

Using Spatial Tradeoffs to Build Consensus and to Value Non-Market Services in Forest Management

Sándor F. Tóth

Keywords: harvest scheduling, spatial optimization, non-market forest services, conflict resolution

Abstract: This study summarizes work that focused on quantifying the spatial tradeoffs behind conflicting forest management objectives. The term “spatial tradeoff” refers to the spatial consequences of different management objectives. The techniques build on spatially-explicit forest planning models and have the capability to identify Pareto-optimal harvest schedules with respect to various timber and non-timber objectives. The focus of this study is to demonstrate how tangible information on forest resource tradeoffs and production possibilities can be used to (1) identify efficient compromise management alternatives, (2) build consensus among stakeholders with conflicting interests, and (3) help realize and market environmental forest services.

1. Introduction

Forests can have many conflicting uses. Logging can compromise habitat conservation efforts, fire protection can fragment sensitive wildlife habitat and cut off migration routes, while recreation can reduce the aesthetic value of the forest. These are but a few of the conflicts that typically arise during a forest planning exercise. As a result, it can be challenging to identify the best compromise of management alternatives, especially when a spatially and temporally explicit allocation of management actions is necessary for landscape-level planning. How should we assign harvesting and other silvicultural treatments across the landscape

and over time so that certain spatial habitat requirements are best met while revenues are maximized? How should fuel treatment options be allocated to minimize overall fire risk, while maintaining large tracts of mature forest habitat? Questions like these often arise in natural resource management.

One way to address these questions is to generate all the management alternatives that are *efficient* (Koopmans, 1951), or *Pareto-optimal*, with respect to the conflicting objectives. A management alternative is *Pareto-optimal* if no other alternative exists that would better achieve one of the objectives without compromising any of the others. Pareto (1909) is credited with developing this concept, which is useful for quantifying the tradeoffs among competing goals. As an example, consider the set of Pareto-optimal management options in Figure 1. Each point represents an alternative and the locations of the points relative to the two axes define the extent to which the objectives are achieved. If, for example, alternative A were chosen, revenues would approach almost \$2.45 million, but no mature habitat would be preserved. If, on the other hand, one chooses alternative C, more than 60 ha of mature forest habitat would be preserved in large patches at a cost of \$20,000. This \$20,000 represents the opportunity cost of switching from alternative A to C. If the hypothetical owner of this forest was willing to forego even more revenue, then more mature habitat could be preserved (see alternatives D, E, F, G, or B). However, no more than 170 ha of mature forest habitat could be preserved, no matter how much profit is foregone (see alternative B). A nice feature of these opportunity costs is that they capture the costs of certain spatial attributes, such as the minimum contiguous size of mature forest patches, in an explicit manner, hence the term, “spatial tradeoffs.”

The curve connecting the Pareto-optimal solutions is called the *Efficient* or *Production Possibilities Frontier*. This frontier separates the region in the objective space where additional feasible management alternatives might be found from the region where no solutions exist (Tóth *et al.*, 2006). Any alternative that lies below the frontier is inferior to the corner points because at least one of the corner points would provide a better optimization for at least one of the objectives.

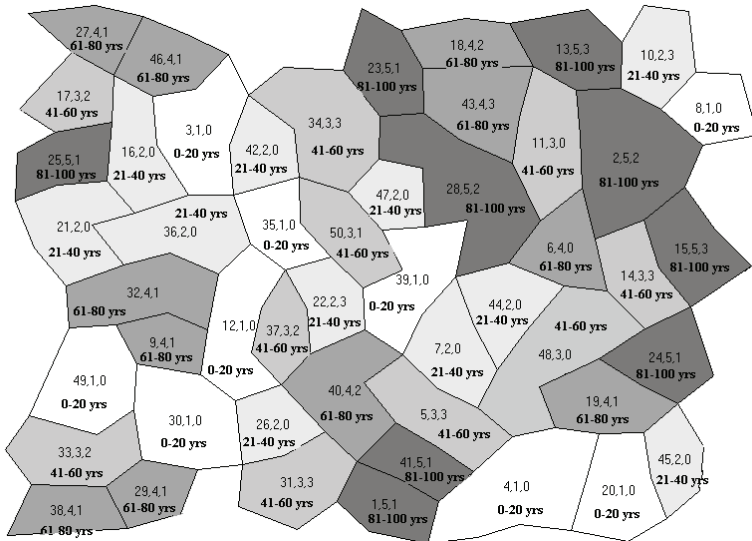


Figure 1. Efficient management alternatives for a hypothetical forest planning problem with two objectives.

