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Dealing with Ecological Objectives in the Monsu Planning System

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Abstract. The article describes some approaches to incorporate ecological objectives into numerical forest planning when using the Monsu software. Monsu first simulates alternative treatment schedules for all stands in the planning area, over a user-specified planning horizon. It then seeks the best combination of stands' treatment schedules using numerical optimisation. Management objectives are included in the optimisation model either as objective variables or constraints. The ecological variables that Monsu can calculate – and which can therefore be considered in optimisation – include (1) ordinary but ecologically oriented forest characteristics such as deadwood volume and area of old forest, (2) a special biodiversity score calculated for the forest, and (3) a set of landscape metrics. Landscape metrics are variables that measure the sizes, shapes, relative arrangement and connectivity of habitat patches as well as their total area. The most recent development of Monsu has concentrated on the use of landscape metrics, which measure the forest's ecological quality at the landscape level. A proper scale of ecological planning depends on the size of the territory of the species considered, and it seems that most of the keynote species have rather large territories and therefore require forest rather than stand level evaluations of ecological quality.
Key word: ecological planning; forest planning; heuristics; landscape metrics; numerical optimisation

Sumário. Este artigo descreve algumas aproximações para incorporar objectivos ecológicos no âmbito da utilização de métodos numéricos em planeamento florestal com recurso ao software Monsu. O programa começa por simular alternativas de gestão para todos os povoamentos na área objecto de planeamento, de acordo com um horizonte de planeamento especificado pelo utilizador. Em seguida procura a melhor combinação de alternativas de gestão para o conjunto de povoamentos com recurso à optimização numérica. Os objectivos de gestão são incluídos no modelo de optimização como variáveis-objectivo ou como restrições. O programa permite calcular – no âmbito do processo de optimização – o valor de variáveis ecológicas como (1) características florestais comuns com interesse ecológico (e.g. o volume de madeira morta ou a área de floresta com idade avançada), (2) um indicador de biodiversidade na área florestal, e (3) um conjunto de métricas espaciais. As métricas espaciais são variáveis que quantificam a dimensão, a forma, o arranjo espacial e a conectividade de manchas de habitat bem como a área total ocupada por estas manchas. Os desenvolvimentos mais recentes no programa Monsu focaram a utilização de métricas espaciais para estimar a qualidade ecológica da floresta ao nível da paisagem. A escala apropriada para o planeamento ecológico depende da dimensão do território das espécies consideradas. A generalidade das espécies focais ou indicadoras distribuem-se por territórios vastos o que sugere que a estimativa do valor ecológico se deva

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fazer à escala da paisagem e não do povoamento.
Palavras-chave: planeamento ecológico; planeamento florestal; heurísticas; métricas espaciais; optimização numérica

Résumé. L'article décrit quelques approches pour incorporer des objectifs écologiques à la planification numérique de la forêt en utilisant le logiciel Monsu. Monsu simule d'abord les alternatives de gestion pour tous les peuplements forestiers dans l'aire de planification, au-dessus d'un horizon de planification personnalisé par l'utilisateur. Il cherche alors la meilleure combinaison d'alternatives de gestion, pour l'ensemble des peuplements forestiers, en utilisant l'optimisation numérique. Les objectifs de gestion sont inclus dans le modèle d'optimisation comme des variables-objectives ou de restriction. Les variables écologiques que Monsu peut calculer - et qui peuvent donc être considérées dans l'optimisation – incluent (1) caractéristiques forestières communes avec l'intérêt écologique (volume de bois mort ou l'aire de forêt vieille), (2) un indicateur de biodiversité calculé pour la forêt, et (3) un ensemble de métriques de paysage. Les métriques de paysage sont des variables qui mesurent les tailles, les formes, l'arrangement spatial et la connectivité des pièces rapportées d'habitat aussi bien que leur surface totale. Les développements plus récents de Monsu sont concentrés sur l'utilisation de la métrique de paysage, qui mesure la qualité écologique des forêts au niveau du paysage. L'échelle appropriée de la planification écologique dépend de la taille du territoire des espèces considérées, et il semble que la majeure partie des espèces principales soit distribuée pour des territoires plutôt grands, et suggère donc que l'estimative de la valeur écologique soit faite à l'échelle du paysage et non du peuplement forestier.
Mot clé: planification écologique; planification forestière; heuristique; métrique de paysage; optimisation

Introduction

Ecological forest management objectives have become important and even "obligatory" in Finnish forestry. Ecological objectives in forest planning aim at retaining or improving the biodiversity of the forest. Forest biodiversity is retained if the populations of all forest-dwelling species remain viable. Forestry legislation sets the minimum standards for ecologically acceptable forest management. Forest certification and international agreements set additional requirements that do not necessarily force the forest owner to certain type of management, but can still be seen as outcomes of normative forest planning.

