

Article

Spatial Forest Harvest Scheduling for Areas Involving Carbon and Timber Management Goals

Lingbo Dong ^{1,†}, Pete Bettinger ^{2,†}, Zhaogang Liu ^{1,*} and Huiyan Qin ^{3,†}

¹ Department of Forest Management, College of Forestry, Northeast Forestry University, Harbin 150040, China; E-Mail: farrell0503@126.com

² Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA 30602, USA; E-Mail: pbettinger@warnell.uga.edu

³ Department of Forestry Economic, College of Economic & Management, Northeast Forestry University, Harbin 150040, China; E-Mail: huiyanqin@hotmail.com

† These authors contributed equally to this work.

* Author to whom correspondence should be addressed; E-Mail: lzg19700602@163.com; Tel.: +86-1-394-608-3132.

Academic Editors: Shibu Jose and Eric J. Jokela

Received: 10 February 2015 / Accepted: 15 April 2015 / Published: 21 April 2015

Abstract: Forest carbon sequestration has become an important ecological service for human society. Given the widespread attention paid to global climate change over the last few decades, a potential need has arisen to develop forest management plans that integrate carbon management and other spatial and non-spatial goals. The objective of this research was to develop a spatial forest planning process by which one could assess either a carbon stocks objective, a timber production objective, or a spatial objective related to the arrangement of forest management activities. This process was used to evaluate the maximization of (1) volume scheduled for harvest; (2) carbon stocks; and (3) spatial aggregation of the management activities through a utility function where all are equally weighted objectives. The process was employed for the development of 30-year plans for a forested landscape in northeast China that was approximately 120,000 ha in size. In addition, the sensitivity of the results with respect to four initial forest age structures was tested. Constraints mainly included those related to the need for an even flow of scheduled harvest volume and to the need to adhere to a maximum harvest opening size. The proposed scheduling process employed a simulated annealing algorithm to schedule harvests in an

attempt to produce a high value of the utility function. Results showed that carbon stocks in the case study forests could significantly increase in the next 30 years under the proposed harvesting plans. Of the case study forest landscapes, the values of both the utility function and the computing time required were significantly different between different initial forest age structures ($p < 0.05$), *i.e.*, the older forest landscape obtained the highest average solution value (0.6594 ± 0.0013) with the fastest processing speed (2.45 min per solution). For a fixed harvest level, the average carbon density (tons per hectare) at the end of planning horizon also increased by 4.48 ± 9.61 t/ha, 8.73 ± 10.85 t/ha, 2.99 ± 9.19 t/ha and 1.03 ± 9.77 t/ha when maximizing the total utility functions for the actual, young, normal and older forests, respectively, when compared those at their initial conditions. This heuristic spatial forest planning process can allow forest managers to examine a number of different management activities, for both timber production and carbon stocks, prior to selecting a preferred alternative.

Keywords: carbon stocks; timber production; spatial objectives; utility function; simulated annealing algorithm

1. Introduction

Forests play an important role in society's efforts to mitigate greenhouse gas emissions. Under the guidance of the United Nations Framework Convention on Climate Change Kyoto Protocol [1], many researchers have concentrated their attention on different scales of carbon inventories [2–4], models of carbon stocks by forest and carbon production [5–7], simulations of the effects of forest management [8–10], and analyses of the effects of climate change on carbon sequestration by forest types [11,12]. However, more information is needed regarding greenhouse gas mitigation options, and in this context there is considerable interest in using forests for carbon sequestration efforts, and therefore in assessing how forest management can contribute to enhancing carbon sequestration efforts.

Carbon sequestration in forest ecosystems involves numerous components that include above-ground biomass carbon and below-ground soil carbon [13]. Given the importance of forest carbon sequestration, it comes as no surprise that efforts have been put forth to value the potential additionality provided through changes in forest management practices [14]. Several studies have examined the effects of varying rotations lengths [15,16], thinning intensities [8,10], and green-up and maximum opening size constraints [17–19] on the amount of timber produced and carbon sequestered (stocked) in forests. What all these studies have in common is that suitable forest management activities can enhance forest carbon sequestration efforts and timber production over the long-term. Therefore, it is valuable to determine which forest management activities (combinations of cutting regimes (if used), silvicultural treatments, assumptions on the placement of activities, and management intensities) are more efficient and effective for these purposes for special management areas, and when to implement the selected activities in order to better reach timber production and carbon sequestration (or other) goals in the future.

Forests not only store carbon, they provide a wide range of economic, ecological and social value. Therefore, understanding ecosystem service interactions represents a challenge in land management

decision-making [20]. Generally speaking, the interaction can either be viewed as a trade-off or a synergy. As Cademus *et al.* [21] described, a trade-off occurs when production of one ecosystem service compromises the provision of other services. Conversely, a synergy occurs when the productions of multiple ecosystem services either increase or are provided at similar levels [21]. However, a large-scale experiment that physically examines these types of forest management goals would be too costly and time-consuming to implement across a broad area [22]. Therefore, a number of mathematical and heuristic methods have been used by forestry organizations over the past fifty years in an effort to support decision-making processes related to complex and interrelated forest management objectives [22], e.g., those that involve economic and commodity production, wildlife habitat, forest structure, biodiversity and other objectives. To our knowledge, some previous research efforts have examined the tradeoffs (or synergies) between commodity production goals and carbon stocks [23–26]. These analyses generally indicated how changes in scheduled timber harvest levels could affect a land management organization's ability to address carbon-related goals (whether measured as a carbon stock or a carbon sequestration rate). Commodity production goals from a forest and the ability of a forest to store carbon are two areas of emphasis for land managers that are closely associated; therefore, depending on the management option employed, the outcomes of a forest plan can result in either positive or negative achievement of either area of emphasis.

However, most previous studies lack the spatial or temporal detail necessary to adequately evaluate the changes of forest landscapes and the spatial distribution of management activities. Nowadays, forest planning problems are becoming more complex because of the need to integrate spatial relationships in long-term planning process, to address certification requirements, aesthetic concerns, or issues related to fragmentation of older forests. One reason for this is that a spatial model for scheduling harvests requires characterization not only of the state of each stand, but also of the state of its neighbors, implying that nonlinear relationships between decision variables or integer variables will have to be used [27]. While exact mathematical methods (*i.e.*, mixed integer programming) can be used to address these types of problems, heuristic techniques are increasingly being employed in forest planning efforts as an alternative to produce near-optimal solutions with much shorter computational times. A variety of heuristic techniques can be used to address these problems, such as Monte Carlo integer programming (MCIP) [28], simulated annealing (SA) [27], tabu search (TS) [29], genetic algorithms (GA) [30], threshold accepting (TA) [31] and other hybrid algorithms [20,32]. However, the performance of heuristics may vary depending on the complexity of the planning problem and rationality of the parameters. Previous work in this area has illustrated that a well-designed SA algorithm can produce forest plans as good (or better) than others heuristics for forest-level spatial planning problems with different scales [32,33]. Bettinger *et al.* [32], for example, noted that SA was as good at developing forest plans as TA, great deluge (GD), TS with 1-opt and 2-opt moves and TS combined with GA, but was significantly better than TS with 1-opt moves (basic tabu search), GA and random search, when three increasingly difficult timber and wildlife planning problems were addressed.