These inferior alternatives, which also include those that lie between the corner points, are called *dominated* solutions and are of no interest to the analyst or decision maker. Thus, only the corner solutions are necessary to generate a good pool of management alternatives.

The immediate benefit of the efficient frontier is that it defines the extent to which conflicting objectives can simultaneously be achieved. It shows, for example, that it is not possible to design a management scheme that simultaneously yields \$2.3 million in revenues and preserves 150 ha of mature forest habitat. Another immediate benefit is the opportunity cost structure associated with the Pareto-optimal alternatives. One can determine how much discounted net revenue must be forgone to achieve a given habitat requirement, or alternatively how much mature forest habitat must be forgone to increase profits by a given amount.

The concept of Pareto-optimality has been studied in forestry and wildlife applications to map out the efficient frontier with respect to various timber and non-timber objectives (e.g., Roise *et al.*, 1990 or Arthaud and Rose, 1996). Before

moving on to propose the use of the efficient frontier as a conflict resolution and non-market valuation tool, I will discuss how this unique set of management alternatives can be generated in spatial forest planning.

2. Multi-Objective Programming in Spatial Forest Planning

Harvest scheduling models have been used for more than 40 years in the United States to optimally prescribe harvest treatments. Some of these models were formulated as linear programs (e.g., Kidd *et al.*, 1966; Ware and Clutter, 1971, or Johnson and Scheurman, 1977) and were applied extensively to the National Forest System (Kent *et al.*, 1991). Although these models could specify when and how much of a certain analysis area (an aggregate forest area with the same forest type, site class, and initial age-class) should be cut to best meet some objectives, they had limited capability to address spatial concerns (Tóth and McDill, 2008). Linear programming-based models could not tell the forest planner which stands on the ground should be treated and when. More recently, integer programming formulations were introduced to address these shortcomings by using 0-1 variables that provide more spatial control. Many of these models were built to restrict clear-cut sizes (e.g., Carter *et al.*, 1997 or Jones *et al.*, 1991) to minimize damage caused by the concentration of logging activities.

It is commonly assumed in forest management that a forested land-base consists of management units that can be represented as polygons on a map (Figure 2). The boundaries of these units are delineated by topography and the location of roads, trails and streams, and based on silvicultural and operational considerations. For the remainder of this paper, I will assume that management or cutting units, as well as stands, are synonymous.

In forest planning, the primary goal is to determine how, when, and which stands should be treated in order to best meet management objectives. For simplicity, we will consider only harvesting decisions here, which are to be made over a finite

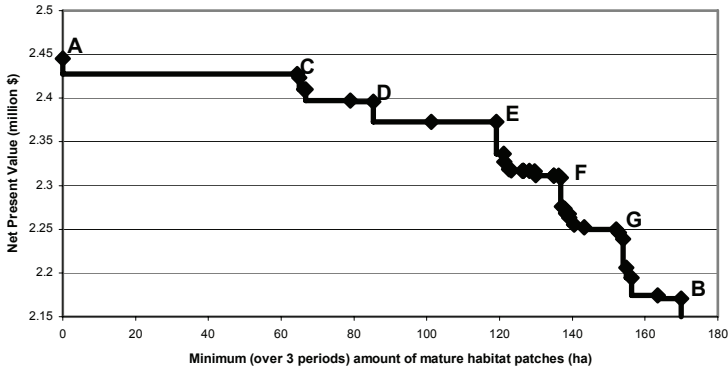


Figure 2. A hypothetical forest comprising 50 management units. Each unit is represented as a polygon and is grey-scaled based on age; units with older stands are assigned a darker color. The top three figures in each polygon indicate the unit ID, initial age-class, and the planning period when the units should be harvested.

