quality 1.4% over the best standard heuristic solution value from threshold accepting. The best improvement in solution quality from a 3-algorithm heuristic was 1.2% better than those produced from a best standard heuristic (threshold accepting). Results also indicate that meta heuristics which started a search with simulated annealing or threshold accepting produced much better solutions than those that started a search with tabu search or the raindrop method.

Keywords: Tabu search, Simulated annealing, Threshold accepting, Raindrop method, Unit restriction model, Woodflow constraints, Cubic spline smoothing

INTRODUCTION

Spatial forest planning has gained wide acceptance over the past decade, as people have gradually recognized the importance of tactical planning and forest sustainability. Knowing the exact location of management activities can help forest managers better understand forest planning problems and thus make appropriate decisions. In addition, many forest regulations and voluntary guidelines require or suggest that harvesting activities follow certain rules regarding clearcut sizes and landscape patterns (Bettinger & Sessions 2003). Therefore, involving spatial components in forest planning is of great importance.

It has been widely acknowledged that spatial forest planning problems are difficult to solve (Lockwood & Moore 1993), especially for those with green-up or adjacency constraints, since they are combinatorial in nature (Bettinger & Sessions 2003; Baskent & Keles 2005; Boston & Bettinger 1999; Bettinger et al. 1999). Using traditional exact mathematical methods, including integer programming and mixed integer programming, to solve large spatial forest planning problems is tremendously difficult with respect to locating the optimal solution and the excessively long computing time required. For these reasons, heuristic methods have recently been introduced in this field to solve spatial forest planning problems, and they have been accepted as a practical approach to generate near-optimum solutions in a reasonable time limit. The most commonly used heuristic methods in forestry include simulated annealing (Nelson & Liu 1994; Dahlin & Sallnas 1993; Boston & Bettinger 1999; Chen & Gadow 2002; Lockwood & Moore 1992; Baskent & Jordan 2002), tabu search (Bettinger et al. 1997, Caro et al. 2003, Boston & Bettinger 2002), genetic algorithms (Falcao & Borges 2001, Heinonen & Pukkala 2004, Boston & Bettinger 2002), threshold accepting (Bettinger et al. 2003; Bettinger et al. 2002), and Monte Carlo random search (Clements et al. 1990). Some of heuristic methods have been enhanced to further explore the solution space and possibly improve the quality of solution values. For example, Richards & Gunn (2003) designed an oscillating reactive tabu search and found it improved solution values by 20%. Bettinger et al. (1999) developed 2-opt tabu search and also obtained better results over standard tabu search. Other research efforts have shown that combining two algorithms may allow one to locate better solutions (Bettinger, et al. 2002; Boston & Bettinger, 2002). However, this combination has generally been limited to two heuristic algorithms, and the decision criteria for switching processes has been relatively rote (i.e., change after x iterations).

In this study, we utilized five standard heuristic algorithms — Monte Carlo integer programming (MCIP), simulated annealing (SA), threshold accepting (TA), tabu search (Tabu), and the raindrop method (Bettinger & Zhu 2006) — to study their searching behavior, and then combined them into 24 meta heuristics. We systematically evaluated the searching abilities of 24 3-algorithm meta heuristics by comparing and testing their solution values and computing times against the five standard heuristic algorithms. We hope our results and discussion can give a useful insight into meta heuristic development in the forest planning field.

METHODS

Problem formulation

A geographic information system (GIS) database containing 1,123 vector polygons of stands covering 92,975 acres was used in the forest planning exercise. Forest stand polygons in this dataset were based on a real southern forest land ownership. We modified polygon sizes in a GIS environment to ensure that the area of each stand polygon ranged from 60 to 120 acres, because we assumed later that the maximum clearcut limitation was 120 acres, and when using the unit restriction model (URM) (Murray 1999), only one stand in the adjacent neighborhood can be treated in each planning period. The initial forest age class distribution over the entire forest land was simulated as uniformly distributed between age 1 and age 30 (Figure 3.1).

The spatial forest planning problem in this study was formulated with a planning objective of maximizing the net present value. We assumed that timber products were the only profitable outcome. The planning horizon is 15 years with 1-year long planning periods. For simplicity, we also assumed that the only treatment on the forestland was the clearcut. Four constraints were considered. First, a URM adjacency constraint, under which any two contiguous stands were not allowed to be treated in the same planning period, was incorporated into the problem. Even wood-flow constraints, which ensured sustainable and stable yields over the 15 year planning horizon, were also assumed. In other words, the harvested volume in each period should not deviate too far from each other (maximum 20% deviation in this case). An ending inventory constraint was assumed, which prevented the depletion of timber stands at the end of planning horizon, where at least 90% of the original timber volume was required to remain. Finally, a minimum cutting age constraint, where trees less than 20 years old are not considered to be cut, was incorporated into the problem. In sum, this is similar to a typical planning problem for a southern U.S. company.

The formulations are as follows:

Maximize

$$\sum_{t=1}^{T}\sum_{i=1}^{N}(X_{it}((V_{it.saw}P_{saw}+V_{it.cn}P_{cn}+V_{it.pulp}P_{pulp})-A_iC_r)/1.06^{t-0.5}-C_aT_A(1.06^t-1)/(0.06)(1.06^t) \tag{1}$$

subject to

$$X_{it}+X_{jt}\leq 1 \quad \forall i, j\in N_i \tag{2}$$

$$0.8*\sum_{i=1}^{N} X_{it}V_{it} \le (\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \text{if } \sum_{i=1}^{N} X_{it}V_{it} > (\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \forall\, t$$
$$\sum_{i=1}^{N} X_{it}V_{it} \ge 0.8*(\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \text{if } \sum_{i=1}^{N} X_{it}V_{it} < (\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \forall\, t \tag{3}$$

$$\sum_{i=1}^{N} V_{il} \ge 0.9*\sum_{i=1}^{N} V_{i0} \tag{4}$$

$$\sum_{t=1}^{T} X_{it} \le 1 \quad \forall i \tag{5}$$

$$\text{Age}_{\text{it}} \ge 20 \text{ if } X_{it} = 1 \tag{6}$$

Where:

A_i = area of management unit *i* (acres)

Age_{it} = the age of management unit *i* at time *t* period

C_a = annual cost ($/acre)

C_r = regeneration cost ($/acre)

i, *j* = an arbitrary harvested unit

N = total number of harvest units

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

P_{cn} = stumpage price for chip-n-saw timber

P_{pulp} = stumpage price for pulpwood

P_{saw} = stumpage price for sawtimber

t = period in which harvest activities occur

T = total number of time periods in the planning horizon

T_A = total planning area (acres)

V_{i0} = total timber volume in the stands before any harvest activities

V_{il} = timber volume left on the stands after the planning horizon

V_{it} = timber volume harvested in time period t, from management unit i

$V_{it.cn}$ = chip-n-saw volume harvested in time period t, from management unit i

$V_{it.pulp}$ = pulpwood volume harvested in time period t, from management unit i

$V_{it.saw}$ = sawtimber volume harvested in time period t, from management unit i

$$X_{it} = \begin{cases} 1 & \text{if management unit } i \text{ is treated in time period } t \\ 0 & \text{otherwise} \end{cases}$$

Equation 2 refers to the URM adjacency constraint. Equation 3 describes the even-flow constraints. Equation 4 represents the ending-inventory constraint. Equation 5 indicates that a unit can only be harvested once during the planning horizon. And Equation 6 represents the minimum harvest age constraint.

When the exact integer programming is used to solve the problem, different formulations in adjacency constraints may have different impacts on solution generating speed. Adjacency constraints here were formulated as the pairwise type among the various adjacency formulations (e.g. Type I nondominated, new ordinary adjacency matrix). McDill and Braze (2000) stated that pariwise constraints performed better for mature forest problems than other two formulations and found no difference in their performance for a regulated forest such as the one used here.

We used a growth and yield model developed for southern pine stands by the Plantation Management Research Cooperative (Warnell School of Forest and Natural Resources, University of Georgia, 1996). The stumpage prices were obtained from Timber-Mart-South (4Q, 2006), and were \$36.58 per ton for sawtimber, \$20.40 per ton for chip-n-saw and \$6.68 per ton for pulpwood. The costs include a regeneration cost of $245.30/acre (preparation, planting, seedling and herbaceous control) and an annual management cost of $4.50/acre.

Heuristic algorithms

This research involves investigating methods to intelligently combine standard heuristics into a meta-heuristic. The standard heuristics include Monte Carlo integer programming, simulated annealing, threshold accepting, tabu search and the raindrop method. All but the latter have been used extensively in forest harvest scheduling research. The raindrop method is a recently introduced heuristic that has been shown to very effectively solve certain kinds of harvest scheduling problems. Each of these heuristics is briefly described below.

Monte Carlo integer programming

Monte Carlo integer programming (MCIP) was first applied to forest harvest scheduling problems almost two decades ago (Clements et al. 1990, Nelson and Brodie 1990), and has been used to solve a variety of spatial harvest scheduling problems (Boston & Bettinger 1999). MCIP is actually a sampling technique. The basic idea of this technique is to find a good solution by randomly selecting choices from the feasible solution set. When this algorithm is used in harvest scheduling, a planning unit (stand or compartment) is randomly selected and assigned a treatment (e.g. a clearcut period). Since the basic implementation of MCIP does not involve any advanced intelligence to direct the searching process to the optimum solution, the result may vary considerably from the global optimum solution.

Simulated annealing

Simulated annealing (SA) is derived from the process of annealing first described by Metropolis et al. (1953). As a search process, simulated annealing began to be used in a widespread manner in other fields in the early 1980s (Dawsland 1993). A number of papers have shown the usefulness of simulated annealing in forest harvest scheduling (Boston & Bettinger 1999; Nelson & Liu 1994; Lockwood & Moore 1992; Baskent & Jordan 2002). SA performs a search process by emulating the physical annealing process of metal. The program starts with a high temperature, and after a certain number of iterations, if the solution is not improved, the temperature cools off. This "temperature" acts, in part, as a threshold — any inferior but feasible solutions near a correct solution may be visited. The program stops when the stopping criterion is met (e.g., the temperature gets too low). As the temperature drops from high to low, the search moves from a random feasible solution set to a limited group of good candidate solutions. At the beginning of the search, an initial random solution is generated, and then a small change is made on this solution. If the change results in a better solution, it remains in the solution set. If the solution is not improved, whether this new solution should be accepted or not depends on the resulting solution quality and a probability defined by the following equation:

$$P(T) = e^{-|S_c - S_p|/T_t} \tag{7}$$

where s_c = current solution value

s_p = previous solution value

T_t = temperature at time t

$P(T)$ = probability critical value

P(T) is then compared to a randomly drawn number. The process accepts the inferior solution if the critical probability value defined by equation 6 is greater than the randomly drawn number. An inferior solution is likely to be accepted at a high temperature level (at the beginning of the search) and likely to be refused at a low temperature level (near the end of the search), since at a higher temperature the critical probability value is larger.

The essential component of the simulated annealing algorithm is the cooling schedule it employs. The parameters required for a cooling schedule include: the initial temperature T_0 and the cooling function $T_{k+1}=f(T_k)$. The cooling function can be very complicated, which may involve self-adapting at each temperature during the searching process. For simplicity, we chose to use a fixed cooling schedule in present study, which only includes an initial temperature and a cooling rate.

Threshold accepting

Threshold accepting (TA) was introduced by Dueck and Scheuer (1990) and later applied to forest planning problems by Bettinger et al. (2002, 2003). TA works similarly to SA except there is no annealing criteria to compute. A small change on a solution is proposed, and if there is an improvement, then the proposed change is kept as the current best solution. The difference from SA lies in how to deal with solutions that do not improve the quality of a forest plan. Instead of using a probability to determine which solution is acceptable, TA sets a threshold, and if any solution is worse than the current solution value by more than the amount of the threshold value, it is not accepted. The threshold value is initially large, allowing the search to move relatively freely throughout the solution space. The threshold changes, as the search progresses, until it becomes very small. At some point, when the threshold is very small, the search terminates.

Tabu search

Tabu search was introduced by Glover (1989, 1990), and has been applied to forestry problems by Bettinger et al. (1997, 1998, and 1999) and Batten et al. (2005). Along with simulated annealing, tabu search is one of the most frequently used techniques in forest planning. Unlike other heuristic techniques, tabu search largely involves a deterministic component in its search activity. This deterministic feature may cause large computation costs, however. On the other hand, this deterministic mechanism may provide very good solutions that are close to the global optima if the search process can avoid becoming trapped in local optima. Basic tabu search can be summarized into two steps: 1) a neighborhood local search, which aims at finding the best feasible solution in the neighborhood of the current solution; and 2) an improvement mechanism which attempts to use tabu tenure to avoid being trapped in the local optima. Other variations of tabu search may use diversification techniques to explore further the feasible solution space, or use the intensification to exploit deeper areas surrounding elite solutions. But in this study, only the basic tabu search is developed and tested. The key parameter for basic tabu search is the tabu tenure.

The neighborhood search examines a large set (if not all) of the potential changes to a solution, and the best choice is chosen. This choice could either increase the quality of a forest plan or decrease it. In the latter case, the choice that reduces the quality the least is chosen, no matter how much reduction in quality occurs. An improvement mechanism is called the aspiration criteria. Within tabu search, a choice is generally forbidden (taboo) if it has been made recently (within the last x number of iterations, where x= the tabu tenure). However, if a choice is tabu, but will lead to the highest quality solution found thus far during the search, the choice is selected, and the tabu tenure is over-ridden.

Raindrop method

The raindrop method was first developed by Bettinger and Zhu (2006) and is aimed at mitigating adjacency constraint violations in a URM situation in a radiating manner away from an initial forced choice. Similarly as other heuristics, the process starts with a random solution, and then makes a random change. In most other heuristics, if this change causes any infeasibility (e.g., violating the adjacency constraints), the choice will be discarded and the heuristic will consider other choices. The raindrop method, instead, keeps this change (a forced choice), but records all the constraint violations, then attemps to mitigate the violations. Activies assigned to units are altered until no constraints are violated. Units closest to the forced choice are altered first. Such change-violate-fix sequence continues until there is no violation on the record list, and a new iteration starts. After a certain number of iterations, the process reverts to the previous best solution if no improvement has been found. Therefore, the only two parameters required in raindrop method are the total number of iterations and the revert iteration. This method has been shown to produce higher quality and more consistent forest plans when modeling the URM model of adjacency in forest planning (Bettinger & Zhu 2006).

Determining the best parameter values for each individual algorithm

In this study we used empirical methods to find the best parameter values for each algorithm by searching a wide range of possible parameter values and locating a narrow parameter interval. We determined that all values falling in this interval would more likely lead to steady and high-valued solutions. Although we can not guarantee the parameter values used are exactly the best choice for the problem, we are confident they are reasonable values and would allow us to generate good solutions.

MCIP used the total iterations as the only parameter. It is obvious that longer iterations might have more chance to encounter a better solution. But this is a tradeoff between solution quality and time consumption. It was difficult to determine what number of iterations would provide good solutions within a minimum computing time. In our case, we assumed 10,000 iterations.

For SA, an initial temperature was tested that ranged from 10,000 to 5,000,000 with an interval of 10,000. The cooling rate was tested using five different values: 0.9999, 0.9995, 0.999, 0.995, 0.99; Similarly for TA, the initial threshold was tested that ranged from 10,000 to 1,000,000 with an interval of 10,000, and the decreasing rate was examined using five different values: 0.9999, 0.9995, 0.999, 0.995, 0.99; for tabu search, the tabu tenure was tested ranging from 100 to 20,000 with an interval of 100; and for the raindrop method, the parameter of the reversion rate was tested from 5 to 1000 using an interval of 5. Except for the raindrop method, all other 3 methods were stopped when the solution did not improve for a certain number of iterations. The raindrop method used total iterations as a stopping criterion.

The graphs relating to locating the best parameter values are listed in Figures 3.2 to 3.6. For SA, the solution quality decreased as the cooling rate decreased. With cooling rates of 0.99 and 0.995, solution values appeared to be lower quality compared with solutions with cooling rates of 0.999, 0.9995 and 0.9999 (Figure 3.2). This suggested that we were not allowing free movement in the initial period of the search. In our program we assumed a 0.9995 cooling rate for SA. The reason we did not choose 0.9999 (which seemed to result in the best solution quality) was because it took more than twice as long to generate a solution than when using 0.9995. When viewing more detailed results (Figure 3.3), we noticed that the initial temperature did not matter too much as long as it was above about 7,000. After this point, the quality of solutions was stable with respect to the initial temperature, and the cooling rate thus had the most influence on solution quality. For these reasons, we assumed an initial temperature of 10,000 for SA. TA showed similar results as SA. Threshold change rates of 0.9999, 0.9995 and 0.999 seemed to provide high quality solutions compared with threshold change rates of 0.995 and 0.99 (Figure 3.4). As with SA, we assumed 0.9995 was the threshold change rate in our TA program. To determine which initial threshold should be used, we examined more closely the solutions generated with initial threshold values between 1,000 and 30,000 (Figure 3.5). The quality of solutions stabilized after an initial threshold of about 15,000, so we chose to assume an initial threshold of 20,000 for the remainder of this work. For tabu search, we located the stable interval for the tabu tenure ranging from 4,500 to 5,500 iterations. This represented about 1/3 of the potential choices available in adjusting a solution from one iteration to the next. Solutions produced using the tabu tenure in this interval maintained a high quality level (flat peak in the graph, Figure 3.6). Therefore, we chose 5,000, the median of this interval, as the tabu tenure used in this work. The process terminated when the solution made no improvement after consecutive 10,000 iterations. The raindrop method did not suggest any solution pattern with the increase in the value of reversion rate. We determined to use a value of 5 for this parameter.

Preliminary analysis

A better understanding of the searching pattern of each individual algorithm would provide us insightful perspectives and logical reasons regarding how to combine different algorithms. Before developing combined meta-heuristics, we applied each individual algorithm to the same study problem, and observed and analyzed their different solution-development behavior.

Break-point analysis

Bettinger et al. (1997) studied tabu search behavior in a minimization problem and analyzed the search path into three phases: hill-climbing phase, adjustment phase and steady state phase. Whether algorithms other than tabu search used in a maximization problem have the same search pattern, is unknown. To further study search patterns of TA, SA, Tabu and the raindrop method in a context of solving a spatial forest planning problem with a maximization objective, we utilized the techniques of break-point analysis to detect significant changes in patterns for a series of data (i.e. a search path).

Break-point analysis has been mostly used in analyzing economic time series data. The foundation for estimating breaks in time series regression models was proposed by Bai (1994) and was extended to multiple breaks by Bai (1997ab) and Bai & Perron (1998) and implemented as an algorithm in Bai & Perron (2003). The basic idea is to estimate break points by fitting multiple linear regression models simultaneously and minimizing the residual sum of squares.

In our study, we tracked the searching path by recording, at each iteration, the current solution value. We treated this search path as a time series data with iterations representing time slices and current solution values as response values. Four randomly selected searching paths from each of SA, TA, Tabu and the raindrop method were analyzed to find structure break points using break-point estimation techniques.