The means devised by normative planning for ecologically sound forest management include delineation and cautious treatment of so-called key biotopes, leaving groups of old trees in clear-felling areas (to become eventually large-sized dead trees), and setting aside larger ecologically important areas (like Natura 2000 areas), among others. This kind of enforced ecological orientation in forest management is an example of exogenous planning (KURTTILA, 2001); the ways in which ecological objectives are pursued are not devised in planning but instead they are given exogenously before the onset of planning. The shortcoming of the exogenous approach is that forest management may be inefficient: the maintenance of viable populations is not guaranteed, and the loss in other management objectives may be unnecessarily high.

Another way to deal with ecological objectives is endogenous planning with voluntarily set targets. This means that the ecological targets are given casewise by the forest owner or other decision-makers, after which forest planning tools are used in such a way that the targets are fulfilled with a minimum loss to other management goals. The means to achieve ecological targets are not given exogenously but they are found as a solution of a forest planning problem formulated separately for every planning situation.

This article discusses different ways to integrate ecological objectives in this kind of endogenous goal-based forest planning. The article describes the possibilities available in a forest planning software called Monsu. At the same time, the article is a reasonably complete review of recent approaches to integrating ecological and economic goals in numerical planning that have been tested in Finnish forest planning research.

Monsu software

Simulator

Monsu is a calculation and planning program for multiple-use forestry. In addition to timber yields, it calculates variables describing non-wood forest products and services like berry and mushroom yields, and scenic beauty and recreation scores. In the recent developpment of the package, much attention has been paid on improving its capabilities in ecological planning.

The forest under planning is divided into compartments, and each compartment is inventoried in the field. The field data are imported to a compartment database. In addition to living trees, also dead trees can be inventoried and input to Monsu. This possibility was included because dead trees are considered important for biodiversity.

In the first step of forest planning, alternative treatment schedules are simulated for the stand compartments. All combinations these schedules form the decision space from which the best decision should be selected. Every treatment schedule is described by treatments attached to it, timber removals, and development of the growing stock characteristics. The development of deadwood is also simulated. The deadwood of a stand consists of the inventoried cohorts as well as all new cohorts resulting from mortality. Simulation of deadwood development means partitioning mortality into downwood and standing deadwood (snags), simulating the falling-down of snags, and changing the decomposition stage of each cohort as a function of years since death.

Another set of variables calculated for different treatment schedules are stand-level habitat suitability indices (HSI) for certain keynote or umbrella species. These indices are based on user-specified formulas, and they describe how suitable the stand is as a habitat patch of the species. At the moment, there are formulas for just a few species but more may be added when required. The HSI values can later be used to calculate various landscape metrics that can be used as landscape-level ecological objectives.

Every state of every treatment schedule is described by variables telling whether or not the stand is economically or biologically old. The limiting age is different for different species, which means that the limit is calculated separately for every stand based on species composition. These binary old-forest variables make it possible to use the area of old forest as an objective or constraining variable in numerical optimisation.

Planning model

The second stage of planning consists of formulating a planning problem (planning model) and solving it. For this, Monsu has a planning model writer and various optimisers. The planning model writer combines information on decision maker's objectives, on one hand, and production possibilities of the forest, on the other hand. Information about objectives is asked directly from the decision-maker whereas information about production possibilities comes from the simulated treatment schedules of stands, which in turn are based on inventory data, models, and instructions that guide the simulation.

Monsu is able to write linear programming and goal programming models, as well as utility theoretic problem formulations. The utility theoretic problem formulation is the most versatile and most interesting from the standpoint of ecological planning. The problem looks as follows:

Maximize

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

subject to

$$q_i = Q_i(\mathbf{x}) \quad i = 1, \ldots, I \quad (2)$$

$$\sum_{k=1}^{N_n} x_{kn} = 1 \quad n = 1, \ldots, N \quad (3)$$

$$x_{kn} = \{0,1\} \quad (4)$$

where U is the total utility, I is the number of management objectives, a_i is the importance management objective i, u_i is a sub-utility function for objective i, and q_i is the amount of objective i. Q_i is an operator that calculates the value of objective i, $\mathbf{x}$ is a vector of binary decision variables (x_{kn}) that indicate whether stand n is treated according to schedule k, N_n is the number of alternative treatment schedules in stand n, and N is the number of stands.

The objective variables (q_i) can be any functions of decision variables ($\mathbf{x}$). The values of objective variables are calculated with "operators" or routines programmed in Monsu. This means that optimisation is not restricted to objectives that are linear combinations of decision variables. Because the utility theoretic problem formulations go beyond the capabilities of linear programming, they are solved with heuristics. Optimisation proceeds so that the heuristic optimisation algorithm, once provided with an initial solution, makes changes in the combination of schedules that are currently in the solution, and calls a calculation routine that first calculates the values of objective variables using operators $Q_i(\mathbf{x})$ and then evaluates the total utility of the combination using Equation 1. The new utility value is passed back to the optimisation algorithm, the functioning of which depends on how good the new combination (new solution) is as compared to the previous one.

The sub-utility functions transform the absolute value of the variable measured in its own units to a relative sub-utility value. These functions are determined through the smallest possible, target level, and the largest possible value of the objective variable, and the respective priorities.