The aim of this study was to develop and demonstrate a method which allows one to examine the synergies between timber production goals and carbon stocks goals. A utility function that includes timber production, carbon stocks and spatial considerations was developed as the objective. The process was subjected to an even flow of scheduled harvest volume and maximum size limit constraints. We described the results of the forest plans developed in terms of (a) scheduled timber harvest volume; (b)

carbon stocks (standing, live trees) obtained across the forest; and (c) carbon density (amount of carbon per unit area) of each management unit. We hypothesized that for certain management options (combinations of cutting regimes (if used), silvicultural treatments, assumptions on the placement of activities), land managers can achieve desired timber production goals as well as desired carbon management goals. To investigate how well the heuristic performs in developing a management plan in a realistic setting, it is applied to a national forest area of 123,293 ha in northeast China. We developed four sets of forest landscapes (one actual, and three hypothetical age class distributions with young, normal and older forests), and subsequently estimated the spatial dynamics of management activities, timber harvest levels and carbon stock levels associated with these age class distributions.

2. Materials

A number of structural and management variables can have significant influence in the forest management decision making process. However, when compared with other approaches, the use of age classes has a more explicit and credible application to forest management planning practices some parts of the world [34,35] as in China, particularly with respect to partial harvesting activities. Therefore, the forest data used in this research involved one actual and three hypothetical forest landscapes with different age class distributions. The actual landscape database comprised 123,293 ha of national forest in northeast China. The Forest Inventory and Planning Center of Great Xing'an Mountain surveyed the forests using visual compartment inventory. The total area consisted of 352 stand compartments. The vegetation was divided into five forest types: (1) natural *Larix gmelinii* dominated forests (70% composition); (2) natural *Betula platyphylla* dominated forests (70% composition); (3) coniferous forests dominated by *Pinus sylvestris*, *Picea asperata* and mixed with *Larix gmelinii*; (4) broad-leaved forests dominated by *Populus davidiana*, *Salix matsudana*, *Quercus mongolica* and mixed with *Betula platyphylla*; and (5) mixed broadleaf-conifer forests dominated by *Larix gmelinii* and mixed with *Betula platyphylla* and *Populus davidiana*. In this classification, 106 compartments were considered natural *Larix gmelinii* forests (36,286 ha), 50 compartments were considered natural *Betula platyphylla* forests (17,207 ha), 125 compartments were considered coniferous forests (44,927 ha), 59 compartments were considered broad-leaved forests (20,522 ha), 4 compartments were considered mixed broadleaf-conifer forests (1614 ha), and 8 compartments were represented by non-forest land (2737 ha).

In addition to the actual age class distribution (Figure 1), three other age class distributions were randomly assigned to the landscape database (young, normal and older forest), to assess effects on management strategies to maximize scheduled harvest volume or carbon stocks. The young forest represented an age class distribution of a typical forest in northeast China, where past natural disturbances and forest management practices have left many young, over-cut forests. The normal age class distribution was devised simply because many forest management organizations have this as a goal for their long-range forest plans. The older forest age class distribution was developed to represent an approximate, yet realistic inverse of the young forest age class distribution. All four models of the age class distributions of the forest landscapes used for this analysis have similar total areas, polygon sizes and others stand characteristics.

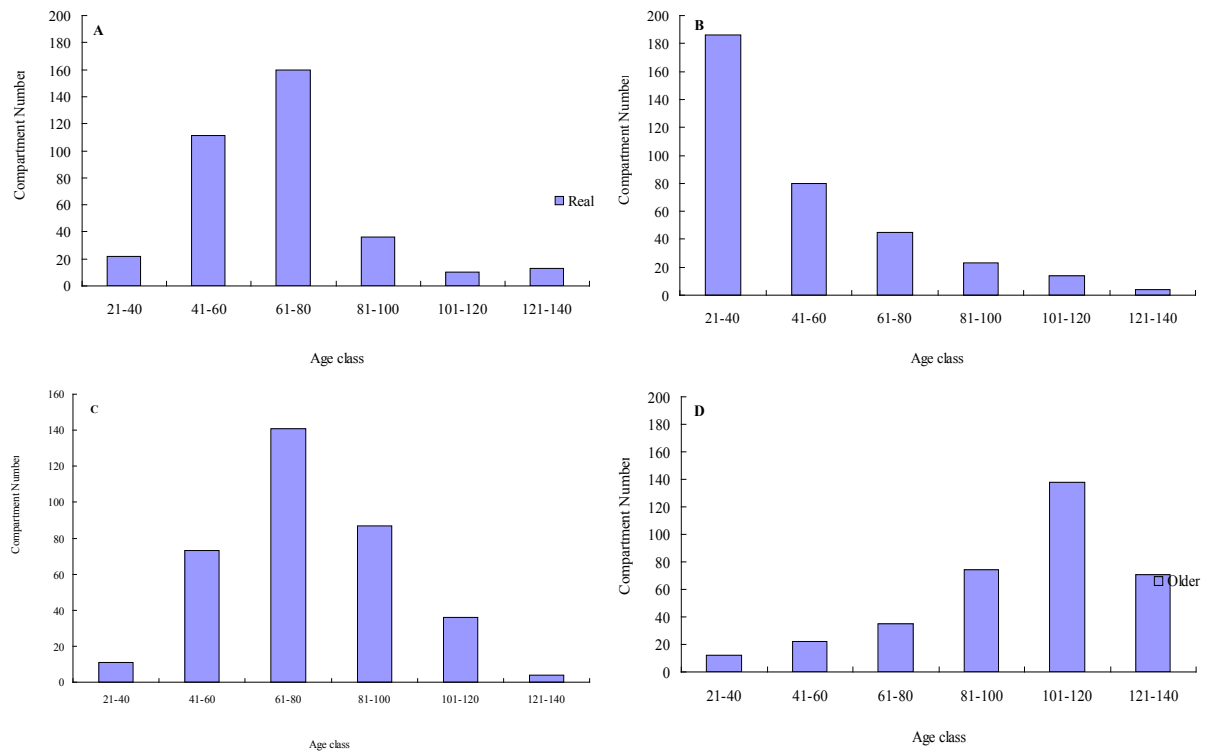


Figure 1. Age class distribution of one actual and three hypothetical forests in a 120,293 ha landscape in the northeast China; (A) actual forest; (B) young forest; (C) normal forest; (D) older forest.

3. Methods

This research describes a forest planning process that integrates carbon management objectives into a wood production modeling environment that is subject to spatial and even-flow timber constraints. The methods consist of three distinct topical areas related to the planning process: (1) the growth and yield models of the five forest types; and (2) the forest planning problem formulation; and (3) the evaluation of the different age class distributions.

3.1. Forest Growth and Yield Models

The forest growth and yield models that the scheduling process used were mostly developed by the Department of Forest Management, Northeast Forestry University (NEFU-FM), and were based on data from the China National Forest Inventory (NFI) of the study area. These models include: average tree height (TH) growth models, average diameter at the breast height (DBH) growth models, site class index (SCI) models, stand density index (SDI) models, SDI dynamics models, stand basal area (BAS) growth models, stand volume (VOL) growth models, stand biomass (BIO) models and stand carbon (CAR) models (see details in [36,37]). Using these stand- and tree-level models, one can predict the forest growth and yield and forest response to different selective cutting intensities.

3.2. Forest Planning Formulation

The forest plans developed cover a 30-year time horizon that is divided into three 10-year planning periods. The objective function of the planning problem is one that seeks to maximize a utility function value that can include timber production, carbon stocks and the spatial pattern of management activities.

