Kirtland's Warbler on the Hiawatha National Forest: A Spatial and Temporal Management Problem

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Abstract

The Kirtland's warbler (*Setophaga kirtlandii*) utilizes actively managed breeding habitat on the Hiawatha National Forest in Michigan's Upper Peninsula. Managing the spatial arrangement of future breeding habitat is a complex forest management problem. While it is relatively simple to identify good areas to create habitat in the near future, it is difficult to foresee, without analysis, whether good habitat patches and amounts can be maintained through a full forestry rotation. Additionally, financial investments required to create suitable habitat are substantial, and managers should carefully consider habitat designs that increase breeding success.

A harvest scheduling model was applied on the Hiawatha National Forest to explore opportunities for habitat management. Results help support implementation of the 2006 Forest Management Plan, which identified goals and objectives to create and maintain 6700 acres of age 6-16 Kirtland's warbler (KW) habitat within a larger 33,500 acre KW habitat system. Applications addressed a mid-sized landscape (174,808 acres), comprised of 12,307 stands and a 60 year planning horizon, consisting of 30 two-year planning periods with KW habitat production objectives.

Three major model explorations are documented. First, a heuristic is developed to solve an intractable dynamic programming (DP) problem. Secondly, a pre-processing heuristic is developed to pare down the number of stand-level management options that must be included in the harvest scheduling model. Finally, the modeling system is applied to the problem to identify a management strategy and show financial and spatial trade-offs of alternative management strategies. Results of the first exploration indicate that an optimal DP solution can be identified with the proposed heuristic with improved solution times. The second exploration shows substantial time savings from eliminating many KW management options without compromising solution value. The third exploration determines a management strategy for where and when to generate habitat on the Hiawatha National Forest along with the associated spatial and financial tradeoffs.

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Chapter 1 : Introduction

The Kirtland's warbler (*Setophaga kirtlandii*) breeding range is limited to one of the most geographically restricted regions of any mainland bird in the continental United States (Mayfield, 1960). Since monitoring began in 1951, over 98% of the population has been detected Lower Michigan, and since 2000, 86% of the population has been detected in just five counties in northern Lower Michigan (US Fish and Wildlife Service, 2012). Since its passage in 1973, the Federal Endangered Species Act (16 U.S.C. 1531 et seq) has classified the warbler as "endangered", which was justified by its low population levels discovered during the 1971 decadal census. Consequently, the Kirtland's Warbler Recovery Team was commissioned in 1975 by the Secretary of Interior and drafted a Recovery Plan in 1976, calling for the population level to increase to 1,000 singing males (Byelich, et al., 1976 Updated 1985). The Plan's strategy for increasing the population included cowbird control and the creation of 38,000 acres of warbler breeding habitat in northern Lower Michigan. Implementation of this strategy has resulted in the warbler's recovery from a low of 167 singing males in 1974 to the 2090 singing males recorded in 2012 (Byelich, et al., 1976 Updated 1985), (US Fish and Wildlife Service, 2012).

Before 1995, the Kirtland's warbler had been sighted outside of the Lower Peninsula of Michigan, but breeding activity had not been detected. Since 1995, breeding activity has been detected with consistency in Michigan's Upper Peninsula, and in 2007 the first nests were recorded in Wisconsin and Canada (Probst, Bocetti, & Sjogren, 2003), (Richard, 2008), (Trick, Greveles, Ditomasso, & Robaidek, 2008). Thus, the recovery of the warbler is associated with breeding activity in new geographic areas. Expansion into new ranges presents both an opportunity and a challenge to forest managers who are concerned about the recovery of the species but are not currently poised to execute management strategies to create and maintain suitable warbler breeding habitat. The desired habitat occurs in young jack pine (*Pinus banksiana*), has a short tenure (10-20 years, depending on site quality), high stocking densities, and a generally cited minimum patch size of 80 acres (32 hectares) (e.g., (Probst & Weinrich, 1993)). Donner, Ribic, and Probst (2010) found that larger, non-isolated patches were associated with earlier colonization and later abandonment, and birds may occupy patches smaller than 80 acres if these patches are positioned in larger complexes of suitable habitat. Financial investments required to create suitable habitat can be substantial, and in the context of covertype and age class imbalances, ensuring a steady supply of habitat in the future can be a challenging management problem to implement. To help offset the relatively high cost of habitat creation due to increased stocking levels, it is desirable to manage jack pine at the commercial rotation age (50 years). Managers faced challenges meeting desired rotation age and spatial arrangement when creating habitat in the Lower Peninsula. During the first 15 years of management, the strategy outlined in the Recovery Plan only met approximately 45% of the habitat creation goals (Kepler, Irvine, DeCapita, & Weinrich, 1996).

Quality habitat has been identified as critical to the warbler's success when population levels are low, as is the case in newly occupied areas (Donner, Probst, & Ribic, 2008). Furthermore, the spatial arrangement and patch size of the habitat is correlated with utilization length. Larger patches are utilized earlier and longer, as are patches that do not exist in isolation (Donner, Ribic, & Probst, 2010). While it may be relatively simple to identify good patches to create habitat in the near future (0-10 years), it can be difficult to foresee whether good habitat patches and amounts can be maintained through a full commercial rotation. Future habitat consideration is potentially the most complex part of the management problem.

Cost-effectiveness is another aspect of habitat management that must be considered, especially given the generally more expensive cost of habitat management (due to site preparation intensities and increased stocking densities that require planting more seedlings) and the limited resources that have historically impeded the full implementation of habitat creation objectives (Kepler, Irvine, DeCapita, & Weinrich, 1996). Earlier studies have emphasized the costs of management to increase the likelihood of species' persistence and minimum population sizes (Marshall, Haight, & Homans, 1998), (Marshall, Homans, & Haight, 2000). Habitat management has proven effective, and recent population increases have resulted in the recommendation to down-list the species classification to "threatened" (Donner, Probst, & Ribic, 2008), (US Fish and Wildlife Service, 2012). Including cost considerations in the analysis for where and when to create breeding habitat may lead to efficiencies in dollar investments while maintaining quality habitat characteristics.

Finally, when there is existing management plan guidance for the landowner (as is the case for National Forests), multiple management objectives may need to be considered, which further complicates the ability to achieve desired KW habitat goals. While management areas in the Lower Peninsula are dedicated almost exclusively to the production and maintenance of Kirtland's habitat, management in newly colonized areas may be accompanied by objectives for other co-located vegetation species such as red pine (*Pinus resinosa*), oak species, and aspen (*Populus tremuloides*) (USDA Forest Service, 2006). The presence of other management objectives allows flexibility in designing where and when to create habitat within the larger context of the forest, but it also creates an added level of complexity, i.e., analyzing cover type conversions and alternate rotation ages associated with different species and land conditions.

Problems that consider the spatial interaction between stands may be addressed with forest management models that consider the interactions between financial efficiency, patch size design, and diverse cover type management objectives. Forest management problems similar to the one faced by the Hiawatha National Forest have been the subject of recent studies, particularly those that have investigated core area management. Core area forest has been described as forest free from edge effects (Baskent & Jordan, 1995). Management for core area objectives is in some ways the inverse of forestry problems with maximum opening limitations, in that maintenance of compact, contiguous patches is the objective rather than dispersing harvests that create small patches of young forest. Other recent studies that have analyzed the core area old forest problem are Rebain and McDill (2003), Wei and Hoganson (2007), Wei and Hoganson (2008), and Toth and McDill (2008). Specifically, the forest management model used to solve the KW management problem in this study is based on a dynamic programming (DP) heuristic first described by Hoganson and Borges (1998). The DP solution process is utilized because it recognizes that the problem can be divided into parts (stages) with each stage having a number of possible states, or unique combinations of conditions in the stage. Solving in parts may be efficient because it need not enumerate all possible solutions. In this study, the management problem on the Hiawatha National Forest is formulated to maximize the present net value of the forest while maintaining a minimum amount of KW core area breeding habitat. Management for large, contiguous blocks of habitat has been advocated by Probst (1988) as beneficial to KW colonization and breeding success. Constraining the amount of core area breeding habitat may be used to identify quality spatial habitat design that creates not just large patches of habitat, but large, compact patches.

Dynamic programming, however, has limited application for forest-wide problems when used alone. A DP formulation can find a maximum objective function value, but cannot directly consider constraints. Often forest management problems involve constraints on timber production, age distribution, or cover type amounts that cannot be directly captured in DP formulations, (e.g., USDA Forest Service (2006)). The DP approach, however, has application when fit with a decomposition approach such as Lagrangian relaxation. Lagrangian relaxation incorporates constraints in an LP or MIP objective function and weights the value of those constraints with multipliers to discourage constraint violation. The formulation results in a feasible optimal solution if the correct multipliers are used. The formulation also results in a problem with an objective function value that incorporates the forest-wide constaints, which may in turn be solved with a DP formulation. The search for valid multiplier values associated with non-spatial forest-wide objectives (such as harvest volume flows or age class distributions) was the focus on research of Hoganson and Rose (1984). Their basic approach is expanded in this study to include a search for multipliers that satisfy both non-spatial forest-wide objectives and a core area constraint for KW habitat.

Study Area

Forest managers on the Hiawatha National Forest (Figure 1.1) in Michigan's Upper Peninsula capitalized on the opportunity to develop management strategies to aid in the warbler's recovery during the 2006 Forest Plan Revision (USDA Forest Service, 2006). The Forest's management plan contained two KW objectives: creating and maintaining 6700 acres of suitable habitat, and allowing KW habitat management activities in blocks of up to 1100 acres in a given year. The stem densities of these stands are to correspond with the latest science provided by the U.S. Fish and Wildlife Service (USDA Forest Service, 2006). Suitable breeding habitat is managed on glacial outwash plains owned by the Hiawatha National Forest (Figure 1.1). Overall, the area for potential breeding habitat consists of approximately 174,500 acres comprised of 12,307 stands. Of the total potential area, the Forest has agreed to manage 33,500 acres in the

Kirtland's warbler breeding habitat system comprised of jack pine stands between 0 and 50 years of age. The specific acres managed as suitable breeding habitat, however, have not been explicitly identified. The Forest has discretion in where it places the 33,500 acres of breeding habitat within the total 174,500 acres, and therefore has the opportunity to design a management system that is both financially and spatially efficient.

The desired conditions for the forest's glacial outwash plains consist of a mix of jack pine (*Pinus banksiana*), red pine (*Pinus resinosa*), aspen (*Populus tremuloides*), white pine (*Pinus strobus*), maintained open grasslands, and hardwood mixes including oak (USDA Forest Service, 2006). While generally it is easier to identify existing jack pine sites to include in the Kirtland's warbler breeding habitat system, the forest has the opportunity to convert other cover types both in and out of jack pine. This opportunity is particularly poignant for red pine, which is readily converted to or from jack pine with even-aged management systems. Desired conditions for all cover types and size classes described by the Forest Plan are necessary considerations when identifying and scheduling the Kirtland's warbler breeding habitat system on the National Forest.

Short-term (within the next 10 years) sites suitable for habitat creation were readily identifiable, and the Forest was confident the 6700 acre habitat goal could be met in the near future. However, projections by wildlife biologists indicated that mid-term habitat opportunities (15-35 year) may be limited due to the current age distribution of jack pine on the forest (Henderson, 2006). Additionally, managers were concerned that the shapes and sizes of stands as currently configured may not efficiently generate compact patches desirable for KW habitat. This study attempts to address these two concerns and provides managers with options and trade-off analyses for creating and sustaining the desired level of Kirtland's warbler habitat.

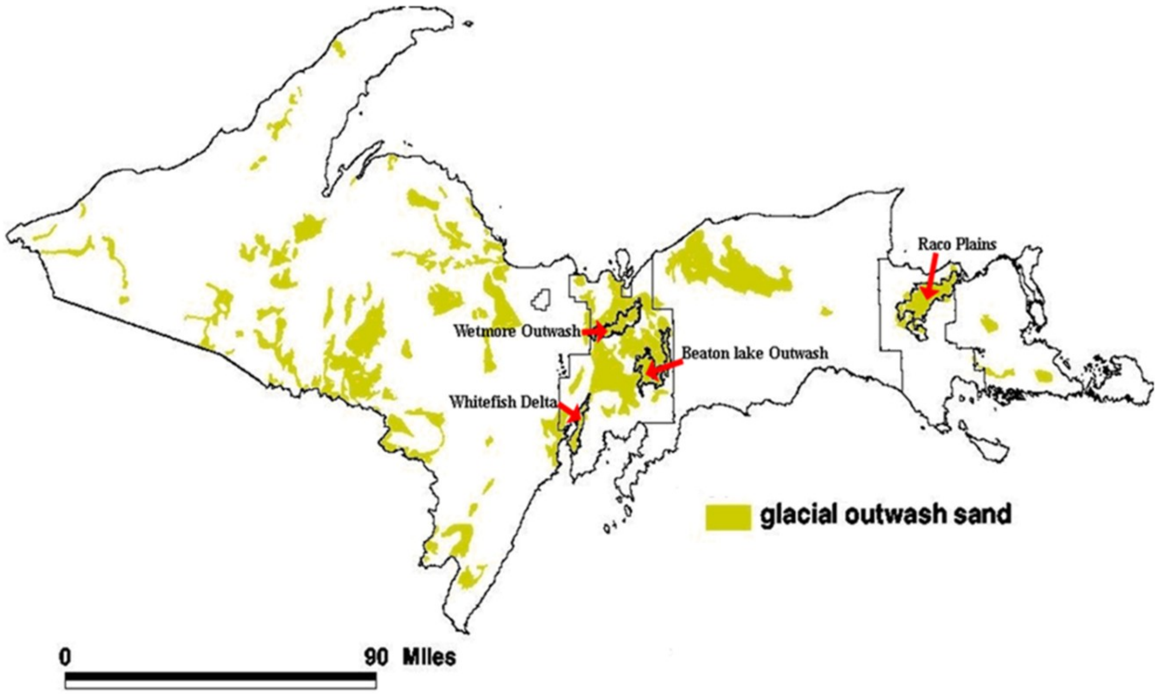


Figure 1.1: Kirtland's warbler potential habitat areas on the Hiawatha National Forest

Objectives of the Study

The main objective of this study is to provide managers with information that contributes to effective strategic planning for Kirtland's warbler habitat management on the Hiawatha National Forest. Several scenarios are developed to examine trade-offs of different habitat management levels and management treatment options. Spatial information for managers is presented, such as the amount, arrangement, and timing of habitat design.

First, however, the modeling solution method for finding good scenario options must be developed. Thus, a second main objective is to develop this modeling solution method. The size of the problem means it may be difficult to solve with an exact mathematical formulation. Therefore, there are two secondary objectives associated with the modeling solution method. Secondary objective (a) is to develop a heuristic search that proves capable of identifying the optimal solution to a problem too large to solve practicably with a full formulation. Secondary objective (b) is to develop a detailed pre-processing routine to substantially simplify the exact mathematical formulation of the problem without compromising optimality.

Model Solution Method Background

The main focus of chapters 2 and 3 of this dissertation is to develop a heuristic solution method to solve a dynamic programming (DP) problem (Bellman, 1954) otherwise too large to solve with a complete formulation. The DP is used to capture mathematically an important spatial facet of the KW management problem; namely, how to arrange future KW breeding habitat into large patches by recognizing the value of core area breeding habitat.

The problem is formulated mathematically recognizing the synergistic benefits of grouping stands into patches that produce core area of KW habitat. Core area measures the area of a patch free of edge effects (Baskent & Jordan, 1995). The amount of core area within a patch depends on more than patch area alone; patch shape is also important, with a low patch edge to area ratio having a higher proportional amount of core area. By changing the focus in the model from total area of KW patches to core area of KW patches, the model is able to consider spatial interactions when scheduling stands for management.

The problem formulation to schedule the desired level of core area is solved with a DP optimization model. While DP has been widely applied in other disciplines (e.g., scheduling production jobs on manufacturing machines (Tang, Xuan, & Liu, 2006) or scheduling power generation activity (Balci & Valenzuela, 2004)), its application in forest-level management planning has been somewhat limited. Dynamic programming formulations in forestry have been used extensively to solve a stand-level thinning problem (e.g., Hool (1966), Amidon and Akin (1968), Haight, Brodie and Dahms (1985), and Arthaud and Klemperer (1988)). At the forest level, Hoganson, Borges, and Wei (2008) describe some of the recent DP applications that include planning for contiguous areas of old forest on National Forests in Minnesota. In these applications, the value of core area of old forest was assumed to be known, and that value was used to determine the specific locations of where core area old forest should be developed (or maintained) within the larger forest.

Finally, the Hiawatha National Forest's forest-wide vegetation desired conditions are considered. The problem is not as simple as scheduling a predefined geographic area with a single desired condition for KW habitat. The 2006 Forest Plan (USDA Forest

Service, 2006) describes desired conditions that include a range of size and species compositions other than KW habitat to be managed in the same ecosystem type as KW habitat. This broader, forest-wide modeling process uses a Lagrange multiplier, or shadow price, search. At least two methods for identifying shadow prices in forestry applications have been identified. Hoganson and Rose (1984) suggest an iterative search process to identify prices that meet forest-wide constraints, while Paredes and Brodie (1989) suggest prices reflect the public's willingness to pay for the goods and services produced by the forest. In this dissertation, multiplier search heuristics based on Hoganson and Rose (1984) are applied through a series of searches where multipliers are iteratively estimated, and the spatial problem is re-solved with the DP with the goal of meeting predetermined constraint levels. In the end, a solution is determined that managers may determine reasonably satisfies not on the total amount of desired KW habitat, but habitat that has a good design in large, contiguous patches. Additionally, the solution will reasonably accommodate the other desired conditions outlined by the forest plan, such as maintained openings, mature red pine, and evenly scheduled management activities through time.

Organization of the Dissertation

The objectives of this study are explored by logically conducting a series of tests to develop and refine a forest management model that can efficiently and accurately identify good management strategies for KW habitat in the context of other forest-wide objectives. There are three main explorations of the study, and a series of appendices with additional background information.

In Chapter 2, a heuristic is described that allows an optimal solution to be found to a dynamic programming problem too large to solve with a single problem formulation. The heuristic likens the decomposition of the large DP to solving a jigsaw puzzle in logical steps. First, the easiest portions of the puzzle are solved, which in turn simplifies the solution search in the more difficult areas. The heuristic is proven capable of identifying the optimal solution to a DP even when the full problem is not solved with a single formulation.

Chapter 3 explores two methods that simplify the DP by logically eliminating sub-optimal stand management options from the DP formulation. The size of problem solved by the DP is dependent on the number of management options for each stand. If before the DP is formulated, the number of management options to include is reduced, the resulting DP is smaller and solves in less time. The stand-based trimming method looks at available management options stand-by-stand to eliminate those with the least amount of value. The grid-based building method uses pre-defined spatially compact subforests (grids) that attempt to encompass the patches of the optimal solution. Within each grid, the management options associated with the best patches are identified and ranked. The ranked options are then compared with the optimal solution for the forest to evaluate the effectiveness of the predefined grids on identifying the optimal management option for each stand. Finally, both methods are applied to the DP to determine how well and how quickly the optimal solution can be identified.

Chapter 4 synthesizes the DP solution methods explored in Chapters 2 and 3 to demonstrate practical exploration of the main study objective; that is, to evaluate different management strategies for developing and maintaining a supply of Kirtland's warbler habitat on the Hiawatha National Forest. Financial trade-offs of different levels of habitat management and projected patch dynamics are explored. The study shows various management strategies that allow for sustainable habitat management with desirable patch size and habitat amounts.

Finally, there are three Appendices that offer further insight into some of the background analytical processes developed for this study.

Appendix A introduces the Bouncing Ball algorithm for designing logical places to split stands into subcomponents that facilitate better patch scheduling. Some stands in the forest's inventory may be non-compact; that is, they have a high edge to area ratio. Often these stands have portions that are "leggy", narrow extensions that protrude into and amongst adjacent stands. The bouncing ball algorithm utilizes properties of a hexagon-based grid to split off leggy portions of stands that may be better managed with stands where they can contribute to more compact patch shapes.

Appendix B documents some Lagrange multiplier search[1] trials that were used to identify efficient solution methods applied in Chapter 4. Since the model is comprised of 30 constrained periods, and includes constraints for cover type and age classes in addition to KW habitat, the search for good multipliers is complex. Methods are introduced that adjust the magnitude of the search direction to be responsive to how close a proposed multiplier comes to identifying feasibility for a constraint.

Appendix C describes a mapping tool that was developed to facilitate visual examination of model inputs and outputs. It was developed in response to the lack of access to GIS software, but ended up being quite useful for identifying model formulation improvements and interpreting model outputs. One interesting feature is that a time series of outputs can be loaded with a single file, and the program allows the user to automatically visualize habitat conditions and landscape changes as if watching a time-lapse photography series. The tool was initially developed for hexagon-based displays, but was readily adapted for square-based displays used in a study based in Idaho.

[1] Lagrange multiplier search is discussed in Chapter 2

Chapter 2 : A Proposed Heuristic to Solve a Forest Management Problem with High Temporal and Spatial Complexity

Introduction

Harvest scheduling that considers spatial arrangement of activities has emerged as an established field of research. Cost savings may be realized when harvests are considered in a spatial context (Weintraub & Navon, 1976). Federal and state policies sometimes place restrictions on the size of clearcut openings that should be considered when scheduling management activities (Boston & Bettinger, 1999). When the spatial arrangement of harvesting activities is considered, managers may be able to either minimize negative impacts or maximize positive benefits to patterns on landscape (Hof & Bevers, 2002). The spatial arrangement and pattern of forest management activities impacts the quality and quantity of other resource uses of a forest, and should therefore be considered in context of the timing of expected activities (Snyder & ReVelle, 1997). Finally, spatial patterns can be designed with harvest scheduling activities to benefit (or reduce negative impacts on) habitat characteristics for wildlife (Bixby, 2006).

Improved solution techniques, recent advances in computing technology, and the need to recognize spatial considerations at tactical and strategic planning levels are factors that have caused spatial components of forest management problems to be explicitly incorporated into strategic forest planning models. Recent examples of this are extensive, but generally they focus on one of two common problems, namely, adjacency and old forest reserve. The adjacency problem places restrictions on the maximum opening or clearcut size, and the old forest reserve problem schedules contiguous large patches of similarly-aged older forest. Problems involving adjacency constraints were investigated beginning in the early 1990s, and were used to address, among other issues, spatial harvesting restrictions associated with USDA Forest Service National Forest management (Murray & Church, 1996). There are two basic formulations of the adjacency constraint, the Unit Restricted Model (URM) and the Area Restricted Model (ARM) (Murray, 1999), (Murray & Snyder, 2000). The URM is straightforward; adjacent units are not allowed to be harvested such that they create young forest at the same time. The ARM allows several units to be harvested at the same time so long as they do not create an opening larger than a specified size. Additional examples of early adjacency constraint studies include Torres-Rojo and Brodie (1990), Lockwood and Moore (1993), Murray and Church (1995), Hoganson and Borges (1998), and McDill and Braze (2000). More recent adjacency studies often use formulations solved with exact methods. For example, Martins, Alvelos, and Constantino (2012) introduce a branch and price formulation for solving problems involving 45 to 2945 stands and three to twelve planning periods. Another example is a study by Goycoolea et al. (2009) that described solving adjacency problems with a branch and bound algorithm.

Recent studies have also focused on designing forests in contiguous patches of similarly-aged cohorts to address wildlife habitat requirements. Interior dependent wildlife species may require certain levels of undisturbed forest free from fragmentation (Ohman & Lamas, 2003). Bixby (2006) discusses the concept of patch-size effect, where a species response to an amount of habitat is affected by the spatial arrangement of that habitat. The problem has been addressed by managing for target levels of core area forest, or forest free from edge effects (Ohman & Eriksson, 1998), (Ohman, 2000), (Bixby, 2006). The core area problem is in some ways the inverse of the adjacency problem, in that maintenance of contiguous patches is the objective rather than dispersing harvests to create small patches of young forest. Other recent studies that have analyzed the core area old forest problem are Rebain and McDilll (2003), Wei and Hoganson (2007), (Wei & Hoganson, 2008), and Toth and McDill (2008).

Another type of problem has been explored is one that involves the clustering of harvest activities to realize cost savings. The earliest examples of these problems accounted for road building and access concerns, which in turn resulted in harvest units being clustered along commonly used road segments. Examples include Jones, et al. (1991), Weintraub, et al. (1995), Richards and Gunn (2000), and Contreras, Chung, and Jones (2008). A second generation of studies, such as Ohman & Lamas (2003), described a method to constrain timber volume that is generated in close spatiotemporal proximity. Their study explored the trade-offs from requiring harvest aggregation at different intensities, and was solved with a simulated annealing technique. A more recent study by Ohman & Eriksson (2010) used a mixed integer programming technique to minimize the edge caused by harvest activities. Another study by Heinonen, Kurttila, and Pukkala (2007) brought together the old growth reserve and harvest clustering problem. They focused on aggregating hexagon-raster forest into cutting units and old growth reserves by maximizing shared borders of cut units and minimizing the border between cut and uncut units. The harvest clustering problem, however, has remained largely unexplored, as indicated by the relatively few studies that have addressed it.

Forest management problems with spatial solution components can easily fall in a realm of combinatorial problems too large to solve with exact optimization methods due to computing time and/or memory limitations. Goycoolea, et al., (2005) noted the difficulties in solving problems with increased planning periods. Martins, Alvelos and Constantino (2012) cited difficulties formulating the problem when the number of stands is too large. They also encountered problems so large that the branch-and-bound algorithm could not identify an optimal solution. Goycoolea, et al., (2009) encountered difficulties finding a feasible solution when green-up constraints were imposed. Computing limitations have resulted in numerous heuristic, meta-heuristic, and hybrid approaches used to solve spatial forest management problems. Heuristic searches are designed to find a good solution by incrementally evaluating a solution space with local search procedures, such as "hill climbing" (Laguna, 2002). In a hill climb search, an initial solution is determined, often at random, and the solution is modified with small, incremental moves until all possible local moves result in inferior solutions (i.e., the current solution is the best among the possible moves). The solution, however, is prone to arrive at a local optimum inferior to an undiscovered global optimum. Heuristic searches have also been used to modify exact solution methods such as Linear Programming (LP). Hoganson and Rose (1984) describe three heuristic search methods to determine dual variable values that satisfy LP constraints. These heuristics, while able to derive optimal solutions, are challenged with arriving at an exactly feasible solution.

The shortcomings of simple heuristic search resulted in the development of "meta-heuristics", a term coined by Glover (1986). In his paper, Glover indicates the purpose of a meta-heuristic is to modify a heuristic search procedure to escape locally optimum points. Many meta-heuristic solution strategies have been applied to forest management and spatial forest management problems. Baskent and Keles (2005) provide an extensive review of many of the methods that have been applied in recent times. In this review, they classify meta-heuristics into broad categories that include Monte Carlo Integer programming, controlled randomization (simulated annealing), tabu search, genetic algorithm, and user-specific methods. Most meta-heuristic methods can be classified in the first four categories (Monte Carlo Integer programming, controlled randomization, tabu search, and genetic algorithm), including those with unconventional names such as “ant colony optimization” (i.e., tabu search, according to Laguna (2002)), and “great deluge”, which is a derivation of simulated annealing (Bettinger, Graetz, Boston, Sessions, & Chung, 2002)). One example of a user-specific method cited in the Baskent and Keles (2005) paper is the dynamic programming approach developed by Hoganson and Borges (1998). In this approach, an exact solution method (dynamic programming) is modified for computational feasibility by decomposing the problem into a series of overlapping windows. Each window, or cohort of stands smaller than the larger forest, contains stands that belong to one or more other windows. Schedules for stands that are included in more than one window are not accepted until all windows in which they are a part of are solved. Windows overlap in such a way to ensure multiple solution options are explored before a solution is accepted for a given stand. Arguably, this method is not a true “meta-heuristic” in that it does not modify a heuristic to escape local optima, but rather modifies an exact solution method so that it can be solved with modern computing capabilities. The commonality it has with meta-heuristic methods, of course, is that it does not guarantee identification of the global optimum.

Other research has focused on combining two or more solution techniques to leverage advantages of each and produce superior solutions. Such studies fall into the realm of hybrid algorithms. Hybrid algorithms used to solve forest management problems may combine two or more meta-heuristic methods (e.g., Bettinger et. al (2007)) or a meta-heuristic method with an exact solution method (e.g., Hoganson and Borges (1998)). One such study that combined a meta-heuristic with an exact method was conducted by Ohman and Eriksson (2002). In this study, simulated annealing (SA) was used to identify stands to manage for continuous old forest conditions, while linear programming was used to derive management schedules that satisfied harvest flow and ending inventory constraints. The study, however, resembles a lexicographic goal programming problem, where the spatial solution derived with SA is used to constrain the LP. A lexicographic goal programming formulation uses two objective functions; the solution value obtained from the first objective function is used as a constraint in solving the second objective function. In this case, the first objective function was to manage for old forest, while the second was to maximize net present value. The authors concede the sequential nature of this method may result in a sub-optimal solution. Still, the method produced better solutions than simulated annealing, even though SA considered both objectives simultaneously.

Contemporary studies for spatial forest management problems are becoming more solely focused on exact solution methods, most commonly mixed-integer programming (MIP). Previously, moderately sized spatial problems were unsolvable with exact methods due their large formulations that exceeded the available computing capacity required to solve them. Examples of some recent MIP applications focused on creating large patches of contiguous forest include Wei and Hoganson (2007), Toth and McDill (2008), and Ohman and Eriksson (2010). Mixed-integer programming has also been extensively employed to address adjacency constraints. Goycoolea M. , Murray, Vielma, and Weintraub (2009) evaluate three common formulations of the Area Restriction Model solved with the branch-and-bound algorithm. However, they note the solution time for these formulations is “painfully slow”. Another solution tactic, branch-and-price, has been demonstrated to solve adjacency problems faster than branch-and-bound (Martins, Alvelos, & Constantino, 2012). Finally, solution speed can be increased by including constraints in the objective function. In a study designed to identify reserve site selections, Snyder, ReVelle, and Haight (2004) discovered that using a weighted two-objective formulation yielded faster results than a single objective function with forest-wide constraints.

Dynamic programming (DP) is another common model structure in operations research (Bellman, 1954) that has proven useful in solving forest management problems. The DP solution process is utilized because it recognizes that the problem can be divided into parts (stages) with each stage having a number of possible states, or unique combinations of conditions in the stage. Solving in parts may be efficient because it need not enumerate all possible solutions. For example, a problem with 9 stages and 10 options per state would have 10^9 possible solutions (1 billion). Yet using DP, the problem can potentially be solved by linking solutions to 81 subproblems each with only 10 choices. Hoganson, Borges, and Wei (2008) describe some of the history of DP in forestry problems. They outline early applications such as stand-level thinning, where the stages of a problem are the timing choices of the thin before an even-aged management action. More recent applications have involved solving problems for forest-wide spatial constraints such as adjacency (Hoganson & Borges, 1998), and patches of older forest core area (Hoganson H. M., Bixby, Bergmann, & Borges, 2004), (Wei & Hoganson, 2008). The DP formulations in forest-level modeling are often too large to be solved exactly with a single DP network. Therefore, Hoganson and Borges (1998) describe a solution strategy involving a series of overlapping subproblems, or moving windows. In this strategy, each window defines a group of stands that formulate a DP problem small enough to be solved exactly. Solutions to a portion of the stands in the window are accepted and used to formulate the next window. The stands with accepted solutions do not add to the size of the problem, and therefore the next window includes all the first window stands plus additional stands that span further across the forest. The strategy continues until all stands in the forest have been evaluated. The moving windows heuristic has been adapted a number of times, beginning with Borges, Hoganson, and Rose (1999), who explored stand sequencing strategies with irregular polygons. Later, Hoganson et al. (2004) modified the heuristic to address core area management by using the concept of influence zones, or areas of the forest that are dependent on coordinated management of one or more stands to meet the spatial objectives of the problem. Since the size of the windows can influence both solution speed and solution quality, Wei and Hoganson (2008) investigated model simplification strategies with the goal of increasing solution speed with minimal effects on solution quality. Dynamic programming has also been used in recent stand-level decision models that account for stochastic disturbance events (Ferreira, Constantino, Borges, & Garcia-Gonzalo, 2012). Model II structures of LP harvest scheduling problems (Johnson & Scheurman, 1977) are easily represented as DP networks, with the Model II variables basically representing a DP structure of breaking the timing horizon for individual stands into parts, thus eliminating the need to enumerate all management options like in a Model I formulation.

Dynamic programming, however, has limited application for forest-wide problems when used alone. A DP formulation can find a maximum objective function value, but cannot directly consider constraints. Often forest management problems involve constraints on timber production, age distribution, or cover type amounts that cannot be directly captured in DP formulations, (e.g., USDA Forest Service (2006)). Additionally, even with the simplified nature of examining solutions with a DP formulation, the problem may be too large to be solved with a single formulation, and requires heuristics to solve (Hoganson & Borges, 1998). The DP approach, however, has application when fit with a decomposition approach such as Lagrangian relaxation. Lagrangian relaxation incorporates constraints in an LP or MIP objective function and weights the value of those constraints with multipliers to discourage constraint violation. The formulation results in a feasible optimal solution if the correct multipliers are used. The multipliers can be referred to by several different names, including Lagrange multipliers, marginal values, shadow prices, shadow costs, and dual variables. While there are few examples in forestry, the approach is more common in other disciplines such as scheduling production jobs on manufacturing machines (Tang, Xuan, & Liu, 2006) or scheduling power generation activity (Balci & Valenzuela, 2004). The Hoganson, Borges, and Wei (2008) chapter outlines some of the forestry related DP/Lagrangian relaxation studies that have occurred to date. Specifically, the Hoganson and Borges (1998) study used DP to address adjacency constraints. The DP approach was later adapted to address core area for old forest without explicit constraint levels for core area (Hoganson, Bixby, & Bergmann, 2003), (Wei & Hoganson, 2005). Extensive work was conducted to improve the solution time of core area problems by Wei and Hoganson (2008). This study encountered two influential complexities: a large number of areas where 10 or more stands required coordinated management actions to create core area and buffer conditions that were less restrictive than core area itself which caused sub-influence zones to be evaluated separately. Sub-influence zones are the portion of an influence zone within a particular stand.

Another challenge with DP formulations is that they become disproportionately large with moderate increases in stand-level decision options, a condition known as the “curse of dimensionality”. For example, in a DP stage that consists of five management options per state across eight state dimensions, there are 5^8 (390,625) unique states. If for each of these eight state dimensions the number of management options increased from 5 to 10 (as would occur if there were more timing possibilities for the management choices), the size of the problem would increase by a factor of 2^8, or 256 (resulting in 100 million states). Clearly, this results in a challenging problem to solve and currently relies on the use of the aforementioned heuristic techniques to break the problem into smaller pieces.

The main objective of the study presented here is to extend the moving windows heuristic of solving a large dynamic programming problem by exploring techniques that find better solutions in less time. The moving windows heuristic is applied to the wildlife management problem that sets explicit constraints for the amount of core area habitat desired. The study employs the use of shadow prices, or the opportunity cost associated with producing core area habitat. An explicit constraint on core area is an extension of the DP/Lagrangian relaxation studies in forestry that to date have set the shadow price of core area exogenously and allowed the DP to determine the levels achieved at those prices (Wei & Hoganson, 2005). This study assumes that the shadow price estimates are known or can be estimated correctly using Lagrange multiplier search techniques. Shadow price estimates need to be modified if the solution is infeasible or if complementary slackness conditions are violated excessively. The search technique may take hundreds, if not thousands of iterative trials before prices that result in an acceptable solution are found. With a solution method that calls for many DP solution trials combined with the fact that each DP formulation is potentially large, it is advantageous to explore additional heuristic methods and simplification techniques that allow the problem to be solved faster.

The methods are applied to a real forest and wildlife management problem faced by managers on the Hiawatha National Forest (HNF) in Michigan. The Forest's land management plan has an objective to create and maintain 6700 acres of suitable Kirtland's warbler (*Setophaga kirtlandii*) habitat that can be created from regeneration harvest patch sizes of up to 1100 acres in a given year. Suitable habitat consists of young jack pine (*Pinus banksiana*) 6-16 years old. The forest has committed to maintaining 6700 acres of suitable breeding habitat on a 50-year rotation, which equates to a total of 33,500 acres in the habitat system (USDA Forest Service, 2006). Suitable areas for habitat management (sandy glacial outwash plains) on the HNF consist of approximately 174,500 acres comprised of 12,307 stands. The specific areas managed as suitable breeding habitat, however, have not been explicitly identified. The Forest has discretion in where it places the 33,500 acres of breeding habitat within the 174,500 acres, and therefore has the opportunity to design a management system that is both financially and spatially efficient.

Methods

Problem Formulation

The basic problem explored in this study is to create a sustainable level of Kirtland's warbler (KW) habitat, aggregated into large compact patches. Suitable patches can range from 80-1100 acres in size, (USDA Forest Service, 2006). The overall level of KW habitat is achieved by requiring a minimum level of core area, hereafter referred to as the spatial constraint or spatial objective of the problem. Core area forest is free from edge effects, and exists a certain buffer distance from an edge, (Ohman & Eriksson, 1998), (Ohman, 2000), (Baskent & Keles, 2005). Core area definition in this study was simplified by using a two acre hexagon grid to define the stands in the forest. The grid was intersected with the Hiawatha National Forest's vector-based stand layer and the stand with the most area in hexagon was used to attribute that hexagon. Hexagons that were part of the same original stand were then combined to form the stands used in this problem. Hexagons were chosen to simplify the core area calculation since they have regular spatial interactions with all adjacent hexagons (as opposed to squares or irregular polygons). The buffer distance implemented in this study is the area outside a center hexagon formed by connecting the centers of the six adjacent hexagons. The concept is displayed in Figure 2.1. There are portions of seven 2-acre hexagon-based stands depicted in this figure (they are numbered). The buffer is the large hexagon in the center that overlaps all seven stands to some degree. In order to produce core area, a cluster of at least 3 hexagons must meet the overall definition of KW habitat. In Figure 2.1, the area in the triangle represents the amount of core area KW habitat created if Stands 1, 3 and 4 were managed in a coordinated manner. Core area is created by coordinating the management options of "influence zones" (see Bergmann (1999), and Hoganson, Bixby, and Bergmann (2003)). Any influence zone is unique and it is comprised of all of the stands that must have coordinated management to achieve core area. An influence zone can be fully within one stand, or it may include parts of up to several stands. In this study, influence zones were designed such that an influence zone was never comprised of more than three stands. An example of an influence zone is the shaded triangle in Figure 2.1. For this zone to be core area, conditions in Stands 1, 3, and 4 must all meet core area conditions. Influence zones can be very large, in the instance of the core area of a single large stand (the center of the stand as buffered inward) or between two large stands that share a long border. Other buffer distances can be used that would result in more stringent requirements to produce core area (e.g., if the buffer distance was assumed to be 1 hexagon, all 7 stands in Figure 2.1 would have to be coordinated to produce core area in Stand 1). Efficiencies can be gained as more stands are managed together to create core area in their influence zones and the proportion of core area to total stand area managed increases. Thus, the best solutions likely consist of large, contiguous patches.

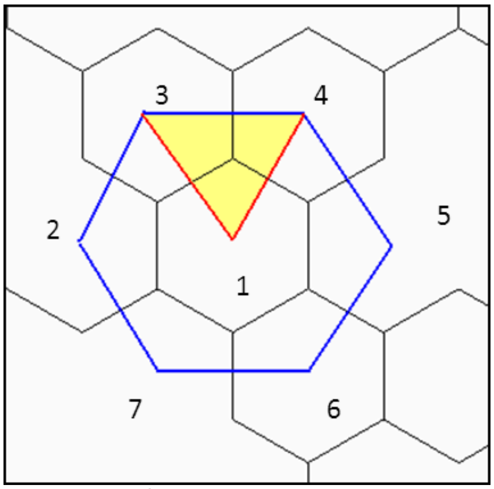


Figure 2.1 Influence zone and core area illustration for hexagon-based raster. The area influenced by stand 1 is represented by the large surrounding hexagon. The triangle represents the influence zone that consists exclusively of Stands {1,3,4}, which is also the core area created by coordinating their management.