The heuristic optimisation algorithms of Monsu are programmed so that only one management schedule of a compartment at a time can belong to the solution. Therefore, constraints of Equation 3 need not to be checked during optimisation, and there is no need to consider the feasibility of solutions; all solutions including exactly one treatment schedule per stand are feasible, and only such solutions are produced during the optimisation process.

Heuristics

The heuristic methods currently available in Monsu are; random ascent heuristic, Hero, simulated annealing, tabu search, genetic algorithm and a combination of Hero and simulated annealing. The way they are used is shortly described in the following.

Random ascent

In random ascent (RA), an initial solution is produced by selecting a random treatment schedule for each forest stand from among the treatment alternatives generated for the stand. Then, a stand and one of its treatment schedules, which is not in the current solution, are selected randomly. The effect of the suggested change on the objective function value is calculated. If the selected treatment schedule improves the objective function value, it is included in the solution, otherwise not. The search procedure is stopped when the maximum number of trials, as specified by the user, is reached.

Hero

In Hero, maximization of the objective function (additive utility function) consists of two steps (PUKKALA and KANGAS, 1993). First, a random selection of a treatment schedule for each stand produces an initial solution. Second, the technique tests one stand at a time to see whether another treatment schedule would improve the objective function value. The stands and their treatment schedules are inspected sequentially. If increase is detected, the treatment schedule that improves the solution replaces the previous one. When all treatment schedules of all stands are examined in this way, the process is repeated until no schedules can be found that would further improve the solution.

Simulated annealing

The search process of simulated annealing (SA) resembles the process of RA. The difference is that SA attempts to avoid getting trapped in local optima by allowing random deteriorations in the objective function value. The moves that improve the value of the objective function are always accepted. Non-improving moves are accepted with a probability of $p = \exp(-(U_{New} - U_{Old})T_i^{-1})$, where T_i is the current "temperature", and U is objective function value (utility in Monsu). During the optimization process, the temperature cools (which imitates the cooling process of melted metal), according to a given cooling schedule. At high temperatures the probability for accepting inferior moves is rather high (the melted metal moves easily), but as the temperature decreases (the metal solidifies), the probability decreases. The user defines the cooling schedule by giving the starting and stopping temperature and a multiplier (<1) that leads to the new temperature prom the previous one. The user also specifies the number of iterations per temperature. The number of iterations can change during the cooling process, for example increase when the temperature cools.

Simulated annealing + Hero

In the combination of simulated annealing and Hero (SA+Hero) the idea of cooling and that of accepting inferior solutions are applied in the same way as in SA, whereas the neighbourhood is searched in the same way as in the Hero, i.e. sequentially. All moves that improve the objective function value are accepted. At every temperature, all schedules of all compartments are inspected once and sequentially after which the temperature is changed and the same process is repeated until a stopping temperature is reached.

Tabu Search

Tabu search (TS) uses search memory in the form of tabu lists. The lists control the search process by prohibiting the repetition of recent moves. The length of the tabu list defines the number of iterations when the schedule may not be included in or removed from the solution. As in previous techniques, the search process of TS starts from a random initial solution. Then, several candidate moves, i.e. randomly selected treatment schedules of random compartments, are produced. Among these moves, the best non-tabu move is made. If all moves are in the tabu list, the move that has the shortest tabu tenure is selected. However, an elite move, which is a move that produces the best solution so far, is always accepted. In Monsu, the length of the tabu list (duration of tabu tenure) is shorter for schedules that enter the solution than for schedules that are removed from the solution.

Genetic algorithms (GA)

Unlike the heuristic optimisation techniques described above, the search process of GA is not based on neighborhood search. Instead, GA is based on an initial population of solutions, their evaluation and their breeding. The terminology is also different: the alternative solutions are called parent chromosomes, which are processed by crossing over (combining parts of two or more chromosomes) and by mutation (random change in one or several genes, or compartments). These operations result in a new chromosome (offspring). In the incremental GA technique used in Monsu, the new chromosome replaces one initial chromosome. The updated group of chromosomes is called generation. One of the two parents of a new chromosome is selected with the probability proportional to ranking. The second parent is chosen randomly with an equal probability for all chromosomes. The removed chromosome is selected based on its objective function value, the probability of removal being inversely proportional to the chromosome's ranking.

Combinations and additions

Monsu allows the user to combine different heuristics in a few ways. An example of such a combination is the SA+Hero method described above. In addition, the solutions found by RA, TS, SA and GA can be used as a starting solution for a Hero search, with a result that some improvement can often be made. Another possibility is to produce some of the initial chromosomes of GA with Hero and RA.

A recent option is to use two-neighbourhood instead on one-neighbourhood in RA, TS, SA and Hero. This means that a move consists of changing the treatment schedule simultaneously in two compartments instead of one compartment as done in one-neighbourhood search. It seems that the use of two-neighbourhood improves the result especially in spatial problems when using the RA, Hero and SA techniques (Figure 1). Two-neighbourhood has been implemented in Hero so that one of the compartments whose management schedule is changed is selected sequentially but the other one randomly. This technique, which is a combination of Hero and RA, seems to work better in difficult problems than the basic techniques alone.