3.2.1. Objective Function

As we noted, the objective function for the planning problem involved simultaneously maximizing timber volume, carbon stocks and spatial aggregation of the management activities. The objective function was described as an additive utility model [38]:

$$U = \sum_{i=1}^I a_i u_i(q_i) \quad (1)$$

where U is utility function value, I is the number of objectives, u_i is a scaled sub-priority function for management objective i , q_i is the amount of objective variable i , and a_i is the relative importance of objective variable i , and all objectives were assumed to be equally important, *i.e.*, all a_i in Equation (1) were 0.3333 throughout this paper. The three goals used in all utility functions were timber production, carbon stocks and spatial aggregation of management activities. Timber production and carbon stocks are predicted using the forest growth and yield models mentioned earlier. The clustering index of management activities of a planning period was calculated from [39].

$$FSV = \sum_{i=1}^N NV_i = \sum_{i=1}^N \sum_{k=1}^N \frac{R_{ik} L_{ik}}{D_{ik}} (i \neq k) \quad (2)$$

where FSV is the forest spatial value, N is the number of compartments in the study area, NV_i is the value of adjacency relationship for the i -th stand; L_{ik} and D_{ik} are the border length and the distance between the i -th stand and its k -th adjacency stand, R_{ik} is a binary variable indicating whether (1) or not (0) the i -th stand and its k -th adjacent stand have an identical management activity (both planning period and selective intensity).

The sub-utility function for timber production was represented by two symmetric line-segments, one that increased linearly to a maximum value of 1.0 when a user-specific scheduled volume was achieved, and another that decreased linearly to a minimum value of 0.0 when the volume was equal to the user-specific scheduled volume multiplied by 2 (Figure 2A). For carbon stocks, the sub-utility function increased linearly to a maximum value of 1.0 which represented a user-specific carbon stock goal value, after which the sub-utility function was replaced by 1.0 (Figure 2B). For the forest spatial value, the sub-utility function increased linearly to a maximum value of 1.0, which represented the user-specific goal value (Figure 2C). In this research, the same set of sub-utility functions were applied to the four different forest landscapes.

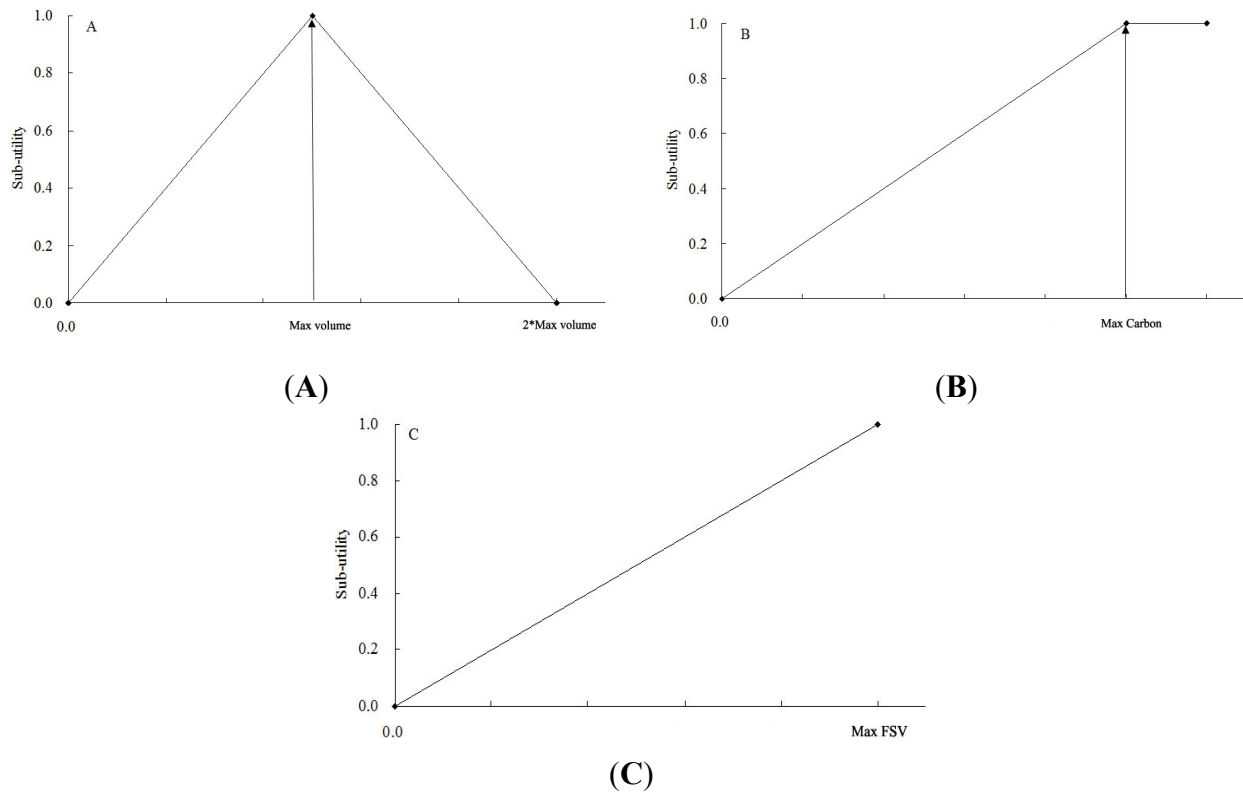


Figure 2. Shape of sub-utility functions for the planning formulation: **(A)** the timber production sub-utility increases linearly from 0.0 to 1.0 until a user-defined scheduled volume is achieved, after which it decreases linearly back to 0.0; **(B)** the carbon stock sub-utility function increases linearly from 0.0 to 1.0 until the user-defined carbon stock goal is achieved, after which it is 1.0; **(C)** the forest spatial value sub-utility function increases linearly from 0.0 to 1.0, which is achieved at the point of maximum forest spatial value for the landscape.

3.2.2. Constraints

There were three main constraints within the planning formulation to guide the development of a forest plan. Two were designed as a proxy for some aspect of the decision-making process, where ecological and economic goals are recognized. Due to both the behavior of industrial landowners and the desires of state landowners, an even flow of harvest volume seems to play an important role for forest sustainable management. Rather than using a strict even-flow rule, the harvest volume constraints limited the ranges of the scheduled volume during each time period.

$$b_l VOL_{t-1} \leq VOL_t \leq b_u VOL_{t-1} \tag{3}$$

where VOL_t and VOL_{t-1} are the scheduled harvest volumes in time periods t and $t - 1$, b_l and b_u are the lower and upper limits harvest volume for each period, b_l must be less than 1.0, and b_u must be greater than 1.0. In this research, we assume the $b_l = 0.8$, and $b_u = 1.2$, respectively.

The second constraint defined a maximum harvest size limit for each compartment n and its set of adjacent neighbors (U_n) with a same management activity within each time period. Therefore, a size constraint not only can affect the scheduled volumes during each time period, but also affect the

arrangement of management activities around each compartment scheduled during time period t . We defined the size constraint as:

$$\sum_{k=1}^{U_n} A_k x_{nk} + A_n \leq A_{\max} \quad \forall n \quad (4)$$

where again U_n is the set of adjacent neighbors to unit n , k is the adjacent neighbors to unit n , A_k is the area of unit k , x_{nk} is binary variable indicating whether unit k has the same management activity (including the harvest time and intensity) with the unit n , A_n is the area of unit n , A_{\max} is the user-specific value.

The third constraint was a singularity constraint, which limited each management unit to one activity during the planning horizon:

$$\sum_{t=1}^T x_{nt} \leq 1 \quad \forall n \quad (5)$$

where T is the number of total planning periods, and x_{nt} is a binary variable indicating whether (1) or not (0) the management unit n has been assigned a management activity during time period t .