This problem is solved with a dynamic programming (DP) formulation. Each *stage* of the problem represents the decision space for a single stand in the problem, and associated arcs for the stage include information about all of the decision variables, or management options, associated with that stand. Each *state* at the start of a stage in the problem is a unique combination of management options for stands addressed in earlier stages of the DP formulation. A stand is dropped as a state descriptor after all stands it interacts with directly (through common influence zones) have been addressed as a stage in the formulation. Paths between the stages (connecting states of different stages) are known as *arcs*, and can be used to indicate the value of choosing the management strategy associated with the two states the arc connects. The number of state dimensions at a given stage in this problem corresponds directly to the number of stands wide that the formulation ("forest") is addressing. This width depends on the side of the "forest" that corresponds with stage 1 of the formulation. For example, if the formulation has the first stages associated with stands on the west side of the "forest" then width relates to width in the north-south direction. Generally, if the DP formulation starts with stands (stages) on the west side of the forest, then the farther west a stand is, the sooner it is addressed in the DP formulation.

The DP concept is illustrated in Figure 2.2 with a simple four stand example. There are two opportunities to create core area with these four stands, indicated by the two triangles in the upper portion of the figure. The objective is to manage for the highest value of core area possible. For each stand, there are two management options, *a* and *b*. If core area is the only value recognized by the problem, and core area is valued at 2 when management option *a* is used and 1 when *b* is used, the problem becomes solvable by inspection (schedule all stands with option *a* for a total value of 4). The bottom portion of the figure, however, is included to show the enumeration of the entire problem. While other formulations may be generated to sequence the stands in alternative orderings (Borges, Hoganson, & Rose, 1999), the one presented is likely one of the simpler formulations. The network created with the states (ovals), arcs (lines), and stages (there are 4, associated with each set of arcs that connect states, e.g., “start” to 1a or 1b) is a complete enumeration of all possible management option combinations of the four stands. Each state is labeled with the stand number(s) and management option(s) associated with the management strategy of the state (e.g., 1*a* is stand 1 option *a*). Tracing a path from “start” to “end” represents a complete scheduling strategy for all stands. The arcs with positive value are labeled with their value, and are shown at the top and bottom of the network. Again, by inspection, the path with the highest value can be traced through a path that schedules all four stands with management option *a*, indicated by the path at the top of the network.

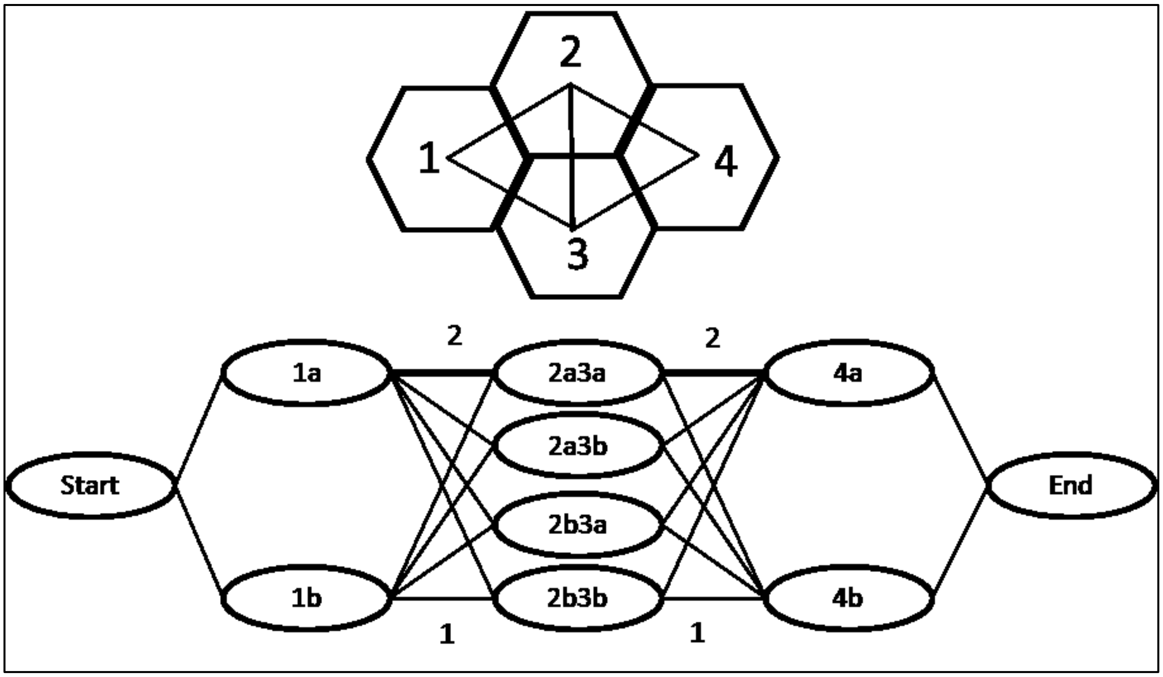


Figure 2.2: Four stand forest with two management options per stand and corresponding DP formulation

The general DP formulation is described in Hoganson et al. (2004) and in Wei and Hoganson (2008). Below is a simplified description of the formulation.

Find

$$f_1^*(1) \tag{2.1}$$

Where

$$f_i^*(s_j^i) = \max_d [r(d_i) + c(s_j^i, d_i) + f_{i+1}^*(s_k^{i+1})] \tag{2.2}$$

$$s_k^{i+1} = s_j^i \otimes d_i \tag{2.3}$$

$$f_{N+1}^* \; 1 \; = 0, \quad \forall i \tag{2.4}$$

In this formulation, there are N stands (and stages), represented individually as stand *i* with stands numbered to match their stage number. Equation (2.1) describes the optimal value of the one starting node at Stage 1, representing the maximum value of all paths through the network. Equation (2.2) defines how the value of each node at each stage is determined. In Equation 2.2, s_j^i represents the states (nodes) at stage *i*, state *j*, and consists of the set of unique management combinations for all stands used for state descriptors for the start of the stage. Each d_i is a decision option (management option), for stand *i.* The term $r(d_i)$represents the discounted value of the non-spatial benefit of d_i, which includes both value of financial flows (revenues and costs) and the value of the constraints that d_i impacts (the shadow price of a constraint multiplied by the area of *i* if d_i partially satisfies the constraint). Term $c(s_j^i, d_i)$ is the net present value of core area production resulting from d_i if at state *j* at the start of stage *i.* and includes only the shadow priced value of core area associated with the associated stage i decision. The final term of Equation (2.2), $f_{i+1}^*(s_k^{i+1})$, represents the optimal value of state k at the start of stage *i+1*. Equation (2.3) identifies the state *k* at the start of the next stage (*i+1*) if at stage *i* and state *j* decision d_i is made for stand *i.* Equation (2.4) is included to allow Equation (2.2) to be generically applied to the final stage of the formulation, and simply means that at the final stage, the value of stage *N+1* is 0. The formulation is solved with a backwards solution approach, beginning with evaluating the final stage of the formulation associated with stand N, and searching through the network to find the value of $f_1^*(1)$.

A Search Heuristic

An objective of this study was to strengthen the moving windows heuristic (Hoganson & Borges, 1998) to solve a large DP problem with more precision. The study builds on work by Wei and Hoganson (2005) and Wei and Hoganson (2008) by testing several different problem formulations before scheduling any given stand. Stand management options can be accepted as part of the solution if they are consistently scheduled regardless of the problem formulation (i.e., they are robust schedules). Those stands where different formulations result in different management option schedules are less robust and should undergo more testing before they are accepted as part of the solution.

As stands' schedules are accepted as part of the solution, it can result in a simpler problem formulation for the remaining stands. The solution process can be likened to solving a jigsaw puzzle, where the easiest portions of the puzzle are solved first, which in turn may make the difficult areas easier to solve. Consider a rectangular jigsaw puzzle 50 pieces wide by 20 pieces tall. The puzzle has two components: the pieces and the spaces that pieces occupy. Spaces represent stands in the forest and the pieces represent the management choices for those stands. The analogy deviates slightly from a jigsaw puzzle that has an equal number of spaces and pieces. In this puzzle, there is a known and unique set of pieces for each space (say, 1 to 30 potential pieces), each having a different color, but not all spaces include the same color choices. The colors represent the different management options available for the stand. The problem can also be thought of a map coloring problem (e.g., Appel and Haken (1976)) yet a jigsaw puzzle comparison highlights the sequential nature which potentially reduces the size of the problem substantially as the scheduling process unfolds.

The proposed heuristic will put the entire puzzle together multiple times. Each time, the puzzle is solved in parts by selecting a starting edge of the forest and defining a width (in pieces) along that edge to solve all at once with a DP formulation as described earlier. Assume the rows of the puzzle are numbered 1-20, starting at the bottom edge. Consider attempt 1 comprised of rows 1-4 along the bottom edge of the puzzle with 200 pieces. This set of rows is termed a “window”. Assume this window is solved exactly with reasonable speed, i.e., the optimal solution is determined for rows 1-4. However, since the global optimal solution depends on context in the larger puzzle, only the solutions of rows 1 and 2 are accepted as optimal and are in turn used to help solve the remainder of the area. After the first window is solved, a second window is formulated to include the first four rows of stands in addition to the next two rows towards the top (5 and 6) of the puzzle. Since the solutions to rows 1 and 2 have been determined, they do not add to the size of the problem formulation. When this second window is solved, the solutions to rows 3 and 4 are accepted as optimal, and the process continues until the top of the puzzle is reached. This use of overlapping windows and DP is similar to process initially used by (Hoganson & Borges, 1998) to address adjacency constraints.

To check the efficacy of this solution, one can consider starting from a different edge, and perhaps even using a window a different number of rows wide. Attempt 2 might start at the left side of the puzzle, use windows 5 rows wide, and accept 3 rows’ solutions in each window moving left to right. Subsequently, the solutions from Attempts 1 and 2 could be compared for each stand. If a stand has the same solution (piece) in each Attempt, one might assume it is a good or robust solution. Alternately, one could solve from more directions with varying numbers of rows solved each time (window widths) before accepting the solution for any stand.

With this proposed heuristic, as more pieces are put into place, the remaining puzzle is likely easier to solve. As the process unfolds, there may be smaller “holes” that become mini-puzzles and relatively easy to solve exactly with a single window (i.e., all rows are included). A solution to a “hole” found with a single window can be fully accepted, since is the optimal solution for that portion of the puzzle.

The proposed heuristic is illustrated in Figure 2.3. Once the possible management options for each stand have been identified, the maximum window width is defined by the modeler. This information is used to identify and solve spatially distinct subdivisions, or smaller puzzles that can be solved independently of each other. Subdivisions are the result of physical boundaries (such as roads, private lands, non-forest, etc.) that spatially isolate portions of the forest. Each spatially isolated portion of the forest is a subdivision. If a subdivision is too large to be solved with a single DP formulation, it is solved with a series of overlapping windows according to the current window direction and size (i.e., a “trial”). Two parameters (θ and δ) were considered for accepting the schedule (management option) for an individual stand. If the consistently chosen management option contributed to the spatial constraint (minimum level of core area), it was accepted after θ trials. If the consistently chosen option did not contribute to the spatial constraints (i.e., it was more valuable in contributing to net present value or other problem constraints), it was accepted after δ trials. Accepted management options were then the only options used for those stands in the ensuing DP formulation. One might consider different values for θ and δ to allow a solution to converge more gradually, or to explore options to expand patches solved after θ trials with a higher δ. Accepting management option schedules for stands simplifies the DP and can result in fewer windows with more stands included in each window.

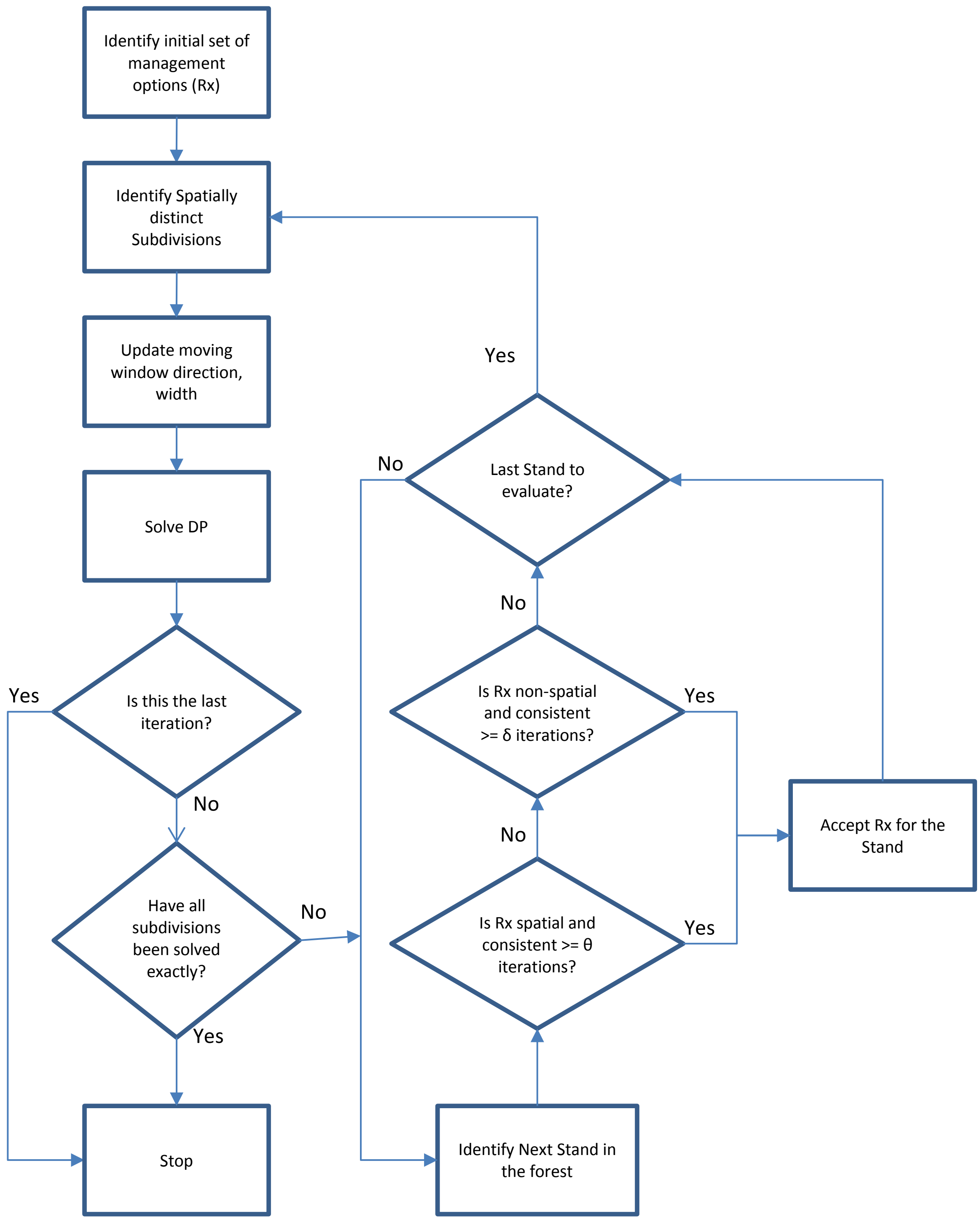


Figure 2.3: The heuristic used to solve a large Dynamic Programming problem with a series of smaller formulations. “Rx” is an abbreviation for management option.

Using Subdivisions to Solve Spatial Problems

This solution method exploits the phenomenon that a forest can be decomposed into smaller, spatially isolated portions of the forest called "subdivisions" that can be solved independently. First, there are natural barriers to achieving spatial objectives, such as roads, private inholdings, major water bodies, ecological site potential, etc. that can be recognized before the problem is formulated. Secondly, there is an economic factor that allows for decomposition; some stands are poor financial candidates for producing core area, either because of their proximity to other stands or their value in meeting other desired forest conditions (such as old growth or growing more valuable timber) exceeds the value in meeting spatial objectives. Natural barriers are considered exogenously by ensuring that areas incapable of contributing to core area constraints are either removed from the model or assigned only management options that do not produce core area. Such areas include non-forested areas, areas of non-ownerships, or ecological site conditions not suited for growing jack pine, and were identified with stand-level data maintained by the Hiawatha National Forest. The financial factor is considered by comparing the value of a stand in meeting other desired conditions (i.e. shadow prices) to the stand's value in producing core area. If the stand is more valuable in contributing to other desired conditions, it need not be considered for core area production. Alternately, poor candidates may be recognized simply by virtue of them never being selected to satisfy the core area constraints in any DP formulation. Subdivisions are linked together to the overall problem formulation by the spatial shadow price (Lagrange multiplier) estimates. This assumption enables equal accountability across the different subdivisions. Searching for spatial independence based on proximity and financial value can identify small subdivisions that can be solved independently with a complete, exact DP formulation.

The act of accepting solutions that do not contribute to spatial objectives creates another phenomenon that can be exploited by the proposed heuristic. That is, when stands are determined to be financially undesirable for contributing to the spatial constraints, they are removed from the problem formulation (after δ trials with a consistent solution). If these stands are physically located between good spatial candidates, and removing them isolates groups of good candidates on either side, the forest might be further split into smaller, easier to solve subdivisions. Therefore, it is advantageous to evaluate the remaining problem for more subdivisions after each trial if polygons that do not contribute to spatial value are eliminated for consideration by the DP.

Overlapping Windows Formulation

After the problem is decomposed into subdivisions, some subdivisions are likely too large to solve with a complete dynamic programming formulation. When this is the case, the subdivision is further decomposed into overlapping subproblems (windows), a solution technique first described by Hoganson and Borges (1998). The concept is illustrated in the Figure 2.4 below, which represents the 1256 stands in the largest subdivision solved in this study. The subdivision has been processed to remove private inholdings, areas with no ecological potential to create KW habitat, roads, and water bodies. It has further been processed to remove all stands that have greater value contributing to constraints other than the core area constraint. Finally, those stands that have a single management option that contributes to the spatial objective (such as those already identified by managers) are recognized since they contribute to overall core area but do not add to the complexity of the DP formulation. In Figure 2.4, the first window is comprised of those stands at the top-right portion of the forest (“Included” and “Schedule”). The first stage of the DP network is in one of the two narrow ends of the window (either on the left or right, depending on what the user specifies) and adds stands to the network as it moves horizontally toward the other end of the window. The nature of the problem allows one to drop stands as state variables once all of its spatial interactions have been enumerated, thus keeping the stands used for state identifiers to those along a “front” that separates stands addressed in an earlier stage from stands yet to be included in the DP network. Once an exact solution to the DP formulation for the window is found, the solutions for the topmost rows of stands (“Schedule”) are accepted and used to help inform the next Window DP formulation. The illustration in Figure 2.4 represents acceptance of solutions for the 40% of the area that is farthest from the stands yet to be included in a window (“Schedule”).

Window size is dependent on the maximum number of nodes allowed at any one stage of the formulation. The number of nodes for each stage depends on the number of stands needed as a state identifier for the stage as well as the number of management options associated with those stands. For example, a DP formulation that has 4 stands along the front at the start of a given stage with 5 options available to each stand will have 5^4 nodes at the start of that stage. Figure 2.4 shows a 25 million maximum node limit for stands that had a maximum of 5 management options available. This generally means the narrowest portion of the formulation is 9 stands, and the widest could be much greater if fewer than 5 management options are available to some of the stands defining the front.

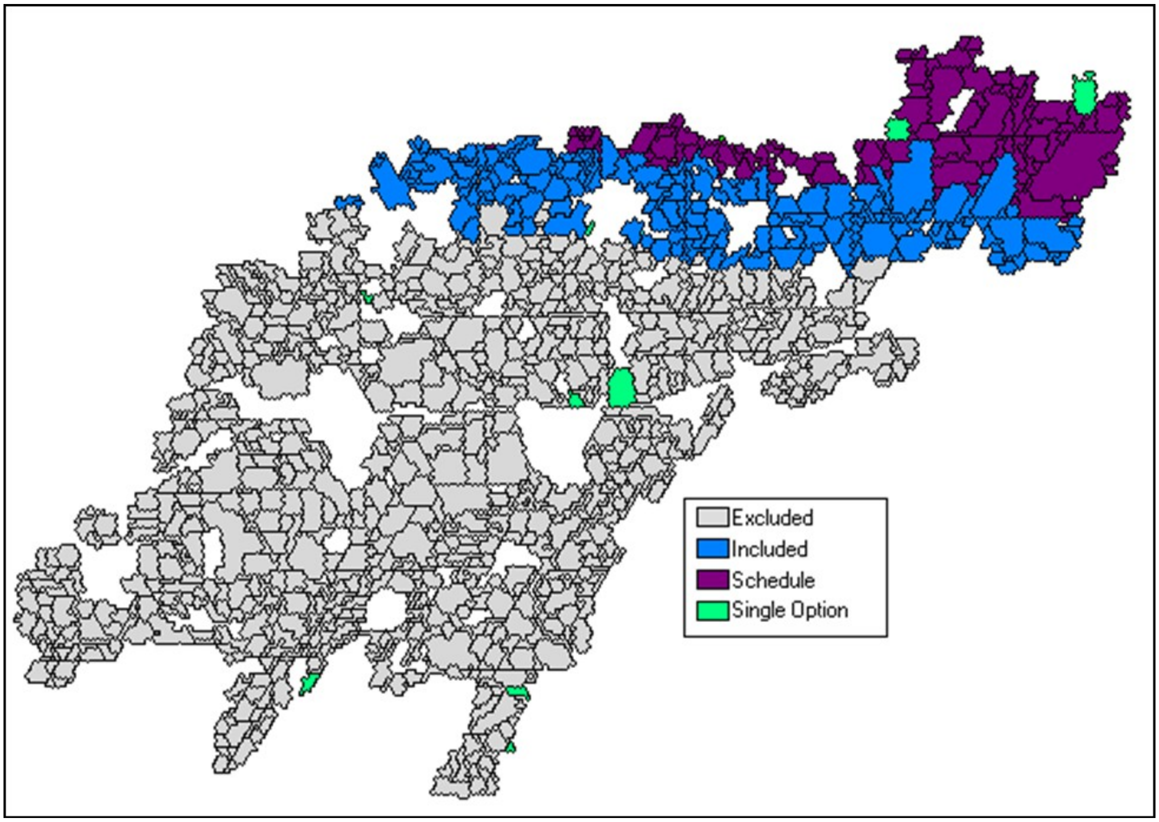


Figure 2.4: Moving Window illustration: 1256 stands in a subdivision solved with the model. Stands are aggregations of two-acre hexagons. Single option stands have a single known solution that contributes to the spatial objective. “Included” and “Schedule” stands are those included in the first DP Moving Window formulation. Solutions found for the “Schedule” stands are accepted before the next Window is formulated.

Window Design

Eight different window designs were used to test the efficacy of using overlapping windows to find good solutions. The side of the forest where the windows began and the direction of the DP formulation within that window were used to construct different problem formulations. Consider the simple illustration in Figure 2.5:. The oval represents a generic forest (the puzzle). Windows would be constructed of stands beginning at one edge of the forest (one of the four long, narrow arrows). Each window is solved by assembling the pieces starting at one end of the window and working in the narrowest direction toward the other end. Each of the eight diamonds represents a different starting point for the DP; the narrow arrows represent the side of the forest the window starts from. The wide arrows illustrate the direction in which the windows overlap until the other side of the forest is reached. For example, windows that start at the top of the widest direction of the forest and move down can have a DP formulated from the left or the right. This particular formulation is also illustrated in Figure 2.4.

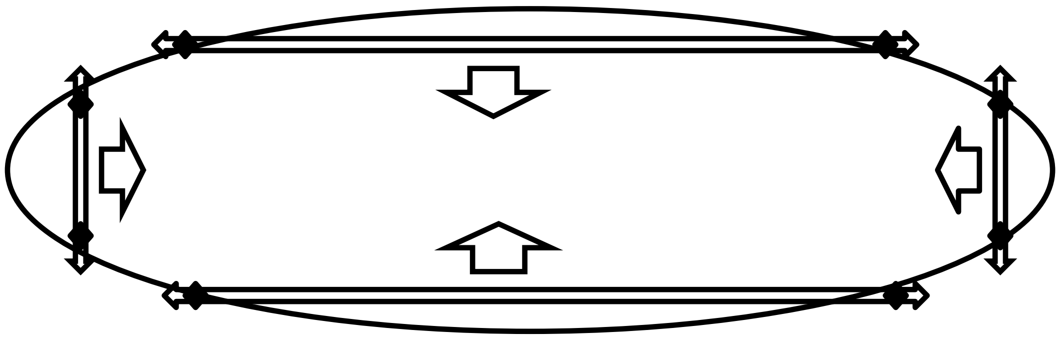


Figure 2.5: Illustration of the eight different Moving Window designs.

Case studies

The dataset for this study was derived from information provided by the Hiawatha National Forest (HNF) in Michigan. The entire National Forest is 895,000 acres; however, suitable breeding habitat for the Kirtland's Warbler is only possible on ecosystems that can support the host species, jack pine. Therefore, the problem was solved on the 174,500 acres with the greatest potential to create suitable habitat, a land type with well-drained, sandy soils. The dataset consisted of 12,307 stands, comprised of aggregations of two-acre hexagons with the process described above. Stands ranged from 2 to 446 acres in size, with an average size of 14 acres. Financial information for management costs and potential timber revenues was derived by HNF personnel, based on 2010 transaction information. Yield information was derived from the Forest Vegetation Simulator (Dixon, 2002. Revised: 2013), and is consistent with the yields recognized in the 2006 HNF forest planning effort. Stand-level data was derived directly from the database maintained by the HNF and reflected information current in 2010.

This formulation used cover type constraints to move the forest toward the desired conditions outlined in the 2006 Hiawatha National Forest Land Management Plan (USDA Forest Service, 2006), displayed in Table 2.1. Constraints 2-7 did not include a spatial component; they could be met anywhere in the forest. Constraint 1 is the

Kirtland's warbler habit constraint, which calls for 4500 acres of core area to be produced in each period of a 30-period planning horizon.

Table 2.1: Simplified Constraint levels

	Constraint	Type	Level (acres)
1	Spatial - KW Core Area	Lower	4500
2	Red Pine - total	Lower	41000
3	Red Pine - old age	Lower	27500
4	Maintained Openings	Lower	9950
5	Maintained Openings	Upper	11150
6	Young (age 0-10)	Upper	19550
7	Regeneration (age 0)	Upper	2000

This study uses a 60-year planning horizon comprised of 30 two-year planning periods for addressing constraints. This constrained planning horizon was chosen to accommodate a feasibility study of at least one full rotation of jack pine (*Pinus banksiana*) suitable for KW breeding habitat. Acres currently in the KW habitat system may be sub-optimal in the long term, and conversely, some longer-rotation species such as red pine (*Pinus resinosa*), that are young today, may be converted to KW habitat in the future. Spatial interactions between stands are determined for 180 years in order to calculate the discounted financial value of these interactions. Spatial conditions are valued 60 time steps beyond the end of the constrained planning horizon to help ensure that the model does not artificially truncate KW habitat at the end of constrained planning horizon. Two year time steps were used to accommodate the relatively short-lived nature of the suitable habitat (10 years). Harvest was assumed at the mid-point of each planning period, and this would cause problems for practical implementation of the derived strategy if those time periods are long relative to the temporal scale of the desired spatial conditions. Therefore, using two-year planning periods allows one to better refine harvest timing options, and recognize potential spatial interaction between stands. Solutions may reflect coordinated management that slowly "walks" a habitat patch across the landscape through time.

Conversion into, out of, and between the different cover types, combined with the many different timing options for these management options, results in an abundance of different management options for any given stand. For the 12,307 stands recognized in the model, there were a total of 1.08 million management options analyzed, or an average of 88 per stand. Management options were also classified by whether or not they contributed to the spatial constraints of the problem. In this model, management options that do not contribute to meeting spatial constraints (KW habitat) are substantially simpler to model than those that involve a spatial interaction with other stands. The value of each management option for each stand can be evaluated before the DP formulation (with equation (2.5)), and one can identify the single best non-spatial management option and a suite of candidate spatial options to evaluate with the DP formulation. The DP formulation includes the best non-spatial management option to identify areas that are not good KW habitat. The best non-spatial management option can be found with the process outlined by Hoganson and Rose (1984), where one evaluates all options based on the sum of their financial value and their value in meeting forest-wide constraints (a function of potential multiplied an estimated shadow price, or Lagrange multiplier) and chooses the option with the highest value.

The set of spatial management options used in the DP was based on $V_{d_i,}$ where:

$$V_{d_i} = r(d_i) + \sum_{t=1}^{T} \sum_{z=1}^{Z} \mathrm{s_t} * \prod_{j_z=1}^{J_z} k_{j_z,t} * \ \mathrm{a_z} * \varepsilon \qquad (2.5)$$

To apply equation (2.5), one first determines $r(d_i)$, the present net value of the non-spatial value of management option *d* of stand *i*, as a sum of discounted net financial flows and shadow prices multiplied by constraint levels to which they contribute. Added to that is the spatial value of the management option, which is dependent on the management options of the stands with which it shares influence zones. To calculate the spatial value, all influence zones *Z* are evaluated in which stand *i* is found. Each influence zone *z* contains a set of stands (J_z). A search is conducted for all stands in the influence zone to determine the suite of management options for all stands that maximizes the spatial value of the influence zone. This is done by looking at the value of $k_{j_z,t}$, a 0/1 value associated with the potential of stand j_z to produce core area with any management option at time *t.* The search of course, ensures that the *k* values for each stand j_z are from only a single management option for j_z in the end. If all stands j_z have a $k_{j_z,t}$ =1 then V_{d_i}, is increased by the area of the zone a_z multiplied by the spatial shadow price s_t multiplied by the weight ε one gives to the value of influence zones. A weight of 1 would add the value of the entire influence zone to the value of the management option, including portions that occur in other stands.

Equation (2.5) was applied to initially to be optimistic about the value of spatial management options and to eliminate all options that did not beat the best nonspatial solution using ε = 1 (Hoganson H. M., Bixby, Bergmann, & Borges, 2004). Values determined with equation (2.5) were then evaluated to pare down even further the number of management options used in the DP formulation. The spatial alignment assumption was optimistic; that is, when evaluating the current option *d*, management options for other stands in the influence zone were chosen that added the greatest spatial value to *d*,. The maximum number of spatial management options available to any given stand was used as a starting point to pare down the number of management options per stand used in the DP formulation. In this study, the maximum number of spatial management options was 27, which was pared this down to as low as five. Figure 2.7 shows the number of spatial plus non-spatial management options of the full problem presented in this paper. To pare down the number of management options used in the DP formulation, the first iteration would eliminate a single option from the 95 stands with 27 initial spatial options. The eliminated management option would be the one with the lowest V_{d_i} according to equation (2.5). Eliminated management options are then *not* used to calculate V_{d_i} for the remaining management options, for any stand, in subsequent iterations. The second iteration would pare polygons with 26 spatial management options down to 25 and so forth, until the desired maximum number of options for any stand was reached.

Several test cases were used to examine the performance of the proposed heuristic. The first case presented is a small, baseline scenario that is used to extrapolate the lessons learned to a larger problem. The intent of the baseline scenario was to keep the problems small enough to derive exact solutions, large enough to be a meaningful test, and have starting conditions diverse enough to insulate against the possibility that a particular set of shadow prices would cause an anomaly in the evaluation of the solution method. To help simplify the problem, the above-described pre-processing was used to pare down management options to 6 per stand (5 spatial and 1 non-spatial). Paring down management options almost certainly eliminated optimal management options to the global problem, but information learned from these tests can be applied to a larger formulation that does not eliminate optimal management options. A simplified problem allows one to find a global optimum for comparison of the heuristic parameters. Ultimately, the best heuristic parameters can then be used to solve a more complete enumeration of the problem that includes more management options.

Test cases varied the following parameters:

1. Window size: the maximum number of nodes in any given window was varied to assess how much simplification might be possible without sacrificing objective function value. Some scenarios held the window size constant; other scenarios allowed for the window size to expand as solutions were accepted and the problem was simplified.
2. Window direction: eight different potential window directions were tested originating from four different sides of the forest, enumerated from each end of those four sides.
3. Window direction and size: Schedules for stands were accepted after varying numbers of test directions and/or window sizes that all yielded the same stand management option for consecutive trials. The parameter varied by whether the chosen management option contributed to the spatial value of the solution.
4. Core area shadow prices (Lagrange multipliers): So that a single core area price was not indicative of a unique situation, tests were conducted that varied the value of core area. Three sets of prices were chosen to reflect low, medium, and high core area values. It is important to note that the prices in these trials are not independent of other, non-spatial constraints. Other constraints that were violated due to satisfaction of spatial constraints had their corresponding values changed simultaneously.
5. Maximum number of management options per polygon considered by the DP: The fewer the number of options for the DP to consider, the fewer number of moving windows to evaluate and the quicker the solution time. A problem with limited management options per stand is evaluated in the context of a problem with the maximum defined options per stand.

Results

Baseline Scenario Description

The first scenario analyzed (Baseline) used financial information derived at an intermediate stage of the overall solution process to find good shadow price estimates for all forest-wide constraints. That is, further adjustment to these price estimates is necessary to derive at an acceptable solution. The shadow prices for the spatial constraints (Figure 2.6) in the Baseline scenario generated a nearly feasible solution (i.e., constraints were generally satisfied). These prices were used in Equation (2.5) (as s_t) to determine that 3826 of 12,307 stands were good candidates for KW habitat. Full discussion of these price levels is not warranted since they are mere approximations, but two observations are worth noting. First, core area is not valued in the first six periods since existing and recently planted KW habitat on the landscape meets the constraints for those periods. Secondly, there is a cyclical nature to these prices that indicates the interaction between the constraint levels; e.g., habitat that originates in period 7 is still present in period 11 and contributes to meeting constraints for each period between and including periods 7 and 11. A high price in period 7 may cause habitat to first appear in that period, but that habitat persists on the landscape for ten years, therefore causing it to be more-or-less "free" for periods 8-11. The history of management on this forest has created enough habitat to last through period 6, but it declines rather quickly (is beyond 16 years old), meaning that a large area must become habitat in period 7 to accommodate the decline.

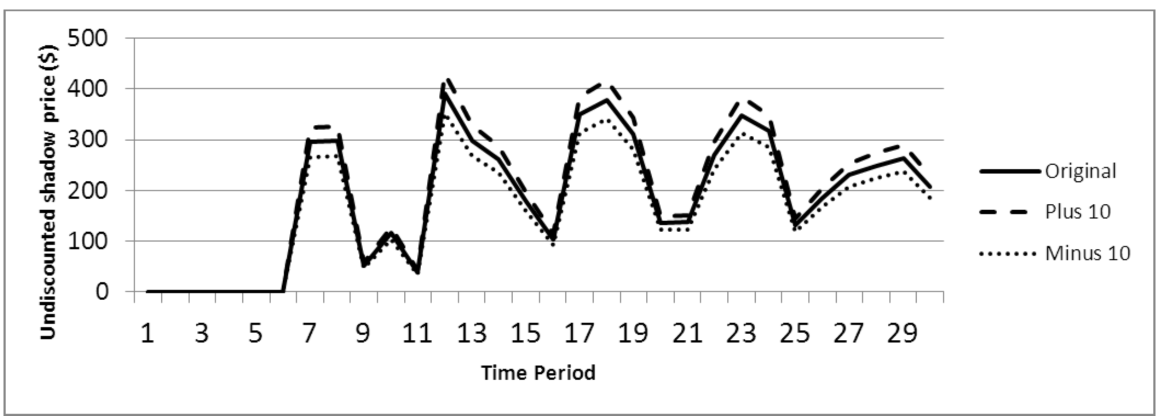


Figure 2.6: Core area shadow prices used in Initial Scenarios (undiscounted dollars per acre). The center line is the baseline scenario, and the upper and lower lines reflect an increase and decrease of 10%, respectively.

The problem size of each subdivision can be calculated by using the price information in Figure 2.6 and paring the problem down to a maximum of 5 spatial management options and 1 non-spatial option. Efficient DP problem formulation is an optimization problem by itself, since there are, for instance, 200! ways to formulate a problem involving 200 stands. Some of those formulations will be more efficient and allow for faster solution times with smaller overall formulations. Detailed description of how the DP was formulated is beyond the scope of this exercise, but the approach was basically the same as what was used for applications in Minnesota for National Forest Planning (Hoganson H. M., Bixby, Bergmann, & Borges, 2004). In a general sense, stands were added to the DP sequentially according to their location. If their inclusion in a stage resulted in a breach of the maximum node limit, they were placed into a queue while other nearby stands were tried. If, after a certain number of tries, the DP could not be formulated without breaching the maximum node limit, the window boundary was drawn, and the analysis proceeded to the next stand. This continued until windows were formulated across each subdivision in the forest.

Tests for Varying Window Sizes

The initial test of the baseline scenario was to incrementally increase the maximum number of allowable nodes in a DP from each window direction. This is a modification of the study done by Wei and Hoganson (2008) that studied the effect of different maximum node limits combined with simplification routines that eliminated small influence zones. The search presented here was modified to include larger maximum node limits and evaluate the problem from eight different perspectives, and did not trim out small influence zones. Computing time ranged from less than a minute for the 1000 node limit to 82 minutes for the ten million node limit. As expected, with a higher node limit, one can achieve better results. The highest objective function value (28608733) was found with the 10 million node limit and was consistent for directions 2, 3, 4, and 8 (bold font in Table 2.2). The first part of Table 2.2 shows that even with a 1000 node limit, values within 0.3% of the highest known objective function value could be found. Increasing the node limit to 100,000 or 1,000,000 yields values to within thousandths of a percentage point of the maximum value found. The second part of the table shows the percentage of the spatial value associated with the maximum objective function value (8423033). Spatial value is indicative of how much core area is produced by the solution, and is the discounted value of the core area produced over time (using the values in

Figure 2.6). Again, one can see how increasing the node limit increases the value of core area produced. What is striking is that the two values (overall NPV and core area NPV) are not correlated. An extreme case is seen with window direction 4, where the overall objective function value is within 0.3% of the found maximum, but the spatial component value is 32% lower. This indicates that while the value of the management scenario is nearly indistinguishable in financial terms, the spatial outcomes are quite different. The other notable phenomenon is seen in window direction 5, where the core area value is measurably higher than the maximum solution, yet the overall objective value is measurably lower. These two outcomes suggest there are many local optima for the problem very close to the global optimum, and that the quality of the solution should be evaluated on not only the overall financial value, but also the financial value of the spatial component.

Table 2.2: Objective function percentage value and spatial value percentage results from evaluating varying node limits of the eight window directions. Bold values indicate maximum overall financial value. Italicized values indicate the lowest and highest financial values of the spatial component of the problem.