planning horizon. The length of the planning horizon is typically 50 to 150 years in North America and it comprises planning periods that are 5, 10, or 20 years long. In the simplest case, we would like to know which stands should be cut in each planning period to maximize profit, given a set of sustainability and production constraints. Since the question of whether or not to cut a certain unit in a certain planning period is a “yes or no” question, the harvesting decision can be modeled using a binary, or 0-1 variable. For example, x_{it} could denote the choice of whether or not stand i should be cut in period t . We can say that x_{it} takes the value of one if stand i is to be cut in period t , otherwise it takes the value of zero. These choice variables, along with others representing decisions such as whether or not to build a road link to access a stand, or if a stand should be selected for preservation or not, can be structured into a linear system of inequalities. Forest planning models typically include timber volume or revenue flow smoothing constraints, target inventory or target age-class distribution constraints, and many other timber or non-timber restrictions. One or more objective functions can accompany the constraint set, defining management goals such as profit maximization, mature forest habitat conservation, carbon sequestration, and so on. Together, the set of production and sustainability constraints and the objective functions form a spatially-explicit harvest

scheduling model, which is technically a mathematical program. If all the inequalities and the objective functions are linear, and the variables are binary, then the harvest scheduling model is a 0-1 program. In this paper, the focus is on those 0-1 programs that have more than one objective function.

The optimal solution of a multi-objective 0-1 program is a finite set of vectors (consisting of the values of the x_{it} variables) that define a non-convex set of objective function achievements. This unique, non-convex but finite set of solutions can be represented graphically and is called the *efficient frontier*. The curve on Figure 1 is one example of an efficient frontier derived by solving the harvest scheduling problem depicted in Figure 2.

Solving multi-objective 0-1 programs is not trivial primarily because of the non-convexity in the objective function values. This non-convexity is a result of the discrete, binary nature of the choice variables; the management units can either be cut or not—partial harvesting is assumed to be operationally infeasible. Several multi-objective programming techniques have been developed to handle this non-convexity. The Weighted Method (Geoffrion, 1968), the ϵ -Constraining (Sadagopan *et al.*, 1982), and the Tchebycheff Metric-based methods (Eswaran *et al.*, 1989) are some well-known algorithms. Tóth *et al.* (2006) have also developed a method, called Alpha-Delta (named after the two parameters used in the algorithm), that tested well against traditional techniques on a bi-objective, spatially-explicit harvest scheduling problem (Tóth and McDill, 2008). Alpha-Delta was able to scan the entire efficient frontier quicker in terms of computing time than the other methods. Tóth and McDill later have extended Alpha-Delta and the three techniques mentioned above to handle three or more objectives simultaneously. The modified Weighted Method performed the best in approximating the efficient set within a given timeframe by generating the greatest number of efficient solutions along the length of the frontier. Alpha-Delta, on the other hand, was able to provide solutions more densely, but, as a result of this density, it progressed at a slower pace along the frontier than the Weighted Method.

For mathematical reasons, the Weighted Method cannot identify solutions other than corner points of the convex hull of the efficient set. Non-corner solutions are called *non-supported Pareto-optima* (e.g., Point D in Figure 1) and might be valuable in decision making if *supported* solutions (such as Points A, E, G, or B in Figure 1) are too few and far between. Alpha-Delta can identify non-supported solutions, hence the greater solution density along the frontier. Tóth and McDill recommend applying the Weighted Method first to obtain a rough estimate of the frontier, and then, based on stakeholder input, focusing on one or more smaller sections of the efficient set where more solutions can be explored using the Alpha-Delta method.

These multi-objective optimization techniques are computationally very expensive because at each iteration of the algorithms one or more 0-1 program must be solved, and these are often quite challenging. Therefore, the computational performance of the respective methods must be extensively tested.

It is important to add that multi-objective forest planning problems have traditionally been treated in one of two ways. The first option is to select one objective as the objective function and to model the other objectives as constraints. One must define the constraints by setting up minimum or maximum restrictions on the associated objectives. Goal programming is another, more sophisticated way of dealing with multi-objective forest planning problems. See Field (1973), Mendoza (1987), Roise *et al.* (1990), or Rustagi and Bare (1987) for applications in forestry. Again, goals or targets must be set up for each objective, but now, either the weighted sum of deviations from these targets is minimized, or each deviation is minimized individually in a pre-emptive order. In either case, the decision makers set up the targets for each objective. This could be trivial in situations where a given net revenue must be generated or one has a very clear idea of how much habitat must be present to ensure the survival of a species. However, it is often difficult to specify these requirements, primarily because the problems tend to be too complex, making it impossible to predict what can and cannot be done with the resource. It is difficult to determine what should be without knowing what could be. The

requirements might be infeasible, or perhaps much more could be produced than is actually required, at no additional cost. Multi-objective techniques can overcome these shortcomings at a higher computational cost.