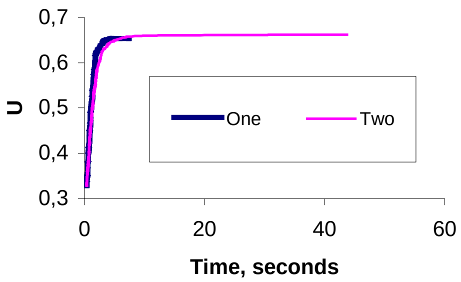

Figure 1 - Development of objective function value in a planning problem including a spatial objective (habitat–habitat boundary) when using one- or two-neighbourhood in the Hero method. The method converges quicker with one-neighbourhood but two-neighbour-hood finds slightly better solutions

Presentation tools

The solution that the optimisation finds is a candidate plan that must pass all the post-optimisation evaluations carried out by the decision-maker. Monsu includes some tools that ease the comparison of alternative plans and the evaluation of a single plan. One of them is a visual interface to interactive optimisation (Figure 2), which enables the user to see instantly how changes in the importance of goals (a_i in Equation 1) or in the form of a sub-utility function (u_i in Equation 1) affect the solution.

Another evaluation tool is the landscape visualiser. Monsu's visualisation uses computer-generated tree symbols drawn on a digital elevation model. The user may visualise the present forest or its future states after implementing the plan being evaluated. Visualisation is possible during an interactive optimisation session (Figure 2) or after it. The latest additions in the visualisation front are the VRML (Virtual Reality Modelling Language) files that Monsu can generate from a user-specified view. Internet programs like Internet Explorer and Netscape Communicator can interpret these files and generate the visualisations using photographs of trees. A good feature of the VRML visualisation is the possibility to move smoothly in the forest, which yields a virtual reality effect.

Dealing with ecological objectives in Monsu

Forest planning evaluates the future states of the forest. Therefore, a measure of ecological quality that describes the current status of the forest is insufficient for forest planning. For example, biodiversity assessments or plant species inventories are not enough for forest planning unless there are models for predicting the temporal change of the inventoried biodiversity characteristics and how forestry operations affect the change. However, assessments of the current forest may greatly help forest planning in specifying key locations and key species to be considered in planning calculations.

Figure 3 indicates some ways to numerically measure the ecological quality of forestland (PUKKALA, 2002). Out of these possibilities, Monsu enables the following ones: ordinary forest characteristics, thresholds, biodiversity scores, and landscape metrics.