Results from break-point analysis

We found two significant break points in each of those four search paths (Figures 3.7 to 3.10). Based on these two break points, we divided the searching path into 3 intervals, which matched with three phases of their searching behaviors: hill-climbing phase, adjustment phase and steady-state phase (Bettinger et al. 1997). In general, solution values increased very fast in the first hill-climbing phase, and slowed down in the adjustment phase, eventually moved into the steady-state phase. However, for some algorithms (e.g. raindrop method) the search path continued moving upward even in the steady-state phase, but basically with a very slow increasing rate.

TA and SA vibrated up and down during their search, particularly the SA algorithm. This could well be explained by their algorithm behavior in that they temporarily allowed low quality solutions enter the current solution space. Tabu search presented a different pattern. Due to its partially deterministic characteristic, it moved straight up in the hill climbing phase, then stopped for a while and jumped to a high value. This stop-jump pattern continued until the end of the search. Differing from the others, the raindrop method spent a lot of iterations making small movements after the first phase. As for the computing time, TA and SA required much less time than did tabu search and the raindrop method. It was clear that by themselves TA and SA had stronger searching abilities with respect to both solution quality and computing time. Therefore, a question rises as: are meta heuristics composed only by good standard algorithms more likely to produce better solutions than ones composed by both strong and weak algorithms?

Algorithm integration

A concentration of this work was placed on developing an intelligent mechanism for combining different algorithms. In other words, how to automatically locate integration points and switch the search from one algorithm to another during the search process, was one emphasis of this work. Simply using the break points from the previous change point analysis as integration positions turned out to be a bad choice, because 1) the positions of break points were constantly changing corresponding to different runs; 2) change point analysis was done after the whole solution was generated, but we needed to decide during the generation of a solution where to stop one algorithm and start another one; and 3) each algorithm had its own internal mechanism which determined the searching path pattern, therefore the phase separation was only meaningful within one algorithm, and thus there was no simple equivalence of the same phase between different algorithms. For example, the hill climbing phase of the raindrop method was slower, with respect to the best solution found, than the adjustment phase of the simulated annealing.

Cubic spline smoothing technique

Since the purpose of combining different algorithms in a meta heuristic is to enhance the searching ability by taking advantage of the beneficial aspects of different algorithms, the best time to switch from one algorithm to another should be where the one algorithm's performance wanes. In order to quantify the subjective term 'wane', we needed to know the relative solution improving speed at each iteration. Because solution values increased and decreased constantly in one search, it was moot to calculate the solution developing speed by using the difference between the current solution value and the previous solution value. If we could generalize the searching path into a smooth line with a clear trend, ignoring all small movements, we then could derive the slope (i.e. solution developing speed) at each iteration point. The statistical cubic spline smoothing technique (Chambers & Hastie 1992) was utilized to complete this task. This smoothing technique could date back to Schoenberg (1964). It was later designed as statistical functions by Chambers & Hastie (1992). Using this technique, we fitted cubic smoothing splines to each search path during the search process. In other words, while the heuristic algorithm searched for the best solution, cubic smoothing splines were simultaneously fitted to the current search path with a frequency of every 200 iterations. The fitted smoothing splines to SA, TA, tabu search and the raindrop method, after the search was complete, were illustrated in Figures 3.11, 3.13, 3.15 and 3.17. Since the fitted lines were smooth at every point, the first derivative (i.e. slope) can be obtained. Based on the value of derivative at each iteration, we decided whether the switch should be made at that moment. A large derivative value indicated a strong and fast searching ability, and a small derivative value indicated a slow and weak searching ability. A negative derivative value meant a decrease in current solution value. If derivative values stayed at zero for a certain number of iterations, it was probably a sign of the stagnation of the search. The time we considered to switch algorithms could be the time when derivative values turned from a positive number to a negative number, or when derivative values became constant at zero for many iterations.

Determining best integration points

For the same combined meta heuristic, different integration points lead to different results. In order to increase the possibility of producing high quality solutions, we first experimented with four different positions of linking two standard algorithms together in one search, for each of 12 possible links. These 12 links were SA-TA, TA-SA, SA-Tabu, Tabu-SA, TA-Tabu, Tabu-TA, SA-Rain, Rain-SA, TA-Rain, Rain-TA, Tabu-Rain, and Rain-Tabu and represented 12 different 2-algorithm meta heuristics. The four positions of linking two algorithms were 1) the first interception point of the smoothed line with the horizontal zero line; 2) the third interception point of the smoothed line with the horizontal zero line; 3) the fifth interception point of the smoothed line with the horizontal zero line; and 4) the point where the smoothed line begins to flatten out (Figures 3.12, 3.14, 3.16 and 3.18). The reason we only chose the odd number of interception points (1, 3 and 5) was because these points were positions where the first derivative value changed the direction from positive to negative, which indicated that further search contained no contribution to the solution value until the derivative value turned back to a positive number. These four integration positions were labeled as ‘a’, ‘b’, ‘c’, and ‘f’. We ran each combined algorithm formed by two different standard algorithms using each of four integration positions 50 times, and recorded the final solutions and the time required for each run. We then calculated the mean and the standard deviation of the solution values, the computing time, and the maximum solution value for each 50 runs. At last, we used ANOVA to test if any significant difference of the final solution values occurred due to varying integration positions, and identified the best integration position for each of 12 links.

3-algorithm meta heuristic combination

Using the best integration position, three of the four standard algorithms (TA, SA, tabu search and raindrop method, not including Monte-Carlo method which was used to develop an initial solution for all other algorithms) were further combined to form 3-algorithm meta heuristics. We examined 24 total possible combinations of these (Table 3.1). Corresponding to each combination, we developed one meta heuristic and used this meta heuristic to solve the same forest planning problem. In the end, we compared solution values obtained by using the 3-algorithm meta heuristics with solution values obtained by using standard algorithms, to find out how much the meta heuristics might improve solution quality.

When TA or SA were the second or third algorithms in a meta heuristic, the initial temperature each assumed needed to be adjusted accordingly. In other words, we located an appropriate initial temperature for SA or TA if they were the first algorithm in a meta heuristic, not if they were the second or third. In our program this initial value was set as proportional to the inverse of the current best solution value. i.e.

$T_{ic} = T_{ii}$ * 20,000,000/the best solution

T_{ic} = the initial temperature for SA or the initial threshold for TA in a combined algorithm where SA or TA is in posterior position

T_{ii} = the initial temperature for individual SA algorithm or the initial threshold for individual TA algorithm (i.e. 10,000 for SA, 20,000 for TA)

Validation

The best way to validate heuristic solutions is to locate the exact optimal solution and compare it to our heuristic solution values. But it is impractical to find the exact optimum solution for the planning problem in this case due to its large size (1,123 units, 16 choices) and the number of adjacency restrictions necessary. Boston and Bettinger (1999) listed a few other ways to validate heuristic solutions, including comparing heuristic solutions with solutions from other heuristic methods, finding the upper bound solution value through relaxed linear programming, and using the extreme value theory. In this study, we compared solutions produced by all newly developed meta heuristics with solutions produced by standard algorithms. But this relative comparison only gives us a rough idea of the quality of the meta heuristic solutions. In addition to the relative validation, we also used integer programming to solve a planning problem on a smaller dataset with 100 polygons to test if our results are stable. The objective and all constraints remained the same for this small size problem. We then applied all 24 3-algorithm meta heuristics to this smaller dataset. We calculated how close solution values produced from meta heuristics and standard algorithms were to the optimum solution value produced by the integer programming.

All individual algorithms and meta heuristic algorithms were programmed and developed using C# language under Microsoft.Net platform. The change point analysis was performed using the statistical package ‘strucchange’ in R (Bai & Perron 2003). All other data analyses were also performed in the statistical software R. The validation program was performed in LINDO (LINDO Systems 6.1).

RESULTS AND DISCUSSION

In examining the results, we first considered the standard heuristics, then the 12 2-algorithm heuristics, and finally the 24 3-algorithm heuristics. Table 3.2 shows a statistical summary of the solution quality and the computing time required for 50 runs of standard algorithms (TA, SA, tabu search, the raindrop method and MCIP). SA produced the highest mean solution value ($25.55 million), and TA produced the highest maximum solution value ($25.73 million). The standard deviation for SA was slightly lower than that for TA. An ANOVA analysis shows that there was no significant difference between these two algorithms in terms of solution quality. As for the average computing time needed for generating one solution, SA and TA were also the two fastest heuristics (SA:12.35 s; TA: 13.05 s). SA was slightly faster than TA and also had a tighter standard deviation of the computing time. MCIP and the raindrop method did not seem to perform well on their own, and they presented a low efficiency (longer solving time and low solution value) compared to TA and SA in this study. The performance of tabu search suggested that this algorithm could produce good quality solution values, but it needed exceedingly longer time (158.57 s) to generate one solution compared with all other standard algorithms. These results were consistent with smaller problems solved in Bettinger et al. (2002) although the raindrop method was not available for that analysis. It was also indicated by Zhu et al. (in press) that for problems with woodflow constraints, the raindrop method may not perform as well as other heuristics. Although we used a five iteration reversion rate for the raindrop method, finer tests might show improvement, as Bettinger and Zhu (2006) suggested a reversion rate of 2 – 4 iterations.

To determine the integration method for switching between one heuristic and another, 12 2-algorithm combinations were assessed. Table 3.3 presented results from multiple comparisons of four integration positions in each of the 12 2-algorithm combinations. It provided the mean and standard deviation of solution values and computing times for 50 runs of each. Overall, improvements in the maximum solution values (over the standard heuristics) were found with SA-TA, TA-SA, Tabu-SA, and Tabu-TA. This suggested that the SA-TA combination seemed fruitful, as well as starting with tabu search (a slow algorithm) and ending with one of the fast algorithms (TA or SA). However, the TA-Tabu algorithm (fast start, slow finish) using the longest delay before integrating the algorithms (integration position ‘f’) produced the best overall solution. Some improvements were noted in the Rain-TA algorithm and SA-Tabu. In a few of these 2-algorithm combinations, we could not determine a difference (p=0.05) in quality when considering the four integration positions (Tabu-SA, Tabu-TA, Rain-TA and Rain-Tabu). The link type of Rain-SA was only slightly significant with a p-value of 0.03. It should be noted that the above five non-significant or barely-significant links all started with a search using either tabu search or the raindrop method, which did not perform well as standard algorithms. All other seven 2-algorithm combinations show strong significant differences among the different integration positions. Further, Tukey's multiple comparison pointed out which integration position groups are different. We noticed that the difference mostly occurred between 'f' group and other groups. From this table, we observed that the mean solution values of 'f' groups were much larger than those of other three groups for these seven link types. Therefore, we chose 'f' as the best integration point used to develop 3-algorithm meta heuristics, if the meta heuristics included any of these seven links. For the other five links, the integration position with which the solution generation required the least mean computing time would be used. The integration position of 'b' was used if meta heuristics included the link of Tabu-SA, the integration position of 'a' was used if meta heuristics included the link of Tabu-TA, and the integration position of 'f' was used if meta heuristics included the link of Rain-SA, Rain-TA and Rain-Tabu.

When evaluating the 3-algorithm heuristics, we found that most of the combinations improved on the solution qualities obtained via the standard heuristics (Table 3.4). A small set (metas 1, 4, 5, 7, 9 -11, 23) produced results which were significantly better (p=0.05) than other combinations of heuristics. With the exception of meta 23, each of these began with a relatively fast heuristic (SA or TA) to move quickly through the hill – climbing phase, then incorporated tabu search either in the adjustment or steady–state phases. The raindrop method was also employed in some of these meta heuristics for adjusting or fine-tuning the solution. Meta 23 was an exception, where the raindrop method was used initially, followed by a fast heuristic (TA) then a deterministic process (tabu search). One of the 2-algorithm heuristics (TA-Tabu) produced slightly better results, however. Each of these 3-algorithm meta heuristics produced results slightly better than the second best 2-algorithm heuristic (SA-Tabu) in terms of maximum solution values.

Compared with the best mean solution value from five standard algorithms (SA: $25.55 million), 18 meta heuristics (75%) improved their mean solution values to some extent. The other six meta heuristics only had a slight decrease in mean solution values compared to the SA mean solution value. Their maximum solution values, except for meta 21, were still around $25.72 to $25.73 million, which was about the same as the best maximum solution value from standard algorithms. Among 18 improved meta heuristics, six had percentage gains of more than 1%. They were meta 1 (SA-TA-Tabu, 1.16% increase), meta 5 (SA-Tabu-TA, 1.12%), meta 7 (TA-SA-Tabu, 1.16%), meta 9 (TA-Tabu-Rain, 1.23%), meta 10 (TA-Rain-Tabu, 1.23%), and meta 11 (TA-Tabu-SA, 1.18%). The best two meta heuristic based on these 50 runs were meta 9 (TA-Tabu-Rain) and meta 10 (TA-Rain-Tabu) which both had a 1.23% increase, equivalent to around $310,000. As we expected, meta heuristics that started a search from either tabu search or the raindrop method, resulted in small increases in solution values if at all, except for meta 23 and meta 24.

The standard deviation of solution values for most 3-algorithm meta heuristics were around 0.08 or 0.09, with a few exceptions of larger standard deviations, such as meta 13 ($0.29 million), meta 15 ($0.26 million) and meta 18 ($0.48 million). Compared with standard algorithms TA ($0.10 million) and SA ($0.08 million), more than 85% of meta heuristics have the same variability of solution values as the standard TA and SA algorithms. But compared with standard tabu search ($0.27 million) and the raindrop method ($0.25 million), the standard deviations of most 3-algorithm meta heuristic results were much tighter.

As for computing time, as a general trade-off, all meta heuristics required much longer computing time to generate a good solution than did the standard heuristics. This computing time not only included the running time for three different standard algorithms, but also included time for fitting smoothing splines to a search path and calculating the integration points for switching among algorithms. Meta heuristics 13-18, 21 and 22 had very large standard deviation values for computing times, which was due to the trouble involved in finding the integration point for tabu search to switch to the next algorithm. In some random runs, this integration point appeared early in one search, but in some other runs, it only occured after a great number of iterations.

Table 3.5 is a summary of solution quality and solution speed for 50 runs of 24 meta heuristics when applied to the validation dataset with 100 stand polygons. The integer programming analysis found the optimum solution value as $2.38 million using a tolerance gap of 0.001. We can see that all meta heuristics were within 90% of the optimum solution. The longest time spent on finding one heuristic solution was only a little more than two minutes, while the integer programming spent > 90 hours on locating this optimal solution. If we were to use the integer solution obtained after only one hour of computer processing time, all of the heuristic results would be within 95% of the integer solution.

CONCLUSIONS

Due to its deterministic component, standard 1-opt tabu search does not perform well in most forest planning problems, and it loses its searching ability soon after a short hill-climbing phase. Other advanced tabu search techniques (such as 2-opt tabu search, strategic oscillation method) have been successfully used in forest planning to improve the performance of the search process (Bettinger et al. 1999; Richards & Gunn, 2003). However, rather than modifying a single heuristic, we chose to use standard heuristics in combination to understand if their respective search abilities can be combined efficiently and effectively.

We found that the integration point, or the point at which a switch from one heuristic to another should be made, is when the improvement of solutions using one algorithm flattens out. The only exception is when starting with tabu search, although meta heuristics starting with tabu search are not as effective as the others. The best 2-algorithm meta heuristic combines a fast random search (TA) with a slower deterministic process (tabu search). The best 3-algorithm meta heuristic combines fast random search (TA) with a slower deterministic process (tabu search), and ended with a combined random-deterministic process (raindrop method). However, this meta heuristic is relatively slow, when considering computing time, and the addition of the raindrop method does not seem to add to an increase in solution quality.

This work has shown that meta heuristics that combine the beneficial aspects of standard heuristics and how they behave in the three phases of a search, will generally produce consistently better solutions than standard heuristics alone. In general, a meta heuristic that begins with simulated annealing or threshold accepting, then utilizes tabu search and the raindrop method, seems to enable one to develop better solutions than when using the standard heuristics alone. In other words, starting with tabu search or the raindrop method is not as good as starting with TA or SA algorithm. Ending with tabu search or raindrop method presents better results than ending with TA or SA algorithms. We demonstrate that determining when to switch, or integrate, algorithms can successfully be made based on the behavior of the search, rather than being made based on some *a priori* decision of the planner.

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Table 3.1 A list of all 24 3-algorithm meta heuristics.

Model name	Heuristic order
meta 1	SA-TA-Tabu
meta 2	SA-TA-Rain
meta 3	SA-Tabu-Rain
meta 4	SA-Rain-Tabu
meta 5	SA-Tabu-TA
meta 6	SA-Rain-TA
meta 7	TA-SA-Tabu
meta 8	TA-SA-Rain
meta 9	TA-Tabu-Rain
meta 10	TA-Rain-Tabu
meta 11	TA-Tabu-SA
meta 12	TA-Rain-SA
meta 13	Tabu-TA-SA
meta 14	Tabu-SA-TA
meta 15	Tabu-Rain-SA
meta 16	Tabu-Rain-TA
meta 17	Tabu-TA-Rain
meta 18	Tabu-SA-Rain
meta 19	Rain-TA-SA
meta 20	Rain-SA-TA
meta 21	Rain-Tabu-SA
meta 22	Rain-Tabu-TA
meta 23	Rain-TA-Tabu
meta 24	Rain-SA-Tabu

Table 3.2 A summary of solution quality and solution speed for 50 runs of five standard algorithms.

Algorithms	Solution quality				Computing time	
	Mean (million $)	Standard deviation (million $)	Maximum (million $)	ANOVA groups	Mean (s)	Standard deviation (s)
SA	25.55	0.08	25.72	A	12.35	0.11
TA	25.51	0.10	25.73	A	13.05	0.28
Tabu	24.79	0.27	25.47	B	158.57	49.92
Rain	21.76	0.25	22.41	C	63.77	3.89
MCIP	21.07	0.08	21.27	D	50.92	0.27

SA = Simulated annealing
TA = Threshold accepting
Tabu = Tabu search
Rain = Raindrop method
MCIP = Monte Carlo integer programming

Table 3.3 A summary of solution quality and solution speed for 50 runs of 12 2-algorithm heuristics using four different integration positions.

Link type	Integration position	Solution quality: Mean (million $)	Solution quality: Standard deviation (million $)	Solution quality: Maximum (million $)	Multiple comparison result: P-value	Multiple comparison result: Different pairs [(a)]	Computing time: Mean (s)	Computing time: Standard deviation (s)
SA-TA	a	25.562	0.129	25.782	2.667E-03	f-c	14.951	0.332
	b	25.547	0.130	25.776		f-b	14.983	0.144
	c	25.529	0.132	25.763			15.046	0.121
	f	25.616	0.077	25.780			52.463	2.243
TA-SA	a	25.608	0.075	25.751	7.694E-07	f-c	14.390	0.122
	b	25.569	0.086	25.717		f-b	14.385	0.133
	c	25.565	0.072	25.730		c-a	14.404	0.122
	f	25.642	0.076	25.809			64.489	1.298
SA-Tabu	a	25.051	0.184	25.445	2.200E-16	f-c	53.395	22.449
	b	24.988	0.224	25.339		f-b	53.232	17.932
	c	25.019	0.256	25.547		f-a	59.325	19.735
	f	25.768	0.104	25.974			70.614	8.166
Tabu-SA	a	25.598	0.091	25.789	6.915E-01		15.273	0.253
	b	25.593	0.078	25.753			15.259	0.457
	c	25.583	0.067	25.758			15.642	1.013
	f	25.601	0.076	25.782			182.956	269.271
TA-Tabu	a	25.046	0.171	25.366	2.200E-16	f-c	60.707	24.996
	b	25.086	0.167	25.355		f-b	63.132	22.120
	c	25.071	0.162	25.362		f-a	58.645	22.595
	f	25.892	0.100	26.088			92.713	12.835
Tabu-TA	a	25.537	0.125	25.769	1.230E-01		15.043	0.307
	b	25.543	0.132	25.769			15.270	0.576
	c	25.497	0.128	25.726			15.570	0.947
	f	25.553	0.114	25.766			223.118	257.687

Table 3.3 (continued) A summary of solution quality and solution speed for 50 runs of 12 2-algorithm heuristics using four different integration positions.