In the remainder of this paper, I will propose two areas where knowing the efficient set of forest management alternatives could be especially useful. These are conflict resolution and the valuation and sale of non-market forest benefits.

3. Conflict Resolution

Suppose there are two interest groups with stakes in managing a hypothetical forest for which the set of Pareto-optimal alternatives were identified and are displayed in Figure 1. Suppose that one group is an industrial organization with timber interests and the other is an environmental NGO that wishes to preserve as much mature forest habitat as possible. Clearly, the former group is likely to promote Alternative A, while the latter group is likely to promote Alternative B. Consensus is unlikely without knowing the possible compromise solutions that exist between these two extremes. The timber industry might only focus on generating alternatives that would maximize its profits, while the environmental groups might only want to identify harvesting activities that would not threaten the realization of maximum mature forest habitat area. Would the timber industry be willing to forego \$20,000 in profit to achieve an increase of 65 ha of mature forest habitat in large contiguous patches? They might. Would the environmental groups accept that solution knowing 170 ha of habitat could also be preserved? Would the timber industry forego even more profit to ensure even more habitat? We don't know. We do know that consensus is much less likely without a range of compromise alternatives at hand.

Visual representations of the alternatives and their impacts on achieving the predefined management objectives could facilitate communication between the various stakeholders. Impacts of logging on certain habitat qualities are sometimes hard to assess by using only numerical values. Figure 3 demonstrates how four distinct alternatives can be compared both visually and analytically based on

achievement values. Forest landscape visualization software could be linked to the efficient frontier to incorporate the aesthetic impact of the alternative options.

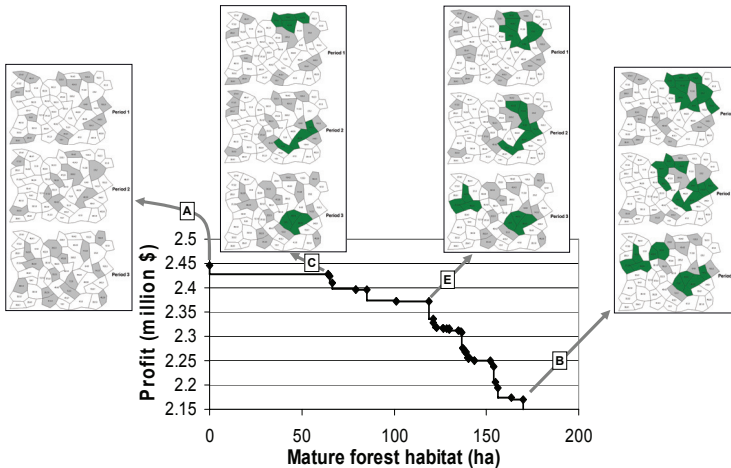


Figure 3. One way to demonstrate the Pareto-optimal alternatives to stakeholders is to visually link the spatiotemporal management plans and their impact on the landscape to the numerical achievement values on a coordinate system. Each alternative is depicted by three maps showing which stands are to be cut (grey polygons) in each of the three planning periods and which areas will form large patches of mature forest habitat (green polygons) as a result.

The knowledge and the visual representation of the efficient frontier can facilitate, but cannot guarantee consensus. Other consensus building tools, such as the Delphi method (Delbecq *et al.*, 1975) or the Nominal Group Technique (Delbecq *et al.*, 1975), might have to be used in concert with multi-objective programming to achieve the most desirable outcome. It is also important to mention that when more than three conflicting objectives are present, the visualization of the alternatives can be very challenging. See Figure 4 for one example of Pareto-optimal alternatives with respect to three objectives.

4. Valuing and Selling Non-Ttimber Forest Sservices

Managed forests produce a range of non-market environmental benefits for society and for individuals. Among many others, these benefits include habitat for wildlife, clean water, and carbon sequestration. Putting a price-tag on these benefits

and selling them like *private goods* is a hard task primarily because of their associated *non-excludability* and *non-rivalry*. Non-excludability arises when no one can be excluded from enjoying a good or service even if they do not pay for the benefit (Pagiola *et al.*, 2004). Non-rivalry occurs when purchasing a certain amount of a good does not reduce its availability to others (Pagiola *et al.*, 2004). In sum, many of the non-timber forest services are *public goods* and are hard to sell on the market. Survey methods like *contingent valuation* are not particularly useful for putting a dollar value on these goods because of the gap between the stated and revealed preferences of consumers. People tend to place a higher value on environmental benefits than they are in fact willing to pay. Thus, relying on stated preferences could lead to poor decisions and poor policies. In this section, I will argue that multi-objective programming could be used as a platform to sell non-market forest services.