	Maximum Node Limit				
Direction	1000	10000	100000	1000000	10000000
Percent Objective Function Value					
1	0.998	0.9994	0.9999	0.99999	0.999998
2	0.998	0.9997	0.9998	0.9999	**1**
3	0.998	0.9994	0.9999	0.99998	**1**
4	0.997	0.9996	0.9997	0.99998	**1**
5	0.998	0.9995	0.9999	0.99997	0.999995
6	0.999	0.9996	0.9997	0.9999	0.99998
7	0.998	0.9995	0.9999	0.99998	0.99999
8	0.997	0.9994	0.9999	0.9999	**1**
Percent Maximum Spatial Value					
1	0.778	0.964	0.991	0.996	0.999
2	0.807	0.943	0.963	0.963	**1**
3	0.753	0.949	0.966	0.993	**1**
4	***0.68***	0.942	0.985	0.989	**1**
5	0.794	0.933	0.977	0.9997	***1.001***
6	0.815	0.936	0.97	0.965	0.996
7	0.774	0.932	0.977	0.988	0.9999
8	0.702	0.921	0.985	0.989	**1**
Avg. Sol. Time (min.)	0.5	0.8	1	6	82

Tests for solution acceptance using multiple window directions

The first scenario used to test the window direction parameter of the heuristic was to use a maximum window size of 28 million nodes. Those stands that had a consistent spatial solution for all 8 window directions had their chosen management option accepted for the remainder of the trials (θ=8). Strategically, one might consider being more conservative in accepting non-spatial options since spatial interactions are complex and might become more apparent after the problem is simplified by accepting spatial solutions for neighboring polygons. Therefore, those stands that had consistent non-spatial management options chosen were accepted after 12 consistent trials (δ=12). The problem is formulated such that after the 8 directions are searched, it cycles through them again in order. Table 2.3 below illustrates how the problem solves. The first Trial is comprised of 3826 stands split into 57 subdivisions, ranging from 6 to 1256 stands in size. In any given Trial, if the subdivision was solved with a single window, the solution was optimal and therefore was accepted for all stands within the subdivision. Fifty four of these subdivisions were solved in a single window in Trial 1 using the first window direction tried, which therefore generates an optimal solution for those subdivisions. Three subdivisions required multiple windows to solve, ranging from 2 to 11 windows. All subdivisions were solved exactly in Trial 13 after solutions for non-spatial polygons were accepted. There were no subdivisions included in the Trial 13 DP since all polygons' solutions have been accepted and there were no decisions to make.

Note that solving with window directions 2, 4, 5, 6, 7, and 8 all found the same (highest) objective function value even before any solutions were accepted, and that this is the same objective function value found with the initial tests of window direction (Table 2.2). This is a strong indication that it is an optimal solution. The same solution was found with differing numbers of moving windows and different window directions. The number of overlapping windows per subdivision is tracked for the three subdivisions that are solved in Trials 2-12 in the last three columns of Table 2.3. Recall that for Trials 1-8 the full suite of management options was available to all stands. The number of stands in each subdivision is in parentheses in the header row. Formulations that found the same, highest objective function value are in bold font. The best solution found with this analysis is referred to as the optimal solution for the remainder of this discussion. For the 54 subdivisions that were solved exactly with a single pass, this holds true. For the three subdivisions that were not solved with an exact formulation, their consistent highest value is strong evidence that the solution is at least near-optimal if it is not exactly optimal.

Solution time for each window direction is indicated in the “Solution Time (Minutes)” column. The total analysis took nearly 18 hours of computation time. Solution time includes the nominal amount of pre-processing time required for identifying subdivisions and moving windows used in the formulation (less than 1 minute per trial).

Table 2.3: Subdivision solution metrics for the base problem with a maximum window size of 28 million nodes. Consistent spatial solutions were accepted after 8 trials (θ=8) and consistent non-spatial solutions were accepted after 12 trials (δ=12). The best solution found with full number of available management options is in bold font.

	Window Direction	Total Included	Multi-Pass Subdivs	Single Pass Subdivs	Total_NPV	Solution Time (Minutes)	SD 25 (255)	SD 32 (322)	SD 45 (1256)
Trial 1	1	57	3	54	28608560	95	2	2	11
Trial 2	2	3	3	0	**28608733**	125	**2**	**2**	**9**
Trial 3	3	3	3	0	28608551	96	4	4	7
Trial 4	4	3	3	0	**28608733**	113	**4**	**3**	**9**
Trial 5	5	3	3	0	**28608733**	109	**2**	**2**	**10**
Trial 6	6	3	3	0	**28608733**	121	**2**	**2**	**12**
Trial 7	7	3	3	0	**28608733**	117	**3**	**4**	**8**
Trial 8*	8	3	3	0	**28608733**	114	**4**	**4**	**9**
Trial 9	1	3	3	0	28608733	26	2	2	3
Trial 10	2	3	3	0	28608733	36	3	2	5
Trial 11	3	3	3	0	28608733	62	3	4	6
Trial 12*	4	3	3	0	28608733	53	3	3	7
Trial 13	5	0	0	0	28608733	0			

Tests for solution acceptance using smaller windows and multiple directions

This same problem was solved using smaller, more numerous moving windows to test the efficacy of the directional search portion of the heuristic (trying formulations from different directions before accepting solutions). The 54 subdivisions that solved exactly in the 28 million node master problem could be used to evaluate the performance of directional search heuristic. A scenario was constructed that constrained the maximum window size to 10,000 nodes wide at any given point. The solution acceptance thresholds were the same as the first scenario (θ=8, δ=12). The problem was run for 25 trials, found a solution (28608193) within 0.001% of Scenario 1 and solved in less than 10 minutes. Compared to the scenario 1 solution time of 18 hours, this is a substantial time savings. Table 2.4 shows twelve of the subdivisions that could not be solved exactly with the 10,000 node limit, the percentage of NPV value found with scenario 1, and the number of moving windows needed to solve them. Solutions that match scenario 1 are noted in bold. Solutions that match the known optimal solution are noted in bold italics. The numbers in parentheses in the first column indicate the window direction used to solve the problem.

Several observations about Table 2.4 are worth mentioning. First, this solution method matched the solution of scenario 1 in all but one subdivision (see the “Final” line; Subdivision 26 did not match the optimal solution). Solutions for the remaining 44 subdivisions are not shown, but all were able to match the optimal subdivision solution found in scenario 1. Secondly, all but 4 subdivisions matched the best scenario 1 solution in one or more of the 8 window directions tried, even though they all required multiple overlapping windows to solve. The subdivision 13 solution matches the scenario 1 solution after the consistently chosen spatial management options are accepted (trial 9). Subdivisions 8 and 45 match the scenario 1 solution after the problem is further distilled by accepting consistent non-spatial solutions (Final). Three subdivisions are solved with fewer moving windows after part of the solution is accepted (subdivisions 1, 13, and 45), as evidenced by trial 1 and trial 9 which both used window direction 1, and Trial 9 had a portion of its solution accepted. The number of subdivisions used to determine the solution is not correlated with the quality of the solution. Trial 3, which used seven windows to solve subdivision 45 had an inferior solution to trial 6, which used 12 overlapping windows. Finally, note that solution performance for each window direction varies by subdivision. Window direction 4 finds an optimal solution for subdivision 1, but not for subdivision 44. Conversely, direction 3 finds the optimal solution for subdivision 44, but not Subdivision 1. It is therefore advantageous to accept the best solution for each subdivision independently, and use these solutions to compile a best overall solution if the problem does not converge after the specified number of trials.

Table 2.4: Select subdivision solution efficiency for the problem limited to a maximum of 10,000 nodes in any one stage of the DP. The top portion of the table shows percentage of the Scenario 1 solution for each subdivision for the first 9 window directions tried, as well as the final solution found. The second portion shows how many moving window formulations were used to find the solution. Solutions that match Scenario 1 are in bold italics. Subdivisions flagged with an asterisk (*) were not solved in one pass by Scenario 1; other values represent optimal solution for the subdivision.

Subdivision	SD 1	SD 4	SD 8	SD 9	SD 13	SD 19	SD 25*	SD 26	SD 32*	SD 44	SD 45*	SD 50
#Stands	107	182	146	95	225	63	255	53	322	123	1256	64
Scenario 1 NPV	344941	669776	1552364	372673	1023852	133728	1006529	299165	1136177	709673	4240394	425690
Trial 1 (1)	***1***	0.99999	0.99807	***1***	0.99841	***1***	0.99797	0.99597	**1**	***1***	0.99839	***1***
Trial 2 (2)	***1***	***1***	0.99991	***1***	0.99939	***1***	**1**	0.99597	**1**	***1***	0.99880	***1***
Trial 3 (3)	0.98702	***1***	0.99987	***1***	0.99865	***1***	**1**	0.99820	0.99970	***1***	0.99935	***1***
Trial 4 (4)	***1***	***1***	0.99902	***1***	0.99806	***1***	**1**	0.99820	**1**	0.99766	0.99855	***1***
Trial 5 (5)	***1***	***1***	0.99991	***1***	0.99861	***1***	0.99797	0.99765	**1**	0.99870	0.99843	***1***
Trial 6 (6)	***1***	***1***	0.99991	***1***	0.99919	***1***	**1**	0.99597	0.99917	***1***	0.99844	***1***
Trial 7 (7)	***1***	***1***	0.99987	***1***	0.99862	***1***	**1**	0.99820	0.99970	***1***	0.99759	***1***
Trial 8 (8)	0.99820	***1***	0.99895	***1***	0.99874	***1***	**1**	0.99820	**1**	***1***	0.99820	***1***
Trial 9 (1)	***1***	***1***	0.99997	***1***	***1***	***1***	**1**	0.99597	**1**	***1***	0.99918	***1***
Final	***1***	***1***	***1***	***1***	***1***	***1***	**1**	0.99820	**1**	***1***	**1**	***1***
Number of windows needed to solve subdivision												
Trial 1 (1)	***3***	4	3	***3***	7	***3***	5	6	**5**	***2***	25	***2***
Trial 2 (2)	***2***	***4***	3	***3***	6	***3***	**8**	5	**7**	***3***	25	***2***
Trial 3 (3)	2	***7***	4	***3***	6	***3***	**10**	3	8	***3***	18	***6***
Trial 4 (4)	***7***	***8***	3	***4***	5	***2***	**9**	2	**9**	5	21	***3***
Trial 5 (5)	***3***	***5***	4	***3***	7	***3***	4	3	**6**	3	23	***2***
Trial 6 (6)	***2***	***4***	3	***3***	6	***2***	**7**	3	6	***2***	25	***3***
Trial 7 (7)	**2**	***7***	4	***3***	7	***3***	**9**	2	9	***4***	20	***6***
Trial 8 (8)	5	***6***	4	***4***	6	***3***	**8**	2	**8**	***4***	21	***4***
Trial 9 (1)	***2***	***4***	3	***3***	***4***	***1***	**5**	6	**5**	***2***	16	***2***

Evidence from Table 2.4 can be used to draw several conclusions. First, decomposing problems into a series of overlapping windows can identify optimal solutions (subdivisions 1, 4, 9, 13, 19, 44 and 50). Secondly, the proposed heuristic of accepting the consistent portions of solutions after a number of trials can identify optimal solutions (subdivision 8). With relatively little effort, the proposed heuristic can also match solutions that were found with considerably more computational effort (subdivisions 25, 32 and 45). Predictably, however, the heuristic does not guarantee that an optimal solution will be identified (subdivision 26). It is feasible that some stands in this subdivision have the same (wrong) management option chosen consistently for all 8 directions, which when accepted can have a cascading effect on identifying a suboptimal solution for the entire subdivision. A larger window size, however, may result in a formulation that identifies the optimal management option in at least one window direction.

Tests for combining Varying Window Directions and Varying Window Sizes

The final tests conducted with the first set of core area prices (Figure 2.6; Baseline) were to evaluate combining multiple direction search with variable window sizes. As more of the solution was accepted and the problem became simpler, more computational power was allocated to those portions of the problem that were most difficult to solve. Thus, the hypothesis was that increasing the window size with each direction of search might lead to finding better solutions without increasing the solution time. Additionally, a different window size might perturb the problem sufficiently so as to allow a substantially different DP problem formulation that might help escape a local optimum. One additional pre-processing step was added to the heuristic to make the process more efficient; that is, after the window size was increased and the window direction for DP formulation was updated, each DP direction was re-evaluated for the possibility of solution with a single window. The logic was that even the direction just evaluated might have been feasible to solve with one window if it had been allowed a formulation with a slightly larger window size, and it could be identified right away. If a subdivision could be solved in a single window in the direction other than the current one searched, that different direction was used to solve the DP. If multiple directions allowed the problem to be solved in a single window, the direction with the smallest (and thus fastest) formulation was used.

There were two different opportunities to increase the window size. First, a linear increase was used to increase window size by a set amount every trial. This might look like starting with a window size of 30,000 nodes, and increasing by 10,000 nodes every trial. The second allowable increase was to define thresholds according to the number of stands in the formulation. Early tests of these methods indicated that the most difficult portions of the problem to solve were where one or two window directions consistently chose slightly different solutions than the other six or seven directions. In these instances, it is likely more efficient to search rapidly for a window size that allows for the subdivision to be solved exactly. Thus, one might define a threshold such as when there are fewer than 100 stands left to solve, increase to a 10 million maximum node limit. A single, large but exact solution might take less time to solve than multiple, faster trials. The parameter variations to search for efficient solutions are shown in Table 2.5. The first column indicates the initial window size and the magnitude of increase each window direction. The first row starts with a maximum node count of 1000, and increases by 1000 with each Trial. Acceptance threshold are shown in the second column, and indicate the number of window directions tried before accepting spatial and non-spatial management options, respectively. The third column indicates a threshold for the number of stands left in the DP before a significant window size jump is triggered, and the fourth column indicates the size of the jump and the ensuing increase each window direction. Columns five and six indicate the absolute magnitude in overall objective function loss and spatial loss, and the last column is the solution time in minutes.

The trial that matched the optimal solution in the least amount of time is indicated in italics. It is not the smallest problem formulation, but it accepts the spatial and non-spatial management options in the fewest number of window directions tried. There are a very large number of parameter variances that are not reflected in Table 2.5. The point is, however, that optimal or near-optimal solutions can be matched exactly by the simplification heuristics presented here in much less time than exact search techniques.

Table 2.5: Trials to test increasing window size, acceptance thresholds, and solution time. Bold values indicate trials that match the optimal solution. Italics indicate the trial that found the optimal solution in the least amount of time.

Initial Size/ Increase	θ/δ	Threshold Stands	Size/ Increase	Total Loss	Core Loss	Solution Time (min.)
1k/1k	2/4	100	50k/10k	3,283	272,882	4.49
1k/1k	4/6	100	50k/10k	1,505	120,220	5.67
1k/1k	8/12	100	50k/10k	719	21,822	9.27
10k/10k	2/4	100	100k/50k	992	103,597	4.78
10k/10k	4/6	100	100k/50k	407	75,030	5.21
10k/10k	**8/12**	**100**	**100k/50k**	**0**	**0**	**11.26**
30k/10k	2/4	100	1M/500k	407	75,030	6.59
30k/10k	**4/6**	**100**	**1M/500k**	**0**	**0**	**7.06**
30k/10k	**8/12**	**100**	**1M/500k**	**0**	**0**	**12.64**
100k/20k	***2/4***	***100***	***2M/1M***	***0***	***0***	***6.29***
100k/20k	**4/6**	**100**	**2M/1M**	**0**	**0**	**8.79**
100k/20k	**8/12**	**100**	**2M/1M**	**0**	**0**	**18.2**

Tests of Different Pricing Schemes

Several core area pricing schema were tested to assess the efficacy of the heuristic on different problems. For these tests, the core area prices for the basic problem were adjusted up and down in intervals of five percentage points. Figure 2.6 shows the 10% increase and decrease levels that were tested (the 5% increase and decrease levels are not explicitly shown, but can be inferred). Each pricing scheme was solved with a window size of 100,000, increasing 20,000 each trial, and a θ/δ of 8/12. These were compared to larger problem formulations with at least a 25 million node maximum window size.

Results for all four additional test cases showed that the solution found with the larger window size could be matched by the heuristic. Again, this gives a strong indication that the heuristic is applicable and relevant to other problem formulations. One interesting observation of the results is how sensitive the solution is to the core area pricing assumption. A test to increase the core area price by five percent corresponded to a 2% increase in overall NPV, but a 50% increase in the spatial portion of that NPV. At a 10% increase in core area price, the effect was more dramatic (a 4% increase in overall NPV and a 100% increase in the core area NPV). One phenomenon that may explain this is that the spatial benefits of more habitat is credited to the core area NPV, but the increased management costs associated with KW habitat is charged to the non-spatial

NPV. Still, the phenomenon highlights the sensitivity of the spatial solution and calls for a solution technique that is robust in determining a spatial value of the solution, not just an overall NPV that is close to optimal.

Tests on Larger Problem Sizes

One simplifying aspect of the problem presented heretofore is the maximum number of management options available to any stand was six; 5 spatial and one non-spatial. Using two-year planning periods, this does not allow a wide range of KW establishment options per stand. The heuristic was tested on a larger problem by formulating a problem that allowed up to 28 management options per stand. Figure 2.7 is a histogram of the number stands with the varying number of management options per stand. Of the 3927 stands in the DP formulations, 3238 have more than 5 options. As expected, the size of the resulting problem increases when more management options are considered.

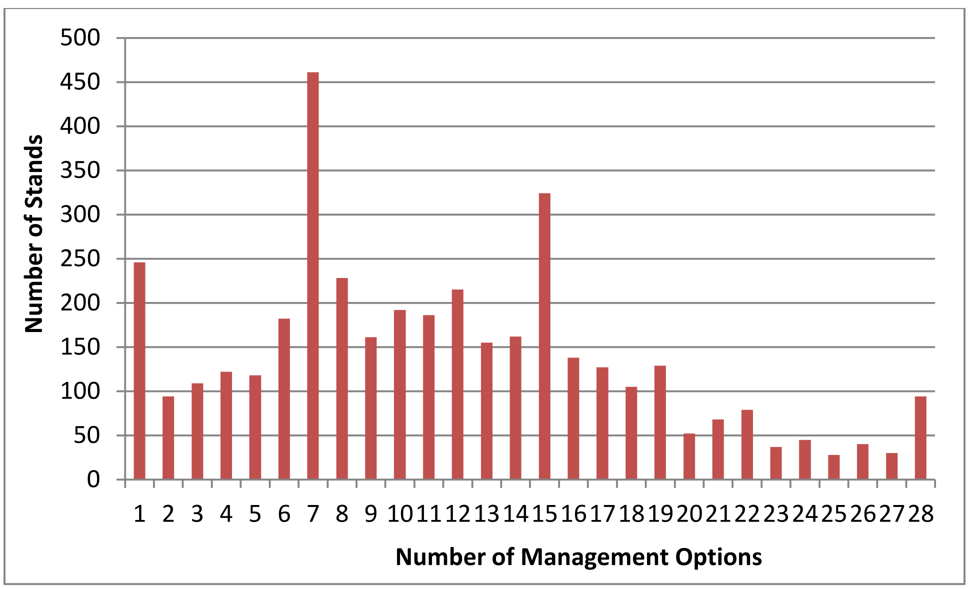


Figure 2.7: Number of management options for stands used in the full analysis

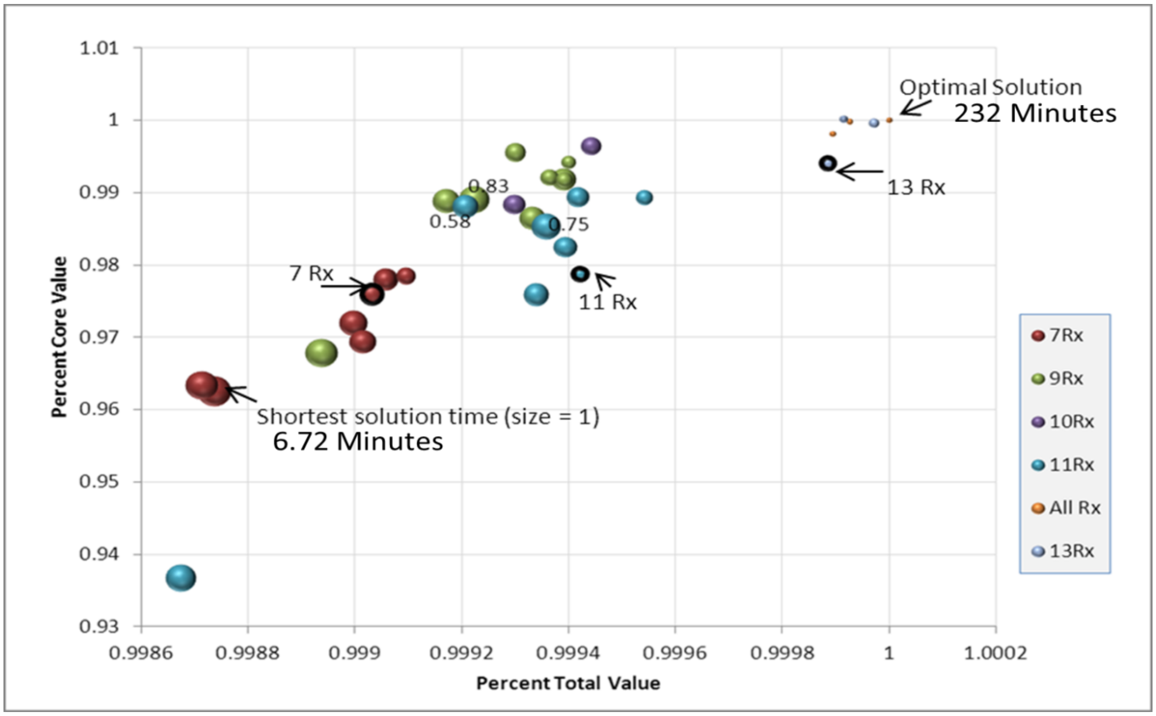
The larger problem was solved with a combination of two different methods. First, the heuristic described above was employed to use all possible management options to the DP. The second method was a strategy that pared down (i.e., trimmed) the number of management options sent to the DP, but followed up each trial with a hill climb search (Laguna, 2002) that used the DP solution as a basis and the full suite of management options for the search. Limiting the number of management options used in a DP formulation has the potential to greatly simplify the problem. The hypothesis was that the trimming routine may have eliminated the global optimal management option for some stands from the DP formulation. Therefore, the hill-climbing heuristic started with the DP solution, and surveyed all possible management options for each stand to see if a different management option would increase the objective function value. If a polygon had a management option chosen by the hill climb that was not included in the initial DP formulation, it was included in all subsequent DP trials.

In all, 50 combinations of maximum management options, window size (and increase parameters) and θ/δ were evaluated. The maximum number of management options initially evaluated ranged from five to thirteen, and the "All" was used as a control. Window sizes were evaluated at the 10,000, 30,000, 100,000, 200,000, 500,000, 1 million, and 2 million levels. Window size increases were set at 50% of the initial window size (i.e., a 30,000 window size was increased by 15,000 with each Trial). Theta/delta thresholds were either 2/4, 4/6, or 8/12. This resulted in nearly 400 unique parameter combinations that could be tested.

Early tests indicated certain parameter combinations were not likely to yield good results. It became apparent that evaluating fewer than 7 management options failed to yield superior results even with large windows and large θ/δ acceptance levels and large initial window sizes. Additionally, θ/δ levels of 2/4 allowed too few trials to identify good solutions and θ/δ levels of 8/12, while yielding better solutions, required additional time that was disproportional to the solution quality improvements they rendered. Finally, initial windows sizes greater than 100,000 seldom produced superior solutions. The resulting tests generally consisted of differing initial management option levels between 7 and 13, a θ/δ of 4/6, and initial window sizes of 30,000 and 100,000.

Results were measured by their overall objective function value, their spatial value, and the amount of time it took to solve the problem. Figure 2.8 displays 36 of the better solutions found. The x-axis shows the percentage of the overall objective function value found with each test, and the y-axis shows the percentage of the overall spatial value. The size of the marker is inversely proportional to the amount of time it took to solve relative to the fastest global solution time (6.72 minutes; size=1). Larger points represent shorter solution times. The optimal solution is found at (1,1), found with "All" management options, and was found in 232 minutes (size=0.029), using a θ/δ of 8/12 and an initial window size of 200,000. Three of the best solutions in terms of time and quality are labeled with their size (for example, the marker labeled “.83” was found in 8.13 minutes using 9 management options, a θ/δ of 2/4 and an initial window size of 30,000).

Figure 2.8: Scatter plot of efficiency frontier associated with tests, represented in percent of the known maximum. Point labels indicate relative solution time, with larger points requiring shorter solution times. Points with a greater horizontal value have values closer to the highest known total NPV value and points with a greater vertical value have higher core area value. Better solutions have a large relative size close to a value of (1,1).



In a final note, it should be recognized that solutions with financial values within one to three percentage points of optimal can have a greater variation of core area production in any single period than the overall solution value. An example of these differences is shown in Figure 2.9. As mentioned earlier, the shadow prices used in this exercise (Figure 2.6) represent an intermediate solution in a search for a feasible solution, and so not all points in time meet the minimum constraint. Further adjustments to shadow price estimates must be made in order to meet the minimum constraints in all periods. This is worth mentioning because in order to make informed decisions about to adjust the shadow prices, it is essential to know which constraints are violated or over-achieved. In Figure 2.9, the final 23 periods of the planning horizon are shown for four of the solutions depicted in Figure 2.8 (the three with arrows, plus the optimal solution). In Figure 2.9, the thick solid line is the amount of core area associated with the optimal solution. The other three solutions are depicted with dotted or dashed lines, and the constraint level is the thin solid line. All non-optimal solutions are within 0.1% of the overall financial value of the solution and within 3% of the spatial value of the optimum solution. Yet, one can observe that in many periods, there are noticeable differences in the estimated amount of core area between the solutions. For instance, in period 26, the optimal solution is within 14% of the desired constraint level, and the 11 Rx solution over-achieves the desired level by 43%. Similar differences can be detected in other periods as well.

Price adjustment magnitudes for subsequent Lagrangian search iterations are based on how severely solutions deviate from the desired constraint levels. Logically, larger deviations should incur larger price adjustments. Consequently, imprecise estimates of core area flows through time at a given price level can cause inefficiencies in determining the correct shadow prices. Adding to the complexity of the problem is the nature of KW habitat that persists for five periods. The price for any given period affects at least four other periods. For example, raising the price in Period 21 could shift acres out of production in Period 16, even without adjusting the price in Period 16. Again, these phenomena highlight some of the difficulties involved in solving this problem.

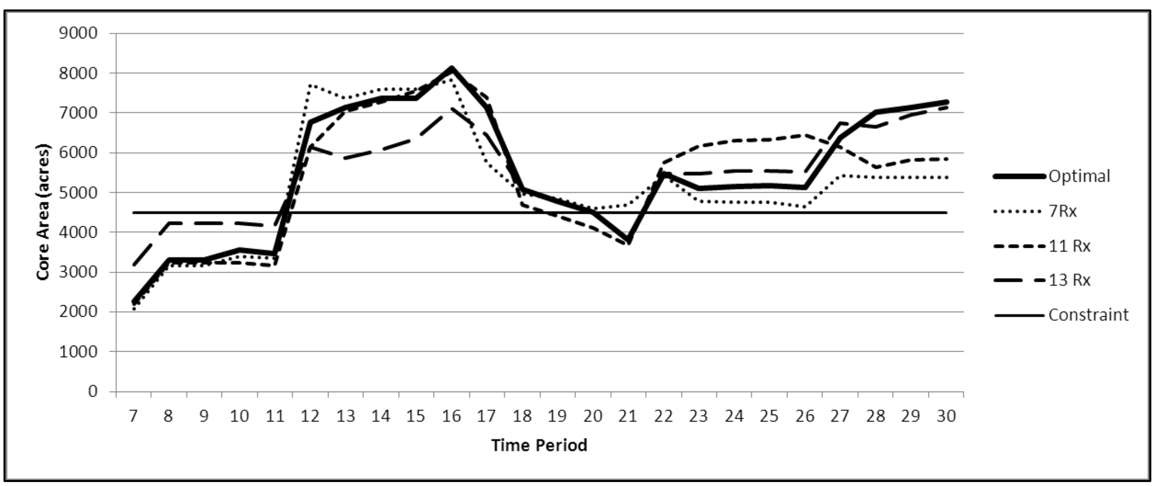


Figure 2.9: Core area production over time for select trials.

Discussion and Conclusions

Singularity and Strengths of the Heuristic

This heuristic herein described is distinct from random-search based heuristics. Other heuristic and meta-heuristic methods start with a randomly generated initial solution and seek ways to improve it (for example, the cellular automaton meta-heuristic described by Heinonen and Pukkala (2007) initiates with a random solution). The heuristic described above starts with an exact solution method and modifies it in order to generate a computationally-feasible solution. It is not an algorithm, as is branch-and-bound, simply because it cannot guarantee an exact solution when exactly executed, and the quality of the solution is sensitive to the parameter values chosen by the modeler. Yet, the heuristic is capable of identifying an optimal solution, which is proven in Table 2.4 where multiple window formulations in some subdivisions match the optimal solution found with a single window. In larger problems, near-optimal solutions are identified by selecting common components of alternate window direction and size formulations after several formulations are solved (see Figure 2.8). Another strength of the heuristic is the time savings that may be realized when parameter settings are set efficiently. Again, Figure 2.8 indicates substantial time savings found with some parameter settings that do not greatly compromise the quality of the solution. In this figure, the shortest solution time is just under seven minutes, compared to the optimal solution, which was found in 232 minutes. This translates into a 97% reduction in solution time associated with a nearly 4% reduction in core area value and 0.14% reduction in overall value. Arguably, this is a valuable trade-off to consider when considering the time budget allowed for problem solution.

It is difficult to extrapolate these findings to general recommendations for parameter settings with confidence, although as stated earlier, there were some patterns that emerged in this particular study. To reiterate, fewer than 7 management options failed to yield superior results regardless of θ/δ acceptance levels and window size. A θ/δ level of 4/6 seemed to balance solution quality with solution time. Finally, since initial windows sizes greater than 100,000 seldom produced superior solutions, an initial window size between 30,000 and 100,000 might be considered. While these parameter settings performed well when applied to this particular forest management problem, the problem did represent some diversity in forest conditions, i.e., the subdivisions. Subdivisions varied in size, complexity and existing vegetation conditions such as cover type and age distributions. The performance of parameter setting values, therefore, may be interpreted as being valid for a wide range of subdivision sizes and initial conditions, which in turn may translate well to other forest management problems.

While perhaps not unique to this study, the presence of other constraints and the dynamics of the patch duration this study add a level of complexity. The approach presented in this study is similar to those such as Ohman and Lamas (2003) where harvest activities are clustered to realize economic efficiencies of scale from spatially coordinated harvesting activities. However, it differs in several key areas that make the problem more complex. First, there are more non-spatial constraints to consider, such as the cover type and size class constraints in Table 2.1. Also, the clustering activity persists over several different time periods, which means that a single stand can conceivably be clustered with different stands depending on the time period. This phenomenon indicates the third key difference, which is that the habitat is allowed to move dynamically across the landscape through time. That is, so long as the core area constraint is satisfied, the design of the habitat might take the form of either a "crawling amoeba", where a single patch grows and changes shape and location through time, or it might consist of spatially distinct patches that are created and then disappear through time. In a historical context, one might have expected habitat to mimic the spatially distinct patches that originate and disappear in large blocks since they were created by wildfire. In practice, the solution will likely be implemented with a combination of these two possibilities. The spatial context of these patches in relation to other patches is an aspect of this study that is not explicitly explored, however. Donner, Ribic, and Probst (2010) found that larger, non-isolated patches were associated with earlier colonization and later abandonment, and birds may occupy relatively small patches if these patches are positioned in larger complexes of suitable habitat. Similar spatial concerns may arise when considering the year-over-year colonization patterns that require birds to locate suitable breeding habitat after seasonal migrations. It may be beneficial to design current habitat with good spatial proximity to suitable habitat from the year before.

Future Improvements

Additional study into the benefits of pre-processing could uncover greater efficiencies in the solution method. If each subdivision were analyzed for the possibility of finding an exact solution with analysis of the problem size in each window direction, more subdivisions might be solved in a single DP formulation. For example, one might vary the allowable window size for each subdivision. If the default window size was 100,000 nodes, but a subdivision could be solved exactly with a window size of one million nodes, one might allow the one million node formulation, thus saving computational time in subsequent trials. However, if another subdivision was billions or trillions of nodes wide, one might use a more conservative maximum node limit (such as 30,000) to solve the problem quickly from varying window directions before accepting solutions for certain stands.

The heuristic described above allows for more exploration into what makes the “hard areas” difficult to solve. One can easily pare down the problem to the most difficult spots to examine by identifying those areas that do not solve exactly and that have differing solutions depending on the window size and direction. For instance, subdivision 26 in Table 2.4 does not find an optimal solution with a 10,000 node limit, but solves rather easily when the window size is increased because it can be solved exactly when the maximum state-per-stage limit is increased to 47,000 nodes. It could be enlightening to study in detail the nature of the subdivision 26 formulation and determine why it is consistently wrong for all 8 window directions at the 10,000 node limit.

Finally, the management option trimming routine that employs equation (2.5) has a potential weakness in that it eliminates the management options for some stands that are included in the optimal solution (e.g., in Figure 2.8, even including the best 13 management options does not allow the DP to find the optimal solution). Even with a follow-up hill climb heuristic search, the optimal solution was not identified. This outcome could mean that the DP never has the opportunity to identify the global optimal solution due to weaknesses in the pre-processing trimming routine. Stronger trimming rules that increase the likelihood of including the optimal management option and eliminate more non-optimal options for each stand would allow the DP to find better solutions with shorter solution times. Development of a more robust trimming routine is the subject of the next Chapter.

Chapter 3 : Selecting an Efficient Set of Management Options for Large Spatial Forest Management Problems

Introduction

One of the earlier studies in optimization techniques to solve forest management problems, Johnson and Scheurman (1977) posed this question of the US Forest Service:

"Has lack of consideration of all possible activities significantly influenced their results?"

In the nearly forty years that have passed since this study was published, the fundamental conundrum remains: If too many management options are excluded from consideration, will the quality of the solution be compromised? Forest management problems are often addressed with mathematical programming techniques that select a management strategy for each stand to satisfy the objectives of the larger forest, and often include a time horizon comprised of multiple decades. Forest objectives may include timber harvest volumes, age class distribution, species composition or spatial arrangement. The basic building blocks of a forest management problem are the stands and the management options available for each stand. Management options in forestry include not only silvicultural prescriptions (e.g., thinning, clearcut, shelterwood harvest, etc.), but the timing of those options (including subsequent activities other than the first), and the resulting regeneration activity (including conversions to different species). One difficulty managers often encounter, however, is that the inclusion of more management options can result in larger problem formulations, which can in turn cause computational limitations when solving those problems. Studies that include spatial objectives such as adjacency constraints and core area scheduling have introduced combinatorial complexities to the mathematical problem formulation, which results in further complications in finding solutions with exact methods. Large spatially-explicit problem formulations were largely responsible for the meta-heuristic movement in forest management (Baskent & Keles, 2005), where solution approximation techniques were employed rather than exact methods.

Recent studies in spatial forest planning, however, have returned to finding solutions with exact methods. Particularly, Integer Programming solved with the branch-and-bound algorithm is the tool of choice for recent studies that evaluate problems such as the Area Restriction Model for adjacency (Goycoolea M. , Murray, Vielma, & Weintraub, 2009), minimizing harvest area perimeters (Ohman & Eriksson, 2010), or core area production (Wei & Hoganson, 2007). In addition to the branch-and-bound algorithm, branch-and-price has also been shown useful for solving larger Integer Programming problems involving adjacency constraints (Martins, Alvelos, & Constantino, 2012), and has shown promise in reducing the computational time required to solve such problems.

However, the issue of problem size is still a limiting factor with exact solution methods. Some studies describe the difficulties in solving exact problems due to the problem size. Goycoolea et al. (2005) noted the difficulties in solving problems with increased planning periods. Martins, Alvelos, and Constantino (2012) cited difficulties formulating the problem when the number of stands is too large. They also encountered instances where the branch-and-bound algorithm could not identify an optimal solution. Goycoolea et al., (2009) encountered difficulties finding a feasible solution when green-up constraints were imposed. Again, the number of time periods (which is correlated with the number of management options per stand) caused difficulties in finding solutions. They suggest investment in the development of advanced pre-processing schemes could allow more efficient problem formulations.

Pre-processing has been used to formulate problems that address spatial concerns. For example, a study by McDill and Braze (2000) evaluated many studies that were concerned with efficient adjacency constraint formulations. They determined that some formulations consistently solved faster than others. Therefore, pre-processing to construct an efficient problem formulation could result in solution time savings. Another study that evaluated pre-processing opportunities was Wei and Hoganson (2008). This study evaluated opportunities to simplify a spatial forest management problem that involved small areas of the forest with large spatial complexities, where where many stand interactions occurred. The trade-offs in solution time and solution value were shown when small but complex areas were ignored in the problem formulation. Examples of pre-processing to eliminate illogical or substandard management options are less common. Hoganson, Bixby, and Bergmann (2003) and Bixby (2006) introduce the concept of a “Treatment Trimmer” with the objective of paring down the number of management options necessary to evaluate in a forest management problem formulation. For a spatial management problem, Bixby (2006) describes two opportunities for trimming. The study is based on a management objective to create patches of core older forest. The first trimming opportunity occurs when a management option that defined potential core older forest (spatial management option) was less valuable than a management option that did not. In this instance, the spatial management option could be eliminated from consideration, or trimmed. The second opportunity occurred if there were two spatial management options with overlapping periods of core older forest production. If one option produces core area in at least the same time periods as the other had a higher value, the management option with fewer periods of core older forest production could be trimmed.

Objectives

This study seeks to develop and evaluate pre-processing routines aimed at paring down the number of management options to include in forest management problem formulations. If many options could be evaluated cheaply and effectively before the problem is formulated, more concise problem formulations could be constructed that solved with increased speeds. The premise of this study is this: If one could identify a limited subset of the full suite of management options that contained the optimal solution, then (a) more management options could be analyzed before setting up the problem and (b) a larger problem could be formulated and solved with exact methods. A solution found with an exact method is preferred because it guarantees the selection of an optimal solution, whereas solution by heuristic methods cannot guarantee optimality.

The study uses a real forest management problem faced by managers in the Upper Peninsula of Michigan, on the Hiawatha National Forest. Within the past two decades, the endangered Kirtland's warbler (*Setophaga kirtlandii*) has successfully utilized breeding habitat within the National Forest. Suitable Kirtland's warbler (KW) breeding habitat consists of 6-16 year old jack pine (*Pinus banksiana*) in larger patches (80+ acres) (USDA Forest Service, 2006). The short-lived nature of the habitat, and the spatial context of its location, combined with the Forest Plan's desired conditions for many different cover types, results in a complex spatial management problem with many different management options per stand. The problem was formulated with a 60-year planning horizon consisting of 30 two-year time periods. The 10-year duration of KW habitat meant that its duration lasted 5 time periods, a phenomenon that could be exploited when designing habitat in neighboring stands. That is, there was quite a bit of timing flexibility that maintained at least some temporal overlap in KW habitat even when habitat is not created during the same 2-year planning period.

Dynamic programming (DP) was the solution technique used to help address the KW problem on the Hiawatha National Forest. The KW problem is similar to studies that have addressed old forest conditions designed in large patches. One main objective of the study is to create KW habitat in large patches on the landscape. The difference with KW habitat is that it has a shorter duration (10 years) than mature forest and it should not be immediately regenerated due to its young (16 year old) age. Dynamic programming has been successfully used to address mature forest conditions on the Chippewa and Superior National Forests in Minnesota (Hoganson, Bixby, & Bergmann, 2003), (Wei & Hoganson, 2007). In these studies, forest wide constraints for desired condition were modeled in addition to core area of mature forest. The amount of mature forest was not explicitly constrained, but it was given a value. Core area of mature forest was scheduled by the model for several different assumed values. The resulting schedules were then compared and presented as alternatives to forest managers. Another study by Wei and Hoganson (2008) searches for ways to speed the solution process of a DP formulated from incomplete overlapping subproblems called windows. The study presented below uses information presented in the Wei and Hoganson (2008) study to determine DP solver parameter values (window sizes) appropriate to address the KW problem.

However, solving a DP problem of the magnitude presented by the KW problem is neither a quick nor a simple task. The number of management options per stand can markedly slow the process and cause inefficiencies in the resulting management schedules (for example, cost more than necessary). Therefore, significant effort was invested in developing and testing the pre-processing techniques presented in this study.

Methods

Two trimming methods were developed and tested to identify management options to be included in a forest management problem formulation: “stand-based trimming” and “grid-based building”. Stand-based trimming begins with a list of all management options and pares the list down to a desirable number stand-by-stand. Grid-based building segments the forest into predefined overlapping grid cells comprised of multiple stands. The builder then determines which stand-level management options are likely to be a part of the global optimal solution based on their performance in the context of each grid cell. These management options are added to a cache of options for each stand that in turn are used in the mathematical problem formulation.