		Solution quality			Multiple comparison result		Computing time	
Link type	Integration position	Mean (million $)	Standard deviation (million $)	Maximum (million $)	P-value	Different pairs [(a)]	Mean (s)	Standard deviation (s)
SA-Rain	a	23.495	0.307	24.057	2.200E-16	f-c	75.175	3.882
	b	23.505	0.273	24.009		f-b	86.892	5.080
	c	23.522	0.321	24.073		f-a	98.883	3.582
	f	25.614	0.072	25.857			159.695	16.368
Rain-SA	a	25.485	0.075	25.647	3.943E-02		482.085	5.241
	b	25.528	0.080	25.685			491.834	11.821
	c	25.496	0.073	25.653			488.886	10.451
	f	25.490	0.093	25.662			15.213	0.575
TA-Rain	a	23.473	0.242	23.837	2.200E-16	f-c	73.918	4.088
	b	23.465	0.215	23.839		f-b	86.350	5.266
	c	23.573	0.224	23.951		f-a	98.207	3.664
	f	25.612	0.087	25.793			167.225	9.190
Rain-TA	a	25.474	0.120	25.678	2.669E-01		483.119	5.215
	b	25.493	0.117	25.724			504.080	9.188
	c	25.491	0.141	25.749			525.902	8.421
	f	25.449	0.121	25.634			15.654	0.318
Tabu-Rain	a	21.670	0.273	22.435	2.200E-16	f-c	76.055	5.698
	b	21.700	0.395	22.444		f-b	88.085	7.052
	c	21.806	0.394	22.783		f-a	100.991	4.697
	f	23.712	0.541	24.990			248.142	245.015
Rain-Tabu	a	24.328	0.408	25.131	4.019E-01		563.249	36.941
	b	24.347	0.310	24.981			632.383	44.133
	c	24.299	0.411	25.087			564.993	34.189
	f	24.422	0.369	25.128			84.240	25.526

SA = Simulated annealing TA = Threshold accepting Tabu = Tabu search Rain = Raindrop method
MCIP = Monte Carlo integer programming [(a)] = A code indicating which integration position results are different.

Table 3.4 A summary of solution quality and solution speed for 50 runs of 24 3-algorithm meta heuristics using best integration positions.

Model name	Solution quality						Computing time	
	Mean (million $)	Standard deviation (million $)	Maximum (million $)	Percentage improved (%)[(a)]	P-value[(b)]	ANOVA groups	Mean (s)	Standard deviation (s)
meta 1	25.85	0.09	25.98	1.16	0.000	AB	115.81	7.75
meta 2	25.60	0.08	25.79	0.20	0.001	EFG	155.18	5.86
meta 3	25.74	0.08	25.87	0.74	0.000	BCD	143.75	25.79
meta 4	25.78	0.09	25.98	0.90	0.000	ABC	72.18	8.07
meta 5	25.84	0.08	26.02	1.12	0.000	AB	119.06	9.99
meta 6	25.61	0.09	25.77	0.23	0.000	EFG	54.85	2.08
meta 7	25.85	0.08	26.03	1.16	0.000	AB	119.62	7.94
meta 8	25.64	0.08	25.86	0.35	0.000	DEF	157.72	6.70
meta 9	25.87	0.10	26.01	1.23	0.000	A	155.39	27.10
meta 10	25.86	0.08	26.02	1.23	0.000	A	84.86	8.73
meta 11	25.85	0.09	26.04	1.18	0.000	AB	99.08	23.54
meta 12	25.62	0.08	25.79	0.29	0.000	EFG	65.89	0.30
meta 13	25.57	0.29	25.84	0.07	0.340	HGF	182.66	154.82
meta 14	25.64	0.09	25.81	0.33	0.000	DEF	199.54	191.87
meta 15	25.55	0.26	25.73	-0.01	0.538	FGHI	245.35	261.61
meta 16	25.52	0.14	25.74	-0.13	0.926	GHI	265.77	289.30
meta 17	25.58	0.11	25.82	0.10	0.113	FGH	328.40	261.35
meta 18	25.46	0.48	25.74	-0.37	0.913	I	260.66	247.24
meta 19	25.57	0.07	25.71	0.06	0.154	FGH	64.78	0.82
meta 20	25.54	0.08	25.73	-0.03	0.687	FGHI	53.68	2.99
meta 21	25.49	0.09	25.68	-0.25	1.000	HI	206.37	259.12
meta 22	25.47	0.14	25.72	-0.32	1.000	HI	282.72	289.87
meta 23	25.76	0.11	25.98	0.81	0.000	ABC	83.00	7.28
meta 24	25.71	0.08	25.84	0.61	0.000	CD	70.26	8.51

[(a)] = Over the mean solution value from simulated annealing. [(b)] = Compared with solutions from simulated annealing.

Table 3.5 A summary of solution quality and solution speed for 50 runs of 24 3-algorithm meta heuristics for the validation dataset.

Solution quality					Computing time	
Model name	Mean (million $)	Standard deviation (million $)	Maximum (million $)	Percentage of the optimum (%)	Mean (s)	Standard deviation (s)
meta 1	2.188	0.024	2.240	91.928	136.626	16.063
meta 2	2.175	0.019	2.218	91.400	125.088	14.631
meta 3	2.156	0.041	2.218	90.606	38.310	6.829
meta 4	2.163	0.034	2.229	90.870	47.431	10.411
meta 5	2.195	0.019	2.233	92.230	137.933	17.880
meta 6	2.177	0.023	2.215	91.468	48.363	7.124
meta 7	2.192	0.022	2.231	92.105	146.640	16.817
meta 8	2.181	0.023	2.229	91.632	133.392	21.669
meta 9	2.177	0.036	2.236	91.455	62.419	3.751
meta 10	2.164	0.040	2.222	90.915	69.506	5.247
meta 11	2.184	0.024	2.234	91.785	77.677	3.916
meta 12	2.177	0.021	2.215	91.486	72.878	4.201
meta 13	2.175	0.048	2.229	91.389	137.558	22.604
meta 14	2.182	0.023	2.224	91.673	126.416	21.221
meta 15	2.155	0.040	2.214	90.531	47.393	15.816
meta 16	2.167	0.041	2.230	91.049	45.514	16.569
meta 17	2.175	0.022	2.214	91.400	126.242	16.709
meta 18	2.167	0.041	2.215	91.045	111.801	14.916
meta 19	2.170	0.025	2.213	91.180	116.947	26.355
meta 20	2.173	0.025	2.218	91.295	107.255	17.031
meta 21	2.150	0.034	2.198	90.340	31.213	1.828
meta 22	2.151	0.055	2.216	90.357	30.440	1.718
meta 23	2.169	0.043	2.225	91.131	118.107	18.668
meta 24	2.179	0.027	2.230	91.552	112.602	5.722

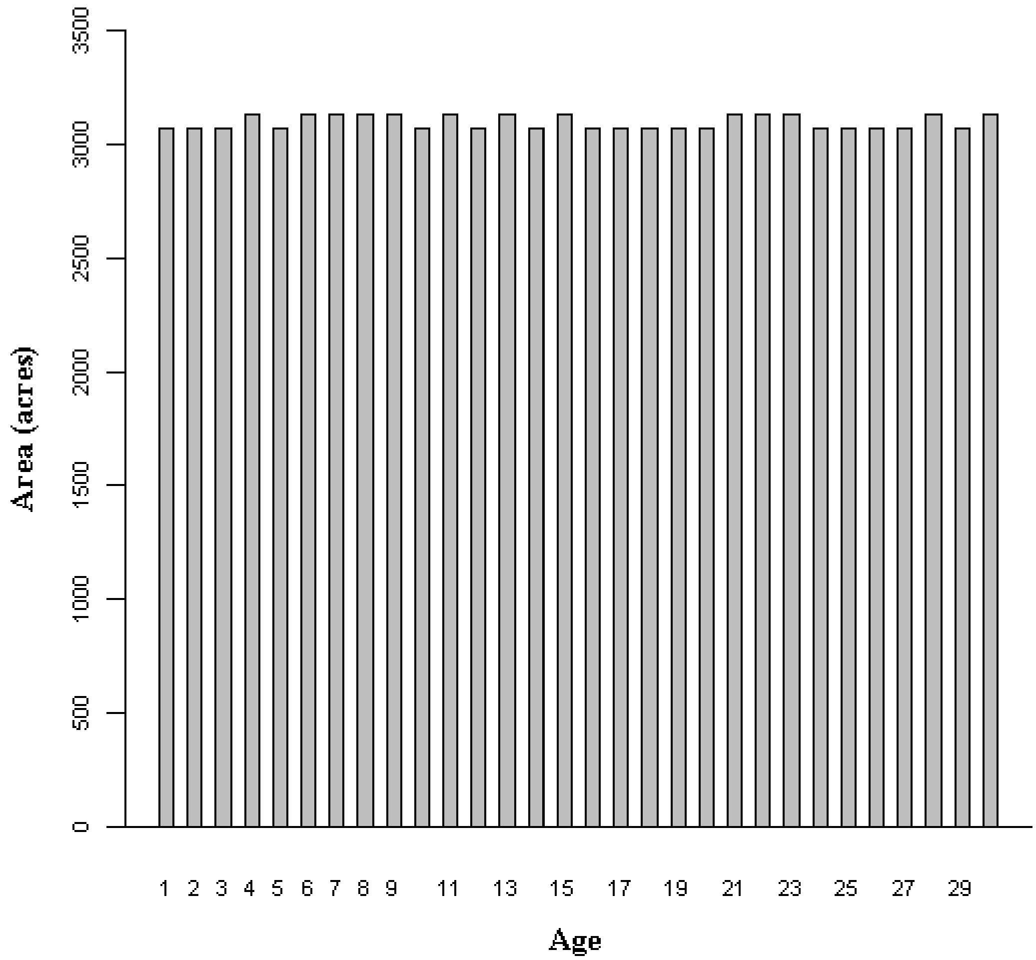

Figure 3.1 Initial age class distribution.

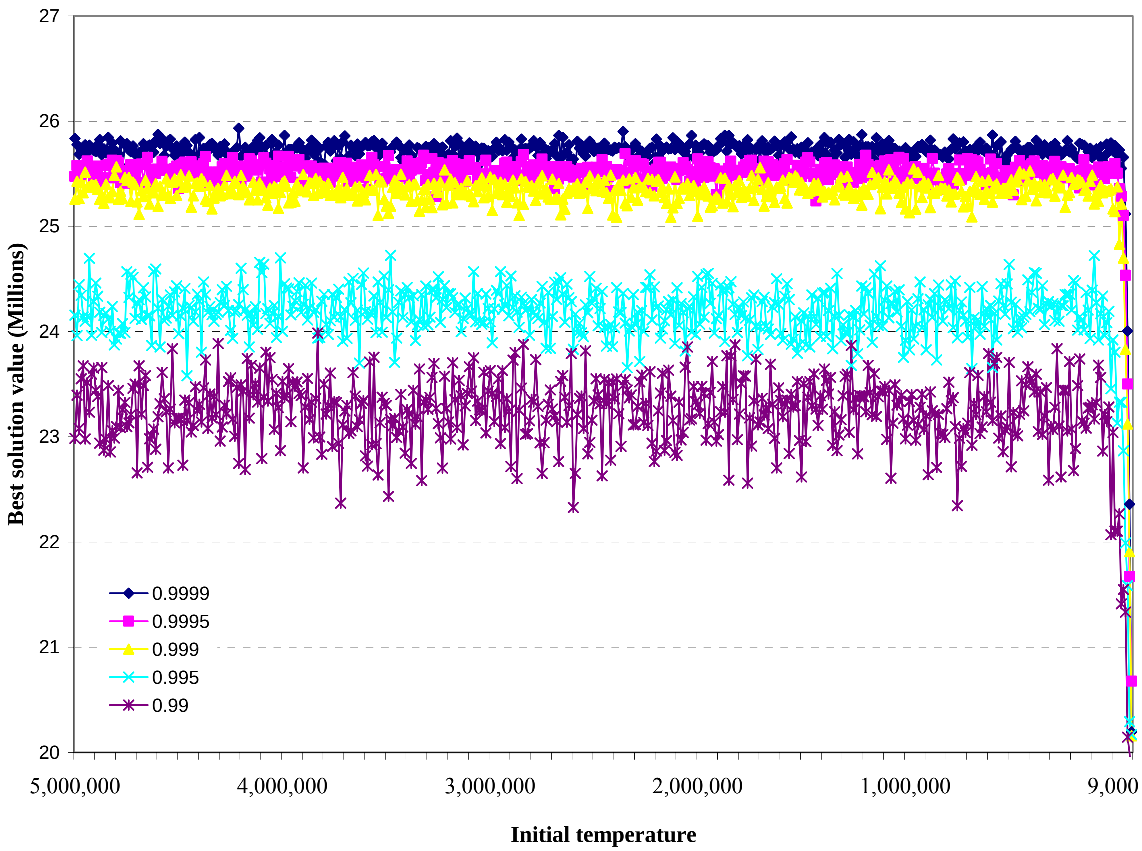

Figure 3.2 SA solutions using 5 different cooling rates and an initial temperature ranging from 5,000,000 to 0.

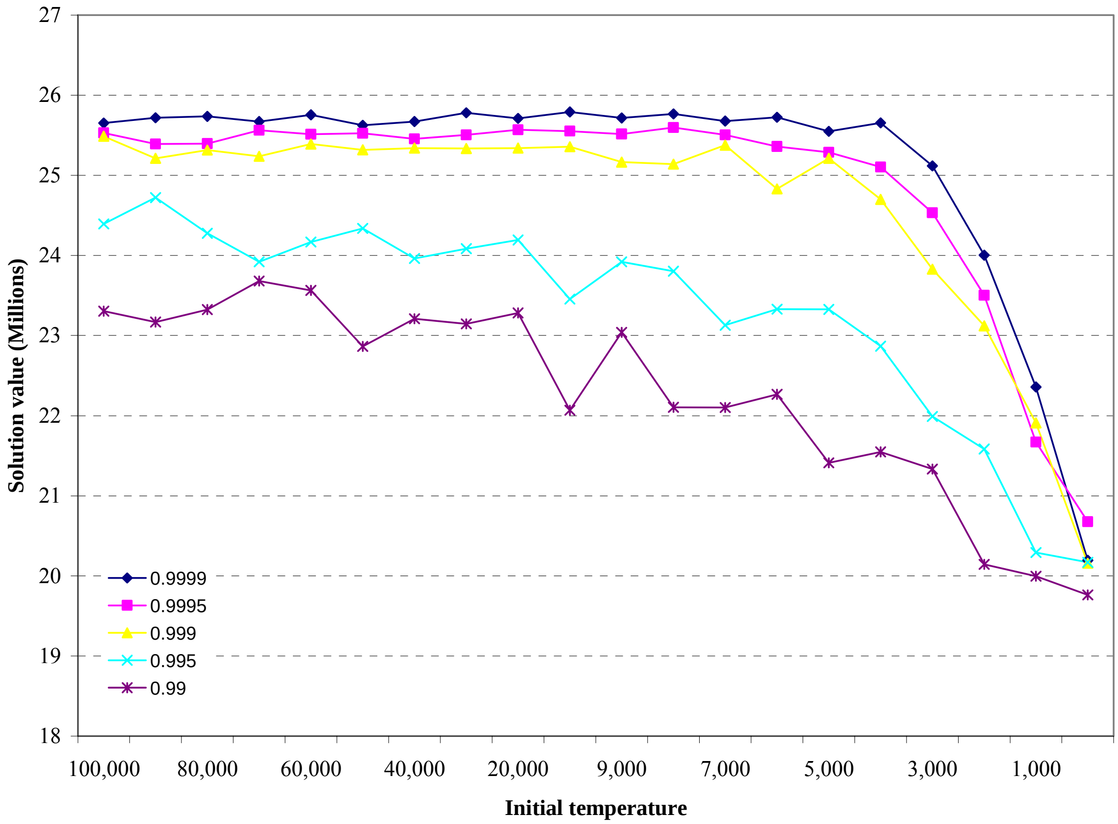

Figure 3.3 SA solutions using 5 different cooling rates and an initial temperature ranging from 100,000 to 0.

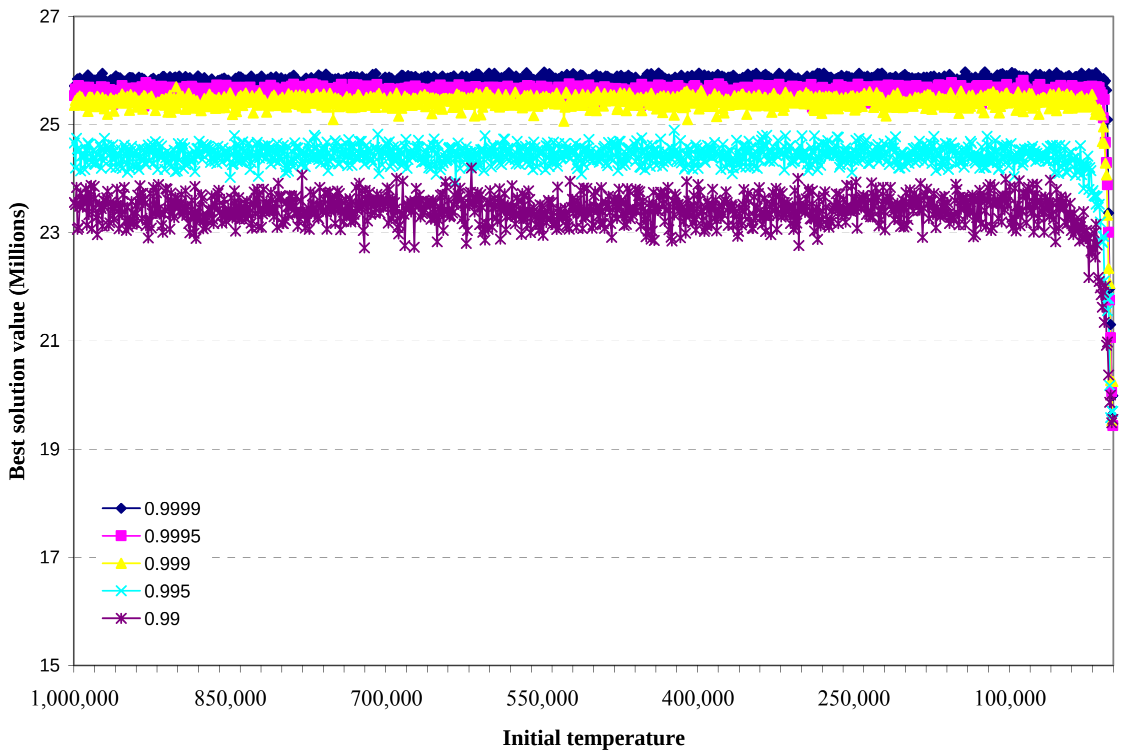

Figure 3.4 TA solutions using 5 different decreasing rates and an initial threshold ranging from 1,000,000 to 1,000.