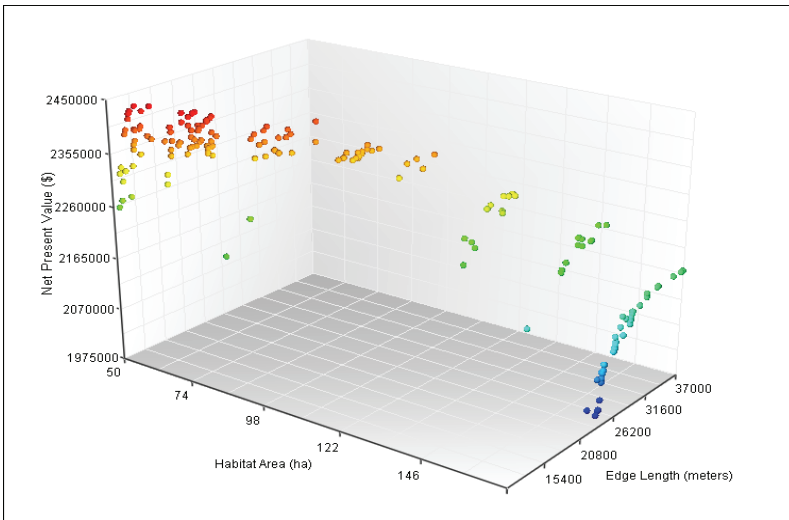


Figure 4. Visualizing solutions with respect to three objectives. Each solution is color-coded with red indicating solutions that will yield the highest profits, versus blue indicating alternatives that will produce the least profit but the resulting patches will contain as much interior mature forest habitat as possible.

As mentioned earlier, by optimizing harvesting decisions, multi-objective programming tools can demonstrate the quantities of services that can be produced

by a forest over a given period of time and the opportunity costs associated with the production of these services. Depending on the underlying tradeoffs and production possibilities of the resource, significant quantities of environmental services could be produced by foregoing only limited amounts of profit. Consider for example Alternative C versus A in Figure 5. For only \$17,660, more than 60 ha of mature forest habitat could be realized in large patches. This is clearly a favorable tradeoff. Compare this to the tradeoff between Alternative C and E (Figure 3). Much more profit must be foregone to get another 60 ha of habitat. The degree of the tradeoff can vary from one alternative to another, and can also vary by problem. Some forest planning situations can give rise to more advantageous tradeoffs than others, and it is impossible to predict and quantify these tradeoffs without a rigorous analytical tool. This is one reason why quantifying these tradeoffs might be worthwhile for the landowner. Potential buyers of environmental forest services are more likely to pay opportunity costs if they can purchase substantial quantities of services for a low price. They can only do that if the landowner's opportunity costs are sufficiently low. If the hypothetical landowner of the forest in Figure 2 does not know that Alternative C exists, he might not consider giving up Alternative A.

Knowing the exact opportunity cost structure that is associated with producing various amounts of environmental services in a given forest property puts the landowner in a position where he can make informed business decisions. Three different scenarios might exist if he wants to sell Alternative A for C. The first is to simply argue that it would cost him \$17,660 in lost revenues to produce the 64.4 ha of mature forest habitat in large patches. Since both Alternative A and C are linked to spatially-explicit forest management plans, he would be able to back up his argument with tangible data and a production plan. The government is more likely to compensate him for the financial loss if it can monitor whether the purchased service is duly produced or not. This could be achieved by tracking implementation of the associated plan, which is provided by the multi-objective optimization tool discussed above. If a departure occurs, the landowner could be held responsible, providing a certain level of assurance for the purchaser. Having the spatial forest

plans in hand would help the landowner as well because he would know exactly what harvesting operations need to take place on the ground and over time in order to deliver the purchased services.