Both methods were based on the assumption that each management option could be evaluated in the context of forest-wide constraints, such as age class or cover type mix conditions of the overall forest. Marginal values (also known as “shadow prices”, “dual values”, or “Lagrange multipliers”) of forest wide constraints were used to evaluate management options at the stand level. Marginal values have long been recognized as a valuable output of mathematical programming models. Marginal value estimates of forest-wide constraints have been determined with linear programming (e.g., Ohman and Eriksson (2002) used them to solve a spatial forest problem), solving a dual formulation (Hoganson & Rose, 1984), and Lagrange multiplier search (Andalaft et al., (2003)). Paredes and Brodie (1989) suggest marginal values represent the public’s willingness-to-pay for the societal and management requirements of the landscape and can be used to connect stand-level analysis with forest-level objectives. In the study presented here, marginal value estimates were derived with an iterative process described by Hoganson and Rose (1984). Once marginal values were estimated, the financial value of each management option (i.e., harvested wood value less management costs) is augmented by the marginal values of the constraints toward which they contribute. For example, if an option contributes to a minimum binding constraint, the value of the option is increased by the marginal value of that constraint. Conversely, an option that contributes to a binding maximum constraint (with a negative marginal value) will reduce the value of that management option according to the magnitude of marginal value. A management option may be affected by several different types of constraints, as in the case of an even-aged harvest option in the context of a problem with a maximum constraint on young forest and a minimum constraint on timber volume.

Once marginal value estimates are known, they can be applied to each management option to eliminate options that would not efficiently achieve the spatial objectives of the problem. The logic is described in detail in Hoganson, Bixby and Bergmann (2003) and Bixby (2006). To reiterate, there is a two-step logic sequence applied to each management option of each stand to evaluate its inclusion in the planning model. First, if crediting a management option for spatial benefits from all the stands with which it may produce core area cannot produce a value greater than the best non-spatial management option for the stand, it may be eliminated from consideration. Secondly, a management option may be eliminated if there exists another option with a higher value that schedules core area in at least the same time periods.

Even with these trimming rules, however, there were often too many management options remaining to solve the problem in an exact or efficient manner (Wei & Hoganson, 2008). Early trials of this KW management study indicated it could take several hours to determine an optimal solution using the full suite of possible management options. This is not a practical solution method in the context of a marginal value search heuristic.

The two trimming methods described in this paper are newly developed methods. Stand-based trimming extends the concepts described by Hoganson, Bixby and Bergmann (2003) and Bixby (2006) by trimming beyond the set of management options described in these studies. Grid-based building is an entirely new concept developed and tested the study presented here. Both methods use a forest-wide map layer of influence zones (see Bergmann (1999), and Hoganson, Bixby and Bergmann (2003)) as the basis for spatial information used in the trimming rules. Each influence zone is an area that can produce core area, or an area sufficiently far from a forest edge (Ohman & Eriksson, 1998), (Ohman, 2000). Each influence zone is defined by the stands that interact to impact the entire area of the influence zone. For this study, the dimension of an influence zone represents the number of stands that influence the zone in terms of KW core area production. For example, in Figure 3.1, the triangle may be sufficiently far from any edge to be an influence zone influenced by stands 1, 2, and 3. The zone is then labeled {1,2,3}, which has a dimension of three. Every influence zone is defined by a unique combination of stands. To determine whether this influence zone produces core area in period t, the condition of every stand defining the stand would need to satisfy required conditions for KW core area. An influence zone is not necessarily contiguous, as all areas dependent on a specific combination of stands for KW core area production need not be contiguous. An influence zone with a dimension of one is within the interior of stand. By definition, an influence zone with a dimension of one it is not influenced by other stands, so it is spatially independent in its potential to produce core area and the value of the zone can be included in the non-spatial value of the stand. Influence zones with a dimension greater than one are recognized explicitly in the DP formulations used to schedule core area spatially for this study.

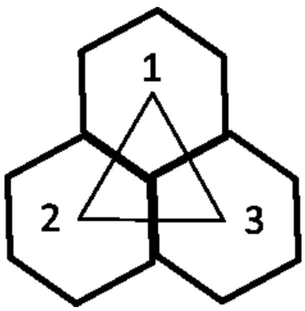


Figure 3.1: Influence zone of a three stand forest

Stand-based Trimming

Before a stand-based trimming heuristic was applied, the maximum value of management option *d* for stand *i* (V_{d_i}) was estimated for all stands and their associated management options:

$$V_{d_i} = r_{d_i} + c_{d_i} \tag{3.1}$$

Where:

$$c_{d_i} = \sum_{z \in Z_i} e_{z,d_i} \tag{3.2}$$

$$e_{z,d_i} = a_z * \max_{j \in Z, j \neq i, d_j} \left(\sum_{t=1}^{T} (k_{t,d_i} * s_t * \prod_{j \in z, j \neq i} k_{t,d_j}) \right) \tag{3.3}$$

Equation (3.1) estimates the maximum value of management option *d* for stand *i* (V_{d_i}) as the sum of estimated non-spatial returns (r_{d_i}) and estimated maximum core area value (c_{d_i}) in areas dependent on interactions between management decisions for stand *i* and its neighboring stands. The estimated non-spatial returns (r_{d_i}) represent the present net value of the non-spatial value of the management option, including the total value of net financial flows and all values associated with impacts on forest-wide constraints that are not dependent on how neighboring stands are managed. Included in (r_{d_i}) but not expressed explicitly in the equations, are value estimates of impacts of option *d* for stand *i* on all forest-wide constraints that are spatially independent impacts. These forest-wide impacts are valued using the per unit marginal value/cost of the associated forest–wide constraint, represented by each associated marginal value estimate. These forest-wide impacts for option *d* for stand *i* would include the benefits from the one dimensional influence zone that may located within the interior of stand *i* and thus not influenced by the management options selected for nearby stands. The maximum spatially dependent core area value (c_{d_i}) is estimated in equation (3.2), using the estimated values of each influence zone with a dimension of two or more that is influenced by stand *i*. The maximum value of each influence zone for management option *d* for stand *i* (e_{z,d_i}) is estimated in equation (3.3) assuming all stands impacting the influence zone ($j \in Z$) will have their management option (d_j) selected to maximize the value of the influence zone assuming stand *i* is assigned to management option d_i. Equation (3.3) uses $k_{t,d}$, a zero-one variable indicating whether management option *d* for the associated stand (*j* or *i*) meets core area condition requirements in period *t*. Equation (3.3) also uses the size of the associated influence zones (a_z) and the shadow price estimates (s_t) for core area for each planning period *t*. By comparing $V_{d_i}$for each management option *d* to the maximum V_{d_i} based only on nonspatial returns (r_{d_i}), Hoganson, Bixby and Bergmann (2003) and Bixby (2006) trimmed management options that could not possibly be optimal management options for assumed values for core area. This trimming method was also utilized in this study. Furthermore, $V_{d_i}$was used in this study as a value metric to rank management options for each stand in a stand-based trimming heuristic.

The application of equations (3.1), (3.2), and (3.3) can be demonstrated with Figure 3.2, which shows the full area of influence for stand 1. Stand 1 is a part of six different influence zones, one of which is displayed as the triangle at the top of the image. The full area influenced by stand 1 is the large hexagon that surrounds stand 1. An example management option for stand 1 might be $d_i = 1_1$, or the first management option considered for stand 1. Assume this management option harvests the stand in period 1, which results in the potential for the stand to create core area in period 4. For simplicity, assume period 4 is the only period for which it potentially meets the core area constraint. The area of stand 1 is 1 unit, and the area of each influence zone (a_z) is 0.5 units. The value of r_{d_i} is calculated based on the financial value and relevant marginal values of constraints the management option impacts. The financial value of harvesting the stand with management option 1 is $100. However, there is a forest-wide maximum constraint on the 0-2 age class that is valued at (-$10) per unit area, since there are many stands that would otherwise be harvested in period 1 and violate the constraint. The r_{d_i} value for management option 1 is therefore $90. To calculate V_{d_i} the value of c_{d_i} is determined next. The value of core area in period 4 (s_4) is $10 per unit area. Stands 3, 4, and 5 all have a management option that can potentially create core area in period 4, but stands 2, 7, and 6 to not. Therefore, k_{t,d_i} = 1 for stand 1, k_{t,d_j} = 1 for stands 3, 4, and 5 and k_{t,d_j} = 0 for stands 2, 6, and 7. The value of e_{z,d_i} for influence zone {1,3,4} using equation (1) is $5 = 0.5 * 1* $10 * 1 (the value of each term in the equation is explicitly stated). The value of e_{z,d_i} for influence zone {1,4,5} is also $5, since it too can potentially managed for core area. None of the other four influence zones can be managed for core area, since they include one or more of stands 2, 6, and 7 which do not have a management option to create core area in period 4. Thus, the value of c_{d_i} is $10 = $5 + $5 + $0 + $0 + $0 + $0, explicitly stating the maximum potential value of all six influence zones. Finally, V_{d_i} = $90 + $10, according to equation (3.1).

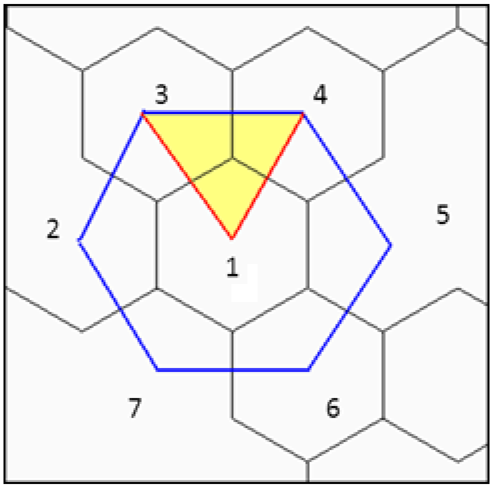


Figure 3.2: Example stand and associated area of influence

The “stand-based trimming” heuristic was developed to further pare down the number of management options in any stand used in the full problem formulation. The heuristic was applied by setting a maximum number of management options α per stand allowed in the full formulation. The heuristic initiates by setting a value of α’ at one fewer than the maximum number of management options available to any stand. If a stand has more management options remaining than α’, the option with the lowest V_{d_i} is trimmed from the stand’s list of available options. That trimmed management option cannot then be used to calculate e_{z,d_i} when evaluating other stands whose influence zones include stand *i.* Once all stands are trimmed to a maximum α’, α’ is decreased by 1 and the process continues until α’ = α.

Grid-based building

Grid-based building is a new concept presented in this study, and was developed in response to some of the difficulties encountered with solving the KW management problem. Grid-based building is a three-step process. First, the forest is divided into a series of overlapping grid cells. Second, an optimization problem is formulated and solved heuristically for the stands within each cell. Finally, the best solutions to each cell are collected to formulate a global optimization problem to be solved with an exact solution method. Perhaps a more simplistic way to state the concept is that the land area is sliced into small pieces, and each piece is sliced further into points in time corresponding to the planning periods. Estimated marginal values of forest-wide constraints are used to evaluate each space/time slice in the context of the global problem, and the best solutions of each slice are used to identify the management options to use in the larger, global problem formulation. Stands are a part of multiple slices, both temporally and spatially, and therefore have multiple opportunities to be a part of a good solution.

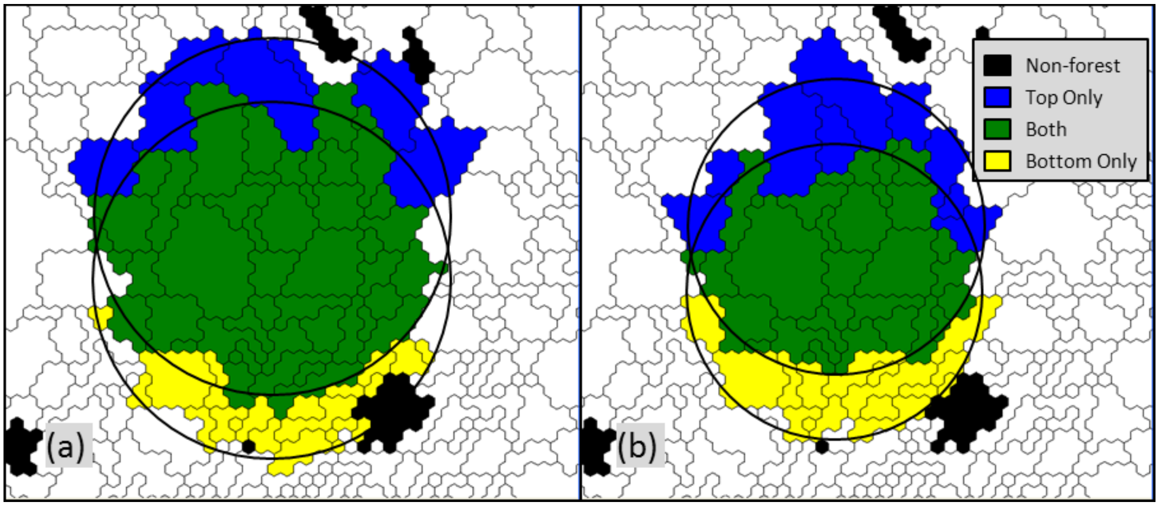


Figure 3.3: Grid cell examples with differing cell size and overlap percentages. Two cells (top and bottom) are depicted in each image with an area of overlap in the center. (a) depicts a 1500 acre cells with 80% overlap; (b) shows 1000 acre cells with 75% overlap.

The first step in the grid-based building heuristic is to define the basic grid cells to evaluate. Grid cells are constructed based on the desired size and the percentage overlap between grid cells. Several combinations of cell size and overlap percentage were tested to evaluate their strength in identifying the portion of a global optimal solution within each cell. Custom software was written to develop a processing routine to enumerate all possible grid cells for a forest meeting the cell size and overlap criteria. The basic cell shape was circular[2], and overlap was considered in both the north-south and east-west directions of the forest. Cell circles were pre-drawn to correspond with the size and overlap parameter settings. Stands were then included in each cell if more than 60 per cent of the area of a stand fell within the circle[3]. Figure 3.3 shows an example of two different cell sizes and overlap percentages in the north-south direction. Each map (a) and (b) shows stands in two overlapping grid cells (top and bottom), with the area in the center common to both cells. Map (a) depicts 1500 acre cells with an 80 per cent

[2] Circular-shaped grids were used simply because they represent a more compact patch shape than squares.
[3] The 60% inclusion rule is perhaps arbitrary, but it is not critical to the success of the heuristic. A higher percentage rule would result in smaller cells and a smaller percentage inclusion rule would result in larger cells that could just as easily be approximated by defining a larger or smaller circle size. The 60% rule was applied consistently to all grid sizes tested.

overlap; (b) shows 1000 acre cells with a 75 per cent overlap. Each map would have similar overlapping patterns in the east-west direction as well (not shown).

As a final refinement in identifying stands in grid cells, stands were eliminated if they were incapable of producing core area. Some stands, due to their situation on sites not capable of even growing jack pine, could be eliminated from the grid because they had no available management options to create core area. Other stands were isolated and small and were not spatially situated with other stands capable of producing core area. In both cases, these stands were not included in any grid.

The second step of grid-based building is to solve an optimization problem for each grid cell. The solution method used for this study resembles a hill-climb heuristic (Laguna, 2002). The hill-climb heuristic initiates with a solution comprised of a selected management option for each stand. Each stand is analyzed with a local search for improvement (i.e., does a different management option improve the overall value of the cell?). If a different management option for a stand other than the initially selected one can improve the value of the cell, the stand's selected management option is updated to the one that creates the higher value. The process continues through all stands until there are no more readily identified improvements, i.e., the top of the hill is reached. The weakness of the heuristic is that in a solution space with multiple hills, there is no guarantee the highest hill was ascended (the highest hill would be the optimal solution). The heuristic specific this study initially assigns a chosen management option (d_i) for each stand in the grid cell, based on the current time slice being evaluated in the cell. A modified version of equation (3.3) was developed to evaluate the value of management options other than the initially assigned option. The modification is that rather than assuming decision d for stand j can be chosen to maximize k_{t,d_j}, the d_j values have already been determined (with either the first selected management option, or the or an option resulting from a previous iteration). Equation (3.1) using the modified Equation (3.3) is then applied to each management option of each stand in the cell to see if a different management option increases the overall objective function value within the grid cell (i.e., the management option with the highest value V_{d_i} is selected). If a better solution (management option) was found for a stand, it was accepted and the next stand was evaluated in the same manner. The process continued until no better solution could be determined by changing a management option for any stand in the cell.

The heuristic was refined with a series of tests and trials to strengthen its performance. These tests generally varied the initially assigned management options and the number and types of hill climb heuristics applied in each cell. The solutions identified with each test were compared with an optimal solution of the problem (derived by solving a dynamic programming problem) to evaluate the strengths of the parameters of that test. These tests are not explicitly discussed here, but rather the final outcome is presented. The resulting heuristic used to solve each grid cell is depicted in Figure 3.4 and described in detail below. Briefly, within each grid cell, the largest feasible patch is identified in each planning period. The patch is comprised of stands with management options that initiate the patch in that period. A series of two hill-climb trials were then applied; one that sought to add KW value to those patches by adding more area (by selecting stands that originated KW patches in a different period) and a second one that sought to add overall value (including both financial and marginal value of constraints) by either adding or eliminating KW options from the current solution.

Figure 3.4 shows the grid-based building heuristic used to determine good treatment options for each stand. It initiates in the first grid cell *g* with period *t* set to 0. For each period in the planning horizon, *t* is increased by 1, and the stands that have a management option that creates habitat that originates in period *t* are initiated with that schedule. For example, a stand with two management options, one that creates habitat from periods 4-8 and the other from 5-9, would be assigned the first when *t*=4 and the second when *t*=5. This group of stands that create habitat all at the same time in period *t* is termed the “parent” patch. The initial tests of the heuristic assigned stands that did not have a management option that created habitat originating in period *t* to the highest-valued non-spatial option. However, the parent patch initiation rule was not strong enough by itself to identify the best management options in a grid, and the concept of “child” patch (groups of stands not part of the parent patch, but that can begin habitat in a different period) was developed to overcome these shortcomings. Observations of the spatial pattern of the optimal solution indicated that a patch could have temporal variation that required analysis beyond the parent patch alone.

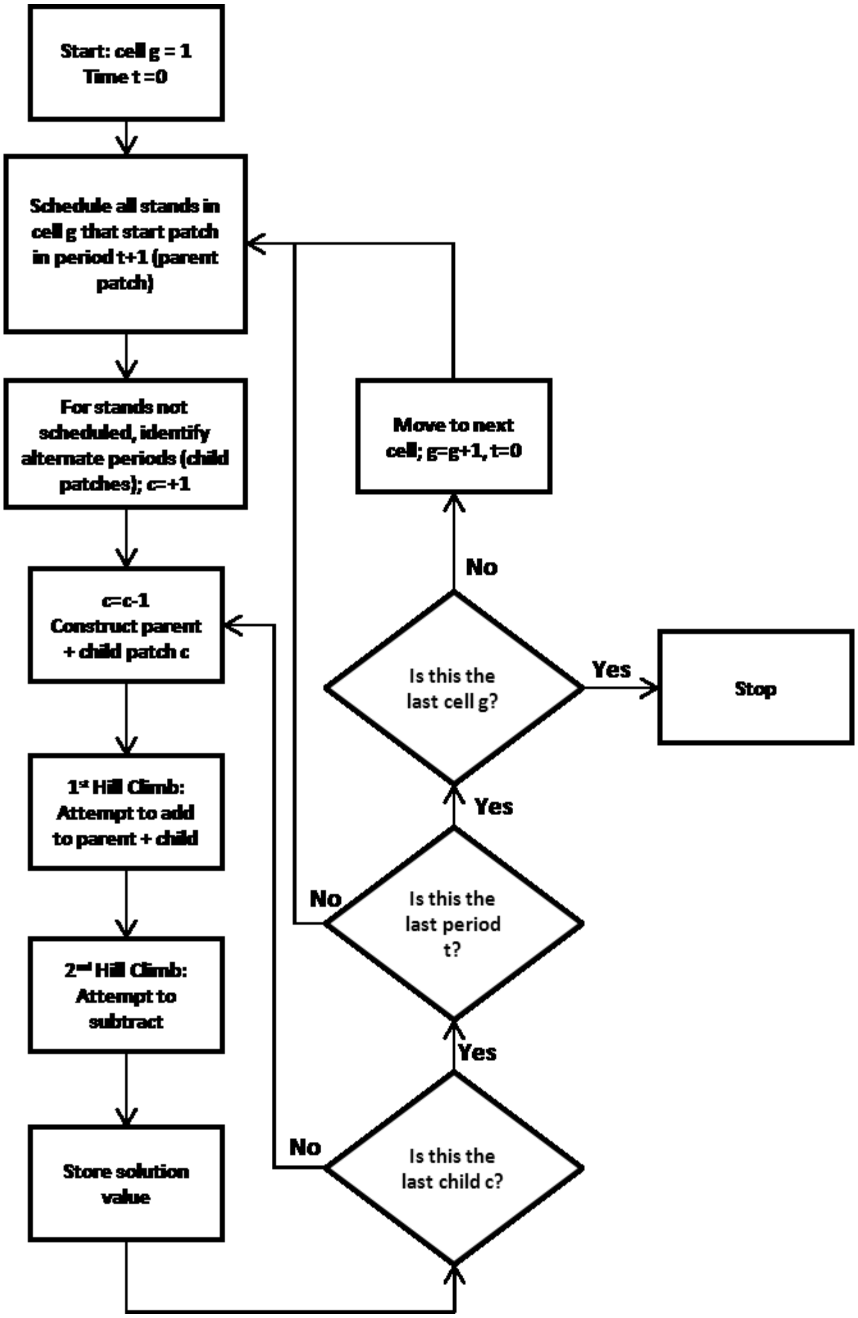


Figure 3.4: Grid-based building heuristic

As an example, Figure 3.5 shows two different planning periods of an optimal solution. Period (a) shows three disjointed patches. By Period (b) they are connected by the patch indicated by the circle. If only the patch originating in Period (b) was evaluated, the heuristic would potentially misidentify the optimal solution for the grid by missing the spatial interaction with patches that originated in Period (a). In other words, evaluating the Period (b) patch (within the circle) alone would miss the spatial interaction with the other two patches shown in (a). Therefore, stands in a grid not included in the parent patch for period *t* are searched to determine alternate management option timings that overlap temporally with the parent patch. Stands initially assigned the alternate timing management option form the child patch. In the problem evaluated in this study, a patch's duration was 5 periods, and a one-way search in time through 4 previous periods was used to create child patches with alternate timing options for other stands in the grid. A one-way search back through time rather than a two-way search (back and forward) was used to reduce redundant analyses. For example, a forward search from Period (a) in Figure 3.5 would identify the situation in Period (b), but a backward search from Period (b) would then identify the same situation and be redundant.

Timing choices for alternate patch creation in period *t* were used to construct child patches in periods *c* in the grid-based heuristic. The value of *c* is initially set to 1 and then decreased to 0 in the first iteration to ensure the parent patch is evaluated by itself. The value of *c* is then decreased until all potential periods of spatial overlap with the parent patch are evaluated. If a stand in the grid has a management option that creates habitat initially in period *c* it is assigned that option for the initial hill climb searches.

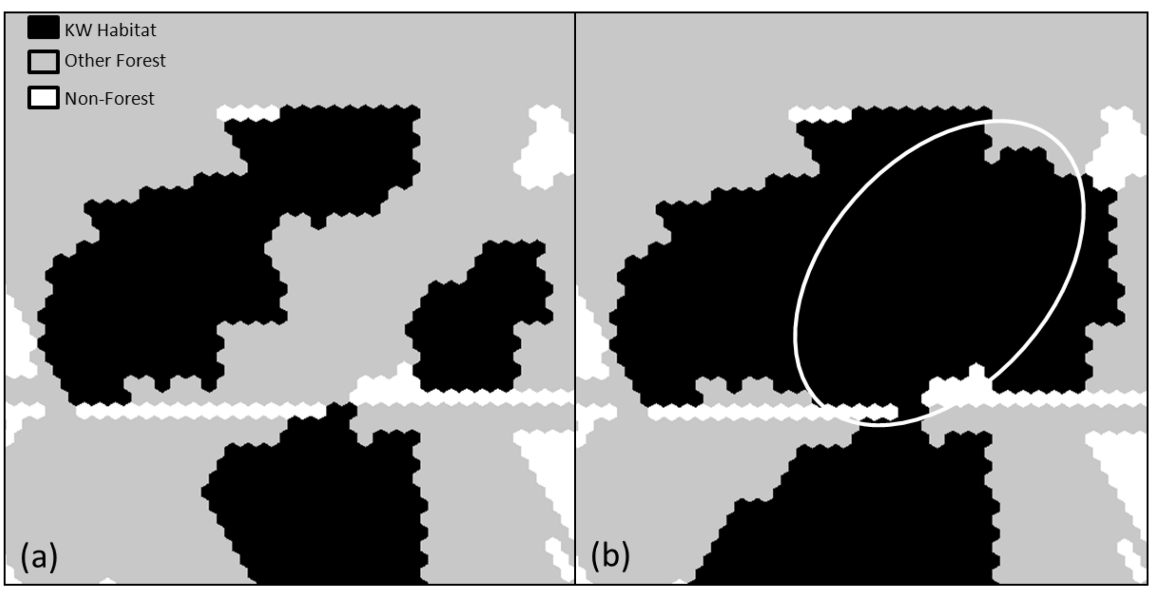


Figure 3.5: Patch dynamics in successive planning periods (a) and (b). The patch originating in period (b) indicated by the circle connects the patches in (a) which originate in an earlier period.

The grid-based building heuristic then proceeds through a series of two hill-climb heuristic searches to find the maximum net present value of the cell using management options that initiate habitat in period *t.* A hill-climb heuristic begins with a stand's assumed management option *m* and evaluates the other options in the context of the stands with which it shares influence zones. If management option *n* results in a higher value, the stand's assumed option is updated to *n*. The heuristic then moves to the next stand, and the search continues until no better options can be identified.

The first hill-climb search holds the management options of stands associated with period *t* or *c* constant and searches management options for other stands in the grid cell that increase the overall value of the cell. An example of this may be when ($c = t$ -2), and a stand that has a management option for ($c = t$ -3) and not ($c = t$ -2) increases the value of the grid. The second hill-climb begins with the solution to the first hill-climb and allows either additions or subtractions to the patch in the current solution. The grid-based building heuristic terminates when all periods of all grid cells have been evaluated.

The third step in grid-based building was to identify the spatial solutions to use in the full-forest problem formulation. In each grid cell, the *t/c* combination that produced the best value was identified for each period *t*. That *t/c* combination value was then compared to the best non-spatial solution value for the cell. If the value of the spatial solution was lower than the value of the best non-spatial solution, the spatial solution was eliminated from further consideration[4].

The spatial solutions retained in each grid cell (there could be multiple periods *t* that had spatial solutions better than the best non-spatial solution) were then ranked by per-acre value of the entire cell. Per-acre value was calculated as the value of the solution divided by the area of the stands in the cell. The highest (best) value was then used to calculate the "inferiority value" associated with other periods. An inferiority value measures how much less than the best cell solution an alternative management strategy is worth. For example, if the best solution was valued at $100 per acre, and another solution was valued at $90 per acre, the inferior solution would have an inferiority value of $10. In application, the best solution was assigned inferiority value of $0 and the other periods

[4] Programmatically, it is possible for the heuristic to pare down an inferior spatial solution for a period *t* in cell *g* to the best non-spatial solution. Tests showed this was not always the case (i.e., the hill-climb heuristic is limited), and therefore, the best spatial solution was always compared to the best non-spatial solution to filter out poor spatial solutions.

were assigned a value that represented the per-acre loss associated with that period ($10 in the example). The per-acre inferiority value was retained by associating the value with the stand-level management options in the cell's solution. For instance, stand *i* management option *d* might result in the second-best solution for grid cell *g* with an inferiority value of $0.25/acre. These ranking rules were applied to all cells, and if a stand's management option was associated with a better ordinal and/or per-acre value, it was modified appropriately. To revisit stand *i* management option *d* in cell *g*, if in cell *g'*, *d* was part of the best solution for cell *g'*, *d*'s inferiority value was updated to $0.

Finally, once all grid cells were processed, the values of each stand's management options were ranked by ordinal position relative to the inferiority values of only that stand's management options. Management options with an inferiority value of $0 were given an ordinal stand option rank of "1". It was possible for several management options for a stand to attain this rank since a stand was generally within several of the overlapping grid cells and different management options for the stand could be part of best solution found for different cells. If a stand had more than 1 management option with inferiority values of $0, the second-best option was given a rank of the next available position. For instance, if two management options had a value of $0, they would both rank 1, and the second-best would rank 3. Two metrics (inferiority value in a cell, and ordinal position in the stand's management options) were used as parameters for selecting management options to include in the model formulation of the larger KW problem.

Test Scenarios

A series of tests was conducted to evaluate the strength of each heuristic and how it is best applied to the larger problem formulation. Three optimal solutions for the larger problem formulation were determined at different spatial constraint levels. The stand-based trimming heuristic was tested by varying the maximum number of management options per stand used in the DP formulation. The grid-based building heuristic was tested by varying the grid cell size and overlap percentages. For each size and overlap combination, the inferiority value and ordinal rank were identified that ensured all stand-specific management options in the optimal solution were included in the model formulation of the larger KW problem.

There were three optimal solutions determined to evaluate the stand-based trimmer and grid-based builder. The three problems represented a range of problem formulations and solution stages one might typically encounter in solving the KW habitat problem. All of them included shadow price estimates for both KW core area (Figure 3.6) and other forest-wide constraints such as old red pine maximum area of regeneration. The marginal values for the 3500 and 4500 scenarios in Figure 3.6 are cyclical in nature due to the five-year persistence of habitat on the landscape. The current landscape condition has a preponderance of habitat that leaves suitability in a relatively abrupt manner fourteen years in the future. Therefore, another “pulse” of habitat must be created to supplant the current habitat, which results in relatively high marginal values in periods 7 and 8. This habitat, in turn, leaves suitability around period 15, which results in the need for another pulse. The trend continues through the planning horizon, and peaks in marginal value for habitat occur approximately every ten years. The three optimal solutions that were tested were as follows:

1. 4500 Constraint: This problem formulation had a core area constraint of 4500 acres per time period. The formulation tested an intermediate solution where core area shadow prices were close to, but not fully discerned, prices that would produce a feasible solution. The resulting core area levels in the optimal solution for these price levels ranged from 2200 acres to 8000 acres. The formulation is typical of an analysis one might conduct part way through a Lagrange multiplier search routine.
2. 3500 Constraint: This problem formulation had a core area constraint of 3500 acres per time period. Prices were refined to the point where the solution was nearly feasible, that is, core area was approximately (but not exactly) 3500 acres in all time periods (2977-4346 acres, with an average of 3583). This formulation represents a typical analysis one could conduct toward the end of a Lagrange multiplier search, when the multipliers yield near-feasible solutions to the primal problem.
3. 231 Price: This test was constructed to mimic an analysis that reflects a measure of society’s willingness-to-pay for a forest’s marginal social benefit (Paredes & Brodie, 1989). In this case, the benefit was Kirtland’s warbler habitat. It is unclear whether social benefit would change or hold constant if habitat or overall KW population is in relative short supply or over-abundance, but the per-acre value of

habitat is likely to decline as overall habitat or population increases. This test represents a scenario where the value is held constant. The price may or may not represent actual marginal social benefit, but is used to mimic an analysis that might seek to use such a value. The price was set at $231 per acre for each time period, which was derived as an average of the prices used in the 4500 Constraint problem formulation. The range of core area acres in the solution is more varied; from a low of about 1500 acres to a high of over 19,000 acres. Overall, the intent of the test is to add to the diversity of management strategies used to evaluate the strength of the two heuristics.

The tests were conducted on a 174,500 acre portion of the Hiawatha National Forest in Michigan's Upper Peninsula. The spatial objective of the problem was to create large patches of age 6-16 jack pine (*Pinus banksiana*) with stocking densities suitable for the Kirtland's warbler (*Setophaga kirtlandii*). This was accomplished by setting acre targets or financial value for core area habitat. The time horizon for the planning problem was 30 two-year time periods. Stands were given up to 28 management options apiece, corresponding to the time period in which they would be harvested and contribute to the spatial objectives of the problem. Twenty eight was the maximum simply because the window for harvesting jack pine is naturally limited: age 45-70 (corresponding to culmination of mean annual increment and the age at which the trees typically are susceptible to the jack pine budworm). Also included was a series of timing choices for second-entry harvests (age 48-52), as well as options to convert existing habitat stands to non-habitat stands toward the end of the planning horizon (to allow the model flexibility to improve inferior habitat designs currently on the landscape). Finally, other cover types such as red pine were allowed treatment options for conversion to habitat. Figure 3.7 shows the distribution of the number of KW management options considered for the 3927 stands in the 4500 Constraint problem (cumulative across all subforests). All 3927 stands had at least one potential KW management option.

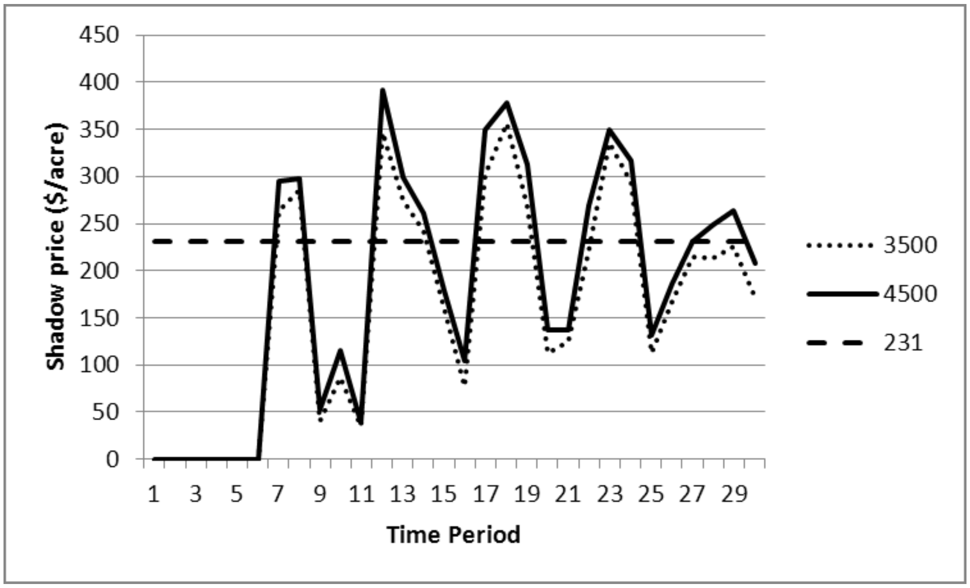


Figure 3.6: Undiscounted shadow prices used in the three scenarios

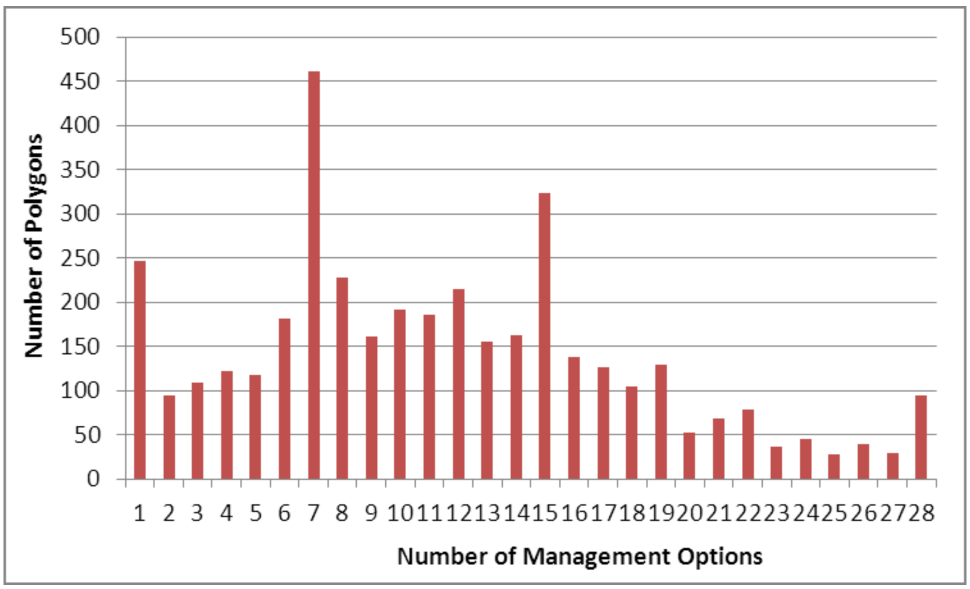


Figure 3.7: Management Options for Stands in Forest

Results were evaluated for each of four spatially-distinct subforests that represented a range of starting conditions. The four subforests are depicted in Figure 3.8. The sizes of the subforests range from 13,562 acres (1035 stands) in subforest 1 to 88,456 acres (6107 stands) in subforest 4. subforests 2 and 3 are 26,116 acres (1749 stands) and 46,674 acres (3416 stands) respectively. Non-colored areas are either sites not suited for jack pine (such as rich soil sites better suited to hardwoods), non-forest (such as roads and lakes), or non-National Forest.

Five grid cell sizes and five overlap percentages were used to test the grid-based building heuristic. Grid cell sizes ranged from 750 acres to 2000 acres and the overlap percentage ranged from 60% to 80%[5]. Figure 3.9 shows the number of grid cells that result from different grid design parameter settings. Generally, the number of cells increases exponentially by increasing the percentage overlap. Smaller cell sizes create more cells to evaluate at the same level of overlap. Design considerations are important because intermediate tests of this study showed that smaller cells are evaluated more quickly than larger cells (there are fewer hill-climb searches to conduct in each cell) and the overall number of cells is positively correlated with evaluation time.

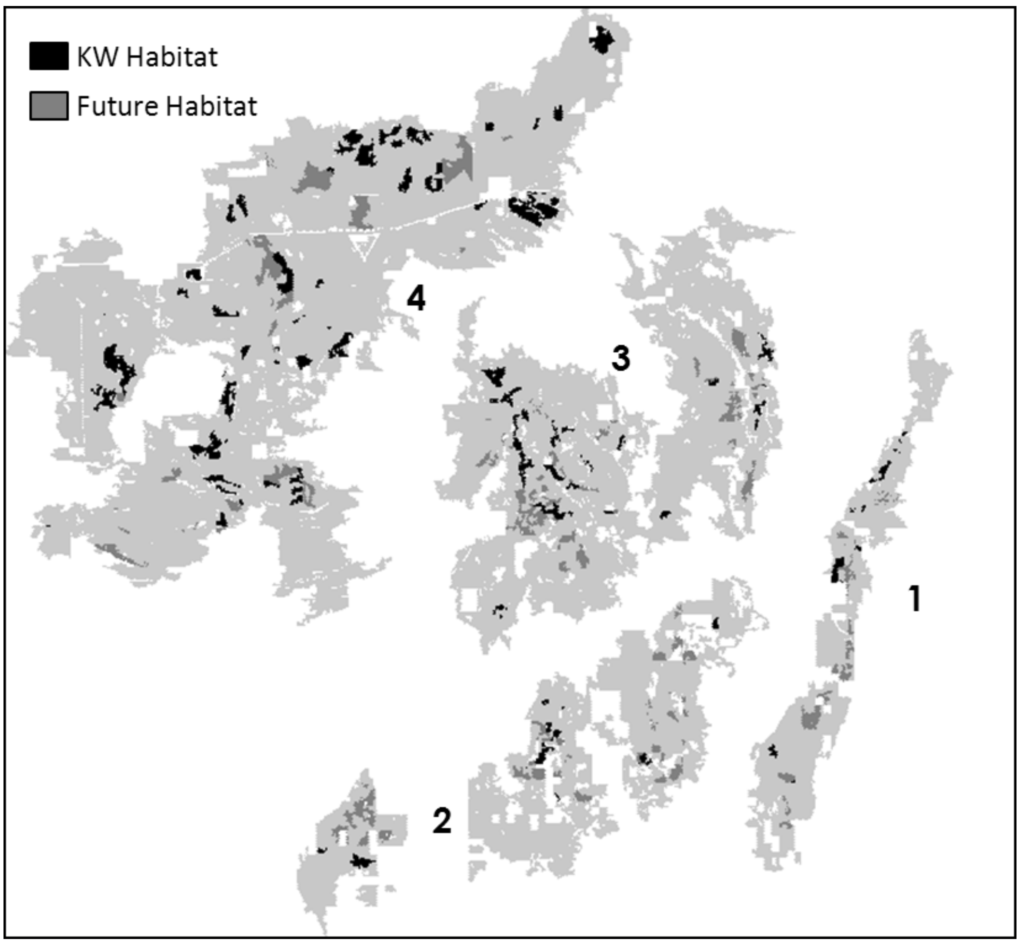


Figure 3.8: Subforests used to evaluate management option rules. Shaded areas represent the portion of the forest in the analysis. Future Habitat is expected future habitat younger than 6 years old. KW Habitat is current KW breeding habitat.