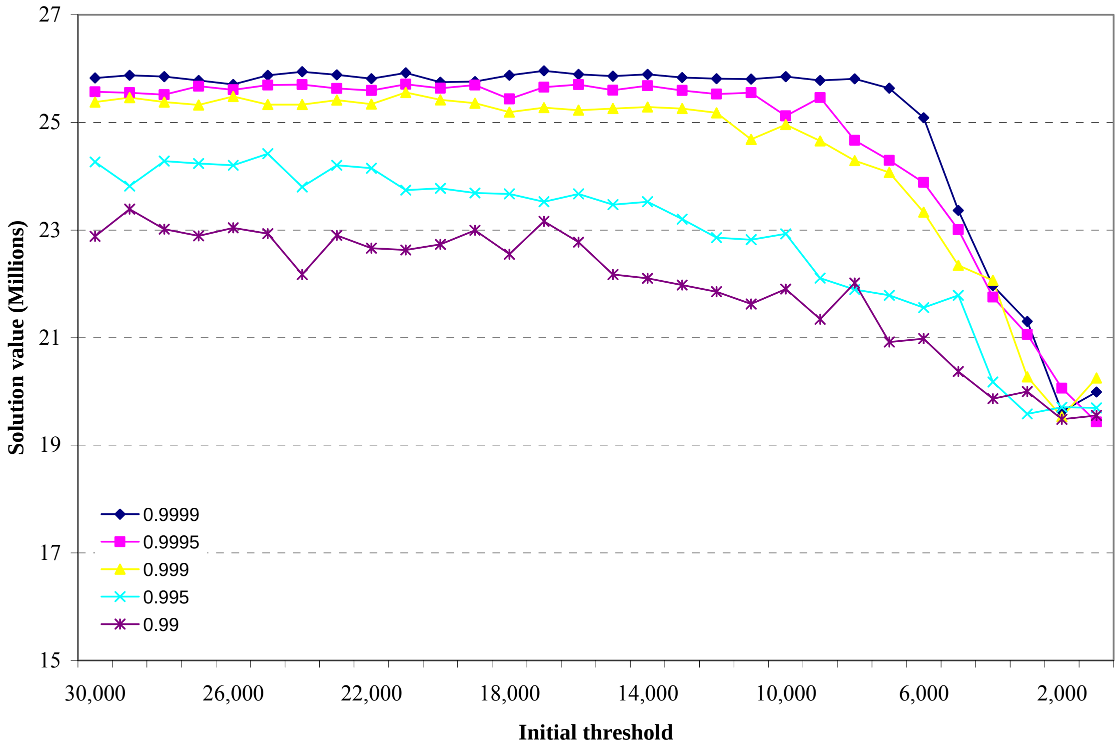

Figure 3.5 TA solutions using 5 different decreasing rates and an initial threshold ranging from 30,000 to 1,000.

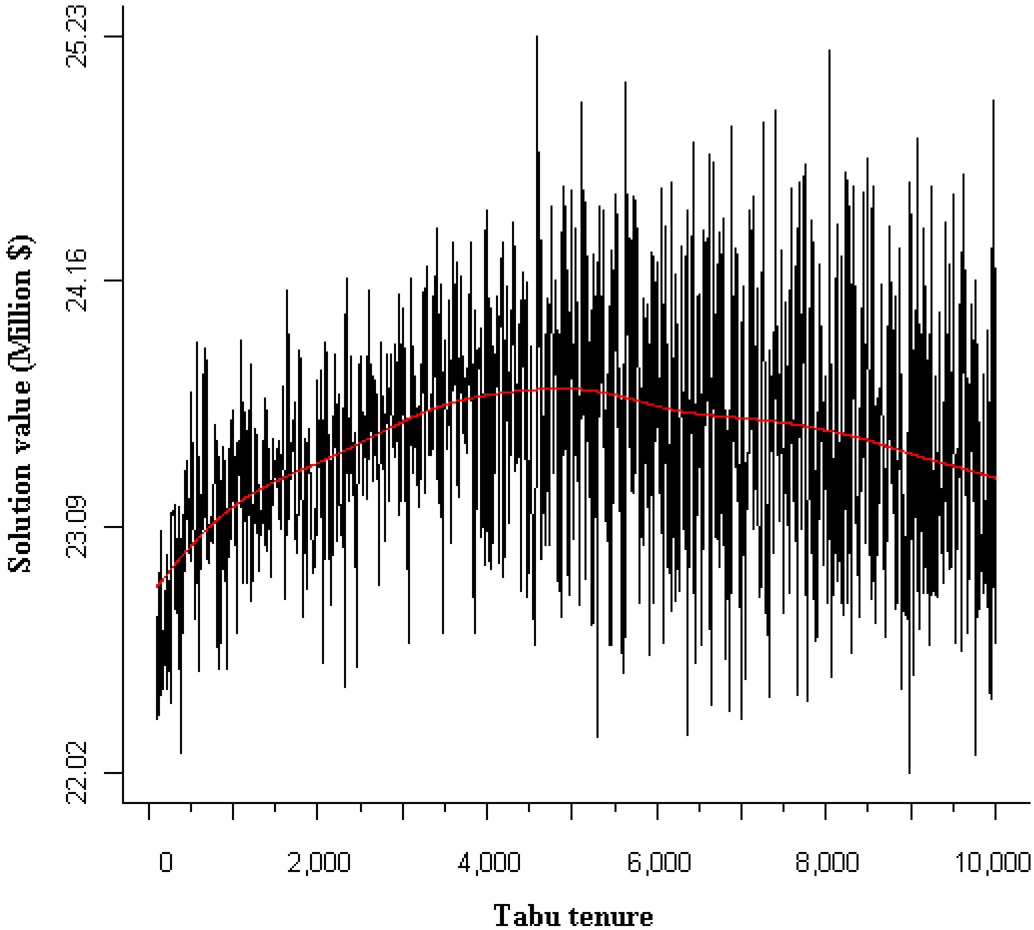

Figure 3.6 Tabu search solutions using tabu tenures ranging from 0 to 10,000 iterations.

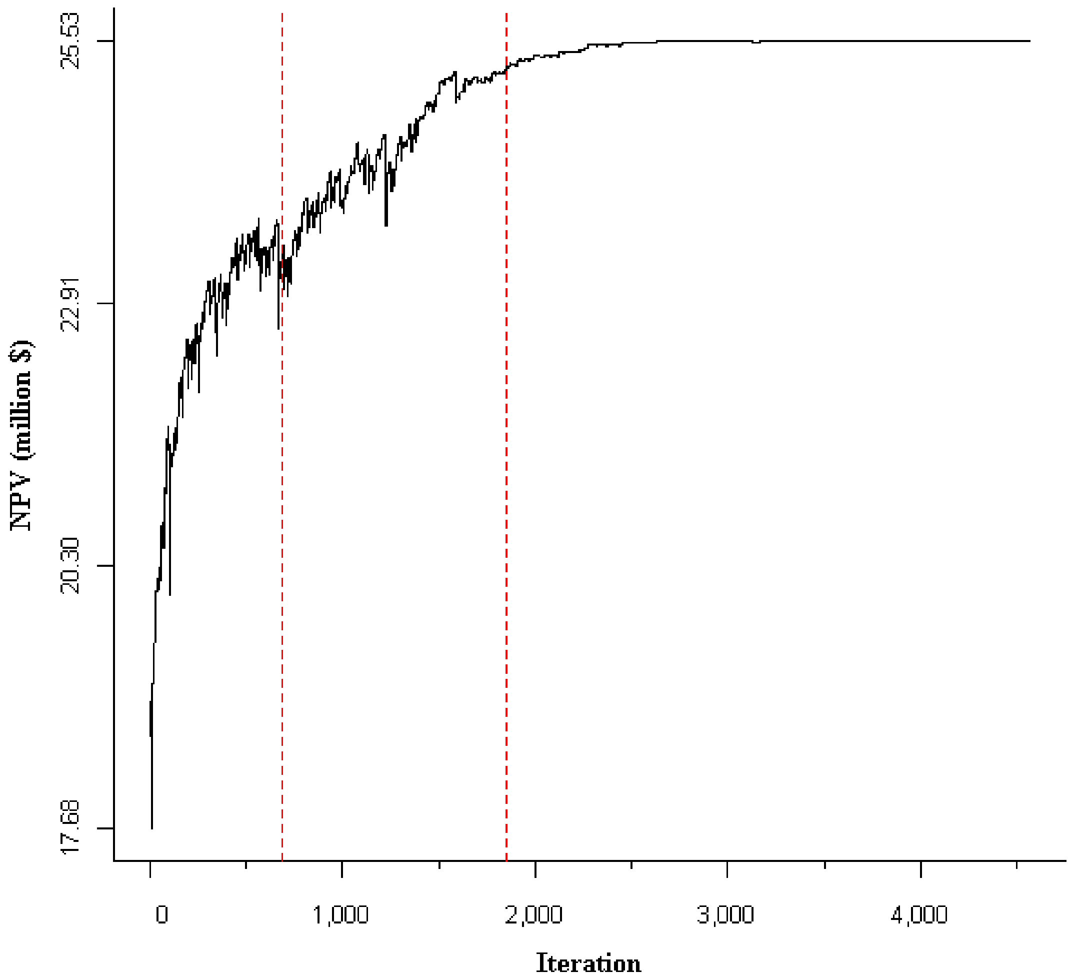

Figure 3.7 SA break-point analysis (dotted lines are two structure break points).

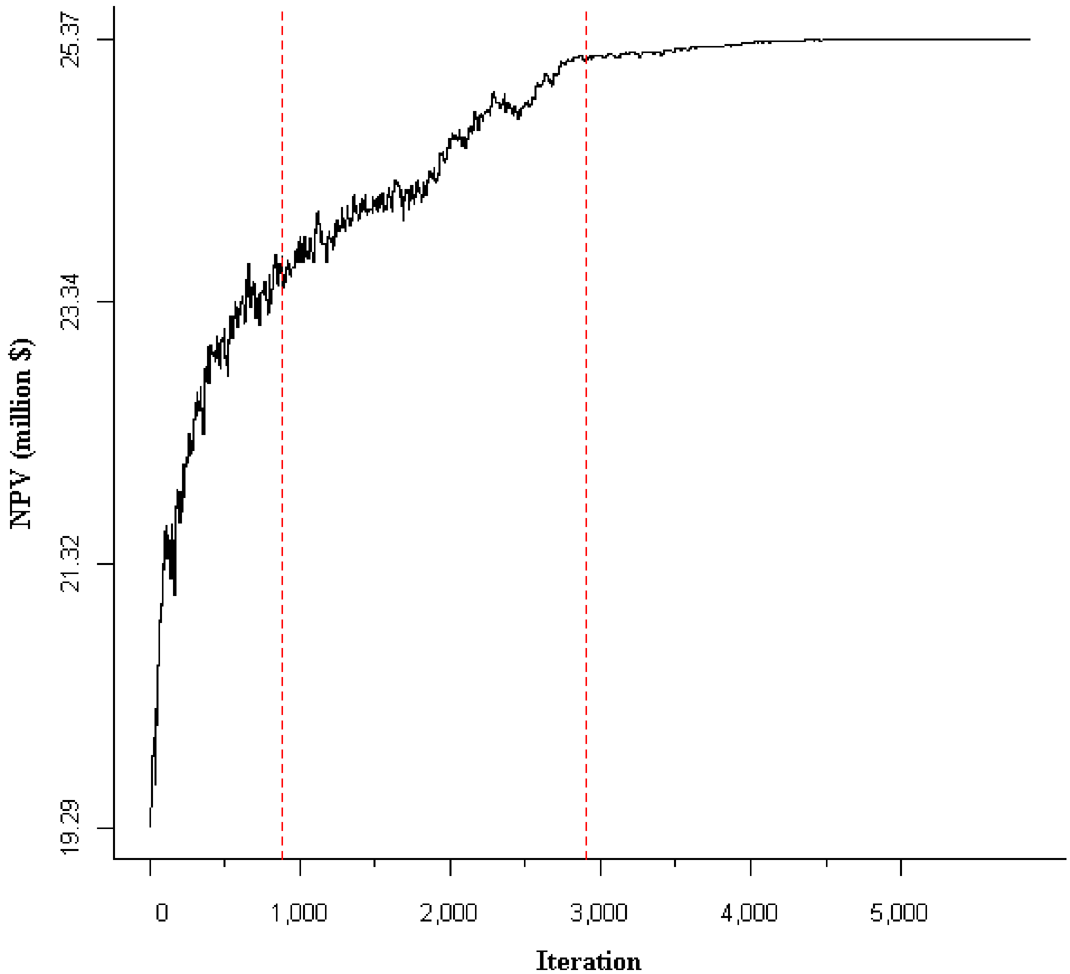

Figure 3.8 TA break-point analysis (dotted lines are two structure break points).

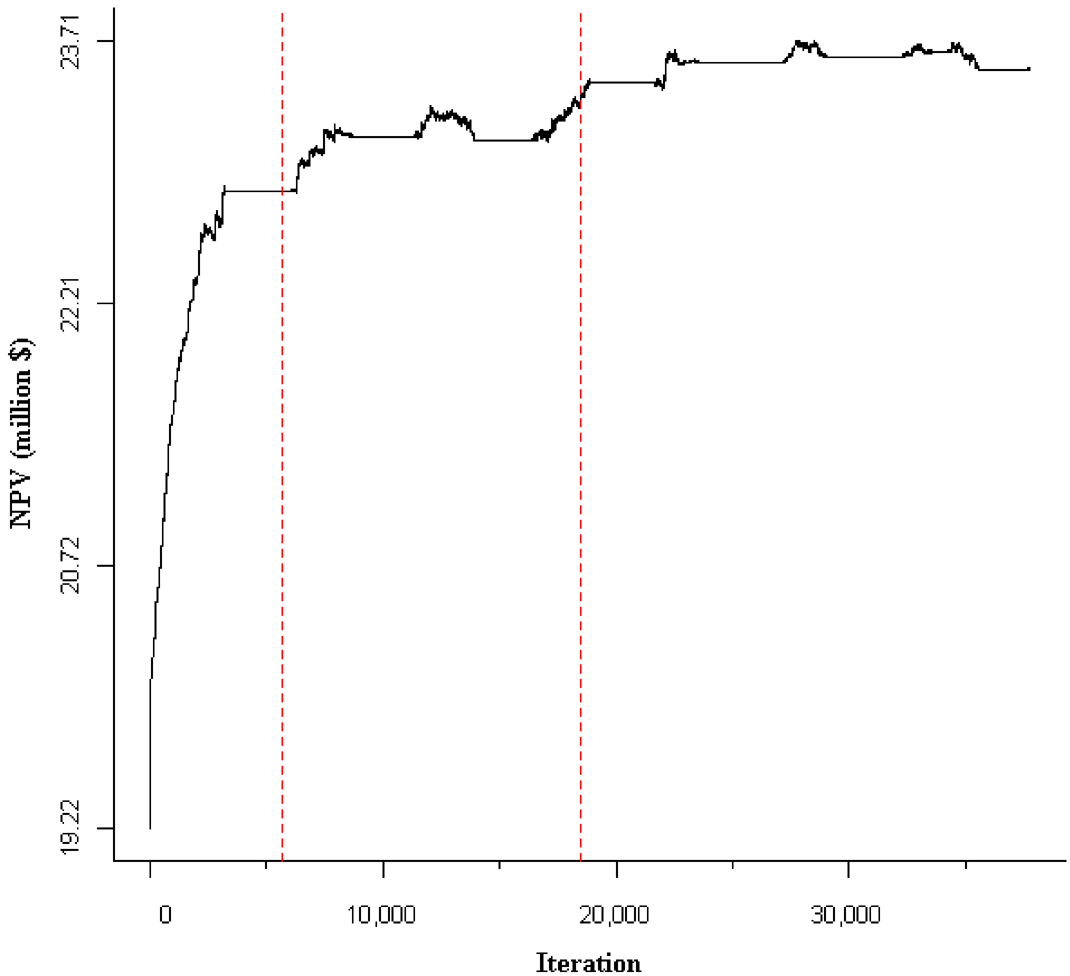

Figure 3.9 Tabu search break-point analysis (dotted lines are two structure break points).

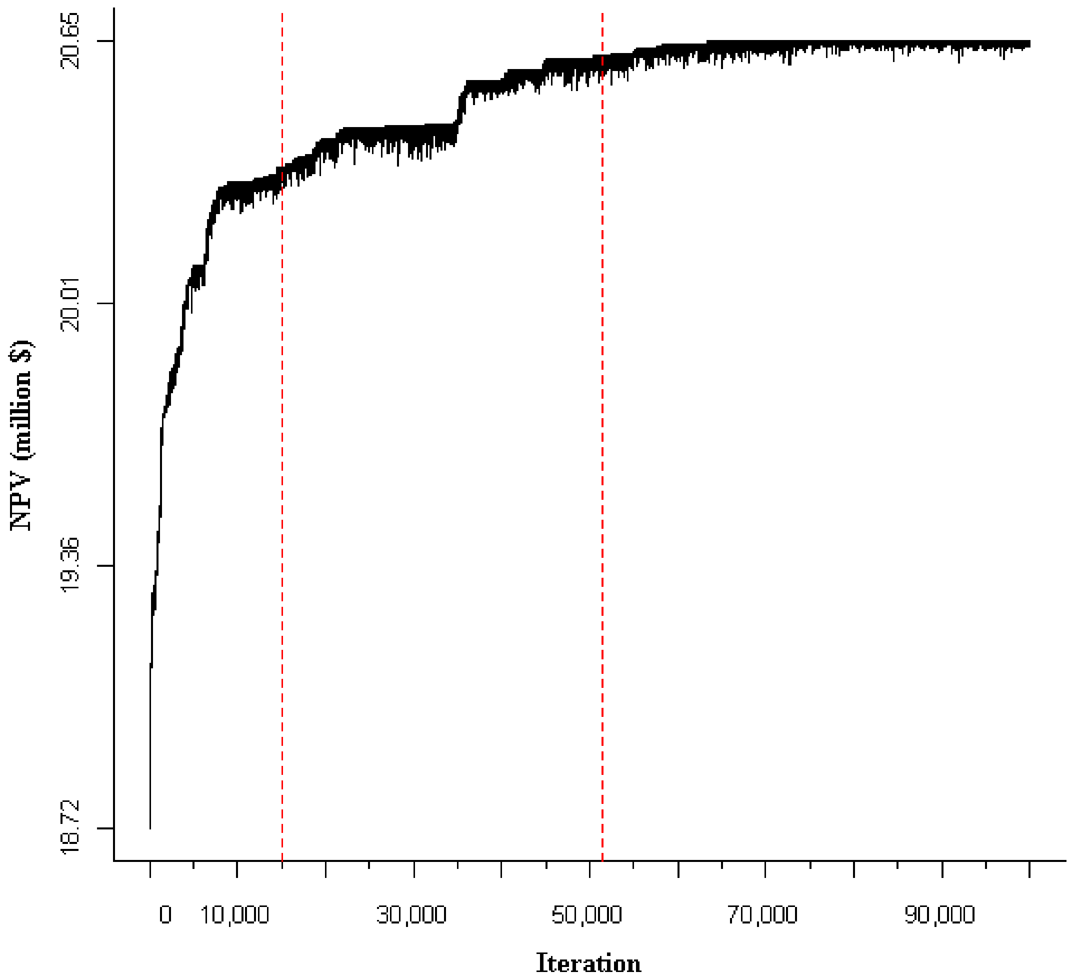

Figure 3.10 Raindrop break-point analysis (dotted lines are two structure break points).