3.2.3. Management Activities

The forests in our study area play an important role in the ecological function and economic development of the country. However, the quality and ecological function of these forests have been seriously degraded due to the adoption of an extensive farming strategy within the last 100 years. In order to restore and protect forest resources, the Heilongjiang Province Law prohibited final felling of forests on 1 April 2014. Based on the stipulations of the Laws, in this research we will assume that the management activities can only include four different selective cutting intensities (*i.e.*, 0%, 10%, 20% and 30%) and each compartment can be managed (entered) only once during the planning time horizon (30 years). These four selective cutting intensities, in conjunction with the three planning periods, provide twelve potential management activities for each compartment. Given that there are 352 compartments, the total number of decision variables is 4224.

3.3. Evaluation of Different Age Class Distributions

When using heuristic techniques, one cannot be certain that the global optimum solution to a planning problem will be found, nor that the resulting solutions are even close to the global optimum [29,32]. Therefore, the optimization process was repeated 20 times for each forest landscape (actual, young, normal, older). The maximum and minimum objective function values, and standard deviations and averages of these were compared as a self-validation of the results [40]. As Barrett *et al.* [41] and Bettinger *et al.* [42] described, if a heuristic search was initiated from a random starting point, each resulting solution generated from a heuristic can be considered an independent sample from a larger population, for which one can assume independence and perform statistical tests. If normally distributed, a Student's t -test can be used to quantitatively detect whether there are significant differences in the forest plans developed for the four heterogeneous forest landscapes. All tests are conducted at the $\alpha = 0.05$ level.

3.4. Heuristic Search Algorithm

A heuristic search process, simulated annealing (SA), was developed and employed to schedule activities for each stand. SA is inspired by the process of annealing (cooling) of metals, and the motivation for it was first described in 1953 [43]. As a search process, SA has shown to be useful in a number of important forestry problems, such as scheduling harvest [32,44], maintaining or developing wildlife habitat [31], maintaining core areas [45] and optimizing forest landscape values [46]. Each of these efforts has shown that although SA cannot guarantee an optimal solution, it should be able to provide a number of good, feasible solutions within an acceptable period of time for large and complex planning problems.

SA is technically considered a *s*-metaheuristic neighborhood search technique [47] that examines a solution to a forest plan, then proposes a change to a single characteristic (harvest time or activity). As implemented here, we utilize 1-opt moves, whereby a forest plan is incrementally developed by changing the status (assignment of harvest time or activity) of a single management unit. SA always accepts every new solution which improves the value of the objective function. Non-improving moves are accepted based on a probability that is determined through a function

$$p = e^{-(U_{\text{new}} - U_{\text{old}}) / \text{Temperature}} \quad (6)$$

where *Temperature* is the current temperature of the annealing process, U_{new} and U_{old} are the value of objective function for the current and previous best solutions, respectively. During the optimization process, the temperature cools according to a given cooling rate. At high temperatures the probability for accepting inferior solutions is high, and as the temperature decreases, the probability decreases. In the forthcoming case study, the initial temperature, ending temperature, cooling rate, and the number of iterations per temperature level of SA were set to 1, 0.000001, 0.95 and 20, respectively. These parameters were based on several trial runs of the search process applied to the case study forest landscapes.

4. Results

The assumption regarding the initial age class distribution not only affected the forest plan values, but also the computing times necessary to develop forest plans (Table 1). The older forest produced the highest mean solution value to the utility function (0.6594) and the highest single maximum solution value (0.6623). The standard deviation for the older forest was also significantly lower than that for other three forest landscapes. A paired *t*-test indicated that there were significant differences ($p < 0.01$) among the four forest landscapes (age class distributions) in terms of the value of objective function. As for the average computing time needed for generating a single solution, plans for the older forest landscape were also developed faster (2.4483 minutes (min) per solution) and had the tightest standard deviations (0.7038 min) for the computing times than the other four forest landscapes. With a few exceptions, the young forest landscape needed approximately half an hour to produce a single solution, and the standard deviation was approximately 15 min. One reason for this is that most of the stands within the young forest landscape had much lower volumes available for harvesting, and thus the search process needed to explore more of the solution space to produce a good and feasible solution. Meanwhile, the higher standard deviations in the computing times also indicate that the quality of the initial solution can affect

(significant shorten) the computing time, e.g., the fastest solution was generated in only 4.6667 min. However, the manner in which SA changed temperature also affected these results, as temperatures were only changed after 20 successful moves per temperature, rather than a pre-defined number of unsuccessful moves that have been used in other work to prevent long computational times.

Table 1. Summary of solution quality and computing time of 20 runs for the four forest landscapes with different age class distributions.

Forest Scenario	Solution Value				Computing Time	
	Min.	Max.	Mean	SD	Mean (min)	SD (min)
Actual	0.6146	0.6253	0.6209	0.0027	4.6417	1.6804
Young	0.5661	0.5927	0.5809	0.0078	37.0208	16.2809
Normal	0.6329	0.6468	0.6392	0.0025	2.9792	0.9740
Older	0.6572	0.6623	0.6594	0.0013	2.4483	0.7038

SD = standard deviation.

In all four of the case study forest landscapes, the total scheduled harvest volumes were very close to the target volume. However, the older forest volumes were significantly different than those provided by the young and actual forest landscapes ($p < 0.01$), as well as the normal forest landscape ($p < 0.01$) (Figure 3A). The scheduled harvest volume of three 10-year periods for each forest landscape all generally represented non-declining even flow, and gradually increased over time (Figure 3B). The forest spatial values were almost the same (approximately 180) for all four forest landscapes, which accounted for about 10% of the total FSV value (Figure 3C). The spatial distribution of harvest activities for the best solution of the 20 runs for each forest landscape is shown in Figure 4. For the harvest level desired for each of the four forest landscapes, the total carbon stocks increased due to the increases in the average stand age ($p < 0.01$, Figure 3D). In our synthesis, the different age class distributions seem to significantly affect the final carbon stock levels.

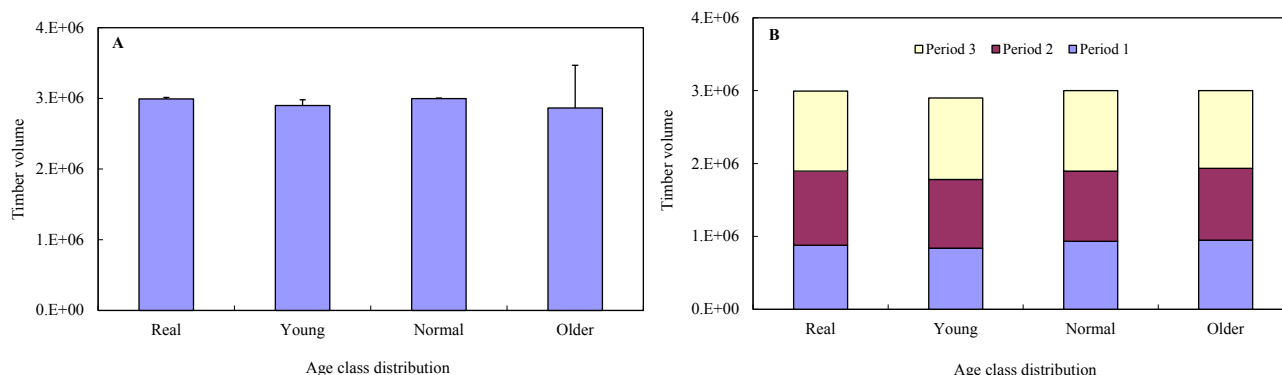


Figure 3. Cont.