[5] Mathematically, circular grids require at least a 19% overlap to ensure full coverage of the area.

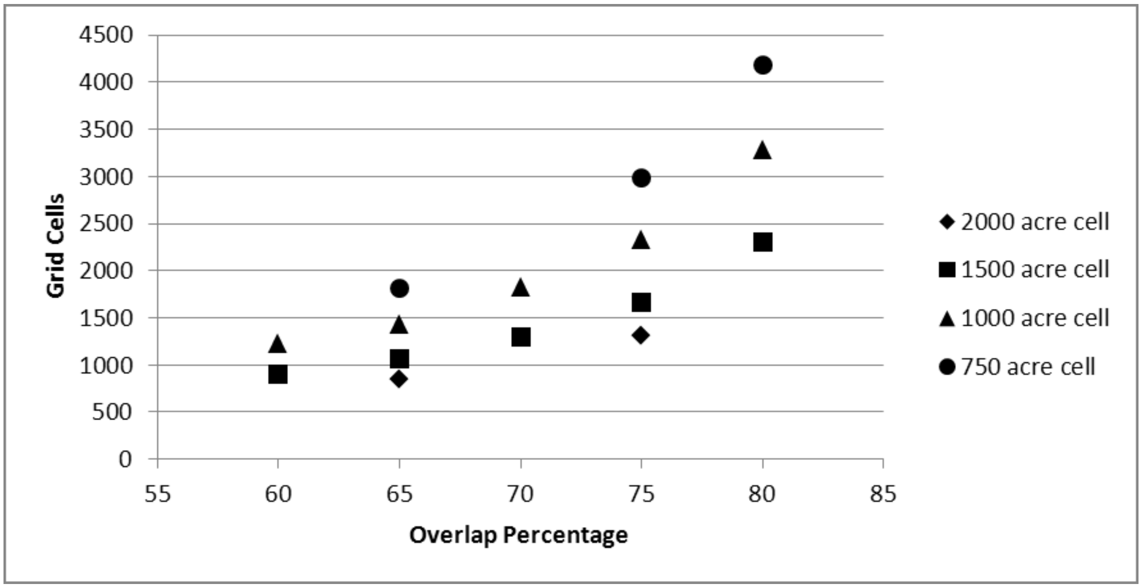


Figure 3.9: Grid cells resulting from varying grid design parameters

The quality of the heuristics and parameter settings are compared based on how well they identify the management options associated with optimal solution as well as how many management options are used in the DP problem formulation. The results of each heuristic's parameter settings were then used to formulate and solve the DP problem. The quality of solution and the time require to solve the DP are also presented in the Results section. Tests were executed on a Hewlett-Packard machine with Intel Core 2 vPro Processor using the Windows XP Operating system.

Results

The grid-based builder outperformed the stand-based trimmer in identifying the optimal solution and resulted in superior dynamic programming problem formulations and shorter solution times. None of the stand-based trimming trials were able to include the optimal management option for every stand in the DP formulation. Conversely, many of the grid-based building trials included all optimal management options while simultaneously filtering out more non-optimal management options than the stand-based trimming, resulting in leaner problem formulations. The leaner formulations not only resulted in identifying the optimal solution, but found it with increased speed.

Solution speed is an important consideration in this exercise, since multiple iterations of the DP formulation are required in the context of a larger Lagrange multiplier search routine used to ultimately solve the management problem. The solution time for the DP formulation was highly correlated with the number of management options in the formulation since the maximum formulation size was held constant (Figure 3.10). The correlation is not 100% since the actual size of the problem and solution time is dependent on areas of the forest that have influence zones with many management option combinations (Wei & Hoganson, 2008). However, the high correlation allows trimming efficacy to be quickly evaluated by quantifying the number of prescriptions that are used in the DP problem formulation. Trimming rules that eliminate more management options without eliminating optimal management options can be interpreted as superior. In a side note, the parameter settings for the DP solver were held constant for all trials to facilitate an unbiased time-to-solve analysis (see Wei and Hoganson (2008) for a discussion of the window size parameter settings of the DP solver). Increasing the maximum allowable DP formulation setting would have yielded better solutions in some of the tests, but would have required additional time to solve.

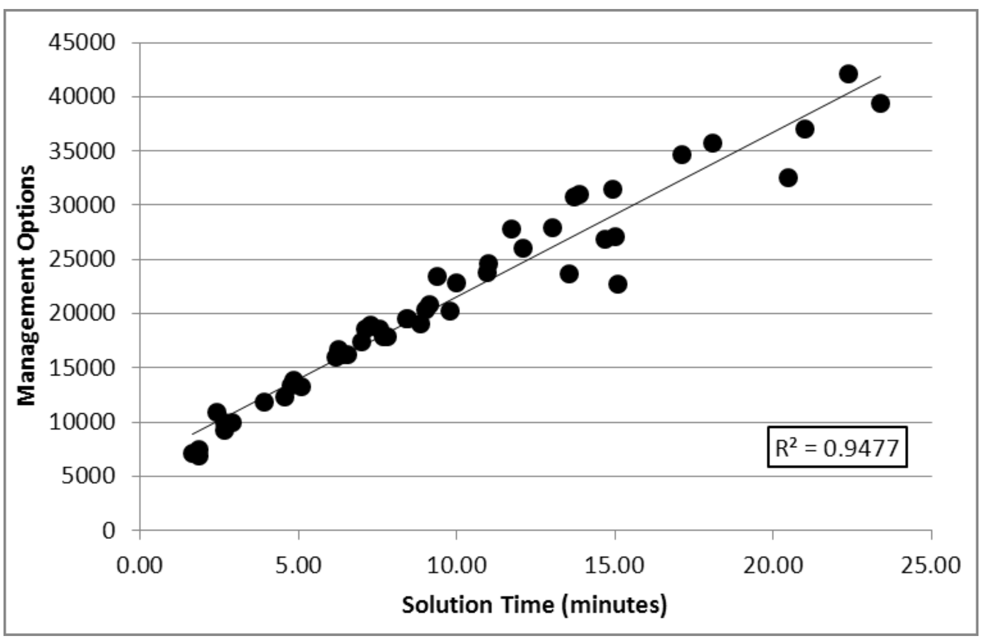


Figure 3.10: Management options used in DP-based heuristic vs. solution time. Points were compiled from all stand-based trimming and grid-based building tests portrayed in these results (48 points)

Stand-based Trimming Results

Results of the stand-based trimmer are summarized in Table 3.1. This table identifies the number of stands where the trimmer did not identify the management option associated with the optimal solution in the DP formulation (the second column) as well as the number of stands in the solution that did not match the optimal solution (the third column). The fourth and fifth columns identify solution inferiority gaps. The fourth column, “Obj. Ftn. Inferiority Gap”, shows the deficiency percentage of the solution measured against the DP objective function of the optimal solution. The fifth column, “Core Area Inferiority Gap”, measures the deficiency percentage of the core area value of the solution measured against the core area value of the optimal solution (the second term of Equation (3.1), adjusted to include only the core area within each stand and summed across all stands in the forest). The Core Area Inferiority Gap is included to show that while the overall value of the objective function may be close to optimum, the core area value may be departed by a relatively large amount (see 3500 Constraint - Trim to 7 Rx, which is within 0.02% of optimal, yet more than 6% departed in the estimated value of the KW habitat produced). Finally, the total number of management options used in the DP formulation is shown in the sixth column. Again, one can quickly evaluate this column to infer information about the solution time (shown in the final column)[6]. The solution time does not include the time required to execute the stand-based trimming procedure, which is minor and generally takes less than a minute of computing time. Trimming more management options takes more time than trimming fewer.

There are a few observations of stand-based trimming worth noting. First, all of the evaluated trim trials eliminate the optimal management option from at least as few stands, which in turn does not allow the solver to identify the optimal solution. The number of stands that miss the optimal management option (column 3) in the solution appears to be correlated with the number of stand-optimal management options missed in the initial formulation (column 2). This is not always the case, as the 4500 Constraint Trim to 15 Rx attempt fared worse than the Trim to 13 Rx attempt. However, this anomaly can be explained by a second observation, which is the problem becomes more difficult to solve with a more complex formulation (more included management options). The solver settings used in the DP, which allow the DP to find the optimal solution for smaller problems, are too restrictive to allow the DP to solve the more

[6] Solution times for the optimal solution are not shown because they required more stringent parameter settings, which resulted in long solution times that cannot be meaningfully compared to the other times in this table.

complex problem. A more thorough search similar to the one used in finding the optimal solutions would likely identify a better solution for the Trim to 15 Rx attempts. Finally, it is readily apparent that in order to include all optimal management options for all stands would result in a problem size (and solution time) similar to the “No Trim” problem size (compare the Total Rx Passed to DP for the 15 Rx trials with those from the “No Trim” trials). Ultimately, stand-based trimming as defined in this study is capable of producing solutions close to optimal in a reduced amount of time, but does not identify optimal solutions.

Table 3.1: Stand-based trimming results, including stands without optimal prescription passed to the DP initially, and solution inferiority gaps in overall and spatial value.

Trim To Rx	Initial Stands with Missed Optimal Rx	Solution Stands with Missed Optimal Rx	Obj. Ftn. Inferiority Gap	Core Area Inferiority Gap	Total Rx Passed to DP	DP Solution Time (m)
			4500 Constraint			
7	156	272	0.097%	2.40%	26078	12.1
9	99	229	0.068%	0.71%	31055	13.9
11	61	182	0.058%	2.13%	35777	18.1
13	33	89	0.012%	0.59%	39393	23.4
15	16	116	0.027%	0.62%	42145	22.4
No Trim	0	0	0%	0%	47921	*
			3500 Constraint			
7	55	119	0.021%	6.38%	20839	9.2
9	39	133	0.017%	5.06%	24599	11.0
11	25	86	0.012%	4.27%	27888	13.0
13	15	85	0.002%	3.93%	30778	13.7
15	8	107	0.011%	8.07%	32555	20.5
No Trim	0	0	0%	0%	36316	*
			Price 231			
4	123	316	0.043%	1.76%	23435	9.4
9	67	213	0.024%	1.27%	27780	11.7
11	38	197	0.017%	0.47%	31472	14.9
13	24	160	0.009%	0.94%	34677	17.1
15	9	136	0.006%	1.22%	37041	21.0
No Trim	0	0	0%	0%	41308	*

Grid-based Building Results

Results of the grid-based builder are shown in Table 3.2. The table is an aggregation of information derived from all four subforests depicted in Figure 3.8. The first two columns of Table 3.2 show the grid cell design: cell size and the percentage overlap of the grid cells. The third column shows the pre-processing time required to evaluate the grids and the fourth column is the time required to solve the resulting DP formulation. The fifth column represents the total time required to solve the problem. In instances where the builder failed to identify the management option associated with the optimal solution in the DP formulation, the sixth column shows a positive number.

Table 3.2 also shows information useful for developing strategies for including management options in the forest-wide analyses. Max Stand Rx (column 7) indicates the maximum rank of any optimal stand management option for the corresponding grid cell size and grid cell overlap. The Inferiority Value (column 8) is the maximum per-acre value (in dollars) from any grid cell that must be allowed in order to include all optimal management options. These two metrics can be used together to pare down the number of management options necessary in the problem formulation. For example, the second line of the table shows the 2000 acre grid at 65% overlap. All optimal management options are captured at the 8th or better ordinal rank or an inferiority value less than \$6.50. Therefore, it is prudent to require a management option to rank 8th or better and have an inferiority value less than or equal to \$6.50 to be included in the full problem formulation. Requiring both metrics to be satisfied would eliminate a management option that had an inferiority value of \$5.00 with a rank of 10 or one that had an inferiority value of \$7.00 and a rank of 6. The last column shows the total number of management options used in the DP formulation when the two metrics are used in combination.

There are several observations about grid-based building worth noting. Primarily, the heuristic out-performs stand-based trimming in both ability to include all optimal prescriptions in the DP formulation and the ability to reduce the number of management options used in the DP formulation. In those tests that were fully evaluated[7], the largest number of missed prescriptions was four; in the 4500 Constraint 1000 acre grid with 65% overlap. However, even this grid test still outperformed the best stand-based trimming tests (Table 3.1) in both including optimal management options and minimizing total options used in the DP formulation. The DP solution times by themselves were generally shorter than the solution times resulting from the stand-based trimmer, which again is likely due to the reduced number of management options used in the formulation.

[7] Not all combinations were evaluated due to poor performance at other constraint levels. For example, the 750 acre grids did not identify the optimal solution at the 3500 Constraint level, so were not evaluated at the 4500 Constraint level.

Table 3.2: Grid-based building test results

Cell size	Overlap %	Grid Build Time (m)	DP Solution Time (m)	Total Time	Initial Stands with Missed Optimal Rx	Max Stand Rx	Inferiority Value ($US/ac)	Total Rx Passed to DP
				4500 Constraint				
No Trimming						28		47921
2000	65	11.2	7.55	18.75		8	$6.50	18604
2000	75	21.19	8.4	29.59		9	$5.85	19519
1500	60	7	15	22		17	$16.17	27111
1500	65	9.2	2.41	11.61		6	$2.40	10864
1500	70	12.1	4.78	16.88		6	$3.96	13365
1500	75	17.13	6.26	23.39		7	$5.78	16745
1500	80	25.9	2.9	28.8		8	$1.47	9952
1000	60	5.21	14.7*	19.9		16	$23.71	26895
1000	65	6.7			4	*	*	*
1000	70	9	10.98*	19.98		16	$10.53	23739
1000	75	12.7	5.1	17.8		7	$3.92	13222
1000	80	19.1	7	26.1		10	$5.49	17406
750	65				Not Evaluated			
750	75				Not Evaluated			
750	80				Not Evaluated			
				3500 Constraint				
No Trimming						28		36316
2000	65	8.8	6.54*	15.34		16	$6.99	16264
2000	75	16.5	4.56	21.06		6	$6.60	12286
1500	60	5.67	1.66	7.33		8	$2.45	7100
1500	65	7.15	2.65	9.8		8	$3.64	9978
1500	70	9.6	2.67	12.27		6	$3.70	9296
1500	75	13.45	1.85	15.3		6	$2.38	7446
1500	80	20.32	1.86	22.18		6	$1.95	6830
1000	60				Not Evaluated			
1000	65	5.25			1	*	*	*
1000	70	7.3			1	*	*	*
1000	75	10	3.91	13.91		8	$6.23	11803
1000	80	15.1	4.84	19.94		10	$7.84	13848
750	65	4.22			1	*	*	*
750	75	8.07			1	*	*	*
750	80	12.24			2	*	*	*
				231 Price Level				
No Trimming						28		41308
2000	65	11.76	15.09	26.85		13	$7.92	22778
2000	75	22.28	13.56	35.84		13	$8.25	23700
1500	60	7.3	6.2*	13.3		12	$2.94	15923
1500	65	9.52	10*	19.52		19	$7.05	22818
1500	70	12.9	9.8*	22.7		13	$5.41	20274
1500	75	18.05	9.03	27.08		13	$4.79	20359
1500	80	27.27	8.87*	36.14		13	$3.84	19042
1000	60				Not Evaluated			
1000	65				Not Evaluated			
1000	70	9.33	7.67*	17		11	$4.67	17822
1000	75	12.87	7.81*	20.68		13	$4.00	17849
1000	80	19.48	6.4*	25.88		13	$2.72	16245
750	65	5.43	7.27*	12.7		13	$6.63	18972
750	75	10.3	7.12*	17.42		13	$5.47	18575
750	80	15.61	8.43*	24.04		18	$5.24	19538

* Solver parameter settings did not identify optimal solution

Not all of the grid based tests found the optimal solution even when all optimal management options were used in the DP formulation. This is particularly evident in the 231 Price tests where only 3 of the 13 evaluated grids designs identified the optimal solution, even when all optimal management options were used in the DP formulation. Missing the optimal solution was due to two primary factors: the DP solver parameter settings and the difficulty in identifying the optimal solution for this particular problem. First, the solution parameter values for the DP were set optimistically; that is, they assumed the formulated problem could be solved without rigorous search. Requiring a more rigorous search can and did identify the optimal solution, but with added computation time (these independent trials not are explicitly reported). Secondly, the suboptimal solutions found with the DP parameter settings used in the tests in this paper are close to the optimal. This indicates the presence of multiple near-optimal solutions that are difficult for the solver to discern. Most of the tests that did not find the optimal solution identified a solution within an objective function value within $92 of the optimal $37.4 million. For at least the problem studied in this application, this inferior solution is both quantitatively and qualitatively very close to optimal.

Interpretation and Application in the Solution Process

The information generated with this series of tests can be used to help calibrate parameter settings used in applied problem solving. Calibration requires interpretation and synthesis of the information generated by these tests, and is not readily apparent from looking at Table 3.2 alone. Additionally, there is a wealth of individual subforest information too voluminous to succinctly display and interpret in an included table (i.e., Table 3.2 would have to be expanded to approximately five times as wide to also show results for each of the 4 suforests). The reader is instead referred to Figure 3.11, where each data set represented on the x-axis is a grid design that performed well for each of the three sets of shadow prices assumed for KW habitat. The horizontal axis labels indicate both grid cell size and overlap percentage. The vertical axis measures “Deviation from Best Identification”. For each subforest, the grid design that resulted in the least number of prescriptions sent to the DP was determined to be the “Best Identification”, and given a value of “0”. The other grid designs were measured according to their percentage deviation from the Best Identification. For example, a grid design that resulted in twice the number of prescriptions as the best would be measured as a 100%

increase, or “1” on the graph. The vertical lines represent the minimum and maximum deviation ranges from the best identified, and the dot represents the average deviation from the best. Each min/max/average dataset summarizes twelve sample points (three constraint/price levels for each of the four subforests). Finally, the right-side y-axis measures the time in minutes required to process the grid design, and each design’s time is represented with a hollow diamond. Accordingly, with larger grids cells and higher percentages of overlap, more time is required to evaluate all of the grids.

Interpretation of Figure 3.11 requires a bit of subjectivity on the part of the modeler. This author offers that the 1500 acre grid with 70% overlap displays the best performance, based on the following arguments: First, it has the second-tightest performance (lowest maximum deviation) and second-lowest average next to the 1500 acre 80% overlap grid design. However, the 70% overlap grid had superior solution time performance as it was solved in half the time of the 80% overlap grid. Finally, the 1500 acre grid size in general performed with more stability than smaller grid sizes, which is why it is favored over the similarly performing 1000 acre 75% overlap grid. At the 1000 acre grid cell size, designs that had lower overlap percentages did not always identify all optimal management options. At the 1500 acre grid size level, all overlap percentage tests identified all optimal management options for all stands.

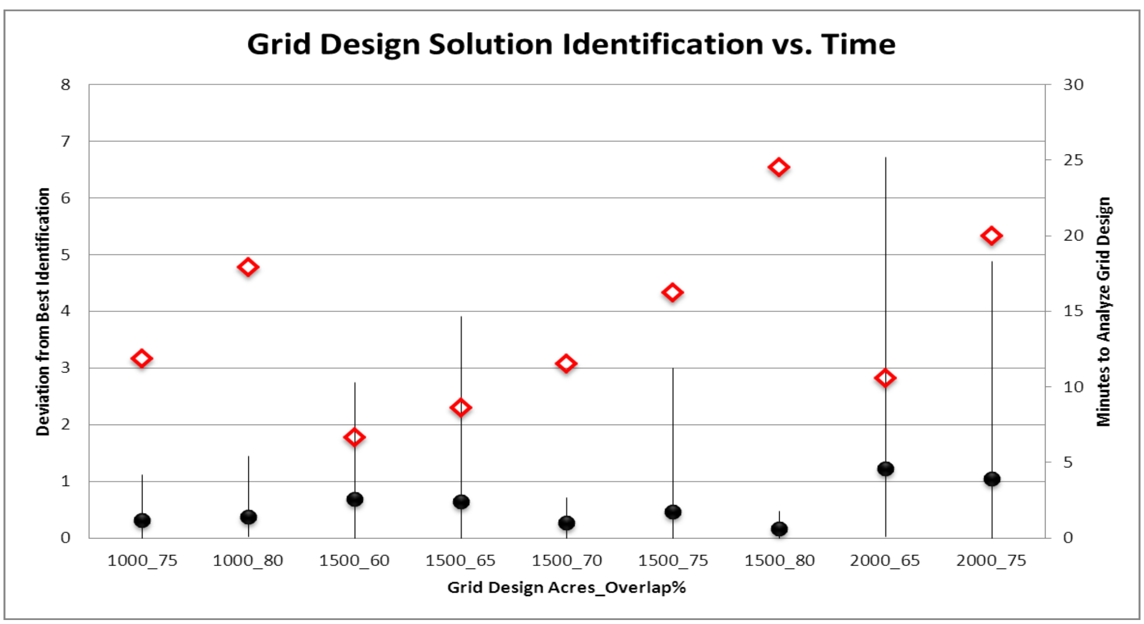


Figure 3.11: Grid-based building results synthesis. Information represents performance quality for different grid designs. Lines and dots represent the min/max and average deviation from the best performing setting. Diamonds represent the computing time required to evaluate the grids.

Discussion and Conclusions

Pre-processing effectiveness and efficiency

The objective to develop a pre-processing routine that simplified the problem without compromising the optimal solution was met with the grid-based building technique demonstrated above. In Table 3.2, the full number of management options potentially used in the full problem formulation is shown in the first line of each test. In grid-based trials, some grid designs reduced the number of management options used in the DP formulation by 80% or more without reducing solution quality (e.g. the 1500 acre 80% overlap test of the 4500 constraint level). The DP solution time reported in Table 3.2 is reduced when the grid builder eliminates more management options from the problem formulation. This evidence presents a strong case that effective pre-processing is both feasible and potentially efficient.

More efficiency in pre-processing may be realized with further investigation. The grid-based builder heuristic presented here (Figure 3.4) is a result of many investigations into the nature of the problem. However, there is likely more unrealized potential that could be exploited. For example, consider the best grid design for the 4500 Constraint trial, 1500 acres with 80% overlap. If one includes up to 8 management options per stand with an inferiority value of $1.47 or less, the problem size is reduced by 79% (1-(9952/47921)). However, if one could efficiently evaluate each subforest (Figure 3.8) independently and customize the inclusion parameters for each, the problem could be theoretically be reduced to 8217 prescriptions, a nearly 83% reduction in problem size. Another example involves evaluating the “last” optimal management option to be identified by the grid builder and question why it was so difficult. Sometimes this is based on luck of the grid design and its ability to evaluate the optimal patches efficiently. However, there may be opportunities to modify the grid-based builder heuristic to account for factors not yet considered. For instance, there was one management option that was not identified with the 750 acre 75% overlap grid design in the 3500 constraint test. This option was the only one not identified with a maximum stand rank of 11 or an inferiority value of $12.50. Why was it missed? Could rules be developed to strengthen the grid-based builder to capture that management option? One reason might be related to the one-way backwards search through time to identify child periods *c.* For example, consider the optimal solution for a grid cell has two patch ages where 25% starts in period 8 and 75% starts in period 5. A forward search starting in period 5 and capturing period 8 might identify this situation more accurately. Finally, another inefficiency with the grid-based builder in that the optimal management option is often times at the top of the list (highest stand rank and/or $0 inefficiency value). Yet, inferior management options are included for those stands in the DP formulation because the global inclusion parameters necessary to include all optimal management options was high. In the 750 acre 75% overlap design applied to the 3500 constraint level, 1211 of the 1263 optimal management options were associated with the best solution for at least one grid, yet the 750 acre grid cell design was inferior enough to be eliminated from detailed evaluation.

A potential weakness of the heuristic is that it may require significant testing before one is confident in the parameter settings used for a given problem. Problem-specific parameter settings are a common problem with meta-heuristic searches that can cause inefficiencies in the solution process (Baskent & Jordan, 2002), (Baskent & Keles, 2005). In grid-based building, the modeler doesn't know beforehand the appropriate inferiority values and stand rank that result in the most efficient problem formulation. Therefore, some pre-testing should be explored to be reasonably confident in the parameter settings to use. However, a strength discovered in this process is that for the problem that was tested, a wide range of grid cell size and overlap percentage parameter settings were successful for different constraint levels and/or problem formulations. The insensitivity of these parameter settings may make it less necessary for extensive parameter pre-testing. Perhaps with further investigation into opportunities to improve the heuristic, grid design parameter values can be determined that are less sensitive to a particular problem.

Another potential area for investigation is in developing other pre-processing routines. One area that was contemplated but not explored is the idea of time-based building. This concept is similar to grid-based building in that it would begin by identifying the single management option per stand associated with habitat generation in a parent or child period, and evaluating these solutions one at a time (Figure 3.4). However, instead of conducting these tests on a cell-by-cell basis, the entire forest would be solved with the resulting simplified DP formulation. After all time periods were evaluated, the solutions to the best time periods could be used to construct a simplified global DP across all time periods. Without actually investigating this strategy it is difficult to conjecture about its performance, but it may overcome some of the inefficiencies of grid-based building that were identified.

Further time efficiencies may be realized from limiting the frequency that the grid building routine is called during shadow price search, or modifying the search using smaller grid cells. For an application that employs an iterative search for shadow prices, the prices may not change substantially between iterations, so that a suite of management options identified for one set of prices may be relevant for a different set of slightly different prices. Therefore, calling the grid builder may not be necessary every iteration. Efficiency may also be realized by using smaller grid cell sizes since they solve faster. If, for instance, the stands around the edge of a cell (adjacent but not included) are assumed to be managed with maximal spatial alignment of the stands within the cell, the test may identify the optimal solution in a shorter amount of time while still limiting the total number of management options used in the full problem formulation.

Computing Efficiency

Another potential weakness of the grid-based builder approach is the time required to pre-process the grid cells negates some of the time savings of the DP solution (there is generally an inverse relationship between the time required to pre-process the grid vs. the time required to solve the DP (Table 3.2)). While some pre-processing time may be due to inefficiencies in computer code, some is due to not capitalizing on opportunities associated with advances in computing technology. The tests presented in this chapter were conducted on a Windows XP machine with an Intel Core 2 processor. This is worth mentioning only because solution times could be improved with technology associated with Windows 7 and later, combined with access to more memory. The grid builder routine is particularly suited to capitalize on the multiple-processor capabilities of modern machines with a technique known as “multi-threading”. Multi-threading utilizes a machine’s multiple processors to analyze discrete data instances simultaneously, thus increasing the overall speed of the problem solution. Windows XP Professional is not as efficient as later versions of Windows, in that a maximum of two physical processors can be executed simultaneously (Microsoft Corporation, 2002). The grid builder is suited to multi-threading because the solutions to each grid cell can be analyzed independently and then ranked after all grid cells have been solved. Multi-threading was utilized for two processors in the tests described here and generally reduced analysis times to 50% of the time it took to analyze the grids without multi-threading. Future applications on machines with more than a two-processor limit would likely show substantially faster times for the grid building analysis. In turn, this would facilitate a more thorough up-front processing analysis before constructing the DP problem formulation.

Incidentally, the DP solver may also be improved with the use of multi-threading. Each subforest (Figure 3.8) is a distinct problem and therefore multiple subforests can be solved on multiple threads and later compiled into a global solution. Furthermore, there are other factors (such as financial information that eliminate stands from consideration, or physical barriers such as roads, streams, lakes, etc.) that may break the forest into smaller distinct units that can be solved simultaneously with additional logical processors. Further investigation into the multi-threading opportunities of the DP solver may result in substantial time savings.

Conclusion

This study demonstrates that effective pre-processing routines can be developed that reduce solution times without compromising solution integrity. There are almost certainly other pre-processing strategies that can be developed based on the type of problem one is attempting to solve. The grid-based building processor described in this study is being used to investigate trade-offs of different management strategies that seek to develop and maintain Kirtland's warbler breeding habitat, which is the topic of Chapter 4 of this dissertation.

Chapter 4 : Long-term planning for Kirtland's warbler habitat: An application in Michigan's Upper Peninsula

Introduction

The Kirtland's warbler (*Setophaga kirtlandii*) breeding range is limited to one of the most geographically restricted regions of any mainland bird in the continental United States (Mayfield, 1960). Since monitoring began in 1951, over 98% of the population has been detected in Lower Michigan, and since 2000, 86% of the population has been detected in just five counties in northern Lower Michigan (US Fish and Wildlife Service, 2012). Since its passage in 1973, the Federal Endangered Species Act (16 U.S.C. 1531 et seq) has listed the Kirtland's warbler as "endangered", which was justified by its low population levels discovered during the 1971 decadal census. Consequently, in 1975 the Kirtland's Warbler Recovery Team was commissioned by the Secretary of Interior and drafted a Recovery Plan in 1976. The Recovery Plan described a strategy for the population level to increase to 1,000 singing males (Byelich, et al., 1976 Updated 1985). The plan recommended a combination of cowbird control and creation of 15,379 hectares of warbler breeding habitat in northern Lower Michigan, which has resulted in the warbler's recovery from a low of 167 singing males in 1974 to 2090 singing males recorded in 2012 (Byelich, et al., 1976 Updated 1985), (US Fish and Wildlife Service, 2012). Lower Michigan, however, is at the southernmost part of the jack pine's range. Jack pine is most widely distributed in Canada (McCullough, 2000). While it is difficult to speculate, global climate change may affect the future range of the jack pine and associated dependent species, including the KW. Correspondingly, the future survival of the species may depend on breeding habitat outside of Lower Michigan.

Before 1995, the Kirtland's warbler (KW) had been sighted outside of the Lower Peninsula of Michigan, but breeding activity had not been detected. Since 1995, breeding activity has been detected with consistency in Michigan's Upper Peninsula, and in 2007 the first nests were recorded in Wisconsin and Canada (Probst, Bocetti, & Sjogren, 2003), (Richard, 2008), (Trick, Greveles, Ditomasso, & Robaidek, 2008). Thus, the warbler's recovery appears to have resulted in population levels that have saturated the Lower Peninsula breeding habitat and caused colonization in geographic areas outside the Lower Peninsula (Probst, Donner, Bocetti, & Steve, 2003). Expansion into new geographic ranges presents both an opportunity and a challenge to forest managers who are concerned about the recovery of the species but are not poised to execute management strategies to create and maintain suitable warbler breeding habitat. Suitable habitat characteristics have been described by Probst (1988) and Kashian, Barnes and Walker (2003). The desired habitat occurs in young jack pine (*Pinus banksiana*), has a short tenure (10-20 years depending on site characteristics), relatively high stocking densities in patchy distributions, and a generally cited minimum patch size of 32 hectares (e.g., Probst and Weinrich (1993)). Donner, Ribic, and Probst (2010) found that larger, non-isolated patches were associated with earlier colonization and later abandonment, and birds may occupy patches smaller than 32 hectares if these patches are positioned in larger complexes of suitable habitat. Financial investments required to create suitable habitat can be substantial (Kepler, Irvine, DeCapita, & Weinrich, 1996), and in the context of cover type and age class imbalances, ensuring a steady supply of habitat in the future can be a challenging management problem to solve.

Quality habitat has been identified as critical to KW breeding success when population levels are low, as is often the case in newly occupied areas (Donner, Probst, & Ribic, 2008). Furthermore, the spatial arrangement and patch size of the habitat is correlated with utilization length. Larger patches are utilized earlier and longer, as are patches that do not exist in isolation (Donner, Ribic, & Probst, 2010). In designing a management strategy to respond to new colorizations, it may be relatively simple to identify good patches to create habitat in the near future (0-10 years). However, it can be difficult to foresee, without analysis, whether good habitat patches and amounts can be maintained through a full rotation (50 years). Future habitat consideration is potentially the most complex part of the KW habitat management problem.

Cost-effectiveness is another aspect of habitat management that must be considered, especially given the generally more expensive cost of habitat management (due to increased stocking densities that require planting more seedlings) and the limited resources that have historically impeded the full implementation of habitat creation objectives (Kepler, Irvine, DeCapita, & Weinrich, 1996). Earlier studies have emphasized minimizing the costs of management necessary to increase the likelihood of species' persistence and minimum population sizes (Marshall, Haight, & Homans, 1998), (Marshall, Homans, & Haight, 2000). Since recent population increases have resulted in the recommendation to down-list the KW to “threatened”, habitat management appears effective (Donner, Probst, & Ribic, 2008), (US Fish and Wildlife Service, 2012) and the cost of management is arguably justified. However, cost consideration in habitat management strategies may lead to efficiencies in habitat investments without compromising the quality of the habitat.

Finally, when there is existing management plan guidance for the landowner in a newly colonized geographic area (as is the case for National Forests), multiple management objectives may need to be considered, which further complicates the ability to achieve desired KW goals. While management areas in the Lower Peninsula are dedicated almost exclusively to the production and maintenance of KW habitat, management in newly colonized areas may be accompanied by objectives for other co-located vegetation species such as red pine (*Pinus resinosa*), oak (*Quercus spp.*), and white pine (*Pinus strobus*) (Kashian, Barnes, & Walker, 2003). The presence of other tree species allows flexibility in designing where and when to create habitat within the larger context of the forest, but it also creates an added level of complexity, i.e., analyzing cover type conversions and alternate rotation ages associated with different species and land conditions.

The study area presented in this Chapter is the Hiawatha National Forest in Michigan’s Upper Peninsula. The forest is located in one of the geographic areas recently colonized by the Kirtland’s warbler (Figure 4.1). The forest is comprised of roughly 362,200 hectares in two distinct geographic units of comparable size. The eastern unit is located between St. Ignace, Michigan on Lake Michigan and the southern shore of Lake Superior’s Whitefish Bay. The western unit is located between Lake Michigan’s Big Bay de Noc and the town of Munising, Michigan on Lake Superior. The 2006 Hiawatha National Forest Plan (USDA Forest Service, 2006) has made a substantial commitment to manage for KW breeding habitat. Suitable breeding habitat can be managed on four distinct glacial outwash plains of the Hiawatha National Forest (Figure 4.1, “Potential KW Habitat”). These four outwash plains are comprised of approximately 12,300 stands representing 70,600 hectares. Of this total area, the Forest has agreed to manage 13,600 hectares (20%) in a KW habitat system consisting of jack pine stands between 0 and 50 years of age, of which 2711 ha are age 6-16 at any given time (USDA Forest

Service, 2006). The stem densities of these habitat blocks are to correspond with the latest science provided by the U.S. Fish and Wildlife Service. Patches of habitat can be generated in blocks of up to 445 hectares in a single harvest activity. The specific stands managed as suitable breeding habitat, however, have not been explicitly identified. The Forest has discretion in where it places the 13,600 hectares of breeding habitat within the 70,600 hectares available, and therefore has latitude to design a management system that is both effective for producing KW habitat and financially efficient.

The Hiawatha National Forest Plan (USDA Forest Service, 2006) identifies an array of desired future conditions that describe diverse cover types and size classes in addition to KW habitat, including red pine, mixed pine and oak stands, maintained openings, and aspen. Kirtland's warbler habitat is one of these desired conditions and has not been deemed more (or less) valuable than the other desired conditions. Thus, other conditions must be considered appropriately when considering the design and placement of KW habitat. Finer scale ecological land type (ELT) information within the sandy, outwash plains ecosystems was used in the Forest Plan as a context to describe desired conditions. Ecological land types are identified by numeric code and described in detail in the plan's Environmental Impact Statement Appendix I (USDA Forest Service, 2006). The following descriptions are brief summaries of information found in Appendix I. The predominant ELT in the outwash plains is 10/20, the driest and sandiest. Plan direction states that KW habitat is to occur primarily on this ELT, and is suitable from age 6-16. Other ELTs include 30, which has better soils and higher site indices than 10/20, and supports jack pine even though it is more suited for red pine management. Jack pine grows at a faster rate on ELT 30, therefore KW habitat was assumed to be suitable only from age 6-12. The 40/50/90 ELT has deeper, richer soil and is generally associated with hardwood species. Jack pine is generally not found on ELT 40/50/90. ELT 60 is a transitional area between uplands and lowlands, and is capable of supporting jack pine, but it grows at a slower rate because the ecological conditions are not as ideal for jack pine. On ELT 60, KW habitat was defined as lasting for a longer period of time, from age 6-20. Finally, the 70A ELT consists of wetter, acidic site conditions. Jack pine has been detected on 70A growing reasonably well, and KW habitat on a 70A was defined as age 6-16, the same as ELT 10/20. There were minor inclusions of three other ELTs and non-forest conditions in the study area that were not constrained, managed or otherwise considered except for their locations could adversely affect a potential patch of KW habitat. Table 4.1 shows the total area and percentage of the ELTs included in the study area.

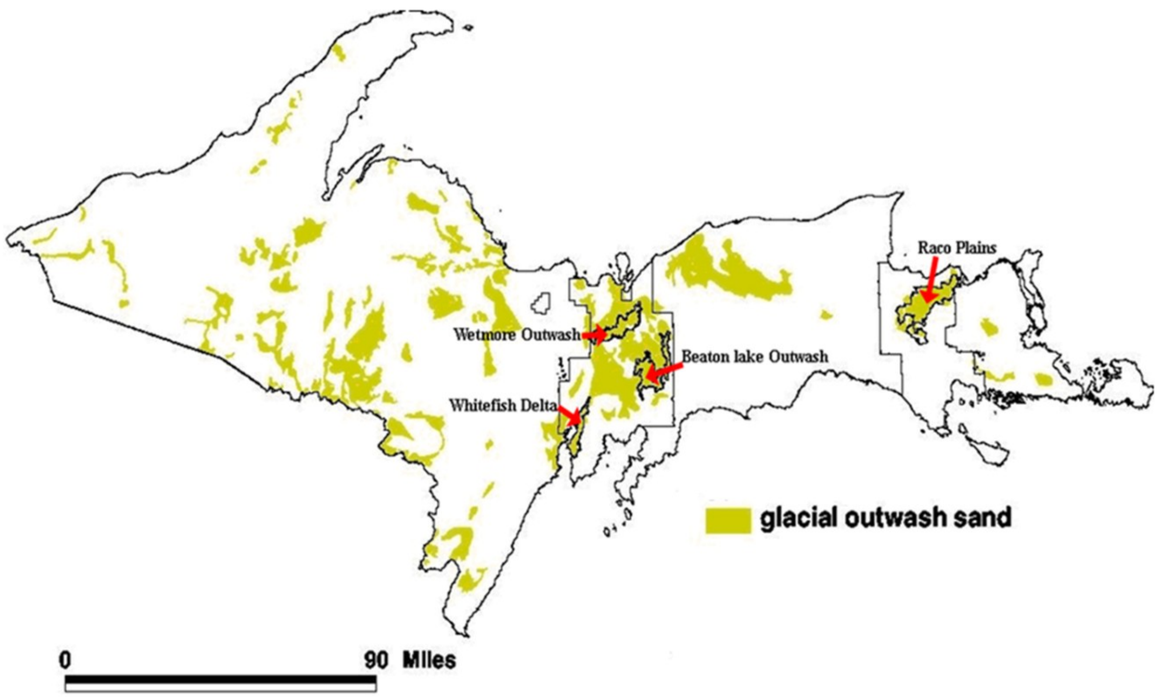


Figure 4.1: Michigan's Upper Peninsula including the Hiawatha National Forest proclamation boundary and glacial outwash plains with potential KW habitat

Table 4.1: Ecological Land Type quantities in the study area

ELT	Hectares	Percent
10/20	46403	66%
30	5243	7%
40/50/90	4151	6%
60	5722	8%
70A	3426	5%
Other	5799	8%
Total	70745	100%

Another important factor to consider when designing KW habitat is the current condition of KW habitat on the landscape. Managers on the Hiawatha National Forest have been intentionally creating habitat for the past several years which has resulted in a substantial area that currently meets the age definition of suitable habitat, or will meet that definition within six years (data current 2010). The current condition of KW habitat on the Hiawatha National Forest is shown in Figure 4.2[8]. Currently, there are 2544 hectares of age 6-16 KW habitat stands on the forest and an additional 2508 hectares that will become suitable habitat within the next six years. The impacts of these stands on habitat spatial arrangement will last for at least sixteen years until the most recently planted stands grow beyond the age of suitable habitat.