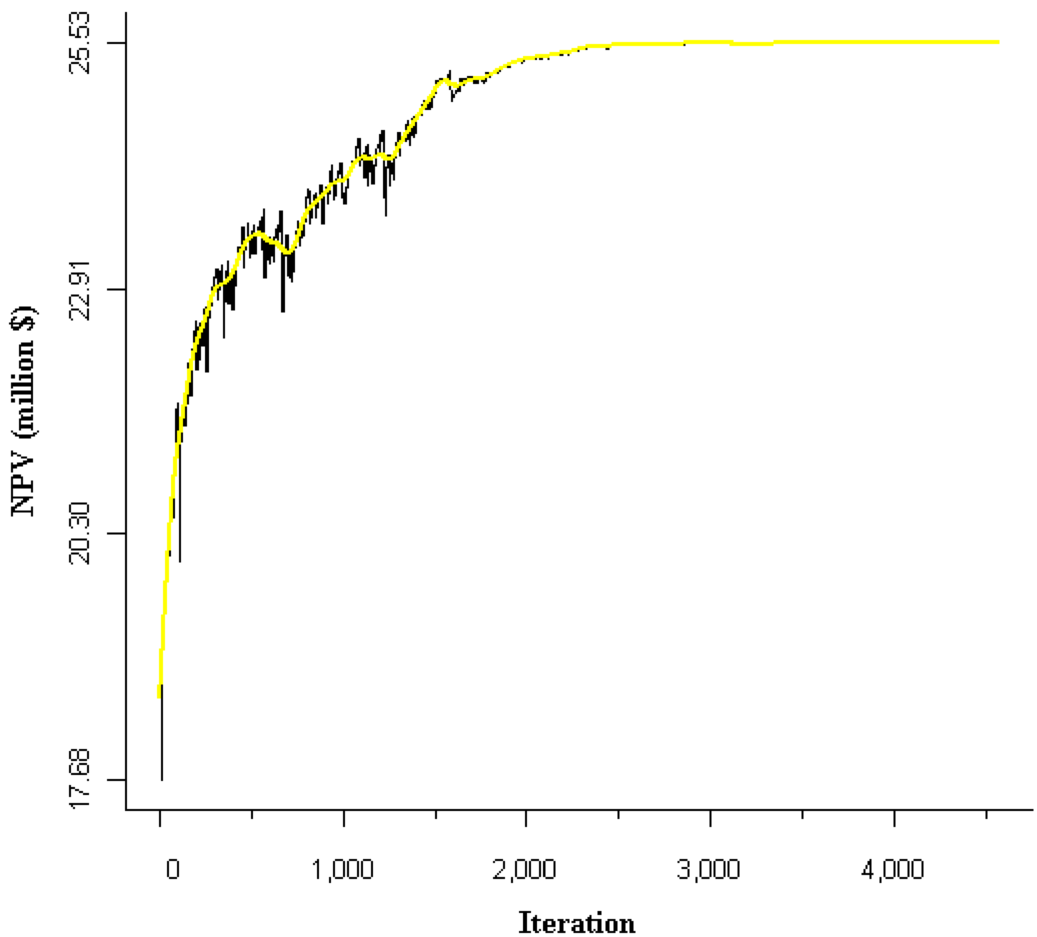

Figure 3.11 Fitting smoothing splines to a SA solution developing process (the light grey line is the fitted line and the black line is the solution value developing process).

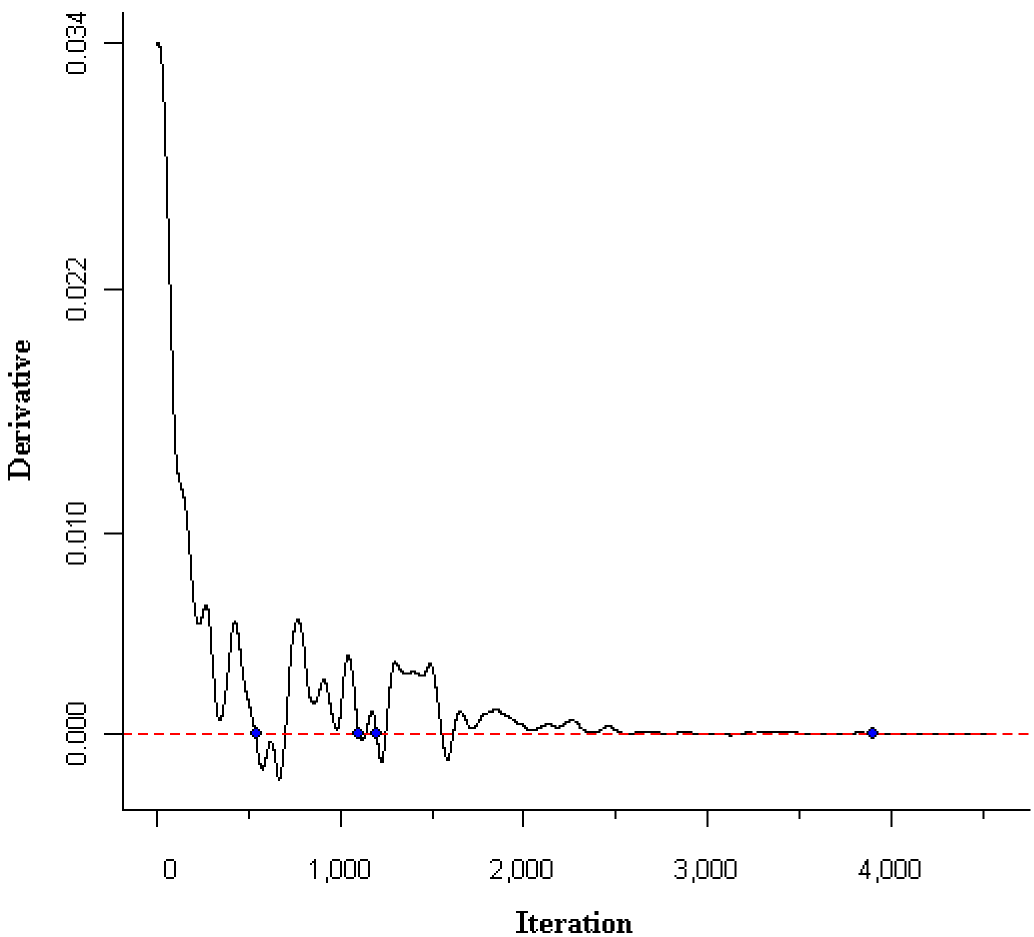

Figure 3.12 Derivative plot of a SA solution developing process (solid line: derivatives of the fitted smoothing splines of solution values; dotted line: zero line when derivative = 0; circles: interception points of derivative line with zero line).

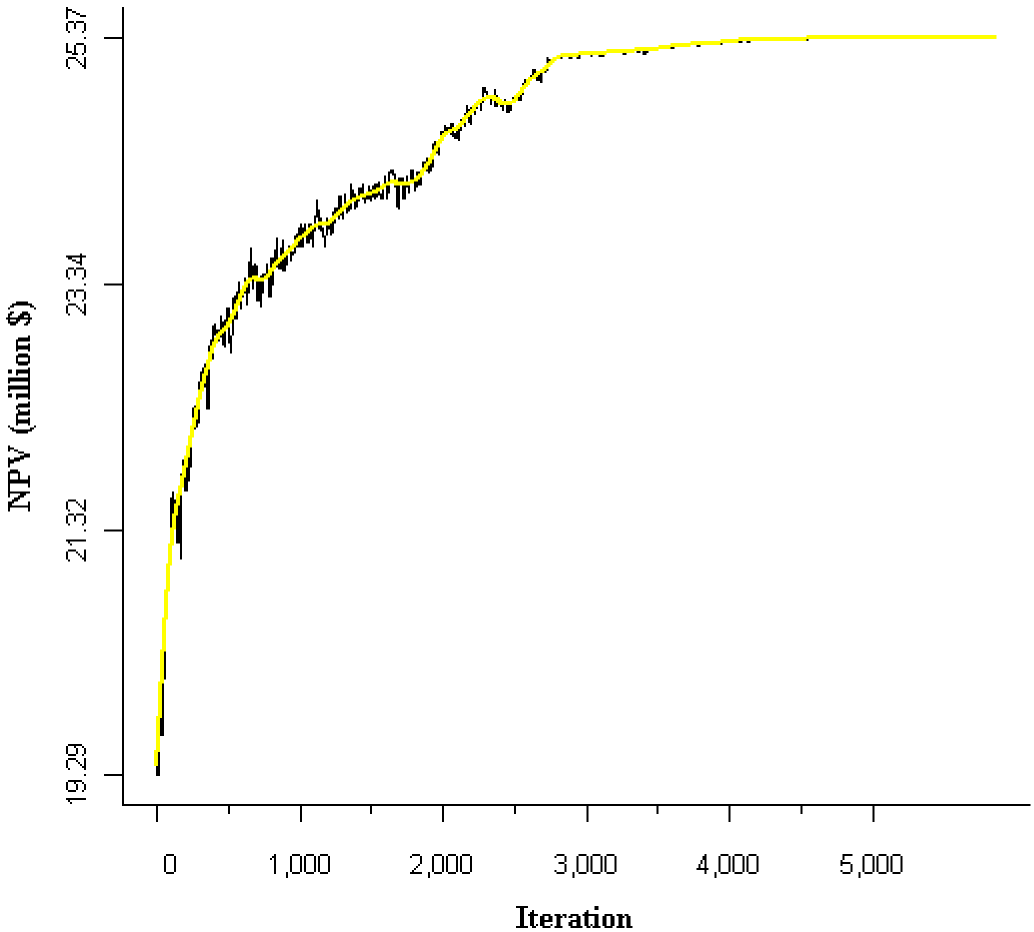

Figure 3.13 Fitting smoothing splines to a TA solution developing process (the light grey line is the fitted line and the black line is the solution value developing process).

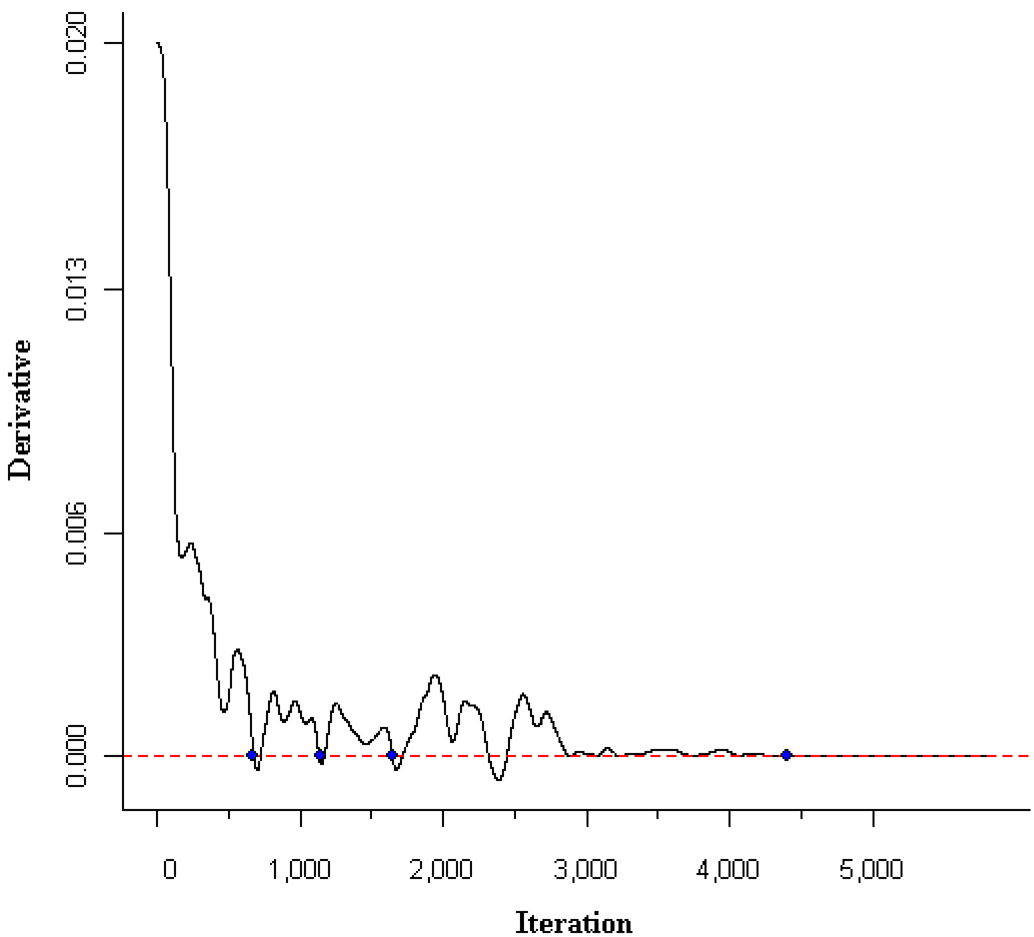

Figure 3.14 Derivative plot of a TA solution developing process (solid line: derivatives of the fitted smoothing splines of solution values; dotted line: zero line when derivative = 0; circles: interception points of derivative line with zero line).

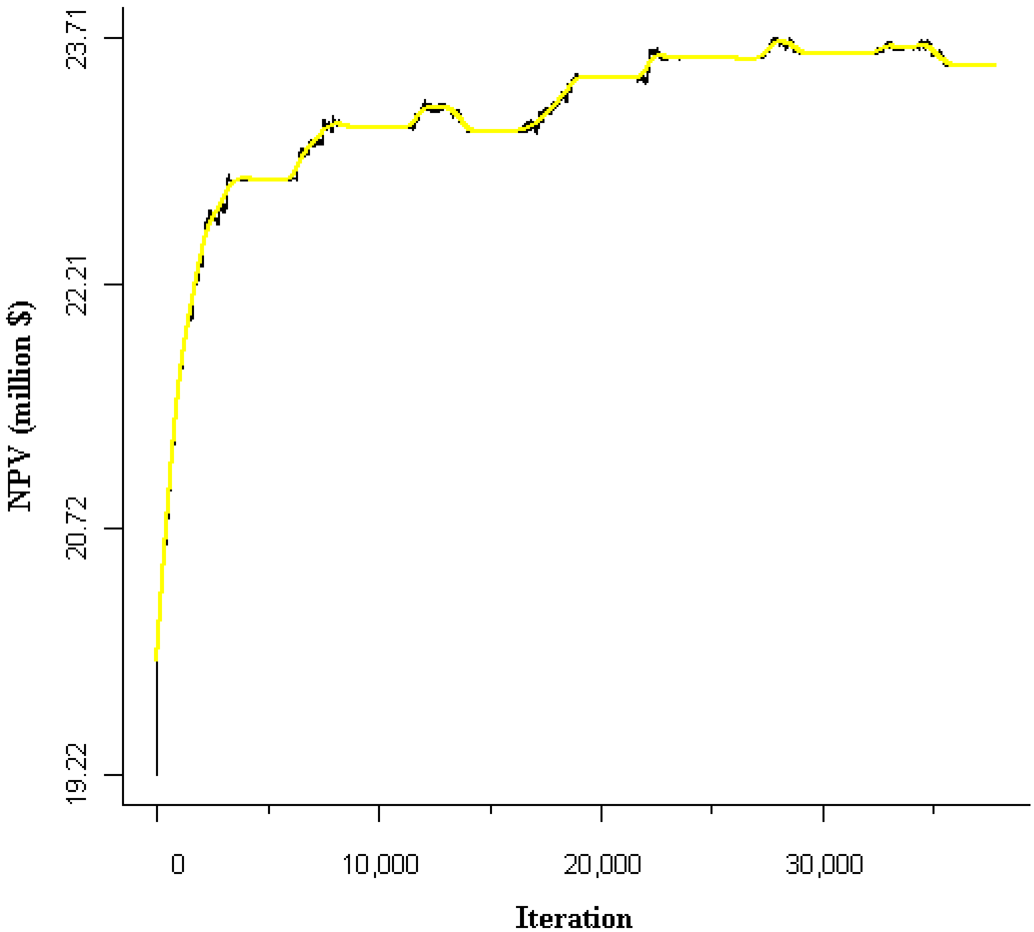

Figure 3.15 Fitting smoothing splines to a tabu search process (the light grey line is the fitted line and black line is the solution value developing process).