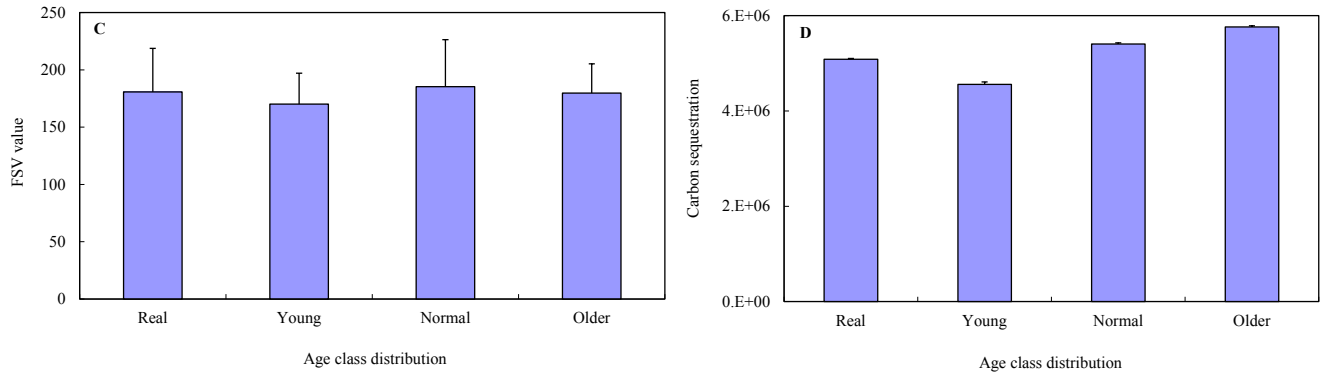


Figure 3. The results of planning for 30-year time horizons of the four forest landscapes with different age class distributions; (A) total harvest volume; (B) sub-period harvest volume, (C) forest spatial value; (D) carbon stocks.

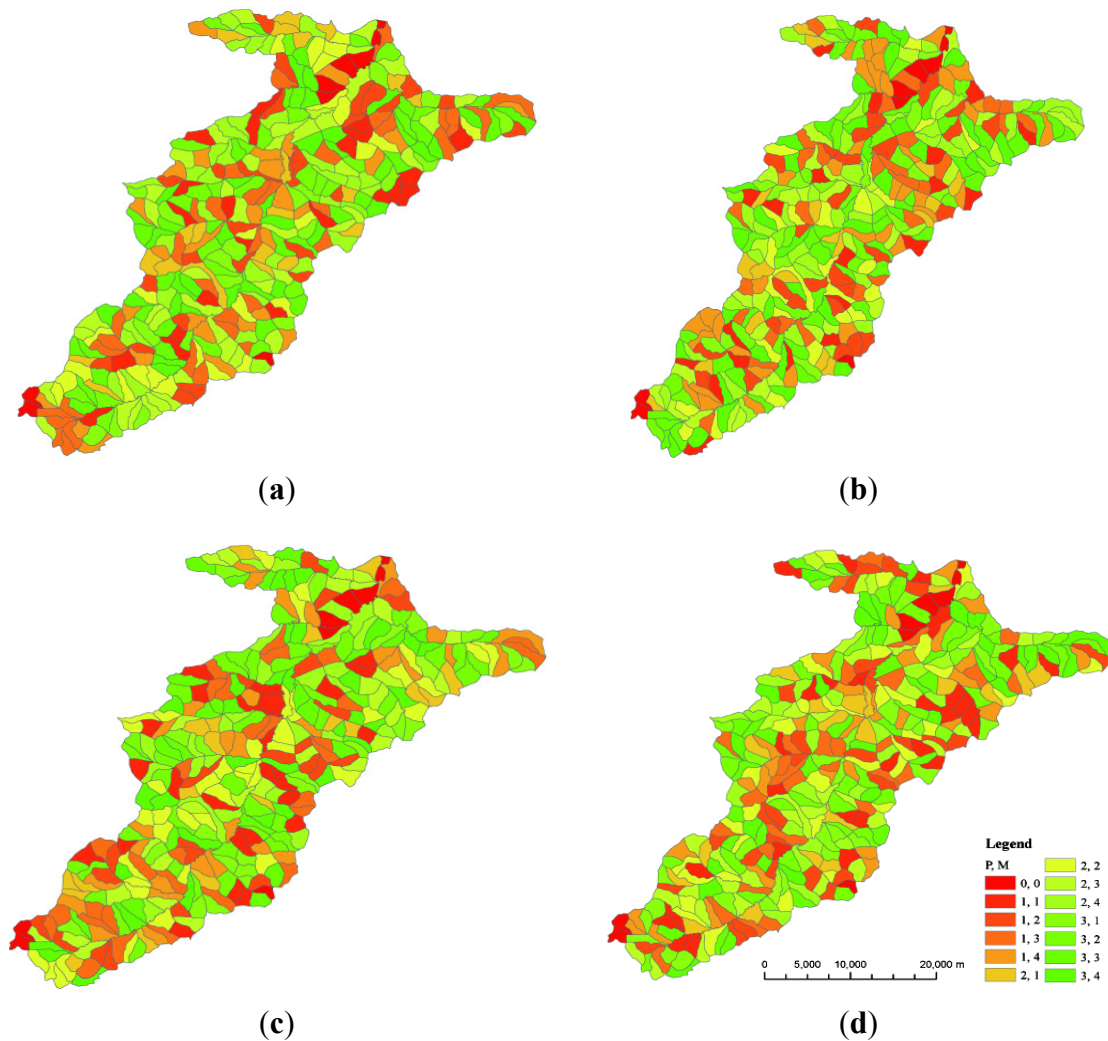


Figure 4. The locations of management activities for forest landscapes with four different age class distributions; (a) actual forest; (b) young forest; (c) normal forest; (d) older forest (Note: *P* denotes the periods ($P = 1, 2, 3$); *M* denotes the management activities ($M = 1, 2, 3, 4$), which represent the selective cutting intensities of 0%, 10%, 20% and 30%, respectively; and $P = 0$ and $M = 0$ denotes non-forest land).

Figure 5 illustrates the relative changes in carbon density for the four heterogeneous forest landscapes. The average increments of carbon density for the actual, young, normal and older forest landscapes were 4.48 ± 9.61 t/ha, 8.73 ± 10.85 t/ha, 2.99 ± 9.19 t/ha and 1.03 ± 9.77 t/ha, respectively, indicating appropriate forest management practices can effectively achieve the desired synergies between forest timber production and carbon stocks within different age class structures in the next 30 years. However, the number of stands with an increase in carbon sequestered for each forest landscape was significantly different ($p < 0.05$), *i.e.*, which was reduced with the increases in average stand age. For the young forest landscape, approximately 80% of the stands increased their carbon levels. However, the percentage of the increase reduced to 65% for the normal forest landscape, and the value was much smaller (55%) for the older forest landscape.