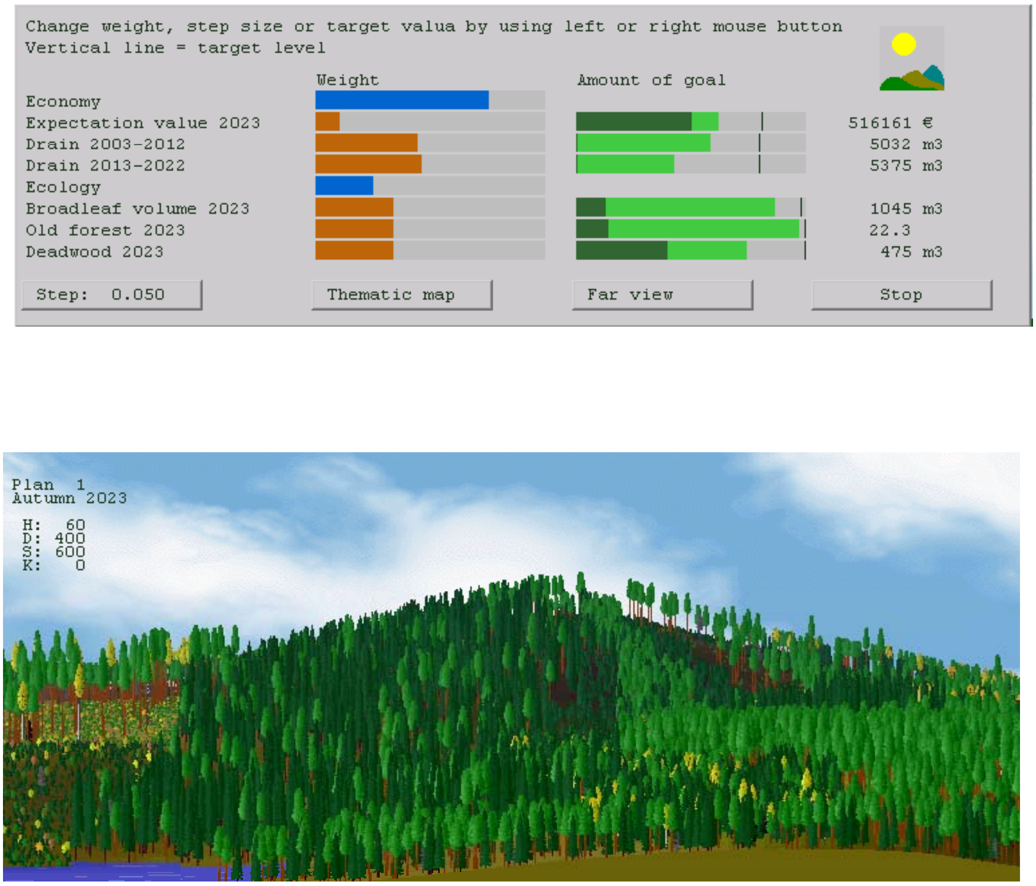

Figure 2 - The interface of visual interactive optimisation in Monsu (top). The user may change the weights of the goal groups (economy & ecology in this case) or individual goal variables, or the target levels of goals (vertical lines on the right). The problem is re-solved after every change. The Thematic map button shows the location of cuttings in the current solution and the Far view button allows instant landscape visualizations (bottom)

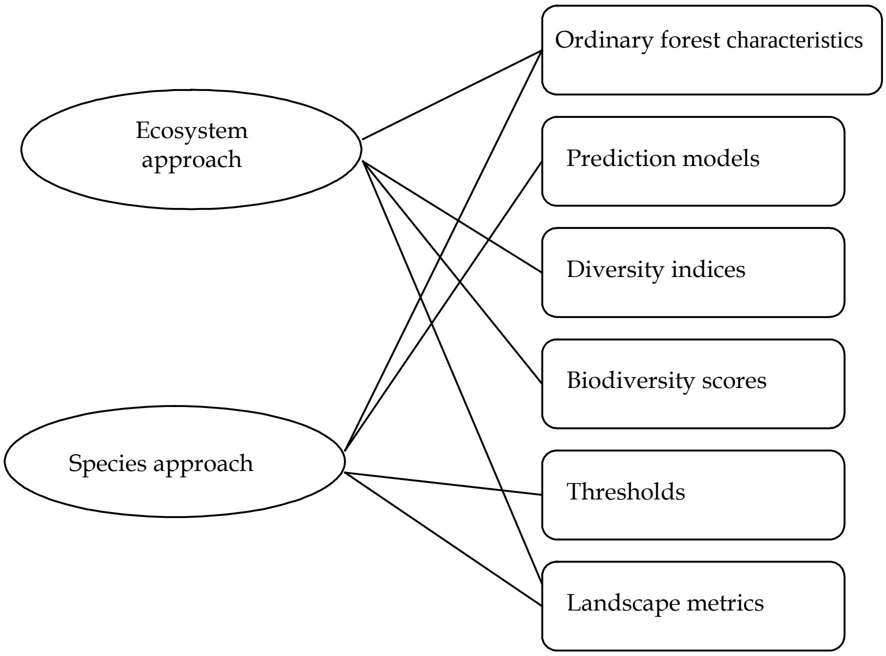

Figure 3 - Alternative ways to measure the ecological quality of forestland in numerical forest planning (PUKKALA, 2002).

Ordinary forest characteristics

Ordinary forest characteristics refer to measurable variables which correlate with biodiversity and are known in forest planning calculations. Examples of these are the area of forest older than a specified age, total volume of a certain tree species or species group, and volume of trees larger than a user-specified diameter. When using these kinds of forest characteristics as objective or constraining variables, the user may think of the forest biodiversity as a whole, or from the standpoint of the viability of a single species.

Thresholds

Thresholds mean that a special minimum or maximum value be specified for one or several ecologically interesting variables that the planning system can calculate. These thresholds may be used as constraints of LP models, or they can be included in the utility theoretic objective function maximised using heuristics, in the form of a step-wise sub-utility function. However, because the additive utility function (Equation 1) implies that utilities through different objectives are interchangeable meaning that a lack of threshold variable may be compensated for by good achievement of another objective variable, it might be better to use a multiplicative utility function when the threshold approach is adopted (the symbols are the same as in Equation 1):

$$U = \prod_{i=1}^{I} a_i u_i(q_i) \qquad (5)$$

The usability of ordinary forest

characteristics and thresholds in ecological forest planning is enhanced in Monsu by augmenting the list of forestry variables with ecologically-oriented descriptors such as deadwood volume, area of old forest, and amounts of economically unimportant (but ecologically important) tree species.

Biodiversity scores

Biodiversity scores represent the ecosystem approach and calculate an overall biodiversity score based on selected criteria and indicators (KANGAS and PUKKALA, 1996; PUKKALA *et al.*, 1997). The criteria and indicators, as well as their weights, are specified beforehand by experts or with experts' help.

Such forest characteristics are used as the criteria and indicators of biodiversity that limit or reduce it (KANGAS and PUKKALA 1996). In Finland, lack of old forest, deadwood and some broadleaf tree species are believed to reduce biodiversity. These forest features are therefore used as the criteria of the biodiversity score of Monsu (Figure 4). Each criterion is further measured by several indicators, which are variables that the planning system can calculate. The priorities of different quantities of an indicator variable are described by a sub-priority function, determined separately for each indicator (Figure 4).