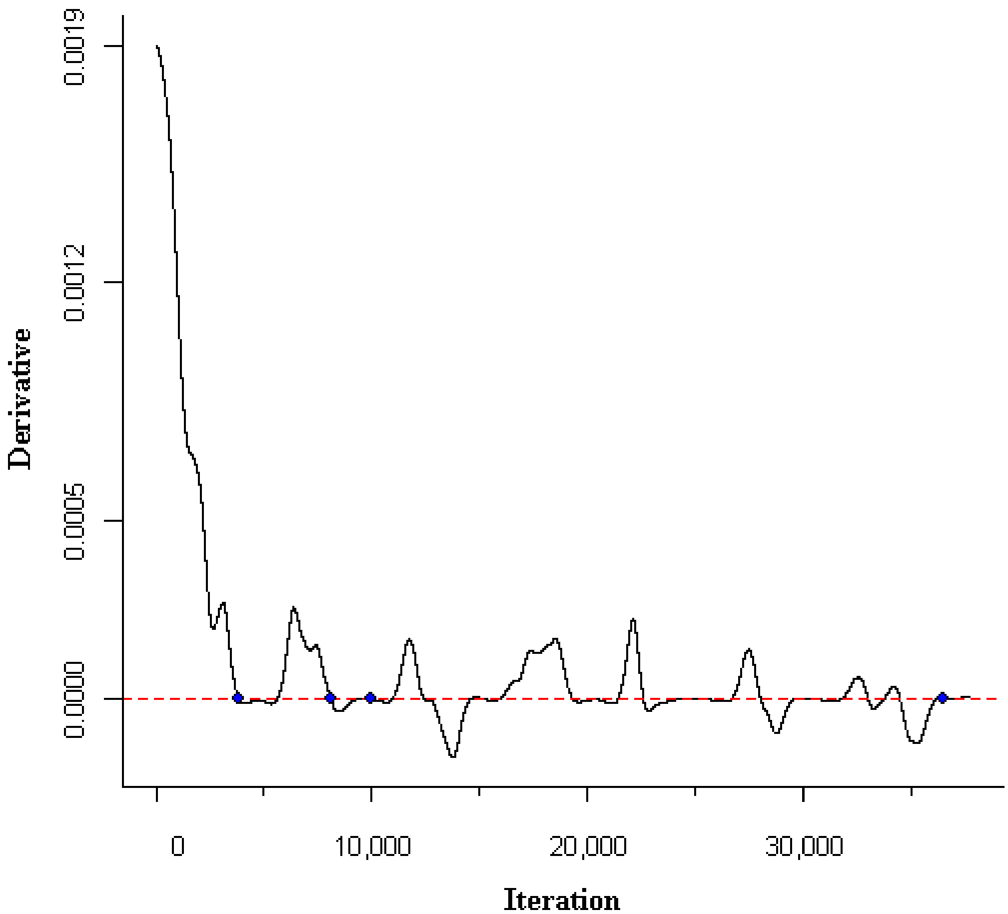

Figure 3.16 Derivative plot of a tabu search process (solid line: derivatives of the smoothing splines of solution values; dotted line: zero line when derivative = 0; circles: integration points)

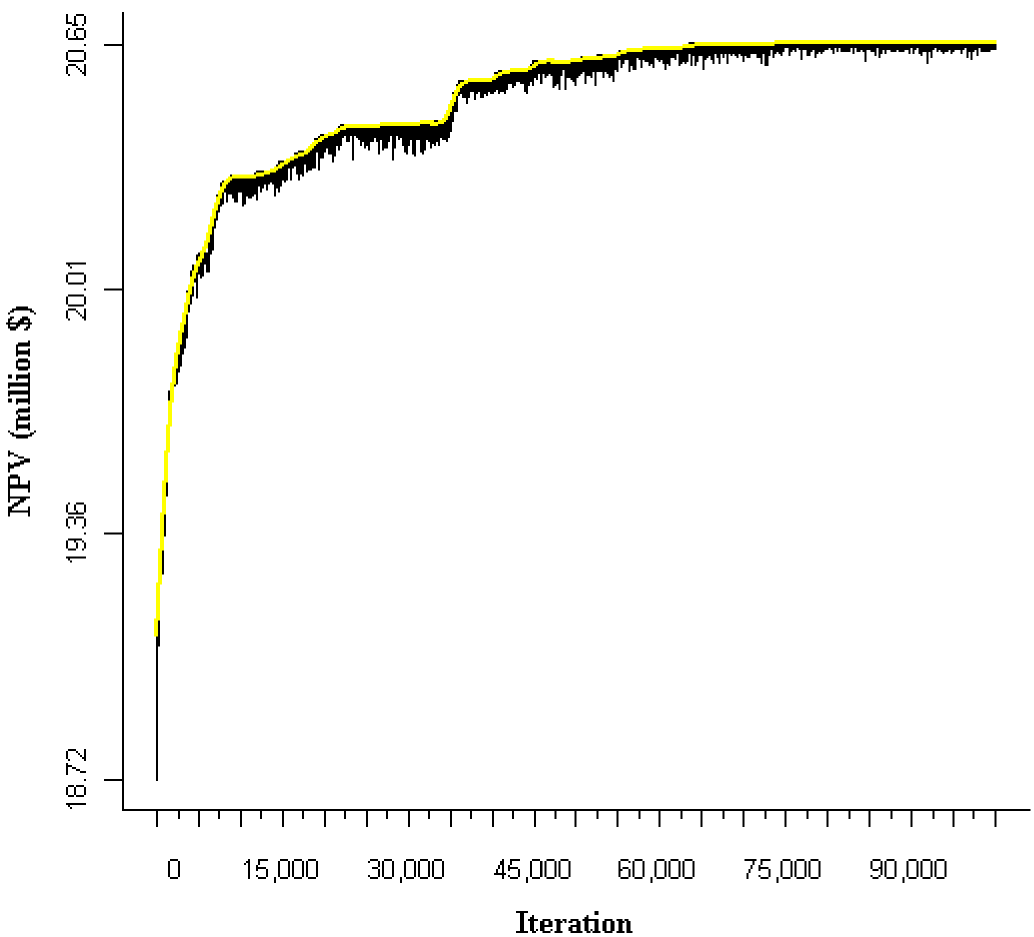

Figure 3.17 Fitting smoothing splines to a raindrop solution search (the light grey line is the fitted line and the black line is the solution value search path).

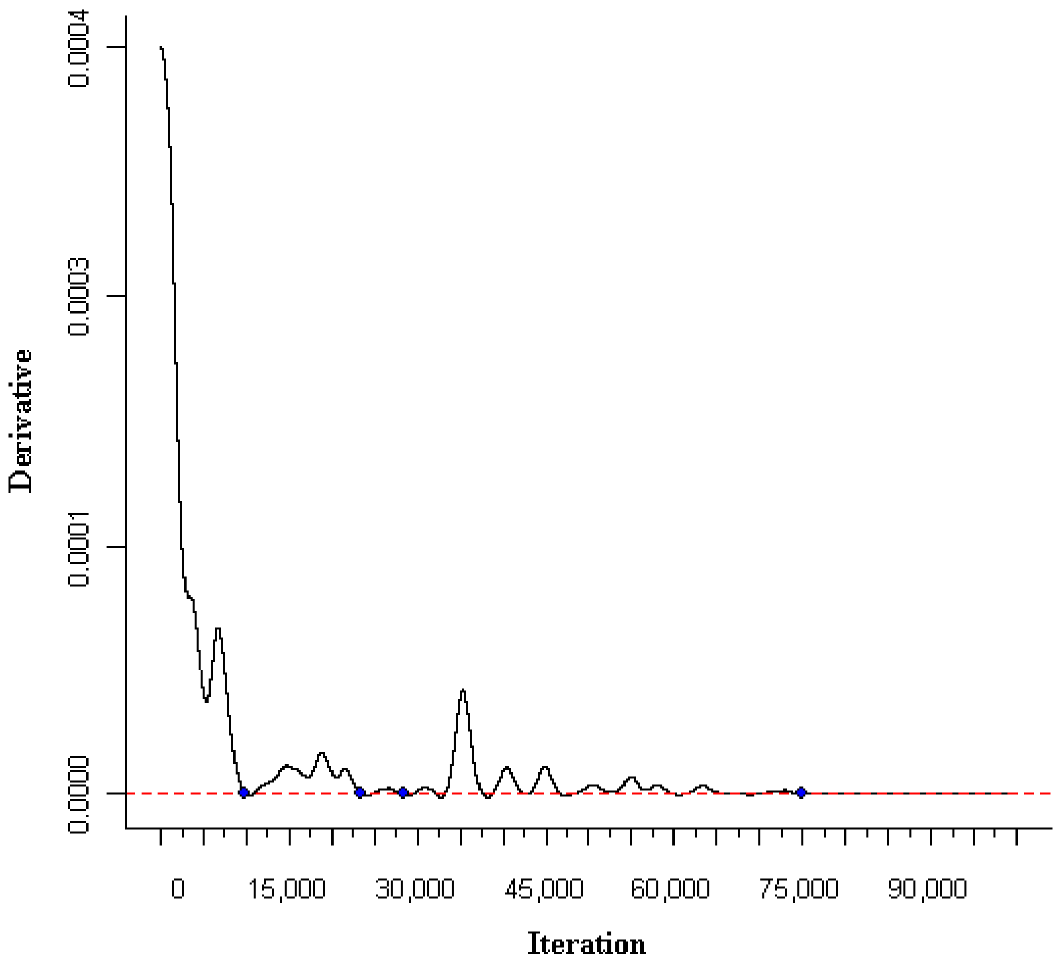

Figure 3.18 Derivative plot of a raindrop solution search (solid line: derivatives of the smoothing splines of solution values; dotted line: zero line when derivative = 0; circles: integration points).

CHAPTER 4

INTEGRATION OF GIS TECHNIQUES TO ASSESS FOREST FRAGMENTATION IN PLANS THAT ACCOMMODATE DIFFERENT CLEARCUT SIZE RESTRICTIONS[1]

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[1]Li, R., P. Bettinger, and K. Boston. To be submitted to *Silva Fennica.*

ABSTRACT

Forest fragmentation has become an ecological concern in managed forests. Clearcut size limitations, established both for private land and public land, may affect and compound the fragmentation process of the forested landscape. To better understand how these restrictions influence the forest fragmentation process, we designed an experiment to test and assess the potential fragmentation effects caused by different maximum clearcut size restrictions for landscapes with different spatial patterns of land ownership. First, we used a simulated annealing heuristic algorithm to solve a forest planning problem with woodflow constraints and six different maximum clearcut sizes using seven datasets with different land sizes (small, medium, and large) and different spatial patterns (clumped, dispersed, and random). The six maximum clearcut sizes were 40, 80, 120, 160, 200 and 240 acres. Seven landscape metrics were selected as indicators of forest fragmentation and they were applied to each landscape after harvesting was simulated. The seven landscape metrics were number of patches, patch density, total edge, edge density, perimeter-area fractal dimension, mean proximity, contagion. We used multivariate analysis of variance (MANOVA) and Turkey's HSD multiple comparison to test if there was any significant difference in landscape indices among the six clearcut size limitations when applied to forest plans for the seven datasets. Results show that regardless of forest size and spatial pattern of land ownership, the number of patches, patch density, total edge and edge density decreased, while mean proximity increases for all seven datasets as the maximum clearcut size increased. Results also suggest that woodflow constraints have an impact on fragmentation. By adding this constraint in the forest planning problem, it mitigates the effects on forest fragmentation due to different clearcut size restrictions.

Keywords:

Landscape metrics, Simulated annealing, Harvest scheduling, Multivariate analysis of variance, Multiple comparison, Edge density

INTRODUCTION

The role of forestlands in many areas of the United States has shifted from commodity production to multiple functions, including environmental protection, biodiversity and wildlife habitat conservation. As a result, more attention is paid to the impact of harvesting activities when developing forest plans. Therefore, developing a forest plan is not only a question of how many timber products a forestland can provide, but also a question of how much and in what way harvest activities may affect the broader ecological system.

Recent insight in landscape ecology suggests that management actions (e.g. thinning, clearcut) are one method of landscape change and influence human perception of forest fragmentation (Geoghegan et al. 1997), in part because the spatial pattern of landscape features may affect ecological processes occurring on the landscape (Turner 1989). Carsjens and van Lier (2002) describe fragmentation as a process that spatially segregates landscape features that would normally need to belong in close proximity in order to function optimally. The major impacts of forest fragmentation are on wildlife species that are dependent on size and configuration of habitat, however habitat is defined. Most research on forest fragmentation, has attempted to test the hypothesis that habitat loss is important to the maintenance and recovery of specific late-seral forest-dependent wildlife species (Opdam 1991, Wickham et al. 1997). However, measurable effects of fragmentation will vary depending on the broader landscape context and the patterns and processes under investigation (Robinson et al. 1995, Donovan et al.

1997). For example, forests fragmented by agriculture have been shown to result in a higher level of bird nest destruction than forests fragmented by logging (Bayne and Hobson 1997). Also, forest edges created by management activities can be considered either beneficial or detrimental, depending on the wildlife species or context under consideration (Kremsater and Bunnell 1999).

In most U.S. National Forest plans, the maximum clearcut area is either regulated or provided as a guidance. For example, the George Washington National Forest management plan gives guidance of 40 acres for the clearcut size limitations in Virginia (USDA Forest Service, Southern Region 1993). Some U.S. states have also enacted laws to limit the forest clearcut sizes on private forestlands, such as Oregon and Washington (Bettinger & Sessions, 2003), whereas in the southeastern U.S., there are few state regulations on harvesting private forest lands. Different regulations may inadvertently cause different levels of forest fragmentation. Barrett et al. (1998) examined 4 ha and 32 ha clearcut limitations on some California private forestland and determined that 4 ha clearcut size limits resulted in higher edge-to-area ratio than 32 ha limitations. One question that lacks an answer is whether fragmentation is affected by both clearcut sizes and the spatial configuration of an ownership. To better understand this, we undertook this study, which is aimed at assessing and comparing levels of fragmentation effects due to varying maximum clearcut sizes and ownership patterns.

In the field of forest planning, GIS techniques have been used as a data development and visualization tool, because the data required increasingly has a spatial component and because viewing the future condition of the forest allows managers to better understand impacts of a plan (Bettinger & Sessions 2003). By quantifying the adjacency, proximity, and juxtaposition of patches, GIS technology can provide valuable information for spatial forest management planning (Baskent & Keles 2005). We believe as harvest scheduling problems involve more spatial components, GIS techniques should be considered an essential tool for pre-processing data and post-processing results.

The objective of this study is to provide insight into the relationship between the forest fragmentation and the clearcut size limitations. At the same time, we demonstrate an example of how GIS techniques can be incorporated into planning and fragmentation analysis.

METHODS

Several landscape-related metrics can be used to quantify the structural properties of a landscape (Herzog et al. 2001), although landscape indices commonly reported in the fragmentation literature have rarely undergone field testing for their association with the life requisites of wildlife species of interest (Schumaker 1996). In any event, landscape metrics are useful for the quantifying of landscape pattern from a human perspective (Lindenmayer at al. 2002). All spatial pattern measurements involve measuring basic spatial elements, such as area, edge, shape, and distance, which further compose complex metrics. An increase in the number of small patches, lengths of edges, complexity of the patch shape, and isolation level may imply, for example, forest fragmentation is being aggravated. Therefore, by measuring these elements, one can know how severe a forestland is currently fragmented, and by projecting harvests into the future, one can understand how fragmentation may change as a result of a forest plan. Therefore, some of the more commonly used landscape metrics include those related to edges, areas, and the juxtaposition of patches of various types. Edge density, for example, is typically described as the total length of patch edge per unit area in a landscape (McGarigal and Marks 1995), and it is sensitive to the spatial resolution of the data but not landscape pattern (Hargis et al. 1998). Perimeter-area ratio and fractal dimension are other metrics that describe the irregularity of edges within a landscape. Contagion and nearest-neighbor distance metrics describe the extent to which patches are aggregated within the landscape. These measures generally provide landscape-level statistics that make comparing alternative forest management plans, with respect to forest fragmentation, possible.

In this study, seven commonly used metrics were selected for assessing the forest fragmentation. These include number of patches (NP), patch density (PD), total edge (TE), edge density (ED), perimeter-area fractal dimension (PAFRAC), mean proximity index (PROX_MN), and contagion (CONTAG). NP and PD measure area-related characteristics, TE and ED measure edge, PAFRAC measures shape, PROX_MN measures isolation, and CONTAG measures contagion or the degree of aggregation. Although number of patches and patch density imply the same characteristic for a given land with a fixed area, we included both in our analysis so that the change on the mean value of both indices can be observed explicitly among different clearcut size settings. The same reasoning was applied to metrics of total edge and edge density.

In landscape ecology, a patch is usually defined as a homogeneous surface which is spatially continuous (Forman 1995). In this study, a patch is a continuous forest area with one single age class, and an edge is formed at the shared border between two adjacent stands with different age classes. Background boundaries along the edge at a stand were not counted as edges. Therefore, number of patches should be equal to or less than the number of stand polygons for each forest land. Increasing values of NP or PD indicate a more fragmented forested land. Similarly, increasing values of TE or ED also indicate a potentially high level of fragmentation. The value of PAFRAC ranges from 1 to 2, and higher values suggests a departure from simple Euclidean geometry, like a square or a circle (McGarigal & Marks 1995), thus perhaps suggesting higher complexity in the landscape. PROX_MN requires a searching radius, which in this study was set as 100 m. A large value of this index implies a less fragmented landscape. CONTAG values range from 0 to 100, and a high value of this index implies that patches are highly aggregated, i.e., less fragmented. The mathematical formulation of each index can be found in McGarigal & Marks (1995).

Data description

In forest planning problems, forest stand datasets are generally composed of two parts. One part is GIS polygon datasets, which describes spatial relationship between stands, such as adjacency, and also provides stand area information. The other part includes forest data, which primarily comprises current stand age classes, and a dynamic timber growth projection based on a growth and yield model. GIS datasets we used here came from those created by Zhu (2006), which were based on real-world forestland datasets. According to the size and the spatial pattern of each forestland, Zhu (2006) classified them into small, medium, large, and clumped, dispersed and random groups. Seven out of nine datasets were used in this study: large clumped, small clumped, small dispersed, small random, medium clumped, medium random, and median dispersed. Small datasets have around 300 polygons. Medium datasets have around 500 polygons, and large datasets have more than 2,000 polygons. Forest stand age classes were originally created randomly to a uniform distribution ranging from 1 to 30, which means each age class has almost the same area percentage over the entire forest land. The growth and yield model used to project timber production within the planning horizon was developed by the Plantation Management Research Cooperative, Warnell School of Forest and Natural Resources, University of Georgia.

Timber stumpage prices were obtained from Timber Mart-South (4Q, 2006). We assumed \$36.58 per ton for sawtimber, \$20.40 per ton for chip-n-saw and \$6.68 per ton for pulpwood. The costs include regeneration cost of \$245.30 per acre (preparation, planting, seedling and herbaceous control) and annual management cost of \$4.50 per acre.