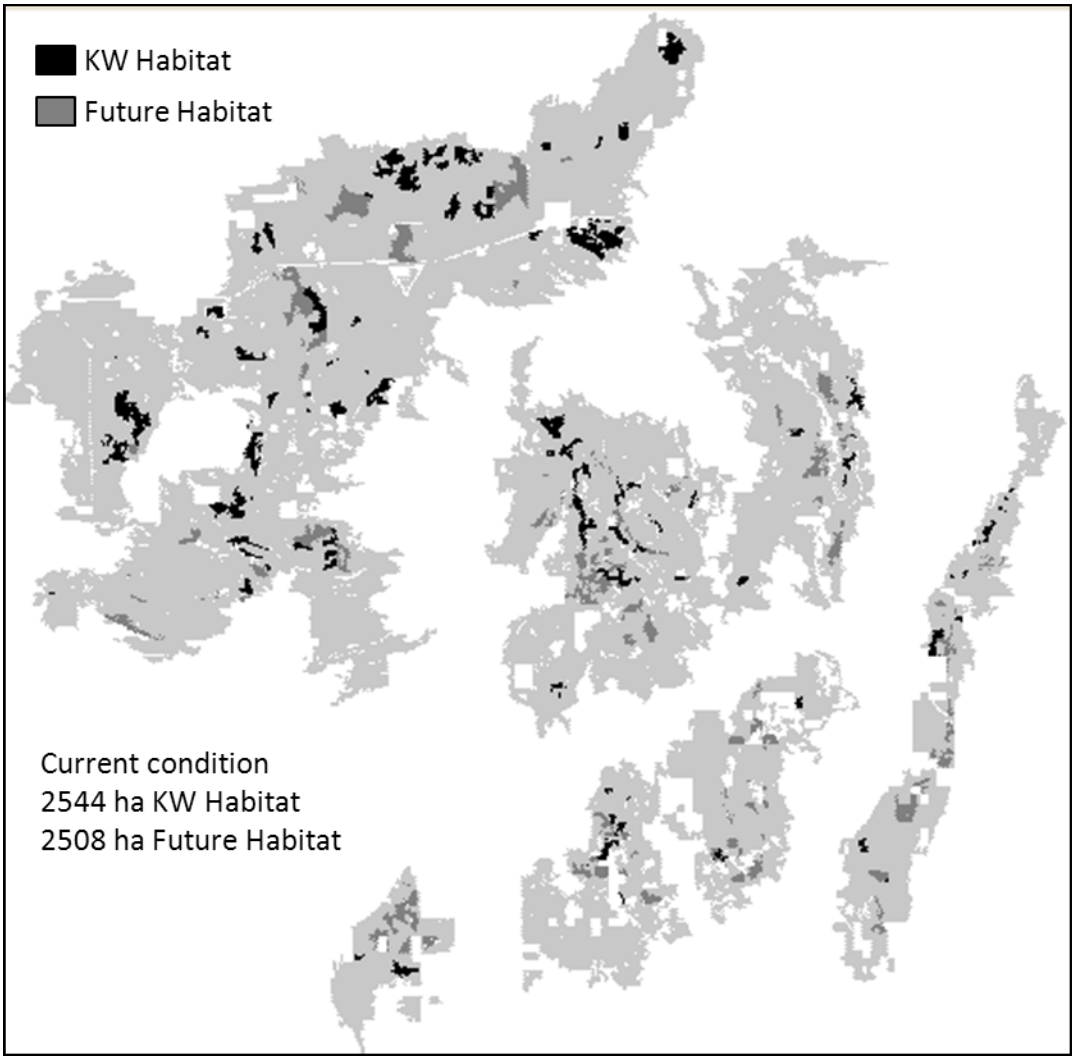


Figure 4.2: Current and planned future KW habitat distribution

Spatial problems similar to the KW habitat management problem faced by the Hiawatha National Forest have been the focus of past forest management studies. Several studies have focused on designing old forest in contiguous patches to provide habitat for

[8] The relative spatial arrangement of the outwash plains in this figure (and others) has been altered in order to compact the display. The actual geographic arrangement of these four areas is displayed in Figure 4.1.

species that inhabit forest interiors, e.g., Ohman (2000), Rebain and McDill (2003), and Toth and McDill (2008). Large, compact patches are associated with core area forest, or forest free from edge effects (Baskent & Jordan, 1995), (Ohman & Eriksson, 1998). Other recent studies that have analyzed the old forest core area problem are Wei and Hoganson (2007), and Wei and Hoganson (2008). While these studies generally describe techniques to schedule old forest core area, similar principles can apply to scheduling the young forest core area associated with KW habitat. A key difference is that KW habitat has a relatively short life, as it generally becomes too old to be suitable breeding habitat at age 16.

Dynamic programming (Bellman, 1954) was the solution technique used to address the KW management problem on the Hiawatha National Forest. Dynamic programming (DP) has been successfully used to address mature forest conditions on the Chippewa and Superior National Forests in Minnesota (Hoganson, Bixby, & Bergmann, 2003), (Wei & Hoganson, 2007). In these Minnesota studies, forest wide constraints for desired condition were modeled in addition to core area of mature forest. Solutions were found by integrating a spatial model with a non-spatial planning model in a process described by Hoganson, Wei and Hokans (2005). The solution methods described by these Minnesota-based studies were used as a basis for addressing the objectives of this study.

Objectives

The objective of this study is to provide managers on the Hiawatha National Forest with a management strategy to create and maintain persistent Kirtland's warbler breeding habitat. Specifically, the study seeks to answer the following questions:

- Where should the HNF locate the 13,557 ha in the KW habitat management system?
- Where and when should the forest schedule KW habitat regeneration within the KW habitat management system?
- What level of core area should be managed to produce the total desired 2711 ha of KW habitat at any point in time?

- To what extent would managing for KW core area help increase patch sizes and compactness as compared to managing for low-cost KW habitat?
- What are the likely financial tradeoffs between alternative KW management strategies for the Hiawatha National Forest?

Methods

Model Assumptions

A set of basic modeling assumptions was used to construct a series of scenarios designed to help answer the questions posed as objectives of the study. The reason for keeping the assumptions consistent was to provide a basis for comparison between the scenarios. Key assumptions are described in detail in the following subsections.

Planning Horizon and Time Periods

The planning horizon was 60 years and was modeled as a series of 30 two-year time periods. Sixty years was chosen to accommodate the average jack pine rotation length of 50 years, but with added flexibility to allow stands to convert to KW habitat later in the planning horizon for better spatial arrangement. KW habitat on the landscape at the beginning of the planning horizon will remain as KW habitat for no more than 15 years, including recently planted areas that will grow into suitable habitat within the next 5 years and remain suitable for 10 years after that. Some of the areas currently in the KW habitat system may be sub-optimal in the long term, and conversely, some longer-rotation species (such as red pine), that are young today, may be in areas ideal for conversion to KW habitat in the future. The 60-year planning horizon allows for a full-rotation feasibility study with some flexibility for conversion to occur both during and towards the end of the analyzed time period.

Two year time periods were chosen to accommodate for the relatively short-lived nature of the suitable habitat (10 years). Using short planning periods allows one to better refine harvest timing options and recognize potential management coordination between stands. One then has the added option to design coordinated management options that might slowly “walk” the habitat patch through the landscape over time, in addition to the creating discrete patches that do not overlap temporally.

Management Options

The model allowed a wide range of management option timing choices and conversion options for most stands in the forest. The outwash plains ecosystem in the Upper Peninsula where KW habitat is found has historically supported a mix of short and long-lived species, open savannahs, and small inclusions of broad leafed species (USDA Forest Service, 2006). The spatial arrangement of these different cover types was and is dynamic, depending on the disturbance history and seed source availability. Many opportunities exist to convert land areas not currently forested with jack pine to jack pine forest. Conversely, current jack pine stands may be converted to another cover type to help meet desired conditions of the forest.

The timing of the management options is another dimension that adds complexity to the model. Not only do the harvest timings of an existing stand vary, but the timing of future harvests of the regenerated stand has variation as well. In the discipline of forest management, using these alternative management option timing choices in a problem formulation is commonly referred to as a Model I (Johnson & Scheurman, 1977). To demonstrate, the modeling assumption used for red pine was the stand may be treated after reaching age 56 through the end of the planning horizon. If the existing stand is currently greater than 56, this represents 30 different timing options. The stand may be converted to any of five different cover types, including jack pine. If converted to jack pine, the assumption was it could be treated at any time between age 46 and 56, which represents 5 timing choices for each of the initial 30 timing choices. This is tempered somewhat by eliminating from the analysis those choices that occur after the end of the planning horizon.

Conversion into, out of, and between the different cover types, combined with the many different timing options for these prescription options, results in an abundance of possible management options for any given stand. To revisit the example of the mature red pine stand, the assumptions resulted in 332 unique management options. For the 12,307 stands recognized in the model, there were a total of 1.08 million management options analyzed, or an average of 88 per stand.

Each management option was associated with a set of outputs that resulted at different time steps as the management strategy is implemented. Outputs included revenues, costs, and timber yields. Saw log and pulp volumes and revenues were recognized for up to four species per stand (to accommodate stands with a mix of cover types). Costs included sale administration, planting, and several types of site preparation activities. Costs and prices were derived from National Forest databases that store information about timber sales and were current as of 2010. The costs of regenerating KW habitat are displayed in Figure 4.3 where they are contrasted with the costs of regenerating jack pine at normal stocking levels. In the figure, there are several source cover types that can be used to create KW habitat, namely, aspen, openings, jack pine, former KW habitat, mid seral (mix of broadleaf and conifer species), and red pine. The horizontal axis label shows the source cover type on top and the regenerated cover type underneath. Generally, KW habitat regeneration is more expensive due to increased site preparation and planting costs associated with the high stocking densities required for KW breeding habitat. The lowest cost option for regenerating KW habitat is from a jack pine or former KW habitat stand. The highest cost option is to convert aspen. Aspen conversion requires rigorous site preparation and maintenance activities to rid the site of roots that are prone to coppice regeneration. Product volumes were consistent with those determined for the 2006 Hiawatha National Forest Land Management Plan. In all, there were 2.42 million outputs associated with 150,000 unique management options used in the model.

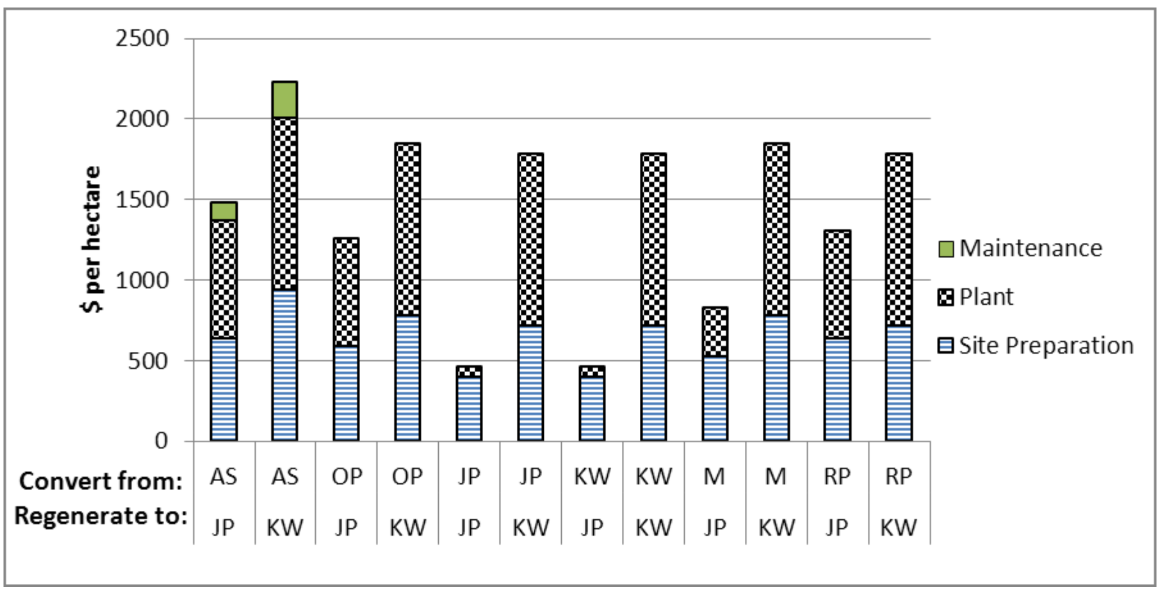


Figure 4.3: Jack pine and KW habitat management costs by different origin cover types. AS = Aspen, JP = Jack pine, KW = KW habitat, OP = Opening, M = Mid-seral, RP = red pine

Other model assumptions: Objective Function, Ending Inventory, and Constraints

The objective function for this exercise was to maximize financial net present value of the overall management strategy for the forest. This is simply the difference between management costs and the timber revenues realized through time summed across all stands and time periods at a 4% annual discount rate. Ending inventory of the forest was valued by calculating an infinite series of management actions mirroring the last full rotation applied to the stand before the end of the planning horizon. Spatial interactions between stands were valued by projecting conditions over an additional 60 two-year periods beyond the first 30 periods used to address forest-wide planning constraints. Value was given to forest conditions and KW habitat beyond the end of the planning horizon to help ensure that ending inventory values do not assume atypical harvesting right after the planning horizon and that adequate KW habitat was persistent beyond the end of the planning horizon.

Constraints in a forest management model address objectives other than maximizing financial value, such as achieving sound ecological conditions, perpetual timber harvest, or desired levels of wildlife habitat. Constraints in this exercise were formulated to achieve the desired conditions described in the Hiawatha National Forest Management Plan (USDA Forest Service, 2006). Specific constraints were used to define limitations on regeneration (to control timber volume/even flow) and desired amounts of specific cover types, such as openings and red pine. Table 4.2 shows a simplified version of the constraints used in the model, as well as the current condition on the landscape. In the table, a constraint set represents the set of 30 constraints (one for each planning period) used to achieve the desired condition of the set. Values of individual constraints in a constraint set may change over time to allow the model to feasibly achieve them, as in the case where current condition is above or below the long-term desired condition and time is required to meet the constraint. Therefore, both short-term and long-term constraint levels are shown. Lower constraint types indicate a minimum desired level and Upper constraint types indicate the maximum desired level allowed. In all, these 18 constraint sets represent 540 period-specific constraints used to define desired conditions in the model. One constraint that is conspicuously absent from Table 4.2 is KW habitat on the 10/20 ELT. The majority of KW habitat on this ELT was achieved by setting Upper constraints on the amount of KW habitat that could be created on other ELTs. The rest of the habitat, by default, must therefore be created on ELT 10/20.

Additionally (not shown in Table 4.2), there was a constraint set of 30 constraints for the desired level of KW habitat core area, set to create large, compact patches of habitat consistent with the overall minimum level of habitat (2711 ha) described in the Forest Plan. Determining the appropriate constraint level to achieve the overall habitat acreage is one of the objectives of this study, and therefore several levels were tested.

Table 4.2: General constraint levels used to represent multiple management objectives of the Hiawatha National Forest

Constraint Set	Constraint Type	Constraint beginning (ha)	Constraint long-term (ha)	Starting condition (ha)
ELT 30 KW Habitat	Upper	40	40	0
ELT 60 KW Habitat	Upper	121	121	0*
ELT 70A KW Habitat	Upper	61	61	0*
ELT 10/20 Red Pine all ages	Lower	12950	12950	17517
ELT 30 Red Pine all ages	Lower	2711	2711	2711
ELT 60 Red Pine all ages	Lower	931	931	1044
Mature red pine - all ELTs	Lower	11129	11129	11162
ELT 10/20 Openings	Lower	3683	4007	3718
ELT 30 Openings	Lower	20	20	219
ELT 10/20 Openings	Upper	4249	4371	3718
ELT 30 Openings	Upper	243	61	219
ELT 60 Openings	Upper	486	81	454
ELT 10/20 Regeneration < 10	Upper	6597	6475	6824**
ELT 30 Regeneration < 10	Upper	870	870	189
ELT 40/50/90 Regeneration < 10	Upper	81	81	49
ELT 60 Regeneration < 10	Upper	688	202	721**
ELT 70A Regeneration < 10	Upper	405	405	324
ELT Non-KW Age 0-2	Upper	809	809	1177**

*Currently, habitat is scheduled to occur, but is younger than 6

** The first period constraint is not violated due to growth out of the age class

The total amount of KW habitat in each period was constrained indirectly by searching, outside the model, for a core area constraint level that achieved the total habitat desired condition of 2711 hectares in each period. The reason for constraining core area rather than total area was to design habitat areas in compact, large patches. A constraint on total habitat without spatial consideration was surmised to be less effective at creating large patches. A constraint on total habitat in addition to core area had the risk of creating a few small patches with little core area just to meet the total habitat constraint.

In this study, core area was defined by using a buffer distance around the basic unit used to describe the landscape; the hexagon. Hexagons were chosen to simplify the calculation required to define spatial interactions between stands since they have regular spatial interactions with all adjacent cells, which is not the case for stand designs such as squares or irregular polygons (Heinonen, Kurttila, & Pukkala, 2007). The dataset was created by generating a 0.81 hectare hexagon grid that was intersected with the Hiawatha National Forest's vector-based stand layer. The stand with the most area in each hexagon was used to attribute that hexagon. Hexagons that were part of the same original stand were then combined to form the stands used in this problem. The buffer distance implemented in this study is the area outside a center hexagon and inside of a larger hexagon formed by connecting the centers of the six surrounding hexagons. In Figure 4.4, the largest hexagon represents the buffer around stand 1. If all area within this buffer was KW habitat, stand 1 would qualify as core area habitat. This is generally accomplished by managing the adjacent stands for KW habitat. If stands 1, 3, and 4 were all managed for KW habitat, the resulting core area would not only occur in a portion of stand 1, but portions of stands 3 and 4 as well (the area inside the triangle). As seen in Figure 4.4, the buffer distance required to create core area varies somewhat, as it is based on a hexagonal landscape. It can be approximated by calculating sizes of circles with the same proportional areas area. The area of the buffer surrounding each hexagon is twice the area of a single hexagon. A circle of area 0.81 ha surrounded by a circle of 2.43 ha would have a constant buffer distance of approximately 37 meters. The buffer distance affects the amount of core area required to meet the overall desired level of habitat (2711 hectares). The constraint level for core area required to meet the overall level of habitat was explored with a series of modeling scenarios.

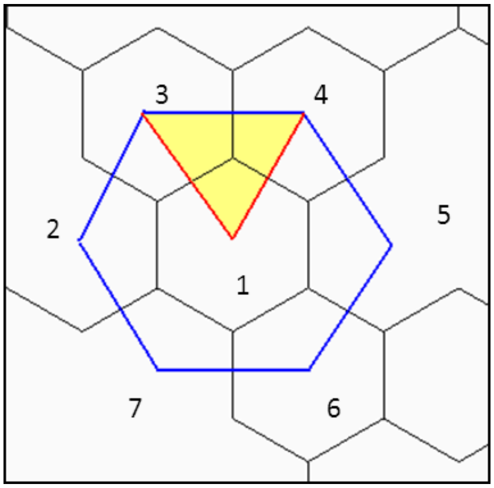


Figure 4.4: Buffer distance used to define core area in this study. The area within the triangle will provide KW core area only when stands 1, 3 & 4 all meet the requirements for KW habitat.

Scenarios

Several scenarios were evaluated to provide information about the objectives of the study, including the spatial and financial trade-offs of alternative designs of Kirtland's warbler breeding habitat. Three "benchmark" scenarios were developed to provide baseline information about the potential value of the forest with and without KW habitat consideration. A set of three full model scenarios were developed by varying the core area constraint to explore what level of core area should be targeted to meet the overall habitat goal of the Hiawatha National Forest.

Benchmark 1(No KW) solves the forest management problem without KW habitat consideration. This benchmark provides a basis for the financial value of the forest if KW habitat concerns are not considered and can subsequently be used to evaluate the total cost of KW habitat.

Benchmark 2 (No Core) introduces a KW habitat constraint of 2711 hectares per time period, but does not consider the spatial arrangement of KW habitat. The value of this benchmark can be compared with Benchmark 1 to determine the minimum financial costs of creating the desired level of KW habitat.

Benchmark 3 (Core only) uses a minimum constraint of 2226 hectares of KW habitat core area as well as constraints on regeneration. The constraint was set at 2226 ha level to correspond with the 2226 hectare full scenario (described below) that was largely successful in achieving 2711 ha total KW habitat. Constraints for other cover types are not considered. The benchmark provides a basis from which to compare the impact of the other constraints on KW patch and core area potential.

The full model scenarios were developed to determine a management strategy that addressed all constraints, including hectares of KW habitat core area. Three scenarios were developed, using per-period core area constraints at 1416 ha, 1821 ha and 2226 ha. Due to the overabundance of planned KW habitat in the next 12-14 years, both the 1415 and 1821 scenarios had core area constraints from periods 7-30, and the 2226 scenario had core area constraints for periods 6-30 to maintain a minimum of at least 2711 ha of total habitat. These scenarios are the basis from which to compare the financial and spatial impacts of KW habitat management as well as establish the amount of core area that should be managed to meet the Forest Plan objective of 2711 ha of total habitat. Finally, these scenarios are evaluated to describe the amount of area in patches greater than particular size thresholds including 32.4 hectares, which has been cited as a minimum desirable patch size for effective KW habitat (Probst & Weinrich, 1993).

Solution Method

The solution method used to identify the management strategies in this study was a combination of two planning models, DualPlan and DPSpace. Prior to this study, these two models had been integrated and used in National Forest planning in Minnesota to address core area of mature forest (Hoganson, Wei, & Hokans, 2005). The function of the DualPlan model is to identify the financial cost (marginal value) of management limitations (constraints) to satisfy an objective to maximize financial value of the forest-wide management strategy. The DPSpace model then uses the marginal value information from the DualPlan model to schedule the stands for management. The DPSpace model is used because it has the ability to evaluate spatial interactions between stands assuming the marginal values are correct.

The DualPlan model is based on a solution method developed by Hoganson and Rose (1984). The primary objective of the model is to determine how to manage the forest for maximum financial net present value in the context of other management and resource objectives. These other objectives are also known as “constraints”, as they often limit management activity for financial value alone. The formulation in this study involves two types of constraints. Non-spatial resource constraints define desired levels of cover type classes (such as red pine) and/or age classes. In other studies, they may also include timber outputs or limits on certain activities such as clearcutting. Spatial constraints in this study are minimum levels of KW breeding habitat core area. DualPlan functions by searching for marginal values (also known as shadow prices or dual prices) of these constraints; that is, it attempts to determine the minimum level of foregone financial value the manager must incur in order to meet the constraints. For example, recognizing that stands are assigned to their management alternative that maximizes their estimated value, including their value in contributing to the forest-wide constraints, a 90-year old red pine stand might need to receive a marginal value (or "credit") of $200 per hectare in order to maintain it as a stand contributing to a constraint requiring at least 1000 hectares of mature forest in the solution. The $200 per hectare marginal value is suggesting that the manager could increase the objective function (financial value of the forest in this study) by about $200 per hectare if she was willing to accept only 999 hectares of older forest and realize $200 per hectare from managing the marginal stand in another way. Alternately, managing for 1001 hectares would cost the manager about $200 more than necessary to meet the 1000 hectare constraint.

The DPSpace model is based on work done by Hoganson and Borges (1998) to address adjacency constraints. The model has been adapted in this study to address the core area constraints for KW breeding habitat. Briefly, DPSpace determines the management schedules of stands by incorporating the shadow price information determined by the DualPlan model. DPSpace considers the spatial interactions of stands to schedule them simultaneously in such a way to meet both the non-spatial and the spatial constraints of the problem.

The modeling process is an iterative one; that is, the DPSpace solution is used to evaluate how well the constraint levels are met. If the solution does not meet constraint levels, DualPlan is called again to determine new estimates of marginal values, and the process continues until an acceptable solution is reached. One phenomenon to consider with this system is the potential imprecision of the model solution. Since the DualPlan model searches for the marginal values that meet the desired constraint level, there are usually small deviations in how well the outputs meet the desired constraint levels. Deviations are partially due to the difficulty in identifying precisely accurate marginal values and partially due to the whole-stand management nature of the model. To revisit the red pine example, consider the marginal stand; that is, the last stand that would qualify financially to meet the 1000 hectares constraint level[9]. Suppose that the marginal stand is two hectares, and suppose that at a marginal value (shadow price) of $199 per hectare, this marginal stand is not scheduled to help satisfy the constraint so only 999 hectares are scheduled by the model. Suppose at a marginal value of $200 per hectare the marginal stand is scheduled to help satisfy the constraint, but then including it would result in managing 1001 hectares of red pine as mature forest. At a first glance, perhaps the problem seems solved; a 1- hectare excess meets the minimum constraint level and the manager should be satisfied and accept the solution. Yet, by definition, the 1-hectare excess could be costing the manager $200 too much. So, does the manager accept the 999 solution for a financial gain, or lose $200 but achieve more than the desired minimum 1000 hectares of red pine? A related problem that may be even more pronounced than the marginal stand is the problem of the marginal patch. The value of a patch is dependent in part on all of the stands that comprise that patch. Therefore, a small change in marginal value may result in a patch comprised of several stands to enter or exit a solution.

Results

Solutions Evaluated

The solution method will often identify a management strategy with small imprecisions in meeting constraint levels. Therefore, it is desirable to measure the total imprecision across all constraint levels to determine whether it is an acceptable solution; that is, a solution that closely meets the desired constraint levels. The benchmark and scenario solutions presented in this study were each inspected to ensure that no singular constraint had a large deviation under or over the desired constraint level. Additionally, constraint sets were examined to ensure that any particular type of constraint was not consistently violated. In the solutions presented in this study, each constraint set was within 1% of the desired level cumulatively over all 30 planning periods. Furthermore, the

[9] Some stands will likely be managed at a $0 marginal value; these are the first to be included in the bin of stands managed to meet the 1000 hectare constraint level. If the total area is less than 1000 at a particular marginal value, the value is increased incrementally until the constraint is met. In a set of heterogeneous stands, stands are likely added to the bin incrementally as the marginal value estimate increases.

solutions presented in this study met the core area constraints within 400 ha cumulatively over the 30 planning periods and all other constraints (Table 4.2) within 4000 ha cumulatively over the 30 planning periods. Figure 4.5 shows how core area constraints were met for the 1416, 1821, and 2226 scenarios. The largest constraint violation in periods 7-30 is the 2226 scenario period 21 which is four percent below the desired constraint level.

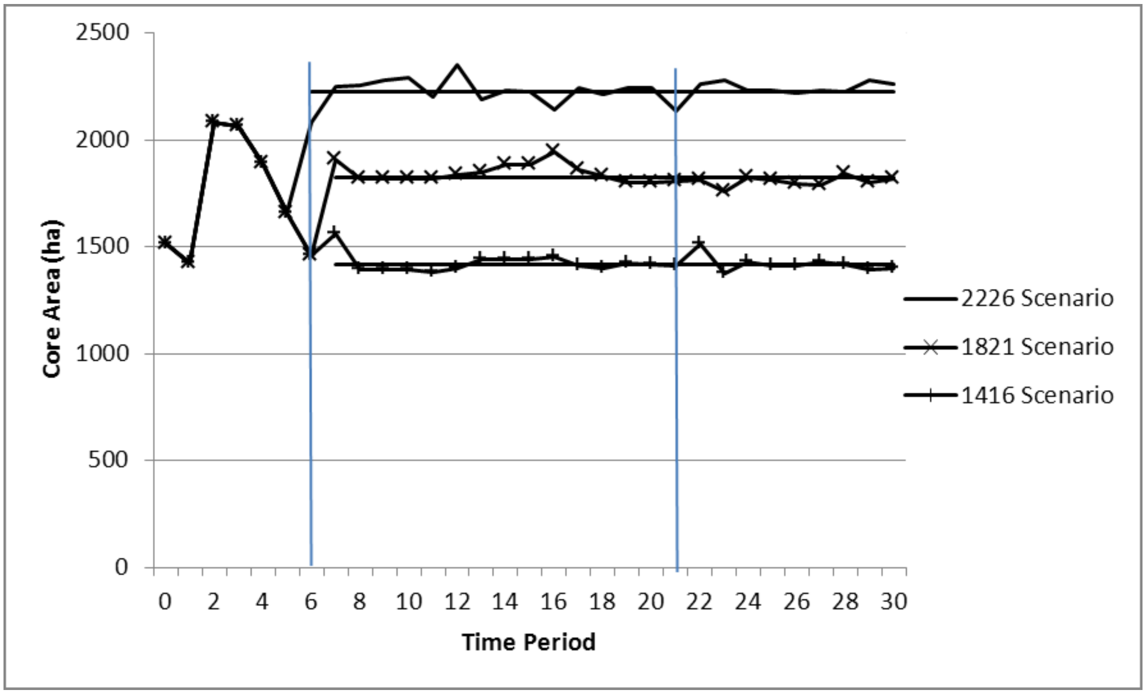


Figure 4.5: Core area constraint satisfaction. Horizontal lines are the core area constraint levels.

Core area required for desired level of KW habitat

The total amount of KW habitat through time resulting from the 2226 hectare core area constraint produced results the closest to the desired 2711 hectares of habitat in each time period. Figure 4.6 shows the total KW habitat resulting from constraints on core area at the 1416, 1821, and 2226 hectare levels. At the 2226 hectare core area constraint level, the poorest performing time period was period 11, which resulted in only 2535 hectares of overall KW habitat. This is not surprising since the model was not explicitly constrained to meet the desired 2711 hectares of habitat. However, as discussed below, the patches produced in period 11 arguably have the best design of any of any planning period. The large patches of this period may be a positive trade-off for not maintaining the full 2711 desired hectares. Another observation about the 2226 hectare core area constraint level is that there are some potential inefficiencies, most notably in period 6. In period 6, the overall amount of KW habitat produced was 3244 hectares, over 500 hectares more than required by the management plan. This result is mainly a holdover from the design of existing habitat that could not be effectively augmented. As a result, new patches needed to be created in order to meet the overall core area constraint (which at 2078 ha was still more than 100 ha below the constraint level – see Figure 4.5). Since the 2226 core area scenario resulted in a management strategy closest to the direction in the Forest Plan, it is used as the basis for most of the analysis described below.

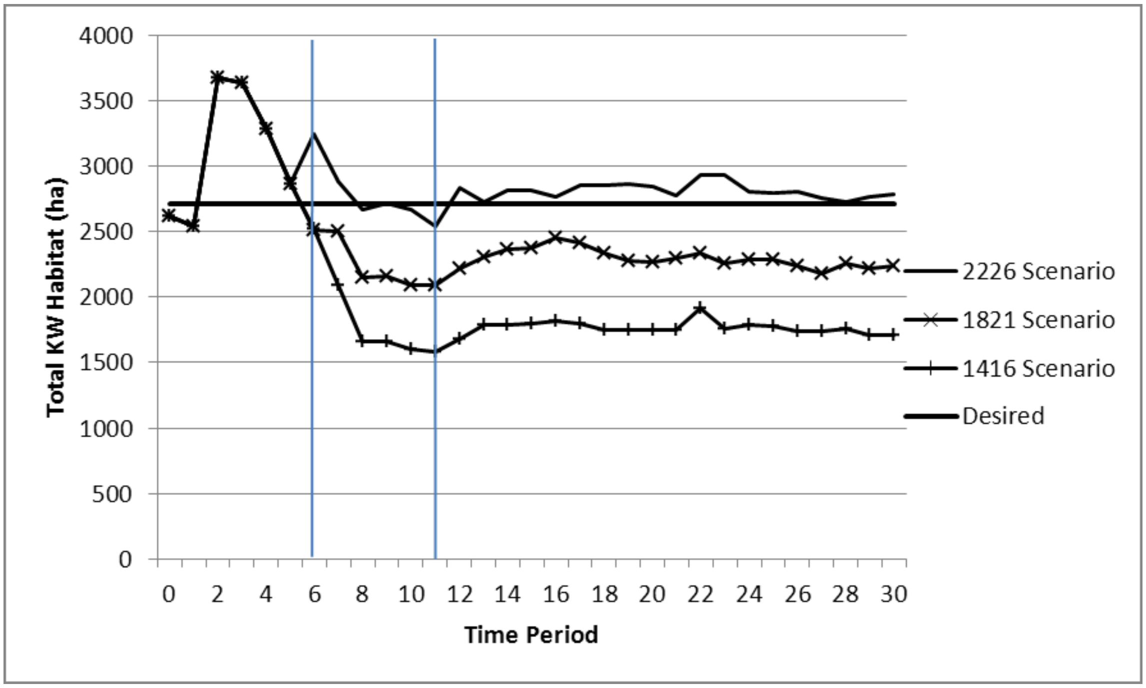


Figure 4.6: Total KW habitat resulting from constraints on core area. The horizontal line represents 2711 ha of desired KW habitat.

Location and timing of KW habitat

A possible solution for the long-term KW habitat management system on the forest is shown in Figure 4.7. This figure depicts results of the full 2226 scenario. The solution is to manage a total of 13,856 hectares of KW habitat managed in perpetuity starting in period 8 (after the effects of current habitat have passed). To reiterate, there are currently 2544 hectares of age 6-16 KW habitat stands on the forest and an additional 2508 hectares that will become suitable habitat within the next six years. Figure 4.7 also shows 2819 hectares of the forest that are currently habitat or planned habitat that are not maintained through time. Most of the areas not maintained in the long term appear smaller and more isolated than the areas chosen as part of the long-term system. Small, isolated patches of habitat that are currently on the landscape may be a relic of natural disturbance or successful natural seeding from forest management activity not explicitly designed to create KW habitat. They do not necessarily reflect explicit management decisions to create KW habitat. The data to distinguish current natural or unintentionally created KW habitat from intentionally designed habitat was not available for this study.

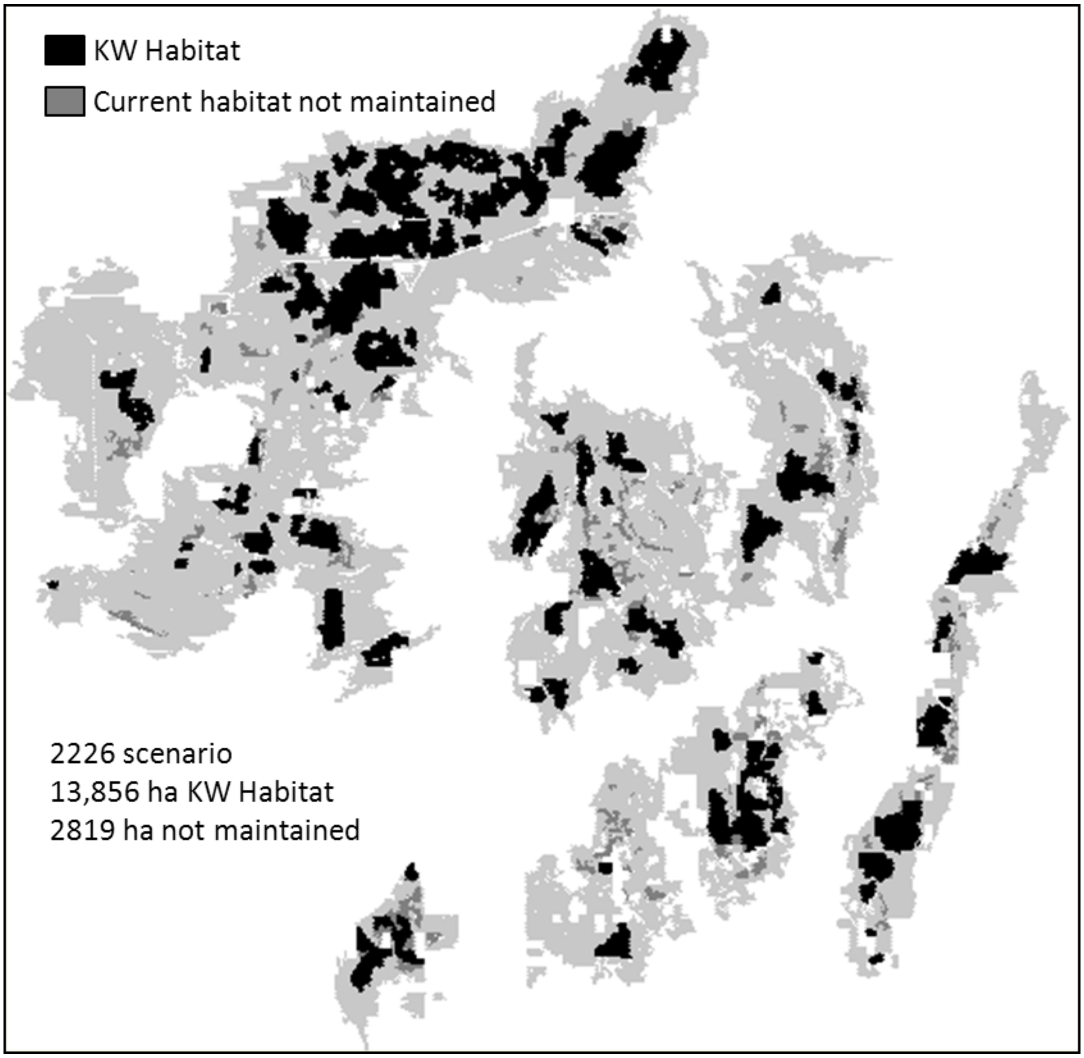


Figure 4.7: Core KW habitat areas found in the 2226 scenario (13856 ha) and current KW habitat not maintained in the long term (2819 ha)

The timing and location of when and where habitat should be generated on the landscape is a bit more difficult to display concisely. The timing for regeneration of KW habitat is displayed in Figure 4.8, which shows the hectares of KW habitat regeneration over time scheduled by the model. Regeneration peaks every 10 years (5 time periods) with corresponding lower levels of regeneration every 10 years. The regeneration schedule corresponds to the 10 year duration of KW habitat (age 6-16). Note that the present and expected future habitat on the landscape does not necessitate any regeneration until time period 3. Also note that at the end of the planning horizon, there are sufficient plantings scheduled to ensure that KW habitat is maintained beyond the end of the planning horizon, even though such habitat is not explicitly constrained. Figure 4.9 displays where the habitat occurs on the landscape at distinct points in time. In this figure, “Future Habitat” is recently regenerated KW habitat (less than 6 years old) and “KW Habitat” is currently suitable habitat 6-16 years old. In Figure 4.9, period 3 (a) is consistent with the first regeneration activities scheduled by the model. Period 11 (b) corresponds to arguably the best patch design and period 16 (c) has the poorest patch design (see discussion below). Finally, period 28 (d) is shown to contrast the spatial arrangement on the landscape one full 50-year rotation after period 3 (a).