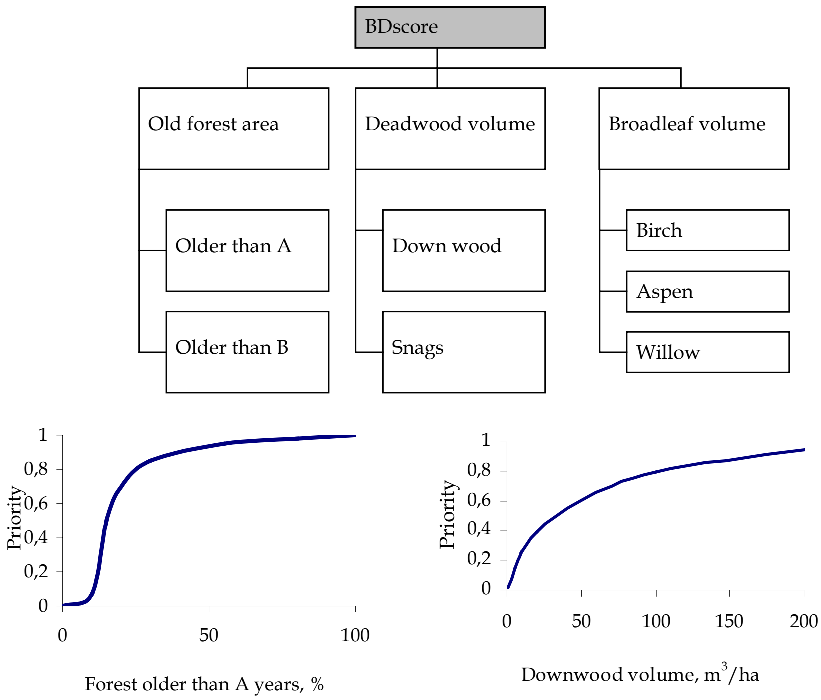

Figure 4 - Criteria and indicators of the biodiversity score of Monsu (top). Bottom: examples of functions for calculating sub-priorities for the indicators of the biodiversity score (PUKKALA, 2002)

A biodiversity score calculated in this way may be used as an objective variable in the numerical optimisation of Monsu. The exact way in which the score is calculated is specified in a parameter file that the user can modify. The parameter file includes the weights of different variables (indicators) contributing to the score, as well a sub-priority function for every variable. The easiness of modification of the formula allows the planners to use expert knowledge to formulate an index which is suitable for a particular planning case.

Landscape metrics

Landscape metrics are variables measuring the sizes, shapes, relative arrangement and connectivity of habitat patches as well as their total area (McGARICAl and MARKS, 1995). The use of landscape metrics usually corresponds to the species approach meaning that one or a few umbrella species are specified first, after which the ecological quality of the future landscape is evaluated from the viewpoint of these species.

The use of landscape metrics often requires that the stands be classified into suitable or unsuitable habitat patches. The stand level HSIs with thresholds specified for them can be used for this purpose. In the absence of a HSI formula it is possible to use any stand variable that is supposed to describe the stand's suitability for the species in question. At the moment, Monsu calculates HSIs for only a few species, but variables such as deadwood volume, stand age and volume of broadleaf species might be usable for some other species. Some landscape metrics, like the mean HSI or spatial autocorrelation do not require bisecting stands into habitats and non-habitats.

The landscape metrics currently available in Monsu are as follows:

- Non-spatial
  - Percentage of suitable habitat
  - Mean HSI
  - Location-weighted mean HSI
- Spatial
  - Spatial autocorrelation (Moran's I)
  - Percentage of habitat–habitat boundary (H–H boundary)
  - Percentage of habitat–non-habitat boundary (H–NH boundary)

The percentage of suitable habitat is the share of compartments in which the HSI exceeds a user-specified limit in a particular year. Mean HSI is the area-weighted mean of the stands' HSIs. Location-weighted mean HSI uses user-specified location weights, in addition to area weights, for calculating mean HSI. The location weights may be high for instance in known dwelling areas of the umbrella species considered in planning.

Spatial autocorrelation measures the general similarity or dissimilarity of neighbouring stands at the forest level (KURTTILA *et al.*, 2002). Moran's I is one measure for spatial autocorrelation, which is calculated by the following formula (CHOU *et al.*, 1990):

$$I = \frac{n\sum_{i=l}^{n}\sum_{j=l}^{n} a_i a_j W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=l}^{n}(x_i - \bar{x})^2} \qquad (6)$$

where n is the number of stands, x the value of variable of interest (for instance HSI), a the stand surface area, and $S_0 \sum_{i=l}^{n}\sum_{j=l}^{n} a_i a_j W_{ij}$ is the sum of the area-weighted spatial weights. In Monsu, the spatial relationship is defined by contiguity, i.e., W_{ij} is 1 if stands i and j are adjacent, otherwise 0. The values of Moran's I may vary between -1 and +1. A low value indicates that neighbouring stands within a landscape have different values of the stand variable of interest while a high autocorrelation value implies a smooth landscape with gradual changes between adjacent stands.