Forest planning problem formulation

We formulated a forest planning problem with the objective to maximize the net present value over the entire planning horizon. The planning horizon is 15 years with 1-year long planning periods. We assumed that timber products are the only profitable outcome. For simplicity, we also assumed that the only treatment was the clearcut. Four constraints were considered: 1) an ARM (area restriction model) where the summed area of all contiguous stands scheduled to be harvested in the same period can not exceed the predefined maximum clearcut area; 2) wood-flow constraints, which ensure sustainable yields over the entire planning horizon, i.e. the harvested volume in each period should not deviate too far from each other (maximum 20% deviation in this case); 3) an ending inventory constraint which prevents the depletion of timber stands at the end of planning horizon, and ensures that at least 90% of the original timber volume should remain; and 4) a minimum cutting age constraint, under which trees less than 20 years old are not considered to be cut. These constraints are typical for southern U.S. forest products companies. The formulations are as follows:

Maximize

$$\sum_{t=1}^{T}\sum_{i=1}^{N}(X_{it}A_i(V_{it.saw}P_{saw}+V_{it.cn}P_{cn}+V_{it.pulp}P_{pulp}-C_r)/1.06^{t-0.5}-C_aT_A(1.06^{14.5}-1)/(0.06)(1.06^{14.5}) \tag{1}$$

subject to

$$X_{it}A_i + \sum_{j \in N_i \cup S_i} X_{jt}A_j \le MCS \quad \forall i,t \tag{2}$$

$$\begin{aligned} &0.8 * \sum_{i=1}^{N} X_{it}V_{it} \le (\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \text{if } \sum_{i=1}^{N} X_{it}V_{it} > (\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \forall\, t \\ &\sum_{i=1}^{N} X_{it}V_{it} \ge 0.8 * (\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \text{if } \sum_{i=1}^{N} X_{it}V_{it} < (\sum_{t=1}^{T}\sum_{i=1}^{N} X_{it}V_{it})/T \quad \forall\, t \end{aligned} \tag{3}$$

$$\sum_{i=1}^{N} V_{il} \ge 0.9 * \sum_{i=1}^{N} V_{i0} \tag{4}$$

$$\sum_{t=1}^{T} X_{it} \le 1 \quad \forall i \tag{5}$$

$$\text{Age}_{\text{it}} \ge 20 \ \text{ if } X_{it} = 1 \tag{6}$$

Where:

A_i = area of management unit *i* (acres)

Age_{it} = the age of management unit *i* at time *t* period

C_a = annual cost ($/acre)

C_r = regeneration cost ($/acre)

i, j = an arbitrary harvested unit

MCS = maximum clearcut size

N = total number of harvest units

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

P_{cn} = stumpage price for chip-n-saw timber

P_{pulp} = stumpage price for pulpwood

P_{saw} = stumpage price for sawtimber

S_i = the set of all harvest units that are connected with any unit in the set of N_i

t = period in which harvest activities occur

T = total number of time periods in the planning horizon

T_A = total planning area (acres)

V_{i0} = total timber volume in the stands before any harvest activities

V_{il} = timber volume left on the stands after the planning horizon

V_{it} = timber volume harvested in time period t, from management unit i

$V_{it.cn}$ = chip-n-saw volume harvested in time period t, from management unit i

$V_{it.pulp}$ = pulpwood volume harvested in time period t, from management unit i

$V_{it.saw}$ = sawtimber volume harvested in time period t, from management unit i

In order to examine the forest fragmentation effects due to various clearcut size restrictions, we selected 40, 80, 120, 160, 200 and 240 acres as six maximum clearcut sizes.

Scheduling process

It is generally not an easy task to find the exact optimal solution in a complex combinatorial problem by traditional methods due to current limited computation abilities. Heuristic approaches are an alternative to solve such problems and find good feasible solutions. In our study a heuristic method — Simulated Annealing (SA) — was used to solve the above forest planning problem. SA performs a search process by mimicking the physical annealing process of metal. As the SA search process proceeds, it moves from a random feasible solution set to a limited group of good candidate solutions. At the beginning of the search, an initial random solution is generated, and then a random small change is made on this solution. If the change results in a better solution, it is acceptable and the search proceeds with this better solution. If the change does not result in a better solution, whether this new solution should be accepted or not depends on the solution quality and a probability calculated using the following equation:

$$P(T) = e^{-|S_c - S_p|/T_t} \tag{7}$$

where s_c = current solution value

s_p = previous solution value

T_t = temperature at time t

$P(T)$ = probability critical value

$P(T)$ is then compared to a randomly drawn number between 0 and 1. We accept the solution if the randomly drawn number is less than $P(T)$. A worse solution is likely to be accepted at a high temperature, likely to be refused at a low temperature. Initially, the temperature is high (allowing more non-improving changes to take place). However, as the search progresses, the temperature is “cooled”, allowing fewer and fewer non-improving changes to take place.

Parameters required for SA include an initial temperature and a cooling rate. After trial and error, we found the initial temperature of 10,000 for the large dataset, and the initial temperature of 8,000 for the medium and small datasets, and the cooling rate of 0.9995 to be the most appropriate parameters for this problem.

Statistical analysis

We developed 50 solutions for each clearcut restriction problem (40 – 240 acre maximum clearcut size). Each of the 50 solutions were based on the same data, yet started with a different initial random solution in the SA process. Therefore, the difference among these 50 solutions was only caused by the randomness of the initial solution and the randomness inherent in the SA searching process. Each solution resulted in a forest plan, and the projected condition of the landscape could be easily represented by a vector GIS map (Figure 4.1). We then converted each vector map into a raster map with a cell size of 5 m. Bettinger et al. (1996) showed that relatively small changes to the vector polygon shape and size occur when the conversion process involves grid cells less than 10 m in size. For each resulting raster landscape, the potential fragmentation effects caused by different harvest activities were quantitatively assessed at the end of the time horizon (15 years into the future).

Multivariate analysis of variance (MANOVA) was used first to test if the factor of maximum clearcut size had an overall effect on all response variables which were indicators of the degree of fragmentation. The response variables were the seven landscape indices: number of patches (NP), patch density (PD), total edge (TE), edge density (ED), perimeter-area fractal dimension(PAFRAC), mean proximity (PROX_MN) and contagion (CONTAG). One independent factor was the maximum clearcut size (MCS). If MANOVA test showed significant effects by the treatment factor, then univariate analysis of variance (ANOVA) and Tukey's HSD multiple comparison method were used to find further which variable was mostly affected by clearcut size restrictions and which factor group was significantly different from the others.

During the analysis, we suspected there were some confounding factors related to the problem formulation and the GIS data, which may substantially affect the results. One important factor was woodflow constraints, which controlled the amount of timber harvested in each time period, thus to prevent the situation where most harvests occurred in the beginning periods due to discounting of revenues. However, woodflow constraints may impact fragmentation, since cutting activities were spread out evenly over 15 years, which made the chance of producing large patches with the same age class remote. We also observed there were many small roads (less than 10 m in width) that separated stands. In our initial analysis, all roads were treated as background and did not enter the calculation process. In this case, if two stands with the same age class were only separated by a small road (Figure 4.1), they did not form one contiguous patch, which technically, they could in some cases (if the stands are very young). Older stands separeated by a small road might still contain an edge. This depended on what might be affected by fragmentation and what wildlife species were considered. In this study, if two stands with different age classes were only separated by a small road, this road in between would not be counted as an edge in the landscape metric calculation. A mathematic algorithm was developed to sense the size of the gaps in the raster databases created by the woods roads. We considered woods roads to be small enough to only result in a 2 pixel (10 m) or less gap between stands of trees. If this sized gap was located, the resulting pixels representing the roads were allocated back to the neighboring stands. While such a process may slightly skew the size of stands, it has little effect on their shape, and effectively removes the artificial barrier (the woods road) to the fragmentation analysis. To explore further these potentially confounding effects, we analyzed three other situations using the large clumped dataset to see if there are any significant changes on the results: 1) no woodflow constraint; 2) ignoring all small roads; and 3) no woodflow constraint and ignoring all small roads.

GIS techniques

Throughout the entire project, GIS techniques were closely integrated with the forest planning problem at the stages of pre-planning, mid-planning and post-planning (Figure 4.2). At the pre-planning stage, GIS techniques were largely used in spatial database management, which includes data storage, editing, conversion, and other manipulations for seven vector GIS datasets. During the planning, GIS techniques were used in two ways: information extraction as an input to the plan and forest plan visualization as an output. As many may know, in spatial forest planning, adjacency relationship between stands is an essential piece of information, which is used to compose adjacency constraints in the optimization problem formulation. The extraction of the adjacency information is very problem-specific. For instance, we may consider two stands adjacent in one problem, if the distance between edges of these two stands is less than a certain value. We may also treat two stands as neighboring stands in another problem, if the centroids of these two stands are within a certain distance. Through GIS functions, extraction of the spatial information can be convenient and flexible. All forest plans produced by the heuristic search can be presented as a GIS thematic map. In the post-planning state, the landscape spatial pattern analysis used a raster representation of the resulting vector database. Fragstats (McGarigal & Marks 1995) was used to develop the spatial pattern indices based on the forest plans developed with SA. In the landscape spatial pattern analysis, landscape structure was calculated through many spatial indices. Without GIS techniques, this work would be much more difficult and tedious, if not impossible.

RESULTS

For each of the seven hypothetical landscapes we generated 300 forest plans using a simulated annealing heuristic, 50 for each of the six clearcut size restrictions. The resulting forest structure after the end of the time horizon (15 years) was described using GIS, and each of the 300 forests was then input into Fragstats for landscape-level analysis. The multivariate analysis of variance indicated that all seven datasets have a significant Wilk's likelihood ratio test (p<0.0001), which indicates that the maximum clearcut size restriction has an overall effect on the forest fragmentation. These results are consistent with Barrett et al. (1998) and Gustafson (2007) who demonstrated this in other areas of North America.

Tables 4.1 to 4.7 provide more depth to the analysis. Tables 4.1-4.3 are for the 3 small landowner datasets, Tables 4.4-4.6 are for the 3 medium landowner datasets, and Table 4.7 is for the large landowner clumped dataset. What we found is that NP, PD, TE, ED and PROX_MN were all significantly different among different clearcut size groups (p<0.01). Except for the large clumped dataset, CONTAG was not significantly different among the clearcut size restrictions. When examining the shape index PAFRAC, only the large clumped dataset showed a strong significant effect (p<0.0001), and the small clumped dataset showed a weak significant different effect (p=0.0291). The multiple comparison of the results should be ignored if the univariate ANOVA test failed to suggest evidence of any significance, although different group labels may still be assigned to different groups for some indices.

When viewing Tables 4.1-4.7, one can see a clear trend that with an increase of maximum clearcut size from 40 acres to 240 acres, index values of NP, PD, TE and ED decreased, and index values of PROX_MN increased, except that for some datasets, this trend was not as clear when moving from 200 to 240 acres. This decrease in the number of patches, patch density, total edge, edge density and increase in the mean proximity implied less fragmentation as the maximum clearcut size increased from 40 to 240 acres. It was also interesting to notice that the CONTAG value seemed to decrease slightly as the clearcut size increased when using the large clumped dataset, which indicated less aggregation for the larger maximum clearcut sizes. But we believe this did not mean more fragmentation for the larger clearcut size groups, because all values for CONTAG ranged around 52 or 53. It should also be noted that the relationship between index values and clearcut sizes was not linear. Therefore, linear regression models were not suggested for use in this analysis.

For the small and medium datasets, it seemed that the spatial pattern (clumped, dispersed and random) did not affect multiple comparison results much, although fewer significant differences for some landscape indices have been shown for the small random dataset compared to the small clumped and the small dispersed datasets. For the 3 small datasets, the clumped dataset had more significantly different groups than the dispersed dataset and the random dataset for the significant landscape indices (NP, PD, TE, ED and PROX_MN). One major difference attributable to the different spatial patterns was the magnitude of the value PROX_MN. Clumped datasets (both small and medium sizes) had much larger PROX_MN values than their corresponding dispersed and random datasets, which was self-evident, since PROX_MN measures isolation, and random or dispersed datasets contained more isolated polygons than the clumped datasets.

As we noted earlier, the original GIS data contained roads that spatially separated timber stand polygons. To test the effect that these roads had on the analysis of fragmentation, we concentrated on the large, clumped dataset and the 300 forest plans that were developed for it. After removing the influence of the roads, we found that the number of patches and patch density declined to some extent (Table 4.8). This was because two or more adjacent small patches with trees at the same age, separated only by small roads were now treated as a single patch. We also found that the total edge and edge density largely increased after small roads were removed. This could be explained by new edges formed between two adjacent stands with different ages at places where small roads were. Thus, the increase of edges did not conflict with the decrease of number of patches. Results also show that the PROX_MN values decreased substantially after roads were removed, and the PAFRAC values now increased slightly as the clearcut size increased, which was opposite from what is reported in Table 4.7. Thus, it was not clear whether the measures of forest fragmentation were aggravated or diminished after small roads were removed, but it was obvious that how one handled small roads did have an effect on results. In any case, the results did not change thoroughly, and we can still come to the same conclusion that with the increase of clearcut sizes, the fragmentation effects decreased.

To further examine the impact of woodflow constraints on the level of fragmentation, we relaxed the constraint and generated 300 new forest plans using the large, clumped database. In this case, the influence of small roads was not removed. Comparing Table 4.9 with Table 4.7, we can see that the removal of woodflow constraints led to slightly fewer patches, slightly fewer edges, a drop in the PROX_MN values and an increase in the CONTAG values. We can also see that more significant groups were formed for all seven landscape indices. For example, for the NP, PD, TE, ED, PROX_MN, and CONTAG indices, each clearcut size formed its own unique group. Prior to removing woodflow constraints, PROX_MN and CONTAG only had two significantly different group levels. These changes were dramatic, because not only the index values were changed, but also the multiple comparison results were different. However, despite observed differences, the overall pattern of fragmentation with an increase of maximum clearcut size remained the same.

We finally tested whether the combination of a removal of woodflow constraints and the removal of small roads would significantly change the results (Table 4.10). These results were similar to those presented in Table 4.9, except that the PAFRACF values dropped as the clearcut size increased, as in the previous analysis in which small roads were. Therefore, this final analysis reinforced our belief that while removing small roads and woodflow constraints changed the values of the landscape metrics, the impact and significance were unchanged.

DISCUSSION AND CONCLUSIONS

Regardless of different forest sizes and landscape spatial structure, all seven datasets support the idea that effects on forest fragmentation decrease in terms of number of patches, patch density, total edge, edge density and mean proximity, as the maximum clearcut size increases. In other words, larger maximum clearcut size restrictions can reduce the forest fragmentation to some extent. However, patch shape and level of contagion are not affected much by different clearcut size restrictions, especially when forest size is relatively small and even woodflow constraints are used in forest planning process.

Effects on forest fragmentation due to different maximum clearcut sizes do not differ much for different landscape spatial patterns, although clumped datasets tend to strengthen the impact from different clearcut size restrictions. Constraints of even woodflow have an obvious impact on the forest fragmentation, and by adding these constraints in the forest planning problem, it mitigates the effects on forest fragmentation due to different maximum clearcut sizes. Whether small roads (less than 10 m in width) should be counted as edges in landscape metrics calculation or be treated as pure background affects results slightly, but the overall trends in forest fragmentation effects due to maximum clearcut size restrictions do not change dramatically. We also need to notice that this study is only applied to the southeastern region in the U.S., because our spatial data and the growth and yield model are all based on southern loblolly pine stands. One should be cautious in extending our results to other locations with different tree species and different geospatial characteristics.

Although we used one year green-up period in this study, future studies may be able to expand our research by extending the green-up period to 2 or 3 years and observing whether there are any changes in fragmentation pattern in the projected forest plans. Future studies may also extend what we have done to create or enhance a single fragmentation index that can be used to visualize the extent of fragmentation of the landscape graphically, similar to the vegetation similarity index created by Bettinger (2003).

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Table 4.1 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the small clumped dataset.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	CD	D	D
		Mean	270.40	269.28	268.46	267.80	267.46	267.62
PD	<0.0001	Group	A	B	C	CD	D	D
		Mean	9.32	9.29	9.26	9.24	9.22	9.23
TE	<0.0001	Group	A	B	B	C	CD	D
		Mean	113,207	112,803	112,564	111,911	111,711	111,475
ED	<0.0001	Group	A	B	B	C	CD	D
		Mean	39.04	38.90	38.82	38.60	38.52	38.44
PAFRAC	0.0291	Group	AB	ABC	BC	C	A	AB
		Mean	1.135	1.134	1.134	1.134	1.135	1.135
PROX_MN	<0.0001	Group	D	C	C	B	BA	A
		Mean	71.45	83.50	85.51	100.73	108.51	109.76
CONTAG	0.2183	Group	A	AB	AB	AB	B	AB
		Mean	52.12	51.99	52.00	51.88	51.80	52.04

Table 4.2 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the small dispersed dataset.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	BC	C	C
		Mean	271.06	270.26	269.50	269.76	269.4	269.52
PD	<0.0001	Group	A	B	C	BC	C	C
		Mean	9.31	9.28	9.25	9.26	9.25	9.25
TE	<0.0001	Group	A	A	B	B	C	BC
		Mean	73,166	72,831	72,389	72,362	72,009	72,328
ED	<0.0001	Group	A	A	B	B	C	BC
		Mean	25.12	25.00	24.85	24.84	24.72	24.83
PAFRAC	0.4275	Group	A	A	A	A	A	A
		Mean	1.212	1.214	1.213	1.213	1.211	1.213
PROX_MN	<0.0001	Group	C	B	B	A	A	A
		Mean	22.41	27.63	30.17	38.23	36.03	34.57
CONTAG	0.1337	Group	A	AB	B	AB	AB	A
		Mean	52.15	51.90	51.80	51.93	51.96	52.11

Table 4.3 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the small random dataset.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	0.0046	Group	A	AB	AB	AB	C	AB
		Mean	313.42	313.04	312.60	312.48	312.38	312.66
PD	0.0047	Group	A	AB	AB	AB	C	AB
		Mean	10.66	10.65	10.64	10.63	10.63	10.64
TE	<0.0001	Group	A	AB	B	C	C	C
		Mean	72,580	72,458	72,294	71,886	71,922	71,983
ED	<0.0001	Group	A	AB	B	C	C	C
		Mean	24.70	24.65	24.60	24.46	24.47	24.49
PAFRAC	0.9328	Group	A	A	A	A	A	A
		Mean	1.235	1.236	1.236	1.235	1.235	1.234
PROX_MN	<0.0001	Group	C	BC	B	A	A	A
		Mean	12.12	16.23	20.29	25.55	25.07	27.08
CONTAG	0.1303	Group	AB	B	A	AB	A	AB
		Mean	52.49	52.20	52.52	52.25	52.51	52.39

Table 4.4 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the medium clumped dataset.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	D	D	D
		Mean	501.28	499.48	498.48	497.22	497.20	496.54
PD	<0.0001	Group	A	B	C	D	D	D
		Mean	8.77	8.74	8.72	8.70	8.70	8.69
TE	<0.0001	Group	A	B	C	D	D	D
		Mean	221,873	220,932	220,275	219,243	218,944	219,172
ED	<0.0001	Group	A	B	C	D	D	D
		Mean	38.81	38.64	38.53	38.35	38.30	38.34
PAFRAC	0.3644	Group	A	A	A	A	A	A
		Mean	1.213	1.213	1.213	1.212	1.212	1.213
PROX_MN	<0.0001	Group	E	D	C	B	A	A
		Mean	74.19	84.54	93.73	107.58	116.47	117.96
CONTAG	0.6541	Group	A	A	A	A	A	A
		Mean	52.26	52.30	52.31	52.19	52.25	52.33

Table 4.5 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the medium dispersed dataset.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	BC	C	D	D
		Mean	480.62	479.48	479.04	478.72	478.02	477.92
PD	<0.0001	Group	A	B	BC	C	D	D
		Mean	8.24	8.22	8.21	8.21	8.20	8.20
TE	<0.0001	Group	A	B	B	C	D	D
		Mean	119,726	119,285	118,904	118,378	117,548	117,823
ED	<0.0001	Group	A	B	B	C	D	D
		Mean	20.52	20.45	20.38	20.29	20.15	20.20
PAFRAC	0.348	Group	A	A	A	A	A	A
		Mean	1.230	1.230	1.230	1.230	1.230	1.231
PROX_MN	<0.0001	Group	E	D	C	B	A	A
		Mean	10.98	16.92	20.84	25.80	31.80	34.34
CONTAG	0.3129	Group	A	A	A	A	A	A
		Mean	52.77	52.71	52.82	52.90	52.89	52.90