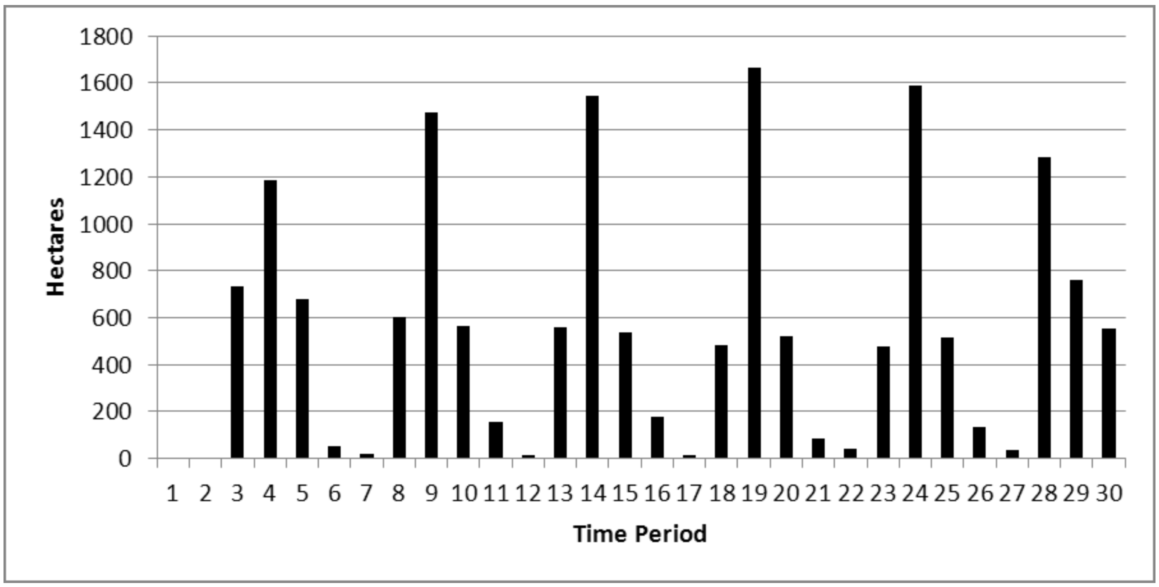


Figure 4.8: hectares of KW habitat regeneration by time period in the 2226 scenario

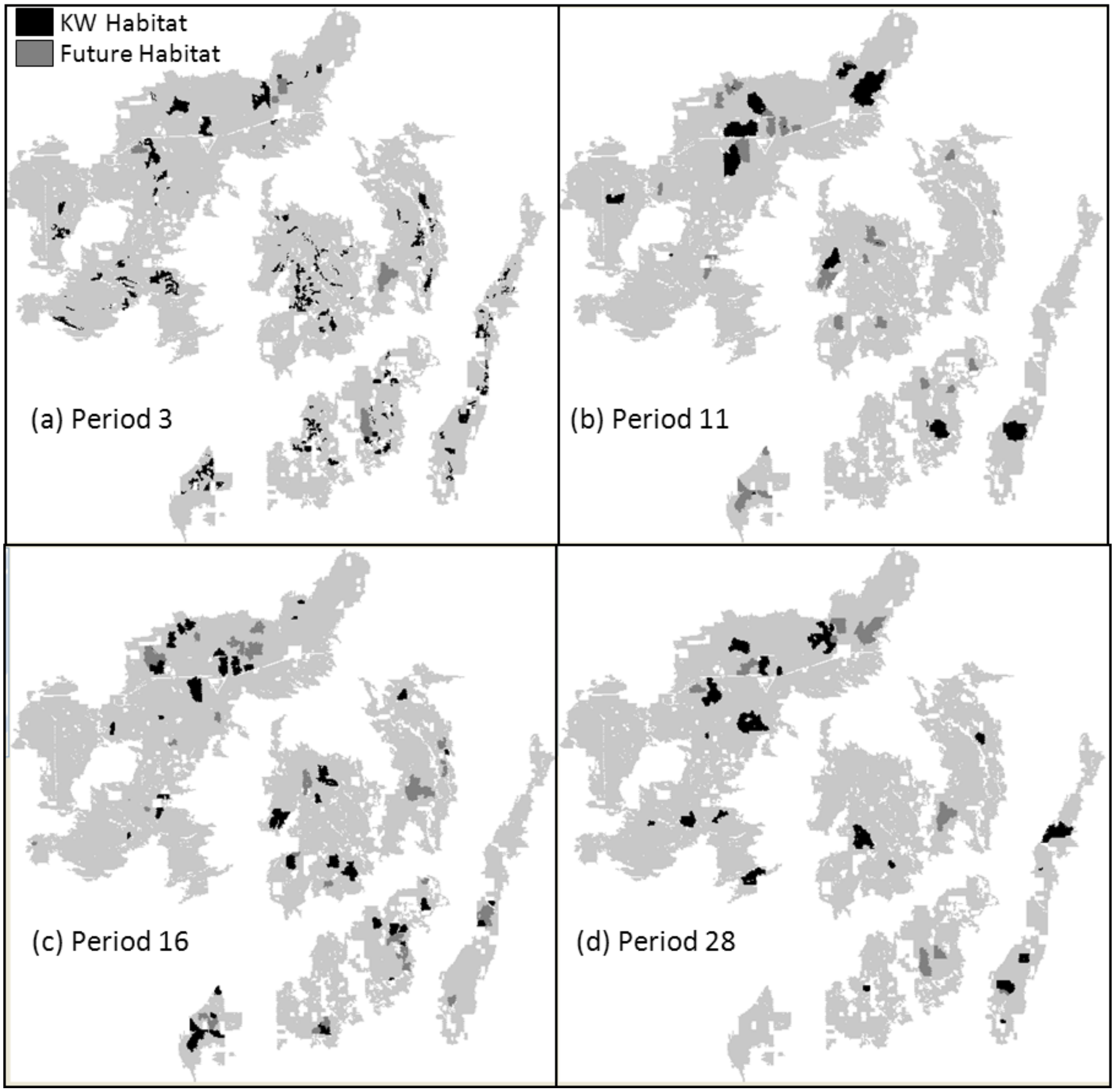


Figure 4.9: Results from 2226 scenario (2226 ha core area constraint) for select time periods. KW Habitat is KW habitat between the ages of 6 and 16, and Future Habitat is future KW habitat between ages 0 and 6.

Patch Dynamics of KW habitat

Patch dynamics are displayed by quantifying the total area of habitat in patches of varying minimum sizes. Total area in patches greater than 32.4 ha is displayed to correspond with the minimum patch size described by Probst and Weinrich (1993). The 80.9 ha level has been described as a standard management size that is adequate to accommodate the KW habitat area requirement (Probst J. R., 1988). The 202.4 ha level corresponds to historic habitat occupation. Probst and Weinrich (1993) cite that 77% of the singing males were found in patches larger than 200 ha from 1979-1989.

Figure 4.10 shows the patch outputs through time for the 2226 ha scenario. The total area in KW breeding habitat is displayed along with the area of habitat in patches of at least the sizes listed. The “Desired” horizontal line is the 2711 hectares described in the Forest Plan. The period 1-5 solutions of this scenario are reflective of the nature of the current habitat arrangement on the landscape. These periods are characterized by an overabundance of total habitat, with an average of 67% in patches greater than 32.4 hectares. In later periods, the total habitat is lowered, and the area in patches greater than 32.4 hectares is raised both absolutely and relatively. In the 2226 scenario, each period from 7-30 has at least 91% of the KW habitat in patches of at least 32.4 hectares (Figure 4.10). Arguably the best performing period of the 2226 scenario is period 11. Period 11 has the highest level of area in patches greater than 202.4 hectares in both absolute and percentage terms (2077 ha, or 82% of the period 11 total). Interestingly, period 11 also has the least amount of total habitat of the constrained periods (6-30). Period 16 appears to have the poorest performance as it has the least amount of area in patches greater than 80.9 hectares (69%) and 202.4 hectares (28%) over periods 6-30. Depictions of the patches in periods 11 and 16 are shown in Figure 4.9 (b) and (c).

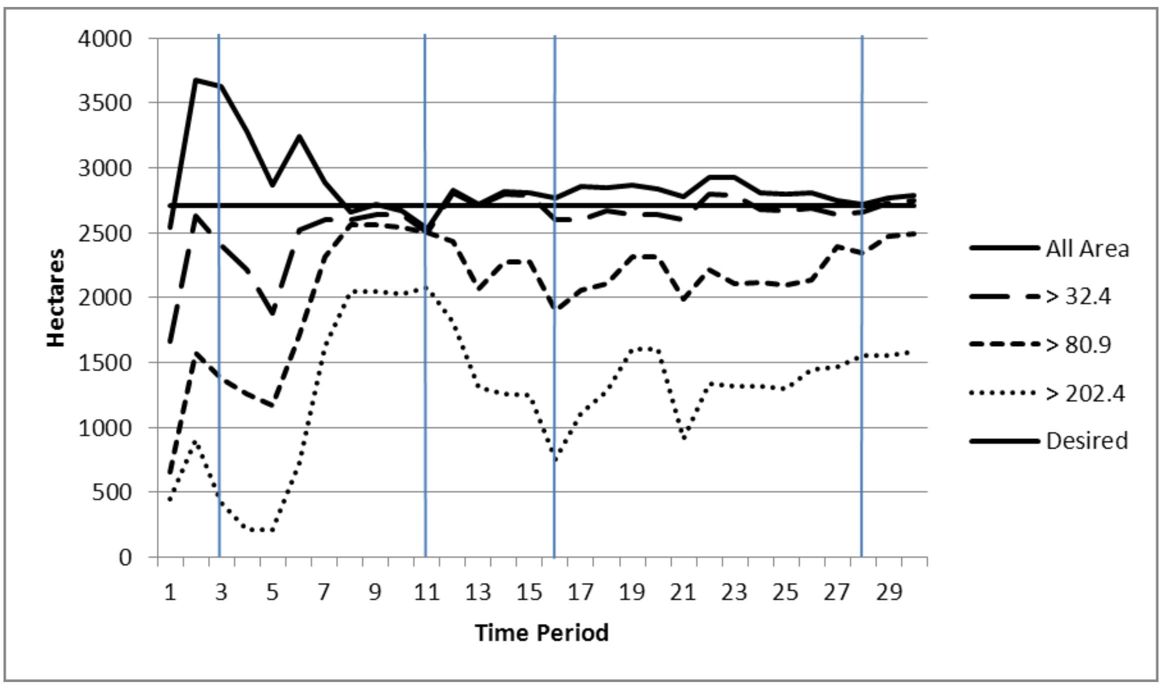


Figure 4.10: Full scenario 2226 – KW habitat area in patches of various minimum sizes

The graphical display of patch sizes in Figure 4.10 does not capture the shape dynamics of the patches. Ideally, patches would not only be large, but would be as round as possible to minimize the edge to area ratio of each patch. Patches with a low edge to area ratio can be thought of as “compact”. A limitation with this metric is that its value changes with the relative size of the patch. For example, a small circle will have a high edge to area ratio relative to a larger circle (McGarigal & Marks, 1995). However, the metric is relevant in this study because the desired amount of core area is the same for all time periods. Fortunately, compact patches are the natural result of valuing core area, since a circular patch has the greatest amount of core area for any shape with the same area. Potential compactness of patches on the ground is limited by the age and cover type heterogeneity of contiguous stands, as well as non-ownership and non-forested stands or inholdings such as roads, lakes, or lowland areas. The core area to total area ratio, or “compactness ratio”, is presented in this study as an indicator of patch compactness. Again, the metric can be meaningfully interpreted since the desired total amount of core area is the same for all planning periods, which means the compactness ratio between different periods can be compared to infer changes in compactness over time. To compute the metric, the buffer distance used to define core area was approximately 37 meters. That is, KW habitat at least 37 meters from the edge of that habitat is part of core area. For comparison purposes, if all KW core area was created in a single circle, the maximum compactness ratio is 97.3% for the 2226 scenario (slightly less for the 1826 and 1416 scenarios, but still greater than 96%). Results with a higher compactness ratio are considered to have more compact patches.

Results for all three full scenarios have similar compactness ratios through time; therefore, compactness is presented explicitly for only the 2226 scenario. Compactness ratio for the 2226 scenario and two benchmark scenarios is displayed in Figure 4.11. The current compactness ratio on the landscape is 58%, and is indicative of either small or non-compact patches. After the influence of current habitat wanes beyond period 7, the ratio reaches a maximum of 87% in period 11 and a minimum of 77% in period 16. The long-term ratio (periods 25-30) stabilizes at about 81%. The core only benchmark has generally higher compactness ratios in periods 8-16, but in the longer-term (periods 17-30) has compactness ratios lower than the 2226 scenario. This indicates that the presence of other cover type constraints does not generally inhibit the patch dynamics possible on the landscape. Management for 2711 ha of KW habitat without considering core area (no core benchmark) produces compactness ratios between 52% and 65%, similar to the current condition of the landscape. An example of compactness ratios 77%

and 56% is shown in Figure 4.12. This figure shows period 16 results for the 2226 scenario (one of the poorest performing periods of the scenario) and the no core benchmark (a relatively representative depiction of any period of the benchmark). The figure also represents a condition of newly regenerated KW habitat fully determined by the model (the effects of existing landscape condition have passed). For context relative to other planning periods, period 16 is represented as the vertical line in Figure 4.11.

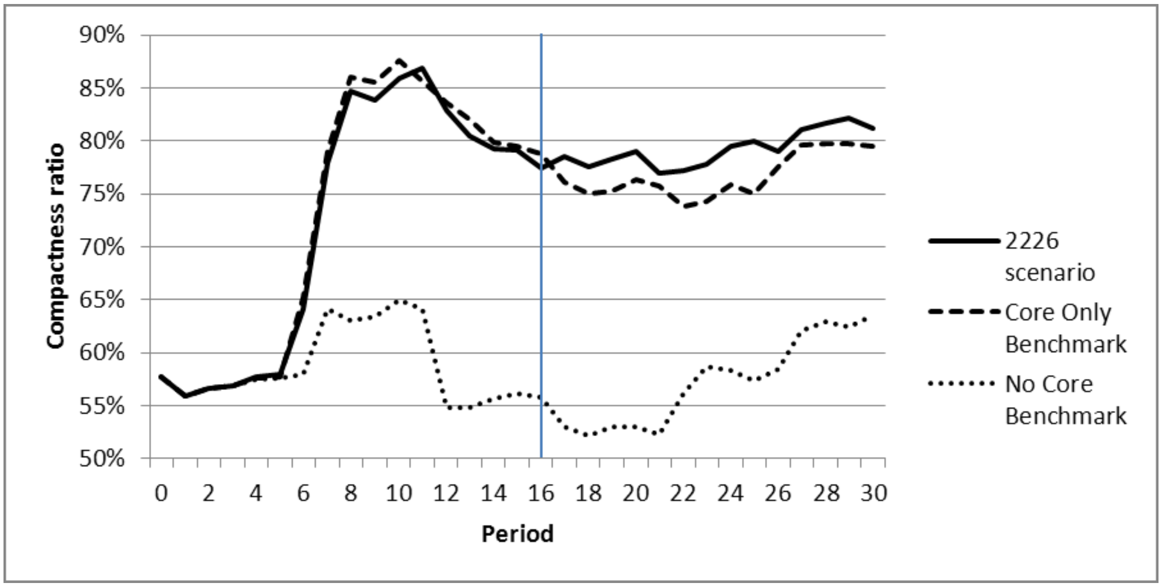


Figure 4.11: Compactness ratios for the 2226 scenario and two benchmark scenarios

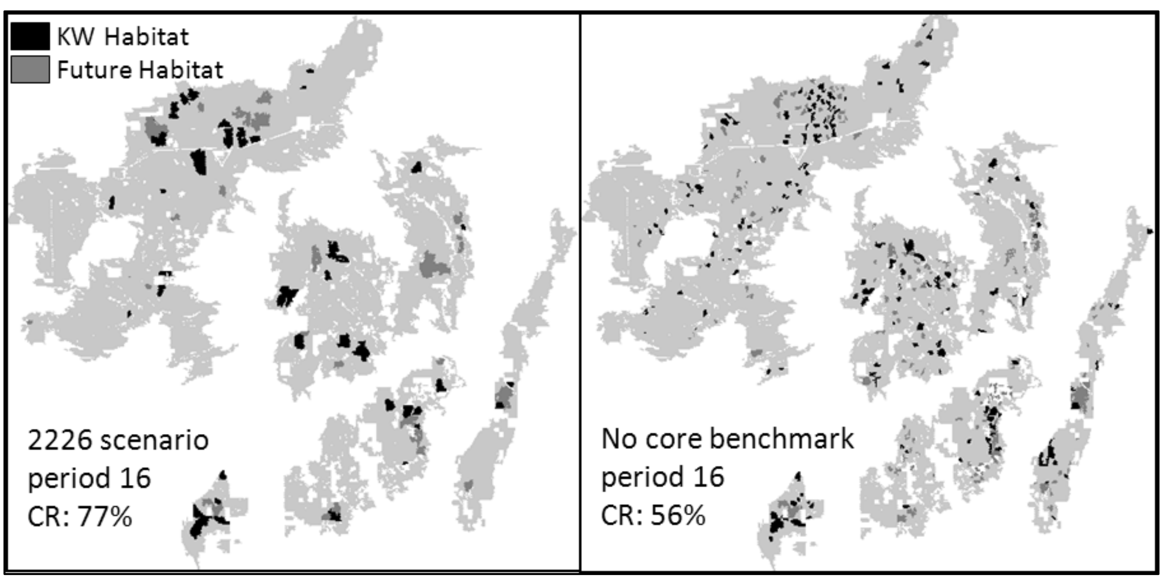


Figure 4.12: Period 16 compactness ratio for 2226 scenario (77%) and no core benchmark (56%)

Financial costs of KW habitat

The final objective of this study was to evaluate the financial cost of managing for KW habitat. Cost evaluation was achieved by measuring the present net value of timber revenues less management costs with a discount rate of four percent annually. There are two metrics of interest when considering financial value; the actual financial value of the management options determined by the model and an estimate of the financial value if the constraints were met exactly. The marginal values of the constraints are used to adjust the financial value of the management strategy up or down according to whether the constraints are over- or under- achieved. Recall the model finds a near-feasible solution where some constraints are not met exactly. If constraints are violated (e.g. only 999 of 1000 desired hectares are managed), it means that the financial value of the management strategy is probably too high. That is, if the constraints were met exactly, it would cost the manager more than the solution value would indicate. Conversely, if constraints are over-achieved, and if those constraints come at a marginal value cost, the manager could realize a higher financial value if those hectares of over-achievement were managed in a different, more cost-effective manner. Marginal values are multiplied by the amount of over- or under- achievement and added to (or subtracted from) the actual financial value to derive the estimated financial value.

Financial values of the benchmarks and scenarios are shown in Table 4.3. The Financial Value of Solution is the net present value of the revenues and costs associated with the management schedules determined by the model expressed in millions of dollars. “Estimated value of solution” is the adjusted net present value that would be realized if constraints were met exactly, expressed in millions of dollars. The “financial fit to estimated” is how close the financial value is to the estimated value in absolute percentage terms (expressed as a percentage of the estimated). Smaller values of this ratio are associated with generally balanced over- and under- constraint achievement levels. The solutions chosen in this study were inspected to ensure that both over- and under- achievements were similarly small in magnitude (rather than similarly large in value, which could also result in a small “financial fit to estimated”). The final columns express the financial value of the scenario or benchmark relative to the No KW benchmark.

Table 4.3: Financial values of benchmarks and scenarios

Benchmark/ Scenario	Financial Value of Solution ($MM)	Estimated Value of Solution ($MM)	Financial Fit to Estimated	Financial % of No KW benchmark
No KW	14.92	14.89	0.26%	100%
No core	8.10	7.88	2.83%	54%
Core only	16.33	16.25	0.46%	109%
1416 Scenario	10.34	10.38	0.39%	69%
1821 Scenario	8.69	8.78	0.94%	58%
2226 Scenario	6.92	6.90	0.29%	46%

Several observations are worth noting in Table 4.3. The Core only benchmark is higher than the No KW benchmark due to the absence of constraints on cover type conditions such as red pine and openings. The Core only benchmark represents the maximum financial value of the forest if KW core area habitat was the only management consideration other than financial value. The No core benchmark values can be compared with the No KW values to determine the approximate cost of managing for 2711 hectares of KW habitat in any spatial arrangement. Managing for KW habitat reduces the financial value of the management strategy by an estimated 46%, nearly $7 million in absolute terms. Aggregating KW habitat into larger patches that create 2226 hectares of core area further reduces the present value of the management strategy by approximately $1 million (observed by comparing the 2226 scenario to the No core benchmark). While this may seem to be a large trade-off in absolute terms, percentage-wise, the 2226 scenario estimated value is approximately 88% of the estimated value of the No core benchmark. Thus, most of the cost ($7 million) associated with total KW habitat appears to the actual costs of management activity (site preparation and planting), rather than the tradeoffs associated with the spatial arrangement of that habitat. However, $1 million cost incurred from the spatial arrangement of the activity is probably foregone timber value. Foregone timber value might have resulted from managing sites before or after their age of maximum value, managing low value sites that would have otherwise been left unmanaged, or from converting sites that would have generated better revenues as a different cover type. Finally, the 1416 scenario and the 1821 scenario show the potential financial value that can be realized by lowering the overall habitat management objectives on the forest, while maintaining the favorable spatial arrangement of the habitat.

Discussion

Results of this study indicate that using core area constraints to create large, compact patches of wildlife habitat can be an effective way to design a management strategy for habitat through time. Specifically, the 2226 scenario that considered core area in management design created similar amounts of total habitat with substantially larger, more compact patches than when core area was not used to consider management design. In this study, the presence of resource constraints did not appear to substantially impact the compactness of the patches that could be created (see Figure 4.11, Core Only Benchmark compared to the 2226 scenario). Furthermore, the planning horizon and management options used in this study allowed the solution model to identify areas of present or expected future habitat that should be considered for conversion to cover types other than KW habitat. The set of stands in Figure 4.7 represents the areas to be considered for the KW habitat system described by the Hiawatha National Forest Plan due to their financial and spatial value in meeting the objectives of the plan.

Unsurprisingly, KW habitat management has an associated cost. Table 4.3 shows that there are substantial costs incurred from managing for KW habitat regardless of its spatial arrangement. Aggregating KW habitat into large, compact patches (patches that have associated core area) incurs more costs. The reality of the cost of KW habitat only further emphasizes the importance that should be placed on making informed management decisions where to invest in habitat. With the proper up-front analysis, smart investment decisions can be made that benefit both the land manager and the warbler.

To implement the management strategy proposed in this study, the Hiawatha National Forest management team would need to closely consider the site-specific recommendations of this study. The forest-wide datasets that were used to solve the problem do not necessarily fully capture the on-the-ground knowledge of forest personnel. There are likely areas of the solution that managers would identify as having difficulty practically applying. Furthermore, the solution to the 2226 scenario identified 300 ha more than required by the plan. There are 13,856 ha in the solution represented in Figure 4.7, rather than the 13,557 ha expected in an exact solution. This opens an opportunity for further adjustments that could be made if necessary to refine the solution, or these excess hectares could be retained in the system to act as a buffer against stochastic disturbance events, such as wildfire, that are historically present in this ecosystem. In either instance (adjusting for feasibility or lowering the overall area managed for KW habitat), the assumptions in the model (such as available management options for the stand) could be refined and the model re-run. Another application of the model could be to investigate the implications of proposed future management on the landscape other than what is recommended by the model. The solution provided by this study (2226 scenario) could be used as a benchmark against which to evaluate alternative management strategies. Both financial value and spatial design trade-offs of alternative strategies could be analyzed, as well as the effect of the alternative on the ability to maintain a persistent level of suitable habitat into the future.

One facet of the problem not explored in detail in this study is the conversions that occur in stands other than KW habitat stands. Generally, constraints maintained cover type quantities at their current levels. Presumably, there were current acres of red pine or openings (for instance) that were converted to KW habitat, and acres currently jack pine or KW habitat that were converted to red pine and openings. When converting a non-jack pine stand to be part of the KW habitat system, mangers should consider whether the area of the converted cover type needs to be replaced somewhere on the landscape. Management for KW habitat alone does not necessarily meet the other objectives in the planning area. Furthermore, the revenue generated by management of other cover types was an important consideration in the management strategy proposed in this study. In the future, the forest could use revenues generated from timber management of other cover types to offset the increased planting and site preparation costs associated with KW habitat management.

Finally, the implications associated with the proposed buffer distance have not been fully explored. The 37 meter buffer distance was a relic of using 0.81 hectare hexagons as the basis for the modeling exercise and is used only by the model to create large, compact patches. Alternative buffer designs may result in different spatial solutions. For instance, another simplistic buffer could be calculated as the set of six hexagons that surround a center hexagon. Conversely, the same buffer design strategy (i.e., buffer to the center of adjacent hexagons) could be used with a different base hexagon size. Wider buffers would likely lower the core area constraint level necessary to achieve the desired overall level of habitat. But, a wider buffer distance might result in larger, more compact patches than those shown in this study. However, as Table 4.3 indicates, those larger patches might come with greater financial costs. The modeling system presented in this study allows managers to explore many alternative management strategies with the goal of creating and maintaining a steady amount of quality KW habitat on the Hiawatha National Forest.

Chapter 5 : Discussion

The management direction of the 2006 Hiawatha National Forest plan (USDA Forest Service, 2006) includes an objective to manage for 6700 acres of Kirtland's warbler (KW) breeding habitat from 6 to 16 years old in a total KW habitat system of 33,500 acres. Ideally the habitat would be arranged in large, compact patches to maximize the utility of the habitat (Donner, Ribic, & Probst, 2010). Upon plan implementation, there are opportunities to make informed management decisions that are not only effective from a wildlife standpoint, but cost efficient as well. There are over 174,500 acres of potential habitat from which to choose the 33,500 acres of KW habitat system. Yet, there are other complicating factors managers face when making site-specific decisions for habitat placement. General forest management problems are complicated by objectives such as cover type and age distributions, spatial arrangement of wildlife habitat, harvest volume, and financial efficiency. When developing a management strategy for KW habitat, the objective for KW habitat should not be considered in isolation from these other factors.

The main objective of this study was to provide managers with information that contributes to effective strategic planning for KW habitat management on the Hiawatha National Forest. This was accomplished with a series of explorations and tests to develop a decision support tool capable of addressing the spatial considerations of KW habitat, management direction for other objectives such as cover type and size class, and cost efficiency.

Much of the study is to address KW habitat planning in substantial spatial and temporal detail. The solution method used to solve this problem builds off of a dynamic programming (DP) based heuristic first described by Hoganson and Borges (1998). Prior to this study, the DP heuristic was modified and used in developing the forest management plans for the Minnesota National Forests to address core area of older forest (Hoganson, Borges, & Wei, 2008). For this study, attention focused on addressing spatial arrangement of management to provide core area of KW habitat. The short-lived nature of KW habitat combined with the long-term nature of forest planning added substantial complexity to the overall planning situation. To recognize the short-lived nature of KW habitat, many more planning periods are required in a model that also addresses common forest management concerns associated with forest planning. Shorter planning periods substantially increases the number of plausible treatment timing options for each stand. Past applications with the DP heuristic tracked no more than ten planning periods. Thirty planning periods were tracked explicitly in this study. In the DP formulation of the problem, timing of management options for a stand is used to enumerate management option combinations between a stand and its neighbors. This is necessary so that spatial conditions can be addressed. In some instances within the DP it may be desirable to enumerate potential conditions for 10 or more neighboring stands. In a problem with 10 planning periods, each stand may have 10 timing options considered in the enumeration. Doubling the number of timing options may not sound like a major increase in model size, yet utilizing twice as many treatment options for each of 10 neighboring stands increases the number of possible combinations in the DP by 2^{10} or over 1000 fold. When that number is increased threefold, as moving from 10 to 30 periods might entail, 3 times as many options for 10 neighboring stands translates to 3^{10} or over 59,000 times as many combinations. This is the “curse of dimensionality” that is a weakness of dynamic programming.

These difficulties are addressed by a series of explorations described in Chapters 2 and 3. Chapter 2 describes how the DP heuristic was modified to use multiple manageably-sized DP formulations and find consistent solutions across these formulations before accepting a proposed management option for a given stand. Test results presented in chapter 2 were convincing: that this approach can find solutions that are optimal or near-optimal for a set of assumed core area values. The heuristic allows one to schedule the more obvious stands first and then focus more attention on the more difficult areas of the forest to schedule. Chapter 3 examined two problem simplification strategies with the goal of reducing the size of the problem to be solved by reducing the number of stand-level management options recognized. The number of management options considered for each stand was pared down to a limited subset that resulted in problem formulations that were capable of being solved exactly with increased speed. Finally, Chapter 4 applied the problem formulation and solution strategies described in Chapters 2 and 3 to the management problem on the Hiawatha National Forest to derive recommendations for where, when, and how to develop the KW habitat system as well as meet the other management objectives of the forest.

The results of the study described in Chapter 2 showed that the proposed heuristic was capable of identifying an optimal solution, even when the problem was solved in parts. By testing several smaller problem formulations before accepting any portion of the solution, the heuristic was shown to match or outperform solutions that were derived from a single, larger problem formulation. Furthermore, the heuristic proved effective at reducing the time required to find a solution with relatively small compromises in objective function value. One solution cited in Chapter 2 reduced solution time by 97%, with an associated loss in objective function value of less than 0.2% relative to the optimal solution value. Results show promising efficiencies in problem solutions that have a relatively small objective function value trade-off.

In Chapter 3, the results showed that effective pre-processing methods could reduce the size of a spatial problem formulation without compromising solution quality. Specifically, the grid-based building pre-processor proved capable of reducing the number of management options required to formulate a full mathematical forest management problem by 80% without compromising the optimal solution. The best identified pre-processing design solved the problem described in Chapter 2 exactly with a 95% reduction in solution time, including the time required for pre-processing. Further reductions in the time required for pre-processing may be realized by using the multi-threading capability of computers. The pre-processing method is also complicated in that it can be repeated throughout the solution process. A desirable feature of this is that treatment options not considered at one point in the solution process can be re-introduced later in the process as more is learned about the problem and the marginal values associated with the forest-wide constraints.

Finally, in Chapter 4, the problem faced by the Hiawatha National Forest is addressed using the information developed from the explorations described in Chapters 2 and 3. In Chapter 4, several amounts of core area were used as constraints to test whether managing for core area could help in designing total amount of KW breeding habitat in large, compact patches, and sustain KW habitat close to levels targeted over time in the forest plan. Results indicate that constraining a minimum level of core area can result in overall habitat amounts close to that described by the 2006 Hiawatha National Forest management plan. The patches of habitat created with the core area constraints are substantially larger and more compact than patches created without targeting core area production. Patch design, however, comes at a cost; the financial value of managing for large compact patches reduces the Net Present Value of this portion of the forest from $8 million to $7 million relative to the financial value that could be realized from achieving the desired level of overall habitat without spatial considerations.

The ultimate objective of this study was to positively affect management decisions to create sustainable KW breeding habitat. While meeting this objective is technically beyond the capacity of this project, the utility of the model has been recognized by the Hiawatha National Forest. The modeling system was used by the forest during project-level planning involving the largest outwash plains ecosystem (on the East side of the forest) in 2010. Planners were concerned with the effects that proposed KW habitat might have on the future sustainability of the habitat. One district-level wildlife biologist projected a reduction in KW habitat in 2040 by managing habitat on a 50-year rotation. In response to this concern, the model was run to determine alternate management strategies, such as conversion from other cover types not currently part of the KW management system. The model solution showed that habitat could be maintained in sufficient quantities in the future. Managers were then able to confidently proceed with the proposed treatments. In the future, the results of this study may be used to help identify the specific areas to include in the KW habitat management system (similar to the solution shown in Figure 4.7). These areas could then be included in a documented KW management strategy developed for the forest.

The central area of focus for this study was on efficient problem formulation and solution strategies. This type of research is likely to have application well into the future. Even though some day computing technology may develop to the point of making the problem addressed in this study feasible to solve with exact methods, it is difficult to foresee a time when efficient problem formulations will not be useful. It may be likely that the size and complexity of the problems keep pace with advancements in computing technology. This has happened in the past, when spatial considerations were included in forest management models that may not have been possible with older computing technology, and there is no reason to believe that with better tools, managers won’t seek to gain more knowledge that may be realized with larger, more complete problem formulations. The brief investigations described in Chapters 2 and 3 of this study begin to reveal some of the gains that can be realized immediately with current technology. More rigorous investigations into studies similar to these will likely reveal more opportunities for solution speed improvements and more efficient problem formulations which will in turn allow for the capability to solve larger problems with better accuracy.

There are several areas of future study that would improve the overall quality and timeliness of the solution methods described in this paper. First, there are several unanswered questions posed in Chapter 3 associated with grid-based building that would be worthwhile investigating. Some of these questions are: What are the characteristics of the most difficult stand for which to identify the optimal solution? Could better pre-processing rules be written to further pare down the problem size? Is the proposed pre-processing routine successful on other landscapes or other spatial problems? The area of pre-processing seems largely unstudied, but may have associated large savings in problem design, and enable larger forest management problems to be solved with conventional exact solution methods.

Another area of future study that may yield dividends is the search for valid marginal values of constraints. The spatial problems presented in this study require hundreds, if not thousands, of iterations to identify good values. Each of these iterations may take several (up to 30) minutes of computing time. If a more efficient marginal value search routine could be developed, the overall time required to solve the problem might be substantially reduced. Some initial investigations into such savings are described in Appendix B, but these were not developed thoroughly enough to present as formal results.

Finally, investigations into the influence of different buffer widths and initial stand designs were not explored in this study. Alternate buffer widths may enable design of even larger, more compact patches. However, the study in Chapter 4 showed that there is a financial trade-off associated with patch compactness. Nonetheless, if several buffer designs were investigated, one might be able to construct a trade-off curve to show loss in financial value vs. gain in patch compactness. Initial stand design is another potentially influential factor not explicitly explored. Stand boundaries were modified from their original boundaries with the process described in Appendix A. Yet, one can’t help but surmise that the initial spatial design of the stand boundaries has an effect on the potential financial value of a management strategy in a similar way that a predefined, finite set of management options for each stand may be potentially limiting. This was the premise of a study by Heinonen, Kurttila, and Pukkala (2007). They analyzed hexagon cells individually to allow the management model to identify logical places to create stand boundaries. Cell-level planning would also likely overcome some of the difficulties the model encountered in meeting constraint levels exactly in instances where the marginal stand (or marginal patch) was larger than the area required to meet the constraint exactly. However, analysis at the individual hexagon level would result in a much larger problem formulation that would potentially require more time and computing power to solve. Perhaps solving a problem of this magnitude would be feasible if some of these suggested studies were conducted to strengthen pre-processing and the search for marginal values.

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Appendix A: A stand splitting algorithm for stands represented by a hexagonal raster

Methods

Stand boundaries used in this analysis were generated with a three-step process. First, the forest-maintained stand level, irregular vector-based polygons were intersected with a grid of regular hexagons (using a GIS). Regular hexagons are ideal for this problem because they not only overcome adjacency issues that arise from using a regular grid, but they also facilitate the identification of influence zones commonly used in spatial modeling. Slivers resulting from the intersection of the two datasets were reconciled to ensure that each hexagon represented only a single stand. This was accomplished with a simple process to identify which stand comprised the majority of the hexagon and assigning the attributes of that stand to the entire hexagon. Secondly, all hexagons with the same original stand identifier were combined into the analysis stands. This resulted in a landscape where the edges of the stands had regular, predictable relationships, and the minimum distance between edges was the shortest diameter of a single hexagon. Again, this facilitated the identification of influence zones, and ensured that the maximum dimension of any influence zone was a predetermined, manageable size. Finally, the pixelized stands were split with the Bouncing Ball algorithm, which is introduced in this Appendix.

Since one of the objectives of the problem is to identify compact patches for habitat management, it would be beneficial to split stands at logical points that would allow the pieces to be managed independently in order to spatially align with adjacent stands and form more compact patches. Consider the leggy, non-compact stand indicated in Figure A.1 by stands 113 and 115 highlighted near the top of the figure. These two stands were originally part of the same stand, and are arguably non-compact; a relatively large amount of core area could be created in 113, but if managed with 115, it would lessen the compactness of the entire stand. The proposed algorithm splits the stand at the line between 113 and 115 and allows them to be managed independently (for example, 113 may now be managed by itself as a compact stand and 115 may be managed with stand 116, the two-hexagon stand to the lower right of stand 115).

The Bouncing Ball algorithm was developed as a way to split the original stand comprised (in part) of stands 113 and 115 and allow the two pieces to be managed independently. There are three main parameters in the algorithm specified by the modeler; the ball size (π), the narrowness of a stand where a split should be considered, or "pinch point" (θ), and the minimum number of hexagons (λ) that must be isolated when a split is defined. To visualize the algorithm, imagine constructing a "ball" consisting of π=7 hexagons – that is, a center hexagon and the six adjacent to each of its sides (stands 9 the lower left of Figure A.1 represents such a ball). For each polygon, determine whether the ball can fit inside, and if so then "bounce" it around inside until it gets stuck at a pinch point. When it gets stuck, determine if there is enough of the stand on the other side of the ball to merit a split. Applying this algorithm to a map will result in polygons that are smaller, yet rounder in shape. To revisit stands 113 and 115, the ball reached a pinch point at the narrow portion between them (when bounced from the stand 113 side) and the algorithm split the stands at the indicated boundary between them. Stands created with the algorithm are used as the basic units in all time periods of the subsequent problem forest management problem formulation.

There are some detailed situations the programmer must consider when developing such an algorithm. First, the portion of the stand in which the ball originates matters. Consider stands 8 and 31, highlighted in the lower right portion of Figure A.1 which originally defined a single stand. The ball size used was π=7 and pinch point (θ) was defined as two hexagons wide. The ball originated in the stand 31 portion, resulting in the indicated split between stands 31 and 8. Had the ball originated in stand 8, the split would have occurred closer to the bottom of the figure and the size of stand 8 would have been two hexagons larger (and stand 31 would be two hexagons smaller. Also, if several ball sizes are used to split the stands, the order in which they are bounced matters. Consider stands 4 and 57 highlighted towards the bottom of the figure. The original stand (consisting of stands 4, 51, 27, and 41) was split with both a 19-hexagon ball[10] and a 7-hexagon ball (π=19 and π=7). However, the 19-hexagon ball was bounced first to create stand 57. Had the 7-hexagon ball been bounced first, the split would have occurred farther to the top and right, and the split would have isolated only 3

[10] A 19-hexagon ball is comprised of a center hexagon and two "rings" of hexagons around it.

hexagons instead of 6[11]. Finally, stands completely enveloping smaller stands create an especially confounding situation. Consider stand 129, which is completely surrounded by highlighted stands 113 and 120 at the top of the figure. Stands 113 and 120 were originally part of the same stand. The split above stand 129 would not result in an isolated stand unless it was simultaneously considered with the split identified below stand 129. Programmatically, one must consider whether to identify both of these potential splits before executing the split.

In practice, the splitting done for this dissertation was done using two-step process. First a 19-hexagon ball was used to identify 3 and 4 hexagon pinch points (θ=3 and θ=4). Secondly, a 7-hexagon ball was used to identify 1 and 2 hexagon pinch points. For a split to occur with either ball size, a minimum of 3 hexagons must be isolated with the split (λ=3). This strategy resulted in splitting a map of 9989 stands with an average size of 7.1 hectares into 12,307 stands with an average size of 5.7 hectares.

Discussion

The influence of model results on stand design was not explicitly investigated in this study. Presumably, there were at least some stand splits that added value to the solution, but further research would have to be done to determine the magnitude of the influence. Additionally, the algorithm likely results in a larger problem size, since more spatially distinct stands are created. A larger problem may negatively impact the ability of the solution heuristic to efficiently identify an optimal solution. This impact was not explicitly explored with this study, but could be a useful piece of information when considering if and how to apply the Bouncing Ball algorithm.