The habitat–habitat stand boundary refers to the physical distribution or spatial character of patches within the landscape (landscape configuration). Stand boundaries are bisected into two groups, separating two similar or dissimilar stands, according to a threshold value of HSI (KURTTILA *et al.*, 2002). Then, the proportion of habitat-habitat stand boundary of the total boundary length can be calculated. When the habitat–habitat stand boundary is maximised, suitable stands tend to be clustered into groups or corridors, which increases connectivity and decreases fragmentation.

When habitat–non-habitat stand boundary is maximised the edge zones of habitat patches will increase. Minimising habitat–non-habitat boundary decreases habitat edges resulting in less fragmented landscape. At the same time, the total habitat area may also decrease because habitat–non-habitat boundary is minimised either if all stands or none of the stands are suitable for the species in question.

The spatial information needed for Moran's I, H–H boundary and H–NH boundary is contained in an adjacency file, which tells which stands are neighbours and how much common border they have. This information must be produced before Monsu optimisations with suitable GIS or map programs.

Example of the use of landscape metrics

The use of landscape metrics is illustrated in a grid-like test forest of 900 compartments one hectare each. Compartment inventory data from North Karelia, Finland, were assigned to these compartments in a "systematic" way so that possible trends in the true forest from which the data were taken are also reflected in the grid-forest.

Alternative treatment schedules for a 60-year planning horizon were simulated for the compartments. Then, four planning problems were formulated, each containing a different landscape metric as a management objective. The other objectives aimed at harvesting 60000 m^3 during every 20-year sub-period of the 60-year planning horizon. The landscape metrics tested were percentage of flying squirrel habitat in 2063 (HSI > threshold), spatial autocorrelation of HSI in 2063, habitat–habitat boundary in 2063, and habitat–non-habitat boundary in 2063.

The results show that habitat–habitat boundary tends to connect habitat patches to larger areas and corridors (Figure 5, bottom left). Connectivity is reasonably good also when the non-spatial habitat percentage was used as the objective variable. The probable reason for this is positive autocorrelation in growing stock and site characteristics in the test forest (similar stands close to each other) with a consequence that stands that are suitable to become flying squirrel habitat are often close to each other.

Spatial autocorrelation yields a smooth landscape with large continuous areas of high or low HSI. Spatial autocorrelation only considers the similarity of compartments, and because two zero HSIs are equally similar than two ones, spatial autocorrelation can be maximised with either a low (like in this example) or high overall HSI depending on what is easier together with the other objectives within the forest under planning. Therefore, the use of spatial autocorrelation often requires another objective variable, like the percentage of habitat, to guarantee high enough total habitat area. The use of habitat–non-habitat boundary results in an extremely fragmented landscape.