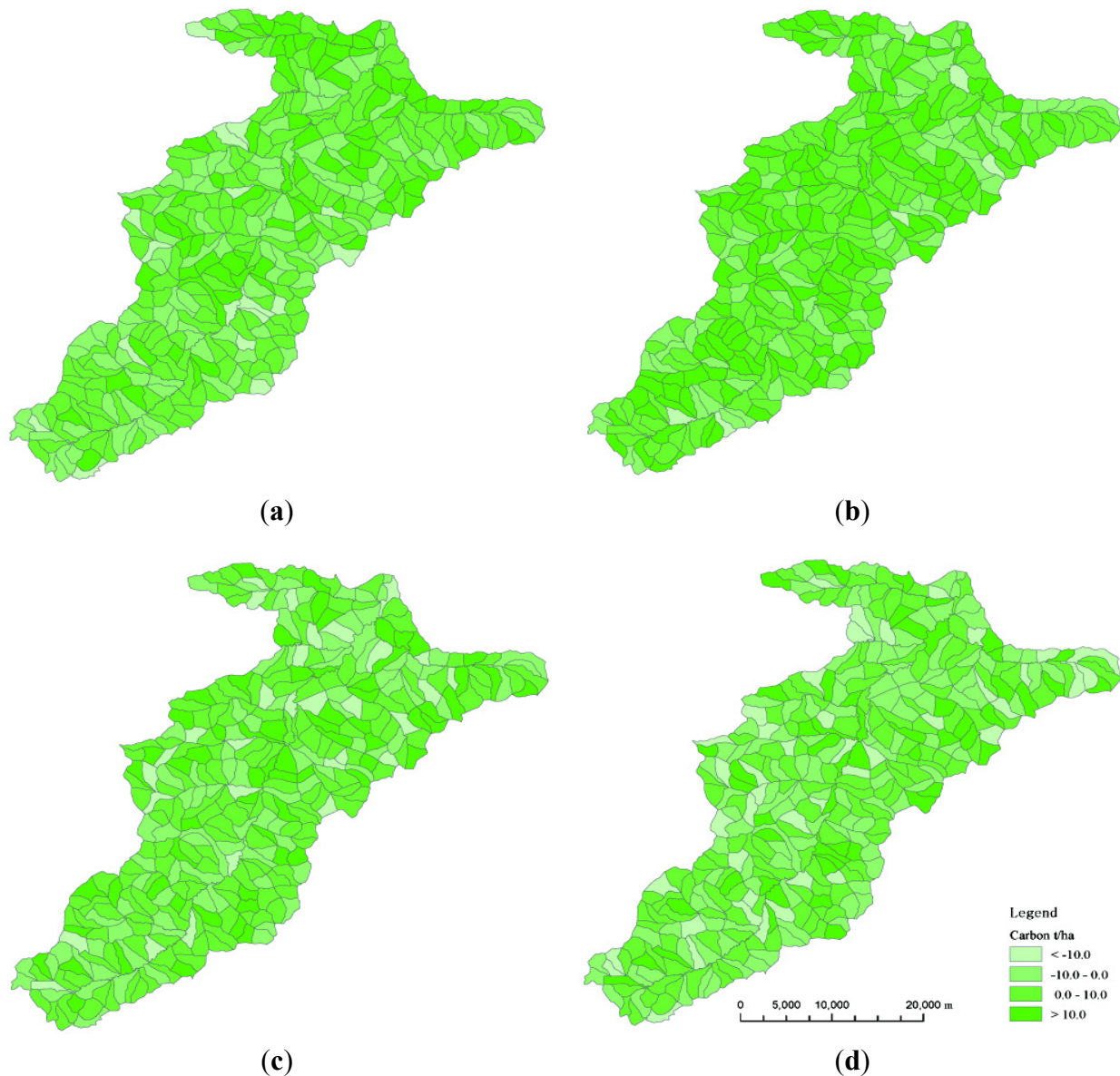


Figure 5. Changes in forest carbon levels for the four forest landscapes with different age class distributions; (a) actual forest; (b) young forest; (c) normal forest; (d) older forest.

5. Discussion

The major focus of this study was to develop and demonstrate a new method which can allow policy makers to predict future timber production and carbon stocks simultaneously. This was addressed by presenting and solving a forest planning problem with a desired high carbon stock level and a desired scheduled harvest volume, as well as an appropriate spatial distribution of forest activities. The planning problem was also subjected to even flow of harvest volume and maximum harvesting size constraints. In this case study, the three parts of the objective function were combined into a utility function using scaled sub-priority functions. The utility function was maximized, using simulated annealing, to obtain high-quality forest management plans for the next 30 years. Other methods capable of solving complex spatial planning problems could have been selected, and other methods for optimizing the search parameters may have been investigated [48]. However, considering the effort of implementing the algorithm and running these problems, SA seemed to be an expedient choice. In addition, in other studies where heuristics have been compared, SA was shown to perform well [32,33]. Further, we developed three typical hypothetical forest landscapes to estimate the effect on timber production and carbon stocks of different age class structures and therefore to assess the sensitivity of the results when the process was applied to other landscapes.

Technically, the approach presented in this study is immediately available for forest planning practice, because: (1) the harvest levels are in line with the actual harvest levels in the region and the average carbon level is 43.26 t/ha, which is close to the previously reported values (45.06 t/ha) [49]. However, it should be noted that not all of the components of carbon stocks related to forests and forestry were included. For example, soil carbon sequestration, comprising as much as 50%–85% of current carbon stocks in the world's forests [15], plays an important role in the global carbon cycle. Unfortunately, incorporating below-ground carbon stocks into a forest planning process is challenging and not possible at this time, due to a lack of the necessary predictive models for the forests examined in this research. Further, the constraints we analyzed are required by law or are based on guidance from policy makers and evidence from recent management behavior, yet some technical issues may hinder their common use in the near future. Finally, the shape of the sub-utility functions can have a great influence on the level goals produced and their temporal development [38]. In the case studies it was assumed that all goals use linear sub-utility functions, meaning the assumptions we employed may not completely match realistic situations.

Given the widespread attention paid to global climate change over the last two decades, a potential need has arisen to develop long-term forest management plans that consider climate change [50]. For this purpose, either a set of process-based growth and yield models or adjustments to empirical growth and yield models (where growth is affected by climate) is needed. Along with changes in climate, the probability of occurrence for many unpredictable events (e.g., forest fires, disease and insect outbreaks) will likely change, and thus planning processes may need to incorporate natural disturbance regimes through the use of stochastic process methods [50]. Another technical reason that may hinder the application of the process involves a subjective determination of the weights that are applied to the three portions of the objective function. The relative importance of the goals we examined may vary, and forest managers may want to develop forest plans that emphasize one or more of the three goals over the others. In weighting a goal, a planner may value preference (or avoidance) of the goal using the

weighting term, rather than using a normalizing process to do so [51]. Therefore, when one goal is weighted differently from the others, the search process may be biased [52]. In our work, we assumed all three goals were of equal weight in the objective function, and that they were normalized appropriately to adequately reflect their equal importance.

The SA algorithm, like some other metaheuristic techniques, is a stochastic search technique and is particularly highly parameterized [31], so it is obvious that a single run of the model would be insufficient to assess the quality and the stability of the results [31–33]. Therefore, with respect to the quality of results generated by the heuristic technique, we attempted several trial runs with varying combinations of annealing parameters to determine which would best suit the problem (as in [32,39,44]). The ones we presented in this work were deemed the most appropriate among several sets of others. In assessing the stability of results generated, we observed the objective function variability through 20 runs, and found that the results vary only from 0.20% to 1.34%, indicating adequate solution stability. However, each heuristic process also has its disadvantages. The most prominent is that these methods cannot ensure optimality [32,33,53]. The quality of solutions generated by a forest planning model can be evaluated by comparing results with exact techniques for their “relaxed” problems, or by estimating a global optimum solution from a set of heuristic solutions, as proposed in Bettinger *et al.* [41]. Due to the complexity of the objective (the spatial aspect in particular), we did not solve the problem exactly using non-linear mixed integer programming methods. Further, given problems that others have noted with the estimation of a global optimum (e.g., Bettinger *et al.* [29]) we did not pursue that course of action either, and thus our solution validation process can be considered a *self-validation* [39].