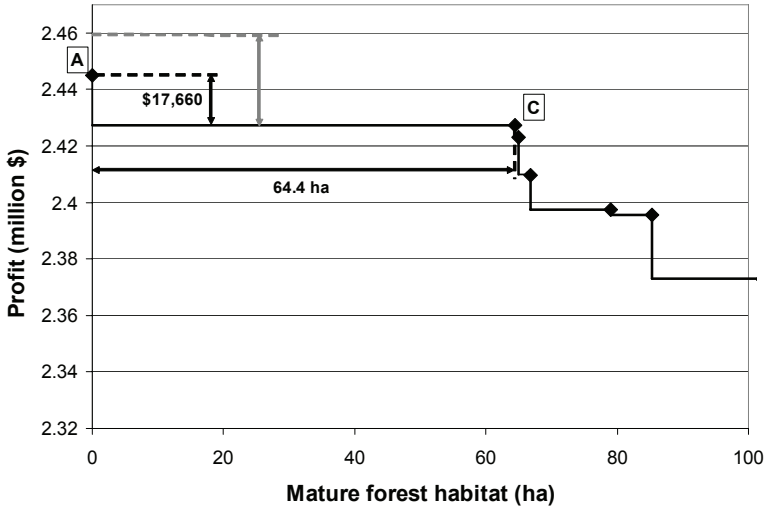


Figure 5. A decision tool to sell 64.4 ha of mature forest habitat.

Another marketing option might exist for the landowner if one or more of the services he intends to sell have a functioning market and a market price. Carbon or biodiversity credits might eventually become such private goods. The landowner could use the market price as a benchmark against which he could compare his opportunity costs and decide if it is worth switching the alternatives and selling the service or not. Again, the associated spatial production plans could serve as a monitoring tool for the buyers to evaluate the transaction. The grey dashed line and the arrow in Figure 5 illustrate a hypothetical situation when the market price (in this case, \$500 per hectare for mature forest habitat) would make it profitable for the landowner to sell.

The third option is auction. The landowner could put all the Pareto-optimal management alternatives (which define the production levels of the non-market services) up for bid. The opportunity costs that are associated with each alternative, plus the sales and administrative costs, could serve as the reserve prices. Unlike in

conventional auctions, however, the environmental credits would not go to the highest bid, rather to the bid that most exceeds the reserve price. Accordingly, the lowest cost alternative that yields the purchased amount of services would be implemented. The non-market services could, of course, be sold in bundles. This might be advantageous for the landowner in a situation where many services can be produced simultaneously at a cost not much higher than that of producing the services individually. Again, using the proposed multi-objective programming tool, the landowner could guarantee that the purchased outcomes would be duly produced by supplying the spatial production plans to the buyer. This way, the buyer(s) can monitor implementation of the plan, assuring the desired outcomes. Similarly, the landowner will know exactly what harvesting operations need to take place on the ground and over time in order to deliver the purchased services.

5. Conclusion

In this paper, I have demonstrated how the multi-objective programming tools developed and tested in Tóth *et al.* (2006), Tóth and McDill (2008), and elsewhere could be used to facilitate consensus in forest management and to realize non-market forest services. The power of the tool lies in its capability to identify Pareto-optimal forest management alternatives in the form of spatially-explicit plans, along with the associated tradeoffs and opportunity costs. This paper provides a theoretical proposition, but the techniques ultimately must be applied to on-the-ground forest planning and tested with real constituents.

Acknowledgements

The author thanks the Hyogo Science and Technology Association for partially funding this study.

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森林管理における空間的トレードオフによる
コンセンサス確立とノンマーケットサービスの評価
トース・サンドール

要約：本研究は競合する森林管理目的に関わる空間的なトレードオフの定量化に関する研究を要約する。"空間的トレードオフ"とは、異なる管理目的を空間的に解決することを示す。その技術は森林の空間的性質を記述できる森林管理モデルに使用され、様々な市場財・非市場財の生産目的に関して、パレード最適な伐採計画を特定することができる。本論文では、森林資源のトレードオフについてここで使用できる情報と生産可能曲線が如何に管理オプションの折衷案を提供し、競合する興味を持ったステークホルダーの間でコンセンサスを築き、そして、森林環境サービスの認識と市場性を把握させるかについて、論証する。

キーワード：伐採計画, 空間的最適化, ノンマーケット森林サービス, 競合解法