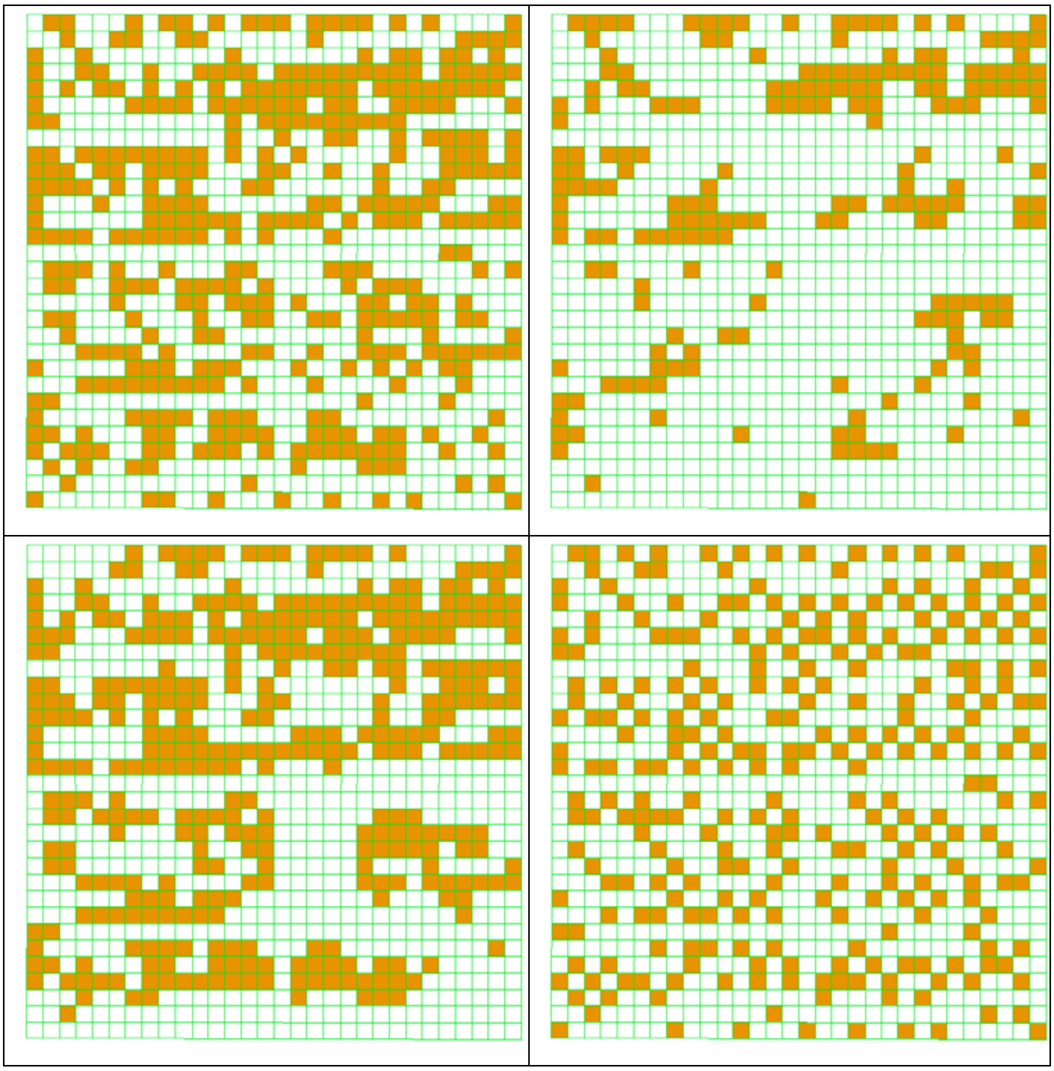

Figure 5 - Examples on the use of different landscape metrics as an objective variable in numerical optimisation. The shaded compartments are suitable habitat patches for flying squirrel in 2063. The landscape metrics used as objectives were: percentage of habitat (top left), spatial autocorrelation of HSI (top right), habitat–habitat boundary (bottom left), habitat–non-habitat boundary (bottom right).

Discussion

The article described some of the approaches tested recently in Finland to incorporate ecological objectives into numerical forest planning. The most recent research has concentrated on landscape metrics because of the belief that the landscape or forest scale is more appropriate than the stand scale for measuring the ecological quality of forest. In the recent research, there has been a shift from the ecosystem approach to species approach, which means that critical species are specified first, after which these species are taken under special scrutiny in the planning calculations. A proper scale of ecological evaluations depends on the size of the territory of the species in question, and it seems that most of the keynote species have rather large territories and therefore require forest level measures of ecological quality.

A suitable scale for measuring ecological quality is often much larger than a single private forest property. Because of this, forest plans should ideally be compiled for areas that cover many forest holdings. In this situation, the planning problem includes holding-specific goals specified by the owners, as well as ecological goals concerning areas larger than the holdings. Technically, this type of planning problem can be solved with similar tools as described above, only the objective function needs to be modified (KURTTILA and PUKKALA 2003):

$$U = w_l \sum_{j=1}^{J} a_j u_j(q_j) + \sum_{k=1}^{K} w_k \sum_{i=1}^{I_k} a_{ik} u_{ik}(q_{ik}) \qquad (7)$$

where w_l is the weight of the landscape level, J is the number of goals at the landscape level, a_j is the relative local importance of landscape level management objective j, u_j is a sub-utility function for management objective j, q_j is the value of objective j, K is the number of forest holdings, w_k is the weight of holding k, I_k is the number of holding-level management objectives in holding k, u_{ik} is a scaled sub-utility function in holding k for management objective i, q_{ik} is the value of objective i in holding k, and a_{ik} is the relative importance of management objective i in holding k. The study of KURTTILA and PUKKALA (2003) shows that tools for this king of planning that integrates the stand, holding and landscape levels exist and work technically well. Therefore, the greatest obstacle in numerical goal-based ecological forest planning in Finland is no longer the lack of technical tools but the unwillingness of forest owners to participate in simultaneous planning on several holdings. Another bottleneck is hesitation among foresters to adopt and use new planning methods and procedures.

This article discussed alternative ways to develop ecological objective variables for numerical optimisation. Another possibility in ecological planning is to affect the decision space from which numerical optimisation looks for good solutions. In Monsu, this can be done by modifying the instructions that guide the automated simulation of treatment alternatives for stands. It is for instance possible to lengthen rotation times to increase old forests and overall stand ages. Another possibility is to delay thinning to increase the amount of deadwood. In addition, it is possible to deny certain treatments in certain stands. If a stand is or contains a "key biotope" it is possible to prohibit all treatments or all strong treatments in this particular stand.

Another possibility, also available in Monsu, is to divide the forest into blocks or zones and specify the objectives separately for every zone. A known dwelling area of flying squirrel may for instance be given a high deadwood volume as an additional zone-specific goal while the other goals are pursued in the whole area.

In most cases, good ecologically oriented forest planning uses several approaches simultaneously. As seen from the above description, the Monsu software allows the user to combine the exogenous stand level "instruction-approach" and the zoning approach with the endogenous forest level optimisation approach. The result of such a planning is a combination of enforced and voluntary maintenance of viable populations of species in the forest, reflecting the priorities of both the society and individual forest landowners.

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