Table 4.6 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the medium random dataset.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	C	C	D
		Mean	556.60	555.88	555.20	554.90	555.04	554.12
PD	<0.0001	Group	A	B	C	C	C	D
		Mean	9.55	9.54	9.53	9.52	9.53	9.51
TE	<0.0001	Group	A	B	C	C	C	D
		Mean	141,514	140,991	140,357	140,180	140,009	139,463
ED	<0.0001	Group	A	B	C	C	C	D
		Mean	24.29	24.20	24.09	24.06	24.03	23.93
PAFRAC	0.4739	Group	A	A	A	A	A	A
		Mean	1.256	1.256	1.256	1.257	1.256	1.256
PROX_MN	<0.0001	Group	D	C	C	B	B	A
		Mean	44.67	50.31	52.82	57.57	57.96	62.07
CONTAG	0.4753	Group	A	A	A	A	A	A
		Mean	53.17	53.13	53.07	53.03	53.13	53.15

Table 4.7 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the large clumped dataset with woodflow constraints.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	D	CD	CD
		Mean	2,650.14	2,639.38	2,622.00	2,619.52	2,620.02	2,620.40
PD	<0.0001	Group	A	B	C	D	CD	CD
		Mean	9.24	9.20	9.14	9.13	9.13	9.13
TE	<0.0001	Group	A	B	C	D	D	D
		Mean	1,153,566	1,149,285	1,133,629	1,131,518	1,132,126	1,131,756
ED	<0.0001	Group	A	B	C	D	D	D
		Mean	40.20	40.05	39.51	39.43	39.45	39.44
PAFRAC	<0.0001	Group	A	A	B	B	B	B
		Mean	1.182	1.182	1.181	1.181	1.181	1.181
PROX_MN	<0.0001	Group	E	D	C	B	B	A
		Mean	53.78	65.04	112.73	115.98	116.39	119.77
CONTAG	<0.0001	Group	A	A	B	B	B	B
		Mean	53.20	53.22	52.47	52.47	52.48	52.45

Table 4.8 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the large clumped dataset with woodflow constraints after small roads have been removed.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	D	D	D
		Mean	2,560.02	2,537.02	2,512.14	2,508.42	2,508.50	2,507.56
PD	<0.0001	Group	A	B	C	D	D	D
		Mean	8.77	8.70	8.61	8.60	8.60	8.60
TE	<0.0001	Group	A	B	C	D	D	D
		Mean	1,876,720	1,868,716	1,849,104	1,846,822	1,847,323	1,845,740
ED	<0.0001	Group	A	B	C	D	D	D
		Mean	64.32	64.05	63.38	63.30	63.32	63.26
PAFRAC	<0.0001	Group	C	C	B	AB	A	AB
		Mean	1.183	1.183	1.184	1.185	1.185	1.185
PROX_MN	<0.0001	Group	C	B	A	A	A	A
		Mean	16.09	18.20	28.37	28.86	28.39	28.69
CONTAG	<0.0001	Group	A	A	B	B	B	B
		Mean	52.57	52.59	51.85	51.86	51.86	51.83

Table 4.9 Multiple comparison of landscape indices among 5 maximum clearcut size groups for the large clumped dataset without woodflow constraints.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	D	E	F
		Mean	2,648.84	2,629.12	2,586.10	2,574.66	2,570.40	2,566.66
PD	<0.0001	Group	A	B	C	D	E	F
		Mean	9.23	9.16	9.01	8.97	8.96	8.94
TE	<0.0001	Group	A	B	C	D	E	E
		Mean	1,153,365	1,142,165	1,109,468	1,100,263	1,097,633	1,097,923
ED	<0.0001	Group	A	B	C	D	E	E
		Mean	40.19	39.80	38.66	38.34	38.25	38.26
PAFRAC	<0.0001	Group	A	B	D	D	D	C
		Mean	1.182	1.181	1.180	1.179	1.179	1.180
PROX_MN	<0.0001	Group	F	E	D	C	B	A
		Mean	52.12	78.07	174.75	194.53	210.93	224.24
CONTAG	<0.0001	Group	B	A	F	E	D	C
		Mean	59.11	59.42	56.17	56.51	56.65	56.85

Table 4.10 Multiple comparison of landscape indices among 6 maximum clearcut size groups for the large clumped dataset without woodflow constraints after small roads have been removed.

Landscape indices	P_value		Maximum clearcut size restrictions					
			40	80	120	160	200	240
NP	<0.0001	Group	A	B	C	D	E	F
		Mean	2,562.04	2,517.58	2,436.56	2,418.72	2,408.92	2,398.80
PD	<0.0001	Group	A	B	C	D	E	F
		Mean	8.78	8.63	8.35	8.29	8.26	8.22
TE	<0.0001	Group	A	B	C	D	E	F
		Mean	1,876,647	1,857,942	1,810,050	1,798,804	1,793,074	1,790,202
ED	<0.0001	Group	A	B	C	D	E	F
		Mean	64.32	63.68	62.04	61.65	61.46	61.36
PAFRAC	<0.0001	Group	D	D	C	B	B	A
		Mean	1.182	1.183	1.185	1.186	1.186	1.187
PROX_MN	<0.0001	Group	F	E	D	C	N	A
		Mean	16.80	22.51	37.78	43.14	47.24	50.36
CONTAG	<0.0001	Group	B	A	F	E	D	C
		Mean	58.48	58.80	55.57	55.92	56.06	56.26

Vector

Raster (recognizing roads)

Raster (ignoring roads)

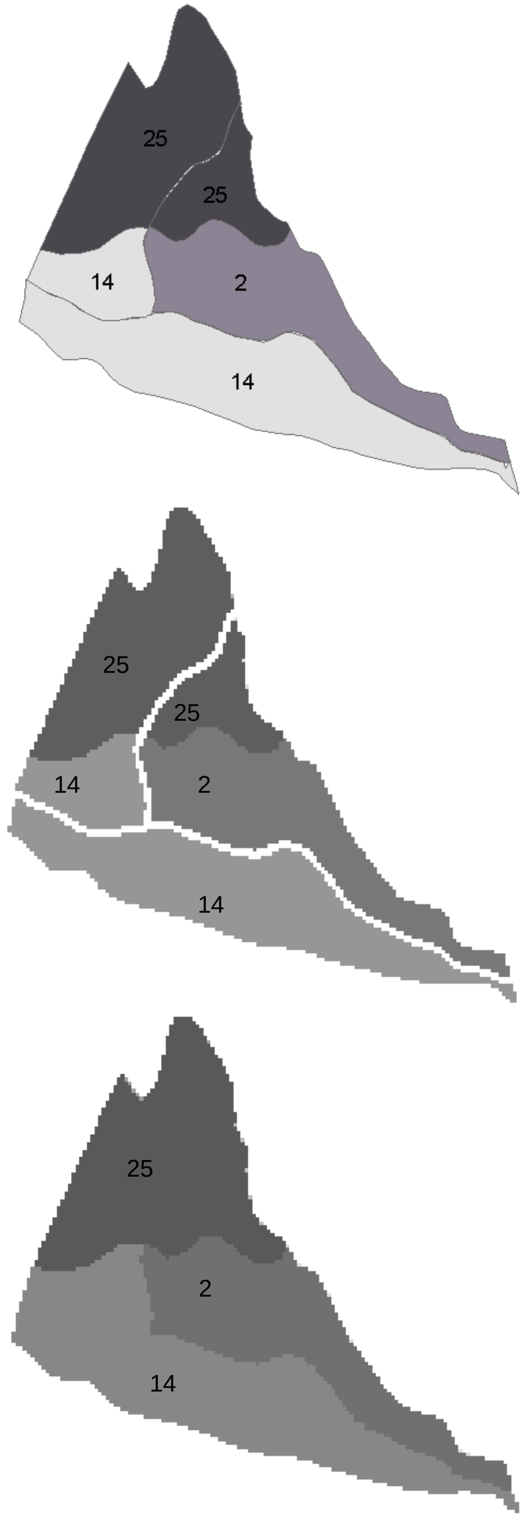

Figure 4.1 Three GIS representations of forest landscapes resulted from the same forest plan (the labels on the maps indicate the stand age classes).

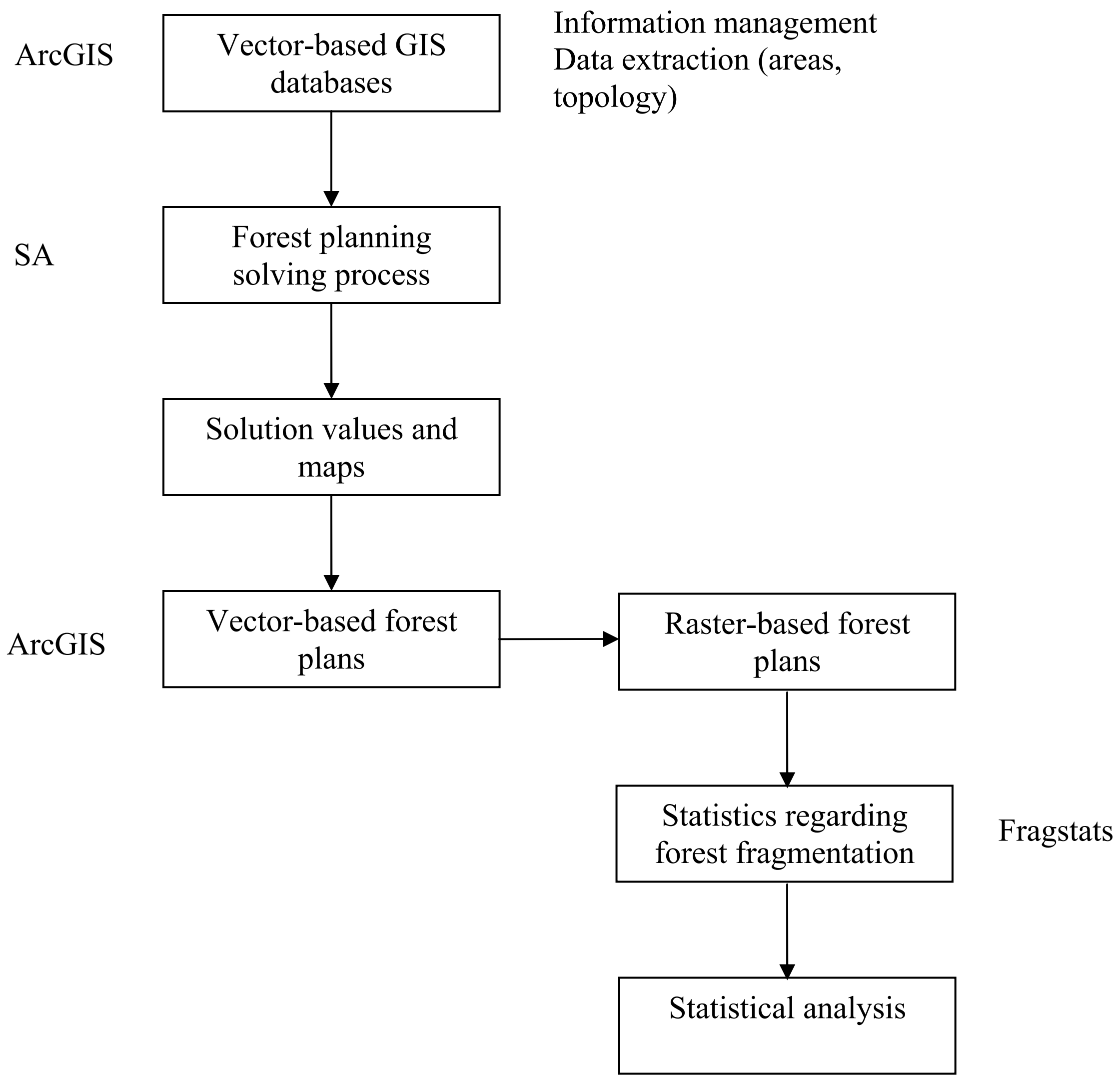

Figure 4.2 Integration of GIS into the forest planning process.

CHAPTER 5

SYNTHESIS OF GIS AND FOREST PLANNING RESEARCH

GIS and forest planning technology have both become useful tools in forestry and natural resource management. Just 10-20 years ago, many natural resource managers were developing maps and performing analyses with manual methods, and forest plans were developed using methods that could not accommodate spatial concerns. The required skills seem to have evolved from those that involved a steady hand to those that now require knowledge of computerized mapping systems. With advances in computer software and hardware technology, as well as advances in our knowledge of the sciences, we can now model and simulate processes that were once considered to require considerable physical and mental effort. The review of the use of GIS in forestry and natural resource management (Chapter 2) indicates that GIS is now heavily and widely used in many diversified areas, and may continue to delve deeper into complex analyses based on the needs of customers who have an increasing understanding of the capabilities of spatial analysis.

The advances in GIS and remote sensing that are being adopted by natural resource management today seem to be focused on land use and land cover change, other large-scale spatial analyses, and the integration of natural resource fields (wildlife, fire, etc.) with GIS. Most landscape-level analyses have used satellite imagery and have focused on other parts of North America. I saw this as an area of opportunity where I would focus on operational data (along with a typical planning situation) and focus on a problem related to southern U.S.

managed forests (clearcut size restrictions). This review of GIS also suggested that GIS represents an area of science in itself, provides a fertile ground for advancements in spatial analysis and visualization algorithms. However, many of the uses of GIS in practice today are not the types of processes normally reported in journal articles; they are adoptions of basic processing techniques to common management problems. The approach I used was one of many ways to perform an analysis of the adoption and use of GIS in natural resource management, is obviously subjective, and reflects the biases and special interests of the reviewers (Current & Marsh 1993).

Forest planning involves the scheduling of activities across space and time. A forest plan provides guidance to field-level managers and helps them develop operational plans and budgets that best meets the objectives and constraints of the organization as a whole. Forest plans can be developed independently of computer systems, however computer systems are required to locate optimal (or near-optimal) plans of action when hundreds or thousands of choices are available to the manager. Exact mathematical methods, such as linear or integer programming can facilitate the planning process. Linear programming, however, cannot accommodate spatial constraints easily. Integer programming can accommodate spatial constraints, however the drawback is that as the number of decision variables increases, the size of the problem being solved increases exponentially. This, in turn, may require a significant amount of time to solve a problem, or may require the analyst to make concessions regarding the search process that indicate an integer programming search is not different than a heuristic search (although the integer programming search still may require a long time to solve a problem).

As a result, the use of heuristic methods for locating near-optimal solutions to forest planning problems has increased over the past two decades (Bettinger & Chung 2004). GIS is integral to contemporary planning problems, as spatial concerns in forest plans require spatial information. The manner in which a heuristic searches through a solution space, and recognizes and values spatial and non-spatial concerns, has an effect on both the quality of solutions (forest plans) and the time required to generate them. For example, threshold accepting and simulated annealing are both fast heuristics compared to tabu search, genetic algorithms (Bettinger et al. 2002), and the raindrop method (Bettinger & Zhu 2006). However, the latter, relatively slow heuristics contain processes that may allow a search to diversify (explore many other options) or intensify (concentrate on very good solutions), two general types of behavior that threshold accepting and simulated annealing generally do not emulate very well. A number of researchers have suggested that combining the strengths of two or more heuristics may result in a search process that produces higher quality solutions more reliably than standard heuristics. Until now, each of these examples in the literature required human intervention. For example, an analyst designed a meta heuristic that performed one type of search for a while, then switched to another type of search at the time the analyst determined.

One of the contributions of this dissertation (Chapter 3) was to utilize the behavior of a search process to inform the process of when to switch to another type of search. This effectively removes the analyst from the process with the minor exception of selecting the condition upon which the switch is made. While this may seem similar to previous research, the search actually is allowed to proceed indefinitely until a condition is met (a behavior is recognized). This type of informed combination of heuristic methods is unique, and results in higher quality forest plans with a moderate increase in computing time, which is still measured in minutes rather than hours (as in the case of integer programming). Results indicated that meta heuristics that began with threshold accepting or simulation annealing were more favorable than others. These two heuristics use stochastic processes and 1-opt moves (a change in a single aspect of a forest plan) and allow only the incorporation of changes to plan when the resulting value is within some small distance (value) from the previous or from the best plan. Simulated annealing generally rejects more changes than threshold accepting, but either seems beneficial as the initial heuristic to use, since either very quickly moves from a random and poorly valued plan to a fairly high quality plan. Adding tabu search (a deterministic search process) and perhaps the raindrop method (a stochastic and deterministic search process) further enhances the quality of the resulting solutions, since these tend to intensify the search around previously-located good solutions.

One of the main concerns related to managed forests is the effects of management activities on forest fragmentation. Most of the discussion around this issue relates to the fragmentation of large expanses of older forest, reducing interior forest habitat and increasing the amount of edges between older forest and younger forest. Given the expansion of human activity during the twentieth century, it is of no wonder that large expanses of older forest are declining. However, the effects of fragmentation vary from one wildlife species to another, and an assessment of the potential for further fragmentation is important in informing management decisions. Another contribution of this dissertation (Chapter 4) is to assess how rules pertaining to clearcut size limits may affect quantitative metrics related to fragmentation of the landscape. I noted earlier in Chapter 1 that landscape-level applications have been reported for many areas of North America, except the south, and that these applications have generally used satellite imagery. Here, I study a landscape-level problem (fragmentation) using operational vector data as the original input representing several southern U.S. managed forests.

Previous research examined the effects of just a few clearcut sizes on forest patch shapes and sizes. Here, I examine some realistic clearcut size limitations that range from 40 acres (a maximum size for some U.S. National Forests) to 240 acres (a maximum size once suggested by a voluntary certification program). In addition, I examined how a typical planning problem for a managed southern forest may influence fragmentation. This problem includes both clearcut size restrictions and wood flow constraints. Finally, I examined how the use of an operational GIS database might affect the fragmentation indices, given that the operational database needed to be converted to a raster database for further analysis. From this area of work I found that most of the landscape indices suggest increased fragmentation will occur as maximum clearcut sizes decrease (contrary to one of the intents of the rules). In addition, these results occur regardless of the pattern of land ownership (clumped, random, or dispersed parcels). Further, while the woodflow constraint may ensure a stable supply of wood to processing facilities, it compounds the effects of fragmentation by spreading harvests out over a longer period of time.

While examining these results, I noted that the original GIS database contained many small roads that in effect separated stands of trees for purposes of the fragmentation analysis. This condition is an artifact of the original, operational vector GIS data, where the shape and size of roads are explicitly recognized. Since small woods roads should not be seen as a buffer between two types of forested stands, to examine the effect further, I developed a mathematical algorithm that senses the size of the gaps in the resulting raster database, and effectively removes the small roads from the analysis. When subjected to an analysis using the resulting fragmentation indices, I found that the trends remain the same (increased fragmentation will occur as maximum clearcut sizes decrease) even though the absolute values of the fragmentation indices changed.

This dissertation produced three contributions to the forestry sciences. First a synthesis of GIS-related research in North American forestry journals was developed to identify the gaps and suggest future research prospects (Li et al. 2007). Second, an analysis of the development of meta heuristics using informed, intelligent methods was developed, representing a new area of quantitative forest planning work. Finally, an assessment of a wide range of policies on forest fragmentation in a southern U.S. managed forest using operational data and a typical planning situation provides further insight into the effects of both data and policies on fragmentation indices.

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