As may be evident in the methods of this research, the standard version of simulated annealing was used in this case study. Other forestry research efforts have shown that some enhanced heuristic methods can further explore the solution space through intensification and diversification and possibly improve the quality of solution values. For example, Heinonen and Pukkala [53] developed 2-opt heuristic search for random ascent, Hero, SA and TS, and found it can improve solution values by 0.61%, 1.35%, 0.25% and 0.38% for five different scales of spatial forest planning problems. Li *et al.* [33] combined two and three heuristic algorithms (among SA, TS, TA and the raindrop method), finding that more than 75% of the 3-algorithm and the best 2-algorithm (TA + TS) produced better solutions than the best standard heuristic in terms of mean and maximum solution values. In addition, one also can combine heuristic methods with exact techniques (e.g., linear programming) to produce a new method (e.g., Öhman and Eriksson [54]), where the exact techniques can be used for solving the non-spatial dimension, and the heuristic methods are used for solving the spatial dimension of the problems. Very recently, it was also observed that search reversion can help an *s*-metaheuristic solve a problem, such as the one described here, more effectively [55].

6. Conclusions

Opportunities for enhancing carbon sequestration planning research often center on forest policy makers who are seeking strategies to address global climate change and on forest landowners with multiple-use and less intensive timber production goals [56]. In certain forested areas of the world, there may be opportunities to both reach the commodity production goals of a land management organization

while also positively addressing carbon stock management goals. For example, of the three forest landscapes with hypothetical age class distributions used in the case study, all of them were shown to potentially obtain higher carbon stock levels in commercial forests while sufficiently satisfying a timber production objective. This work illustrated one planning process that could be employed to assess the trade-offs among goals and whether synergies might be achieved. However, the initial condition of a forest can influence the achievement of these goals, and therefore processes are necessary to assess whether these types of goals are compatible or incompatible.

Acknowledgments

The authors are appreciative of the financial support provided by the National Science & Technology Pillar Program during the 12th Five-year Plan Period (NO. 2012BAD22B0202 and 2011BAD37B02) and the Fundamental Research Funds of the Central Universities of China (NO. 2572014AA28).

Author Contributions

Lingbo Dong directly conducted the development of the mathematical formulation of the harvest scheduling model and wrote the manuscript. Pete Bettinger assisted with the simulated annealing algorithm and manuscript preparation. Zhaogang Liu conceived and designed the idea, and also assisted with mathematical formulation. Huiyan Qin assisted with the data analysis and manuscript preparation.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Kyoto Protocol to the United Nations framework convention on climate change. Available online: <http://unfccc.int/resource/docs/convkp/kpeng.pdf> (accessed on 9 February 2015).
2. Neilson, E.T.; MacLean, D.A.; Meng, F.R.; Arp, P.A. Spatial distribution of carbon in natural and management stands in an industrial forest in New Brunswick, Canada. *For. Ecol. Manag.* **2007**, *253*, 148–160.
3. Malhi, Y.; Aragão, L.O.C.; Metcalfe, D.B.; Paiva, R.; Quesada, C.A.; Almeida, S.; Anderson, L.; Brando, P.; Chambers, J.Q.; Dacosta, A.C.L.; *et al.* Comprehensive assessment of carbon productivity, allocation and storage in three Amazonian forest. *Glob. Chang. Biol.* **2009**, *15*, 1255–1274.
4. Pan, Y.D.; Birdsey, R.A.; Fang, J.Y.; Houghton, R.; Kauppi, P.E.; Kurz, W.A.; Phillips, O.L.; Shvidenko, A.; Lewis, S.L.; Canadell, J.G.; *et al.* A large and persistent carbon sink in the world's forests. *Science* **2011**, *333*, 988–992.
5. Joosten, R.; Schumacher, J.; Wirth, C.; Schulte, A. Evaluating tree carbon predictions for beech (*Fagus sylvatica* L.) in western Germany. *For. Ecol. Manag.* **2004**, *189*, 87–96.
6. Guo, Z.D.; Fang, J.Y.; Pan, Y.D.; Birdsey, R. Inventory-based estimates of forest biomass carbon stocks in China: A comparison of three methods. *For. Ecol. Manag.* **2010**, *259*, 1225–1231.

7. Grote, R.; Kiese, R.; Grünwald, T.; Ourcival, J.M.; Granier, A. Modelling forest carbon balances considering tree mortality and removal. *Agric. For. Meteorol.* **2011**, *151*, 179–190.
8. Finkral, A.J.; Evans, A.M. The effects of a thinning treatment on carbon stocks in a northern Arizona ponderosa pine forest. *For. Ecol. Manag.* **2008**, *255*, 2743–2750.
9. Thürig, E.; Kaufmann, E. Increasing carbon sinks through forest management: A model-based comparison for Switzerland with its Eastern Plateau and Eastern Alps. *Eur. J. For. Res.* **2010**, *129*, 563–572.
10. Powers, M.; Kolka, R.; Palik, B.; McDonald, R.; Jurgensen, M. Long-term management impacts on carbon storage in Lake States forests. *For. Ecol. Manag.* **2011**, *262*, 424–431.
11. Manusch, C.; Bugmann, H.; Wolf, A. The impact of climate change and its uncertainty on carbon storage in Switzerland. *Reg. Environ. Chang.* **2014**, *14*, 1437–1450.
12. Selmants, P.C.; Litton, C.M.; Giardina, C.P.; Asner, G.P. Ecosystem carbon storage does not vary with mean annual temperature in Hawaiian tropical montane wet forests. *Glob. Chang. Biol.* **2014**, *20*, 2927–2937.
13. Lal, R. Forest soils and carbon sequestration. *For. Ecol. Manag.* **2005**, *220*, 242–258.
14. Ter-Mikaelian, M.T.; Colombo, S.J.; Chen, J. The burning question: Does forest bioenergy reduce carbon emissions? A review of common misconceptions about forest carbon accounting. *J. For.* **2015**, *113*, 57–68.
15. Liski, J.; Pussinen, A.; Pingoud, K.; Mäkipää, R.; Karjalainen, T. Which rotation length is favorable to carbon sequestration? *Can. J. For. Res.* **2001**, *31*, 2004–2013.
16. Seely, B.; Welham, C.; Kimmins, H. Carbon sequestration in a boreal forest ecosystem: Results from the ecosystem simulation model, FORECAST. *For. Ecol. Manag.* **2002**, *169*, 123–135.
17. Daust, D.K.; Nelson, J.D. Spatial reduction factors for strata-based harvest schedules. *For. Sci.* **1993**, *39*, 152–165.
18. Boston, K.; Bettinger, P. The economic impact of green-up constraints in the southeastern United States. *For. Ecol. Manag.* **2001**, 191–202.
19. Nalle, D.; Arthur, J.L.; Montgomery, C.A. Economic impacts of adjacency and green-up constraints on timber production at a landscape scale. *J. For. Econ.* **2005**, *10*, 189–205.
20. Bennett, E.M.; Peterson, G.D.; Gordon, L.J. Understanding relationships among multiple ecosystem services. *Ecol. Lett.* **2009**, *12*, 1394–1404.
21. Cademus, R.; Escobedo, F.J.; McLaughlin, D.; Abd-Elrhman, A. Analyzing trade-offs, synergies, and drivers among timber production, carbon sequestration, and water yield in *Pinus elliotii* forests in southeastern USA. *Forests* **2014**, *5*, 1409–1431.
22. Bettinger, P.; Chung, W. The key literature of, and trends in, forest-level management planning in north America, 1950–2001. *Int. For. Rev.* **2004**, *6*, 40–50.
23. Meng, F.R.; Bourque, C.P.A.; Oldford, S.P.; Swift, D.E.; Smith, H.C. Combining carbon sequestration objectives with timber management planning. *Mitig. Adapt. Strat. Glob. Chang.* **2003**, *8*, 371–403.
24. Backéus, S.; Wikström, P.; Lämås, T. A model for regional analysis of carbon sequestration and timber production. *For. Ecol. Manag.* **2005**, *216*, 28–40.