The algorithm appears to work well for which it was intended; that is, to create a basic map of stands more compact than their original design. However, it does not address the differences in size of the resulting stands. In this dissertation, stand sizes ranged from 0.4 hectares to over 160 hectares. While large stands may be compact, their size may have caused limitations in the solution value if splitting them into two or more discrete units would have allowed for better patch design in some periods.

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[11] However, when the 19-hexagon ball was bounced later, the indicated split would still have occurred, for an ultimate result of the current stand 57 being split into two 3-hexagon stands.

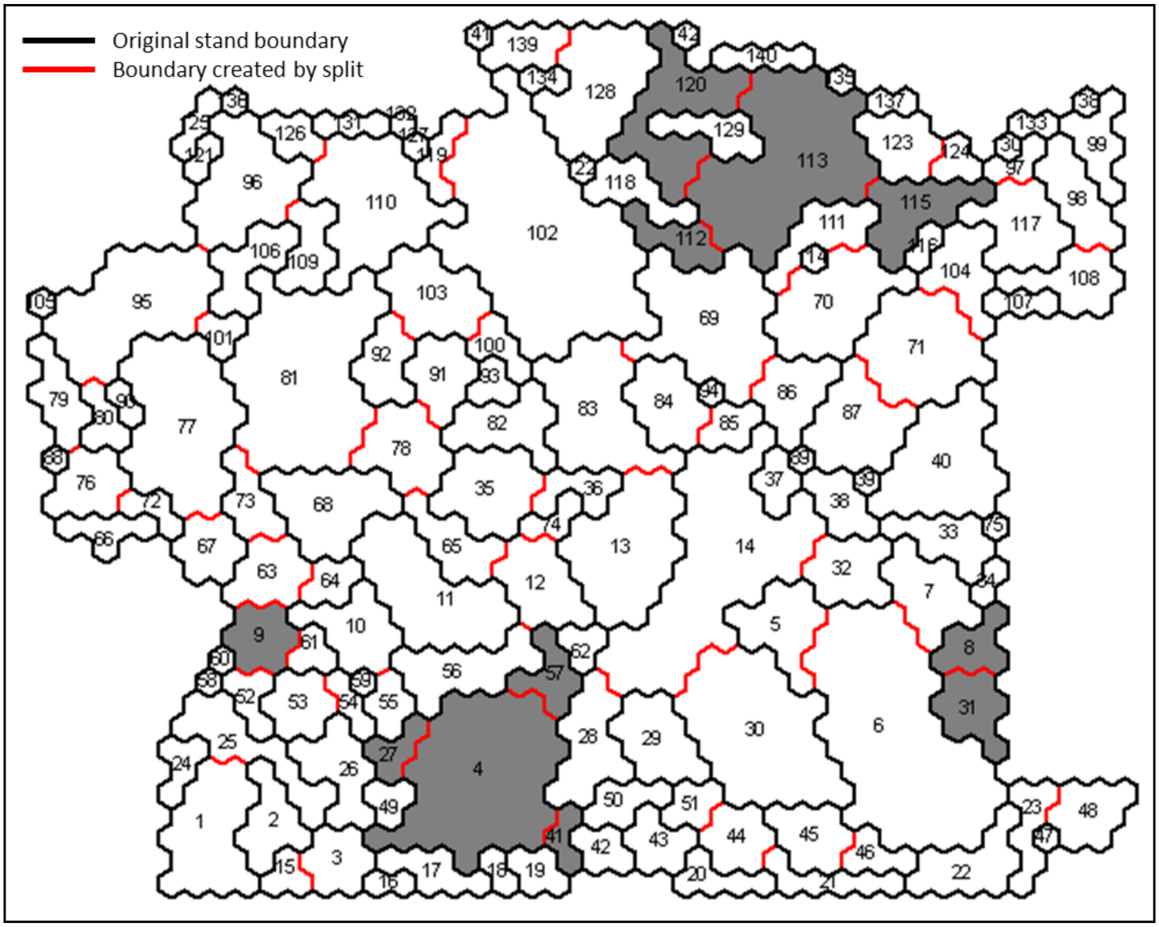

Figure A.1: Illustration of original stand boundaries and boundaries created by splitting with the bouncing ball algorithm

Appendix B: Additional Shadow Price Search Techniques

Introduction

The solution heuristics presented in Chapters 2 and 3 of this dissertation are predicated on the notion that good shadow price multipliers (marginal values, Lagrange multipliers) are efficiently and accurately identified. The search for good multipliers is based on work done by Hoganson and Rose (1984). Specifically, the “Smooth” type of iteration is employed whereby the quality of a set of multipliers is measured by how closely they achieve the desired constraint level and adjusted accordingly. For each constraint, a deviation is determined in terms of the percentage of the associated absolute constraint level. The deviation is in turn used to determine the magnitude of the price adjustment tested in the next iteration of prices. For instance, if the constraint level is a minimum of 300 hectares, and the associated multiplier resulted in 297 hectares, the deviation is 1%. This implies that the multiplier should be increased. Had the price resulted in a solution with 310 hectares, the multiplier is likely too high and should be adjusted downward in the next iteration.

The magnitude of the increases and decreases (price adjustments) associated with different deviations is set by the modeler as a curve of linear segments, consisting of percentage breakpoints and associated absolute dollar adjustment (multiplier) levels (for example, see Figure B.1). The actual level of the multiplier adjustment is determined using the slope of the curve between the two points that bracket the deviation level. Generally, with smaller deviation percentages, it is good practice to use smaller multiplier adjustments since logically the price is closer to being correct. Different curves can be constructed for different constraint sets, since the magnitude of absolute constraint levels can vary greatly (e.g., a 30,000 hectare minimum constraint may reference a different curve than a 300 hectare minimum constraint level).

There are two difficulties the modeler encounters when constructing these curves and pairing them with constraints. First, it can be difficult to easily anticipate an efficient curve for the constraint, especially in the context of the other constraints and multipliers that may also influence the given constraint. For example, a constraint on the overall level of red pine may also be influenced by a constraint on the overall level of forest age 0-10, since some of that forest may be in the red pine cover type. Adjusting the price of the 0-10 age class may indirectly influence the red pine constraint.

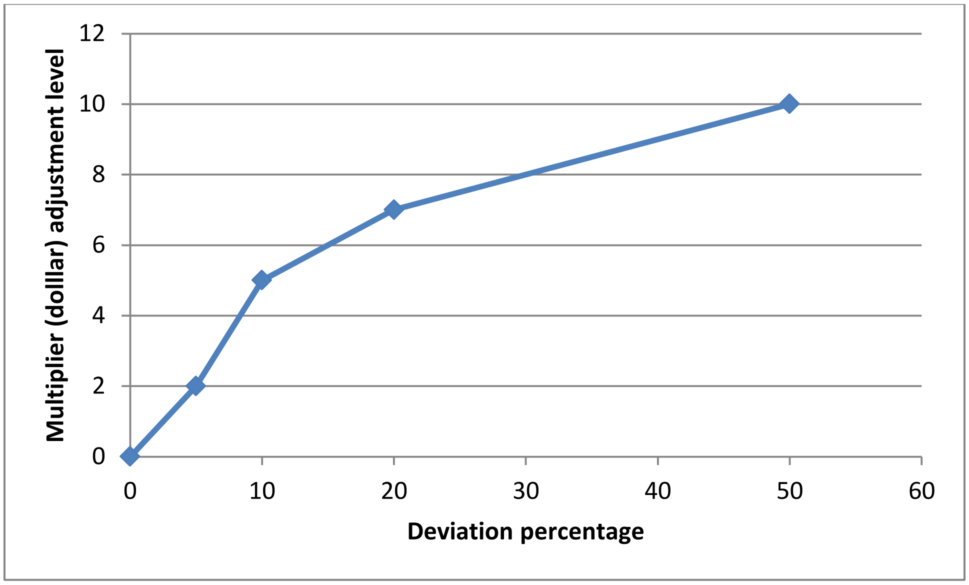

Figure B.1 Example price adjustment curve

The second difficulty is encountered when the percentage deviation is not indicative of the absolute multiplier adjustment that must occur in order for the constraint to be met. If a constraint is met at the 99% level, the corresponding adjustment according to the curve is \$.01, and the actual multiplier must be increased \$1.00 before the last percentage is met, it will take a minimum of 100 adjustments to satisfy the constraint. Conversely, if a constraint is met at the 99% level and the curve indicates an increase of \$1.00, when only \$.01 is needed to meet the level, the resulting schedule may indicate a large overachievement of the constraint (which, in turn would cause a downward adjustment of a certain magnitude, probably larger than \$1.00).

Methods

To mitigate the difficulties associated with accurately anticipating efficient price adjustment curves, two adjustment controls were developed and tested; a decay factor control and a procedure termed “flop control”. The decay factor was used to reduce the absolute magnitude of the multiplier adjustments with subsequent iterations. The flop control was developed to intelligently detect when a) the multipliers were close to accurate and only required small absolute adjustments or b) the multipliers were rather far from accuracy and could be adjusted with a greater magnitude than what the associated adjustment curve identified. The decay factor is straightforward, and the flop control requires more detailed explanation and testing.

Decay Factor Control

The decay factor was introduced to the model as the half-life of the price adjustment curve, expressed in the number of iterations since the modeling began. The hypothesis is that the modeler can more easily approximate the number of iterations before multiplier convergence occurred (i.e., were close to identifying feasible solutions) and use a corresponding decay factor, rather than predefine a precise price adjustment curve. The hypothesis was tested with a series of runs described below. Calculation of the decay factor is straightforward:

$$C = e^{\ln(0.5)/H}$$

Where C is the decay factor, and represents the per-iteration decay in adjustment magnitude. In other words, price adjustment values in the original curves are multiplied by C every iteration. Term H is the half-life of the original multipliers represented in number of iterations. If H was set to 100, the cumulative effect of multiplying by C every iteration would be adjustment values at ½ of the magnitude defined by the original price adjustment curve.

Flop Control

The flop control can be used in conjunction with the decay factor. The control applies to each unique constraint in the model, specific to each desired output level in each time period. The control was developed in response to the notion that if subsequent iterations show respective over- and under- (or under- and over-) achievement of a given constraint, the actual multiplier value for that constraint lies somewhere between the two multiplier values used for those iterations. Consecutive iterations that show over- and under-achievement (or the inverse) of a constraint signify a “flop”, and result each time in a solution that is close to correct, but is at risk of consistently failing to estimate the actual value. Consider an extreme example of a price adjustment that causes a 10% overachievement and triggers a $1 downward price adjustment. The adjustment results in a 15% underachievement, which in turn calls for an upward $1.50 price adjustment, which causes a 20% overachievement, and so forth. The appropriate price is within $1 to $2 of the approximated price, yet the adjustment rules are set too high. Thus, we introduced another parameter to the multiplier adjustment scheme aimed towards minimizing, or controlling flops.

The opposite of a flop is when the magnitude of an adjustment is too small to move the solution to meeting a desired constraint level. Small, incremental movement of, say, $0.05 are not all that useful if the appropriate price is $100 different from the current estimated price. In these instances, one might assume an adjustment magnitude larger than the default until the point of flopping or exact constraint satisfaction is reached.

The flop control parameter was developed to respond to both large over-adjustments and inadequate under-adjustments that may occur concurrently in the same iteration, as would be the case if one multiplier was close to convergence while another one was quite far. Two flop control methods were developed and tested that represented derivations of an “S” curve; the backwards “S” curve and the sideways “S” curve. Curves were constructed by specifying the number of breaks in their construction (the number of iterations required to reach the minimum or maximum adjustment factor), the maximum factor (multiplier) value, and the shape of the curve. A backwards “S” curve example is shown in Figure B.2, and generally resembles the shape of the mirror image of an “S” figure. The sideways “S” generally resembles an “S” rotated 90 degrees (either direction). An example of a sideways “S” curve is shown in Figure B.3.

The rationale for constructing curves with these designs was to test whether the search for multipliers is aided more by sensitive (backwards “S”) or insensitive (sideways “S”) adjustment parameters. The backwards “S” curve was constructed based on the notion that the model could quickly detect flopping instances and rapidly decrease the adjustment magnitude to accommodate the flop, and the sideways “S” was more conservative before making large adjustments, but once adjustments were made, they were substantial.

The backwards “S” curve was constructed by specifying three parameter values; the number of increments (breaks), the maximum factor value, and the curve shape factor. The number of breaks affected the number of iterations needed to reach the maximum (or minimum) factor value specified. The maximum factor value described the maximum modification of the default multiplier adjustment value (e.g., the default adjustment might be $1.00, but a constraint using a maximum factor of 5 would adjust the price by

5*$1.00). The shape factor controlled how quickly the factor was adjusted toward the maximum or minimum value. As an example, the curve in Figure B.2 was constructed from 40 breaks, with a maximum factor value of 5 and a shape factor of .85. A backwards "S" curve was constructed from the center of the total number of breaks, and initiated with a value of 1. From the center of the curve, the right-side tail was constructed by multiplying each break by the shape factor. So the first break to the right-of-center was in Figure B.2 is valued at 0.85, the second is 0.7225, and so forth. The shape factor may result in values very close to 0 at the far right end of the curve. Values to the left-of-center were determined with a more complicated calculation. The intention was to mimic the inverse of the right-of-center curve, adjusted so that the maximum specified value was the limit at the extreme end. Values were determined with the equation:

$$V_{c-i} = 1 + (M - 1) * (1 - r_{c+i}) \quad \forall i \tag{B1}$$

Where V_{c-i} is the value of the break relative to center c [for example, in a graph of curve with 40 breaks the center break is 20], and the maximum value of *i* is *c*, which represents the value V_0, or the value of the first break. The term r_{c+i} is the corresponding right-hand value of the curve measured *i* breaks from center. Finally, *M* is the maximum value specified by the modeler. To return to the value of the first break left-of-center in Figure B.2, it is 1.6 = 1+ (5-1) * (1-0.85).

The sideways "S" curve was developed with the notion that the default look-up table price adjustment curve (e.g., Figure B.1) is reasonably accurate and deviating from it requires more extreme circumstances. Therefore, sideways "S" curves are relatively flat in the center and more severely curved toward either end. Break values to the right-of-center were calculated such that the largest breakpoint value defined by the modeler resulted in a 0 price adjustment. The right-of-center curve was constructed with the following equation:

$$V_{c+i} = 1 - (i/I)^2 \quad \forall i \tag{B2}$$

Where V_{c+i} is the value of the break relative to the center, and *i* is the break incrementally to the right of center. The total number *I* is equal to the value of *c*, or the break index of the center value. The value of the first right-of-center adjustment factor in Figure B.3 is calculated with i =1, I = 10 and is 0.99 = $1-(1/10)^2$. Break values to the left-of-center were determined with the same equation as the backwards "S" curve, using Equation B1. Values to the right-of-center were used in the equation to construct the shape of the curve to the left-of-center with the maximum value specified by the user.

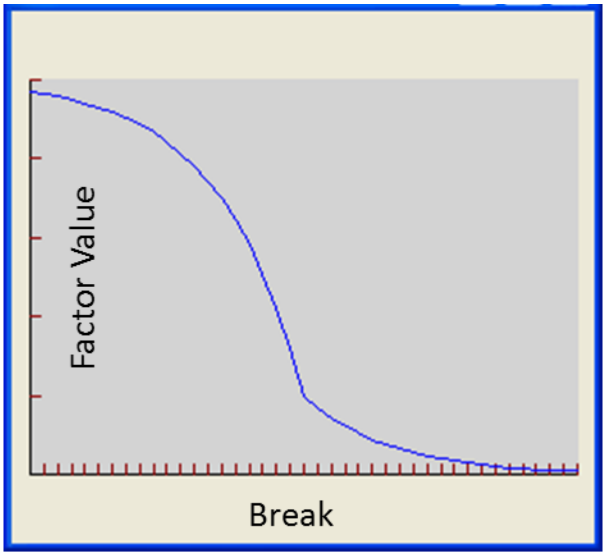

Figure B.2: Backwards S curve with 40 breaks (x-axis), a maximum factor value of 5 (y-axis) and a shape factor of 0.85

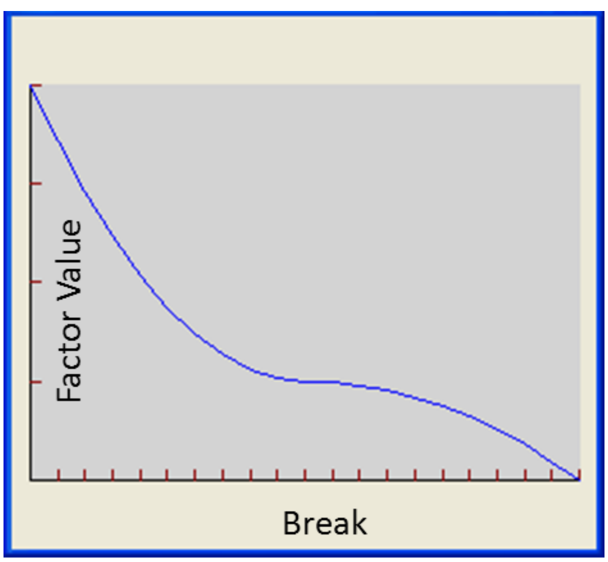

Figure B.3: Sideways S with 20 breaks (x-axis) and a maximum value of 4 (y-axis)

The application of the flop control curves in price adjustments was the same for both curve designs. A measurement of position (break number) along the curve was constructed for each time period of each constraint defined in the model, and initiated at the center break of the curve, at *c* (with a corresponding value of 1). With each iteration, a flop control factor was used to modify the default price adjustment defined by the look-up table price adjustment curves (e.g., Figure B.1). If a flop was detected in a constraint, the break position for that constraint was moved incrementally one position to the right. With each flop, the break position was incremented by 1 until the maximum break value was reached. In an instance where there was a flop iteration followed by an iteration that did not flop, the magnitude of the deviation was considered to determine the break position. If a constraint value did not flop, but the deviation was the same or smaller, the break position remained the same. If, however, there was not a flop and the deviation was larger than the last iteration, the position was decreased by 1 so that a larger flop factor was used. For instances of consistent non-flopping, the position was decreased until it reached 0, at which the maximum price adjustment factor was used. One exception to these rules was that if a constraint suddenly flopped and the break position was less than the center break position, the break position was set at the center break so that the flop factor could be rapidly decreased.

Flop Control and Decay Factor Tests

To test the proposed search controls, a series of tests was conducted consisting of different control combinations and beginning price adjustment curve levels. To speed the tests, we used only non-spatial constraints, consisting of the constraint types and levels described in Chapter 2 in addition to a minimum constraint level on the desired amount of Kirtland's warbler habitat (6700 acres) in each time period. Initial shadow price estimates were recycled from an intermediate solution that utilized a spatial constraint and were consistent for all tests[12].

Six types of tests were conducted, representing a range of possible combinations of the proposed controls. Additionally, a "Default" test was conducted to show a comparison effect for not using any of the proposed controls.

> **Default:** This test did not use either of the proposed controls. It was initiated with small price adjustment curves (1/100th of the magnitude of the largest price adjustment curves used in these tests). The hypothesis of this test was that a large

[12] The search heuristic should, in theory, work independently of the initial price estimates. Therefore, the original estimates are not described in detail.

number of multiplier searches each with small adjustments would eventually identify an acceptable solution. We made the adjustment curves small to begin with since experience showed that larger price adjustment curves were too severe to ever converge on a good solution. The test was run for 2000 iterations.

Decay only: This test utilized the decay function only. Several beginning price adjustment curves were tested as well as several half-life factors, generally between 100 and 300 iterations.

Backwards S only: Several combinations of parameter values were used to test this control. Tests included variations in the number of breaks, shape factor, and maximum factor value. Several initial price adjustment curves were tested, including flat price adjustment curves that did not vary the price adjustment by deviation percentage.

Sideways S only: Several parameter values were tested that adjusted the number of breaks and the maximum factor value. The shape factor is not used to define the shapes of sideways S curves.

Backwards S with decay: Several backwards S curve shapes and decay factors were tested.

Sideways S with decay: Several sideways S with decay factors were tested.

Identifying a Good Solution

The solution method will often identify a management strategy with small imprecisions in meeting constraint levels. Therefore, it is necessary to measure the total imprecision across all constraint levels to determine whether it is a good solution, or if the search should continue for a better solution. Solution quality is measured with the following equation:

$$Q = \frac{D}{F} \tag{B3}$$

Where:

$$F = \sum_{i=1}^{I} \sum_{j=1}^{J_i} d_{ij}\, x_{ij} \tag{B4}$$

$$D = \sum_{p}^{P} \lambda_p * \left| M_p - \sum_{i=1}^{I} \sum_{j=1}^{Ji} v_{ijp}\, x_{ij} \right| \tag{B5}$$

Equation (B3) measures the quality of the solution. The expression Q represents the quality of the solution and is a function of the financial inferiority D of the output levels divided by the financial value F of the management strategy. Lower Q values are associated with solutions that have shadow price levels set that closely meet the constraint levels of the problem. However, a good solution must not rely on the value of Q by itself. The absolute value of constraint deviations must also be considered, since a low Q value may be associated with high levels of low-valued deviations from constraint levels. Nonetheless, Q may be a useful metric in identifying how closely prices have been adjusted to appropriate levels.

Equation (B4) defines how the financial value of the management strategy is determined. Financial value F can be determined with model output values x_{ij}. The x_{ij} values are the acres of stand i managed according to management option j. The term d_{ij} represents the discounted financial value of managing each acre of i with management option j. Management option financial values the net financial value of revenues (such as sold value of the timber) less costs (such as planting after harvest). Summed over all stands I in the forest, F represents the financial value of the chosen management strategy for the forest.

Equation (B5) describes in financial value how closely the constraints in the problem are met. The λ_p values are marginal values of the constraint levels in the model. The other terms in the equation are all model inputs. Term M_p represents the desired level M of constraint p. Finally, v_{ijp} represents the value that management option j applied to stand i contributes to constraint. The value D is determined by calculating the absolute value of deviations from desired constraint levels multiplied by the marginal value of those constraints and summed over all constraints.

In a cautionary note, a good solution must not rely on the value of Q by itself. The absolute value of constraint deviations must also be considered, since a low Q value may be associated with high levels of low-valued deviations from constraint levels and may not represent a feasible management strategy. Nonetheless, for this study of convergence on appropriate shadow price values, Q may be a useful metric.

Results

For the limited number of control combinations and parameter tests that were conducted, the backwards “S” flop control combined with a decay factor performed the best, according to how quickly a relatively low Q factor was identified. Even with low initially defined price adjustment curves, the “Default” test had an average Q of 0.18 (averaged over iterations 1900-2000), which stabilized in about 1000 iterations and never improved. The “Decay Only” test, using a half-life of 300 iterations, had an average Q of 0.09 after 2000 iterations (averaged over iterations 1900-2000). Tests using the backwards “S” or sideways “S” without an associated decay factor did not produce remarkable results.

Four of the best control combinations and parameter settings tests are shown in Figure B.4. The graph depicts the average Q over ranges of 100 iterations, displayed on the x-axis. The associated parameter settings of these tests are shown in Table B.1. All four tests converge to an average Q value between 0.04 and 0.05 by iteration 900-1000. The tests with the strongest performance are arguably the “65Back_Same_100Decay” test with the “75Back_100Decay” tests which show the lowest average Q values over all iteration ranges.

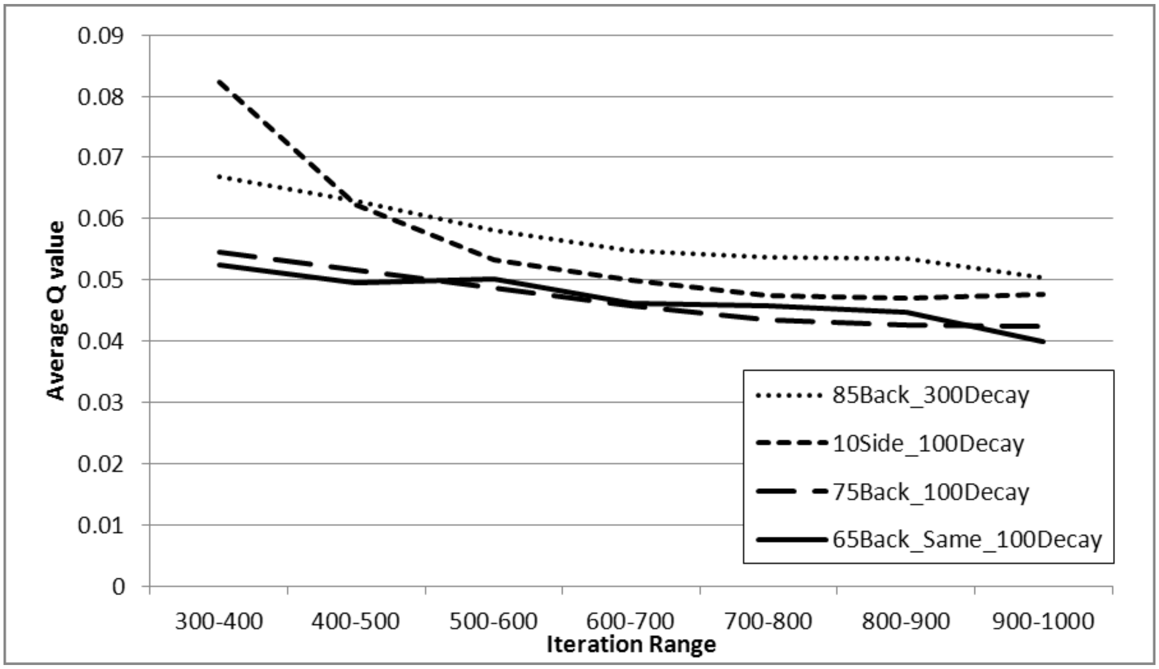

Figure B.4: Results from select control tests

Table B.1: Parameter settings for select control tests

Test	Start Price	Decay Factor	Design	Max Factor Value	N Breaks	Shape Factor
85Back_300Decay	Mid	300	Back	5	40	0.85
10Side_100Decay	Mid	100	Side	5	10	
75Back_100Decay	Mid	100	Back	5	20	0.75
65Back_Same_100Decay	Flat ($2)	100	Back	5	12	0.65

Discussion

One potentially surprising result of this study is the effect to the modeler's need to estimate good price adjustment curves such as the one depicted in Figure B.1. A well designed backwards "S" curve combined with a reasonable decay factor appears to nullify any weaknesses in an estimated price adjustment curve. This contention is supported by comparing the "65Back_Same_100Decay" test with the "75Back_100Decay" test in Figure B.4. These two tests produced results similar in quality, yet the "65Back_Same_100Decay" test was initiated with a single flat price adjustment curve referenced by all constraints. Thus, the modeler's time may be better spent designing a single backwards “S” curve paired with a decay factor rather than designing multiple price adjustment curves.

Efficient shadow price search is one of the most under studied portions of this project, and has the potential to yield some of the strongest increases in solution efficiencies. The science of shadow price (Lagrange multiplier) search has no doubt evolved since Hoganson and Rose (1984) developed the initial “Smooth” price adjustment search heuristic, and further research into modern search heuristics may be fruitful. No parameter test was able to determine a feasible solution, which is not surprising given the sheer number of multipliers and the potential interactions between them. A more rigorous exploration of the parameters described here, or a diligent literature search across disciplines other than forest management may reveal opportunities for greater improvements, and would be a welcome addition to the discipline of forest management.

Appendix C: Displaying Hexagon-based Stand Maps

Many of the map figure displays of forests and forest conditions through time in this dissertation were created with custom software created specifically for this exercise in response to limitations in standard GIS software. One difficulty encountered in the development and testing of the solution model described above was a simple and accurate way to spatially display the inputs and outputs to detect whether the code was working accurately. Additionally, the output information from the model included vegetation conditions for over 12,000 stands for 90 time periods, which was cumbersome to load into a GIS program and view.

Therefore, a display tool (MMaPPit) was developed to readily display the inputs and outputs of the modeling exercise. The main strength of the tool is that it enables the user to load information for multiple time periods with a single file and automatically generate a map for each time period according to a predefined color scheme. The tool then allows the user to “play” the maps through all time periods automatically to inspect the vegetation changes on the ground. The effect is similar to time-lapse photography of the solution. However, the user may stop the “play” at any time to inspect specific areas of the forest with a number of other tool features, such as zoom, identify attributes, and highlight specific stands.

Methods and Inputs

The MMaPPit tool was developed “from scratch” (i.e., did not use any commercial GIS dependent object libraries) with Visual Basic .NET (2005). The tool draws standard bitmap images to render the displays. The tool is manifested in a simple executable that can be used, theoretically, on any Windows-based machine. Simple text files are used as inputs, which may be easily generated, modified and viewed with a standard text editor. The main inputs required to display the maps are:

1. A grid cell center coordinate file that includes polygon center coordinates and associated stand ID number

2. A time period file that includes stand ID number and attributes through all time periods (1 line for each stand; stand ID followed by a column for each time period)
3. A color file that lists the unique attributes in the time period file and the associated color that should be displayed
4. A stand attribute file (optional) that includes additional (static) characteristics of each stand.

To display the map (or adjust to a pan or zoom request) there are three scales that must be considered. First, the overall size of the map must be determined from the minimum and maximum x and y coordinates in the coordinate file. This is used to determine the initial size of the grid cells to be displayed. Secondly, the map must be scaled to the size of the display window, indicated by the large, gray area that contains the map display in Figure C.1. Third, when a pan or zoom is invoked, the desired portion of the display must be determined, and scaled to the size of the display window. For instance, if a tall, narrow rectangle is selected to zoom to, but the display window is short and wide, the desired display must be appropriately adjusted in order to avert a potentially distorted rendering of the map image.

Hexagons are drawn by utilizing information about the distance between hexagon centers determined from the full map scale and the proportion of the map to be drawn in the display window. This proportion is used to determine the spatial location of the six corner points surrounding the hexagon center. Trigonometric functions are used to draw these points in space, connect them with lines to form the hexagon, and fill the hexagon with the appropriate color, determined by the attribute of the hexagon for the time period and the associated color for that attribute described in the color file. The surrounding hexagons can be examined to determine whether they are part of the same stand or not. If an adjacent hexagon is part of an adjacent stand, the border between them is identified as an edge that may be displayed. The MMaPPit tool has a feature to display stand edges when desired.

Features

Figure C.1 highlights some of the features developed for the MMaPPit tool. These are described beginning with the label at the bottom right and moving in a counter-clockwise direction.

Automatically “Play” through all maps: When this button is clicked, all time periods are displayed sequentially, with a second or two between displays. This feature allows the user to watch the projected forest changes through time. The tool was initially developed specifically to enable this capability.

Show stand location: This feature allows one to type in a stand ID number, or series of stand ID numbers. The associated stands are then highlighted on the map in an aqua color. This is useful for gaining insights into the spatial position of a stand, or seeing what other stands are nearby.

Return to previous map view area: Resets the display to the portion of the forest you were viewing before. If you had zoomed into a particular area and want to return to the area that was zoomed from, use this feature.

Identify: If the stand attributes file was loaded, this feature allows the user to click on a particular stand to see the attributes associated with that stand. A separate window is opened with a list of these attributes.

Pan: This is a standard image navigation feature that allows the user to navigate around an area of the map. To use it, click on the starting point of the image, drag the hand icon the desired distance and release the mouse button. The image will be shifted accordingly.

Zoom to full map extent: When this button is clicked, the full extent of the map image, including all stands, is displayed.

Zoom in to selected area: This allows one to zoom to a rectangular portion of the map to examine those stands with greater detail.

Show stand edges or not: Click this to toggle between whether stands edges are displayed or not. This feature is useful if the full forest contains many stands and stand edges dampen the display quality. When zoomed into a smaller portion of the forest, stand edges may be drawn to highlight individual stands. In Figure C.1, stand edges have been drawn.

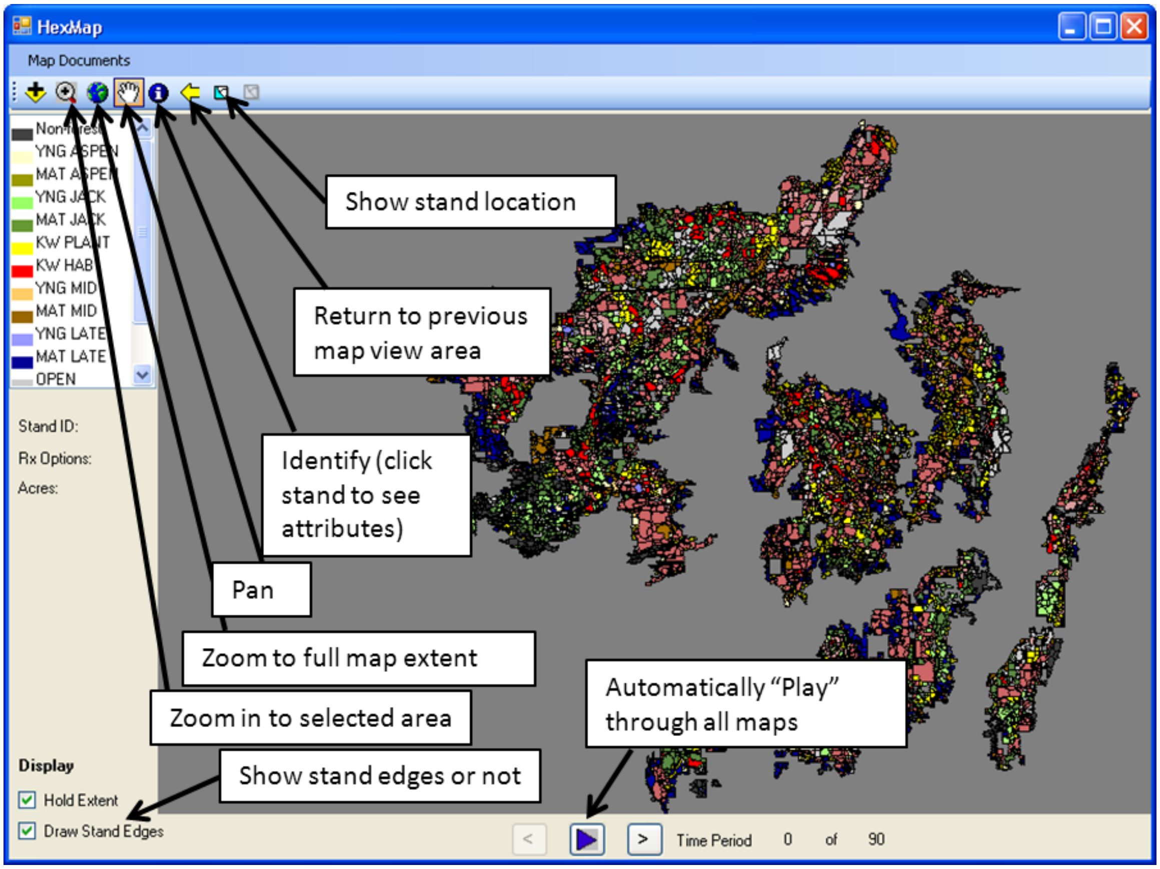

Figure C.1: Standard features for hexagon-based MMaPPit program

Modifications: display of squares, additional features; an example from Idaho

The MMaPPit tool was easily adapted to display squares, which may be more commonly used in forestry mapping applications. Figure C.2 represents an application in the Selway river watershed in north central Idaho. The image depicts approximately 263,000 squares representing 1.6 million acres. Stand boundaries are not shown, as each square was treated as an individual stand and the display quality would have been compromised. Some additional features of the MMaPPit model are highlighted. These features were developed for this application, but are broadly applicable to other studies as well.

Manually adjust display extent: The minimum and maximum X and Y coordinate values are displayed in this text box for any pan, zoom, or full extent shown in the display window. One can manually adjust these parameters to a custom display rather than using a zoom or pan tool. However, the feature is most useful when using two or more tool instances to display different aspects of the problem. The current display shows dominant cover type. Another useful display might be size class. Still another might be the fire or harvest occurrences that have happened recently to influence the current cover type or size class pattern on the landscape. If there is more than one instance of the MMaPPit tool open side-by-side, one can copy and paste the desire view extent in this text box to synchronize the display of each instance.

Adjust color display: This feature can be used to modify the color display of the features in the map. Previously, the only way to adjust the colors was to adjust the definitions in the color file and re-load the entire map dataset.

Dynamic tally or area amounts: This quantifies the area in each classification displayed in the map. These quantities often change through time, and it may be useful to the user to see not only a spatial representation, but to see an associated area in each map category as well.

Skip to any time period: Previously, one had to scroll through all time periods sequentially to arrive at a desired period. This feature allows the user to specify the desired time period and navigate there directly, bypassing all periods between the one currently displayed and the desired time period.

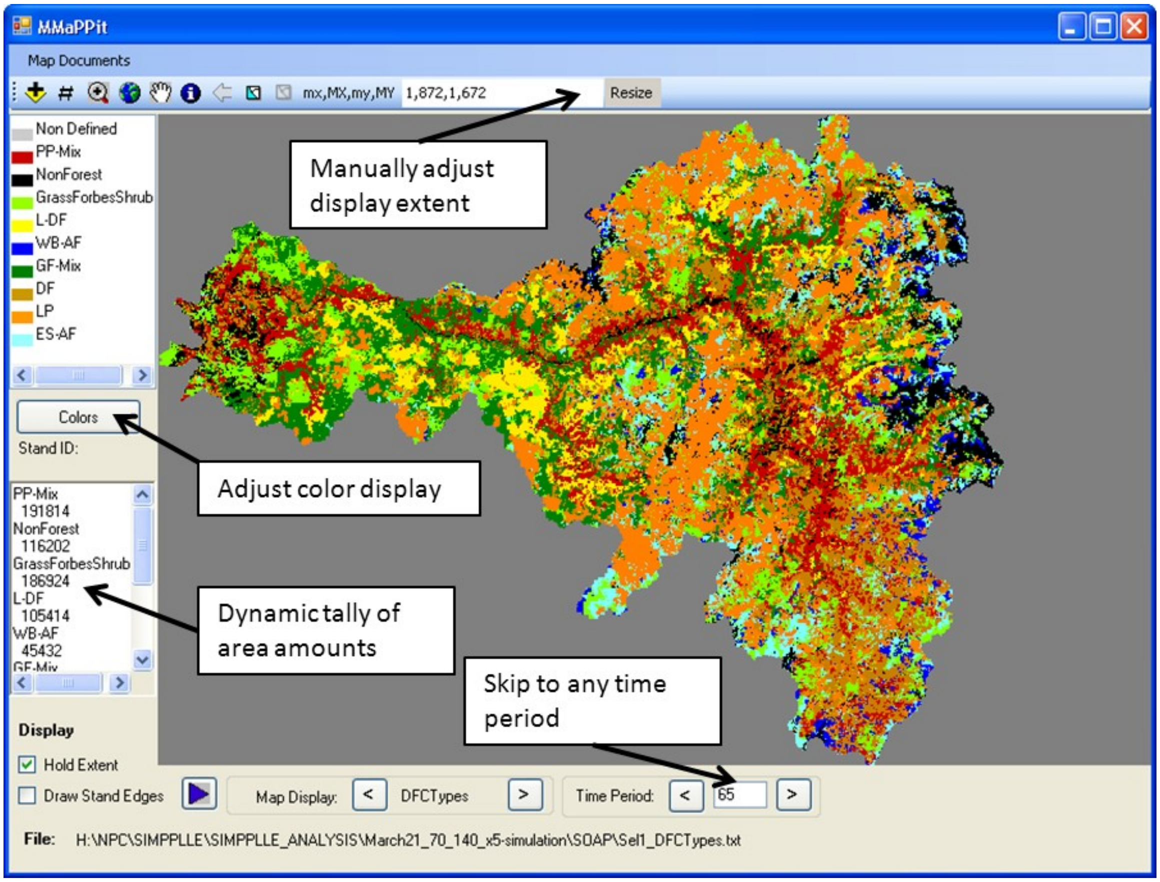

Figure C.2: Square-based mapping tool display of Selway river watershed in Idaho displaying newly developed features.