25. Bourque, C.P.A.; Neilson, E.T.; Gruenwald, C.; Perrin, S.F.; Hiltz, J.C.; Blin, Y.A.; Horsman, G.V.; Parker, M.S.; Thorburn, C.B.; Corey, M.M.; *et al.* Optimizing carbon sequestration in commercial forests by integrating carbon management objectives in wood supply modeling. *Mitig. Adapt. Strat. Glob. Chang.* **2007**, *12*, 1253–1275.
26. Hennigar, C.R.; MacLean, D.A.; Amos-Binks, L.J. A novel approach to optimize management strategies for carbon stored in both forest and wood products. *For. Ecol. Manag.* **2008**, *256*, 786–797.
27. Öhman, K.; Lämås, T. Clustering of harvest activities in multi-objective long-term forest planning. *For. Ecol. Manag.* **2003**, *176*, 161–171.
28. Rempel, R.S.; Kaufmann, C.K. Spatial modeling of harvest constraints on wood supply *versus* wildlife habitat objectives. *Environ. Manag.* **2003**, *32*, 646–659.
29. Bettinger, P.; Boston, K.; Kim, Y.H.; Zhu, J.P. Landscape-level optimization using tabu search and stand density-related forest management prescriptions. *Eur. J. Oper. Res.* **2007**, *176*, 1265–1282.
30. Lu, F.D.; Eriksson, L.O. Formation of harvest units with genetic algorithms. *For. Ecol. Manag.* **2000**, *130*, 57–67.
31. Bettinger, P.; Johnson, D.L.; Johnson, K.N. Spatial forest plan development with ecological and economic goals. *Ecol. Mod.* **2003**, *169*, 215–236.
32. Bettinger, P.; Graetz, D.; Boston, K.; Sessions, J.; Chung, W. Eight heuristic planning techniques applied to three increasingly difficult wildlife planning problems. *Silva Fenn.* **2002**, *36*, 561–584.
33. Li, R.X.; Bettinger, P.; Boston, K. Informed development of meta heuristics for spatial forest planning problems. *Open Oper. J.* **2010**, *4*, 1–11.
34. Čavlović, J.; Antonić, O.; Božić, M.; Teslak, K. Long-term and country scale projection of even-aged forest management: A case study for *Fagus sylvatica* in Croatia. *Scand. J. For. Res.* **2012**, *27*, 36–45.
35. Chen, Y.T.; Zheng, C.; Chang, C.T. Efficiently mapping an appropriate thinning schedule for optimum carbon sequestration: An application of multi-segment goal programming. *For. Ecol. Manag.* **2011**, *262*, 1168–1173.
36. Dong, L.H.; Li, F.R.; Jia, W.W.; Liu, F.X.; Wang, H.Z. Compatible biomass models for main tree species with measurement error in Heilongjiang Province of Northeast China. *Chin. J. Appl. Ecol.* **2011**, *22*, 2653–2661.
37. Wang, H.Z. Dynamic Simulating System for Stand Growth of Forests in Northeast China. Ph.D. Thesis, Northeast Forestry University, Harbin, China, 2012.
38. Pukkala, T.; Ketonen, T.; Pykäläinen, J. Predicting timber harvests from private forest—a utility maximization approach. *For. Policy Econ.* **2003**, *5*, 285–296.
39. Chen, B.W.; Gadow, K.V. Timber harvest planning with spatial objectives, using the method of simulated annealing. *Eur. J. For. Res.* **2002**, *121*, 25–34.
40. Bettinger, P. A prototype method for integrating spatially-referenced wildfires into a tactical forest planning model. *Res. J. For.* **2009**, *3*, 8–22.
41. Barrett, T.M.; Gillies, J.K.; Davis, L.S. Economic and fragmentation effects of clearcut restrictions. *For. Sci.* **1998**, *44*, 569–577.

42. Bettinger, P.; Sessions, J.; Johnson, K.N. Ensuring the compatibility of aquatic habitat and commodity production goals in eastern Oregon with a Tabu search procedure. *For. Sci.* **1998**, *44*, 96–112.
43. Metropolis, N.; Rosenbluth, A.W.; Rosenbluth, M.N.; Teller, A.H.; Teller, E. Equation of state calculations by fast computing machines. *J. Chem. Physics* **1953**, *21*, 1087–1092.
44. Boston, K.; Bettinger, P. An analysis of Monte-Carlo integer programming, simulated annealing, and tabu search heuristics for solving spatial harvest scheduling problems. *For. Sci.* **1999**, *45*, 292–301.
45. Öhman, K.; Eriksson, L.O. The core area concept in forming contiguous areas for long-term forest planning. *Can. J. For. Res.* **1998**, *28*, 1032–1039.
46. Baskent, E.Z.; Jordan, G.A. Forest landscape management modeling using simulated annealing. *For. Ecol. Manag.* **2002**, *165*, 29–45.
47. Talbi, E.G. *Meta-Heuristics. From Design to Implementation*; John Wiley & Sons: Hoboken, NJ, USA, 2009.
48. Pukkala, T.; Heinonen, T. Optimizing heuristic search in forest planning. *Nonlinear Anal.: Real World Appl.* **2006**, *7*, 1284–1297.
49. Li, H.Q.; Lei, Y.C.; Zeng, W.S. Forest carbon storage in China estimated using forestry inventory data. *Sci. Silv. Sin.* **2011**, *47*, 7–12.
50. Bettinger, P.; Siry, J.; Merry, K. Forest management planning technology issues posed by climate change. *For. Sci. Technol.* **2013**, *9*, 9–19.
51. Jones, D. A practical weight sensitivity algorithm for goal and multiple objective programming. *Eur. J. Oper. Res.* **2011**, *213*, 238–245.
52. Jadidi, O.; Zolfaghari, S.; Cavalieri, S. A new normalized goal programming model for multi-objective problems: A case of supplier selection and order allocation. *Int. J. Prod. Econ.* **2014**, *148*, 158–165.
53. Heinonen, T.; Pukkala, T. A comparison of one- and two-compartment neighborhoods in heuristic search with spatial forest management goals. *Silva Fenn.* **2004**, *38*, 319–332.
54. Öhman, K.; Eriksson, L.O. Allowing for spatial consideration in long-term forest planning by linking linear programming with simulated annealing. *For. Ecol. Manag.* **2002**, *161*, 221–230.
55. Bettinger, P.; Demirci, M.; Boston, K. Search reversion within s-metaheuristics: Impacts illustrated with a forest planning problem. *Silva Fenn.* **2015**, *49*, 1–20.
56. Jumppanen, J.; Kurttila, M.; Pukkala, T.; Uuttera, J. Spatial harvest scheduling approach for areas involving multiple ownership. *For. Policy Econ.* **2003**, *5*, 27–38.